NEWCASTLE UNIVERSITY IN SINGAPORE

A DECISION-MAKING TOOL FOR REAL-TIME PREDICTION OF DYNAMIC POSITIONING RELIABILITY INDEX

CHARLES FERNANDEZ

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FACULTY OF SCIENCE, AGRICULTURE AND ENGINEERING
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ABSTRACT

The Dynamic Positioning (DP) System is a complex system with significant levels of integration between many sub-systems to perform diverse control functions. The extent of information managed by each sub-system is enormous. The sophisticated level of integration between sub-systems creates an array of possible failure scenarios. A systematic analysis of all failure scenarios would be time-consuming and for an operator to handle any such catastrophic situation is hugely demanding. There are many accidents where a failure in a DP system has resulted in fatalities and environmental pollution. Therefore, the reliability assessment of a DP system is critical for safe and efficient operation. The existing methods are time-consuming, involving a lot of human effort which imposes built-in uncertainty and risk in the system during complex operation.

This thesis has proposed a framework for a state-of-the-art decision-making tool to assist an operator and prevent incidents by introducing a new concept of Dynamic Positioning – Reliability Index (DP-RI). The DP-RI concept covers three phases, leading to technical suggestions for the operator during complex operations, which are defined as Data, Knowledge, Intelligence, and Action. The proposed framework covers analytics including descriptive, diagnostic, predictive and prescriptive analytics. The first phase of the research involves descriptive and diagnostic analytics by performing big data analytics on the available databases to identify the sub-systems which play critical roles in DP system functionality. The second phase of the research involves a novel approach where predictive analytics are used for the weight assignment of the sub-systems, dynamic reliability modelling and offline and real-time forecasting of DP-RI. The third phase introduces innovative prescriptive analytics to provide possible technical solutions to the operator in a short time during failures in the system to enable them to respond quickly and prevent DP incidents. Thus, the DP-RI acts as an innovative state-of-the-art decision-making tool which can suggest possible solutions to the DPO by using analytics on the knowledge database. The results proved that it is a useful tool if implemented on an actual vessel with diligent integration with the DP control system.

DECLARATION

This is to certify that

- the thesis comprises only my original work towards the PhD,
- due acknowledgement has been made in the text to all other material used,
- the reference to the author's own work which has been published in conference proceedings are indicated appropriately,
- the thesis is approximately 64,000 words in length, exclusive of tables, references and appendices.

Charles Fernandez
Faculty of Science, Agriculture and Engineering
Newcastle University Upon Tyne
July 2021

STATEMENT OF ORIGINALITY

The contents of this PhD thesis are the results of the original research unless otherwise stated and have not been submitted for a higher degree at any other university or institution. The results presented in this thesis have been obtained during the author's candidature under the supervision of Dr. Arun Dev, Dr. Rosemary Norman and Dr. Wai Lok Woo. The database used for the research was collected based on the real projects performed by DNV GL Singapore Pte. Ltd and it is confidential information. For validation purposes, the data of the DP 3 vessels (Semi-submersible drilling rig and Drillship) was used which was obtained during construction and operation phases which reflect actual offshore operating conditions. The PhD provided me with the ability to conceive and implement methodologies to demonstrate an understanding of how to conduct research at the forefront of digital transformation in Marine, Offshore, Oil and Gas industry.

The material presented in this thesis covers all results from the following conference proceedings papers and journal papers which are under review:

[1] Fernandez, C, Shashi Bhushan, K, Woo, WL, Norman, R and Dev, A.K. Year. ASME 2018 37th International Conference on Ocean, Offshore and Arctic Engineering, Madrid, Spain. Pages: 1-10. 17–22 June 2018 2018, 10.1115/OMAE2018-77267.

[2] Fernandez, C, Dev, A.K, Norman, R, Woo, WL and Shashi Bhushan, K. Year. ASME 2019 38th International Conference on Ocean, Offshore and Arctic Engineering, Glasgow, Scotland, UK. 9-14 June 2019 2019, 10.1115/OMAE2019-95485.

[3] Fernandez, C, Dev, A.K, Norman, R, Woo, WL and Shashi Bhushan, K. Year. ASME 2020 39th International Conference on Ocean, Offshore and Arctic Engineering, Virtual Conference. 3-7 August 2020, OMAE2020-18844.

[4] Fernandez, C, Dev, A.K, Norman, R, Woo, WL and Shashi Bhushan, K. "A novel decision-making tool using Long Short-Term Memory (LSTM) for time series prediction of Dynamic Positioning Reliability Index (DP-RI)". Ocean Engineering. Manuscript Number:OE-D-21-00456. Submitted in Feb 2021 and Status is Under Review.

[5] Fernandez, C, Dev, A.K, Norman, R, Woo, WL and Shashi Bhushan, K. "Resilience Management in Dynamic Positioning Vessels using a Prescriptive Analytics BERT Model as a Question Answering System". Knowledge Based System. Manuscript Number:KNOSYS-S-21-01649. Submitted in May 2021 and Status is Under Review.

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Through this journey to Doctor of Philosophy, I was fascinated to see how a simple idea could become more significant, more important, more extraordinary and more authoritative if determination and focus are persistent.

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LIST OF SYMBOLS

β	: Fraction of undetected failures that have a common cause
β_D	: Fraction that has a common cause of those failures that are detected by the diagnostic tests
τ	: Vector of control inputs
ŧ	: Test interval
σ	: Sigmoid activation function
λ	: Failure rate of a component/subsystem
λmax	: Eigenvector maximum
λ_{DU}	: Dangerous Undetected failure rate of a channel in a Subsystem
λ_{DD}	: Detected dangerous failure rate of a channel in a subsystem
$\otimes$	: Pointwise multiplication
$\oplus$	: Pointwise addition
$\odot\ \sigma^L(z^L)$	: Hadamard product
$\frac{\partial C}{\partial W_{jk}^L}$	: Gradient cost function
B^h	: $\{b_1^h, b_2^h, b_3^h \ldots\ldots b_q^h\}$ is the bias vector of the hidden layer
b^o	: Bias of the output layer
b_f, b_i, b_o and b_c	: Biases
$C(v)$	: Coriolis-centripetal matrix (including added mass)
$\tilde{C}_t$	: New candidate values
C_{t-1}	: Old candidate state
$D(v)$	: Damping matrix
f_t	: Forget gate
g_o	: Vector used for pre-trimming (ballast control)
$\widetilde{H}_t$	: New remember gate
K	: Keys matrix
M	: System inertia matrix (including added mass)
MRT	: Mean Repair Time
$MTTR$	: Mean Time To Restoration
MTTF	: Mean Time To Failure

m	: Number of components in the sub-system
n	: Number of sub-systems in the DP system
o_t	: output gate ()
PFD_{System}	: Average probability of failure on demand for DP system
$PFD_{sub-system}$	: Average probability of failure on demand for DP sub-system
PFD_{comp1}	: Average probability of failure on demand for components
Q	: Queries matrix
R(t)	: System reliability represented by exponential law
$RI(t)$	: Survivor Function or Reliability of DP system (DP-RI)
S_t	: Tanh layer to limit values to be between -1 and 1
T_1	: Proof test interval
T_2	: Interval between demands
t_{CE}	: Calculate the channel equivalent mean downtime
t_{GE}	: System equivalent downtime
U^f, U^i, $U^o$and U^c	: Input weights
V	: Values matrix
W^I	: $\{w_1^I, w_2^I, w_3^I \ldots\ldots w_q^I\}$ is the input weights matrix,
W^o	: $\{w_1^O, w_2^O, w_3^O \ldots\ldots w_q^O\}$ is the output weights matrix,
W^f, W^i, $W^o$and W^c	: Recurrent weights
W_n	: Weight or Priority Vector
w	: Vector of environmental disturbances (wind, waves and currents)
Y_j	: Actual values
$\widetilde{Y}_j$	: Predicted values
Z_t	: Remember and forgot gates are deleted by creating a new gate

ABBREVIATIONS

ABS	American Bureau of Shipping
AD	Adversarial Debiasing
ASOG	Activity Specific Operating Guidelines
Adadelta	Adaptive Learning Rate Method
Adam	Adaptive Moment Estimation
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AMS	Asset Management System
ANN	Artificial Neural Network
AO	Analog Output
API	Application-Programming Interface
ASICs	Application-Specific Integrated Circuits
AWS	Amazon Web Services
BERT	Bidirectional Encoder Representations from Transformers
BOP	Blow-Out-Preventer
BV	Bureau Veritas
CAMO	Critical Activity Mode
CAT	Customer Acceptance Test
CEOP	Calibrated Equalized Odds Postprocessing
CCF	Common Cause Failure
CCS	China Classification Society
CCSM	Crane Control System
CCTV	Closed-Circuit Television
CR	Consistency Ratio
DCS	Drilling Control System
DGPS	Differential Global Positioning System
DGNSS	Differential Global Navigation Satellite System
DI	Digital Input
DIR	Disparate Impact Remover

DNV GL	Det Norske Veritas Germanischer Lloyd
DO	Digital Output
DOF	Degrees of Freedom
DP	Dynamic Positioning
DP 1	Dynamic Positioning Class 1
DP 2	Dynamic Positioning Class 2
DP 3	Dynamic Positioning Class 3
DP-CAP	Dynamic Positioning – Capability Plot
DP-RI	Dynamic Positioning -Reliability Index
DPO	Dynamic Positioning Operator
DP vessel	Dynamic Positioning Vessel
E/E/PE	Electrical / Electronic / Programmable Electronic
EOP	Equalized Odds Postprocessing
EPC	Engineering, Procurement and Construction
EUC	Equipment Under Control
FAT	Factory Acceptance Test
FGS	Fire and Gas System
FMEA	Failure Mode Effects and Analysis
FMECA	Failure Mode Effects and Criticality Analysis
FS	Field Station
FSVAD	Flag State Verification and Acceptance Document
FTA	Fault Tree Analysis
FTRL	Follow the Regularized Leader
GCE	Google Cloud Engine
GCP	Google Cloud Platform
GPS	Global Positioning System
GPU	Graphical Processing Unit
GRU	Gated Recurrent Unit
GUI	Graphical User Interface
HIL	Hardware In-the Loop
HPR	Hydroacoustic Position Reference

HRA	Human Reliability Analysis
HSE	Health and Safety Executive
I/O	Input/Output
IaaS	Infrastructure as a Service
IACS	International Association of Classification Societies
IEEE	Institute of Electrical and Electronics Engineers
IMCA	International Maritime Contractor Association
IMO	International Maritime Organization
IMS	Information Management System
IoT	Internet of Things
IRS	Indian Registry of Shipping
IT	Information Technology
JSON	JavaScript Object Notation
KDD	Knowledge Discovery in the Database
KM	Knowledge Management
KR	Korean Register
LC	Learning Curve
LR	Lloyd Register
LSTM	Long Short Term Memory
MAE	Mean Average Error
MASS	Marine Autonomous Surface Ship
MCDM	Multi-Criteria Decision Making
ML	Machine Learning
MLP	Multi-Layer Perceptron
MRU	Motion Reference Unit
MT	Marine Technologies
NDU	Network Distribution Unit
NK	Nippon Kaiji Kyokai
NLP	Natural Language Processing
NMA	Norwegian Maritime Authority

NOPSEMA	National Offshore Petroleum Safety and Environmental Management Authority
OPP	Optimized Pre-processing
OREDA	Offshore and Onshore Reliability Data
OS	Operator Station
OSV	Offshore Support Vessels
OT	Operational Technology
PFD	Probability of Failure on Demand
PLS	Partial Least Squares
PMS	Power Management System
PRR	Prejudice Remover Regularizer
PSA	Petroleum Safety Authority
PWS	Portable Water System
QA	Question Answering
RBD	Reliability Block Diagram
RCA	Redundancy and Criticality Analysers
RCU	Remote Controller Unit
RDBMS	Relational Database Management System
RINA	Registro Italiano Navale
RMSE	Root Mean Square Error
RNN	Recurring Neural Network
RS	Russian Maritime Register of Shipping
RSF	Rich Subgroup Fairness
RW	Re-Weighing
SAP	Systems Applications and Products
SBE	Sequential Backward Elimination
SDP	State-Dependent Parameters
SFS	Sequential Forward Selection
SGD	Stochastic Gradient Descent
SIL	Safety Integrity Level
SIMOPS	Simultaneous Operations

SME	Subject Matter Expert
SoC	System on Chip
SQuAD	Stanford Question Answering Dataset
SR	Sampling Rate
SRNN	Simple Recurrent Neural Network
STCW	Standards of Training, Certification, and Watchkeeping
TAM	Task Appropriate Mode
TF-IDF	Term Frequency-Inverse Document Frequency
TPU	Tensor Processing Units
TSP	Time Series Prediction
UPS	Uninterruptible Power Supply
VCS	Valve Control System
VDR	Voyage Data Recorder
VFD	Variable Frequency Drives
WCF	Worst-Case Failure
WCFDI	Worst Case Failure Design Intent
WCSF	Worst-Case Single Failure
WOAD	World Offshore Accident Databank
WSOG	Well Specific Operating Guidelines
XML	Extensible Mark-up Language
YRAN	Yet Another Resource Manager

Dynamic Positioning System: *The equipment, and hence the ship, knows where it is at all times. It knows this because it knows where it isn't. By subtracting where it is from where it isn't (or where it isn't from where it is, depending on which is the greater), it obtains a difference or deviation. The DP system uses deviation to generate corrective commands to steer the ship from a position where it is to a position where it isn't. The ship arrives at the position where it wasn't; consequently, the position where it was is now the position where it wasn't. In the event that the position where it is now is not the same as the position where it originally wasn't, the ship will acquire a variation. The variation is the difference between where the ship is and where the ship wasn't. If the variation is considered to be a significant factor, it too may be corrected by the DP. The ship must not know where it was. The "the thought process" of the DP is as follows:- because the variation has modified some of the navigation information, it is not sure where it is. However, it is sure where it isn't and knows where it was. It now subtracts where it should be from where it wasn't (or vice versa), and by differentiating this from the algebraic difference from where it shouldn't be and where it was, it is now able to obtain the difference between its variation, the difference is called the error.....*

(Courtesy : Kongsberg)

1. Introduction

In today's world of challenging environments where offshore and marine vessels operate with high precision within metres of each other and with no options for mooring, the need for safe and reliable positioning is particularly important to prevent injury to people and damage to property. In this high pressure and intense environment, the potential for risk and the probability of accidents has increased. The consequences of loss of position can be severe, so the need for reliable and safer systems is more significant than ever [1, 2]. The Dynamic Positioning (DP) system is the only viable option for safe and reliable vessel position control [2, 3]. The Dynamic Positioning system has been under development since 1961 and as the oil and gas industry operates in deeper and deeper waters using vessels without Dynamic Positioning is not feasible. An ultra-deepwater development would be impossible without dynamic positioning. Today virtually all the offshore operations are one way or another dependent on Dynamic Positioning systems. For vessels with DP systems, the most critical safety incidents are loss of position and/or heading [4, 5, 3, 6]. Therefore, it is necessary to design DP systems to be fault tolerant and fault resistant i.e. to be more reliable [1]. This is to ensure that the complex vessel, operating in a harsh environment, could be safer, with greater reliability and efficiency.

With technological evolution, the Dynamic Positioning system diversified its application to various types of vessel including semi-submersible drilling rigs, drill-ships, self-propelling jack-up drilling rigs, Floating Production Supply and Offloading (FPSO), Offshore Support Vessels (OSV), pipe and cable-laying vessels, rock dumping vessels, shuttle tankers, crane and heavy lifting vessels, minesweeping vessels, dredging vessels, cruise ships, floating accommodation vessels/rigs and yachts [4]. DP is no longer just about positioning, but about following a predefined track or staying within a defined area. Loss of position / heading indicates that the vessel is not able to stay in the pre-defined stationary position or path. The loss of position may be due to drive off, drift off or a large excursion [7]. The reliability of DP systems plays a very important role in deciding on the complex offshore marine operation of vessels. The reliability directly depends on various aspects such as equipment selection, design, architecture, functionality, integration, verification, commissioning, operation, maintenance, codes, standards, rules and regulations [5].

1.1 Background

The DP System of a vessel involves complex interactions between a large number of sub-systems. Each sub-system plays a unique role in the continuous overall DP function for safe and reliable operation of the vessel [4]. The level of complexity and sophistication of DP systems has developed significantly over the last few decades. Recent technological advancement has enabled maritime vessels to operate safely and, at the same time, increased the level of autonomy and complexity. During regular operation, the main activities for the Dynamic Positioning Operator (DPO) are to monitor the DP system status and perform adjustment for the required positioning and heading. However, during complex operations or failures in one of the sub-systems, the DPO is forced into a critical situation and has to react within a limited time to fix the problem to prevent an accident. The primary causes for DP incidents are presented in Table 1-1, as reported by International Maritime Contractor Association (IMCA) from 1994-2019, which indicates that Human / Operator Error is one of the most significant contributors to DP related incidents in the Offshore, Marine, Oil and Gas industry [5].

Table 1-1 DP Sub-Systems failure rate acting as main / primary cause for DP incidents

Sub-Systems	**1994-2003**	**2005-2013**	**2014-2019**
DP Control System	53	91	104
Power System	37	83	81
Electrical	18	49	14
Propulsion/Thrusters	65	104	194
Reference System	90	126	84
Environment	33	34	23
Human / Operator Error	**75**	**125**	**99**

This trend, showing a continuous increase in Human / Operator Error is a big concern for the marine and offshore industries as the DPO plays a crucial role in the loop to handle any such situation to prevent an accident. In addition, the IMCA accident database shows that Human / Operator Error is the most significant contributor to secondary causes for DP incidents. It proves that there is a need for a support system to aid the DPO in preventing DP incidents when there is a failure in the sub-systems.

1.2 Description of Dynamic Positioning System

Dynamic Positioning Vessel (DP vessel) means a unit or vessel which automatically maintains its position and/or heading (fixed location, relative location or predetermined track) by means of thruster force [8]. DP vessels can be divided into different classes based on the design of the vessel to meet the industrial mission and its application. DP systems installed on a vessel are designed in compliance with classification society rules and they must be of robust design ensuring capability in

- Preventing loss of position
- Preventing loss of redundancy

The term DP system means the complete installation necessary for dynamically positioning a vessel comprising, but not limited to, the following sub-systems [8]:

- Power system
- Thruster system
- DP control system

In addition to the above system, there are other sub-systems which are integrated to perform the desired function. The complete overview of an advanced DP system is shown in Figure 1-1.

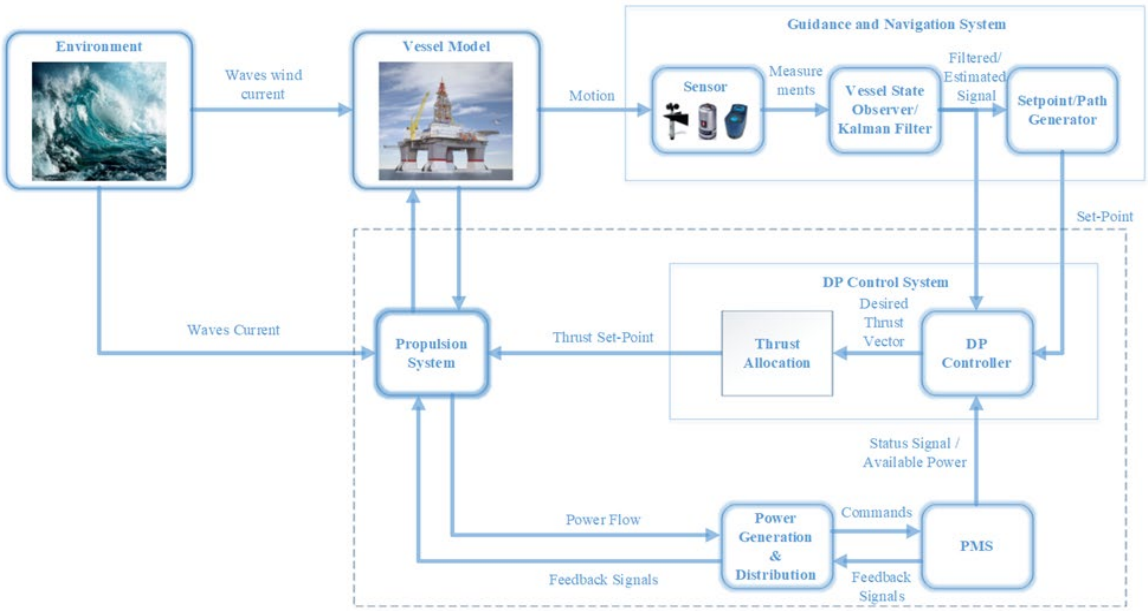


Figure 1-1 Complete overview of Dynamic Positioning System

The design of a DP system is made robust by considering the application of seven attributes below, in one form or another, to all sub-systems to enhance station keeping integrity.

- Independence
- Segregation
- Autonomy
- Fault tolerance
- Fault resistance
- Fault ride-through capability
- Differentiation

A DP vessel should have a sufficient level of station-keeping reliability. Reliability is a product of the quality of the equipment in the sub-systems and the vendor providing the sub-systems. The design and operation of it depends on the competence of the engineers who design and build, the engineers involved in testing and commissioning, the crew and the management who maintain and operate the vessel.

1.3 The Problem Statements

Traditionally, the reliability of a DP system is assessed during the design stage by methodologies such as Failure Mode Effects and Analysis (FMEA), Proving Trials, Hardware In-the Loop (HIL) testing, Site-Specific Risk Analysis, DP capability Analysis and during operation in annual trials to verify functionality. All these methods are time-consuming, involving a lot of human effort and notably, no analysis of previous accidents is indicated in the reliability assessment. It imposes in-built uncertainty and risk in DP systems during operation. It is evident that these risk assessments are insufficient, and factors considered for the safety of station-keeping reliability are too narrow.

The significant phases of the DP life-cycle include design, construction, commissioning, sea-trials and operation. In all of these phases, the system evolves, and changes are implemented for safe, reliable and efficient operation. Historically all the above traditional reliability assessment methods have been implemented in different phases for improving the design of the system. However, they have not made a significant contribution in preventing or reducing the number of accidents based on the DP incidents reports by IMCA over three decades.

Besides, these traditional reliability assessment methods have not demonstrated their ability to provide clear information on faults and provide appropriate solutions during operation. The analysis of existing reliability assessment methods revealed key drawbacks which are listed below [1, 9]:

- Lack of user knowledge and experience from previous incidents / accidents database.
- Lack of visibility of interdependencies between subsystems during failure scenarios.
- Lack of consideration of the relatively short reaction time available for an operator to take corrective actions. This led to unsafe or delayed decision making.
- Lack of inadequate co-ordination between decision-makers.
- Lack of suggestions and preventive measures to avoid any catastrophic failure in case of trivial shortcomings.
- Lack of simulation facility to evaluate a particular failure and its impact during complex offshore marine operation.

Figure 1-2 show the critical pitfalls of the conventional reliability techniques.

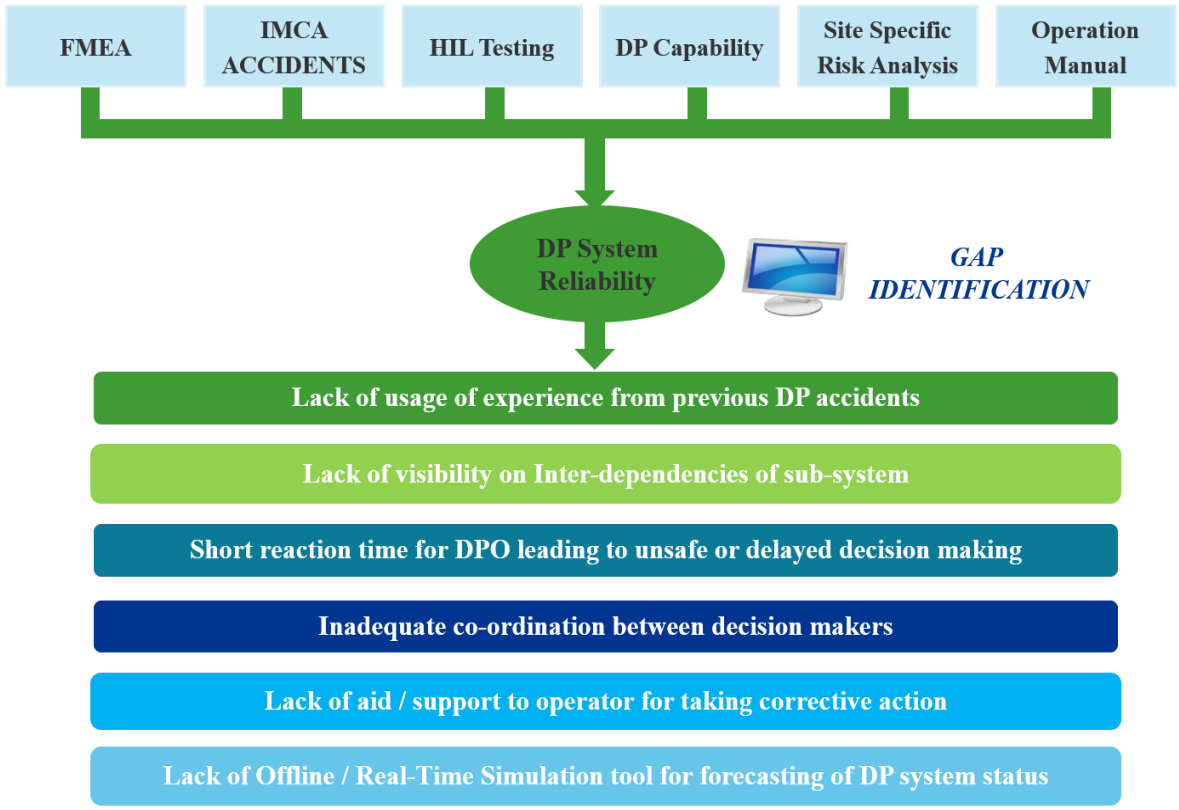


Figure 1-2 Traditional Reliability Assessment – Gap Analysis

The most critical problem in DP related accidents is the time required for the operator to identify the cause of the failure and take remedial action to prevent the failure leading to an accident. The critical point to consider is that preventing a failure from turning into an incident or accident can be achieved in one of two ways. One way is to increase the time by stretching the available time to prevent the incident and the second way is by shortening the time needed to solve the problem. There are five phases involved between fault initiation and final solution implementation: fault detection, fault identification, generation of solution strategy, solution implementation and system reaction [10]. The DP operator influences the time that is required to cover three of the phases, that is fault identification, generation of a solution strategy and solution implementation. The research will focus on developing an advisory support tool using an advanced deep learning neural network algorithm for processing the data from the sensors to forecast the reliability of the DP system to aid the operator in preventing DP incidents. Figure 1-3 shows the time period from the fault initiation to the accident.

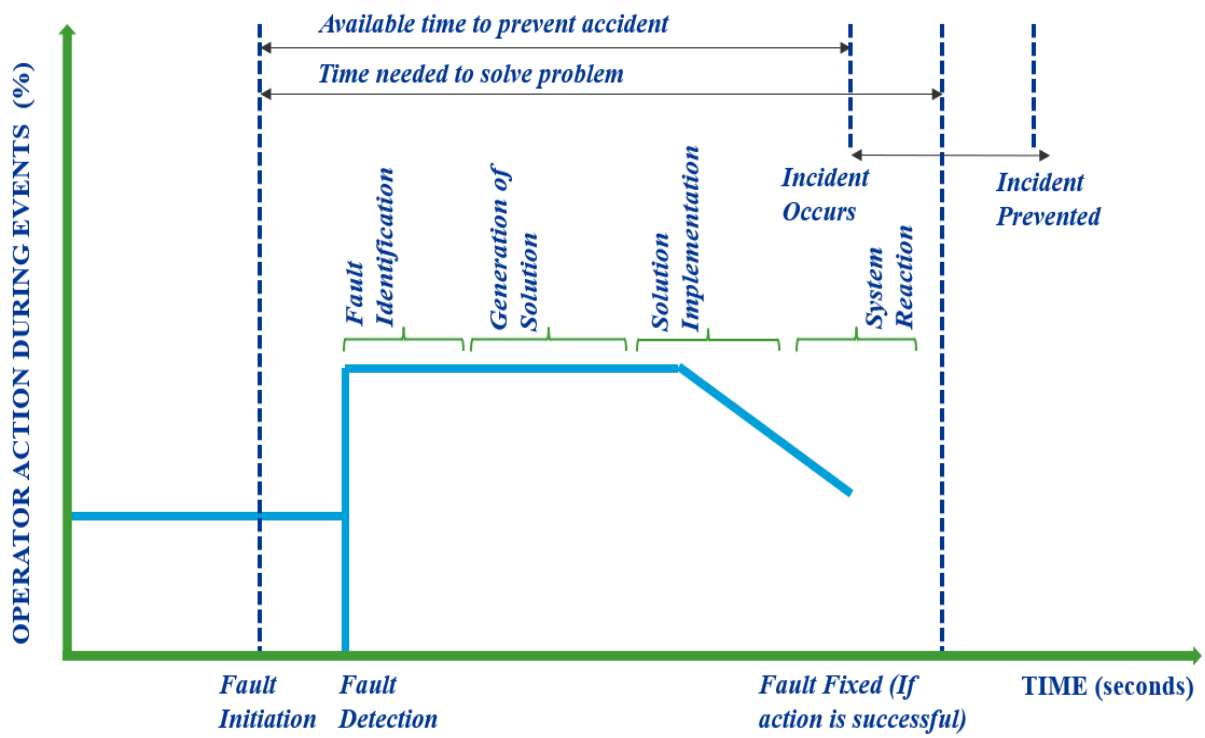


Figure 1-3 Timeline defintion from fault initiation to DP incident

Therefore, it was required to select an intelligent deep-learning algorithm which can perform real-time date time series prediction accurately and with fast response time. DP is a complex system operating in a highly dynamic environment. Reliability of a DP system requires the components of the system to be selected optimally and it factors in the reliability of the components which introduces new challenges to the existing approaches. To support self-optimisation, the reliability prediction should be conducted in near real-time which was not possible in the past because of processing limitations but now, with technological growth, it can be implemented quickly to develop a state of the art advisory tool to prevent offshore accidents and incidents.

1.4 Dynamic Positioning – Reliability Index (DP-RI)

The DP-RI concept is proposed to aid an operator with quantitative and qualitative representations of reliability of DP systems during complex marine operations. This concept is not a replacement method or an alternative solution for the current reliability assessment; it will enhance the existing reliability assessment results by combining them with a newly developed database, actual field datasets, Artificial Intelligence and industry experts' knowledge. In addition, the tool provides prescriptive suggestions to the operator in the case of failure so that the operator can react quickly and implement the most suitable available solution to prevent accidents. To simplify the function of DP-RI the list of functions is provided below:

- Offline-Forecasting of DP-RI for complex Marine Operation
- Real-Time Dynamic Reliability Analysis of DP-RI
- Prescriptive Analytics for Resilience of DP system during failure incidents
- The suggested solutions are prioritised based on a ranking system and presented to the DPO to choose the most suitable solution based on the actual condition.

1.5 Research Aims and Objectives

This research aims to develop an intelligent advisory decision-making tool, DP-RI for offline and real-time prediction of the reliability of DP systems (Quantitative and Qualitative). This is to provide the DP operator with complete control and a clear overview of a situation in the case of failure during complex marine operations along with suggestive solutions to prevent DP incidents.

The aim will be achieved by attaining the following objectives:

1. Creating a database for the existing traditional reliability assessment including DP System Level FMEA, DP Vendor FMEA, HIL, Offshore and Onshore Reliability Data (OREDA), IMCA Station Keeping Accident Analysis Reports, DP capability plot and Site-Specific Operational Risk Analysis.
2. Systematically evaluating the database using Big Data Analytics for classification of sub-systems and identifying the inter-dependencies between the DP sub-systems.
3. Developing Systematic Weight Assignment for DP sub-systems using Multi-Criteria Evaluation Technique, Analytic Hierarchy Process (AHP) and validating with expert judgement.
4. Developing a framework of DP-RI for calculating the DP system reliability through mathematical modelling.
5. Offline Forecasting and Real-Time Prediction of DP-RI using Recurring Neural Network (RNN) Long Short Term Memory (LSTM) for complex marine operation.
6. Implementing Natural Language Processing (NLP) techniques for the prescriptive analytics using the most advanced models through fine-tuning and pre-training.
7. Evaluating optimised suggestive solutions to the DPO during failure through Prescriptive Analytics using Bidirectional Encoder Representations from Transformers (BERT) model as Question and Answering (Q&A) system to prevent DP incidents.
8. Implementation of Softmax activation function to determine the relative probabilities between the possible suggestions based on the criticality of the DP sub-systems.
9. Validating the results of DP-RI tool with actual vessel data and existing traditional reliability assessments.

1.6 Research Motivation

Over the years the regulatory authorities, classification societies and the industry have recognised the urgency in improving the safety and reliability of DP complex operations due to increasing numbers of DP incidents. Incident-free DP operation requires a complete understanding of the risk associated with the complex operation and the result of the loss of station keeping capability and the impacts of Design, Operation and process, by the DPO. As the complexity and automation of DP systems increases, and more and more of the sub-systems are interconnected and controlled by computers, DPO minds have become hard-pressed to cope with, and understand, this enormous and dynamic complexity. It seems likely that human oversight of many of these systems will not be possible in the timescale required to ensure safe operation.

Artificial Intelligence (AI) and data-driven decisions based on Machine Learning (ML) algorithms are making an impact on an increasing number of industries. AI has been used for various application within the Maritime sector, such as condition monitoring and ship navigation route optimisation. To ensure safe operation of DP vessels that might enter high consequence scenarios with low probability, it is necessary to have a large amount of data for proper decision making. However, as DP systems have matured and have been used in the industry for more than 50 years, there are enormous volumes of data available. The research is focused on developing a state-of-the-art advisory tool due to the following motivational aspects.

- Availability of enormous amount of offline data related to DP system
- Availability of real-time data from sensors of DP sub-systems
- Possibility to integrate securely to DP systems for extraction of data to provide holistic information during complex marine operations.
- Acceptance of Artificial Intelligence and data-driven decisions for safe operation in the maritime industry
- Need for a state-of-art advisory tool to provide possible solutions to the DPO in the case of faults using a combination of knowledge-based and experience-based AI models.

1.7 Research Contribution

The research study makes the following contribution:

- An intelligent state-of-the-art decision-making advisory (DP-RI) tool has been developed using Artificial Intelligence and Big Data Analytics for DP system.
- The Information Management System (IMS) was created as a database to act as a central repository. The IMS consists of FMEA reports DB, IMCA accident analysis DB, HIL testing DB, DP-CAP DB, OREDA DB, DP vendor FMEA DB and DP simulator DB along with the sensor data of DP sub-systems.
- Identification and classification of critical DP sub-systems using descriptive and diagnostics analytics.
- An intuitive and conservative approach to determine the weighting between DP sub-systems was proposed using AHP.
- A hybrid approach using a mathematical model and predictive analytics with LSTM to determine system-level reliability for computing DP-RI was proposed.
- A novel approach in generating possible solutions using prescriptive analytics with NLP BERT model as QA system was proposed to prevent DP incidents.
- The testing and case studies proved that the DP-RI tool could result in 80% faster decision making and 90% reduction in DPO error.
- The ability to simulate the unknown scenarios reduced the volume of missing data from 90% to 2%.
- The decision making time reduced by 50% when evaluated against the traditional risk assessment and operation procedures.
- Empirical results and validated test cases on complex DP operations have been generated, providing the following:
    - Safe and reliable
    - Increased operational efficiency
    - Preventing DP incidents
    - Training for DPOs
    - Support the decision-making process

1.8 Thesis Outline

The thesis is organised as follows, and the overview is represented in Figure 1-4:

Part 1: (The Context)

- Chapter 1 : Provides the Introduction, Background, Problem Statement, Objectives, Motivation and Contribution of this thesis.
- Chapter 2 : Reviews related work in a systematic manner, checking the relevant reliability assessment methods, applicable Neural Network model, existing methods for Qualitative and Quantitative estimation of Reliability of DP systems.
- Chapter 3 : Presents the various databases for DP systems and how these data sources can be used as knowledge base for application of Big Data concept.

Part 2: (Research Framework and System Model Analytics for DP-RI Tool)

- Chapter 4 : Presents the DP System – Classification of Sub-Systems through Descriptive and Diagnostic Analytics
- Chapter 5 : Presents a Systematic weight assignment of DP Sub-Systems through Analytics Hierarchy Process (AHP)
- Chapter 6 : Presents the Novel Research Framework for Dynamic Positioning – Reliability Index (DP-RI) through predictive analytics using LSTM.
- Chapter 7 : Presents the Prescriptive Analytics for Resilience of DP System using NLP BERT model as QA system to suggest possible solutions to the DPOs during failure.

Part 3: (Validation and Verification of Effectiveness of DP-RI Tool)

- Chapter 8 : Details the Verification and Validation of Predictive and Prescriptive analytics results performance of DP-RI tool through case studies involving real-life incidents and hypothetical cases.
- Chapter 9 : Discusses the Conclusion, Achievements, Innovative works and Recommendations for future work

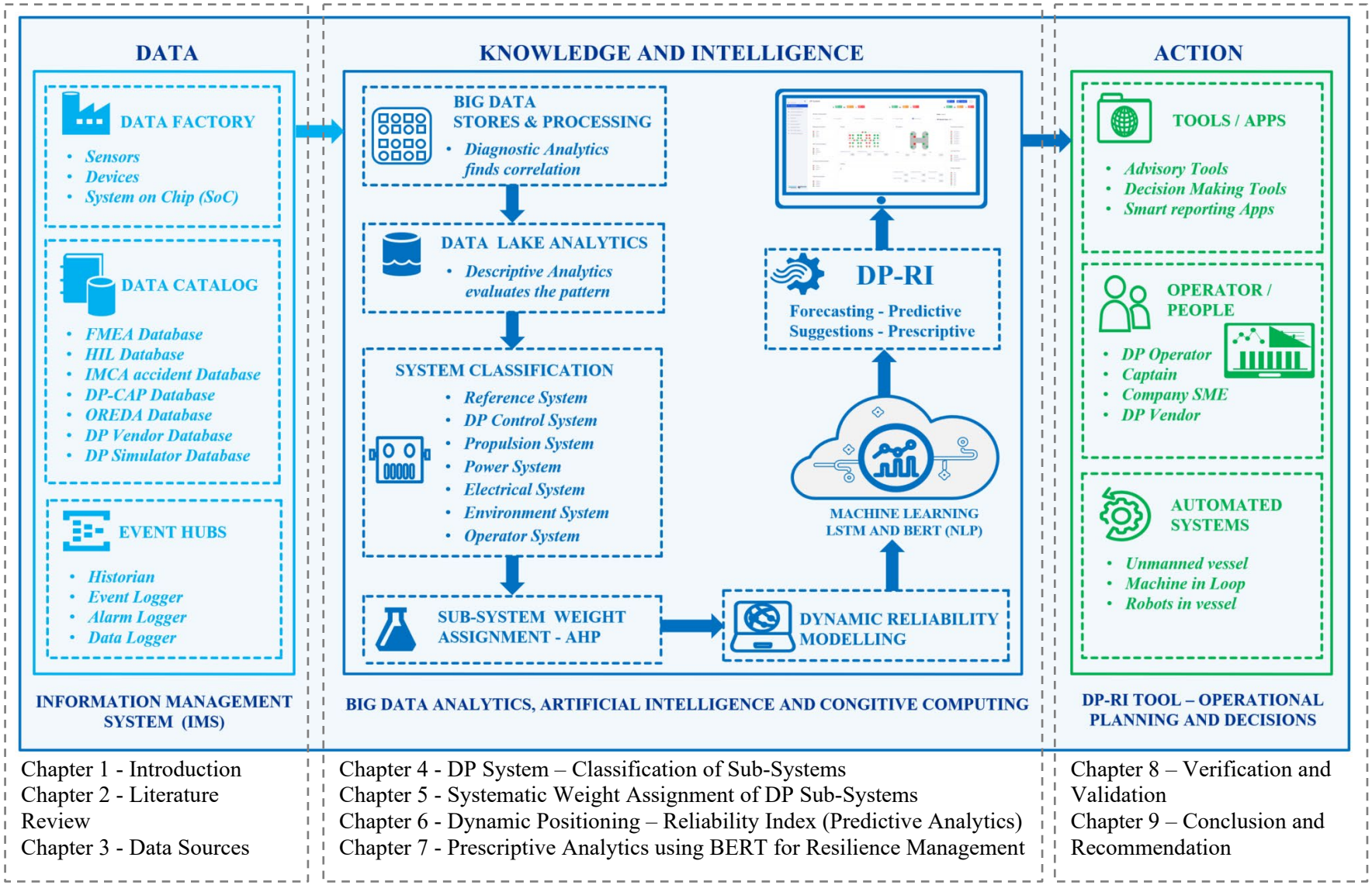


Figure 1- 4 Research Thesis Overview – Chapter Organisation

2. Literature Review

2.1 Introduction

This chapter begins by presenting the definition of Dynamic Positioning, details of DP incidents, and their related impact. The next section offers a review of currently available requirement and assurance frameworks, international standards, and reliability assessment methods governing the design and operation of DP systems. The gap in the existing methodologies is discussed briefly, and analysis presented assessing the role of human factors in DP incidents. Subsequently, the chapter focuses on reliability prediction methods and RNN model concepts. The various available RNN models and their architecture are discussed before implementation in the research study. The links to the main objectives of the research and the methodologies are outlined here and the details are covered in the respective chapters in the later part of the thesis. Finally, the last section draws together a summary justifying the need for a new state of the art decision-making tool to aid the DPO.

2.2 DP Vessel Complexity and Traditional Reliability calculation

Ships are the most complex machines constructed. The demand for increasingly sophisticated ships with integrated systems has added layers to this complexity. A vessel's six Degrees of Freedom (DOF), which includes translatory motions: surge, sway, heave, and angular motions roll, pitch, and yaw are shown in Figure 2-1 [11].

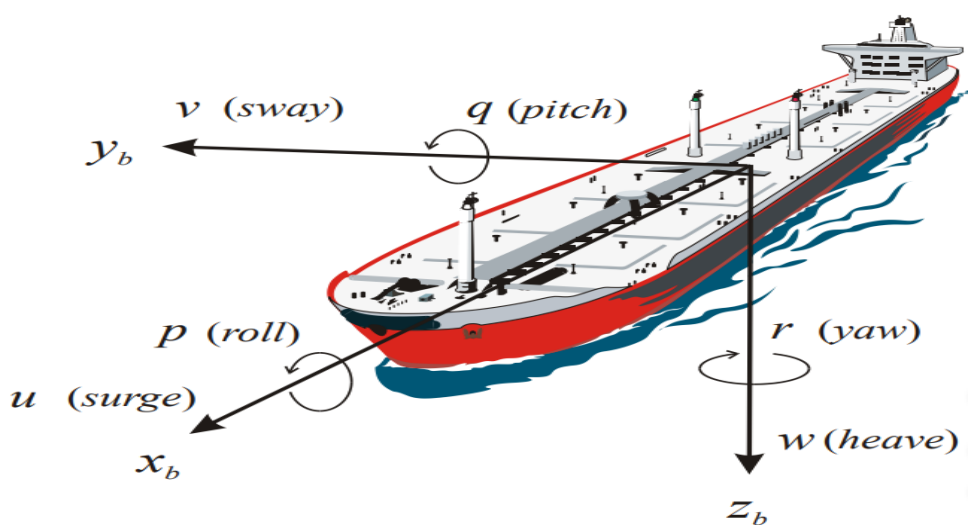


Figure 2-1 Dynamics of the vessel with six DOF

A DP vessel experiences more substantial and more rapidly changing dynamics due to motions when operating in a deep water environment rather than shallow waters. The six DOF equations of motion representing the kinetics and kinematics of a DP vessel are represented as Equation (2-1) [6].

$$M\dot{v} + C(v)v + D(v)v + g(\eta) = \tau + g_o + w \tag{2-1}$$

Where

M	- system inertia matrix (including added mass)
$C(v)$	- Coriolis-centripetal matrix (including added mass)
$D(v)$	- Damping matrix
$g(\eta)$	- vector of gravitational/buoyancy forces and moments
τ	- vector of control inputs
g_o	- the vector used for pre-trimming (ballast control)
w	- vector of environmental disturbances (wind, waves, and currents)

The dynamics of the vessel presented in Equation (2-1) also represent the physical properties of the system, which are further used for control system design. These motions are measured in terms of heading, pitch, roll and yaw. The signals are sent to the DP control system via passing it through a Kalman Filter in order to get the filtered motion values for processing. Besides, the environmental forces (wind, wave and current) play a critical role in the design and operation of the DP vessel as they affect the overall performance of the ships. The calculation of wind and current forces are relatively straight forward when compared to forces produced by waves [12].

To maintain stationary position the thrusters on the DP vessel have to counterbalance the environmental forces. For safe and efficient operation, the number of thrusters required to be operational at a given time is calculated through the thruster allocation algorithm which distributes the required total forces and moments among the available thrusters with minimal use of power [13]. The Power Management System (PMS) communicates between the DP control system and thrusters for required power distribution. The advanced DP system, by design, is itself a complex system with significant levels of integration between many sub-systems to perform diverse control functions, as shown in Figure 2-2.

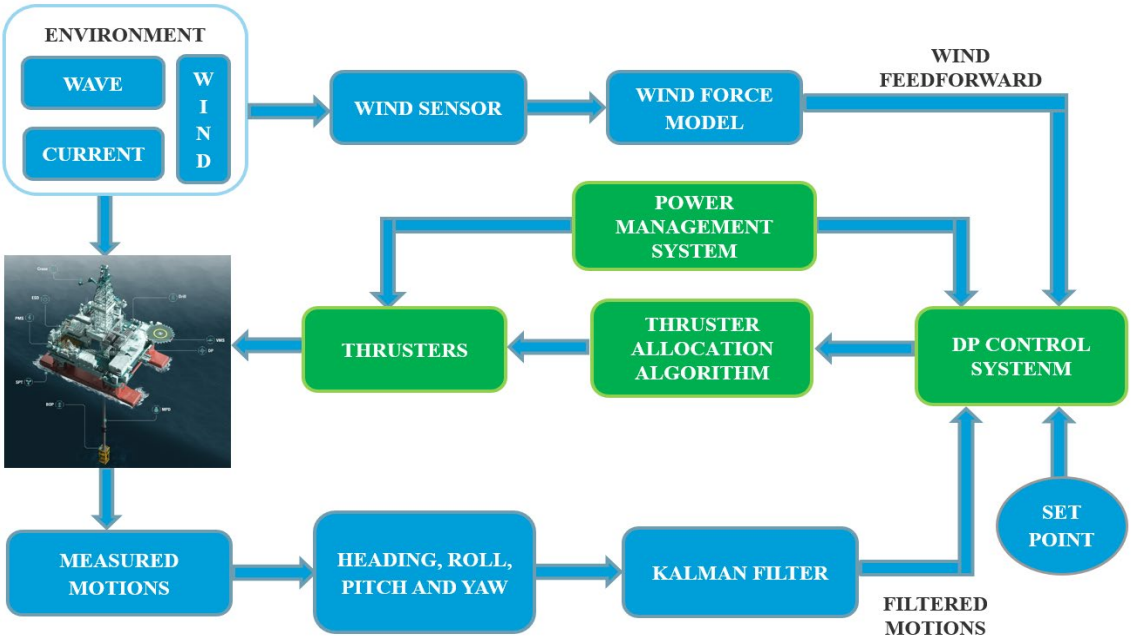


Figure 2-2 DP system architecture block diagram

DP has come a long way since its inception; for more than 50 years developing alongside the marine, oil and gas industry [12]. Modern information technology, software and electronics have gradually penetrated and integrated into a large proportion of the systems on-board marine vessels and offshore rigs. The stakeholders of ships and rigs have made considerable investments in complex and sophisticated designs of DP systems which would have never been possible without digitalisation. All parties in the industry understand the operational advantages of DP in terms of station-keeping. However, in terms of optimum design and efficiency, it remains challenging to understand due to sophisticated design and continuously emerging technologies applied by the vendors.

DP can be considered as a safety-related system as it incorporates one or more electrical and/or electronic and/or programmable electronic devices for its control functions to keep the Equipment Under Control (EUC) in the safe state during any undesirable event [14]. The industry-wide accepted risk assessments for DP focuses on mainly component failures, ignoring human/operator errors which were discussed in detail in Section 1.3 of Chapter 1. Human error, such as delayed decision-making, inadequate coordination between decision-makers and unsafe actions, which have contributed to DP accidents are not taken in account in traditional risk assessments [2, 3, 9, 15, 16, 5].

For many years, the traditional assessments have used reliability calculations on a complex vessel, with integrated systems, based on the general reliability methods [4, 17, 15, 18]. Reliability is represented by the following Equations (2-2) (2-3) (2-4) [4, 19]:

$$MTTF = \frac{1}{\lambda} \tag{2-2}$$

$$R(t) = e^{-\lambda t} \tag{2-3}$$

$$MTTF = -\frac{\lambda}{ln(R(t))} \tag{2-4}$$

Where

MTTF - Mean Time To Failure

λ - Failure rate of a component/subsystem

R(t) - System reliability represented by exponential law

The values are used interchangeably between *MTTF* and *R(t)* based on the application.

2.3 DP Incidents and Related Impacts

The loss of position (LOP) and/or heading of the vessel, either temporarily or for an extended period, is considered to be the DP incident that is the most severe safety breach for station-keeping functionality. The incidents are categorised into three groups as in Table 2-1 [3]:

Table 2-1 IMCA DP incidents defintion

DP INCIDENTS	DEFINITION OF DP INCIDENTS
DP incident / LOP 1	A significant failure in sub-system, environment, or human factor, which results in the loss of DP capability (Major Loss of Position)
DP undesired event / LOP 2	A failure in the sub-system, environment, or human factor, which results in a loss of redundancy and/or reduced DP capability (Minor Loss of Position)
DP observation / LTI	A failure in the sub-system, environmental, or human factor which results in a loss of redundancy and resulted in downtime with no impact on DP capability (No Loss of Position)

The DP incidents occur due to primary causes and secondary causes. The human factor has accounted for 23% of the primary reasons, and 64% of the secondary reasons for DP incidents reported to date [3, 20]. Figure 2-3 shows the DP incidents reported between 1993-2019, with distribution over each year, different sub-systems, and type of DP incident [3].

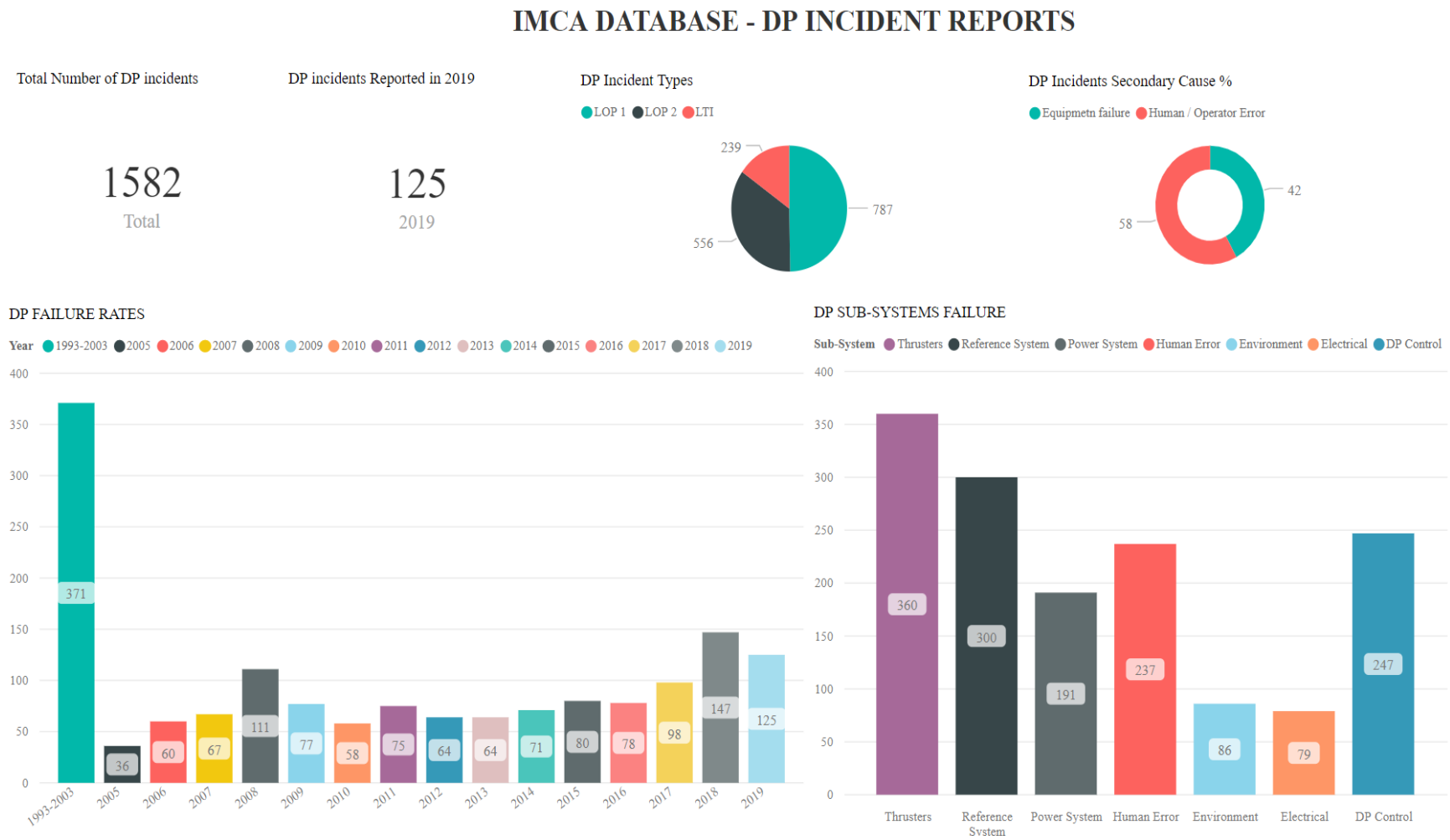


Figure 2-3 DP incidents reported from 1993-2019 and distribution across sub-systems

Similarly, a review of data from the World Offshore Accident Databank (WOAD) from DNV GL also revealed that most of the DP incidents in the offshore industry are related to Human Error [20]. The repository of information on accidents maintained from 1970 shows how the events have escalated from an initial event or fault to an incident where necessary corrective action was not taken at the right time. It is the responsibility of industry experts to make use of the lessons from the databases and facilitate hazard identification for risk reduction and to support the DPO during an emergency. The significant component which differentiates WOAD from other database is the operating hours' feature, which provides information on exposure time to derive accurate failure rates in a given period [20]. However, the currently applied methods for DP reliability assessment do not make use of such data. In addition, research has revealed that sub-system failures and human errors are critical factors for DP incidents [21, 22].

DP incidents may cause a variety of impacts, including risks for incident responders and onboard crew safety, asset damage, environmental damage (oil spills), downtime, and repair costs. The consequence category may vary from very little to catastrophic, and the severity is always unpredictable. Efficient design ensures that the system is fault resistant and, for the given operational mode, the vessel can maintain its DP capability during the worst-case failure (WCF) [23].

The standard loss of position is referred to as one of three possible conditions, as below [7]:
Drive-Off: This is a situation where active thruster forces drive the vessel away from its target position. It is defined as a move under power away from the set position.

Drift-Off: This is a situation where the vessel is incapable of maintaining its target position due to insufficient thrust forces in relation to the environmental forces. The characteristic of drift-off is that there is inadequate thruster force in relation to the environmental loads.

Large Excursion: This is a situation where the vessel is still under DP control and experiences brief excursion of position and/or heading more considerable than the usual excursion due to environmental loads (massive wind gust/wave), thruster fault or degraded position information.

The severity of the incident varies based on the vessel type, operation mode, and application. Table 2-2 summarises the possible consequence effects for different types of vessels based on the assumed application of work for various incident scenarios [24].

Table 2-2 Different ships with possible worst-case scenario effects

DYNAMIC POSITIONING - WORST POSSIBLE EFFECTS				
DP VESSEL TYPES	**WORK ASSUMED**	**DRIVE- OFF**	**DRIFT-OFF**	**LARGE EXCURSION**
Drillship / Semisubmersible Drilling Rig	Well testing < 500m	Blowout, Fire, Loss of Life, and Pollution.	Blowout, Fire, Loss of Life, and Pollution.	Downtime
Heavy lifting Crane vessel	10,000 loads stabbed	Loss of Life Structure damage	Injury and Major Damage	Injury and minor Damage
Dive support vessel	Divers in habitat	Death to 2 or 3 divers	Injury to 2 or 3 divers	Minor injury to 1 or 2 divers
Accommodation vessel	Gangway in use	Injury to 2 or 3 personnel on gangway at auto-lift and damage to the gangway	Minor injury to 2 or 3 personnel exiting Gangway	Gangway auto-lift and downtime
Supply vessel	Close to structure	Collision and Major Damage	Collision with minor damage	Contact, damage negligible but downtime
Rock dumping vessel	Close to structure	Collision and major damage	Collision but minor damage	Contact, damage negligible but downtime
Pipe S-lay vessel	Pipelay with sigh-tension	Pipe Damage (Running buckle) if tension lost	Pipe Damage and minor injury 1-2 personnel in the firing line	Pipe over tension and downtime for closeout

2.4 Dynamic Positioning System Operator Roles

The DPO plays a critical role in the efficient operation of the vessel as it is their primary responsibility to prepare the ship for complex operations, in consultation with the Master and with assistance from the electrician. DP vessels operating offshore have different applications, systems, equipment classes, operation modes, configurations and requirements, and function in various environmental, and weather conditions. Therefore, the failures are different, and the impact of each failure in the sub-systems differs between vessels and cannot be assumed to be

the same when a DPO works in different ships. It is up to the vessel owner to ensure that the DPO familiarises themself with operational constraints/ requirements of these modes and features. Regardless of the vessel type, a DPO performs the following activities [25, 26, 27]:

- Operate the DP systems of the vessel independently, working in a possibly hostile environment and in changing weather conditions
- Judge whether DP operations can commence, continue or should be suspended and take immediate action if required
- Demonstrate that he/she is fully competent, using the systems/modes that apply to the applicable notation(s)
- Demonstrate a holistic view of the vessel's management systems and operations and consider the impact of operating under DP on, e.g., security vulnerability as well as from a legislative and regulatory point of view.

Recent research has revealed that although training and documentation are in place, the DPO reaction during an emergency and tendency to react based on experience does not contribute to preventing accidents [3, 9]. The DPO's ability to perform the required functionality depends on the following factors along with their technical capabilities, which are often missed out, resulting in human error.

1. Situational Awareness
2. Decision Making Ability

2.5 DP Requirement and Assurance Framework

The requirements for DP vessels are governed by various international bodies, including International Maritime Organisation (IMO), IMCA, Classification Societies, Flag States and National Regulators. The National Regulators, including the Norwegian Maritime Authority (NMA), National Offshore Petroleum Safety and Environmental Management Authority (NOPSEMA), Health and Safety Executive (HSE), Petroleum Safety Authority (PSA), etc [28, 29, 30, 31], guide the operator and asset owners for specific requirements in addition to meeting the IMO and Classification Societies' safety requirements . The IMO requirements act as guidelines to facilitate safe and reliable international operations, taking into account that vessels are moved and operated internationally. Therefore, special consideration is given for the design and operation criteria requirements to avoid any additional documentation for the

new area of operation. In addition, compliance with the guidelines is documented in the Flag State Verification and Acceptance Document (FSVAD) for the dynamic positioning system to ensure that the vessel is operated, surveyed, and tested according to vessel-specific procedures and that the results are adequately recorded [3]. These guidelines provide the basis and common platform to recommend design criteria, necessary equipment, operating requirements, and a test and documentation system for dynamic positioning systems to reduce the risk to personnel, the vessel, other vessels or structures, sub-sea installations, and the environment while performing operations under dynamic positioning control. DP class determines the ability of the vessel to achieve position keeping capability under worst-case failure modes. The various classes of DP systems are defined through equipment classes from the IMO for different ships required for a particular operation, as shown in Table 2-3 [3].

Table 2-3 DP Equipment Class definition by IMO

EQUIPMENT CLASS	DEFINITION BY THEIR WORST-CASE FAILURE MODE
Equipment Class 1	• No redundancy. Loss of position may occur in the event of a single fault

Equipment Class 2	• Redundancy of all active components
	• Loss of position is not to occur in the event of a single fault in any active component or system. Typically, static components will not be considered to fail where adequate protection from damage is demonstrated, and reliability is to the satisfaction of the Administration.
	• Single failure criteria include:
	  ○ Any active component or system (generators, thrusters, switchboards, remote-controlled valves, etc.)
	  ○ Any typically static component (cables, pipes, manual valves, etc.) which is not adequately documented concerning protection and reliability

Equipment Class 3	• Redundancy and physical separation of all components

At present, there are no standards or industry guidance to specifically address the DP assurance of vessels performing complex operations in the offshore and marine industry. Currently, DP assurance criteria vary widely across the industry and set out different requirements based on the operator, owner, and shipyard practices [32]. In addition, vessel owners/operators implement a process to ensure the technical suitability of the vessel, determine the configuration for the Critical Activity Mode (CAMO) and Task Appropriate Mode (TAM), which will define the minimum DP equipment class for the particular application. Table 2-4 shows the recommended minimum equipment class for different DP applications [33].

Table 2-4 Recommended minimum DP class for different applications

Application of DP	Minimum DP Class	Remarks
Drilling	2	
Diving	2	
Pipelay	2	
Umbilical Lay	2	
Lifting	2	
Accommodation	2	
Shuttle Offtake	2	
ROV Support (Open water)	1	
ROV Support (Close Proximity -Surface/ Subsea)	2	
Floating Production	2	
Seismic and Survey vessels (Open water-outside 500 m zone)	-	Class in accordance with contractual requirements
Well Stim	2*	Vessels of lesser Class may be used with the appropriate structured risk identification and mitigation measures in place.
Logistics Operations	2*	Vessels of lesser Class may be used with the appropriate structured risk identification and mitigation measures in place.

The Assurance framework has also started focusing on the stringent requirements of training for the DPO that would meet the minimum safety standards. A DPO should have sufficient knowledge and experience to be able to take command of the vessel and identify types of failure and predict required reactions to respond to the failure. Despite the increase of technology, guidance on the requirements and assurance framework, the number of DP incidents has not reduced significantly overtime, which indicates that the risk reduction factor is not sufficient. The main reason is that DPO knowledge is limited due to the complex interconnection of systems and the large volume of documentation, which has been revealed in one of the studies, as below [34]:

"The relentless drive within the shipping community to introduce electronic navigation aids to merchant ships had the principal stated objective of improving safety by enhancing situational awareness. However, some of the doubts expressed at the inception of these initiatives regarding their likely success have been realised, in that there is now a commonly held view that the general standard of bridge watch-keeping has been eroded, leading to several collisions and groundings."

2.6 Classification Society Standards Governing the DP System

Classification Societies, as members of International Association of Classification Societies (IACS) promoting the safety of life, property, and the environment, publish rules containing standards governing the design and operation philosophy of DP systems through notation. These notations correspond to the equipment class defined by the IMO with additional requirements which are accepted by authorities around the world. Classification Societies such as Det Norske Veritas Germanischer Lloyd (DNV GL), American Bureau of Shipping (ABS), Bureau Veritas (BV), Lloyd Register (LR), Registro Italiano Navale (RINA), Indian Registry of Shipping (IRS), China Classification Society (CCS), Korean Register (KR), Nippon Kaiji Kyokai (NK), Russian Maritime Register of Shipping (RS), etc. have developed standards to govern the design of DP systems [1, 35, 36, 37, 38, 39, 40, 41, 42, 43]. Table 2-5 shows the relationship between the equipment classes of the IMO with DP notation from different Classification Societies. In addition, the recommended practice is published by these societies to provide design philosophy guidelines, operation guidance, competence requirements for a DPO, and competence requirements of critical technical personnel [25, 44].

Table 2-5 Classification Societies DP notation for IMO DP equipment Class

IMO DP EQUIPMENT CLASS – CLASSIFICATION SOCIETIES DP NOTATION										
IMO	**DNV GL**	**ABS**	**BV**	**CCS**	**IRS**	**KR**	**LR**	**NK**	**RINA**	**RS**
	DYNPOS AUTS	DPS-0	DYNAPOS SAM				DP (CM)		DYNAPOS SAM	
CLASS 1	DYNPOS AUT	DPS-1	DYNAPOS AM/AT	DP-1	DP (1)	DPS (1)	DP (AM)	CLASS A DP	DYNAPOS AM/AT	DYNPOS-1
CLASS 2	DYNPOS AUTR	DPS-2	DYNAPOS AM/AT R	DP-2	DP (2)	DPS (2)	DP (AA)	CLASS B DP	DYNAPOS AM/AT R	DYNPOS-2
CLASS 3	DYNPOS AUTRO	DPS-3	DYNAPOS AM/AT RS	DP-3	DP (3)	DPS (3)	DP (AAA)	CLASS C DP	DYNAPOS AM/AT RS	DYNPOS-3

DNV GL → Det Norske Veritas Germanischer Lloyd (Norway)

ABS → American Bureau of Shipping (USA)

BV → Bureau Veritas (France)

CCS → China Classification Society (China)

IRS → Indian Register of Shipping (India)

KR → Korean Register of Shipping (Korea)

LR → Lloyd Register (UK)

NK → Nippon Kaiji Kyokai (Japan)

RINA → Registro Italiano Navale (Italy)

RS → Russian Maritime Register of Shipping (Russia)

The IMO equipment class focus has proved that concentrating only on the equipment design will not ensure safety and careful consideration is required for the competence of the technical personnel involved. Competence requirements need to be ensured at different levels of cognition, such as knowledge, understanding, application, and integration to maintain the DP integrity of vessels during complex operations [25, 44]. Several instances of loss of position have ended up as DP incidents mainly because of intervention by a DPO lacking knowledge, skills, and understanding of the system functionality and the effects of various forces acting on the vessels.

Many Classification Society rules, standards, international codes, regulations, and assurance frameworks have been developed and implemented to ensure that the design and operation of DP systems can meet the minimum standards for safe and reliable operation [32, 33]. However, the current advancement in automation and technology development outpaces the rate at which the standards and frameworks are being developed to ensure the safety level. In addition, the energy demand, economic growth, and growing competition will urge operators/vessel owners to adopt technologies as fast as they develop. This forces industry experts to use more advanced technology to assure safe operation through digital advisory tools rather than just codes and standards [2, 17, 15].

2.7 Reliability Assessments

The reliability assessment is a mandatory requirement while designing, constructing, and operating any safety-critical system, and DP systems are no exception [17, 15, 45]. In the marine and offshore industry, the reliability assessment is performed by several stakeholders in different phases and with varying levels of rigour [46, 47]. The vessel owner/operator performs high-level evaluation during the initial phase, along with the development of the specification of a new-build. The shipyard, vendor, and independent consultants perform the assessments during design, construction, commissioning, and sea-trial stages.

Reliability is the capability of the system to perform its intended function during the defined period under pre-established conditions [19, 17]. Often the industry measures DP reliability through the comprehensive equipment class system of DP class notation [15]. The reliability

of DP systems depends on the redundancy so that a sudden failure of one item of equipment or a negligent act will not cause an unexpected loss of vessel position and/or heading.

The reliability assessment of the DP system can be categorised into two parts as below [19, 48]:

- Reliability Estimation
- Reliability Prediction

Only a few of the traditional reliability assessments would cover both the hardware and software related to the system. The hardware part is well established, and often the software reliability assessment is subjected to question due to its difficulty and the outcome is often controversial [49, 47]. The software reliability cannot be trusted as it does not provide accurate results due to errors in the probabilistic models. The reason for such a lack of accuracy in software reliability for DP systems is due to factors such as software complexity, difficulty in identifying suitable metrics, difficulty in conducting exhaustive testing, difficulty in quantifying the effectiveness of test cases, etc. [49]:

> *"Most of the existing quantitative software reliability methods were not developed specifically for supporting the quantification of software failure rates and demand failure probabilities to be used in reliability models of digital systems."*

Software plays a critical role in the safe and reliable functionality of DP vessels, and therefore it cannot be ignored (or assumed never to fail). The fundamental differences between hardware and software failures are [19, 49, 47, 50]:

- Causes of hardware failures include both wear-out and improper design, with the former being most dominant. The predominant cause of software failures is a design failure.
- The software can have dependencies, such as common cause failure mechanisms, very different from those of hardware.
- Hardware failures generally lead to complete loss of function, but the software may also continue running, producing erroneous results.
- When hardware fails, it must be replaced. For fault-tolerant systems, redundant hardware can maintain functionality while the failed hardware unit is replaced, and redundancy is restored.

- When software fails, it can often be restarted and continue to operate after a failure if the combinations of inputs that lead to the failure (e.g., a faulty sensor input) are not present anymore. If the software fault is to be removed, the software cannot be replaced but has to be updated.

Software reliability is not the main focus of this thesis research. Therefore, it is considered that software reliability is ensured through other reliability assessments and it is not evaluated in detail as part of this research.

2.8 Reliability Estimation

Reliability estimation is a process determining the quality of equipment in sub-systems, quality of design, and competence of the crew to achieve the required station keeping integrity. Traditionally several reliability estimation techniques are used for the assessing the reliability of DP systems. These techniques are generally grouped into two categories [15, 46, 51, 52]:

- Qualitative techniques
  - FMEA
  - Failure Mode Effects and Criticality Analysis (FMECA)
  - HIL
  - DP capability plot, Footprint, and Consequence Analysis
  - Site-Specific Risk Analysis
- Quantitative techniques
  - Reliability Block Diagram (RBD)
  - Fault Tree Analysis (FTA)
  - Markov Chain
  - Monte Carlo Simulation (Network Simulation)

The suitable reliability estimation techniques are chosen for a particular vessel based on various factors. These factors are typically defined by end-user, operator, design companies, engineering, procurement and construction (EPC) and shipyard. However, these methods have been proved to have drawback as detailed in Section 1.3. Qualitative and quantitative risk assessment for the DP system has been used as essential risk reduction methods in proactively identifying the shortcomings that might have been unidentified during the design stage. These assessments, if appropriately implemented, prove useful in the optimisation of the design and

have a direct impact on the lifecycle costs. Qualitative techniques support the early identification of potential single-points of failure, which could result in worst-case system failure through a system trip or loss of redundancy [15]. Qualitative techniques ensure that the system design is thoroughly reviewed through a systematic approach. However, these techniques are time-consuming as they need to focus on every detail at the sub-system level, and cost/benefit cannot be directly derived. Quantitative techniques use the output from the qualitative techniques such as FMEA / FMECA. Quantitative techniques overcome the disadvantages of qualitative techniques by supporting cost/benefit through an accurate understanding of the cost of a design change and the benefit of a change. These techniques are more time consuming and require failure frequency databases that are proprietary to either manufacturers or oil companies, which presents limitations [49, 52]. In addition, these techniques often do not focus on the correlation of the failure modes.

2.8.1 Failure Mode Effects Analysis (FMEA)

The objective of FMEA is to verify that the consequence of any single failure does not exceed a pre-defined worst-case single failure design intent [1, 23]. It focuses on equipment redundancy and redundancy group independence for aspects such as the power supply, physical interfaces, computer units, lubrication oil, ventilation, cooling water, etc. to show post-failure station-keeping capability. For DP vessels, the design intent is that the ship should be able to keep its position after a single failure, as required by IMO 645 [8]. All of the Classification Societies and regulations have rules and standards covering FMEA requirements to study the reliability of the DP system [46, 53, 45, 54].

FMEAs are usually conducted by specialised companies and require a cross-competent team covering all engineering aspects of the DP vessel, except software [55, 47]. In addition to the FMEA analysis, a proving trial procedure (test program) will be written and executed as part of the sea trial of a new build vessel. The objective is to verify, on running systems onboard the real ship, conclusions made in the analysis, and possibly investigate aspects that it was not feasible to conclude in a desktop analysis.

The FMEA analysis presumes that the software in the control systems is working as intended concerning functionality and fault handling. Such an assumption relies heavily upon the vendor's internal verification of the software. This practice is questionable when dealing with

safety-critical systems, because a lack of independence undermines objectivity in the verification effort. It reveals that testing and verification of the control system software must be added to achieve a proper independent assessment of the complete DP vessel. However, it is noted that there is no indication that FMEA uses information from IMCA about systematic analysis of DP failure incidents. Even the FMEA guide from IMCA does not provide any guidance on how the experience from DP failure incidents could be used for improving the efficiency of FMEA reports. It is clearly evident that there is a gap in FMEA studies and a need to use the DP failure incident data to bridge the interval [5, 56, 47].

2.8.2 Failure Mode Effects and Criticality Analysis (FMECA)

FMECA is a bottom-up (hardware) or top-down (functional) approach for the risk assessment. It is an extension of FMEA analysis where the failure modes are prioritised, indicating the criticality (or severity) of the various failure modes. It acts as the first step and provides the input to the Quantitative Risk assessment. The vessel operator will develop an asset-specific risk matrix to identify the probability (frequency/likelihood) and consequence severity (criticality) of particular failure modes on the vessel operation [46, 45]. In this way, the assessment will support the operator to perform benchmarking across the vessel and identify the failures having an impact on the operation based on experience.

However, FMECA does not provide a focus on human error, so is suited for a system with little or no redundancy. It is challenging to apply to a system with complex redundancies as it leads to additional documentation, which is time-consuming [15]. This method is often performed without considering the knowledge and experience gained from previous DP incidents.

2.8.3 Hardware in the Loop (HIL) Testing

HIL acts as a simulation tool to test the functions such as verification of correct operation as per specification, performance including capabilities and behaviours operating under different environmental conditions and failure modes of integrated DP systems or various sub-systems [55, 56]. HIL testing is performed at early stages, typically at the manufacturer location during the Factory Acceptance Test (FAT) as a stand-alone system and onboard the vessel during sea-trial Customer Acceptance Test (CAT) as an integrated system.

Studies have revealed that FMEA techniques mainly focus on the physical layout of a system and ensure only the reliability of the hardware [9, 56, 47]. Therefore, ensuring the reliability of software in the control system is complicated and the outcome is controversial. Control system software reliability and its quality depends on the proper, well-defined software development and testing processes [56]. It is mostly the vendor's responsibility and is sometimes overlooked by individuals developing software due to various reasons. An FMEA desktop study will detect and reveal the possible weak points in the physical design and highlight the need for increased attention in critical software functions. FMEA provides essential input to the HIL testing, which in turn will provide crucial information on the functionality and failure handling capabilities of the control system software [47].

Figure 2-4 shows the set-up for HIL testing, where the actual vessel conditions are replaced with the HIL simulator acting as a digital twin [56]. Usually, this is accomplished by isolating the control system and its operator stations from its surroundings. The actual field Input/Output (I/O) is replaced with simulated I/O from a HIL simulator in real-time. The HIL simulator imitates the actual conditions (i.e., dynamic systems, actuators, and sensors) of the control system. It provides realistic, continuous, and consistent measurements and responds to the control signals.

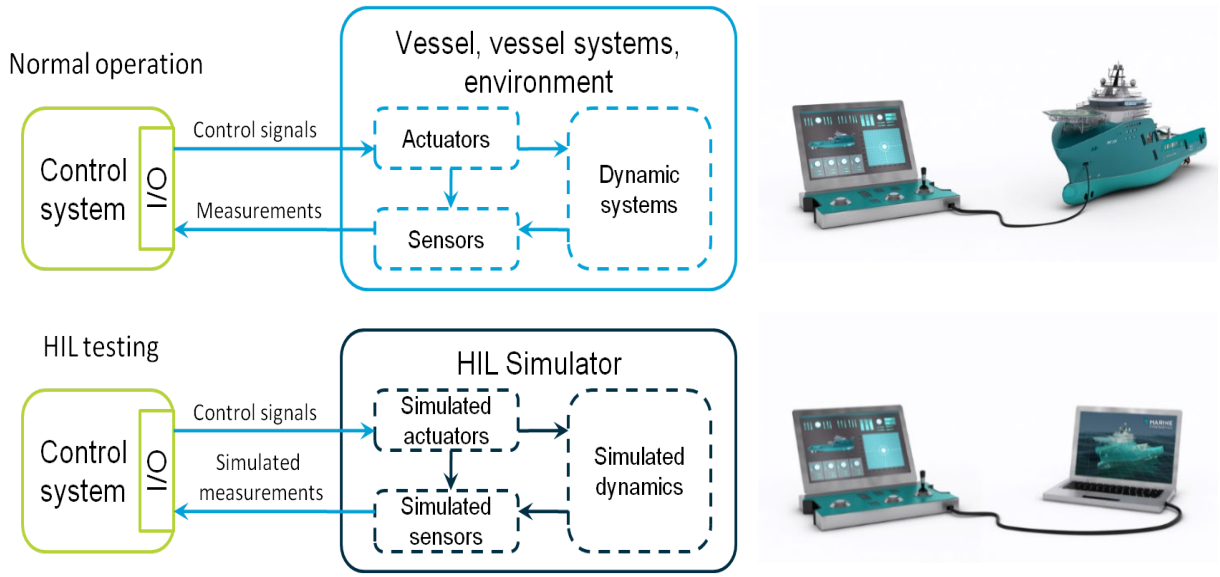


Figure 2-4 HIL simulation setup for testing the Vessel's DP system [56]

The main advantages of using HIL testing are as follows [56, 47]:

- Facilitates closed-loop realistic testing of the DP system during FAT and CAT.
- Enables performance testing over a wide range of environmental and weather conditions.
- Supports testing of each signal failure, which would be painful and undesirable to replicate physically for a complex system such as reference, power, and propulsion/thruster systems.

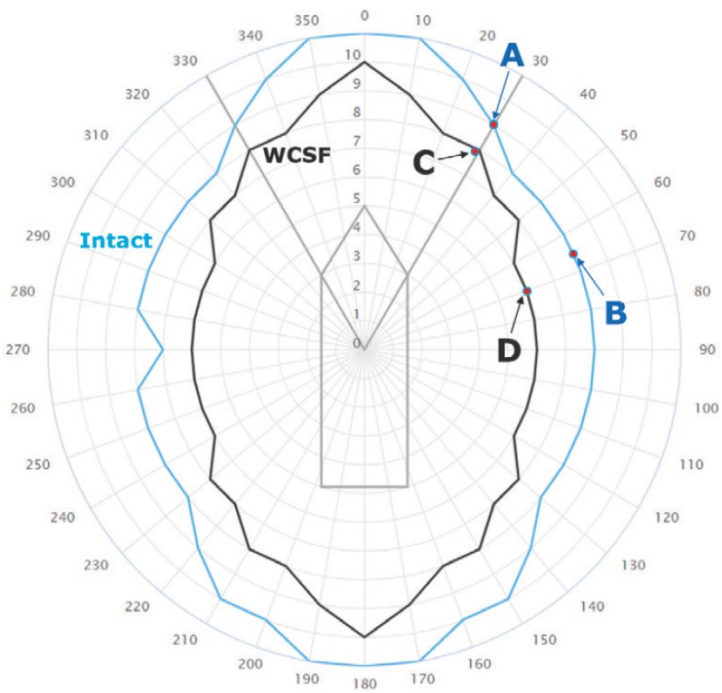
Through experience, it has become evident that it is not possible to perform 100% test coverage of the complex system as each signal may fail in several ways, including broken wires, short circuits, frozen values, slow/fast drift, or noise with typically interfaced signal counts ranging from a few hundred to several thousand [47]. So, the focus area is defined as failures involving high risk considering both probability and the consequences. Furthermore, any hidden, common causes and multiple failures with some level of human error may result in severe consequences leading to DP incidents, which points to the need for research to close the gap.

2.8.4 DP-Capability, Foot-Print and Consequence Analysis

A DP capability plot is a graphical illustration of the vessel's station-keeping (position and heading) capacity in a specified vessel condition and specified environmental condition [57]. It is used to determine the environmental limits of an operation showing the maximum static or quasi-static wind, current, and wave loads in which the vessel can maintain its position for different configurations (e.g., worst-case single failure (WCSF), nominal case). The DP capability plots are governed by specification from Classification Societies and regulators and a typical plot is shown in Figure 2-5 [58, 59].

The traditional DP capability analysis is non-conservative compared with time-domain analysis. In this analysis, the 6 DOF vessel motion, related thrust losses, as well as all other dynamic effects in the propulsion system like rate limits, are usually neglected [57]. Another significant shortcoming of DP capability analysis is that the transient conditions during a failure and recovery after a failure are generally neglected. DP plots are theoretical plots calculated from detailed information of the vessel's hull and superstructure form and available thruster power. The confidence level of the plots is very much reduced when compared to DP Footprint plots. Therefore it is advised by IMCA and Classification Societies that, wherever

possible, the DPO should validate the DP capability plots by taking DP Footprint Plots and through time-domain analysis [59, 60].



DP CAPABILITY – LX (A,B,C,D)

X = 1, 2 or 3 describes the DP capability Level

A = Intact condition, heading 0 - ±30°

B = Intact condition, heading 0 - 360°

C = Worst-case single failure condition, Heading 0 - ±30°

D = Worst-case single failure condition, Heading 0 - 360°

Example: DP Capability L1(9, 8, 8, 6)

Figure 2-5 Typical DP capability plot for DP vessel

DP time-domain simulations prove its ability to keep station accurately and estimate the proper headings for a selected number of sea conditions. Dynamic Capability is the next level of DP capability analysis which is based on systematic time-domain simulations with a sophisticated 6 DOF vessel model, including dynamic wind and current loads, first and second-order wave loads with slowly-varying wave drift, a complete propulsion system including thrust losses, power system, sensors, and a DP control system model [61]. It overcomes most of the shortcomings of DP capability analysis, and the results are much closer to reality. The features enable the user to define the acceptance criteria in the analysis for the site requirements for each vessel and operation, such as station-keeping footprint, sea-keeping criteria, dynamic power load, and transient motion after failure [59]. However, the efficiency in preventing DP incidents during failure scenarios seems to be unsatisfactory due to its lack of ability to analyse the failure scenarios for each signal in the DP system.

DP Footprint plots represent the actual measurements of the vessel's station-keeping performance in the actual operating environmental conditions and with the thruster configuration at the time of the complex operation, with site-specific information. It provides a scatter plot of vessel positions at regular intervals around the required set position. It also enables comparison of points on the limiting wind speed envelope given in the theoretical DP capability plots. The usual practice is to set the configuration of the thrusters as per the DP capability plot and obtain the plot for the loss of the most effective thruster(s) and after a worst-case failure. To better understand the vessel DP station keeping ability and enhance the knowledge, it is advised to combine the theoretical DP capability plots and DP footprint plots [60].

Consequence analysis is prescribed by the IMO requirement to ensure an alarm is raised when the station keeping ability is lost [8]. For DP vessels with equipment classes 2 and 3, it is mandatory to have online consequence analysis. It is a monitoring function in the DP control system to check any abnormalities in vessel heading and position in its current operating mode, in the current weather conditions, in the case of any of the predefined worst-case failures, and raise the alarm to the operator [62]. The main issue is that the result of re-configuration is unpredictable as the integrated system is complex and there are various interdependencies.

2.8.5 Site-Specific Risk Analysis (CAMO, TAM, ASOG, and WSOG)

Site-specific risk analysis was adopted by the industry as there was a clear indication of a decline in experience of DPOs and rapid technology advancement leading to intricate designs [33]. DP redundancy and fault-tolerant system are often over-ruled by a DPO's incorrect understanding of operational design criteria, resulting in DP incidents. Site-specific risk analysis such as CAMO, TAM, Activity Specific Operating Guidelines (ASOG), and Well Specific Operating Guidelines (WSOG) support efficient DP operation by establishing structured operational limit criteria [63]. An advisory status is included to indicate the deviation from the safest mode of operation. The statuses are Green DP Status for Normal Operation, Blue DP Status for Advisory Status representing no immediate risk, Yellow DP Status for high risk should be another failure occur, and Red DP Status for Severely degraded status or Emergency.

The operational planning associated with different risk assessments are detailed as follows [60, 63]:

- CAMO is applied to all the critical activities. It defines the most fault-tolerant configuration for the DP system and associated plant and equipment such that single point failure does not exceed the vessel's identified worst-case failure.
- TAM is applied to less critical activities and uses risk-based operating modes such that the set-up of the DP system is operated so that single point failure could result in exceeding the vessel's identified worst-case failure.
- ASOG defines the operational, environmental, and equipment performance limits for the location and the specific activity the vessel is undertaking.
- WSOG was developed for specific well or drilling activity and is the same as ASOG [63].

These risk analyses guide the DPO in a user-friendly tabular format with actions to be taken by the DPO in response to faults and deteriorating conditions. Often these site-specific guidelines do not provide the actual status of the DP system when any alarm or failure occurs, which leaves the operator in a predicament and referring to the operation manual/FMEA document to understand the system reliability.

2.8.6 Reliability Block Diagram (RBD)

A RBD presents a logical relationship between the system, sub-systems, and components. A system can be modelled for reliability computation and analysis using block diagrams [19]. A DP system consists of sub-systems and components connected to perform given functions and maintain vessel position and heading. Due to the integration between sub-systems, it can become complicated, making reliability analysis difficult. A mathematical model reduces the system to a graphical representation of the interconnection of its sub-systems.

RBD analysis is a deductive (top-down) method, and it is easy to apply for a complex system where it could be broken-up into sub-systems [15]. The RBD application is very practical when DP performs more than one function, and a separate RBD can represent each function. The significant advantage of using RBD for the reliability analysis is that it provides the methodology to explore the residual risk due to the common cause of failure mechanism, as it could lead to a hazardous event if the demand on the Electrical / Electronic / Programmable

Electronic (E/E/PE) safety-related system fails. The Safety Integrity Level (SIL) concept is applied to the RBD to support evaluation of the safety loop from sensors, logic solvers, and final elements [64, 14].

A typical reliability model can be represented, as shown in Figure 2-6 [15, 65]. These RBD can be used for mathematical calculations and prediction of the reliability of sub-systems. The blocks A, B, C, D, E and F refer to the equipment arranged either in series or parallel for calculating the reliability of sub-system using RBD model.

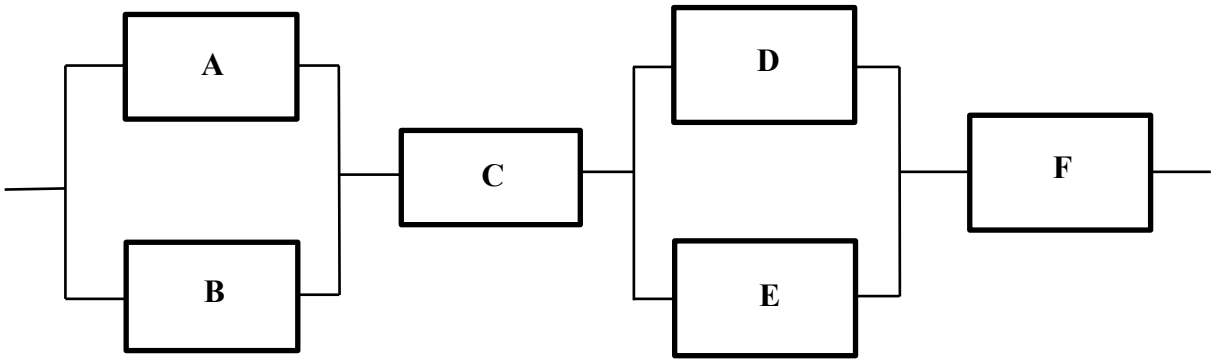


Figure 2-6 Typical Reliability Block Diagram Architecture

The static RBDs are limited in their ability to express varying system states, dependent events, and non-series-parallel topologies. Studies have revealed that the accuracy of RBD is prone to human errors; simulations are inaccurate due to the involvement of pseudo-random number generators and the sample-based nature of computer arithmetic computations [65, 19, 15, 48]. Dynamic RBD, used in combination with the ML concept, will result in more efficient analysis methods.

2.8.7 Fault Tree Analysis (FTA)

FTA is a logic diagram which can be used to represent the inter-relationship between potential critical events and causes of the event in the DP system [19]. It analyses integrated system failures in terms of combinations of sub-systems and lower level faults, and eventually component faults. It is a top-down approach, it is possible to start the analysis at a very early stage, and to complete it as the detailed design is carried out [19, 15]. This method may be qualitative, quantitative, or both depending on the objective of the study. However, it is widely used for quantitative analysis for a DP system.

FTA does not show the causes of all of the failures or accidents in the system, but it does focus on the specified failure/accident. It is also wholly dependent on the individual's capability and knowledge on the system, which could vary and result in in-consistency in the outcome. These methods could also be time-consuming for a complicated system. In addition, there may be inherent uncertainty and consequence from a safety perspective as human error is excluded from the analysis.

2.8.8 Markov Chain

Markov analysis is a bottom-up analysis method suitable for the evaluation of functionally complex structures and complicated repair and maintenance strategies. It is a stochastic model and can be applied to DP, which is a randomly changing dynamic system to predict future events based on the current events neglecting the historical events [52]. It enables the calculation of the probabilities of system elements (components, equipment, sub-systems) being in a particular state at specific points (or intervals) in time. It is efficient and faster in mathematical computation compared to Monte-Carlo simulations (see Section 2.7.9). In addition, the method supports the DPO by providing deep insights into the changes in the system over time.

The main pitfall is that only technical failures of the sub-systems are included in the Markov modelling. However, the human-machine interface plays a critical role in DP operations. The DPO monitors the information from different sub-system sensors and analyses the integrated system status before issuing control commands during complex operations and takes action during an emergency [15]. Therefore, human factors and operational procedures, along with technical aspects, should be taken into consideration for reliability analysis. In addition, for an integrated system with a large number of components, the massive amounts of data will be unmanageable and much useful information will be lost when merging the functional state and failed state [19].

2.8.9 Monte Carlo Simulation (Network Simulation)

The Monte Carlo simulation technique is the most widely used approach for reliability analysis of sophisticated, real-world systems with stochastic elements, which are difficult to evaluate analytically [15]. The simulations are treated as a series of experiments as the features of the

system in a simulated environment resembles the close to reality and supports the measurement of reliability performance metrics. So, it, in turn, helps to estimate the system performance under any set of operating environments and weather conditions and to accommodate any number of failure distributions. For the DP system, the effectiveness of using Monte Carlo analysis in overcoming the complexity of the problem is directly related to the number of events in the fault tree [18, 66].

There is a pitfall in the method, which makes it unsuitable for a specific application, and that is that for a complex system, it is expensive and time-consuming to develop the simulation model. Also, it is suitable only for the comparison of different systems rather than for optimisation. In addition, the simulation results are not useful if the validity of the model is affected due to design changes as it is not adaptive.

2.9 Reliability Prediction

Reliability prediction is one of the more widely used techniques for reliability analysis [48]. The method is a process of forecasting the probability of a system performing its function successfully when it is demanded to operate [67]. It can be done at any phase of the system lifecycle. However, it is most commonly used during the initial system design stage to evaluate the proposed design for reliability concerns [19, 15, 48]. It involves an estimation of the performance of the system over some time and its reliability based on the failure rates of the sub-system components. It helps in identifying the weak point in the design at the early stages of the project to improve it. In recent years, due to technological advancements, reliability prediction has become widely used during the operational phase of DP to support maintenance and inspection [48].

In this research, reliability prediction using RNN is evaluated using different algorithms to understand its suitability and performance. The prediction of the reliability of the DP system uses the following concepts to form a robust research framework:

- Big Data – Data sources (Chapter 3)
- Diagnostic and Descriptive Analytics (Chapter 4)
- Predictive Analytics (Chapter 6)
- Prescriptive Analytics (Chapter 7)

The experimental set-up for reliability prediction should consider the following parameters and boundaries to define uncertainties upfront for reliability prediction during operation [48]:

- Reliability Prediction uses (Why - Station Keeping Capability)
    - Reliability goal assessment
    - Mission Reliability Estimation
    - Prediction of Reliability performance
- Reliability Prediction in the system life cycle (When - Operation)
    - Operational Phase
- Factors to select Reliability Prediction method (What – Consequence of Failure)
    - Product Technology
    - Consequence of failure
    - Failure criticality
    - External influences
    - Available resources (data, knowledge, and technology, etc.)

Reliability prediction is usually performed using test data or field data. Test data refers to actual equipment operational experience in a test environment, and the time required to observe failures is usually accelerated through proper planning to increase the amount of data. Tests are conducted in test environments, which should resemble actual environmental conditions such that reliability of the system, sub-systems, assembly and components obtained can be considered as specific confidence levels. The test environment should necessarily include failures from different possible sources such as electromagnetic disturbances, humidity, thermal environment, human intervention, and at the same time, avoid failures which are not relevant to the operating environment [48, 67]. Reliability prediction based on test data can be widely used as it covers vast possibilities, and it can also be used for validation of other systems.

Field data refers to the actual data from the components, assemblies, subsystems, and systems obtained from an actual operational environment. Therefore, for reliability prediction of the system during the operational phase, field data should be used for greater accuracy and increased efficiency in forecasting. The type and quality of data used for prediction for the integrated DP system on any specific vessel should ideally use the field data from a similar

vessel with the same operating conditions. In the case of missing information, similar items or similar environments may be found, and the impact on the accuracy should be evaluated [48].

2.9.1 Offline Reliability Prediction

Offline reliability forecasting is one of the critical activities of the DPO as part of the operational planning for a DP system for complex operations when allocating the configuration (power and thruster systems, etc.) and making decisions in case of emergencies [60]. The current method of planning and decision making heavily relies on the massive number of documents produced during the initial stages. It is based on knowledge without any proper understanding of the final location of operation (site-specific information), which demands significant efforts in terms of time and cost. With the development of technology, adapting to automation and the use of sensors for components in the sub-systems, there is a massive amount of data generated onboard the vessel related to the DP system. Recently databases have been stored for condition monitoring and maintenance of the systems in a dedicated machine. This massive amount of historical data can be used for predictive planning to prepare the vessel and the DPO for any site-specific activity, which could become critical in terms of the operation [2]. There is need for a digital tool that can be used as a simulation tool to be used offline for the training of the operator. Besides, it also helps planning upfront to understand the method to handle catastrophic events due to single failure causing worst-case failures of design intent.

Big Data and predictive analytics have enormous potential to prevent DP accidents in the offshore marine industry. However, the stakeholders of DP systems tend to be conservative with regard to implementing digital technology to unlock the potential. Recent trends show that the shipping industry is adopting predictive analytics for various applications including route optimisation before a voyage and ship behaviour and wave height prediction for efficient offshore operations [68, 69].

2.9.2 Real-Time Reliability Prediction

Real-Time reliability prediction or Time Series Prediction (TSP) involves the prediction of future system reliability based on the information of the current and past status of the sub-systems. TSP has been implemented to address several real-world problems in the marine and

offshore industry for optimising operational efficiency [68, 69, 70]. Typically, four methods are used for detecting the state of the system and predicting failures: function approximation, classifiers, system models, and time-series analyses [71, 72]. All of these methods have at least one of the following drawbacks [73] :

- Does not consider the effect of a dynamic change in the input
- Supports only discrete input variables
- A large amount of historical data is required to achieve a reasonable accuracy
- Unable to tackle random errors in irregular fluctuations.

Many Artificial Neural Network (ANN) methods have been adopted for reliability prediction and have shown high prediction accuracy and adaptability for stable offline data [50, 74, 75, 76]. However, such methods were not capable of TSP of real-time data. Deep Learning RNNs are more suitable for addressing TSP than traditional Neural Networks as they provide multiple nonlinear mapping levels, which can abstract and extract the features of an input signal and discover the potential underlying relationship at a deeper level [73, 77]. However, the methods are not sufficiently proven in terms of their adaptiveness where TSP is dynamic. At the same time, the sampling speed of models should match the controller capability [59]. Therefore, in this research, four of the widely used RNN models were used to evaluate their suitability for the time series prediction/forecasting of DP reliability.

2.10 Recurrent Neural Network Models

An RNN introduces the concept of timing into the design of a network structure, which makes it more adaptable in time series prediction. The RNN architecture provides hidden layers to share the parameters across the time series. This functionality in the RNN supports built-in "memory" blocks, allowing the system to recognise and predict long sequences [77].

The various algorithms for RNN are used in the research for determining their suitability for reliability prediction of DP systems. The predictive analytics framework is used for the evaluation and for estimating the accuracy. The algorithms are tuned across different hyperparameters for optimising the efficiency. The details of the performance analysis and the hyperparameters are discussed in Chapter 6.

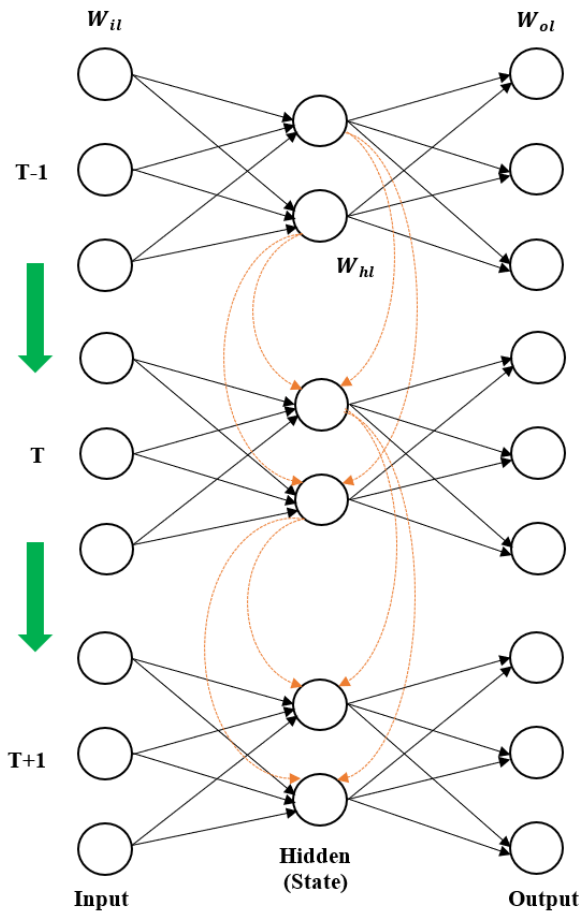


Figure 2-7 Time Sequence in RNN

The most important aspect of the RNN is its ability to analyse sequential data for representing the dynamic performance of the system through network delay recursion [79]. Figure 2-7 demonstrates how the sequential data is processed in the RNN model. For example, consider that W_{il} is the input layer, W_{hl} is the hidden layer, and W_{ol} is the output layer. The output at time "T" not only depends on the input at a time "T", but also on the recursive signal from time "T-1". This illustrates the capability of the RNN delay recursion to support the processing of short term sequential data. However, in a broad context, memorisation, or learning from deep sequences in time series forecasting, the RNN suffers from the vanishing gradient problem [80, 81]. Specifically, in the case of long sequence inputs or time series an RNN is hard to train as the model can only remember the latest information and not the earlier data.

2.10.1 Multi-Layer Perceptron

The Multi-Layer Perceptron (MLP) is a class of feedforward deep leaning Neural Network. An MLP consists of three layers of nodes: an input layer, a hidden layer, and an output layer. The neurons are organised by type into the layers, and the flow of information is in one direction [82]. Therefore, the neurons in the one layer are not related and do not share any information. MLPs are suitable for prediction tasks and are considered universal approximations of functions since their outputs depend only on the current inputs [79, 80, 83]. The output "y" for the MLP is given by Equation (2-5):

$$y = g\left(\sum_{i=1}^{q} w_i^o \, f\left(x^{(t)} w_i^I + b_i^h\right) + b^o\right) \tag{2-5}$$

where $W^I = \{w_1^I, w_2^I, w_3^I \ldots\ldots w_q^I\}$ is the input weights matrix, $W^o = \{w_1^O, w_2^O, w_3^O \ldots\ldots w_q^O\}$ is the output weights matrix, $B^h = \{b_1^h, b_2^h, b_3^h \ldots\ldots b_q^h\}$ is the bias vector of the hidden layer and b^o refers to the bias of the output layer. The f and g terms are the activation functions of the hidden and output layers.

An MLP structure is illustrated in Figure 2-8 [82].

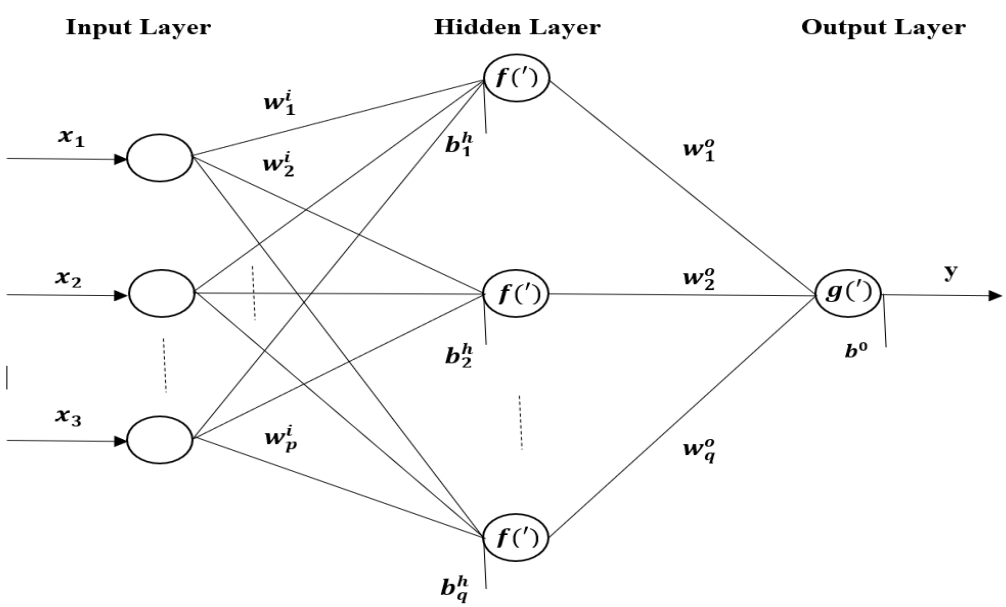


Figure 2-8 MLP Network Structure

Though MLP proves to be very efficient in prediction and pattern recognition, there is an inherent drawback in that the variable selection accuracy depends highly on the choice of the shrinkage parameters. The performance of prediction deteriorates when the shrinkage parameters are chosen inappropriately [82]. In addition, when there is a set of candidate variables among which there is a very high pairwise correlation, the model tends to select only one variable from the pool and ignore the other.

2.10.2 Simple Recurrent Neural Network (SRNN)

In comparison to the MLP, SRNNs support feedback between one or more neurons, which enables historical information of previous inputs to influence each output [68]. The SRNN uses bi-directional loops to address problems in the context of input nodes. The transition between each layer node is no longer the input of a hidden layer. The SRNN is a sequence-to-sequence model that can process sequence data of any length, which makes it relevant for the DP reliability prediction application [74, 80]. The underlying network structure of an SRNN is depicted in Figure 2-9. In the figure, subscript t represents the time, x is input data, O is output data, S is the network state, W is the update weight, V is the weight between the cell and the output, and U is the weight between the input and cell.

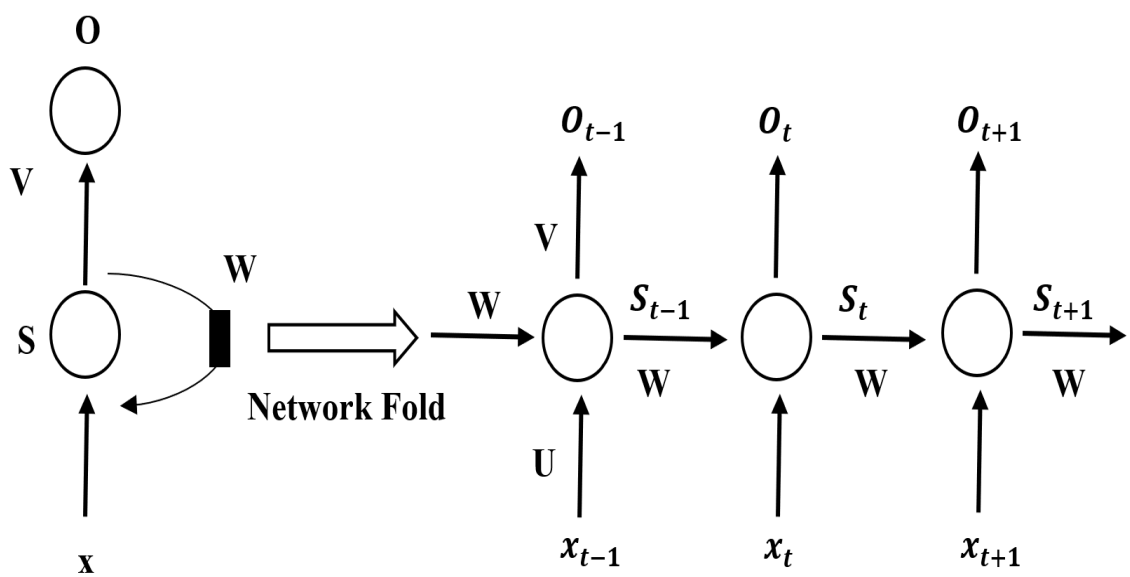


Figure 2-9 SRNN Network Structure

The output "y" for the SRNN is given by Equation (2-6):

$$y = g\left(\sum_{i=1}^{q} w_i^o \, f\left(x^{(t)} w_i^I + x^{(t-1)} w_i^I + b_i^h \right) + b^o \right) \tag{2-6}$$

where $W^I = \{w_1^I, w_2^I, w_3^I \ldots\ldots w_q^I\}$ is the input weights matrix, $W^o = \{w_1^O, w_2^O, w_3^O \ldots\ldots w_q^O\}$ is the output weights matrix, $B^h = \{b_1^h, b_2^h, b_3^h \ldots\ldots b_q^h\}$ is the bias vector of the hidden layer and b^o refers to the bias of the output layer. The f and g terms are the activation functions of the hidden and output layers. The SRNN is suitable for prediction where there is a limited amount of data, and it experiences all the similar drawbacks of the standard RNN as the network structure is equivalent.

2.10.3 Long Short Term Memory (LSTM)

LSTM is an RNN variant, which uses a purpose-built memory cell to represent the long-term dependencies in time series data [70, 84]. The LSTM RNN is suitable for relatively long interval delays in time series prediction. It addresses the vanishing gradient problem of the SRNN through incorporating self-connected "gates" acting as memory cells in the hidden units [68, 83]. The complete architecture of LSTM is represented in Figure 2-10, which shows the flow of information from input to output [81].

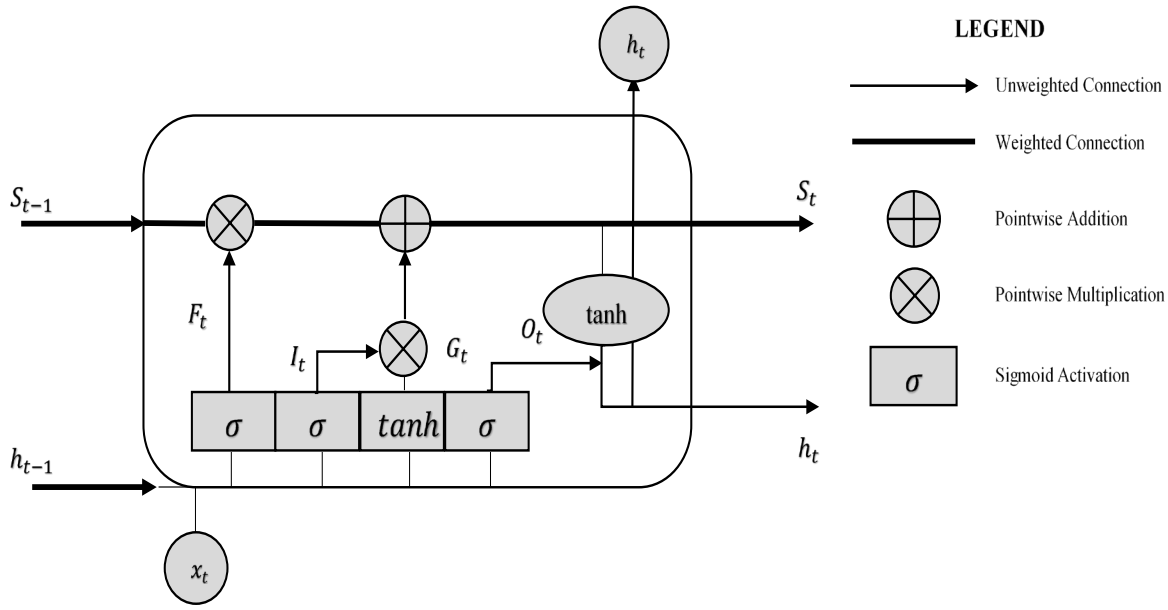


Figure 2-10 LSTM Network Structure

LSTM consists of the following parameter groups.

(i) Input weights : U^f, U^i, U^o and U^c

(ii) Recurrent weights : W^f, W^i, W^o and W^c

(iii) Bias : b_f, b_i, b_o and b_c

The first step in LSTM is to decide what information is new and what information is going to be thrown away from the cell state called the forget gate f_t , sigmoid activation function σ, as shown in Equation (2-7) and (2-8):

$$f_t = \sigma\left(X_t U^f + S_{t-1} W^f + b_f\right) \tag{2-7}$$

$$f_t = \sigma\left(\theta_{xf} x_t + \theta_{hf} h_{t-1} + b_f\right) \tag{2-8}$$

The next step is that the input gate (i_t) layer decides which values are to be updated and a tanh layer creates a vector of new candidate values $\tilde{C}_t$, as represented in Equation (2-9) and (10):

$$i_t = \sigma\left(X_t U^i + S_{t-1} W^i + b_i\right) \tag{2-9}$$

$$\tilde{C}_t = tanh(X_t U^c + S_{t-1} W^c + b_c) \tag{2-10}$$

Then, to update the old candidate state, C_{t-1} , it is combined into the new candidate state $\tilde{C}_t$, pointwise multiplication $\otimes$, and pointwise addition $\oplus$, which can be given as Equation (2-11):

$$C_t = C_{t-1} \otimes f_t \oplus i_t \otimes \tilde{C}_t \tag{2-11}$$

The next step is that the output gate (o_t) decides what parts of the cell state are going to be produced as outputs. Then, the cell state goes through a tanh layer (to limit the values to be between -1 and 1), and it is multiplied by the output gate as shown in Equation (2-12) and (2-13):

$$o_t = \sigma(X_t U^o + S_{t-1} W^o + b_o) \tag{2-12}$$

$$S_t = o_t \otimes tanh(C_t) \tag{2-13}$$

In order to address the vanishing gradient problem of the RNN, the LSTM RNN with input gate, output gate, and cell state was introduced. This model can be trained for sequence generation by processing real data sequences one step at a time and predicting what comes next, which makes it suitable for the DP reliability prediction application. However, the main drawback is that each memory block needs an input gate and an output gate, which makes the training more difficult and increases the training time of the network [79, 80, 81].

2.10.4 Gated Recurrent Unit (GRU)

GRU is a classical variant of LSTM, which uses a new type of hidden unit similar to the memory unit in LSTM. The hidden unit combines the forget gate and input gate into a single update gate. The GRU model is a simpler version as the cellular state and hidden state are combined [81]. Figure 2-11 shows the complete architecture of a GRU network.

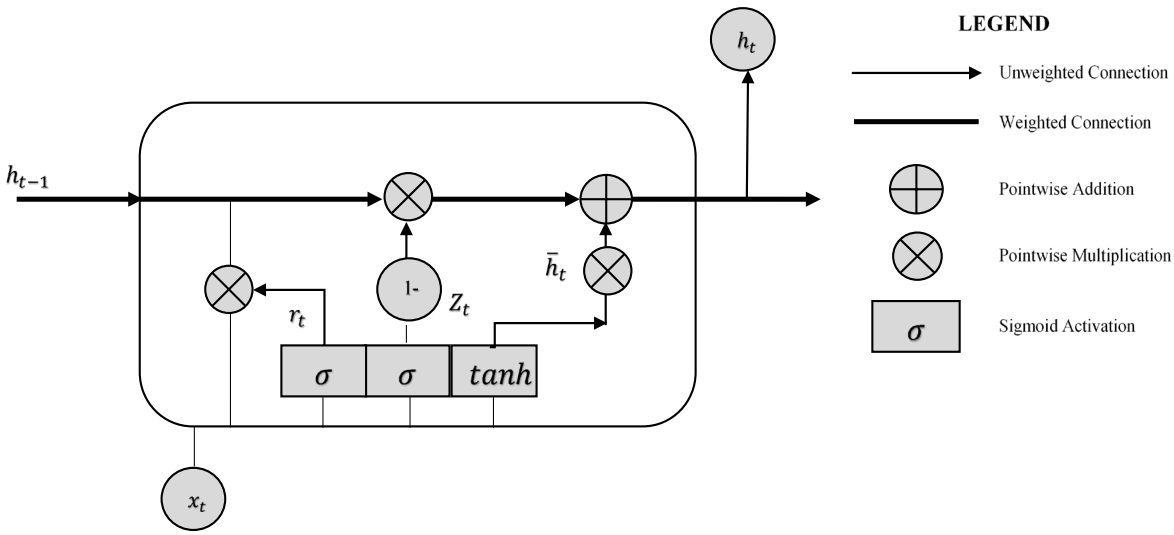


Figure 2-11 GRU Network Structure

In order to determine the activation of the hidden unit at the time step "t" R_t first needs to be computed by Equation (2-14):

$$R_t = \sigma(W_R H_{t-1} + U_R X_t) \tag{2-14}$$

Where σ is the logistic sigmoid function and W_R and U_R are the weight matrices.

The new remember gate $\widetilde{H}_t$, is generated by R_t with a tanh layer in Equation (2-15).

$$\widetilde{H}_t = tanh(W(R_t * H_{t-1} + UX_t) \tag{2-15}$$

After this the remember and forgot gates are deleted by creating a new gate Z_t of Equation (2-16)

$$Z_t = \sigma(W_z H_{t-1} + U_z X_t) \tag{2-16}$$

The hidden state value is updated as represented by Equation (2-17)

$$H_t = (1 - Z_t)H_{t-1} + Z_t * \widetilde{H}_t \tag{2-17}$$

GRU proves its capability in reducing the training time and improving network performance due to its simplified structure when compared to other RNN models [80, 81]. LSTM and GRU both tend to remember features for a long time, allowing backpropagation to happen through multiple bounded nonlinearities, which reduces the likelihood of the vanishing gradient. The suitability of GRU over LSTM is compared through experimental study in this research.

2.11 Prescriptive Analytics – NLP and BERT

Prescriptive analytics analyses the field data from sensors and uses computational models to provide instant recommendations to the DPO to suit the multiple predicted outcomes. Prescriptive analytics is related to and a natural progression from, descriptive and predictive analytics. It searches for and determines the best solution among various possibilities, given known parameters under a defined operational envelope. In this research, the application uses NLP and BERT for prescriptive analytics to suggest possible solutions during failure scenarios. NLP is field of AI which provides the capability to machines to read, understand and decide based on human languages [85]. BERT is an NLP model that is pre-trained by Google and used as a Question and Answer system for the DP-RI application. This made it possible to analyse the enormous amounts of documentation available related to DP systems and provide possible suggestions to the DPO to respond quickly. The research framework, concept, fine-tuning and training of the BERT model are discussed in Chapter 7.

2.12 Human Factors in DP operation

DP vessels are increasingly becoming automated, with interconnected systems, due to demanding operation at sea, safety, and economic benefits and facilitated through recent technological advancement [16, 2]. This advancement and adaptation to technology have grown at a rapid pace; however, the training of DPOs and standards governing DP have not matched the pace of improvement. In a complex, sophisticated, automated DP system, the role of the DPO shifts from active involvement to more an interpretation of the system. In such a situation, during complex offshore operations, the DPO role mainly needs to anticipate the system needs. It is trapped in a situation without any tools to support the function, thus becoming error-prone [86]. The main reason for this is that advanced DP is designed with humans out-of-the-loop, making the DPO distribute their attention to system needs rather than the operational requirements.

The IMCA defined DP incidents as “any loss of position to the surprise of the DPO,” which clearly shows the critical aspect of the human factor in DP related accidents [3]. The incidents are often unplanned and non-routine events that could have been avoided with proper intervention from the DPO. The accidents that occur due to DPO error are related to the undesired consequence of human-automation interaction [26]. Understanding the need for training, there were significant revisions to the International Convention on Standards of Training, Certification, and Watchkeeping (STCW) for Seafarers, and its associated Code was adopted at a Diplomatic Conference in Manila (The Manila Amendments), in June 2010 (IMO, 2011). The Manila amendments define the necessary training and focus on courses addressing situational awareness and decision making. The training program enables the personnel to meet the essential requirements with the ability to handle critical situations in maritime operations independently or as a team [87]. Similarly, a large number of guidelines have been prepared by MTS to train the DPO [33, 25, 44, 60].

As mentioned previously, data has shown that 23% of primary causes and 64% of the secondary causes of DP related accidents are due to human error [3, 20, 21, 22]. Although the human operator is heavily involved in errors, a full understanding of the errors' origins is found within the DP complexity, including sub-systems, assemblies, equipment sensors, and interactions between them. Recent studies proved that human reliability needs to be considered in the design and operation of the DP system, which should be addressed in terms of training and operational documentation guidance for a DPO through automated possible solutions [88, 89, 78, 90]. As socio-technical systems become less centralised and more globalised, there is a necessity to incorporate the ecological concerns in designs that can genuinely support the operators to deal with functional allocation and visualisation of operational risk.

Most DP related accidents reported in the last few decades could have been prevented if the DPO had intervened at the right time and had taken corrective actions. To be precise, about 64% of the accidents where human error was the secondary cause could have been prevented with proper planning in advance [3]. In order to understand the typical root causes of the loss of position and narrow down on how the DPO could have intervened, incidents were analysed, as presented below [7, 26].

A scenario of Drive-Off: This is a situation where active thruster forces drive the vessel away from its target position. Defined as a move under power away from the set position or wanted position. It occurs during full power situations when the vessel is trying to regain its set position, which is mainly due to false information or wrong commands. A DPO would be the secondary cause and observing the situation soon enough to react correctly with the necessary steps could prevent drive-off.

A scenario of Drift-Off: This is a situation where the vessel is incapable of maintaining its target position due to insufficient thrust forces in relation to the environmental forces. It could be due to failure occurring in operation outside of the "worst-case failure" environmental limits or exceeding the theoretical worst-case related to hardware or human error. A DPO would be the primary cause in most of the cases, and in order to prevent such a situation, thrust capability and wind, wave, and current conditions should be analysed before the decision making.

Large Excursion: This is a situation where the vessel is still under DP control and experiences temporary excursion of position and/or heading more significant than the usual excursion due to environmental loads (massive wind gust/wave), thruster fault or degraded position information. It is usually referred to as being in the range of 10m or 10 degrees from the desired position and/or heading. These situations are quite common, and if the DPO reacts promptly, then a large excursion could be easily avoided.

From the above analysis, it is quite evident that the intervention of the DPO could prevent all of the possible loss of position situations at the right time with the correct solution. As the industry is focussing on moving towards the Marine Autonomous Surface Ship (MASS), it is necessary to address relevant human errors through the following steps to ensure that functional requirements concerning risk and evaluation criteria are adequately addressed [88].

1. Minimal Human intervention
2. Intervention from Shore
3. Completely automated

2.13 Summary

In this chapter, the complexity of the DP system due to the external environmental forces, hydrodynamic effects acting on the vessels, and sophisticated integration between different

sub-systems have been discussed. Other categories of DP accidents were presented, and related impacts of the disasters were analysed in detail to identify the primary and secondary causes. DPO roles and responsibilities were discussed along with the technology influence of the complex operation and how the DPO role has changed gradually. Subsequently, various requirements and assurance frameworks, which are guiding the safe and reliable design of the systems, were presented in detail to identify the gaps and limitations. Classification Societies have been continuously updating the rules and standards related to methods to ensure that the technology advancement does not cause any uncertainty in the design, construction, and operation of the vessels. The analysis revealed that the rules mostly cover the essential safety requirement as a mandatory factor, and the operational aspect was left to stakeholders to manage the risk. Various reliability assessment methods traditionally used for the DP system evaluation were discussed in detail. The advantages and limitations of different techniques were analysed to focus on the critical areas in these research studies.

Although the maritime, oil, and gas industry has started using big data and analytics for a few applications, it has not been used adequately to address the problems associated with the DP system. The biggest drawback is the lack of a consolidated or collective database, DP being a system with a lot of sensors and effectively having been an "internet of things" for many decades. It was essential to collect all of the relevant data and form a data lake for the research. The information part of Information Technology (IT) has not been explored much, which needs to be addressed whilst, at the same time, ensuring the quality of data. With the massive amount of data available in the DP system, it can be considered as a Big Data source and analysed systematically. The ANN models have been used for DP control system design; however, they have not been used for reliability assessment or become an industry-wide accepted practice. In the next chapters, all of the limitations of the existing evaluations are addressed through a novel research framework. The research framework was built on years of available trusted data, knowledge of industry experts, and intelligence of data analytics.

3. DP System Data Sources – Data Collection, Storage and Processing

3.1 Introduction

Big data has the potential to transform the marine, offshore, oil, and gas industries by creating opportunities to drive innovation through insights and application. The advancements in automation technology and sensor development along with the analytics revolution, have resulted in an exponential rise in data availability for analytics and efficient prediction in decision making [91]. The chapter begins by presenting the association of DP data to the characteristics of big data. The data related to DP systems are a reinterpretable representation of information in a formalised manner suitable for communication, interpretation, or processing [92]. The data collected in a DP vessel at different phases of the lifecycle are of structured, semi-structured, or unstructured formats. In the next section, the type of data collected from various sources such as risk assessment reports, DP vessel manuals, historical data from event loggers/data loggers, and real-time data collected from sub-systems and stored through the vessel to cloud solutions, are presented. As big data involves substantial data sets and complicated problems, it is essential to have access to innovative and powerful processing and computing technologies. In the subsequent section, various databases and how big data technology is used for storage of the data sets are presented. These robust technologies ensure that data accessibility is very fast through processing units and file distribution systems [92, 91]. The final section outlines the critical characteristics in identifying the complexity of the problem for which the data gathering is conducted. It details the necessary tools used for real-time processing of data and essential formatting, for performing analytics to reveal the underlying correlation between the systems.

The ability to manage all of the data and information from different sub-systems of the DP system, safely and efficiently, enables a new level of analysis and monitoring of situations, critical operations, and installation conditions for the following applications [93].

- Safety performance and integrated operation
- Managing risk and effective decision making
- Management and monitoring of accident and environmental risks
- Energy efficiency (cost and environment)
- Automation of ship operations (long-term)

3.2 Big Data Concept for DP System

Big data refers to data whose sizes go well beyond the ability to capture, manage, and process with traditional computing technology or commonly used software tools [94]. In advanced DP vessels, the most sophisticated operations are dependent on information systems for control and analysis. In the last 30 years, two factors have changed radically for the DP system, the availability and usability of data. Now the current situation is that there is a massive explosion of available data, and the ability to store, combine and analyse these data is now available. DP Data is increasingly being considered a valuable asset of equal worth to physical assets, and considerable infrastructure is required for collecting, storing, and acting upon the data [95].

DP big data collected from a vessel includes unstructured (text, images, audio, video, etc.), semi-structured (Alarm logger, comma-separated variables, etc.) and multi-structured data (different data formats such as excel, tabular results, historical database). Big Data is characterised by attributes of volume, variety, velocity, veracity, and value [94, 96]. Table 3-1 defines these characteristics of big data and their relation to DP system data [96].

Table 3-1 Big Data Characteristics for DP system data

ATTRIBUTES	DESCRIPTION AND ASSOCIATION
VOLUME	The volume of data collected for the DP system for this specific research is more than zettabytes of data.
VELOCITY	The offline and real-time DP data collected at the testing phase & operational phase is at a sampling of 1 millisecond (vessel-to-cloud).
VARIETY	The DP data is of a variety of forms which includes reports, text, time series from sensors, position data from GPS loggers, etc
VERACITY	The veracity (accuracy, precision, and trust) of the DP data was ensured through the DNVGL-RP-0497 data quality assessment framework.
VALUE	The values of DP data are categorised into two goals: • Meaningful information: Descriptive and Diagnostic Analytics results in the classification of sub-system through correlation. • Safe and efficient decision making: Predictive supports forecasting and Prescriptive suggests solutions for preventive and corrective actions.

3.3 Stages in Big Data Analytics for the DP system

The full potential of big data analytics may be unlocked in different stages. For the DP application, stages were used to ensure that a standard systematic approach was followed to mitigate pitfalls and biases that could arise during the experiments. There are five different stages in big data analytics, which are represented in Figure 3-1. The corresponding steps for DP system analysis for each stage are presented in detail in Figure 3-1 to show the level of increased information researched to fill the gaps of the existing assessment methodology [93, 96].

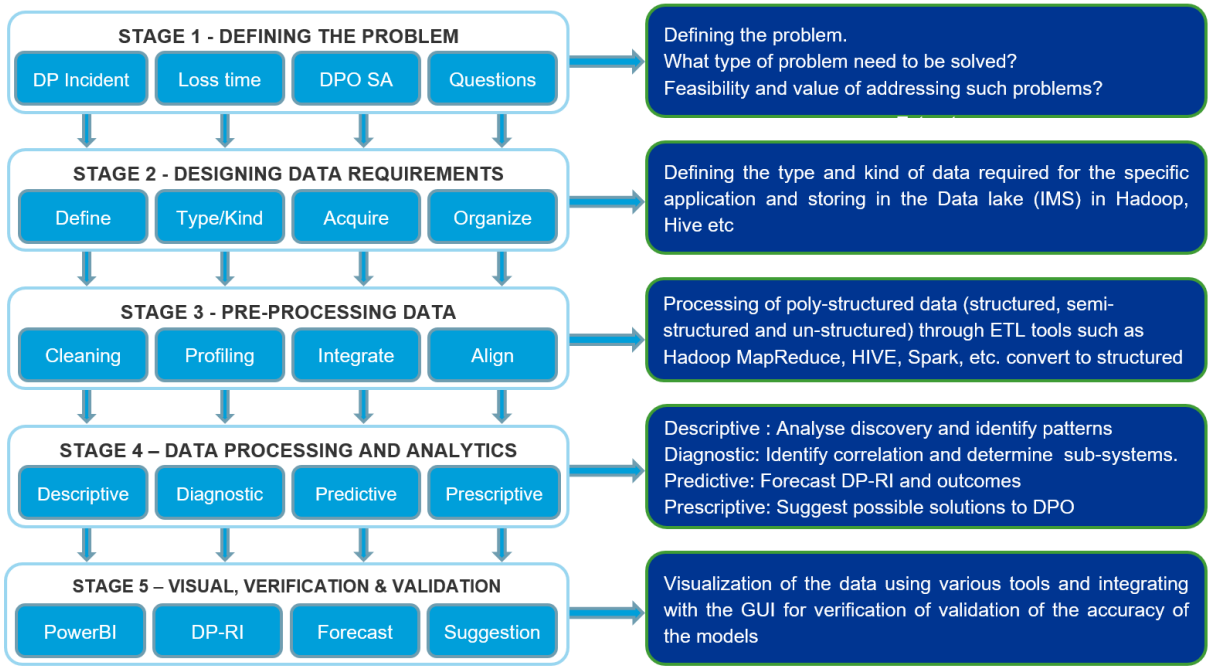


Figure 3-1 Stages of Big data Analytics for the DP system

As explained in the previous section, there is a considerable volume of data. Just having a massive amount of DP data is not enough; it is vital to store and process the data. Due to digitalisation of the data, there are three technological trends: Big Data analytics tools and technology, the concept of digital twins, and the emerging Internet of Things (IoT) platforms, which were used to create value by producing actionable knowledge from data [95].

The first stage of big data analytics was defining the problem, to identify the intended use and context for the DP system. The critical issues related to the DP system were described in Chapter 1 and Chapter 2, focus on the specific problem that will be addressed by the research.

The next stage was designing the data requirements, which involves identifying the type and kind of data required for solving the problem. In this stage, data from operators, vessel owners, flag state, DNV GL, shipyard, vendors, etc. were acquired in various formats and through different media. The data was stored in big data platform tools in the local Hadoop cluster and the cloud, depending on the agreed solutions with operators and vendors. The information is considered to be a data lake where the different databases such as the FMEA database, HIL database, DPCap database, OREDA database, IMCA database, and real-time sensor data are stored in an organised manner [3, 20, 21, 47, 57, 97]. The next stage is the pre-processing of data involving cleaning, profiling, integrating, and aligning the data for analytics. It is the most critical stage as all the inherent biases are addressed to ensure that the output from the analytics is close to reality, and performance accuracy is not compromised. Stage 3 of the Big data analytics is described in detail in Chapter 3. The next stage is the analytics stage, which explores the data through different algorithms to understand the patterns, reveal correlations, perform forecasting, and suggest solutions to respond to failure scenarios. For this research, four analytics concepts are used at different phases of the study to address the problems related to DP systems. The details of this stage are presented in Chapter 4, Chapter 6, and Chapter 7 respectively. The final stage is the visualisation of the models, along with verification and validation, to evaluate the model performance which is described in Chapter 8.

3.4 DP System Data Sources

The types of data that are used for reliability analysis have evolved over time. The traditional methods, for decades, have used lifetime and degradation data to provide reliability information. With the advancement of technology in the era of big data, there are new data types that are available and used for reliability analysis [93]. Massive data sets available in the past were not used for analysis due to limitations in computing capability. Now, with technology breakthroughs and the low cost of collection of complete data sets, there is a motivation for research to explore the data for reliability analysis [95, 98].

A massive amount of data is available from DP systems from sources such as documents, reports, Systems Applications and Products (SAP), automation servers, historical databases, images, videos, JavaScript Object Notation (JSON), Extensible Mark-up Language (XML), mail servers, etc. The part of the overall data generated from these sources is structured, whilst

the rest of the data are either in a semi-structured or unstructured form. Storage and analysis of structured data have been happening for a long time; however, the volume of unstructured data has multiplied in recent times [98, 99]. Offline and real-time data are starting to be used in reliability prediction in other industries due to improved accuracy, and it is having a direct impact on operational efficiency. Following the big data concept used for the DP system, the data are grouped into three categories as follows [95, 98, 99, 100]:

- Structured Data
- Semi-Structured data
- Unstructured Data

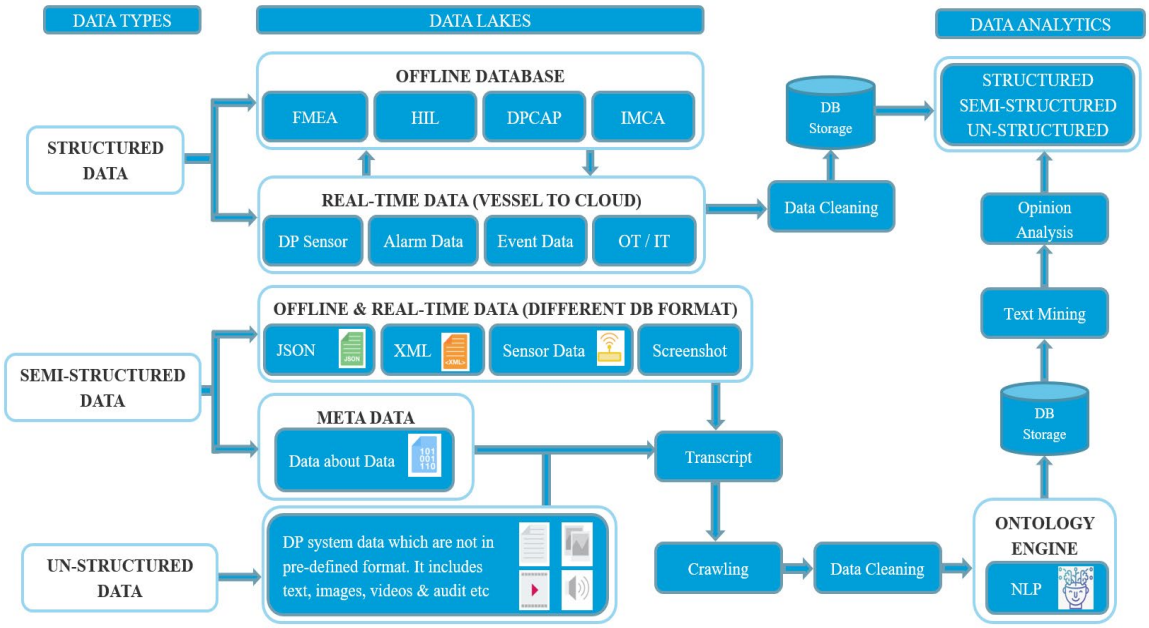


Figure 3-2 DP System – Data Types

Structured, semi-structured and un-structured data must be combined to form the big data before the application of analytic tools. The format of each of the data sets available is different, and so appropriate transcript steps were taken before the combining process. Usually, little effort is needed for the cleaning and profiling of structured data, when compared to semi-structured / unstructured data, due to the variety of formats for the latter which are not suitable to import into a pre-defined relational database management system [99, 101]. Thus, more sophisticated big data tools are required for processing semi-structured / unstructured data. Figure 3-2 shows the complete architecture of the data types and processing steps [99].

3.4.1 Structured Data

Structured data of DP systems is data that is characterised by a pre-defined data model and standard relational database management system [102]. As the data are in a standard format, it is therefore straightforward to analyse. Most of the structured data can be represented in tabular format with the relationship between the rows and columns. Therefore, a systematic method for cleaning and profiling the data may be applied as it can be sorted through columns and rows. The structured data in the tabular format were converted into excel or SQL format for the research studies.

The DP systems' structured data were collected from the following sources, which are categorised into two types:

- Offline data
    - FMEA database
    - HIL database
    - DP capability plot database
- Real-Time data
    - DP Control System (Sensor Data)
    - Power Management (Sensor data)
    - Thruster Control System (Sensor Data)
    - Reference System (Sensor Data)
    - Environmental Monitoring System (Sensor Data)
    - Condition Monitoring System (Sensor and Forecasting)
    - Alarm Logger
    - Event / Data Logger
    - DP Footprint & DP simulation
    - DP capability (online analysis)

The data, generated by humans or machines, is in a pre-defined format to fit into the Relational Database Management System (RDBMS), which can be accessed through queries and algorithms. The data are then pre-processed through standard data cleaning and profiling techniques. This step ensured that biases and unwanted data are removed from the raw information. This type of data is easy to enter, save, find and analyse, and is searchable through

the structured query language. However, due to its inflexibility, sometimes its usage is restricted for specific applications. Once the data was cleaned, they were stored in the HADOOP cluster, which was specially prepared for the research project in dedicated locations in different offices within the DNV GL organisation network. The structured data was combined with semi-structured and unstructured data once the other streams of data became ready for analytics.

3.4.2 Semi-Structured Data

DP system semi-structured data is a form of structured information that does not fit into the pre-defined data model or any standard RDBMS to comply with the defined tabular format [100, 103]. The data is in different tabular formats, which contain tags and other identifiers to separate the semantic elements. Hierarchies of fields within the data also characterise it, and records are systematically arranged. The semi-structured data are defined by self-describing structure differentiating it from unstructured data. The typical format of semi-structured data is JSON, XML, email, and RDF, etc. with metadata.

The DP systems' semi-structured data are collected from the following sources, which are categorised into two types:

- Offline data
    - IMCA database
    - OREDA database
    - DP Operational manual database
    - Proving trial / Annual Trial
    - DP system FAT Procedure
    - DP system CAT Procedure
- Real-Time data
    - Operational Technology (OT) data (not in pre-defined format)
    - IT data (Interface with OT)
    - Time-series trends
    - Graph and Forecast data
    - GPS and DGPS System (Sensor Data)
    - Asset Management System (AMS)

The semi-structured data are more accessible to analyse than unstructured data due to the availability of big data tools with the ability to read and process either from JSON or XML. Therefore, it resembles the features of structured data. The metadata feature of semi-structured data provides additional information which is frequently used by big data solutions for initial analysis.

3.4.3 Unstructured Data

DP system unstructured data is information that either does not have a predefined data model or is not organised in a pre-defined manner. The data usually consists of textual or non-textual records that are human or machine-generated and stored in the non-relational database management system (Text, Pdf, Word, email communication, Images, and Reports, etc.) [99, 102, 103]. Due to the inbuilt attributes of unstructured data, it leads to irregularities and ambiguities that make it difficult to understand using traditional computing tools.

The DP systems' unstructured data are collected from the following sources, which are categorised into two types:

- Offline data
    - Maintenance Records
    - Inspection records
    - Photograph (Images) and Screenshots
    - Videos in Voyage Data Recorder (VDR)
    - Accidents failure investigation reports
    - Manufacturer failure database
- Real-Time data
    - DP Screen recording
    - Closed-circuit television (CCTV) recordings
    - Interviews

In recent years, due to technological developments, new tools are available to store, clean, and analyse specialised types of unstructured data. Therefore, in this research, the big data tools available within DNV GL were used in the context of big data to ensure that its potential is fully utilised to address the problem in hand. Table 3-2 shows the various data types used for the research and its grouping along with features, storage location, size etc.

Table 3-2 DP System – Big Data Sources description

DATA TYPE	DATA COLLECTION	DATABASE DESCRIPTION	FEATURES / ATTRIBUTES	DB STORAGE LOCATION	DATA SIZE
STRUCTURED	OFFLINE	FMEA	SYSTEM	ON-PREMISE	120 GB
		HIL	SYSTEM + OPERATION	ON-PREMISE	60 GB
		DP CAPABILITY	OPERATION	ON-PREMISE	20 GB
	REAL-TIME	DP CONTROL SYS	SYSTEM	CLOUD	40 TB
		ALARM LOGGER	SYSTEM + OPERATION	CLOUD	120 GB
		DP SIMULATION	SYSTEM + OPERATION	CLOUD	40 GB
SEMI-STRUCTURED	OFFLINE	IMCA	SYSTEM + OPERATION	ON-PREMISE	1 GB
		OREDA	SYSTEM	ON-PREMISE	12 GB
		PROCEDURES	OPERATION	ON-PREMISE	40 GB
	REALTIME	ASSET SAP SYSTEM	SYSTEM	CLOUD	20 GB
		TIME SERIES TRENDS	SYSTEM + OPERATION	CLOUD	60 GB
		GPS & DGPS	SYSTEM + OPERATION	CLOUD	8 GB
UN-STRUCTURED	OFFLINE / REAL-TIME	PDF	SYSTEM + OPERATION	ON-PREMISE	10 TB
		IMAGES	SYSTEM + OPERATION	ON-PREMISE	4 TB
		AUDIO/VIDEO (BLACK BOX - VDR)	OPERATION	CLOUD	2 TB

3.4.4 Conversion of Semi / Unstructured Data into Structured Data using NLP

NN models cannot use the semi-structured and unstructured data of the DP system for classification, prediction, and prescriptive analytics applications. The critical step in the research involves the conversion of semi-structured and unstructured data into pre-defined RDMS structured data [104, 105]. The pre-processing of semi-structured and unstructured data is required before performing the conversion. The semi-structured data was converted to structured data using data-mining tools and techniques for information extraction and NLP. However, it was not straightforward to convert the unstructured data into semi-structured or fully structured information. During the pre-processing stage, the steps of transcription and data crawling are performed on the semi-structured and unstructured data. The critical information is filtered and collected before performing data cleaning. After this, the combined data are placed in the data lake ready for conversion.

In this research, a common standardised approach was used to convert both the semi-structured and unstructured data of the DP system to pre-defined structured data and store them in the HADOOP data cluster before classification data analytics to identify the critical sub-systems. An ontology-based NLP concept was used by coupling the reasoning concept of ontology with the lexicon component in NLP [106, 107]. The mix of semi-structured and unstructured data is passed into the system, where the two features of ontology are used for NLP. Firstly, ontology is used as a building block when defining the terms for content words through the lexicon. The second key feature of ontology, acting as a knowledge-base, is where it serves as the primary system/brain for the complex language processing used along with NLP to optimise the efficiency in conversion [108, 109].

The ontology-based NLP uses Morphological analysis, Syntactic Analysis, Semantic Analysis, Pragmatic Analysis, and Discourse Analysis in either a step by step approach or combined efforts. The Term Frequency-Inverse Document Frequency (TF-IDF) defined the descriptive definition and documents and grouped accordingly. In this way, it was ensured that the database with semi-structured and unstructured data is analysed based on how the text is built up, put together, what it means, how it is used in different situations, goals and intentions and the inter-relation between additional text. The steps are modified into critical activities to

perform the conversion of semi-structured and unstructured data into structured data through knowledge discovery in the database (KDD) [105, 107, 108].

The critical activities applied to the database for conversion using NLP are listed below [101]:

- Tokenization: Strings into tokens
- Stemming: Normalise words into its base form or root form
- Lemmatization: Morphological analysis of the words
- POS tags: Extraction of semantic information
- Named entity recognition: Process of detecting the names of the entity
- Chunking: Picking the information and grouping into the sentence

The hybrid data lake is created with semi-structured and unstructured data stored in the Hadoop cluster and cloud infrastructure. The complete architecture of the conversion of semi-structured and unstructured data of the DP system to pre-defined structured data, in the standardised approach through ontology-based NLP, is shown in Figure 3-3. Various tools and libraries such as Google Cloud Platform (GCP), Ghost-script, Google NLP AutoML, Jupyter Notebook, and NLPTK were used for this application. The converted, pre-defined structured data were stored in a data warehouse for machine learning models to perform analytics.

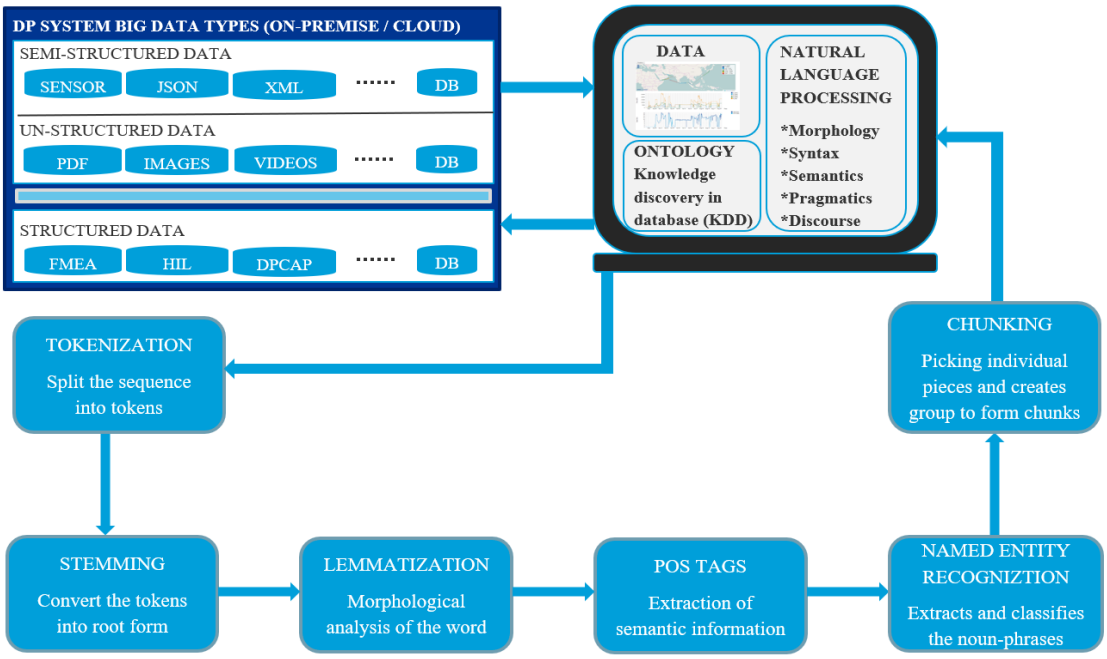


Figure 3-3 Ontology-based NLP – Conversion of semi/unstructured data

3.5 DP System Offline Data Lake – Information Management System (IMS)

The significant phases of the DP life-cycle include design, construction, commissioning, sea-trials, and operation [1, 2]. In all of these phases, the design evolves, and changes are implemented for safe, reliable, and efficient operation. As discussed in Chapter 2, historically several traditional reliability assessment methods have been implemented in different phases for improving the design of the system. However, they have not been able to prevent all the accidents from occurring based on the analysis of the accident database report from IMCA [3]. Besides, the traditional reliability assessment methods have not demonstrated their ability to provide clear information on faults and provide appropriate solutions during operation.

The traditional methods have been proved to enhance the design and increase the safety and reliability of the DP vessels over the years to a certain extent. There is a massive amount of data produced by these methods by various stakeholders at different stages of the DP life cycle. Figure 3-4 shows the relation of data collected from the sources and stages of the DP life cycle. In this research, the databases are organised and stored to form a data lake. Further, it is used to understand the correlation between the sub-systems and inter-dependencies through the risk assessment methodologies.

DP Life Cycle / Data Source	Engineering Design	Construction	Sea Trial and Acceptance	In-Service / Operation
FMEA	X		X	X
HIL	X	X	X	
IMCA				X
WOAD				X
DP CAP	X		X	X
OREDA				X
MAN FD	X			X
REAL TIME			X	X

Figure 3-4 Database collected during DP lifecycle

The Information Management System is a combination of offline and real-time data. In this section, the offline data lake of IMS is discussed in detail. The offline data lake is formed by grouping the below set of databases which consists of structured, semi-structured, and unstructured data [2, 16]:

- FMEA database
- HIL database
- IMCA database
- WOAD database
- DPCAP database
- OREDA database
- Manufacturer Failure database (MAN FD)

The databases of the offline data lake were collected from different sources either from the DNV GL domain, vendor databases or from publicly available sources during the initial two years of the doctoral study. The data are confidential and necessary consent was agreed with the respective data owners to use the data for research purposes. Figure 3-5 shows the database architecture used for the research studies along with its interface with the Hadoop platform and the layer of security.

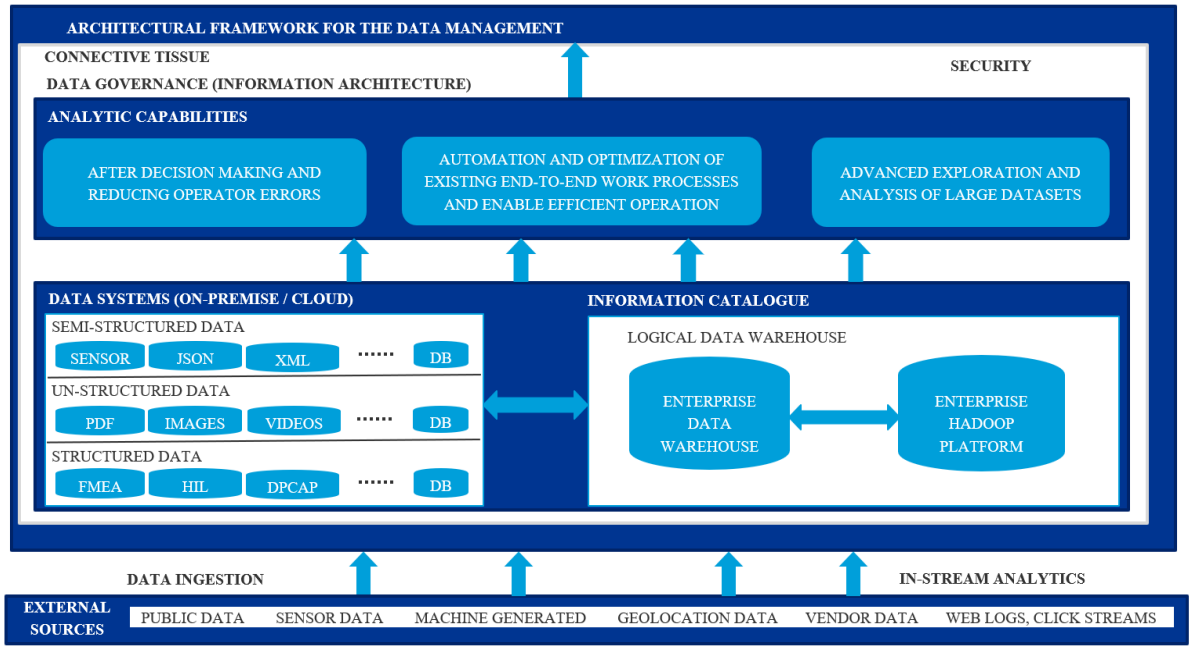


Figure 3-5 IMS – DP system Database Architecture

3.5.1 FMEA Database

The FMEA database was created for this research by collecting the reports of more than 500 vessels for which the risk assessment was performed by DNV GL (DNV and Noble Denton). The data were generated over 30 years and were cleaned before being used in the research study, with the consent of the data owner. FMEA is an industry-wide accepted tool for studying the behaviour of the DP system in cases of single-point failure [15, 45]. It involves a Design Review of the DP system by evaluating the Functional Design Specification, Drawings, IO list, etc., preparing the FMEA worksheet, and finally, the FMEA report categorising the impact of the failure into three categories (Highly Critical, Medium and Low). The FMEA database contributes 120 GB to the total data size and keeps accumulating along with the current increase in the number of DP vessels.

The following key features are extracted from the database and used in the research study [17, 46, 53]:

- Identify all possible failure modes and their effects.
- Generate a list of potential failures with an assessment of the magnitude of their effects.
- Develop corrective action priorities in decision making for prescriptive analytics.
- Evaluate design requirements related to redundancy, failure detection systems, fail-safe characteristics, and automatic and manual override.
- Provides historical documentation for future reference to aid in the analysis of field failures and consideration of design changes.
- Provide an input basis for quantitative reliability and availability analysis.

3.5.2 HIL and Digital Twin Database

The HIL database was created from the test results performed on more than 100 vessels by DNV GL (Marine Cybernetics and DNV GL). The data was generated over 12 years from the ships where testing of the DP system, PMS system, and Thruster system was carried out as integrated and standalone systems. Today most of the complex and sophisticated DP vessels undergo HIL testing to make sure that glitches in the software are identified at the early stages of the projects [47, 56]. Classification Societies like DNV GL, ABS and LR realised the importance of the HIL testing and came up with rules to cover Control System Software testing

by HIL [55]. The safety and Reliability of the DP system have increased to some extent after the different subsystems of the DP system underwent HIL testing.

Recently the Digital twin concept has been used, as a stand-alone testing solution or in combination with HIL testing, to evaluate the performance of the software for the DP system. The digital twin and HIL concepts were applied by major DP system vendors such as Kongsberg, Rolls Royce, GE, and MT etc. This method has enabled stakeholders to gain insights into how different DP systems will respond to any particular failure during real scenarios. The HIL and Digital twin have contributed a total of 60 GB of data to the data lake. Figure 3-6 shows the critical findings in HIL testing, and the following key features are extracted for the research study [47]:

- DP system failure contributors
- Different functions of the DP system and consequence of failure on DP sub-system
- The possible solutions for the failure and addressing consequences
- The sub-system in which major software failures could occur
- Identify the DP vendor occupying the significant market share

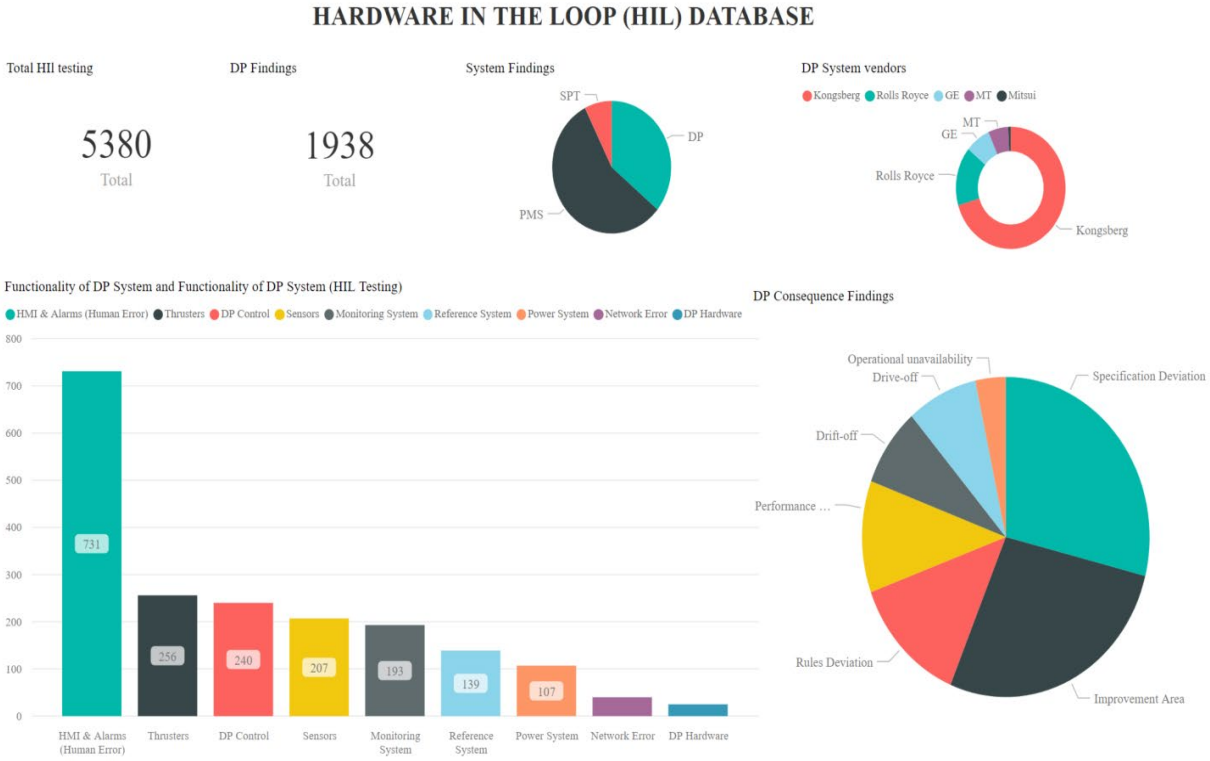


Figure 3-6 HIL database – Key Findings

3.5.3 DP-CAP Database

DP capability plots are mandatory for all DP vessels, and these data were collected from about 300 ships for the research work. This contributes to the off-line as well as real-time data. Those DP capability plots which are generated during the design stages are stored in the offline database in the on-premises Hadoop ecosystem. However, those that are generated on-board during operation along with DP simulations are collected as part of the real-time data and stored in the cloud infrastructure. The static and time series DP capability plots are collected and stored, contributing to a total size of 20 GB in the RDBMS format.

3.5.4 IMCA Database

The IMCA has documented DP incidents internally by technical advisors based on data received from its members and non-members [3]. The data are accepted either in structured or in semi-structured formats and submitted to the database as long as the station keeping incident analysis can be performed on the information received. The systematic approach of research in the report is collected and stored in the database. The data collected was from a report dated from 1990 to 2020, covering 30 years of DP history and a total of 1900 accidents were analysed. The total amount of semi-structured data collected is about 4 GB, which are stored in the on-premises Hadoop ecosystem.

The review and analysis of incident reports are performed by IMCA to encourage and improve reporting throughout the industry. The study provided valuable lessons learned and meaningful analysis insights that were used to enhance this research. Definitive conclusions about the safety of DP operations were not drawn from the statistical analysis of the reports; however, trends or patterns may be determined over time. In this review, initiating events, causes, and comments reported by users have been incorporated into a table for easy comparison [3]. This method enables individual DP vessels to readily complete an onboard comparison of actual events occurring in the industry with the situation on-board their ship.

3.5.5 WOAD Database

WOAD is the world's most comprehensive data source of its kind available for offshore risk assessment and emergency planning. The accident data has been collected since 1970 and includes more than 50 years of world-wide accident history. The database is continuously being updated with the latest information available from authorities, official publications and

reports, newspapers, databases, rig owners, and operators globally [20]. The database collected included data on more than 6000 accidents with a wide range of parameters such as name, type, and operation mode of the unit involved in the accident, date, geographical location, chain of events, causes, consequences, and evacuation details. The total amount of semi-structured data collected is about 76 GB, which are stored in the on-premises HADOOP ecosystem.

The WOAD provides various key and critical information that is used for this research study. Knowledge of past DP accidents serves as an essential input to risk assessment concerning hazard identification, consequence evaluations, decision support, and identification of high-risk areas. Learning lessons from accidents is vital to avoid accidents in the future.

3.5.6 OREDA Database

OREDA is a project organisation sponsored by nine oil companies with worldwide operations. OREDAs' primary purpose is to collect and exchange reliability data among the participating companies and act as the forum for co-ordination and management of reliability data collection within the oil and gas industry. OREDA has established a comprehensive databank with reliability and maintenance data for exploration and production equipment from a wide variety of geographic areas, installations, equipment types, and operating conditions [97]. The data are stored in a database, and specialised software has been developed to collect, retrieve, and analyse the information. The total amount of semi-structured data collected is about 60 GB, which are stored in the on-premises Hadoop ecosystem.

3.5.7 DP Vendor Equipment MTBF Database

Manufacturers of equipment in the marine, oil, and gas industry maintain failure databases for all of the equipment supplied by them. OREDA provides more generic failure data from different manufacturers and collectively addresses the failure data for the equipment. However, for more accuracy, it is necessary to use the actual failure rate of the equipment from the manufacturer. Some of the typical suppliers of DP systems from whom the data was collected are Kongsberg, Rolls Royce, GE Converteam, L3 communication, and Marine Technologies (MT). The data was collected and stored as a database from more than 2000 projects within DNV GL. The total amount of semi-structured data collected is about 120 GB, which are stored in the on-premises Hadoop ecosystem.

3.6 DP System Real-Time Data Lake – Information Management System (IMS)

Real-Time data are critical data which represents the actual state of the equipment during operation. With the development of sensor technology, the IoT, System on Chip (SoC) and cloud computing, it is easy to extract the data during operation and transfer it to shore for processing [110, 111]. Figure 3-7 defines the architecture set-up used for harvesting the real-time data from DP vessels operating offshore. The set-up was established on ten ships to collect and transfer data using vessel-to-cloud infrastructure for further processing and modelling. The amount of real-time data collected and simulated by digital twin is about 40TB and the data are transferred either real-time, near real-time or in batches.

The transfer of data from vessel to onshore are either done independently by each sub-system or from an integrated IMS system which communicates with the DP System. The system which is performing the control function on the vessel is classified as OT and systems which take care of the transfer of data to shore are classified as IT. The information transferred to shore is secured through firewall protection and used for real-time monitoring, processing and forecasting functionality [112, 113].

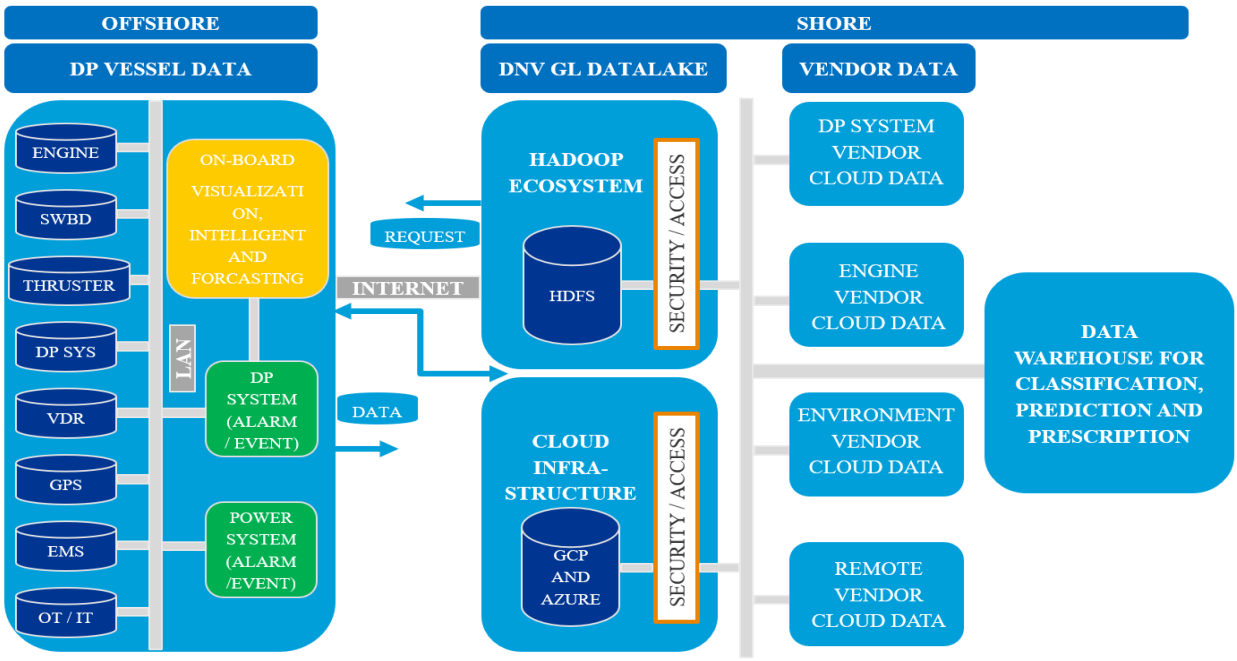


Figure 3-7 Real-Time data transfer from the vessel to shore for Analytics

3.7 Tools and Experimental Set-Up for the DP System Big Data Analytics

The experimental set-up for the research used a local big data Hadoop ecosystem and cloud-based infrastructure for DP system-related data storage, processing, profiling, organising, analysing, and analytics. The Hadoop ecosystem used semi-structured, unstructured, and structured data, which are readily available offline data so that a data lake could be created using an efficient and organised approach [114]. Similarly, for real-time data extracted from operational vessel technology, which are structured, the vessel-to-cloud approach was used for storing the data in the cloud. The hybrid approach was used to process the data before analysis.

The key advantages of using the Hadoop ecosystem for this research are listed below [92, 114]:

- Infra-structure is fault-tolerant and highly reliable
- In-built capability to integrate seamlessly with cloud-based services
- Ability to handle different data formats and address big data problems efficiently

The Hadoop ecosystem was created with a group of tools and applications to support the DP system-related big data management and processing. The Hadoop architecture and ecosystem tools are shown in Figure 3-8 and Table 3-3. Based on the specific requirement, the tools used and functional details of the tools in the Hadoop ecosystem are described below [114]:

HDFS: Hadoop Distributed file system to store data.

YARN: Resource manager to leverage and process big data.

PIG: Data processing for grouping, filtering, joining, and storing to HDFS.

HIVE: Processing of RDBMS data through HQL.

MAHOUT: Implementation of Machine Learning for Clustering and Classification.

SPARK: Real-Time data analytics.

HBASE: Supports grouping and automatic distribution of data across a cluster.

DRILL: Combines the database and executes through a single query.

OOZIE: Sequential and event-based job scheduler.

FLUME: Ingest semi-structured and un-structured to HDFS from multiple sources.

SQOOP: Ingest structured data either real-time or batch ingestion via filtering and enrichment.

ZOOKEEPER: Ensures coordination between various tools in the Hadoop ecosystem.

APACHE AMBARI: A cluster management tool for managing and monitoring.

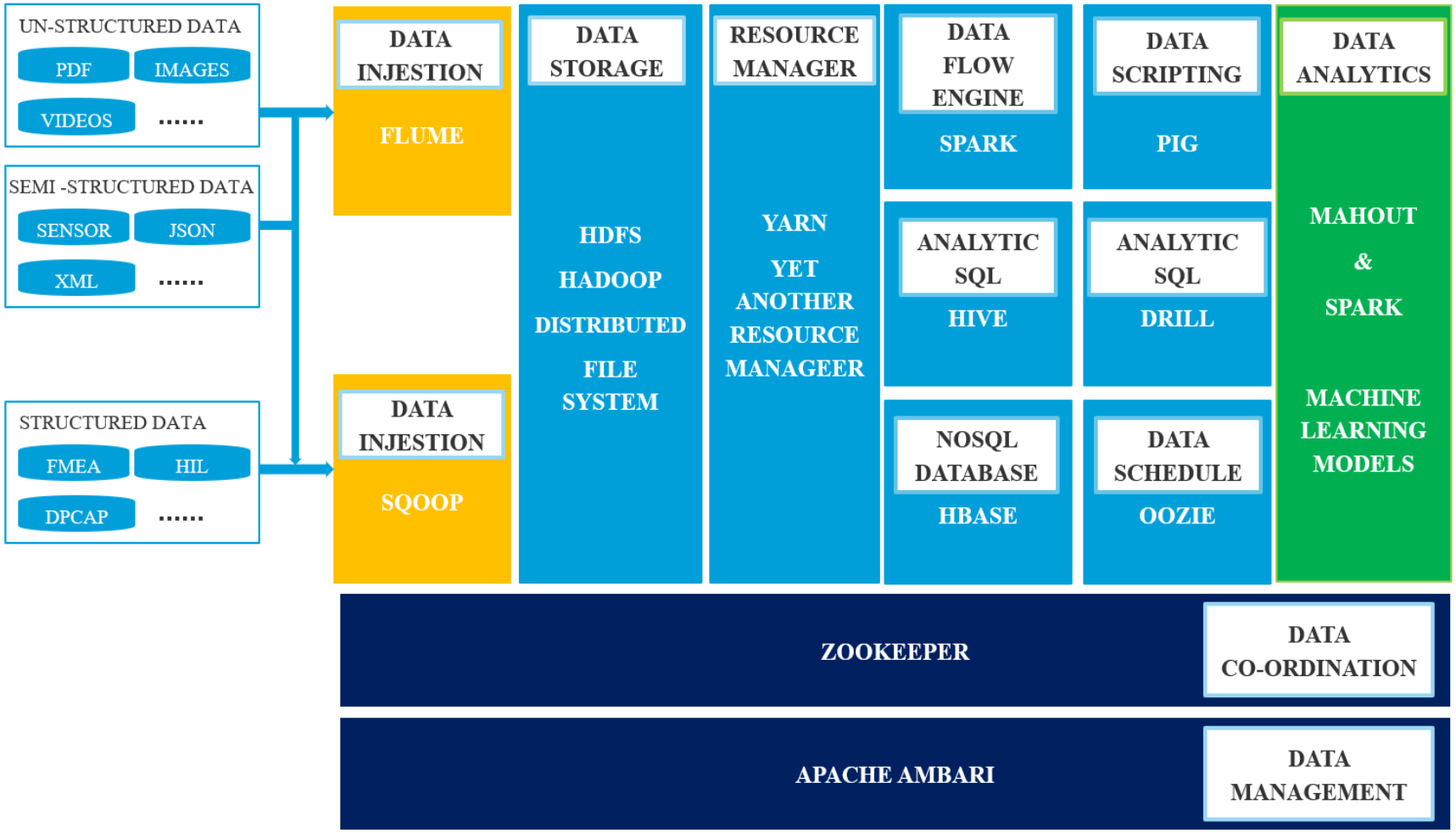


Figure 3-8 HADOOP Ecosystem architecture with tools and applications

Table 3-3 Experimental set-ups on local premises to handle DP system Big Data

EXPERIMENTAL SET-UP WITH HARDWARE	DESCRIPTION AND DETAILS
   DATA STORAGE AND ANALYSIS (HADOOP STACK) SPARK HIVE HDFS HBASE Tensorflow 2.0 was released in 2019 with more capabilities, therefore the later part of research used Colab and tensorlfow applications.	**HADOOP ECOSYSTEM** • 44 nodes • 1280 cores (40 * 32) • 10 TB RAM • 20 Petabytes **TOOLS** • HDFS • YARN • Pig • Hive • Spark • Hbase • Oozie • Flume & Sqoop • Zookeeper • Ambari **CONFIGURATION** • HDFS: Standard + Custom • Disc Usage: 40 % • Data nodes: 40 • Master nodes: 2 • Edge node:1 • Management node:1 • Node Managers: 4 / 4 • Memory usage: 70% • Cluster Load: 30% • Replication Factor: 3

3.8 Need for the Implementation of Big Data Analytics

In recent times, there has been a strong trend in the maritime, oil, and gas industries to move towards data-driven decision making and the use of data analytics for managing performance and risk. For this research study, which focuses on effective decision making for the DP system, Knowledge Management (KM) and ANN models are required. Big data and data analytics techniques play a significant role in KM by active knowledge generation through correlation and result in significant, timely decision making. The technological advancement changes the modes in which the data are collected, stored through high-speed data ingestion, and computed in complicated data structures. The following reasons are identified as the need for implementation of Big Data Analytics for addressing the research problems:

- Increased connectivity, new capabilities for capturing, storing, processing, presenting, and visualising data, and, in particular, the transmission of large volumes of varied DP data at high velocity, have forced the use of Big Data Capability tools.
- Existing lack of consistent knowledge has led to poor performance in the past; therefore, proper strategies need to be devised to create new experience from the existing historical data, which are either semi-structured or unstructured. The information from these data-sets can be used for knowledge generation and used for operational efficiency.
- Selection and accessing of the characteristics that have great significance to the operational reliability assessment were not possible previously. With IoT, Digital Twin, and Big Data tools, the critical features are extracted with useful state features at the same time, reducing the computational burden, even with a massive number of datasets.
- Decisions are made in real-time according to the data generated, and timely and accurate decision-making is what makes all the difference for complex marine operation offshore, and it supports in the prevention of any DP related accidents.

3.9 Summary

Chapter 3 gave a detailed overview illustrating why the data sources of the DP System are considered a big data concept. The correlation between the attributes of big data is evaluated against the DP system data sources to justify the adoption of a big data methodology for this research. Subsequently, various stages in big data analytics are presented and how the chapters in the thesis are connected with each stage. The different types of data: structured, semi-

structured, and unstructured, in the data sources are defined along with the properties, format, and usability for the research. Also, each data source was defined and grouped into offline data and real-time data. The data types which are not automatically usable for the analysis were converted into a usable format using an ontology-based NLP methodology.

In addition, all the databases collected were described with details of size, type of data, number of vessels, projects, and source of the database. Next, the Hadoop ecosystem with complete tools and applications used for the research was described. The experimental set-up with the hardware configuration and software application were defined. Finally, the need for the implementation of big data analytics for this research was presented.

In the next chapters, the data collected, stored, and processed will be used for analytics through knowledge of experts and intelligence of computing capabilities. The data analytics will focus on the following aspects to address the research problem step by step:

- Descriptive Analytics → What has happened in the DP System?
- Diagnostic Analytics → Why did it happen in the DP System?
- Predictive Analytics → What will happen if there is any failure in the DP sub-system?
- Prescriptive Analytics → What should be done in the case of failure (possible suggestions)?

Chapter 4 describes the descriptive and diagnostics analytics used for classification of the DP System and identifies the critical DP sub-systems. The correlation and inter-dependencies between sub-systems are identified. Then each of the sub-systems is presented with system architecture and signal description at the component level.

4. Classification of DP Sub-Systems: Descriptive and Diagnostic Analytics

4.1 Introduction

The next stage of the work is stage 4 of big data analytics, which involves data processing and analytics. This chapter presents the descriptive and diagnostic analytics to ensure that data exploration and preparation are sufficiently thorough in addressing any problems associated with the data. It is proven that more and better data beats a good algorithm every time [115]. Thus, this stage is critical, involving data exploration and decisions as to what data is going to be used for predictive and prescriptive analytics. In addition, effective data preparation steps increase the accuracy of the prediction models by utilising the power of the available data most efficiently. The common issues related to data are addressed by ensuring that the data are collected from a range of available sources, defining the features, identifying and treating missing values, deleting the duplicate observations, and making assumptions. As part of the research study, significant time was spent on meticulously preparing the data. This stage helped in the later phases during predictive and prescriptive analytics to get better and more credible results. The descriptive and diagnostic analytics are the first part of advanced analytics, which identifies the input variables (sub-systems) and its relations with the target variable (DP System Reliability) are presented. The next sections of this chapter describe the sub-systems covering the system description, architecture within the Graphical User Interface (GUI) model, and input variables (signals) at the sub-system level.

Stage 4 of big data analytics involving data processing and analytics (descriptive and diagnostic) comprises the following activities:

- Data exploration and preparation
- Performing quality checks
- Creating a data dictionary
- Understanding and identifying the variables at system and sub-system level
- Creating other derived variables
- Identifying the correlation and interdependencies between variables
- Classification of DP sub-system
- Description of DP sub-system and architecture

4.2 Descriptive and Diagnostic Analytics

Descriptive analytics was used as the first step of the advanced analytics, and helped to analyse and reveal, "What has happened in the DP system?" [96, 116]. It is the critical step in understanding the datasets and the basic content in the data lake. It provides various insights and different metrics captured for the datasets. Typical techniques used for descriptive analytics are statistics and distributions to identify different sub-systems that have effects on DP system functionality [117, 118]. Similarly, diagnostic analytics is the second step which helps to answer "Why did this happen in the DP System?" [116]. It plays a key role in determining the factors that contribute to the outcome along with dependencies between output and input variables. Therefore, it also identifies the sub-system roles and their inter-dependencies in the DP system performance. The two analytics steps are part of data mining and support in-built data processing steps for the next stages to make predictions and provide prescriptive solutions. Thus, data exploration and data processing are covered in the next section along with the different techniques used for descriptive and diagnostic analytics.

4.2.1 Data Exploration and Preparation

The output of stage 3 of data analytics (as shown in Figure 3-1) is the pre-processed data, which are ready for analytics. Data exploration is vital before the analytics step as it helps to understand the dataset [96]. For the DP system, there is a massive number of datasets that have been collected and made available and different tools are used to understand it. A top-down approach was used for this research study where the DP system was split into various sub-systems, and each sub-system divided into various associated components. The components may be designed with one or more sensors that have contributed to the data points. Therefore during the data exploration stage, the dataset is evaluated carefully to identify the variables for the research [116].

Variables are often referred to as the feature engineering properties of a dataset. They denote a specific piece of information about an observation or records in a dataset, which are known as the input, output, and unused variables [119, 120]. In this research context, the sub-systems are considered as variables for the DP system reliability, and the signals at each sub-system level are considered as the variables for sub-system reliability. The variables can be dependent or independent, and this is determined through correlation analysis.

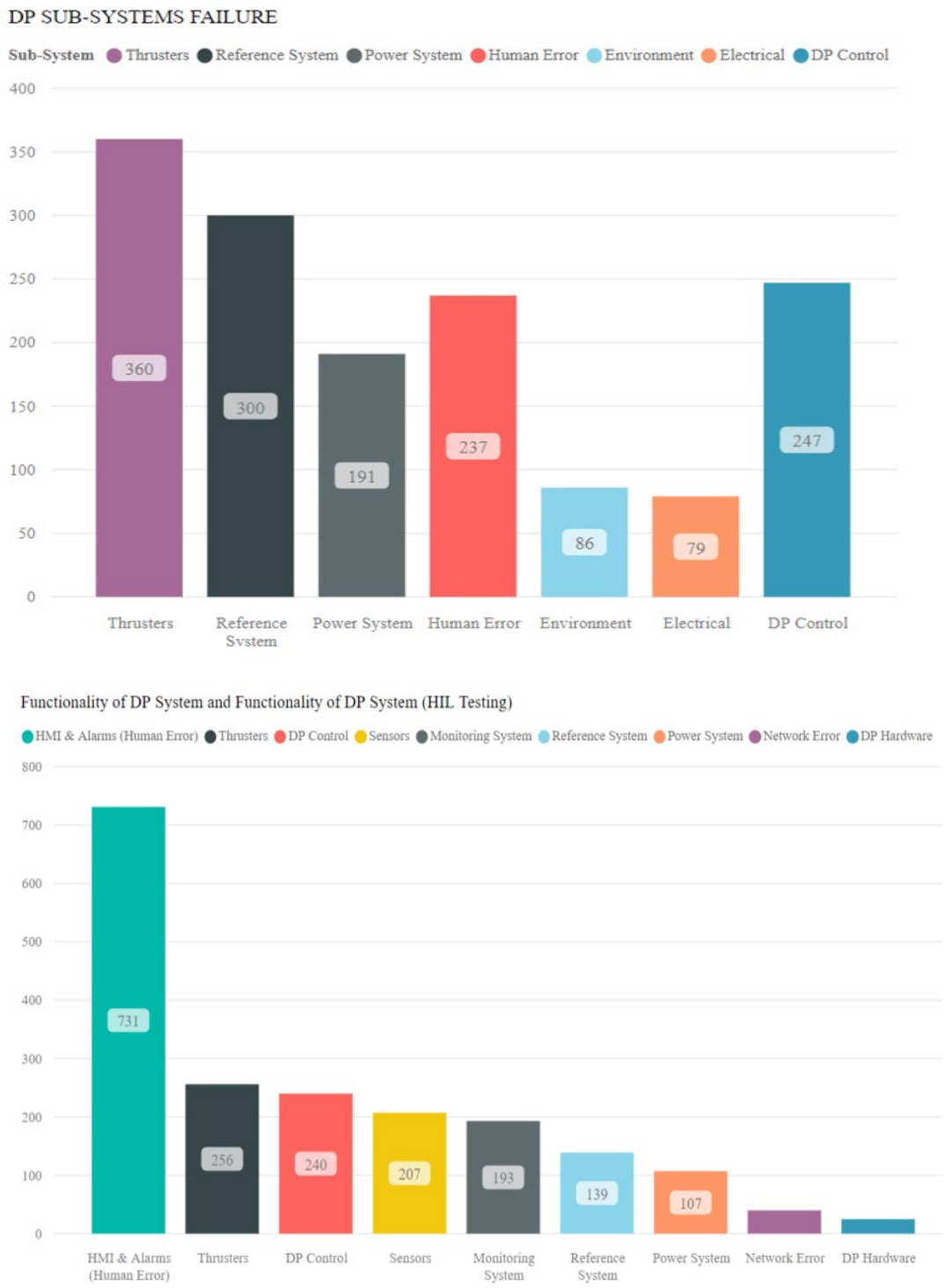


Figure 4-1 Data Exploration to identify the DP sub-systems

The variable selection is a critical step as part of descriptive analytics. Statistics and distribution analysis, which is considered to be a tool of descriptive analytics, are used to determine the system-level variables/feature selection [96, 117]. Statistics put the available

data set in context to identify the variables. Distributions show how the data is distributed over its entire range. If the data is very irregularly distributed, the resulting model will probably be of poor quality [116, 121]. For the DP system, the statistics and distributions are used to identify the sub-systems at a high level as the first step of data exploration. Figure 4-1 shows the typical sub-systems which contribute to the overall functionality of the DP system. As indicated, seven input variables have a direct impact on the DP system reliability.

A systematic approach must be used to identify the variables as the predictive and prescriptive analytics may not operate well if there are numerous inconclusive features [119, 122]. It has been proven that algorithm run-time grows dramatically when the features increase and, at the same time, the accuracy of the algorithm is negatively affected leading to overfitting problems [121]. The primary advantage of feature selection is that it results in the following [120, 123]:

- Improved accuracy of prediction
- Simplification of the visualisation and increase of readability of data
- Accelerated learning and prediction process
- Increased clarity of the generated rules for experts

In this research, the second level of feature selection was applied using the decision tree technique to validate the system level selection. This method also proves that seven sub-systems have an impact on the DP system reliability. Other sub-systems such as the Valve Control System (VCS), Crane Control System (CCS), Fire and Gas System (FGS), Portable Water System (PWS), Bilge System, Drilling Control System (DCS), Blow-out-Preventer (BOP) control system, etc. do not contribute to DP system reliability. The decision tree technique is also applied at the sub-system level to identify the features that contribute to its functionality and reliability. The two primary approaches of decision trees, Sequential Backward Elimination (SBE) and Sequential Forward Selection (SFS) are used for this purpose. At the system level the decision tree approach is used for validation; however, at the sub-system level, it is used for identification / shortlisting of variables [124]. A decision tree is a widely used method for feature selection, and at each node in the tree, it minimises the number of features [123, 122]. This method results in a better understanding of the datasets, possibly better visualisation of data, reduced transfer of data from vessel to shore, reduced training time with improved stability, and model accuracy. Instances / Observations, which

describe the actual data of the variables, are considered as records. The definition of records is described briefly in Chapter 6 and Chapter 7, along with predictive and prescriptive analytics models.

A data dictionary is a collection of descriptions of data objects or items in a data model, containing the attributes of variables for the benefit of others who may need to refer to them [125, 126]. A more detailed data dictionary will include the type, length, and format of the variable. They are created such that they are self-explanatory, and the fields should be easy to understand such that data sets can be used for the algorithms of similar applications. Table 4-1 shows the data dictionary at the DP system level. For each sub-system, there is a separate data dictionary table in the relevant section of the chapter, where it describes the variables along with type, format, and other necessary attributes. All variables used in the prediction are made visible to give an intuitive understanding through the data dictionary that does not happen with more complex representations of data sets [126].

Table 4-1 Data Dictionary for the DP system

VARIABLE	DEFINITION	DESCRIPTION	SUB-SYSTEM VARIABLES
A1	Reference System	Position and heading data	Refer Section 4.4
A2	DP Control System	Control algorithm	Refer Section 4.5
A3	Thruster/Propulsion System	Thrusters produce the required thrust to maintain a set position	Refer Section 4.6
A4	Power System	Generates & Manages Power	Refer Section 4.7
A5	Electrical System	The distribution system of Power	Refer Section 4.8
A6	Environment System	Wind, Wave and Current Loads	Refer Section 4.9
A7	Operator Error	Error during a complex operation	Refer Section 4.10
DP-RI	Reliability Index	Reliability of the DP System	Chapter 6

The output variable, which is the target variable for the research, is the Dynamic Positioning - Reliability Index (DP-RI). In general, DP system reliability is represented in a qualitative format for most vessels. However, a more sophisticated and complex DP vessel, for which quantitative risk assessment was performed, will have a quantifiable reliability value. For this research, both scenarios are handled considering the ship with actual DP reliability in

numerical form and a vessel with DP reliability in a qualitative format. In the qualitative case, a derived variable is used to represent the DP system reliability. The output variable at the sub-system level is a direct measure of reliability in the quantitative format as the values are calculated based on the critical component/equipment arrangement within the sub-system.

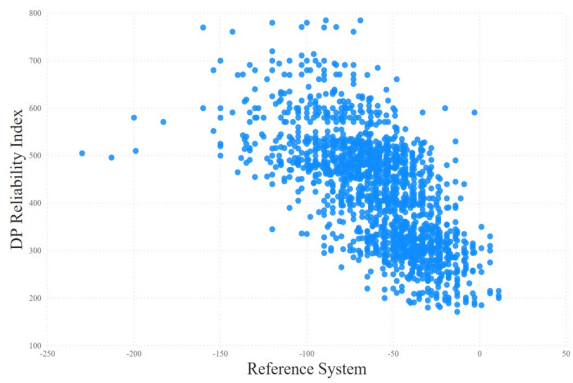
The key advantages of data-exploration and processing as part of the descriptive analytics are as follows [96, 116, 122]:

- Determination of additional dimensions for deeper insights
- Definition of derived variables
- Structure information of variables in the data dictionary for another user to understand the data sets easily
- Prevent incorrect analysis
- Address Missing variable and Perform Quality checks

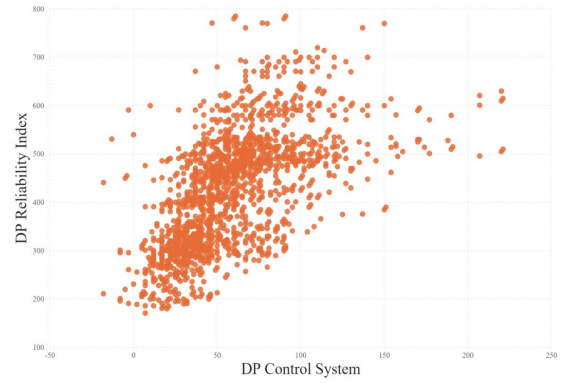
4.2.2 Correlation and Interdependencies

The feature selection step identified the input and output variables, the latter being a target variable derived through mathematical modelling/calculation. The next step is determining the correlation between the input variables and between input variables and the target variable. This step is part of the diagnostic analytics, which performs such activities using defined tools and techniques. For the correlation determination, the Scatter Plot and Correlation matrix are used to identify the interdependencies and correlation between variables [96, 116, 117].

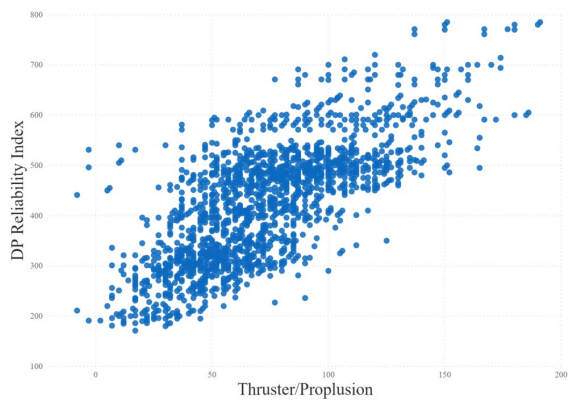
Scatter plots help in discovering the dependencies between the target variables and the input variables. Such charts plot output values versus input values [116, 118]. Figure 4-2 shows the plots of DP system reliability against the DP sub-systems to identify whether they have a positive or negative relationship. The correlation is a numerical value between -1 and 1 that expresses the strength of the relationship between two variables. When it is close to 1 it indicates a positive relationship (one variable increases when the other increases); a value close to 0 indicates that there is no relationship; and a value close to -1 indicates a negative relationship (one variable increases when the other decreases) [127, 128]. Thus, this method can be used to identify and remove redundant data to avoid over complication in the model algorithm.



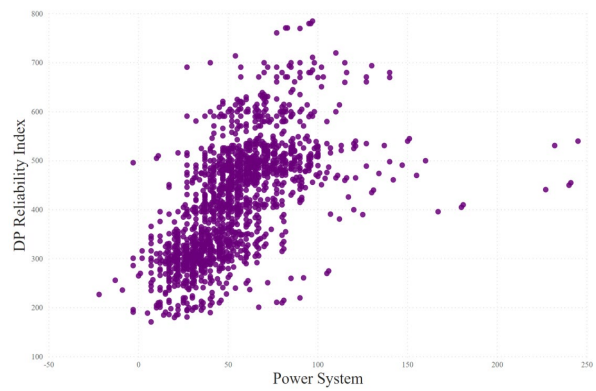
(a) DP Reliability vs. Reference System



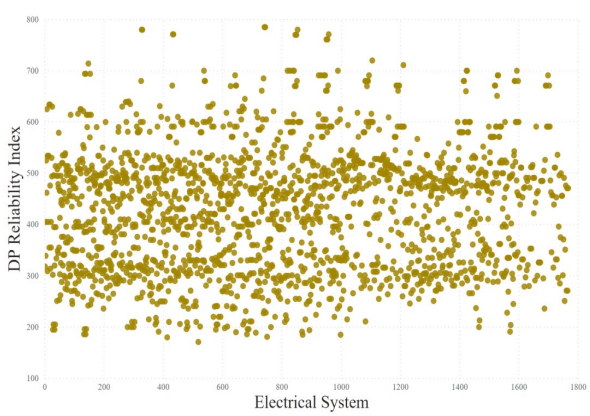
(b) DP Reliability vs. DP Control System



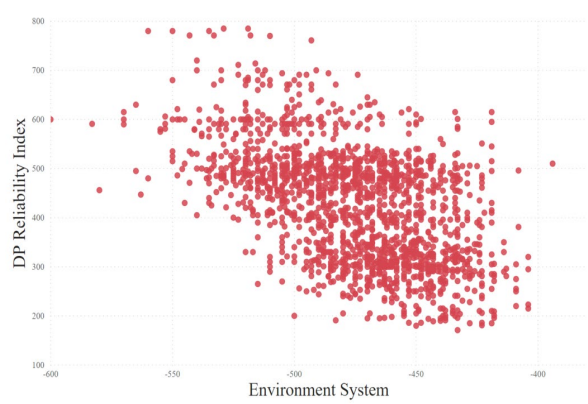
(c) DP Reliability vs. Thruster System



(d) DP Reliability vs. Power System



(e) DP Reliability vs. Electrical System



(f) DP Reliability vs. Environmental System

Figure 4-2 Scatter Diagrams – Correlation between variables

Correlation is a process of establishing a relationship or identifying the interdependencies between variables [128, 129]. Figure 4-3 depicts the correlation matrix indicating the inter-dependencies between the DP system and its sub-systems. The correlation technique is a part of diagnostic analytics that uses correlation coefficients. If the correlation is 0, they are independent of each other, that is, increasing or decreasing one does not increase or decrease another. On the other hand, if the correlation coefficient is 1 or -1, they are directly or inversely dependent, respectively.

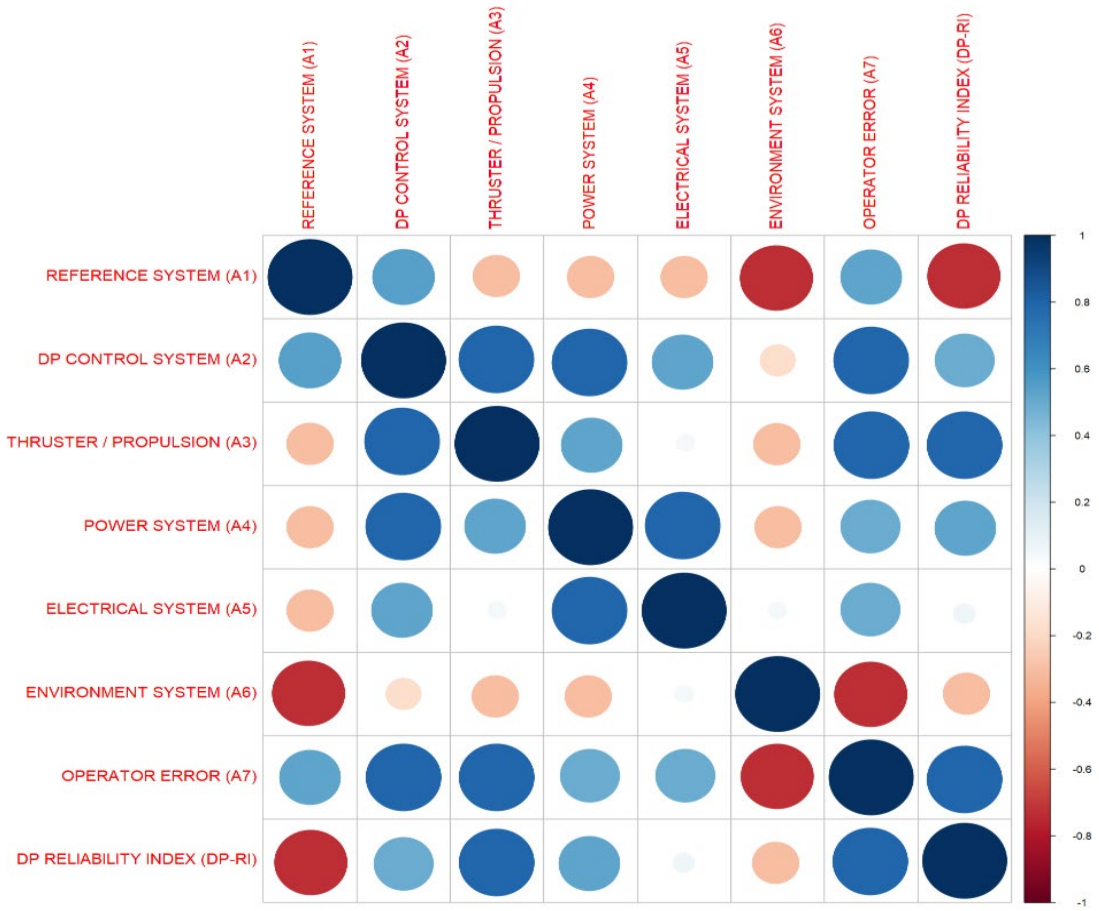


Figure 4-3 Correlation Matrix – DP sub-systems and DP-RI

Besides, the latent relationship was captured using the Partial Least Squares (PLS) regression method [130]. For real-time data, dynamic PLS are implemented in combination with the State-Dependent Parameters (SDP) approach to explicitly identify the relationship and interdependencies of time series [128, 130]. This way, the collinearity between the input variables is removed. At the same time, the accuracy of the model prediction is improved, which is described in later chapters of the thesis.

Figure 4-4 shows the complete architectural overview of the classification of the DP system to identify the critical sub-systems contributing to safe and reliable operation. Through descriptive and diagnostic analytics, it was identified that there is a total of seven sub-systems which have direct dependencies on the DP system reliability. In the next sections, sub-systems are evaluated to determine the critical variables contributing to the functionality and reliability.

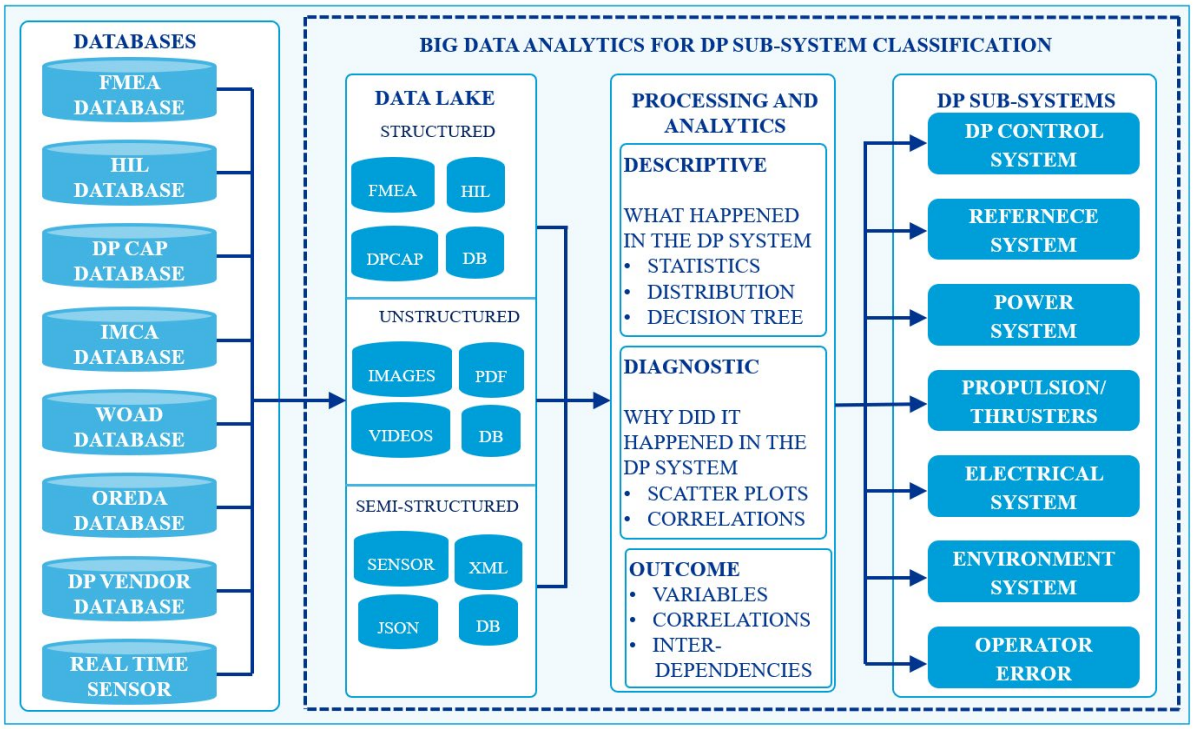


Figure 4-4 DP System classification – descriptive and diagnostic analytics

4.3 Data Dictionary and Critical Attributes at the Sub-System Level

At the sub-system level, a comprehensive data dictionary is created as the number of variables is large. In the evaluation of DP system design, it is often found that the standard connection between the sub-systems that is intended to provide redundancy increases the probability of a fault [4]. A fault in one redundant system can affect another independent system. In the design, the class rules are applied to ensure that the redundant concept is used to achieve no loss of position. However, redundancy does not guarantee a high level of reliability; therefore, it is evident that the fault-tolerant concept needs to follow the above class requirements. Large sets of variables lead to potential configuration errors which are addressed through Redundancy and Criticality Analysers (RCA) and the data dictionary [23].

DP sub-systems are further divided into equipment, sensors, and signals. The following classifications are defined for typical signals for DP sub-systems at a sensor level to achieve higher reliability and availability, and these need to be added to the data dictionary [1, 33, 131]:

- **Critical Redundant:** The equipment and component within the sub-system are required to ensure the vessel is single fault-tolerant. To remove such equipment would either remove the DP system's fault tolerance entirely or reduce its post-failure DP capability. It is sufficient for WCDFI. Sampling rate (SR) is 1 millisecond.
- **Critical Non-redundant:** This is not applicable within the DP system
- **Non-Critical Redundant:** The equipment and components within the sub-system that are required to provide greater availability and higher reliability. SR is 10 milliseconds.
- **Non-Critical Non-redundant:** The equipment and components within the sub-system which do not have a direct impact on the DP functionality. SR is 1 second.

Also, attributes such as whether the signal is Input (monitoring) or Output (control) along with type (Analog or digital) are defined to perform the feature selection and correlation analysis at the sub-system level. The signals are represented as Analog Input (AI), Digital Input (DI), Analog Output (AO), and Digital Output (DO). The equipment configuration is either 1oo1 (one-out-of-one), 1oo2 (one-out-of-two), 1oo3 (one-out-of-three), or 2oo3 (two-out-of-three). For this research study, there are total of 1513 signals identified with 1054 redundant and 459 non-redundant signals.

4.4 Reference System (A1)

4.4.1 System Description

A reference system (A1) is used to measure the position and heading data of the vessel at any point in time [132, 133, 134]. The position and heading data are critical information for the DP control system as it compares the measured values with the set value to determine the error. The DP control system functionality depends on this value to determine the command signal to the propulsion system. Depending on the type of operation, most DP vessels have more than one reference system working actively at the same time, providing either absolute or relative measurement [1, 135]. The position reference systems could be Differential Global Navigation Satellite System (DGNSS), Differential Global Positioning System (DGPS), Laser radar, Hydroacoustic Position Reference (HPR) system and Taut wire or Gyrocompass [1].

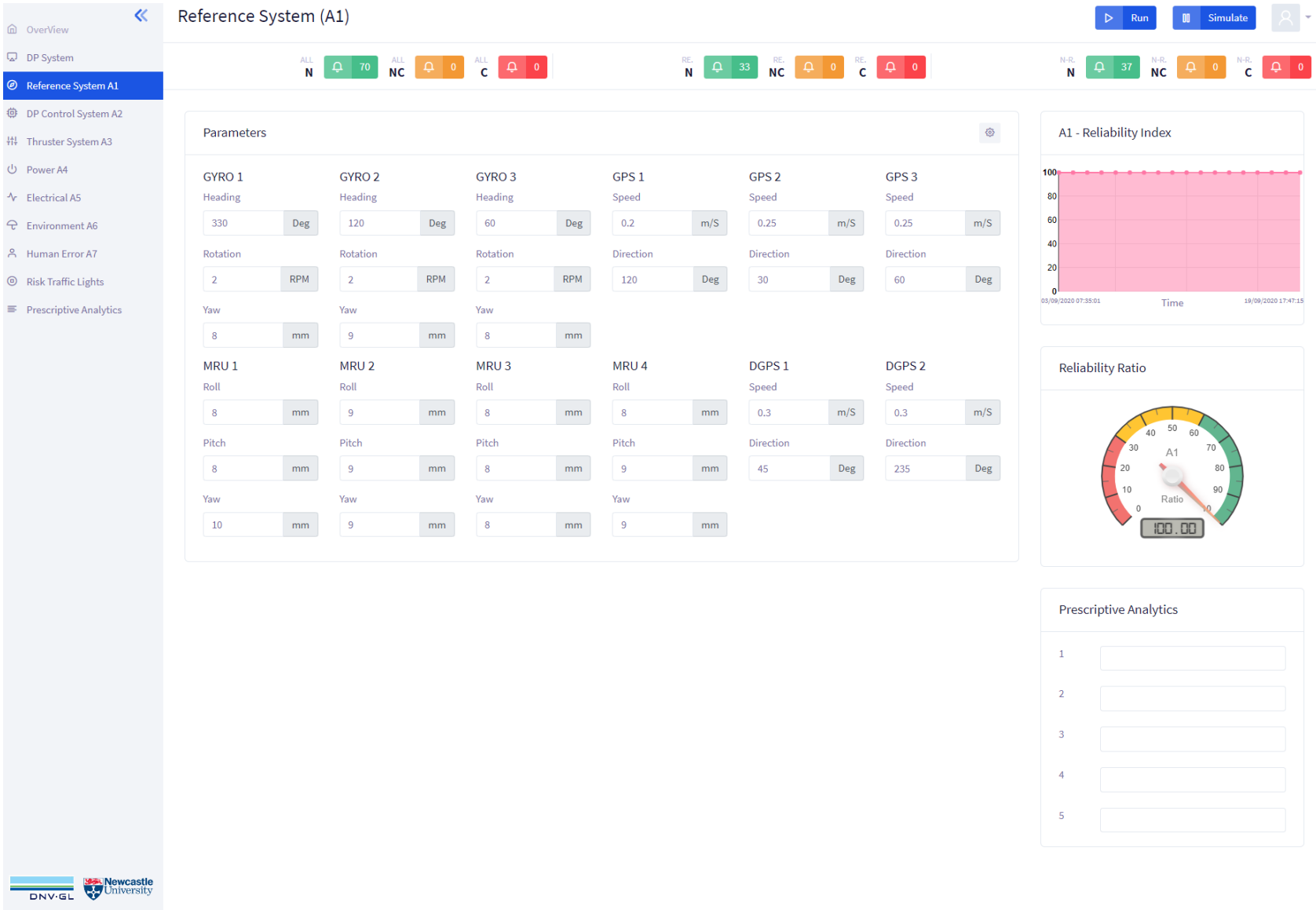


Figure 4-5 Reference System A1 – Input Variables / Signals

The reference system is part of the guidance and control system, which usually consists of a latitude control system and a path control system. The systems consist of hardware, software, and sensors to supply information and corrections necessary to give accurate position and heading references. Figure 4-5 represents the GUI model of sub-system "Reference System (A1)" with the information at equipment and sensor level. The DP 3 vessel considered for the research consists of Gyros (3 units), Motion Reference Unit (MRU) (4 units), Global Positioning System (GPS) (3 units) and DGPS (2 units).

4.4.2 Data Dictionary for Reference System

Table 4-2 shows the data dictionary for the Reference System (A1) along with the details of the equipment configuration. There is a total of 12 equipment items and 67 signals. Out of the 67 signals, 31 are redundant signals, and the remaining 36 are non-redundant signals.

Table 4-2 Reference System (A1)- Data Dictionary

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
GYRO – 3 Unit (1oo3)				
GYRO1_HD	Heading (deg)	AI	Yes	Yes
GYRO1_ROR	Rate of Rotation (deg/min)	AI	Yes	Yes
GYRO1_YAW	Yaw (%)	AI	Yes	Yes
GYRO1_KEY	Preferred	DI	No	No
GYRO1_ENABLE	Enable	DO	No	No
GYRO1_ERR	Failure / Error	DI	No	No
MOTION REFERNECE UNIT – 4 Unit (1oo3)				
VRU1_ROLL	Roll (mm)	AI	Yes	Yes
VRU1_PICTH	Pitch (mm)	AI	Yes	Yes
VRU1_YAW	Yaw (mm)	AI	Yes	Yes
VRU1_KEY	Preferred	DI	No	No
VRU1_ENABLE	Enable	DO	No	No
VRU1_ERR	Failure / Error	DI	No	No
GLOBAL POSITIONING SYSTEM (GPS) - 3 Unit (1oo3)				
GPS1_SPD	Vessel Speed (m/s)	AI	Yes	Yes
GPS1_DIR	Course Direction (deg)	AI	Yes	Yes
GPS1_KEY	Preferred	DI	No	No
GPS1_ENABLE	Enable	DO	No	No

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
GPS1_ERR	Failure / Error	DI	No	No
DGPS – 2 Unit (1oo2)				
DGPS1_SPD	Relative Speed (m/s)	AI	Yes	Yes
DGPS1_DIR	Relative Direction (deg)	AI	Yes	Yes
DGPS1_KEY	Preferred	DI	No	No
DGPS1_ENABLE	Enable	DO	No	No
DGPS1_ERR	Failure / Error	DI	No	No

4.5 DP Control System (A2)

4.5.1 System Description

The DP control system is considered to be the most critical sub-system as it performs the control algorithm based on the set-point and measurement. It consists of a set of hardware (Operator Station (OS), Remote Controller Unit (RCU), Sensors, Field Station (FS), Network Distribution Unit (NDU), etc.) and software (logic implemented in the controller) which automatically controls surge, sway and yaw motion. It maintains the desired position and heading of the vessel based on inputs from the reference systems and sensors, and controls the propulsion system [136]. The DP control system is also defined as a set of computers that combines automatic computation with instruction from operators, enabled through interfaces.

The software logic implemented in the controller consists of various functionalities which are integrated to maintain the desired position and heading, as shown in Figure 2-2 [62, 133]:

Environmental System Input: This logic reads information on environmental data and converts it into ships load for the position controller logic module through feedforward control.

Kalman Filter: This logic reads the measurement of vessel motions from sensors and filters out any noise before sending it to the DP position controller logic.

Power System: This logic module provides the information of total power available in the power plant for a thruster to be brought online and provide the necessary thrust.

DP Position control: This logic calculates the resultant force that thrusters should generate based on the input received from the environmental system and vessel sensors.

Thruster Allocation Algorithm: This logic finds the available thrusters and allocates the required thrust based on the power available from the power system.

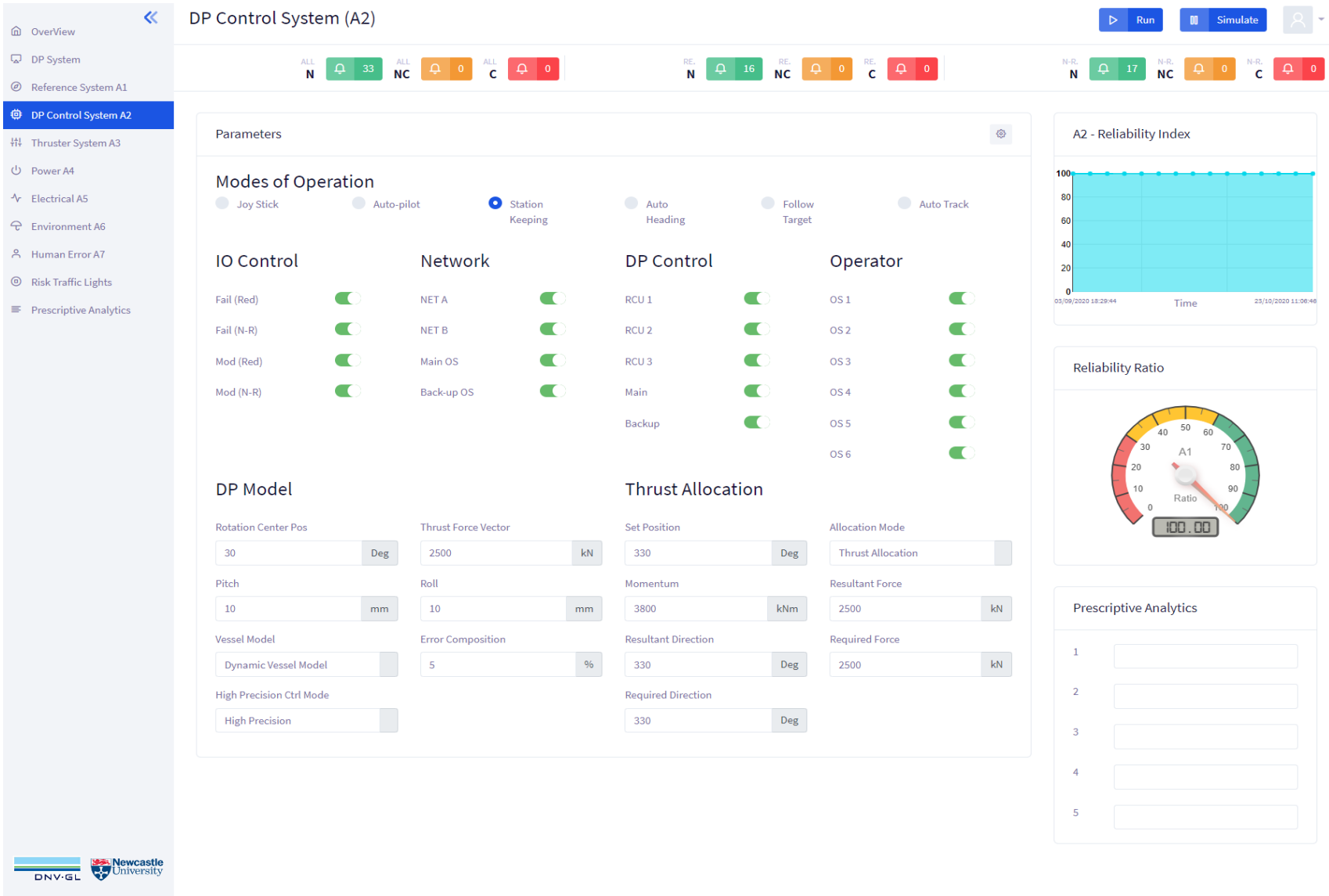


Figure 4-6 DP Control System A2 – Input Variables / Signals

Figure 4-6 represents the GUI model of the sub-system "DP Control System (A2)" with the information at the equipment and sensor level. The DP 3 vessel considered consists of OS (6 units), FS (3 units), RCU (3 units), NDU (6 units) and the model programmed as a software module in the RCU. The hydrodynamic model should predict the position and orientation of the ship in each time step. The hydrodynamic model should include low-frequency and wave-frequency effects and should contain all six degrees of freedom.

4.5.2 Data Dictionary for DP Control System

Table 4-3 shows the data dictionary for the DP Control System (A2) along with the details of the equipment configuration. There is a total of 24 equipment items and 127 individual signals, which are grouped under 33 signal groupings for this research. Out of 33 signal groups, 16 are redundant, and the remaining 17 are non-redundant.

Table 4-3 DP Control System (A2)- Data Dictionary

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
OPERATOR STATION OS – 6 Units (1oo3) 2 sets				
DP_OS_1-6_F	Operator Station (OS)	DI	Yes	Yes
DP_PS_F	Power Supply (PS) Failure	DI	Yes	Yes
DP_COMM_F	Communication Failure	DI	Yes	Yes
NETWORK DISTRIBUTION UNIT NDU – 6 Unit (1oo2)				
DP_NDU_F	Network (Dual Network)	DI	Yes	Yes
FIELD STATION FS – 6 Units (1oo2)				
DP_FS_F	Field Station (FS)	DI	Yes	Yes
DP_IO_C_F	Input/Output Signal Failure	DI	Yes	Yes
DP_IO_NC_F	Input/Output Signal Failure	DI	No	No
DP_IO_MOD_F	Input/Output Module Failure	DI	Yes	Yes
DP_ERR	Failure / Error	DI	No	No
REDUNDANT CONTROLLER UNIT RCU – 6 Units (1oo3)				
DP_RCU_1_2_3_F	Controllers (Triple Redundant)	DI	Yes	Yes

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
DP_MODE	Vessel Mode of Operation	AI	Yes	Yes
DP_1_2_3	Vessel Class (DP 3, DP 2 & DP1)	DI	Yes	Yes
VS_RCP	Rotation Centre Position	AI	Yes	Yes
VS_TFV	Thruster Force Vector	AI	Yes	Yes
VS_PITCH	Pitch	AI	Yes	Yes
VS_ROLL	Roll	AI	Yes	Yes
VS_MODEL	Vessel Model	AI	Yes	Yes
VS_ENV_ERROR	Environmental Error	DI	Yes	Yes
VS_HPC	High Precision Control Mode	AO	Yes	Yes
VS_CURR_POS	Current Position (deg)	AI	No	Yes
VS_SET_POS	Set Position (deg)	AO	No	Yes
VS_ALLOC_MOD	Allocation Mode	AO	No	Yes
VS_MOMENT	Moment (kNm)	AI	No	Yes
VS_RES_FOR	Resultant Force (kN)	AI	No	Yes
VS_RES_DIR	Resultant Direction (deg)	AI	No	Yes
VS_REQ_FOR	Required Force (kN)	AI	No	Yes

4.6 Thruster / Propulsion System (A3)

4.6.1 System Description

Thruster / Propulsion system refers to propellers, thrusters (Azimuth, Tunnel or Bow), Variable Frequency Drives (VFD), Electrical motors, and rudders that receive the command from the DP system and produce the necessary forces to maintain the vessel at a given position set-point and heading. Generally, the propulsion system is defined as a system which makes thrust/force from power delivered by the power system and a control signal from the DP system [62, 13]. The control signals from the DP system generally consist of rotational speed, azimuth angle, etc, to produce enough thrust to maintain the desired position and heading. *Figure 4-7* illustrates the GUI model of sub-system "Thruster / Propulsion System (A3)" with the information at equipment and sensor level. The DP 3 vessel considered consists of 8 azimuth thrusters, VFD, electrical motors, and associated machinery.

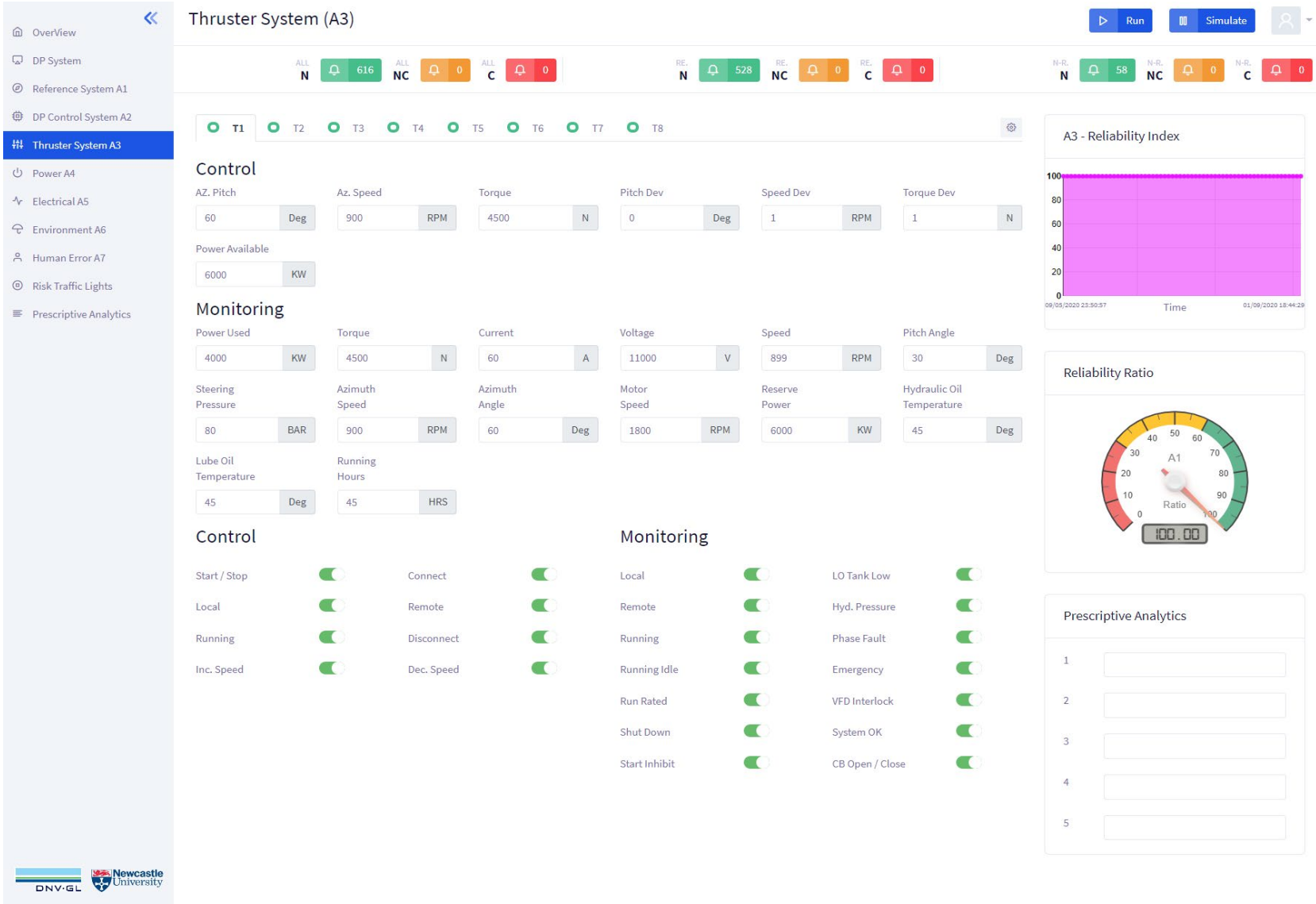


Figure 4-7 Thruster / Propulsion System A3 – Input Variables / Signals

4.6.2 Data Dictionary for Thruster / Propulsion System

Table 4-4 shows the data dictionary for the Thruster / Propulsion System (A3) along with the details of the equipment configuration. There are a total of 8 equipment items, 352 sensors, and 616 signals. Out of 616 signals, 528 are redundant, and the remaining 88 are non-redundant.

Table 4-4 Thruster / Propulsion System (A3)- Data Dictionary

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
THRUSTERS – 8 unit (1oo2) N – 1 to 8				
THR1_P_CMD	Azimuth Pitch(deg)	AO	Yes	Yes
THR1_SPD_CMD	Azimuth Speed(rpm)	AO	Yes	Yes
THR1_TOR_CMD	Torque (N)	AO	Yes	Yes
THR1_P_DEV	Pitch Dev	AO	Yes	Yes
THR1_SPD_DEV	Speed Dev	AO	Yes	Yes
THR1_TOR_DEV	Torque Dev	AO	Yes	Yes
THR1_PWR_AVL	Power Available (kW)	AO	Yes	Yes
THR1_PWR_FB	Power Used (kW)	AI	Yes	Yes
THR1_TOR_FB	Torque (N)	AI	Yes	Yes
THR1_CUR_FB	Current (A)	AI	No	No
THR1_VOL_FB	Voltage (V)	AI	No	No
THR1_SPD_FB	Speed (rpm)	AI	No	No
THR1_P_FB	Pitch Angle (deg)	AI	Yes	Yes
THR1_STR_PR_FB	Steering Oil Pressure (bar)	AI	Yes	Yes
THR1_AZ_SPD_FB	Azimuth Speed (rpm)	AI	No	No
THR1_AZ_ANG_FB	Azimuth Angle (deg)	AI	No	No
THR1_MTR_S_FB	Motor Speed(rpm)	AI	No	No
THR1_RS_PWR_FB	Reserve Power Available (kW)	AI	Yes	Yes
THR1_HO_TMP_FB	Hydraulic Oil Temperature (°C)	AI	Yes	Yes
THR1_LO_T_FB	Lube Oil Temp (°C)	AI	No	No
THR1_RH_FB	Running Hours (hrs)	AI	No	No
THR1_STR_CMD	Start	DI	Yes	Yes
THR1_STP_CMD	Stop	DI	Yes	Yes
THR1_CON_CMD	Connect	DI	Yes	Yes
THR1_DIS_CMD	Dis-connect	DI	Yes	Yes

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
THR1_INC_CMD	Increase Load/Speed	DI	Yes	Yes
THR1_DEC_CMD	Decrease Load/Speed	DI	Yes	Yes
THR1_L_R_CMD	Local/Remote	DI	No	No
THR1_RUN_CMD	Running	DI	No	No
THR1_LOC_FB	Local	DO	Yes	Yes
THR1_REM_FB	Remote	DO	Yes	Yes
THR1_RUN_FB	Running	DO	Yes	Yes
THR1_R_IDL_FB	Running Idle	DO	No	No
THR1_R_RAT_FB	Run Rated	DO	No	No
THR1_SHTDWN_FB	Shutdown	DO	Yes	Yes
THR1_STR_INH_FB	Start Inhibit	DO	No	No
THR1_SYS_OK_FB	System Ok	DO	No	No
THR1_CB_OP_FB	CB Opened	DO	Yes	Yes
THR1_CB_CL_FB	CB Closed	DO	Yes	Yes
THR1_LO_LL_FB	LO Tank Low	DO	Yes	Yes
THR1_HDR_PRL_FB	Hydraulic Pressure Low	DO	Yes	Yes
THR1_PH_FL_FB	Phase Fault Error	DO	No	No
THR1_EMG_FB	Emergency	DO	Yes	Yes
THR1_VFD_INT_FB	VFD Interlock	DO	Yes	Yes

4.7 Power System (A4)

4.7.1 System Description

The Power System comprises engines, prime movers, generators, and all auxiliary machinery systems providing electrical power to the vessel. The power generated is supplied to consumers on-board the ship and the propulsion system, which consumes the majority of the power in almost all DP vessels. The Power Management System is an automatic system that helps to minimise the manual power demand calculation, start/stop of the generators, and connecting of the standby generator in the case of the demand [62, 132, 133]. Figure 4-8 represents the GUI model of sub-system "Power System (A4)" with the information at equipment and sensor level. The DP 3 vessel considered consists of 8 engines, 8 alternators, and associated Fuel oil and lube oil systems.

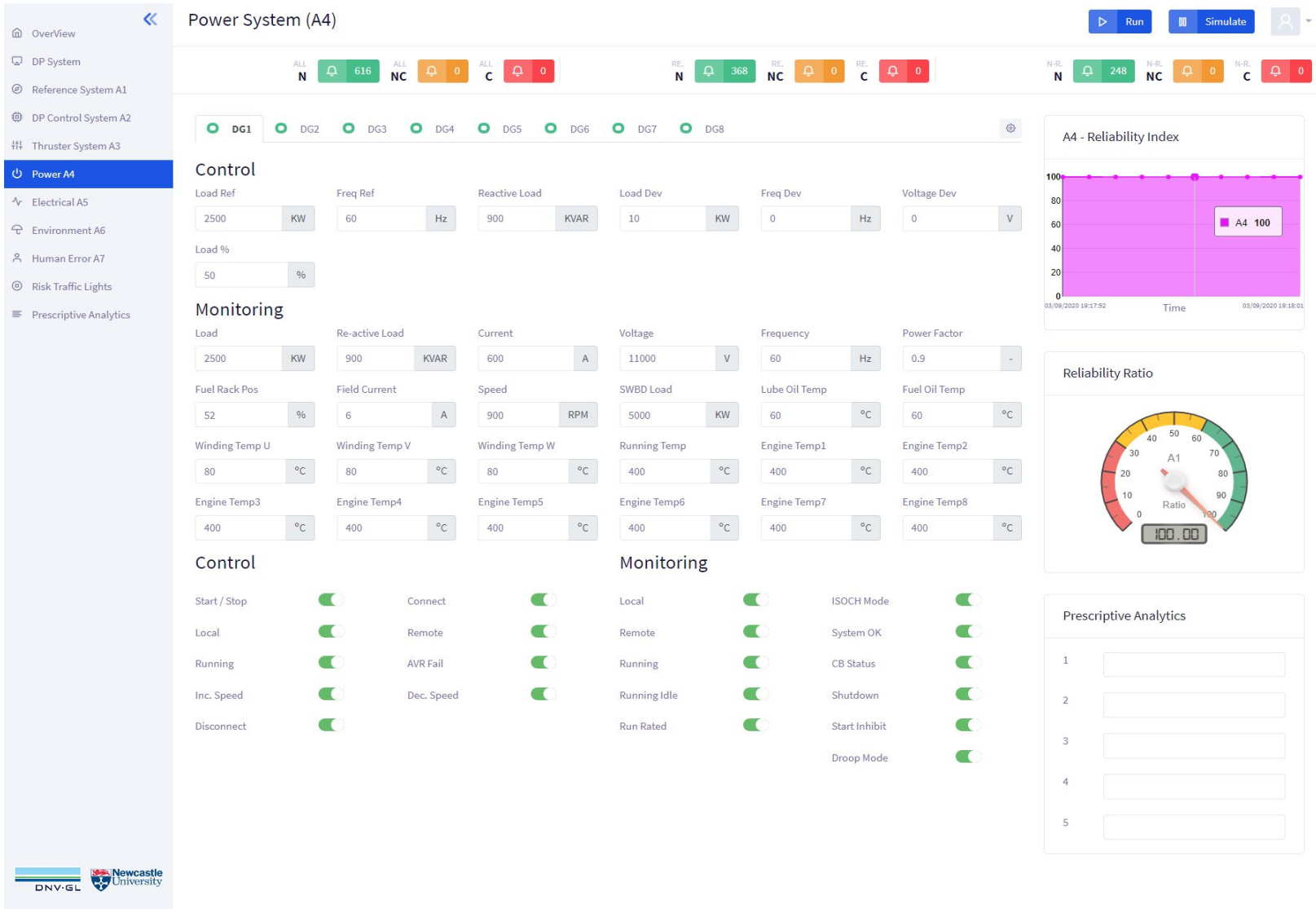


Figure 4-8 Power System A4 – Input Variables / Signals

4.7.2 Data Dictionary for Power System

Table 4-5 shows the data dictionary for Power System (A4) along with the details of the equipment configuration. There are a total of 8 engines, eight generators, 424 sensors, and 616 signals. Out of 616 signals, 368 are redundant, and the remaining 248 are non-redundant.

Table 4-5 Power System (A4)- Data Dictionary

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
DIESEL GENERATOR – 8 unit (1oo2) N – 1 to 8				
DG1_LD_REF_CMD	Load Ref (KW)	AO	Yes	Yes
DG1_FRQ_REF	Frequency Ref (Hz)	AO	Yes	Yes
DG1_RLD_REF	Re-active (kVAR)	AO	Yes	Yes
DG1_LD_DEV	Load Dev (KW)	AO	Yes	Yes
DG1_FRQ_DEV	Frequency Dev (Hz)	AO	Yes	Yes
DG1_VOL_DEV	Voltage Dev	AO	Yes	Yes
DG1_LD_PR_CMD	Load %	AO	Yes	Yes
DG1_LD_FB	Load (kW)	AI	Yes	Yes
DG1_RE_LD_FB	Re-active (kVAR)	AI	Yes	Yes
DG1_CUR_FB	Current (A)	AI	No	No
DG1_VOL_FB	Voltage (V)	AI	No	No
DG1_PF_FB	Power Factor	AI	No	No
DG1_FREQ_FB	Frequency (Hz)	AI	Yes	Yes
DG1_FR_FB	Fuel Rack Pos (%)	AI	Yes	Yes
DG1_F_CUR_FB	Field Current (A)	AI	No	No
DG1_SPD_FB	Speed (RPM)	AI	No	No
DG1_SWBD_KW	SWBD Load (kW)	AI	No	No
DG1_TEMP_U_FB	Winding Tem U (°C)	AI	Yes	Yes
DG1_TEMP_V_FB	Winding Tem V (°C)	AI	Yes	Yes
DG1_TEMP_W_FB	Winding Tem W (°C)	AI	No	No
DG1_TEMP_A1_FB	Cylinder Temp 1(°C)	AI	No	No
DG1_TEMP_A2_FB	Cylinder Temp 2(°C)	AI	Yes	Yes
DG1_TEMP_A3_FB	Cylinder Temp 3(°C)	AI	Yes	Yes
DG1_TEMP_A4_FB	Cylinder Temp 4(°C)	AI	Yes	Yes
DG1_TEMP_A5_FB	Cylinder Temp 5(°C)	AI	Yes	Yes
DG1_TEMP_A6_FB	Cylinder Temp 6(°C)	AI	Yes	Yes
DG1_TEMP_A7_FB	Cylinder Temp 7(°C)	AI	Yes	Yes
DG1_TEMP_A8_FB	Cylinder Temp 8(°C)	AI	No	No
DG1_TEMP_FO_FB	Fuel Oil Temp (°C)	AI	No	No
DG1_TEMP_LO_FB	Lube Oil Temp (°C)	AI	Yes	Yes

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
DG1_RH_FB	Running Hours (hrs)	AI	Yes	Yes
DG1_STR_CMD	Start	DO	Yes	Yes
DG1_STP_CMD	Stop	DO	Yes	Yes
DG1_CON_CMD	Connect	DO	Yes	Yes
DG1_DISCON_CMD	Dis-connect	DO	Yes	Yes
DG1_INC_CMD	Increase Load/Speed	DO	Yes	Yes
DG1_DEC_CMD	Decrease Load/Speed	DO	Yes	Yes
DG1_L_R_CMD	Local/Remote	DO	No	No
DG1_RUN_CMD	Running	DO	No	No
DG1_AVR_F_CMD	AVR Fail	DO	Yes	Yes
DG1_LOC_FB	Local	DI	Yes	Yes
DG1_REM_FB	Remote	DI	Yes	Yes
DG1_RUN_FB	Running	DI	Yes	Yes
DG1_RUN_IDL_FB	Running Idle	DI	No	No
DG1_RUN_RAT_FB	Run Rated	DI	No	No
DG1_SHTDWN_FB	Shutdown	DI	Yes	Yes
DG1_DROOP_FB	Droop Mode	DI	No	No
DG1_ISOCH_FB	Isoch Mode	DI	No	No
DG1_AGS_FB	AGS Mode	DI	No	No
DG1_STR_INH_FB	Start Inhibit	DI	No	No
DG1_SYS_OK_FB	System Ok	DI	No	No
DG1_CB_OP_FB	CB Opened	DI	Yes	Yes
DG1_CB_CL_FB	CB Closed	DI	Yes	Yes
DG1_LOC_FB	Local	DI	Yes	Yes
DG1_REM_FB	Remote	DI	Yes	Yes

4.8 Electrical System (A5)

4.8.1 System Description

The electrical system consists of Power distribution units, switchboards, Uninterruptible Power Supply (UPS) and batteries, and provides interconnection between the power system and the consumers of the DP system [62]. Figure 4-9 represents the GUI model of the sub-system "Electrical System (A5)" with the information at equipment and sensor level. The DP 3 vessel considered consists of 4 switchboards, 4 master circuit breakers, 4 slave circuit breaker, 8 incoming feeders from generators and 8 outgoing feeders to thruster.

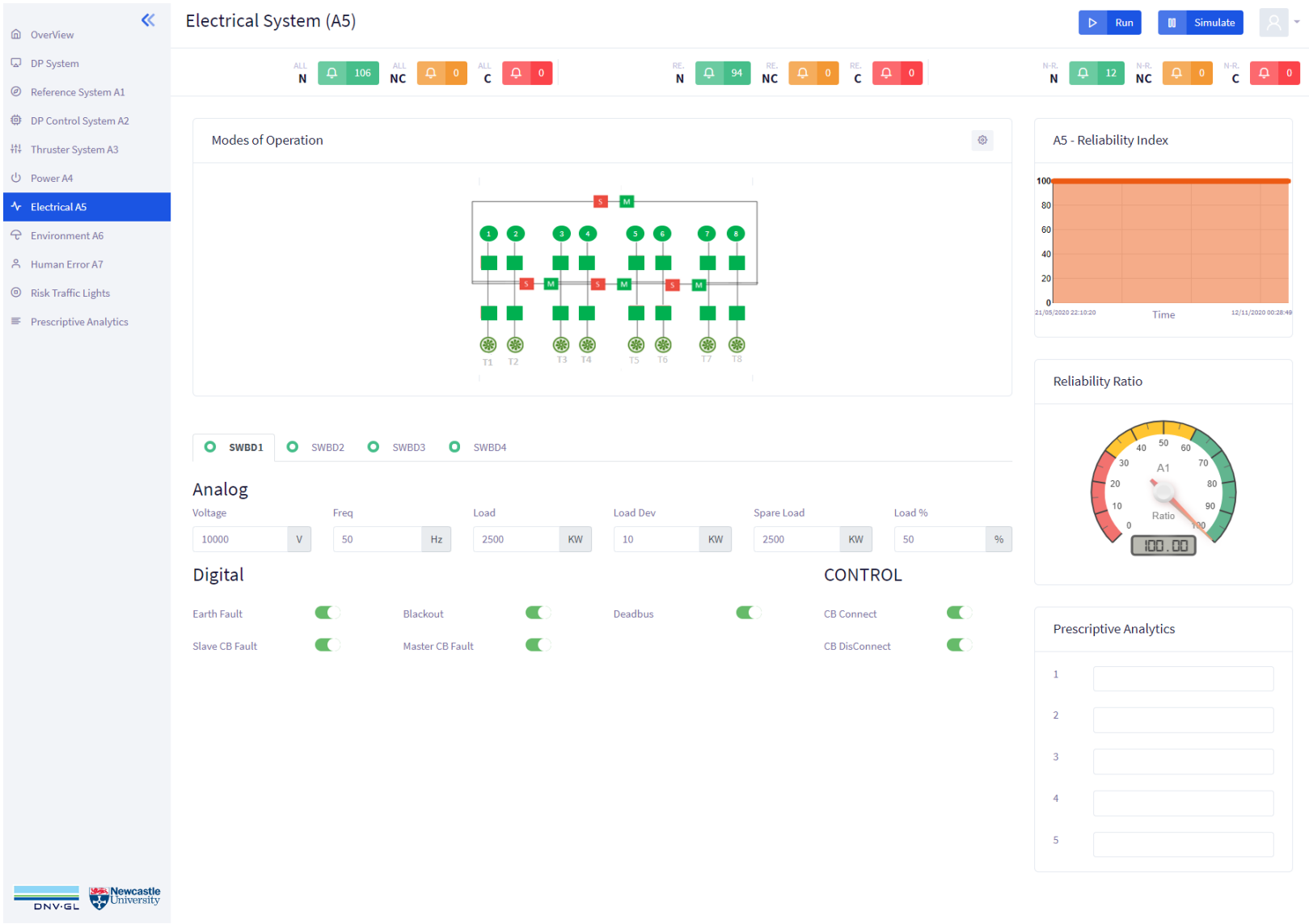


Figure 4-9 Electrical System A5 – Input Variables / Signals

4.8.2 Data Dictionary for Electrical System

Table 4-6 shows the data dictionary for Electrical System (A5) along with the details of the equipment configuration. There are a total of 4 switchboards, 4 slave circuit breakers and 4 master circuit breakers, 59 sensors, and 106 signals. Out of 106 signals, 94 are redundant, and the remaining 12 are non-redundant.

Table 4-6 Electrical System (A5)- Data Dictionary

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
SWITCHBOARD SWBD – 4 UNITS (1oo2)				
SWBD1_VOL_FB	SWBD 1 Voltage (kV)	AI	Yes	Yes
SWBD1_FREQ_FB	SWBD 1 Frequency (Hz)	AI	Yes	Yes
SWBD2_VOL_FB	SWBD 2 Voltage (kV)	AI	Yes	Yes
SWBD2_FREQ_FB	SWBD 2 Frequency (Hz)	AI	Yes	Yes
SWBD3_VOL_FB	SWBD 3 Voltage (kV)	AI	Yes	Yes
SWBD3_FREQ_FB	SWBD 3 Frequency (Hz)	AI	Yes	Yes
SWBD4_VOL_FB	SWBD 4 Voltage (kV)	AI	Yes	Yes
SWBD4_FREQ_FB	SWBD 4 Frequency (Hz)	AI	Yes	Yes
SWBD1_LD_FB	SWBD 1 Load (Kw)	AI	No	Yes
SWBD1_SLD_FB	SWBD 1 Spare Load (Kw)	AI	No	Yes
SWBD1_LD_PER_FB	SWBD 1 Load (%)	AI	No	Yes
SWBD2_LD_FB	SWBD 2 Load (Kw)	AI	No	Yes
SWBD2_SLD_FB	SWBD 2 Spare Load (Kw)	AI	No	Yes
SWBD2_LD_PER_FB	SWBD 2 Load (%)	AI	No	Yes
SWBD3_LD_FB	SWBD 3 Load (Kw)	AI	No	Yes
SWBD3_SLD_FB	SWBD 3 Spare Load (Kw)	AI	No	Yes
SWBD3_LD_PER_FB	SWBD 3 Load (%)	AI	No	Yes
SWBD4_LD_FB	SWBD 4 Load (Kw)	AI	No	Yes

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
SWBD4_SLD_FB	SWBD 4 Spare Load (Kw)	AI	No	Yes
SWBD4_LD_PER_FB	SWBD 4 Load (%)	AI	No	Yes
SWBD1_SL_C_CMD	SWBD1 Slave CB Connect	DO	Yes	Yes
SWBD1_SL_D_CMD	SWBD1 Slave CB Dis-Connect	DO	Yes	Yes
SWBD1_MST_C _CMD	SWBD1 Master CB Connect	DO	Yes	Yes
SWBD1_MST_D _CMD	SWBD1 Master CB Dis-Connect	DO	Yes	Yes
SWBD2_SL_C_CMD	SWBD2 Slave CB Connect	DO	Yes	Yes
SWBD2_SL_D_CMD	SWBD2 Slave CB Dis-Connect	DO	Yes	Yes
SWBD2_MST_C _CMD	SWBD2 Master CB Connect	DO	Yes	Yes
SWBD2_MST_D _CMD	SWBD2 Master CB Dis-Connect	DO	Yes	Yes
SWBD3_SL_C_CMD	SWBD3 Slave CB Connect	DO	Yes	Yes
SWBD3_SL_D_CMD	SWBD3 Slave CB Dis-Connect	DO	Yes	Yes
SWBD3_MST_C _CMD	SWBD3 Master CB Connect	DO	Yes	Yes
SWBD3_MST_D _CMD	SWBD3 Master CB Dis-Connect	DO	Yes	Yes
SWBD4_SL_C_CMD	SWBD4 Slave CB Connect	DO	Yes	Yes
SWBD4_SL_D_CMD	SWBD4 Slave CB Dis-Connect	DO	Yes	Yes
SWBD4_MST_C _CMD	SWBD4 Master CB Connect	DO	Yes	Yes
SWBD4_MST_D _CMD	SWBD4 Master CB Dis-Connect	DO	Yes	Yes
SWBD1_EF_FB	SWBD1 Earth Fault	DO	Yes	Yes
SWBD1_BL_FB	SWBD 1 Blackout	DO	Yes	Yes
SWBD1_DB_FB	SWBD 1 Dead Bus	DO	Yes	Yes

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
SWBD1_SL_CBF	SWBD 1 Slave CB Fault	DI	Yes	Yes
SWBD1_MST_CBF	SWBD 1 Master CB Fault	DI	Yes	Yes
SWBD2_EF	SWBD 2 Earth Fault	DI	Yes	Yes
SWBD2_BL	SWBD 2 Blackout	DI	Yes	Yes
SWBD2_DB	SWBD 2 Dead Bus	DI	Yes	Yes
SWBD2_SL_CBF	SWBD 2 Slave CB Fault	DI	Yes	Yes
SWBD2_MST_CBF	SWBD 2 Master CB Fault	DI	Yes	Yes
SWBD3_EF	SWBD 3 Earth Fault	DI	Yes	Yes
SWBD3_BL	SWBD 3 Blackout	DI	Yes	Yes
SWBD3_DB	SWBD 3 Dead Bus	DI	Yes	Yes
SWBD3_SL_CBF	SWBD 3 Slave CB Fault	DI	Yes	Yes
SWBD3_MST_CBF	SWBD 3 Master CB Fault	DI	Yes	Yes
SWBD4_EF	SWBD 4 Earth Fault	DI	Yes	Yes
SWBD4_BL	SWBD 4 Blackout	DI	Yes	Yes
SWBD4_DB	SWBD 4 Dead Bus	DI	Yes	Yes
SWBD4_SL_CBF	SWBD 4 Slave CB Fault	DI	Yes	Yes
SWBD4_MST_CBF	SWBD 4 Master CB Fault	DI	Yes	Yes
UPS_FAULT	UPS Fault	DI	Yes	Yes
OP_BUS_FAULT	Open Bus Fault	DI	Yes	Yes
CL_BUS_FAULT	Closed Bus Fault	DI	Yes	Yes

4.9 Environmental System (A6)

4.9.1 System Description

The environment system refers to the wind, current, and wave parameters affecting the position and heading of the DP vessels. The calculation of all horizontal forces on a ship is summative, i.e., wave, wind, and current all could be considered collinear, and their forces can be added together to get the total environmental forces. The environment loads are wind speed, wave height, current speed, the direction of the wind, wave, and current [13, 133, 137].

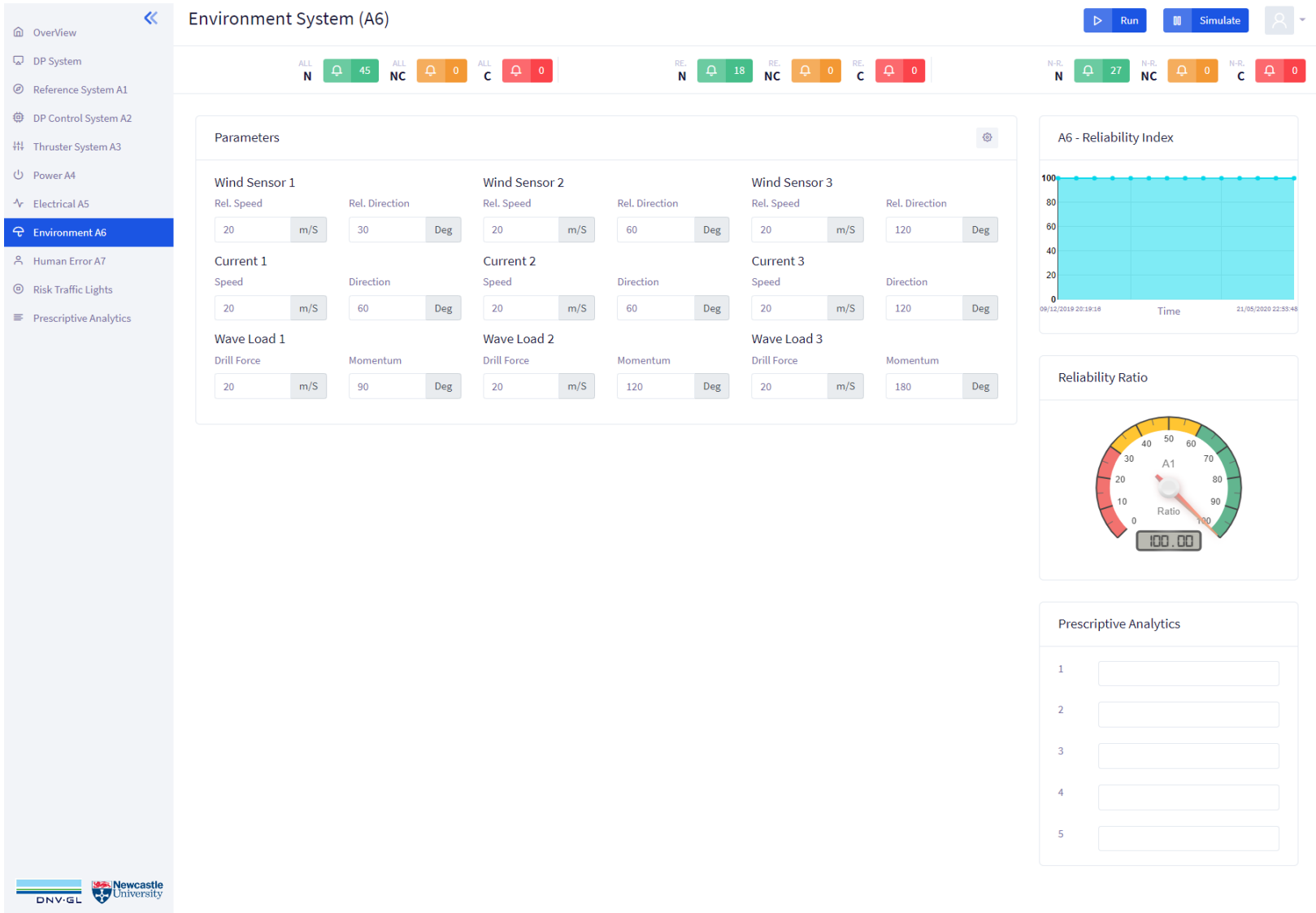


Figure 4-10 Environment System A6 – Input Variables / Signal

Figure 4-10 represents the GUI model of sub-system "Environment System (A5)" with the information at equipment and sensor level. The DP 3 vessel considered consists of 3 wind sensors, 3 wave radars, but as there is no sensor for the current, it is considered to be a contributor to the non-modelled errors in the system.

4.9.2 Data Dictionary for Environment System

Table 4-7 shows the data dictionary for Environment System (A6) along with the details of the equipment configuration. There are a total of 3 wind sensors, 3 wave radars, 6 sensors, and 45 signals. Out of 45 signals, 18 are redundant, and the remaining 27 are non-redundant.

Table 4-7 Environment System (A6)- Data Dictionary

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
WIND SENSOR – 3 Unit (1oo3)				
WS1_SPD	Relative Speed (m/s)	AI	Yes	Yes
WS1_DIR	Relative Direction deg	AI	Yes	Yes
WS1_KEY	Preferred	DI	No	No
WS1_ENABLE	Enable	DI	No	No
WS1_ERR	Failure / Error	DI	No	No
WAVE – 3 Unit (1oo3)				
WV1_FR	Wave Drift – Force (kN)	AI	Yes	Yes
WV1_DIR	Wave Momentum	AI	Yes	Yes
WV1_KEY	Preferred	AI	Yes	Yes
WV1_ENABLE	Enable	DI	No	No
WV1_ERR	Failure / Error	DI	No	No
CURRENT – Model (1oo3)				
CUR1_SPD	Current Speed (knots)	AI	Yes	Yes
CUR1_DIR	Current Direction deg	AI	Yes	Yes
CUR1_KEY	Preferred	DI	No	No
CUR1_ENABLE	Enable	DI	No	No
CUR1_ERR	Failure / Error	DI	No	No

4.10 Human / Operator Error (A7)

4.10.1 System Description

Human / Operator Error is considered as one of the variables (sub-system) contributing to the reliability of the DP system. Though there is no direct mathematical representation of the human reliability that is widely accepted, for some DP vessels, quantitative risk assessment is

used to factor in the DPO contribution to DP reliability. The error could be from the DP operator, Engine Room technicians, Deck officers, instrument technicians etc. which directly or indirectly results in failures of the system leading to DP accidents. The DP operator can influence the complete DP system, and wise decision/interference could prevent DP accidents from occurring [33].

Human error is one of the most significant contributors to DP accidents, which means reducing the number of operators related DP accidents could significantly increase the safety and reliability of DP operation [3, 20]. The DPO is tasked with monitoring a highly automated and complicated system which leaves the DPO "out-of-the-loop". However, the operator is asked to intervene when the DP system is failing in ways unforeseen by designers often with little time available for decision response. For this research, four factors have been considered as affecting the performance of the DPO, namely Situation Awareness, Decision Making ability, Dexterity, and Distraction. They are assigned to a particular level based on the capability of a DPO to respond and take corrective action through a generalised format as below [26, 87]:

- Level 1: Perception refers to the perception of attributes and dynamics of elements in an environment.
- Level 2: Comprehension refers to the integration and interpretation of that information to understand what is happening in a situation,
- Level 3: Projection involves the operator's estimation of the system's future states. The outcome of this continuous assessment of the current situation can be utilised to determine future courses of action.

In addition to the 4 direct factors, 18 potential factors were identified, which are grouped into Tangible (internal and external) and Intangible (internal and external) as shown in Figure 4-11. The system will be provided with the input every time there is a shift change or during complex offshore operations, which will be mentioned in the DP operation manual, including Simultaneous Operations (SIMOPS). Figure 4-11 represents the GUI model of sub-system "Human / Operator Error (A7)" with the information at a different level, having an impact on the DPO ability to respond during emergency scenarios. The DP 3 vessel considered has DP crew consisting of 2 DPO, 1 Captain, 1 Chief Engineer, 1 Chief Mate, 2 Electrician, and necessary supporting engineers.

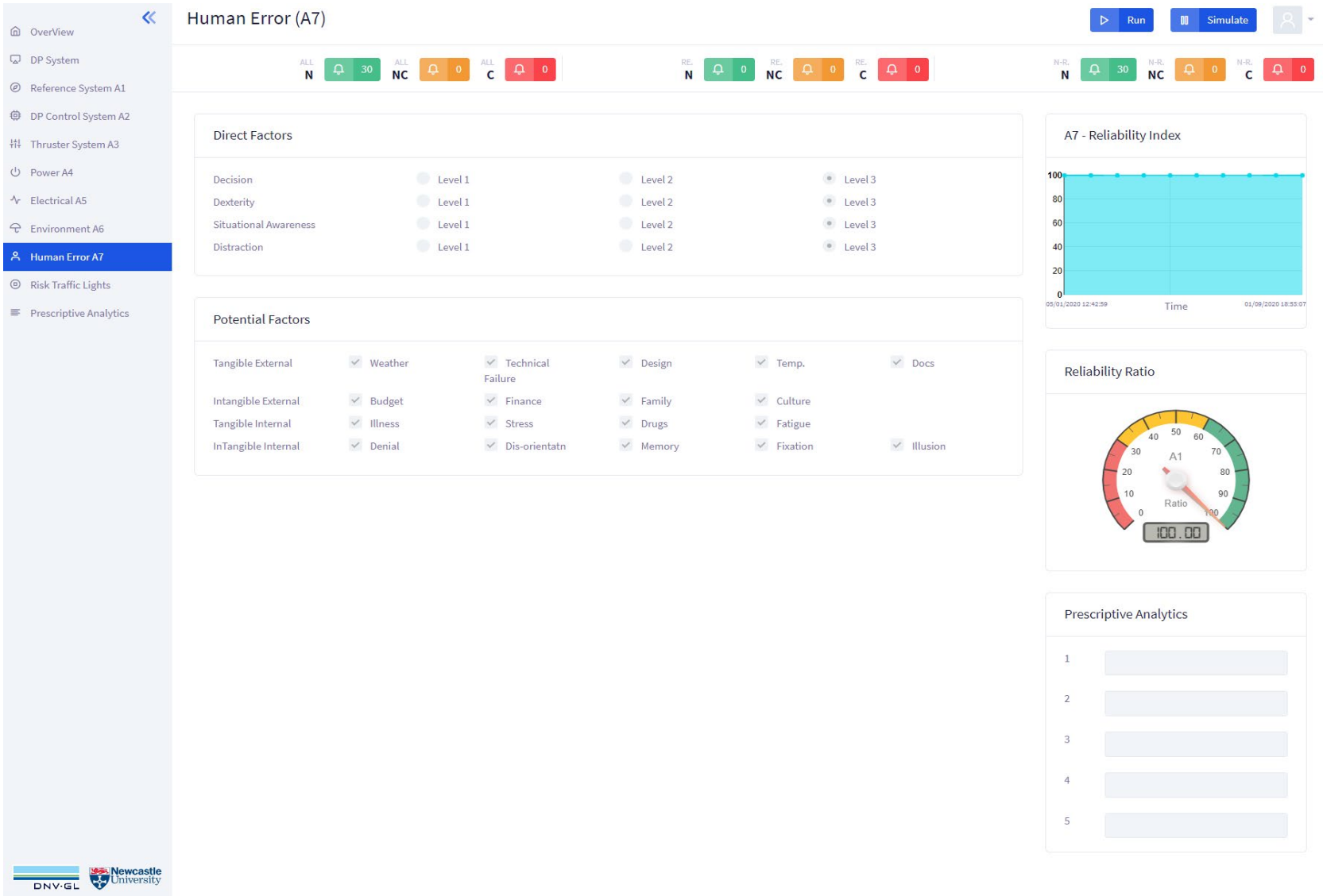


Figure 4-11 Human / Operator Error A7 – Input Variables / Signals

4.10.2 Data Dictionary for Human / Operator Error

Table 4-8 shows the data dictionary for Human / Operator Error (A7) along with the details of the factors affecting the DP reliability. There is a total of 4 factors, each with 3 levels, and 4 sub-components with 18 variables identified. All the signals are considered to be assigned by the Captain for Human Reliability Analysis (HRA) modelling, and a total of 30 signals was identified. Out of the 30 signals, none are redundant, so all 30 are considered as non-redundant.

Table 4-8 Human / Operator Error (A7)- Data Dictionary

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
DEXTERITY (DEX)				
DEX_L1	Level 1	DI	Yes	No
DEX_L2	Level 2	DI	Yes	No
DEX_L3	Level 3	DI	Yes	No
DECISION (DEC)				
DEC_L1	Level 1	DI	Yes	No
DEC_L2	Level 2	DI	Yes	No
DEC_L3	Level 3	DI	Yes	No
DISTRACTION (DIS)				
DIS_L1	Level 1	DI	Yes	No
DIS_L2	Level 2	DI	Yes	No
DIS_L3	Level 3	DI	Yes	No
SITUATION AWARENESS (SAS)				
SAS_L1	Level 1	DI	Yes	No
SAS_L2	Level 2	DI	Yes	No
SAS_L3	Level 3	DI	Yes	No
TANGIBLE EXTERNAL				
TAN_EXT_1	Weather	DI	No	No
TAN_EXT_2	Technical failures	DI	No	No
TAN_EXT_3	Temperature	DI	No	No
TAN_EXT_4	Documentation	DI	No	No
TAN_EXT_5	Design	DI	No	No
INTANGIBLE EXTERNAL				
INTAN_EXT_1	Relationship	DI	No	No
INTAN_EXT_2	Commercial Pressures	DI	No	No
INTAN_EXT_3	Financial	DI	No	No
INTAN_EXT_4	Culture	DI	No	No
TANGIBLE INTERNAL				
TAN_INT_1	Illness	DI	No	No

VARIABLE ID	VARIABLE	SIGNAL	CRITICAL	REDUNDANT
TAN_INT_2	Fatigue	DI	No	No
TAN_INT_3	Stress	DI	No	No
TAN_INT_4	Drugs	DI	No	No
INTANGIBLE INTERNAL				
INTAN_INT_1	Dis-Orientation	DI	No	No
INTAN_INT_2	Fixation	DI	No	No
INTAN_INT_3	Visual Illusions	DI	No	No
INTAN_INT_4	Denial	DI	No	No
INTAN_INT_5	Memory	DI	No	No

4.11 Summary

In this chapter, the first stages of analytics involving descriptive and diagnostic analytics are explained, along with data exploration and processing. The feature selection was performed through descriptive analytics tools such as statistics and distribution plots. The input and output variables (sub-systems) contributing to the DP system reliability were identified. This step performed quality checks on the data, avoided any collinearity and provided clear visualisation of the variables. The data dictionary at the system level was developed to provide a clear understanding of the data sets. The correlation and interdependencies between the variables (sub-systems) were then identified. Finally, each of the sub-systems identified was described along with the system architecture, GUI model, and data dictionary. The number of equipment items, sensors, and arrangement configuration was explained so that during the development of the mathematical model, it can quickly be evaluated against the DL algorithm performance.

Chapter 5 describes a systematic approach for weight assignment to the DP sub-systems through Analytic Hierarchy Process (AHP).

5. Weight Assignment of DP Sub-Systems: Analytic Hierarchy Process

5.1 Introduction

In this chapter, the different sub-systems identified as input variables are evaluated and assigned a relative weighting based on the contribution to the overall functionality and reliability of the DP system. AHP is a structured technique used for dealing with complex decisions, and weighting assignment between alternatives and was used for weighting of the DP sub-systems [141]. The chapter begins with a description of the AHP process, along with the methodology used. In the next section, features of AHP and the step-by-step process involved in the weighting assignment are explained in detail with the overall flowchart. Subsequently, the application of the AHP process to the DP system was performed. The first step of AHP involving the data collection and definition of the system and sub-systems is described. The next step was the decision hierarchy model establishment, which involved defining the main goals and criteria for the DP problem context. After that, the hierarchy of the system to the sub-systems and from sub-system to the components is established. Then technical ranking for the sub-systems was collected from different industry experts, and a pairwise comparison matrix was generated. The relative weighting between the sub-systems was established, and verification was performed using the consistency ratio. Finally, the weighting assignment was validated against results obtained through the LSTM algorithm [16]. Once proven, the weighting assignment for the DP sub-system is fixed for the research study to be used in predictive and prescriptive analytics.

5.2 Analytic Hierarchy Process as MCDM

DP being a complex system, it is necessary to use more advanced tools to increase the accuracy of decision making, eliminate inconsistencies generated from vast numbers of comparisons, reduce inherent limitations, minimise errors, and handle multi-attributes [138]. Each DP sub-system plays a unique role in the continuous overall DP function for safe and reliable operation of the vessel. Rating the significance or assigning weightings to the DP sub-systems in different operating conditions is a complex task that requires input from many stakeholders. The weighting assignment is a critical step in determining the reliability of the DP system during complex marine and offshore operations. Thus, an accurate weighting assignment is crucial as

it, in turn, influences the decision-making of the operator concerning the DP system functionality execution. Often DP operators prefer to rely on intuition in assigning the weightings. However, this introduces an inherent uncertainty and a level of inconsistency in decision-making [139, 140, 141]. The systematic assignment of weightings requires a clear definition of criteria and objectives and data collection with the DP system operating continuously in different environmental conditions. The sub-systems of the overall DP system are characterised by multi-attributes resulting in a high number of comparisons, thereby making weighting distribution complicated. If the weighting distribution was performed by simplifying the attributes, making the decision by excluding part of them or compromising the cognitive efforts, then this could lead to inaccurate decision-making [142].

Multi-Criteria Decision Making (MCDM) methods have evolved over several decades and have been used in various applications within the maritime, oil and gas industries [143, 144]. DP, being a complex system, naturally lends itself to the implementation of MCDM techniques to assign weight distribution among its sub-systems [138]. An AHP model is useful in obtaining the domain knowledge from numerous experts and representing knowledge-guided indexing. The approach involved the examination of several criteria in terms of both quantitative and qualitative variables. AHP provides a comprehensive and rational framework for structuring a decision problem, for representing and quantifying its elements, for relating those elements to the overall goals and for evaluating the alternative solutions. AHP is one of the most well-known and widely used MCDM techniques. It decomposes the multiple-attributes into hierarchies or groups as per their characteristics and entities and then compares them for weighting distribution. In real applications, such as DP sub-systems, the comparisons are subject to judgmental errors. Therefore, a careful evaluation is required after receiving input from subject matter experts, and analysis must be performed without bias or influence from the vendor [60].

5.3 Methodology

AHP is a method of "measurement through pairwise comparisons and relies on the judgments of experts to derive priority scales" [145]. Decision-makers and researchers use it because it is a simple and powerful tool. At the same time, this method seeks a systematic practice to define

priorities and support complex decision making. In AHP, the decision problem is decomposed into different levels as criteria and sub-systems within which the substantial number of pairwise comparisons are completed, and finally, the weighting distribution is determined. In this technique, complete aggregation among the criteria is assumed, and linear additive models are developed. The weights, priorities, and scores will be achieved by pairwise comparison between all the options. AHP is a useful tool for dealing with complex decision making and may aid the decision-maker to set priorities and make the optimum decision. By reducing complex decisions to a series of pairwise comparisons, and then synthesising the results, AHP helps to capture both subjective and objective aspects of a decision. AHP also provides a means of verification and proving the subject matter expert's opinion mathematically by using the consistency ratio. The critical aspect of AHP is that it incorporates the method of verification of reliability by checking the consistency of the decision maker's evaluations, thus reducing the bias in the decision-making process.[145, 146]

For the weighting distribution of the DP sub-system, the following critical information is established to make the right choice or decision for a real-world application. The following high-level information is established before the application of AHP [145]:

- Definition of the problem
- The need, reason, and purpose of the decision/weightings
- The available alternatives/sub-systems
- The alternative actions to take
- The criteria and sub-criteria to evaluate the alternatives/sub-systems
- The hierarchy of arrangement of sub-systems
- Identification of the different stakeholders and groups involved in the problem and how alternatives will affect them.

The criteria and sub-criteria identified can be either tangible or intangible items. However, when they are intangible, there is no way to measure them as a guide to the ranking of the alternatives [147, 148]. The situation involving intangible items is addressed by creating priorities for the criteria to weigh the alternatives and add up all the requirements to obtain the desired overall ranks of the other options. It is a challenging task, and it is usually a complicated

procedure. The execution should follow the steps below when the criteria and sub-criteria are intangible [144, 149]:

- Structuring a decision problem and selection of criteria
- Priority setting of the criteria by pairwise comparison (weighting)
- Pairwise comparison of options on each criterion (scoring)
- Obtaining an overall relative score for each option
- Evaluating results and verifying the reliability of the output

5.4 Application and Advantages of AHP

AHP is a compensatory method and has been applied in various real-life applications for MCDM. AHP has been widely used in the following applications, which makes it suitable for the determination of DP sub-system weighting assignment [145, 150]:

- Finding the optimal decision when multi-decisions are available in any situation.
- Selecting one alternative (system/variables) from a set of other options.
- Determining the quality of a product in a quality management application.
- Weighting distribution / Priority / Evaluation, determining the relative merits from a set of alternatives.
- Allocating resources, determining the right combination of alternatives due to numerous constraints.
- Benchmarking the system/process under evaluation with the known system/process.

The weighting distribution obtained through AHP can be used universally for addressing reliability issue as the AHP has an axiomatic foundation with the following advantages [145, 150, 151]:

- Comparison is reciprocal, meaning that the pairwise comparison matrix that is formed should be invertible. For example, if A is k times more important than B then B is 1/k times more critical than A.
- Homogeneity, meaning that there must be similarity in the comparisons.
- Dependence, meaning that each level is concerned (complete hierarchy) although it is possible that the relationship is not perfect (incomplete hierarchy).

- Expectation, meaning that it includes assessment expectations and perceptions of decision-makers as a priority.

5.5 AHP Framework for Weighting Distribution

The framework of AHP is defined in the form of a step-by-step execution procedure for weighting assignment to the DP sub-systems. It has provided clear guidance during the process of exploring the different scoring techniques and finally agreeing on the values with proper justification [145, 150]. The elaborate process involved in the AHP methodology was made simple by splitting it into many steps and executing the steps sequentially with an iterative process for optimisation. The first step involves data collection from different stakeholders, and significant efforts are required for analysing the data and grouping it appropriately for the next step. The next step is defining the system and sub-system identification. After this step, comes the preparation of the hierarchy, which is a critical step involving defining the goals, criteria, and the sub-system arrangements. Then the weighting distribution of the sub-systems is determined by the assessment of criteria and alternatives [147]. The next step involves the evaluation of the sub-systems by experts with different competence, skills, and knowledge of the DP system. The data were thoroughly filtered and organised using relevant software to avoid bias and influence on the input. The weighting distribution values obtained through this step are used in determining the weights for the DP sub-systems.

The values obtained through AHP are verified through the consistency ratio check method. Further, the weighting assignment has been validated using the LSTM algorithm through reliability prediction. Figure 5-1 represents the framework of AHP, indicating the step-by-step execution used in the DP sub-system weighting distribution. During the verification step, if the results are not within the acceptable range, then the process is again repeated by rating the sub-system using the Saaty rating scale. Therefore, the check related to the consistency ratio plays a critical role in deciding on the final assignment. In case of any deviation, the process should be re-iterated until satisfactory results are obtained.

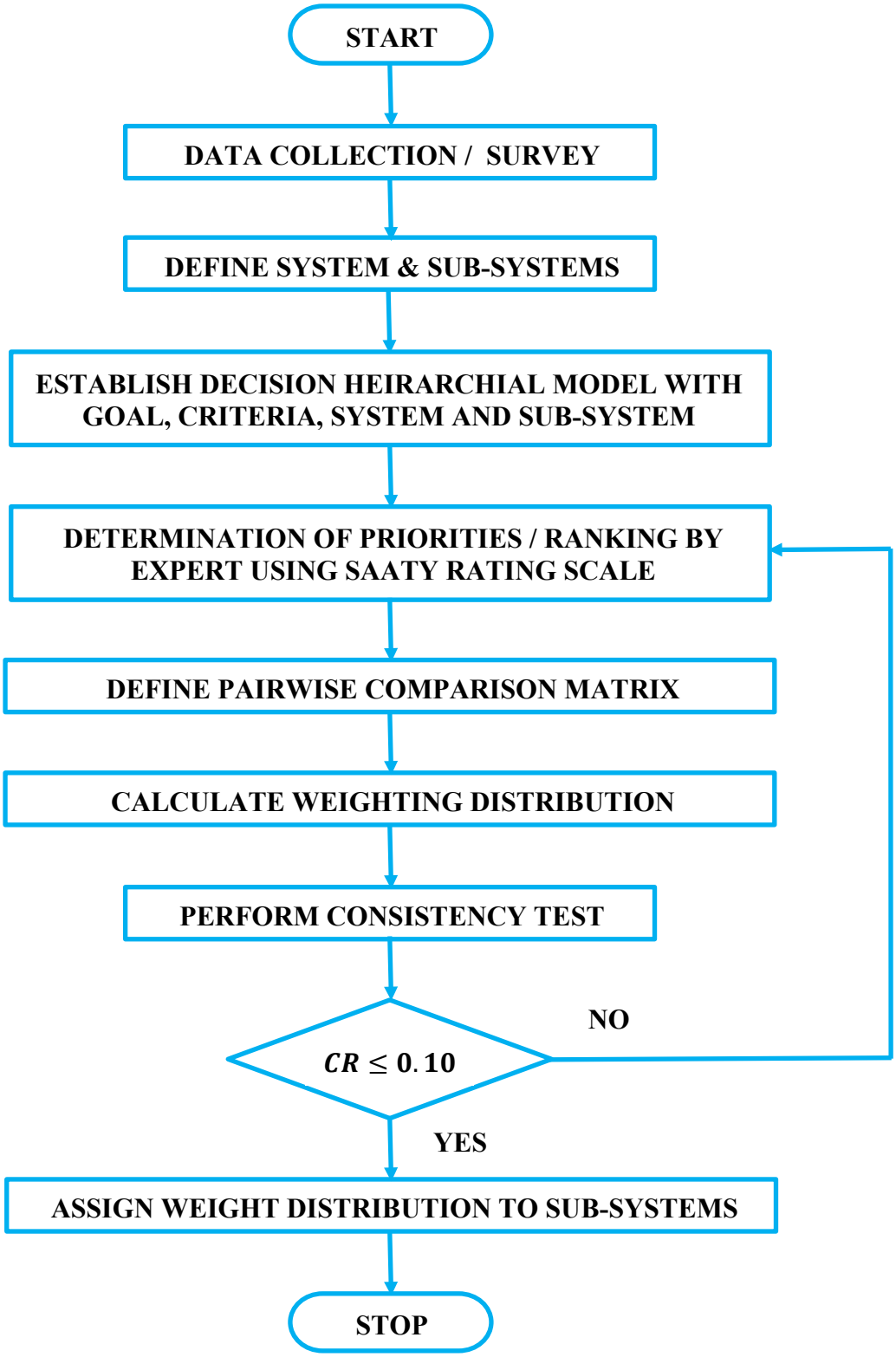


Figure 5-1 Framework of AHP for weight assignment to DP sub-systems

5.6 DP Sub-System Weighting Distribution using AHP

DP sub-systems need to be assigned with appropriate weights, so it is necessary to evaluate the contribution of each to the overall reliability of the DP system [138, 152]. For the AHP methodology, the basic principle of decision making is that the problem needs to be expressed in the form of hierarchical decomposition. Once the decomposition is completed, then the assessment of relative importance between the elements in each hierarchy, a comparative judgment, will be performed [149, 144]. This step is followed by priority synthesis and consistency of assessment evaluation.

In this section, the steps involved in weighting distribution among the sub-systems follows the framework of AHP. The DP sub-system is structured in a hierarchy model, and the criteria for the defined problem are identified. In particular, the framework developed for the application provided clarity, and at the same time, the weighting distribution among the sub-systems are axiomatic and assertive.

This framework of AHP is flexible and easy to adapt for different applications with slight variations. For DP sub-system weight assignment, the framework key concepts are used along with the following variations [143, 150]:

1. To introduce the general underlying principles in obtaining weights, with particular attention to subjective weights
2. To identify and analyse the approaches for obtaining weights:
   a. Statistical approaches (for obtaining “objective” weights), generally applied in the scope of composite indicator construction,
   b. Multi-Attribute approaches,
   c. Scaling approaches, allowing subjective data to be managed; among these, the models should be able
      i. to handle subjective evaluations and judgments, expressed in explicit or implicit ways,
      ii. to obtain subjective weights at the group level and the individual level. These will be identified and described from the perspective of obtaining subjective weights.

5.6.1 Data Collection / Survey Method

The processes of sub-system selection, criteria identification, and sub-criteria identification are conducted through three steps of data collection. The data is collected from databases, correlation analysis, and industry experts such as vendor control system specialists, design engineers, FMEA experts, and vessel operators. Figure 5-2 shows how the big data collected from for the research are used to identify the critical DP sub-systems and criteria for weight assignments through different processes.

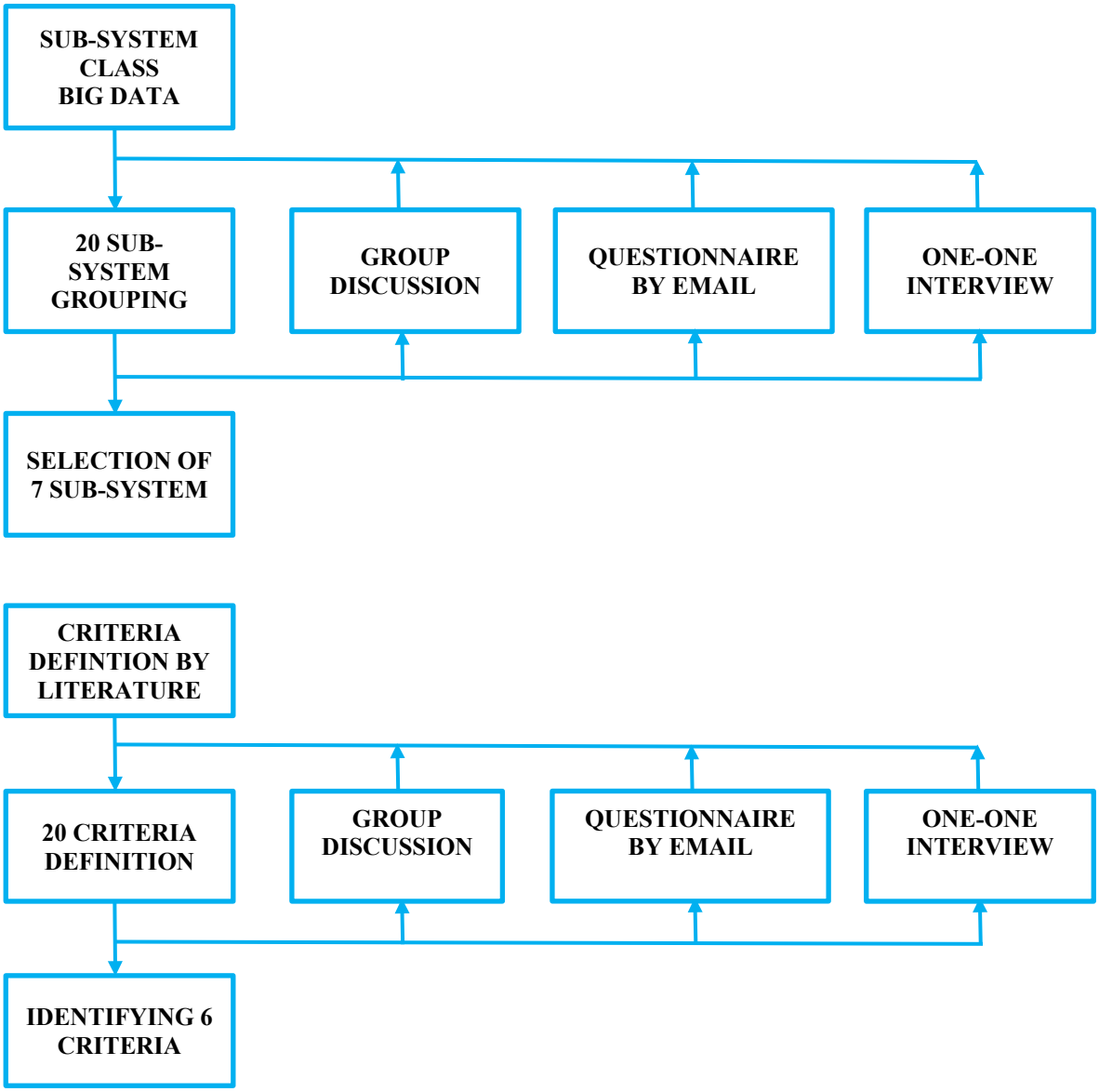


Figure 5-2 Data Collection and Survey on DP sub-systems

The data was collected through different methodologies, and it was ensured that the input was independent, and that one person's decision did not affect other inputs. The data was also collected across various disciplines, regions, shipyards, classification societies, FMEA consultants, design companies, vessel operators, DP vendors, and experts directly or indirectly involved in DP operations. The data collected in the initial stages were grouped and analysed in detail by Subject Matter Expert (SME) for further shortlisting before sending out for another round of Questionnaire with Template as shown in Appendix I data decision gathering [153, 154]. Finally, seven sub-systems were identified as critical, having a direct impact on DP system functionality. Similarly, six criteria were identified as essential, which determine the safe and reliable operation of the DP system.

5.6.2 Define System and Sub-Systems

Once the data has been collected, the next step is to define the system and sub-systems for which the AHP concept needs to be applied. Chapters 3 and 4 already detailed the process of identifying the system and sub-systems. The system is the overall DP system, and the sub-systems were identified as Reference System (A1), DP Control System (A2), Thruster / Propulsion System (A3), Power System (A4), Electrical System (A5), Environment System (A6) and Human Error (A7).

5.6.3 Decision Hierarchy Structure Model

Once the data had been collected, the critical step in the AHP technique is developing the structure of the decision hierarchy. It is generated based on human judgment ability to construct a hierarchical perception of a multi-criteria problem. The hierarchy is a systematic representation of a complex system in a multi-level structure and is created using attributes and entities [144, 150]. By defining the hierarchy, the complex problem will become more transparent for decision-making problems where the entities are interconnected with each other. For this specific application of weighting distribution among the sub-systems, the hierarchy is divided into two levels containing the seven sub-systems and six criteria entities. Figure 5-3 shows the classification of the DP sub-system based on big data analytics and experts' judgments. Figure 5-4 shows the decision hierarchy model with the main criteria and sub-criteria aligned in the hierarchy and its interdependencies with the DP sub-systems. The hierarchy is flexible, and the system is very agile, which enables new criteria to be added once

identified [147]. The hierarchy is prepared based on the inputs collected from SME with many years of field experience.

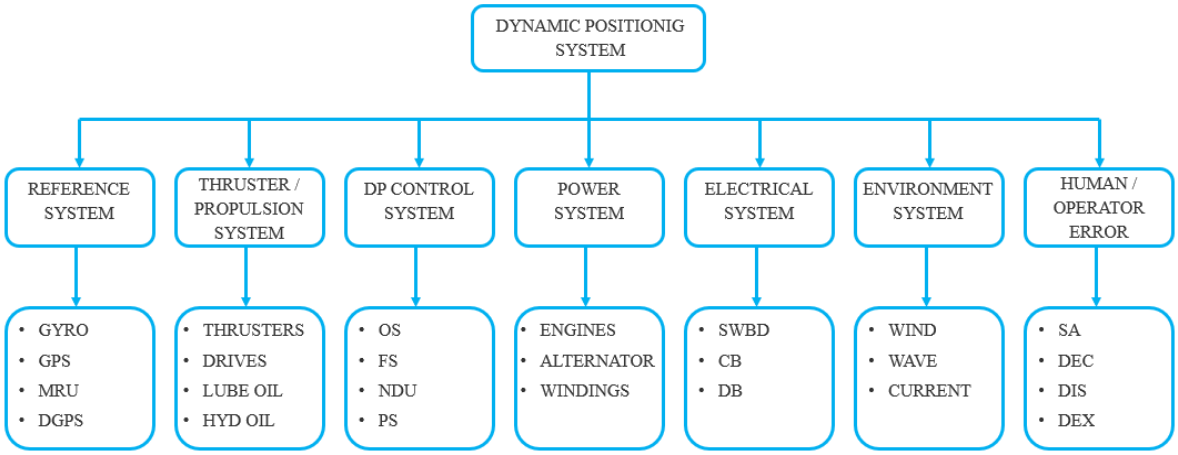


Figure 5-3 Hierarchy of DP sub-systems

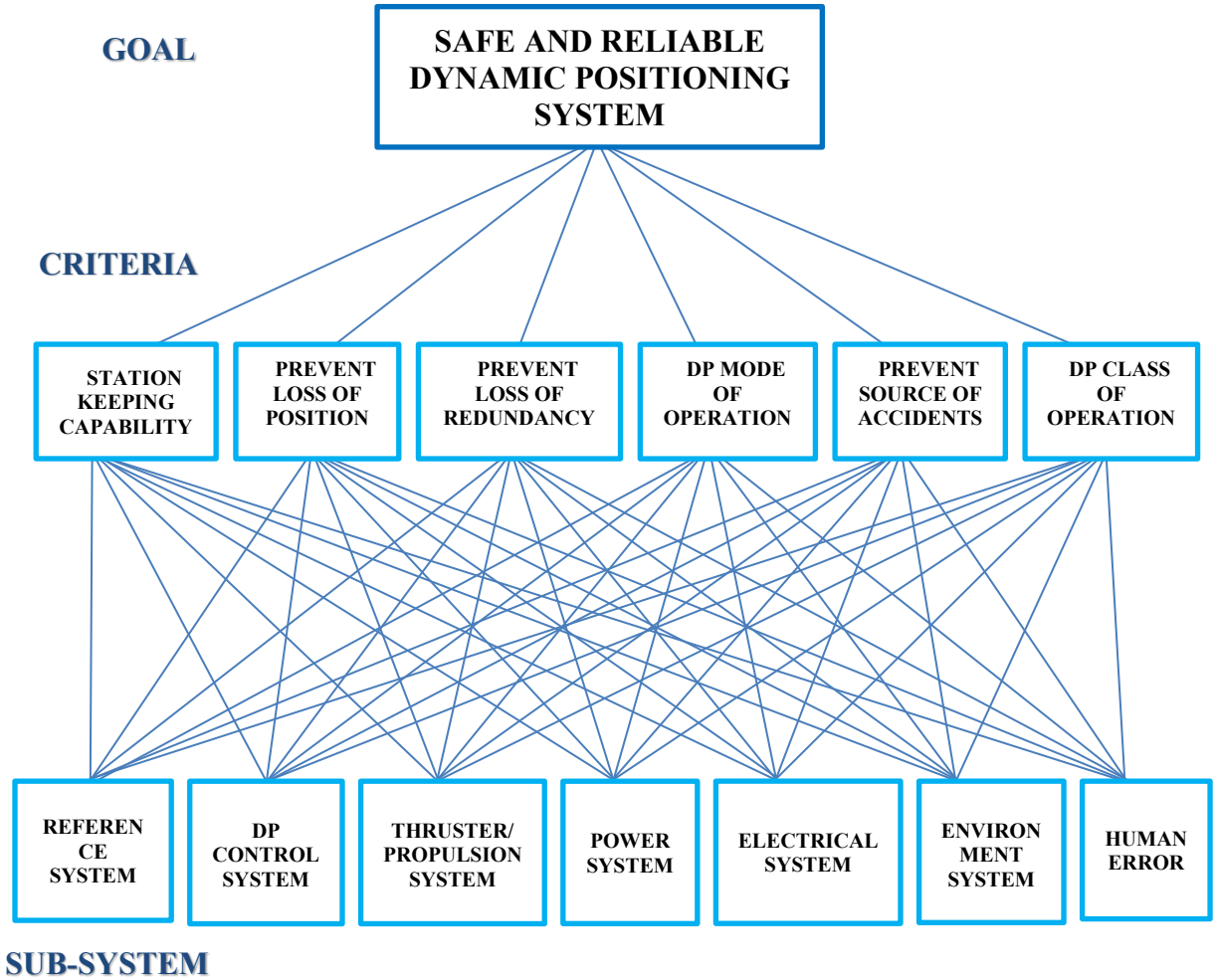


Figure 5-4 Decision Hierarchy Structure Model

5.6.4 Determination of Priorities and Assign Saaty Ratings

AHP gives flexibility to the user for assigning whether a variable is more, less or equally important to another variable. In this step, the user may assign a quantitative value based on qualitative factors. However, experts with similar domain knowledge may give different ratings for the same sub-system. The weighting of the DP sub-systems was collected from SME through various methodologies to have independency on their input, as shown in Figure 5-5. The methods are widely accepted for collecting information from a group for a problem that requires feedback based on field experiences [154].

Table 5-1 represents the "scale of relative importance" in qualitative and quantitative factors, which will be used for pairwise comparisons. The rating for each sub-system for specific qualitative inputs may vary from individual to individual. To minimise the error and avoid inconsistency, the Likert scale methodology is adopted [145, 146]. Once the rating is assigned for a sub-system, the relative rating with the immediately previous sub-system is assigned. From the data of the Likert scale, as shown in Table 5-2, a quantitative suggestion matrix could be developed for a straightforward and convenient pairwise comparison. AHP allows the user to determine the rating for the sub-system intuitively by making a pairwise comparison then to change the pairwise comparison into a set of numbers that represents the relative priority of each criterion consistently.

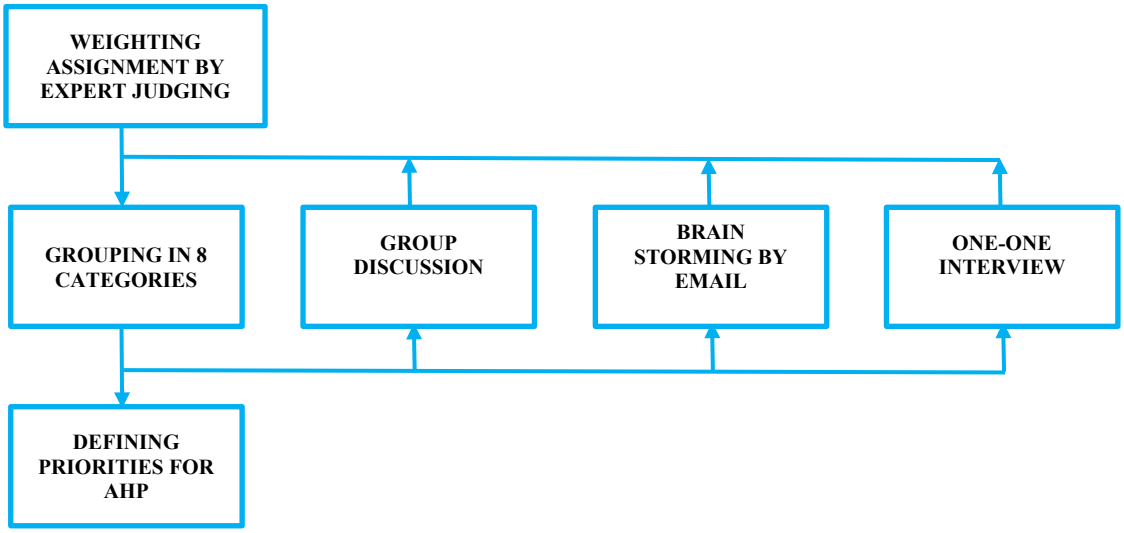


Figure 5-5 Ranking of DP sub-system from industry experts

Table 5-1 Pairwise comparison assessment table for "Scale of relative importance."

NUMERICAL RATING	VERBAL JUDGEMENT OF PREFERENCES	INTERPRETATION
1	Equal Importance	Two categories or variables contribute equally to the objective
3	Moderate Importance	Experience and judgment slightly favour one category or variable over another
5	Strong Importance	Experience and judgment strongly favour one category or variable over another
7	Very Strong Importance	A category or variable is favoured very strongly over another; its dominance demonstrated in practice
9	Extreme Importance	The evidence favoring one category or variable over another is of the highest possible order of affirmation
2,4,6,8	Intermediate Values	Absolute judgment cannot be given, and a compromise is required
Reciprocal	If element *i* has one of the above numbers assigned to it when compared with element *j*, *j* has the reciprocal value when compared to *i*	Element *i* inverse each other with element *j*

Table 5-2 Sub-System Priority assignment - Likert Scale Rating

SUB-SYSTEMS	RATING	RELATIVE RATING
A1 (Reference System)	1	-
A2 (DP control system)	2	0.5
A3 (Thruster / Propulsion)	3	0.666667
A4 (Power System)	3	1
A5 (Electrical System)	5	0.6
A6 (Environment System)	4	1.25
A7 (Human Error)	1	4

Figure 5-6 shows the composition of the participants who are industry experts and contributed to the weighting of the DP sub-systems. The Participants with different backgrounds and knowledge of DP systems contributed to provide the input.

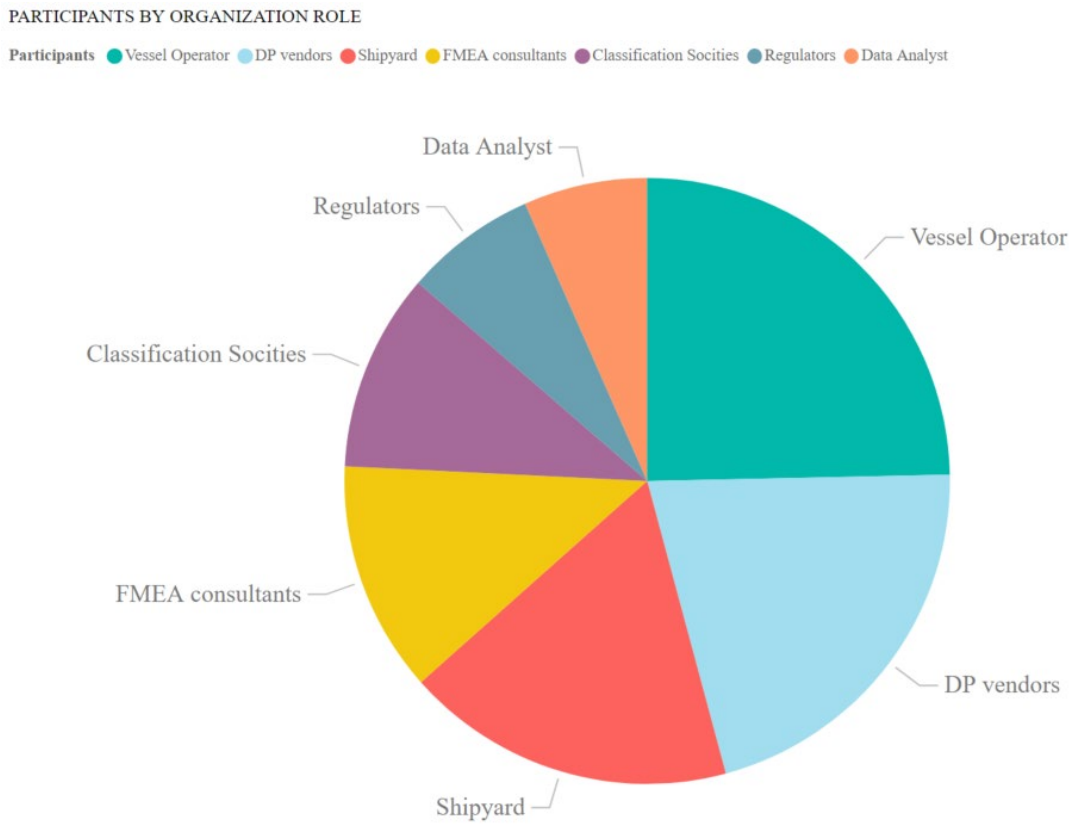


Figure 5-6 Industry experts composition (Organisation group)

Figure 5-7 shows the composition of the participants who are experts in different disciplines and contributed to the weighting of the DP sub-systems.

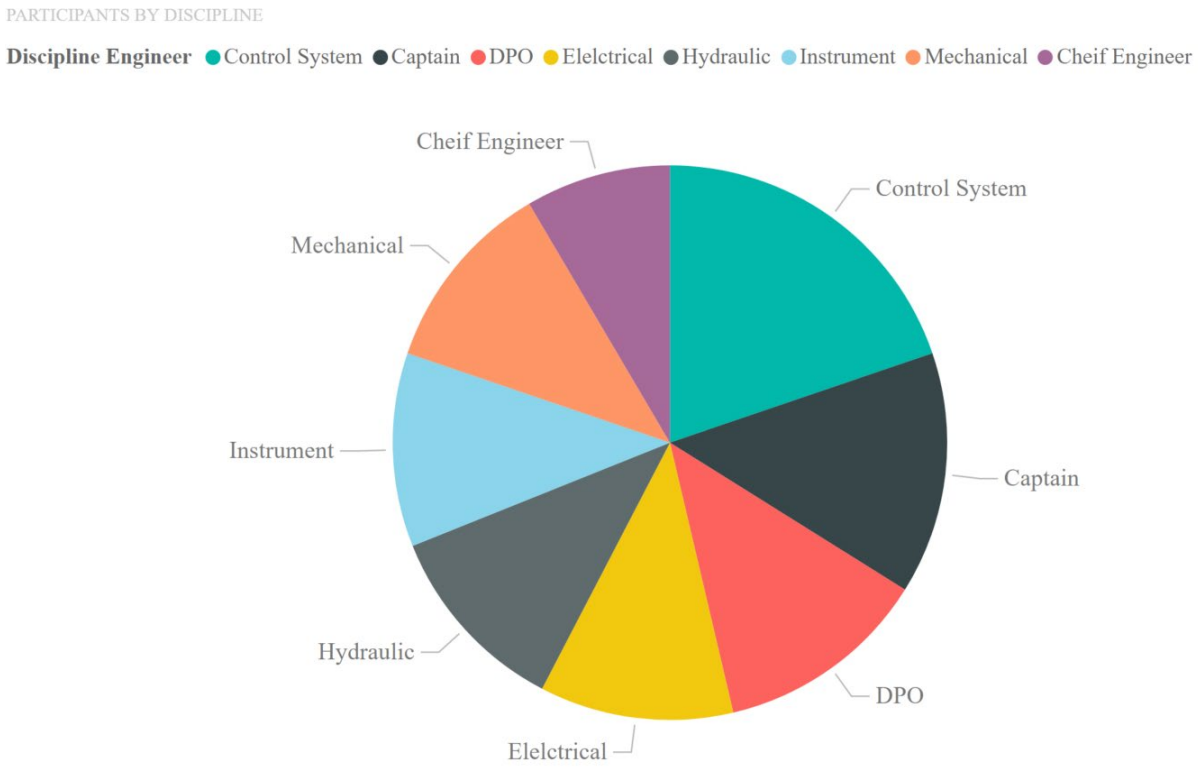


Figure 5-7 Industry experts composition (Discipline)

They are SME from various companies, academic institutions and countries, with different skill sets, working with the DP system to varying phases of the DP life cycle. The questionnaire was prepared based on the criteria and sub-criteria for ranking through several rounds of shortlisting and refinement as shown in Appendix I. The questionnaire was validated against the IMO regulations, IMCA guidelines, and International Association of Classification Societies (IACS) standards for safe assignment of weighting to each of the DP sub-systems.

5.6.5 Pairwise Comparison Matrix for Sub-System

Table 5-3 shows the rating for each sub-system based on the input data collected through the survey method. Once the rating for each sub-system is assigned, then the "scale of relative importance" is determined. Any given set affects only one of the other sets and is affected only by a different one of the other sets for relative rating. However, when ranking the sub-systems, the rating is based on various criteria and sub-criteria affecting the overall complex problem or goal [147, 150]. Thus, the method proved to be useful as ranking was based on all possible criteria relative to each sub-system.

Table 5-3 Pair-Wise Comparison Matrix Template for 7x7 matrix with seven sub-systems

SUB-SYSTEMS	A1	A2	A3	A4	A5	A6	A7
A1	1	1/A21	1/A31	1/A41	1/A51	1/A61	1/A71
A2	A21	1	1/A32	1/A42	1/A52	1/A62	1/A72
A3	A32*A21	A32	1	1/A43	1/A53	1/A63	1/A73
A4	A43*A21	A43*A32	A43	1	1/A54	1/A64	1/A74
A5	A53*A21	A53*A32	A54*A43	A54	1	1/A65	1/A75
A6	A63*A21	A63*A32	A64*A43	A65*A54	A65	1	1/A76
A7	A73*A21	A73*A32	A74*A43	A75*A54	A76*A65	A76	1

The next step of AHP is to form the pairwise comparison matrix between the set of sub-systems. The comparisons between the sub-systems are made for each criterion. For the DP application, there are seven sub-systems classified for weighting distribution. Therefore, the DP sub-system pairwise comparison matrix is formed as a 7x7 matrix table, as shown in Table 5-4. The pairwise comparison matrix reveals the relation between the sub-systems. It analyses whether they are significantly different from one another. Each sub-system is matched head-to-head (one-on-one) with each of the other sub-systems [145, 155].

Table 5-4 Pair-Wise Comparison Matrix for DP sub-systems

PAIRWISE COMPARISON MATRIX							
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
A1	1.00	2.00	3.00	2.00	3.33	1.60	0.50
A2	0.50	1.00	1.50	1.50	2.50	2.00	0.50
A3	0.33	0.67	1.00	1.00	1.67	1.33	0.33
A4	0.50	0.67	1.00	1.00	1.67	1.33	0.33
A5	0.30	0.40	0.60	0.60	1.00	0.80	0.20
A6	0.63	0.50	0.75	0.75	1.25	1.00	0.25
A7	2.00	2.00	3.00	3.00	5.00	4.00	1.00

5.6.6 Calculate Weighting Distribution among DP sub-systems

The critical step for the weighting distribution of sub-systems is determined by multiplying the values in each row together and calculating the Nth root of said product, normalising the nth root of roots products to get the appropriate weights and finally calculating and checking the Consistency Ratio (CR) [146]. It can be explained in the following steps:

Once the pairwise comparison table has been formed, then the Nth root of the product in the matrix needs to be calculated. Consider there are "m" number of sub-systems, and "n" represents the unique number for each sub-system.

The Nth-root-of-product is expressed as shown in Equation (5-1)

$$A_n = (A_{n1} * A_{n2} * A_{n3} * A_{n4} \ldots\ldots * A_{nm})^{1/m} \tag{5-1}$$

In this case, the matrix for the DP system is 7x7. Therefore the 7th-root-of-product in each row is calculated as follows for "m" sub-systems.

For example, the 7th root of Product for each sub-system is calculated using Equation (5-1) as below:

$$A_1 = (A_{11} * A_{12} * A_{13} * A_{14} * A_{15} * A_{16} * A_{17})^{1/7}$$

$$A_1 = (1.00 * 2.00 * 3.00 * 2.00 * 3.33 * 1.66 * 0.50)^{1/7}$$

$$A_1 = 1.64$$

Table 5-5 DP Sub-System Weighting Distribution and Measurement of consistency

PAIRWISE COMPARISON, WEIGHTING DISTRIBUTION AND MEASUREMENT OF CONSISTENCY									
Sub-System	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**Nth root**	**(Wn)**
A1	1.00	2.00	3.00	2.00	3.33	1.60	0.50	1.64	0.20
A2	0.50	1.00	1.50	1.50	2.50	2.00	0.50	1.16	0.14
A3	0.33	0.67	1.00	1.00	1.67	1.33	0.33	0.77	0.10
A4	0.50	0.67	1.00	1.00	1.67	1.33	0.33	0.82	0.10
A5	0.30	0.40	0.60	0.60	1.00	0.80	0.20	0.49	0.06
A6	0.63	0.50	0.75	0.75	1.25	1.00	0.25	0.66	0.08
A7	2.00	2.00	3.00	3.00	5.00	4.00	1.00	2.56	0.32
Sum	**5.26**	**7.23**	**10.85**	**9.85**	**16.42**	**12.07**	**3.12**		
Sum *PV	**1.06**	**1.03**	**1.03**	**1.00**	**1.00**	**0.98**	**0.98**		
λ_{max}	**7.09**								
CI	**0.02**	**(λ_{max} -m)/(m-1)**							
CR	**0.01**	**CI/RI (RI=1.32)**							
TOTAL								**8.10**	**1**

Similarly, the values of the Nth Root of the product for the other sub-systems are calculated using Equation (5-1). The results are listed in Table 5-5 for easy reference and will be used for the determination of Weight / Priority of the sub-system. The 7th-root-of-product values are then added together to give a total of 8.10. Once this is done, the weight determination or priority vectors are calculated. The 7th-root-of-product values and total are normalised to get the appropriate weights for each of the sub-systems.

The weights or priority vectors for each sub-system are calculated below using the AHP methodology formula. The weights or priority vectors for the alternatives are expressed using Equation (5-2):

$$Weight\ or\ Priority\ Vector\ of\ A_n = \frac{Nth\ Root\ Of\ Production\ of\ A_n}{Total\ of\ Nth\ Root\ of\ Product} \qquad (5\text{-}2)$$

$$Weight\ or\ Priority\ Vector\ of\ W_1 = \frac{1.64}{8.103} = 0.20\ \approx\ 20\%$$

$$Weight\ or\ Priority\ Vector\ of\ W_2 = 0.14\ \approx\ 14\%$$

$$Weight\ or\ Priority\ Vector\ of\ W_3 = 0.10\ \approx\ 10\%$$

$$Weight\ or\ Priority\ Vector\ of\ W_4 = 0.10\ \approx\ 10\%$$

$$Weight\ or\ Priority\ Vector\ of\ W_5 = 0.06\ \approx\ 05\%$$

$$Weight\ or\ Priority\ Vector\ of\ W_6 = 0.08\ \approx\ 10\%$$

$$Weight\ or\ Priority\ Vector\ of\ W_7 = 0.32\ \approx\ 30\%$$

Once the weight distribution or priority is assigned for the different sub-systems, it is necessary to verify the consistency of the decisions.

5.6.7 Verification of Reliability of Weighting Distribution

The most crucial characteristic of AHP is consistency. During assessment in the AHP technique, the assessment criteria between sub-systems are not entirely consistent [143, 145]. As in other MCDM methods, AHP allows for inconsistency; however, it limits the inconsistency range not to exceed 10%, which is set as the threshold limit for acceptance. It is defined as the CR.

The CR determines how consistent the decision-maker has been when making the pair-wise comparisons [151]. The consistency ratio is used for verification of the reliability of the weighting distribution among sub-systems of the DP system to ensure the consistency of experts' judgments arranged in pairwise comparisons from the results of the survey. In this way, the weight assignment chosen for the DP sub-system is justified and proven to have a systematic approach for the research application.

CR calculation is performed in five steps as follows:

i. The pairwise comparison values in the 7x7 matrix are added together for each column as the "Sum" values. The sum values are expressed as per Equation (5-3)

$$Sum\ of\ A_n = \sum_1^m A_{mn} \tag{5-3}$$

$$= (A_{11} + A_{21} + A_{31} + A_{41} + A_{51} + A_{61} + A_{71})$$

$$= (1.00 + 0.50 + 0.33 + 0.50 + 0.30 + 0.63 + 2.00)$$

$$Sum\ of\ A_1 = 5.26$$

ii. The Sum values are then multiplied by the respective weight factor for that sub-system from the "Priority Vector" column for that sub-system as shown in Equation (5-4)

$$Sum * Product\ Vector\ for\ A_1 = Sum\ for\ A1 * PV\ of\ A1 \quad (5\text{-}4)$$
$$= 5.26 * 10.2$$
$$= 1.06$$
$$Sum * Product\ Vector\ for\ A_1 = 1.06$$

iii. The λ_{max} of the 7x7 matrix is calculated by adding the (Sum * PV) of each subsystem from the previous step. The measurement consistency of a matrix is based on the eigenvector maximum (λ_{max}). The closer the λ_{max} obtained with the 7 x7 matrices to the 7th-root-of-product, the more consistent the results.

Eigenvector maximum is calculated using the Equation (5-5)

$$\lambda_{max} = \sum_1^m A_m\ (Sum * PV) \quad (5\text{-}5)$$
$$\lambda_{max} = \{A_1(Sum * PV) + A_2(Sum * PV) + A_3(Sum * PV) + A_4(Sum * PV) + A_5(Sum * PV) + A_6(Sum * PV) + A_7(Sum * PV)\}$$
$$\lambda_{max} = \{1.06 + 1.03 + 1.03 + 1.00 + 1.00 + 0.98 + 0.98\}$$
$$\lambda_{max} = 7.09$$

iv. Calculate the Consistency Index (CI) for the 7x7 matrix is expressed as per the Equation (5-6):

$$CI = (\lambda_{max} - m)\ /\ (m - 1) \quad (5\text{-}6)$$
$$= (7.09 - 7)\ /\ (1 - 1)$$
$$= 0.02$$

v. Calculate and check the Consistency Ratio (CR) to ensure that the decision-maker is consistent while making pair-wise comparisons. However, before this step, the Random Index for the 7x7 matrix should be defined. The RI has been chosen based on

vi. Table *5-6*. The value for the CR is determined using the Equation (5-7)

$$CR = CI\ /\ RI \quad (5\text{-}7)$$
$$= 0.02\ /\ 1.32$$
$$= 0.01$$

Table 5-6 Random Index (RI) for AHP

RANDOM INDEX										
N	1,2	3	4	5	6	7	8	9	10	11
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

The numerical values of CR define the consistency of the decision-maker. A higher number means the decision-maker has been less consistent, whereas a lower number means the decision-maker is consistent. The general rule of thumb for the verification of CR is as follows [145, 146]:

- If the CR > 0.10, then the decision-maker should seriously consider re-evaluating the pairwise comparison, which indicates that the sources of inconsistency must be identified and resolved. The analysis needs to be re-performed.
- If the CR ≤ 0.10, then the decision-maker pair-wise comparisons are relatively consistent.

The DP application problem analysed in the above section has **CR = 0.01,** which reveals that the pairwise comparisons between the sub-systems are relatively consistent. Therefore, no corrective actions are required. The weighting distribution factors among the sub-systems of the DP system have been successfully assigned by using AHP, and it has been proved to be consistent and axiomatic. Therefore, the weighting distribution of sub-systems, as indicated in Table 5-7, will be used for further research studies.

Table 5-7 DP sub-system weighting distribution using AHP

SNO	SUB-SYSTEM DESCRIPTION	WEIGHTING -WN
1	Reference System (W1)	20
2	DP Control System (W2)	14
3	Thruster/Propulsion System (W3)	10
4	Power System (W4)	10
5	Electrical System (W5)	06
6	Environment System (W6)	08
7	Operator / Human Error (W7)	32

5.7 Validation of Weighting through LSTM Algorithm

For validation of the weighting distribution among the DP sub-systems, the LSTM algorithm is used on part of the data set. The details of the prediction are discussed in the next chapter. However, a high-level prediction of the reliability of the DP system using the LSTM algorithm was used to determine the weights of the DP sub-system for validation of the AHP results. The structure of LSTM with three layers is shown in Figure *5-8* [79, 80].

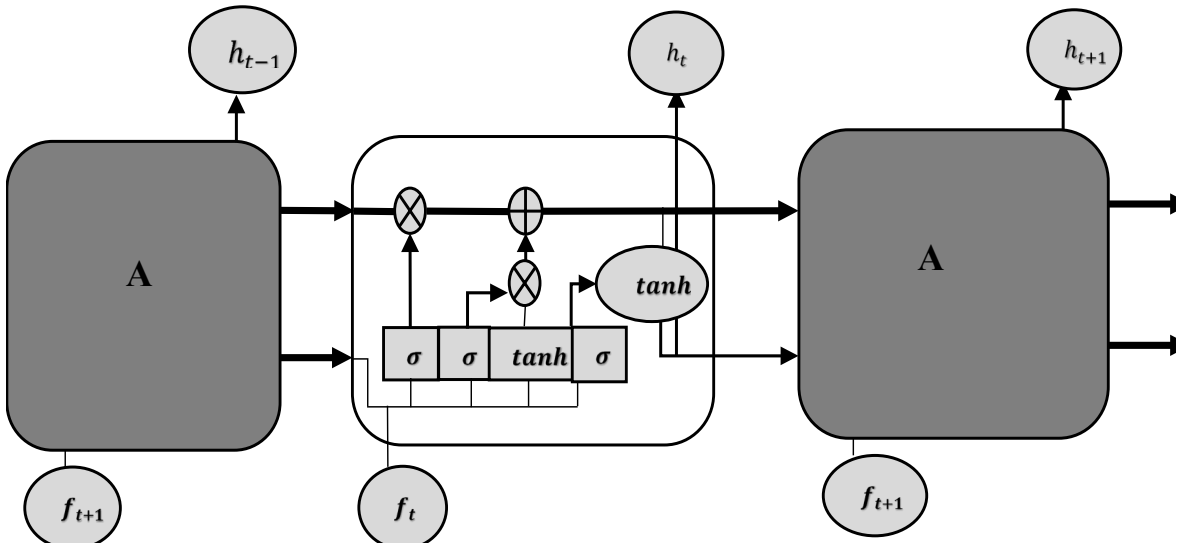


Figure 5-8 Structure of neuron with time-step

For this validation, a simple LSTM architecture is used to retrieve the weights and biases from the dataset. The LSTM has four layers, each of four neurons. The four layers form together with a gate, which is a combination of forget gate, input gate, and output gate (in the order of the sequence) [156]. The architecture of LSTM was defined in Chapter 2 Section 2.10.3, and the detailed implementation is defined in Chapter 6 along with a comparison with other architectures. The validation part used the input shape of (50000 x 7), which refers to 50,000 unique timesteps of data points and seven sub-systems (variables) [157, 156]. For deep networks, a heuristic method may be used to initialise the weights depending on the activation function. The weight value for the sub-system is initialised through Xavier's initialisation [158].

The reliability of the DP system and its relationship with the weight functions of sub-systems are expressed using Equation (5-8) below:

$$DP\ Reliability = (A1 + A2 + A3 + A4 + A5 + A6 + A7) \quad (5\text{-}8)$$

Where

$A1 = W_1X_1 + B_1$

$A2 = W_2X_2 + B_2$

$A3 = W_3X_3 + B_3$

$A4 = W_4X_4 + B_4$

$A5 = W_5X_5 + B_5$

$A6 = W_6X_6 + B_6$

$A7 = W_7X_7 + B_7$

$X_1, X_2, X_3, X_4, X_5, X_6$ & X_7 are the reliability of DP sub-systems

$W_1, W_2, W_3, W_4, W_5, W_6$ & W_7 are the weights for DP sub-systems

$B_1, B_2, B_3, B_4, B_5, B_6$ & B_7 are the bias for DP sub-systems

A1, A2, A3, A4, A5, A6 & A7 are the overall realiability of DP sub-systems

The weights of the sub-systems are determined through backpropagation in LSTM [159]. The overview of the model architecture for sub-system weight distribution through backpropagation of LSTM is shown in Figure 5-9. It shows the data, features, hidden layer, and output arrangements. The main goal with backpropagation is to update each weight in the network so that it tends to converge to the optimal point to ensure that the output is closer to the target output. In this way, it minimises the error for each output neuron and the network as a whole. To understand the mathematical calculation behind the back-propagation, it is essential to implement the forward computation. The forward computation is represented through Equations (5-9) to (5-13) [159, 160].

$$hf_t = \sigma\,(W_f[h_{t-1},\ x_t]\ + b_f) \quad (5\text{-}9)$$

$$hi_t = \sigma\,(W_i[h_{t-1},\ x_t]\ + b_i) \quad (5\text{-}10)$$

$$ho_t = \sigma\,(W_o[h_{t-1},\ x_t]\ + b_o) \quad (5\text{-}11)$$

$$hc_t = tanh\,(W_c[h_{t-1},\ x_t]\ + b_c) \quad (5\text{-}12)$$

$$c_t = h_{ft} * c_{t-1} + h_{it} * h_{ct} \quad (5\text{-}13)$$

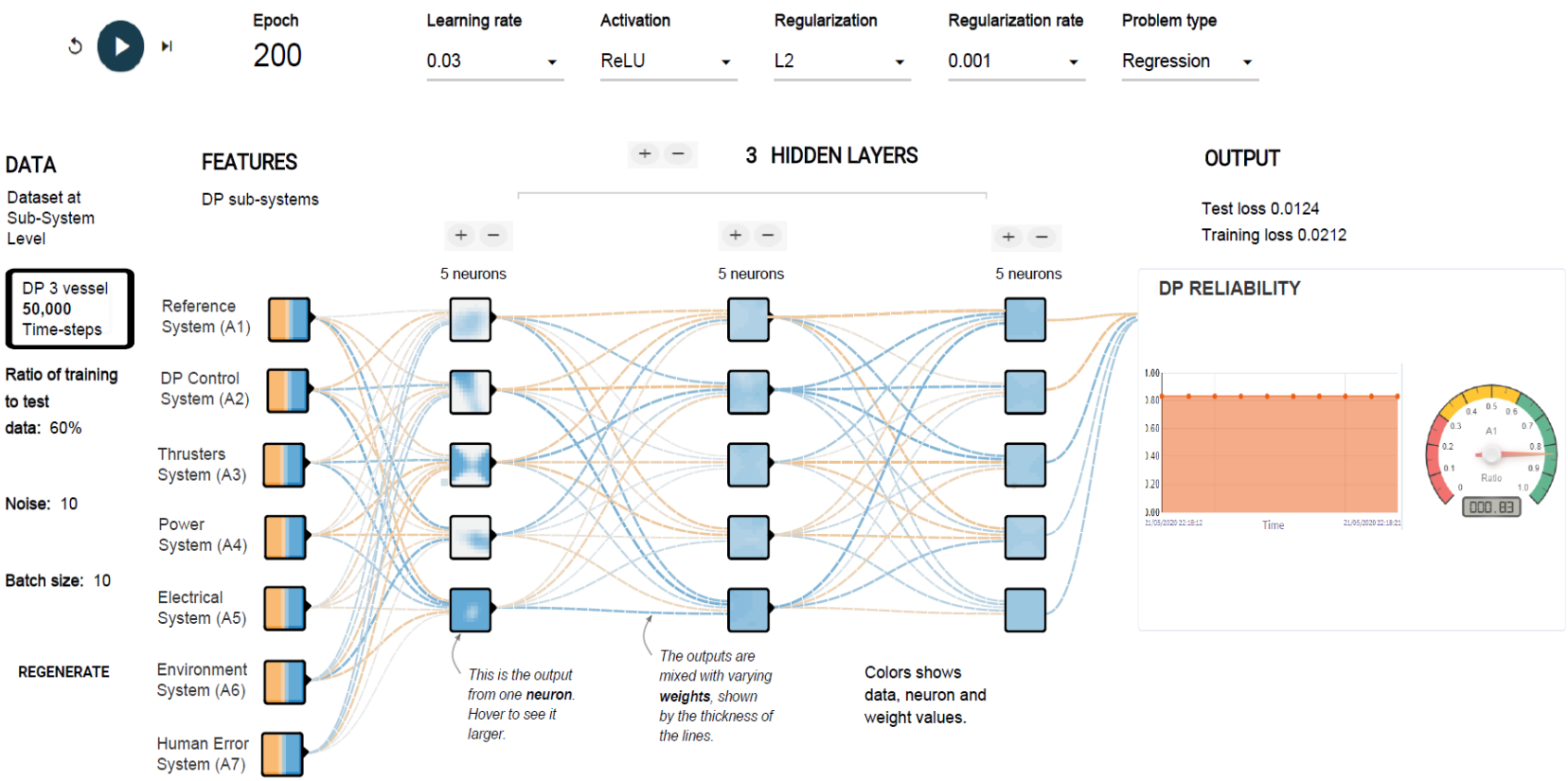


Figure 5-9 LSTM network arrangement with Hidden Layer for backpropagation

In the LSTM cell structure, the old hidden state "H(t-1)" is concatenated with the current input "X(t)", therefore the input "Z" for the LSTM net would be the addition of the number of neurons in the hidden state "H" and the dimension of the input. As the LSTM output layer has "H" neurons, each of the weight matrices would be "Z **x** H," and each bias vectors' size would be 1xH. The weights in the fully connected layer are fed to the SoftMax layer, and the resulting output would be a probability distribution over all possible items with the size of "H **x** D."

The next process is to determine the network gradient analytically through backpropagation. This process involves the partial derivative of a function and the use of the chain rule [161]. The backpropagation is based on the forward step results with a reversal in the direction of step implementation. The backpropagation is implemented in the following four steps to determine the optimised weights for the sub-system.

Step 1:

The relationships between the sub-systems and their weights are defined along with the activation function. Using the input "X" to the activation function as the input layer represented by Equation (5-14) to (5-23). The result of this layer is fed to the next layer (and so on).

$$Z = Wx + b \tag{5-14}$$

$$A1 = W_1X_1 + B_1 \tag{5-15}$$

$$A2 = W_2X_2 + B_2 \tag{5-16}$$

$$A3 = W_3X_3 + B_3 \tag{5-17}$$

$$A4 = W_4X_4 + B_4 \tag{5-18}$$

$$A5 = W_5X_5 + B_5 \tag{5-19}$$

$$A6 = W_6X_6 + B_6 \tag{5-20}$$

$$A7 = W_7X_7 + B_7 \tag{5-21}$$

$$a = \sigma\,(\mathrm{Z}) \tag{5-22}$$

$$a = \sigma\,(\mathrm{A1}) \tag{5-23}$$

Step 2:

In this step, the relationship of the input with the weights is computed for each layer. For simplicity the Equation (5-24) and (5-25) are shown only for the Reference sub-system.

$$A1^L = W_1^L a^{L-1} + B_1^L \tag{5-24}$$

$$a^L = \sigma\,(\mathrm{z}^L) \tag{5-25}$$

Step 3:

The next step is to compute the error vector in the "L" layer, as shown in Equation (5-26).

$$\delta^L = \nabla_a \mathrm{C} \odot \sigma^L(\mathrm{z}^L) \tag{5-26}$$

Then the rate of change of C is expressed concerning the output activations as shown in Equation (5-27).

$$\nabla_a \mathrm{C} = (\mathrm{a}^L - \mathrm{y}) \tag{5-27}$$

Before proceeding to the next step, the generalised error vector formula is determined. Once the error vector at the last layer is computed, then backpropagation is used to determine the error in the previous layer as in Equation (5-28).

$$\delta^L = (\mathrm{a}^L - \mathrm{y}) \odot \sigma^L(\mathrm{z}^L) \tag{5-28}$$

Step4:

In the final step, the process moves backwards from the output layer to the input layer through hidden layers to find the optimum weights and, at the same time, reduce the error through the gradient cross-function [162, 163]. The model consists of 3 hidden layers to determine the optimal sub-system weights. They are defined as below:

L → output layer

L-1 → Hidden layer before the output layer

L-2 → 2nd hidden layer

L-3 → 3rd hidden layer

L-4 → Input Layer

The error vector for the last layer (output layer) is given by Equation (5-29):

$$\delta^L = (\mathrm{w}^{L+1})^T \delta^{L+1} \odot \sigma^L(\mathrm{z}^L) \tag{5-29}$$

Where

$(\mathrm{w}^{L+1})^T$ *is the transpose of the weight matrix of* $L + 1$ *layer*

The transpose is applied to the weight matrix $(\mathrm{w}^{L+1})^T$ so that weights can be expressed intuitively as moving the error back through the network, giving a measure of the error at the output of that L^{th} layer. Similarly, the values of each weight in the hidden layers are calculated by expressing weights in terms of W_{jk}^L with "J" representing the feature and "K" the actual neuron in the hidden layer.

Finally, the Hadamard product $\odot\ \sigma^L(z^L)$ is computed. This step moves the error backwards through the activation function in layer L, giving the error δ^L in the weighted input to layer, L, to determine whether it meets the acceptable level and outperforms other algorithms.

The gradient cost function is then calculated through the Equation (5-30) and (5-31).

$$\frac{\partial C}{\partial W_{jk}^L} = a_k^{L-1}\delta_j^L \tag{5-30}$$

$$\frac{\partial C}{\partial b_j^L} = \delta_j^L \tag{5-31}$$

Then this allows adjustment of the weights and biases to minimise the cost functions. The LSTM model is trained using initial values to find the optimum value for the weights, and at the same time to converge rapidly. During the training of the model using the actual data from the DP vessel, it was found that the weight distribution for the sub-systems converged to optimum results. Table 5-8 shows the weighting distribution of the DP sub-system obtained through LSTM.

Table 5-8 DP sub-system weighting distribution using LSTM

SNO	SUB-SYSTEM DESCRIPTION	WEIGHTING -Wn
1	Reference System (W1)	20
2	DP Control System (W2)	15
3	Thruster/Propulsion System (W3)	10
4	Power System (W4)	10
5	Electrical System (W5)	05
6	Environment System (W6)	10
7	Operator / Human Error (W7)	30

These values obtained through LSTM either matched with or were very similar to AHP results. Therefore, the AHP results were rounded to the nearest value as per the LSTM results for the further research study.

5.8 Summary

In this chapter, the AHP framework was used to assign the weighting for the DP sub-systems. The systematic approach and its application to the research study were described through a step-by-step process. The process involves the work of experts in determining the sub-systems, goals, criteria, sub-criteria, and relative weighting of the sub-systems. The AHP methodology is proven and straightforward, as it addresses all questions on the reliability of the results and consistency such that the approximation can be applied. At the same time, it provided a strong basis for comparison of the model results and evaluating its performance if it is deemed necessary. Finally, the results obtained are verified through CR and validated using LSTM so that they can be used in the other part of the research.

In the next chapter, Stage 4 of big data analytics involving predictive analytics modelling and a new research framework for the reliability of the DP system will be described.

6. Dynamic Positioning – Reliability Index (DP-RI): Predictive Analytics

6.1 Introduction

In this chapter, stage 4 of the big data analytics, shown in Figure 3-1, involving predictive analytics is discussed. The predictive analytics is used for the prediction of the reliability of the DP system for offline simulation and real-time applications during complex offshore marine operations. A new research framework called the Dynamic Positioning – Reliability Index (DP-RI) has been introduced with high-level architecture that is presented in section 6.2. In the next section, the mathematical modelling for DP-RI computation through the RBD is discussed. The RBD for each sub-system has been calculated depending on the vessel and system configuration. Then the overall DP reliability was computed. The next section discusses the basic predictive analytics in terms of the step by step procedure for the prediction of the reliability of the DP system (DP-RI). The section describes the different RNN models, machine specifications, such as Graphical Processing Unit (GPU), and hardware used for this research along with Tensorflow 2.0, which has a vast ecosystem of related components, including libraries like Tensorboard, deployment and production API. In the next section, the datasets used for comparing the performance of the different algorithms and the split between the training, validation, and test data are presented. Other biases affecting the RNN models and the AIF360 framework to address biases are detailed. Finally, the performance results of each algorithm are compared using the evaluation metrics to select the suitable RNN models for the DP-RI advisory tool.

6.2 DP-RI Concept

The DP-RI concept is proposed to aid an operator with quantitative and qualitative representations of the reliability of DP systems during complex marine operations. This concept is not a replacement or an alternative solution for the current reliability assessment; it will enhance the existing reliability assessment results by combining them with a newly developed database and industry experts' knowledge [2]. The DP system is classified into various sub-systems using big data analytics and a correlation method, as described in Chapter 4. The Reliability Index (RI) of each of the sub-systems has been calculated based on the weighting factor, DP class type, configuration, and mode of operation, as in Chapter 5.

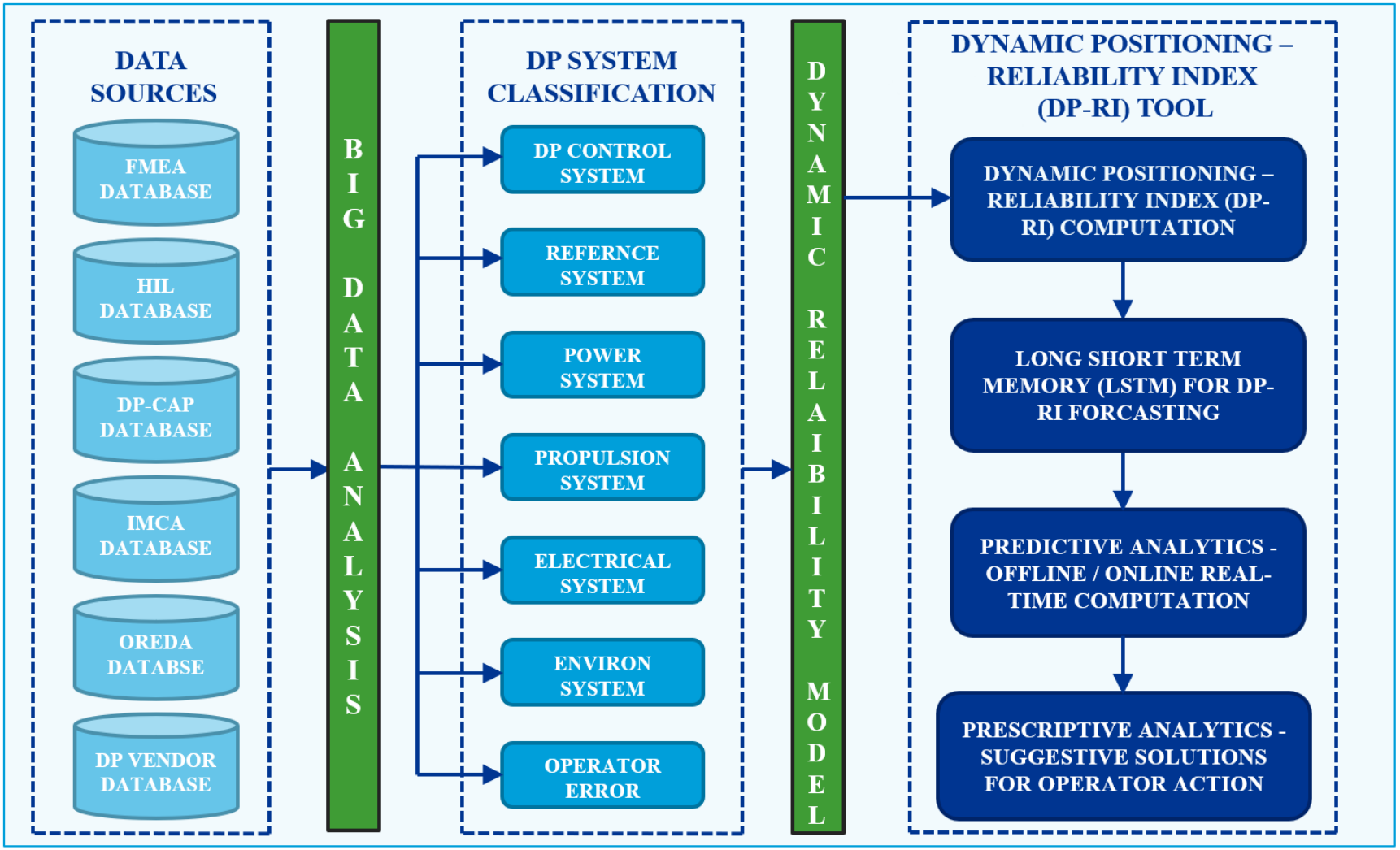


Figure 6-1 Overall Architecture of DP-RI concept

Figure 6-1 shows the overall architecture of the DP-RI concept indicating the complete steps from data sources to prediction and prescriptive solutions. In this chapter, the DP-RI concept is explained through a detailed research framework covering the methodology, dynamic reliability modelling, DP-RI computation through RBD for mathematical modelling and finally, prediction of DP-RI using LSTM. DP-RI concepts support both offline prediction and real-time forecasting based on the current input and historical information.

6.2.1 DP-RI Research Framework

The DP-RI is an advisory tool aiding a DP operator with quantitative and qualitative representations of the reliability of DP systems during complex marine operations [2]. Due to the enormous amount of work and cost involved in traditional quantitative assessment, the DP community can use this research framework as an efficient alternative solution tool. In this chapter, the reliability of the DP system is determined through a mathematical calculation using RBD for the sub-systems and at the same time prediction using LSTM based on field data. Through the process, a simple mathematical formulation for the reliability of the DP system is introduced in the form of the Reliability Index (RI). The reliability representation in DP-RI is closer to reality than the current methodology, providing a complete overview to the operator and aiding them to take the necessary action in the case of any failures within the DP system.

Different models of deep learning algorithms have been used for TSP forecasting in the DP-RI tool to determine their suitability based on the accuracy and speed of prediction. The architecture and framework for the DP-RI are shown in Figure 6-2. It depicts the flow of information from different databases to individual systems to reliability modelling and, finally, the real-time prediction of reliability [2]. The DP-RI research framework can be used for offline forecasting to allow the DPO and vessel to prepare for the specific operation. Similarly, the tool supports real-time prediction during complex offshore marine operations to assist the DPO in understanding the reliability of the DP system and, at the same time, the status of each sub-system to focus on critical areas in the case of failures. The final DP-RI value predicted could be scaled to different DP classes and configurations of a ship as it matches to mathematical calculations.

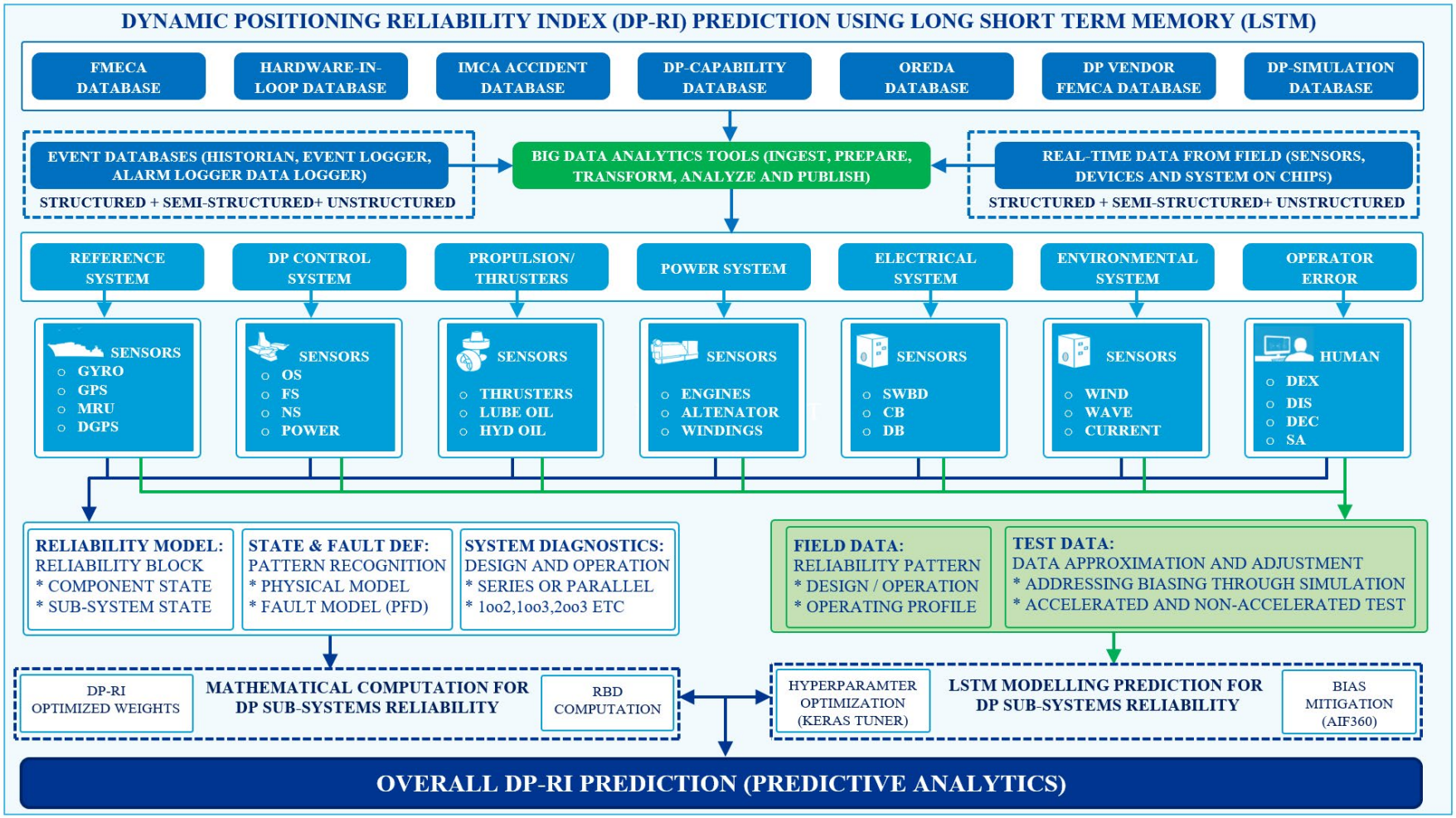


Figure 6-2 DP-RI research framework for the Prescriptive Analytics

6.2.2 Generalised DP-RI Formulation with the Weighting of Sub-Systems

The Reliability Index (RI) is calculated based on the reliability of each sub-system and their weighted contribution to the overall vessel DP performance based on the Analytical Hierarchy Process [2]. The DP class type, system configuration and mode of operation are taken into consideration for an accurate representation of the DP-RI as a result of LSTM prediction defined in Section 6.7 and Section 6.8. With careful analysis of the databases, review of the availability of redundant systems, experience, knowledge from previous accidents, and input from industry experts (consultants, designers, engineers, operators, etc.) RI is represented for normal and fault conditions through Equation (6-1):

$$\boldsymbol{RI}\ (\boldsymbol{condition}, \boldsymbol{type}) = \{(\mathbf{0.20} * \boldsymbol{A1} + \mathbf{0.15} * \boldsymbol{A2} + \mathbf{0.10} * \boldsymbol{A3} + \mathbf{0.10} * \boldsymbol{A4} + \mathbf{0.05} * \boldsymbol{A5} + \mathbf{0.10} * \boldsymbol{A6} + \mathbf{0.30} * \boldsymbol{A7}) * \boldsymbol{K}\} \tag{6-1}$$

where

$$\boldsymbol{K} = \begin{cases} \mathbf{1} & \boldsymbol{if\ condition = normal\ , type = all\ types} \\ \mathbf{0.9} & \boldsymbol{if\ condition = faulty\ , type = DP3} \\ \mathbf{0.8} & \boldsymbol{if\ condition = faulty\ , type = DP2} \\ \mathbf{0.3} & \boldsymbol{if\ condition = faulty\ , type = DP1} \end{cases}$$

Based on the class of DP vessel, the reliability will vary as the redundancy of the components in individual systems is designed for fault tolerance in each type of DP class [4].

6.3 Methodology for Mathematical DP-RI computation

For the mathematical computation of the DP-RI, the RBD method is used due to its efficiency in representing quantitively, the actual status of complex systems. A typical reliability model is represented with series and parallel combinations of sub-systems/components, as shown in Figure 6-3.

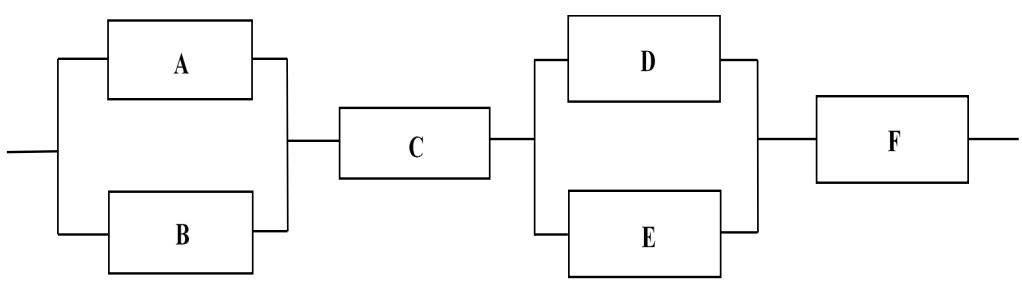


Figure 6-3 Typical RBD arrangement in series & parallel configuration

An RBD presents a logical relationship between the system, sub-systems, and components. A DP system is modelled for reliability computation and analysis using block diagrams [12]. During the formulation of DP-RI, certain factors are taken into consideration, which affect the mathematical computation. These are listed below [19]:

- Sub-Systems / Components architecture
- DP vessel and component Modes of Operation
- Voting Configuration
- Overall System and Sub-System functional requirement

6.3.1 Sub-System / Component Architecture

The sub-systems/components are represented through RBD models based on the system design architecture. The system architecture is one of the below models [19, 64, 14]:

- Static System Models
- Series Model
- Stand-by System
- (K,n) System
- Parallel Model

Based on the system configuration, the sub-system reliability is calculated using the principle of probability theory. If the system had more than one function, each function was considered individually, and a separate reliability block diagram was established for each system function. The system reliability is then modelled using the reliability of the various sub-systems [65, 67]. The mathematical model is used to assist in making changes to the system for reliability improvement. The model is used to identify weak links in the design and to indicate where reliability improvement activities should be introduced.

6.3.2 DP Vessel and Components Modes of Operation

A DP system operates in different modes during complex marine operations depending on the functionalities required by the vessel [1, 59, 164]:

- Station Keeping
- Joystick

- Auto-Pilot mode
- Auto Heading
- Auto track / Follow Target

The DPO and Captain would ensure that the sub-systems are arranged as per the DP operating manuals and site-specific risk assessment instructions. From a functional safety perspective, the components within the sub-system will be operating in specific modes to fulfil the requirements of the safety-related systems. The components within the sub-system determine the reliability of the sub-system based on the mode of operation which will fall into one of the following groupings based on the vessel type and DP configuration [64, 14]:

- Low demand mode
- High demand mode
- Continuous Mode

6.3.3 Sub-System / Component Voting Configuration

The sub-system architecture and modes of operation determine the component's configuration and voting group to prevent failure of a safety function in the case of accidental events. The voting configuration provides redundancy depending on the criticality of the signal, as discussed in Section 4.3 in Chapter 4. The sub-system and the components within the sub-system are grouped under one of the following voting configurations [19, 64]:

- 1oo1 (one-out-of-one)
- 1oo2 (one-out-of-two)
- 1oo3 (one-out-of-three)
- 2oo2 (two-out-of-two)
- 2oo3 (two-out-of-three)

The voting configuration not only provides the reliability but also the availability and safety of the system when hidden failures are difficult to detect.

6.3.4 Overall System and Sub-System Requirement Definition

The mathematical computation model and prediction model for the reliability of a sub-system are computed only when the system design assumptions and uncertainties have been

adequately defined [165]. In this section, the vessel type, class, system set-up, sub-system configuration, critical, non-critical, redundant, non-redundant grouping, and design boundary are defined for the experiment in the next section. The sub-system signals were identified and grouped across different categorisations, considering the design phase for evaluation [1, 9, 59, 164, 166, 167]. The grouping of the signals for the different sub-systems is presented in Sections 4.4 to Section 4.10 in Chapter 4. The sub-systems component arrangement, architecture, voting group, and criticality grouping are shown in Table 4-2 to Table 4-8.

The DP system is a composite entity with complex integration between sub-systems comprising equipment, software, materials, procedures, and personnel. In this research study, the analysis for the sub-systems was performed based on two aspects [48]:

- Structural focus refers to the physical architecture defining the hierarchy of system, sub-systems, and components.
- Functional focus refers to the logical architecture, which depicts the functional relationship between the sub-systems.

The system may be transformed into a functional block diagram or RBD or fault tree to represent the functional architecture. The RBD is built as success-oriented networks illustrating how the sub-systems operate as functional blocks to fulfil the overall DP system functional requirement [8, 167]. The structure of the RBD is described mathematically by structure functions. This structure-function will be used to calculate the sub-system reliability. The experimental set-up for the reliability calculation of the sub-systems was performed with the following parameters defined as a standard for the two approaches and validation [48]:

- System
- System Boundary
- Sub-Systems
- Assemblies / Components
- Outputs
- Inputs
- Boundary conditions
- Support
- External Threats

The DP-RI mathematical computation was based on the failure data from the data lake defined in Chapter 3. The failure data were collected for the equipment at a sensor level and generalised for use for different vessel applications. The uncertainties are treated as known uncertainties, which will introduce minor error in the system, therefore at a broader scale, the efficiency is still at a high level [1, 56]. In the next section, the mathematical computation of the DP-RI is described. The output will act as the target variable for the reliability prediction and is further used as the actual output value for comparison and performance evaluation. If the results prove to be within an acceptable range, then the mathematical calculation of reliability of the DP system based on the weights can be used.

6.4 Mathematical Computation of DP-RI – Failure data

The mathematical computation of DP-RI is highly dependent on the structural focus, which is expressed through the RBDs. The structural architecture defines the basic system hierarchy of each of the sub-systems and the association of lower levels and components with higher-level assemblies and systems. Once the structural aspects of the physical sub-system are defined, the functional focus is taken into consideration for the mathematical computation [4, 48, 165]. As shown in Figure 6-2, for mathematical analysis, each sub-system is further divided into groups of different equipment. The three main activities involved in the calculation of reliability of sub-systems are [168]:

- Reliability Block Diagram based on system configuration
- System Diagnostic based on voting group
- Pattern recognition for functional fault identification

The reliability of the system and sub-systems can be calculated through the Probability of Failure on Demand (PFD) represented by mathematical Equations (6-2) and (6-3) [19, 169]:

$$PFD_{System} = (PFD_{sub-system1} + PFD_{sub-system2} + \cdots PFD_{sub-systemn}) \quad (6\text{-}2)$$

$$PFD_{sub-system} = (PFD_{comp1} + PFD_{comp2} + \cdots PFD_{compm}) \quad (6\text{-}3)$$

Where

PFD_{System} = Average probability of failure on demand for DP system

$PFD_{sub-system}$ = Average probability of failure on demand for DP sub-system

PFD_{comp1} = Average probability of failure on demand for components

n = Number of sub-systems in the DP system

m = Number of components in the sub-system

6.4.1 Sub-System Components Voting Configuration

The components and sensors are designed to increase the reliability depending on operation complexity and criticality of the specific mode of operation. Section 6.3.3 described the various possibilities of the arrangement of the components within the sub-systems and sensors within the components. The reliability formulation or average PFD is highly dependent on the voting configuration. The arrangement and voting of components are in one of the following architectures, as detailed in Section 6.3.3. The architecture and generalised formula for the different voting configurations used for the reliability calculation of the sub-system and in-turn for the DP system are described below [19, 64, 14].

1oo1:

The voting configuration for 1oo1 (one-out-of-one) is shown in Figure 6-4, and the corresponding average probability of failure on demand is represented by Equation (6-4).

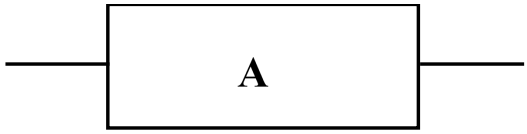


Figure 6-4 1oo1 voting configuration

$$PFD_{AVG} = (\lambda_{DU} + \lambda_{DD})t_{CE} \tag{6-4}$$

1oo2:

The voting configuration for 1oo2 (one-out-of-two) is shown in Figure 6-5, and the corresponding average probability of failure on demand is represented by Equation (6-5).

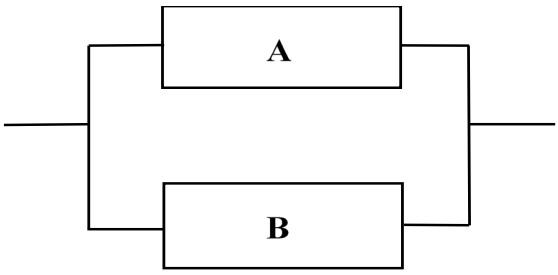


Figure 6-5 1oo2 voting configuration

$$PFD_{AVG} = 2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE} t_{GE} + \beta_D \lambda_{DD} MTTR + \beta \lambda_{DU}(\frac{T_1}{2} + MRT) \quad (6\text{-}5)$$

1oo3:

The voting configuration for 1oo3 (one-out-of-three) is shown in Figure 6-6, and the corresponding average probability of failure on demand is represented by Equation (6-6).

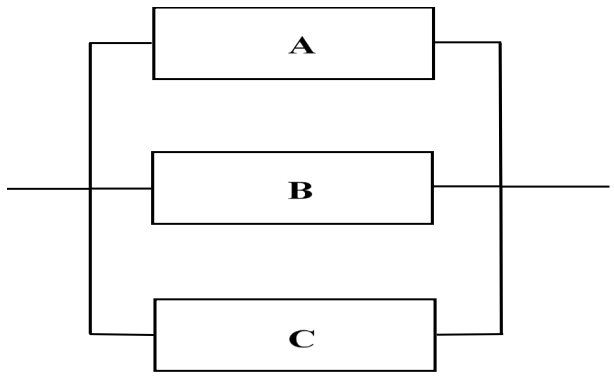


Figure 6-6 1oo3 voting configuration

$$PFD_{AVG} = 6((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^3 t_{CE} t_{GE} t_{G2E} + \beta_D \lambda_{DD} MTTR + \beta \lambda_{DU} \left(\frac{T_1}{2} + MRT\right) \quad (6\text{-}6)$$

2oo2:

The voting configuration for 2oo2 (two-out-of-two) is shown in Figure 6-7, and the corresponding average probability of failure on demand is represented by Equation (6-7).

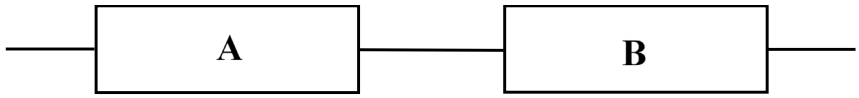


Figure 6-7 2oo2 voting configuration

$$PFD_{AVG} = 2\lambda_D t_{CE} \quad (6\text{-}7)$$

2oo3:

The voting configuration for 2oo3 (two-out-of-two) is shown in Figure 6-8, and the corresponding average probability of failure on demand is represented by Equation (6-8).

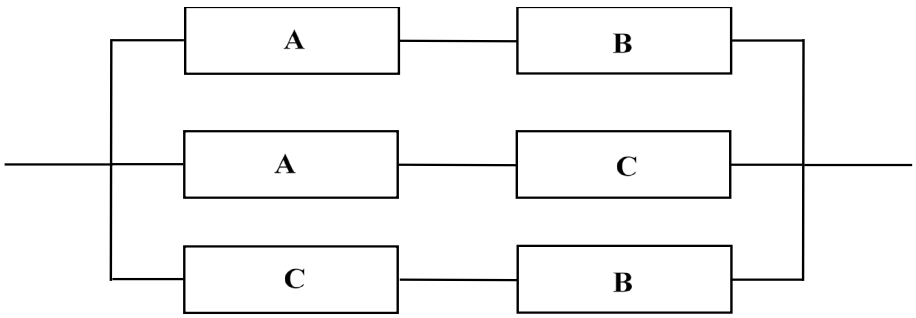


Figure 6-8 2oo3 voting configuration

$$PFD_{AVG} = 6((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE} t_{GE} + \beta_D \lambda_{DD} MTTR + \beta \lambda_{DU}(\frac{T_1}{2} + MRT) \quad (6\text{-}8)$$

Where

λ_{DU} → Dangerous Undetected failure rate of a channel in a Subsystem

λ_{DD} → Detected dangerous failure rate of a channel in a subsystem

t_{CE} → Calculate the channel equivalent mean downtime

t_{GE} → System equivalent downtime

β → The fraction of undetected failures that have a common cause

β_D → the fraction that has a common cause of those failures that are detected by the diagnostic tests

$MTTR$ → Mean Time To Restoration

MRT → Mean Repair Time

T_1 → Proof test interval

T_2 → Interval between demands

6.4.2 Sub-System Reliability Computation

The system architecture/voting was used to calculate sub-system reliability from the PFD. In this section, the component voting for each sub-system was used to determine the reliability of the sub-systems [48, 19]. The seven DP sub-systems' reliability is calculated individually using the RBD architecture, and then the overall system-level reliability is calculated. The model architecture of the DP3 vessel, defined in Sections 4.4 to Section 4.10 in Chapter 4, is used for the calculation of the reliability of the DP sub-systems.

Reference System (A1):

The average PFD of the Reference System (PFD_{A1}) is represented by Equation (6-9) and (6-10) based on the different component voting configurations defined in Section 6.4.1.

$$PFD_{A1} = PFD_{GYRO} + PFD_{MRU} + PFD_{GPS} + PFD_{DGPS} \tag{6-9}$$

$$PFD_{A1} = \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \{2\lambda_D t_{CE}\} + \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\} \tag{6-10}$$

DP control System (A2):

The average PFD of the DP Control System (PFD_{A2}) is represented by Equation (6-11) and (6-12) based on the different component voting configurations defined in Section 6.4.1.

$$PFD_{A2} = PFD_{OS} + PFD_{NDU} + PFD_{FS} + PFD_{RCU} \tag{6-11}$$

$$PFD_{A2} = \left\{2\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \left\{2\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \left\{2\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \{6((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\} \tag{6-12}$$

Thruster / Propulsion System (A3):

The average PFD of the Thruster / Propulsion System (PFD_{A3}) is represented by Equation (6-13) and (6-14) based on the different component voting configurations defined in Section 6.4.1.

$$PFD_{A3} = PFD_{T1} + PFD_{T2} + PFD_{T3} + PFD_{T4} + PFD_{T5} + PFD_{T6} + PFD_{T7} + PFD_{T8} \tag{6-13}$$

$$PFD_{A3} = \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} +$$

$$\left\{2((1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU})^2 t_{CE}t_{GE}+\beta_D\lambda_{DD}MTTR+\beta\lambda_{DU}(\frac{T_1}{2}+MRT)\right\}+$$
$$\{2((1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU})^2 t_{CE}t_{GE}+\beta_D\lambda_{DD}MTTR+\beta\lambda_{DU}(\frac{T_1}{2}+MRT)\} \quad (6\text{-}14)$$

Power System (A4):

The average PFD of the Power System (PFD_{A4}) is represented by Equation (6-15) and (6-16) based on the different component voting configurations defined in Section 6.4.1.

$$PFD_{A4} = (PFD_{DG1}+PFD_{DG2})+(PFD_{DG3}+PFD_{DG4})+(PFD_{DG5}+PFD_{DG6})+(PFD_{DG7}+PFD_{DG8}) \quad (6\text{-}15)$$

$$PFD_{A4} = \left\{2((1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU})^2 t_{CE}t_{GE}+\beta_D\lambda_{DD}MTTR+\beta\lambda_{DU}(\frac{T_1}{2}+MRT)\right\}+$$
$$\left\{2((1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU})^2 t_{CE}t_{GE}+\beta_D\lambda_{DD}MTTR+\beta\lambda_{DU}(\frac{T_1}{2}+MRT)\right\}+$$
$$\left\{2((1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU})^2 t_{CE}t_{GE}+\beta_D\lambda_{DD}MTTR+\beta\lambda_{DU}(\frac{T_1}{2}+MRT)\right\}+$$
$$\{2((1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU})^2 t_{CE}t_{GE}+\beta_D\lambda_{DD}MTTR+\beta\lambda_{DU}(\frac{T_1}{2}+MRT)\} \quad (6\text{-}16)$$

Electrical System (A5):

The average PFD of the Electrical System (PFD_{A5}) is represented by Equation (6-17) and (6-18) based on the different component voting configurations defined in Section 6.4.1.

$$PFD_{A5} = PFD_{SWBD1}+PFD_{SWBD2}+PFD_{SWBD3}+PFD_{SWBD4}+PFD_{CB1}+PFD_{CB2}+PFD_{CB3}+PFD_{CB4} \quad (6\text{-}17)$$

$$PFD_{A5} = \{(\lambda_{DU}+\lambda_{DD})t_{CE}\}+\{(\lambda_{DU}+\lambda_{DD})t_{CE}\}+\{(\lambda_{DU}+\lambda_{DD})t_{CE})\}+\{(\lambda_{DU}+\lambda_{DD})t_{CE}\}+\{(\lambda_{DU}+\lambda_{DD})t_{CE}\}+\{(\lambda_{DU}+\lambda_{DD})t_{CE}\}+\{(\lambda_{DU}+\lambda_{DD})t_{CE})\}+\{(\lambda_{DU}+\lambda_{DD})t_{CE}\} \quad (6\text{-}18)$$

Environmental System (A6):

The average PFD of the Environmental System (PFD_{A6}) is represented by Equation (6-19) and (6-20) based on the different component voting configurations defined in Section 6.4.1.

$$PFD_{A6} = PFD_{WIND}+PFD_{WAVE}+PFD_{CURRENT} \quad (6\text{-}19)$$

$$PFD_{A6} = \left\{6\left((1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E}+\beta_D\lambda_{DD}MTTR+\beta\lambda_{DU}\left(\frac{T_1}{2}+MRT\right)\right\}+\left\{6\left((1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E}+\beta_D\lambda_{DD}MTTR+\beta\lambda_{DU}\left(\frac{T_1}{2}+\right.\right.$$

$$MRT\Big)\Big\} + \Big\{6\big((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\big)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\Big(\frac{T_1}{2} + MRT\Big)\Big\} + \Big\{6\big((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\big)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\Big(\frac{T_1}{2} + MRT\Big)\Big\} \quad (6\text{-}20)$$

Human / Operator Error (A7):

The average PFD of the Human / Operator Error (PFD_{A7}) is represented by Equation (6-21) and (6-22) based on the different component voting configurations defined in Section 6.4.1.

$$PFD_{A7} = PFD_{DEX} + PFD_{DEC} + PFD_{DIS} + PFD_{SA} \quad (6\text{-}21)$$

$$PFD_{A7} = \Big\{6\big((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\big)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\Big(\frac{T_1}{2} + MRT\Big)\Big\} + \Big\{6\big((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\big)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\Big(\frac{T_1}{2} + MRT\Big)\Big\} + \Big\{6\big((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\big)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\Big(\frac{T_1}{2} + MRT\Big)\Big\} + \Big\{6\big((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\big)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\Big(\frac{T_1}{2} + MRT\Big)\Big\} + Intangible\ Factors\ (IF) \quad (6\text{-}22)$$

6.4.3 DP-RI Computation

The overall DP-RI computation is based on the reliability of the sub-systems. As discussed in the previous sections, the PFD for the sub-systems is calculated based on the component voting configuration within the sub-systems, mode of operation, class of vessel, and DP vessel system configuration during a specific offshore complex operation. For the system level reliability computation, the PFD at the system level is computed using Equation (6-23) [170].

$$PFD_{DP-RI} = PFD_{A1} + PFD_{A2} + PFD_{A3} + PFD_{A4} + PFD_{A5} + PFD_{A6} + PFD_{A7} + PFD_{A8} \quad (6\text{-}23)$$

The above equation for calculating the overall PFD has proved useful in various safety system reliability applications [15, 62, 171, 172]. For a sophisticated safety system, the PFD represents the reliability measure, which is an unavailability number. The reliability of the DP system is calculated using Equation (6-24) [170].

$$PFD_{DP-RI} = 1 - \frac{1}{t}\int_0^t RI(t)\,dt \quad (6\text{-}24)$$

Where

$RI(t)$→ Survivor Function or Reliability of DP system (DP-RI)

ŧ → Test interval

The mathematical computation is used for performance evaluation of the RNN, which is used for the prediction of DP system reliability in the next section. The model predicted value is compared with the numerical value to determine the error. The mathematical computation obtained through RBD gives a quantitative representation of the reliability, which consumes a considerable amount of time, effort, and enormous cost due to the experts and consultants involved from different stakeholders. Therefore, this is not a preferred method for all vessels. However, if the prediction results could be proven to have the same effects as the mathematical computation, then reliability prediction can be widely used.

6.5 Predictive Analytics – Prediction of DP-RI through RNN – Field Data

Reliability prediction is becoming the most commonly used method in the oil and gas industry for assessing complex systems [4, 166, 173]. The DP sub-system data from the field (historical and real-time) and test simulations are used for training the RNN models for predicting the near-future values.

The test data was simulated to address bias for the missing system configuration. The reliability prediction through RNN models was performed with the information such as reliability requirements, system architecture, operating environment, operating profile and failure mechanism. The causes are fed into the model to ensure that there would be the desired degree of precision in the prediction, as per Institute of Electrical and Electronics Engineers (IEEE) IEEE 1413 standard [48]. The data used for the prediction of reliability are categorised into two groups as below:

- Field Data: As described in Section 6.5.3
- Test data
    - Accelerated data
    - Non-accelerated data

6.5.1 Recurrent Neural Network Models for Prediction

RNN models have proved to be more efficient in addressing problems related to complex real-time applications. Research has shown that RNN models provide more accurate, faster responses and self-learning capability when implemented in diverse applications with minimal effort from humans [80, 82, 83, 81, 84]. RNN models are more suitable for relatively long interval delays in time series prediction and long-term dependencies in time series data. The following RNN models defined in Section 2.10 are evaluated for suitability in the DP-RI application.

- MLP
- SRNN
- GRU
- LSTM

6.5.2 Machine Specification and Programming Language

In this section, the details of the experimental set-up are given related to the machine specification for cloud computing using RNN models, programming language, an application-programming interface (API), platforms, libraries and debugging plugins for the implementation of research. The details of hardware specification and programming are in Section 8.3. The following tools, platforms, and libraries are used for the experiment related to predictive analytics [174, 175, 176]:

- Compute Engine
- GCP and GPU
- Colaboratory or "Colab"
- Pycharm IDE
- AIF360 Source Toolkit
- Tensorflow 2.0
- Tensorboard and Tensor-graph
- Keras (Model, API & Tuner)
- Numpy and Pandas
- Matplotlib
- Seaborn

6.5.3 Datasets - Data Description and Processing

For the specific task of Predictive Analytics, data from a DP vessel was used. The vessel configuration, DP class, and further sub-systems arrangement were discussed in Chapter 4. The data collected from the DP-3 ship were raw data values from the historic event database. Therefore, the data was characterised by noise and redundant information. Machine learning model output depends on the context of the data, and it is essential to be clear on what the data represents so that domain experts can apply theories and domain knowledge to the data for better validation. The final data used for prediction consisted of 450,000 unique datapoints.

For the evaluation of the RNN models, the DP 3 vessel data samples were stored as time series with a sample interval of 1 millisecond. The sensor data was grouped at the equipment level before grouping into the sub-system level. The sub-system level corresponds to the seven different sub-systems of a complex DP system [2] [16]. As in any data sets, the real-time data collected from the field included redundant information and noise data that could have an impact on the model training resulting in a bias. To ensure fair comparison and avoid biasing, the data sets were pre-processed for relevant feature engineering. The steps and methods are described in detail in Chapter 3 and Chapter 4. A brief introduction is provided below before the research experiments are described.

Data Collection: This is the first essential step for addressing problems through machine learning models. The data sets were recorded by the DP-3 system vendor and stored in a separate machine known as the History Station. The data collection was formulated in such a way that the system automatically determined the relevant attributes of each sub-system and stored the data in a comma-separated variable (.csv) file format.

Data Exploration and Profiling: After the data collection, the next step was to assess the condition of the data to find trends, outliers, exceptions, incorrect, inconsistent or missing data, errors, repeated and skewed information. The time-series data sets were filtered with a weighted average of past data points, within a time-span of 10-points, to generate a smoother estimation of the time series [177]. The profiling also meant that data was not removed from the limited sample, which could have introduced unseen biases.

Formatting data for consistency: The data sets were obtained initially without considering the mode of operation of the vessel or the number of equipment items connected to each sub-system at a given point in time. The time-stamps were compared between the datasets, which were classified with the sub-system data and the overall state of the DP system. In this way, the time-series data, which were non-stationary, exhibiting specific trends were removed from the relational data [177]. The aggregation of data from different data sources was formatted to remove errors and in-consistency and to best fit the proposed machine learning models.

Improving data quality: In the datasets, erroneous data, missing values, extreme values, and outliers were carefully dealt with, with a strategic interest in improving the accuracy of prediction. The outliers in the input data, above the range, below the range, and spurious values were evaluated using data preparation tools such as Excel, Python, Alteryx etc. A standard way of removing trends is by defining the observation from the previous time step (t-1) and comparing it with the current time step(t); this was adopted to remove the repeated values from the dataset [178].

Feature Engineering: This is the most critical step in data processing as it involves the transformation of raw data into the attributes/features that represent meaningful patterns / cognitive targets for the machine learning models. The time-series data was divided into input (A1, A2, A3, A4, A5, A6, and A7) and output (DP-RI). The target models, through mathematical formulae, define the correlation between the input and output variables to capture the specific relationships [177].

6.5.4 Training and Testing Dataset Split

The initial step involved splitting the dataset into two sets: one for training the models and the second one for the evaluation of performance. GCP was used to ensure that the datasets used were non-overlapping sub-sets between the training and testing data. For the first case, the datasets of 450,000 samples were used to evaluate the performance of different machine learning models. Figure 6-9 shows one split-ratio indicating that 67% of the samples were used for Training (Training + Validation), and 33% of the samples were used for Testing (Evaluating the performance).

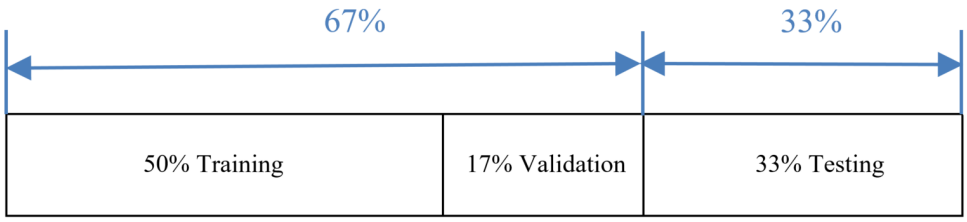


Figure 6-9 Datasets Split ratio

For the optimisation algorithm for each model, the hyperparameters, batch size, and epochs were varied during the sample distribution to prevent over-fitting while at the same time, verifying the results [179]. Therefore, the training samples were further divided into 50% training and 17% validation to address the problem related to model bias, which results in overfitting/underfitting. Additionally, for evaluating the gradient descent, the sample distribution was varied as per Table 6-1, and the performances tested.

Table 6-1 Split-ratio between Training / Validation and Testing datasets

SNO	TRAINING & VALIDATION	TESTING
1	67	33
2	75	25
3	80	20
4	90	10

The performance of the models was tested for all different combinations of ratios in the above table to find the ratio with the highest accuracy measured through evaluation metrics defined in Section 6.8, which was chosen for the DP-RI tool development.

6.5.5 Learning Curve (Loss and Accuracy) Evaluation

The Learning Curve (LC), which provides information on the loss and accuracy of the model prediction, is an excellent method to evaluate the performance. There are two-learning curves used to assess the dynamics which are defined as follows [180]:

Train Learning Curve: Learning curve calculated from the training dataset that gives an idea of how well the model is learning.

Validation Learning Curve: Learning curve calculated from a hold-out validation dataset that gives an idea of how well the model is generalising.

The shape and dynamics of the learning curves were used to diagnose the behavior of different algorithms. There are three common shapes and dynamics that will define the performance of the RNN algorithm, which are usually represented as below [180, 181, 182]:

- Underfit
- Overfit
- Good Fit

In the next section, the learning curve results are discussed in detail to find the models with a good fit for the data collected from the DP-3 vessel. The good-fit learning curves will represent that the loss decreased to the point of stability with a minimal gap between two final loss values of training and validation learning curves.

Underfitting: Underfitting in LC refers to a RNN model that cannot learn the training dataset or is unable to capture the underlying trend in the data. The LC will be a flat line or have high loss values indicating that the model is unable to learn from the training dataset. The data collected from DP vessels is evaluated to ensure that it does not fall into the underfit category [180]. Underfit LC may be represented, as shown in Figure 6-10, where it is either a flat line or training loss is decreasing and continues to decline at the end of the plot implying that it requires further learning. The LC indicates that other improvements are needed as the training process was halted prematurely.

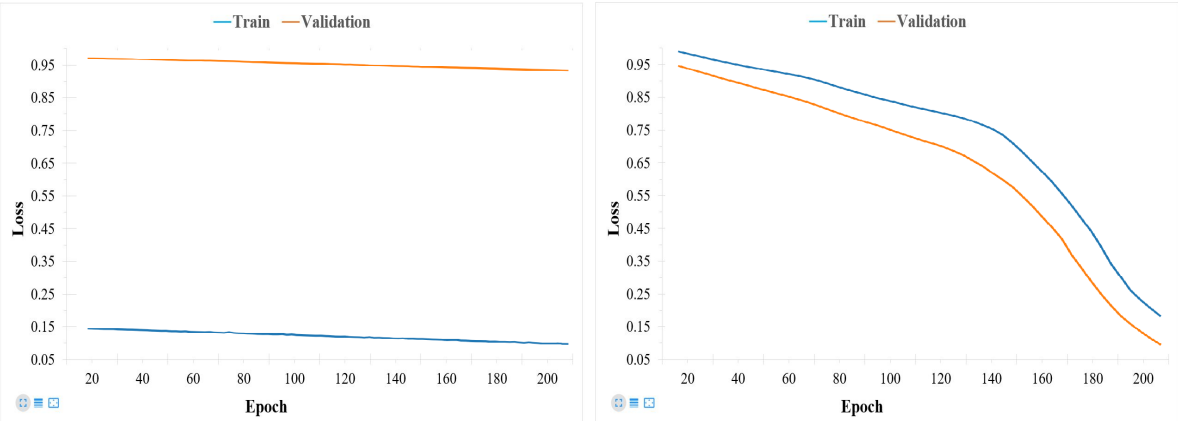


Figure 6-10 Underfitting Loss Curve

Overfitting: Overfitting in LC refers to a model that has learned the training dataset too well, including the statistical noise or random fluctuations. In overfitting scenarios, the models follow the error or noise too closely, resulting in an inability to generalise to new data leading to significant generalisation error. The generalisation error is reflected in validation loss [180]. An overfitting plot can be represented, as shown in Figure 6-11and it could reveal the dynamics of overfitting through the following points:

- The training loss continues to decrease with experience.
- The validation loss decreases to a point and begins increasing again.
- The inflexion/deviation point in validation loss at which training was halted.

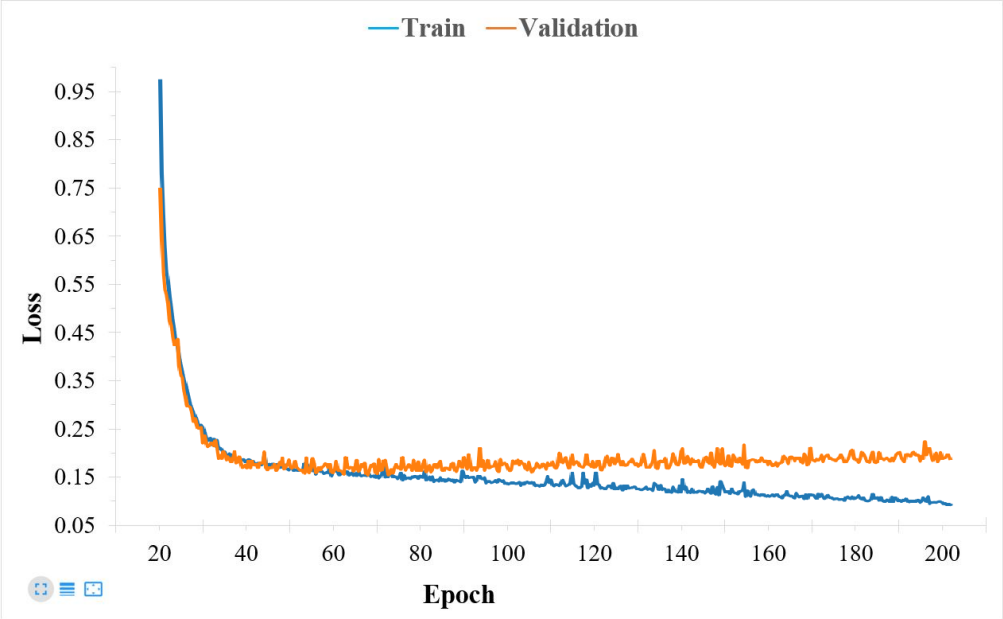


Figure 6-11 Overfitting Loss Curve

Good Fit: A good fit in the LC refers to a model that exists between the overfit and underfit cases. A good fit is represented by an LC in which the training and validation loss decrease to the point of stability with a minimal gap between the two final loss values [182]. The minimal gap is referred to as the "generalisation gap."

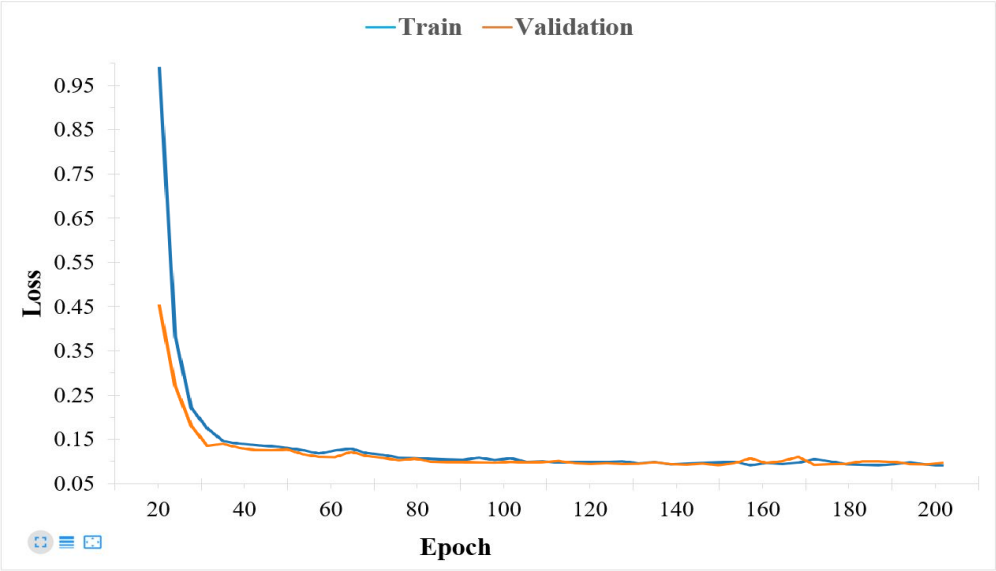


Figure 6-12 Good fit Loss Curve

Unrepresentative Data Set: An unrepresentative dataset means a dataset that does not capture the statistical characteristics relative to another dataset drawn from the same domain. It is used to diagnose the properties of the dataset. There are usually two types, as shown below [52]:

- Unrepresentative Training dataset: Refers to a training dataset that does not contain sufficient information to learn the problem relative to the validation dataset used to evaluate it.
- Unrepresentative Validation dataset: Refers to a validation dataset that does not provide sufficient information to evaluate the ability of the model to generalise.

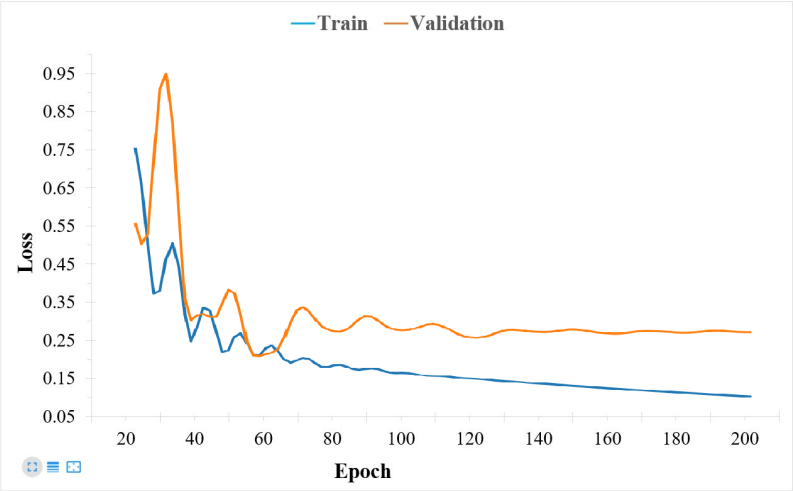
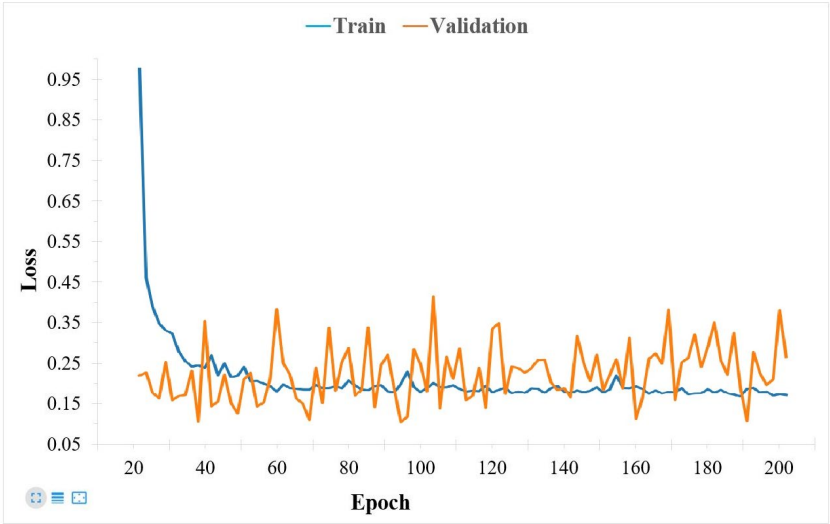


Figure 6-13 Unrepresentative Training dataset Loss Curve



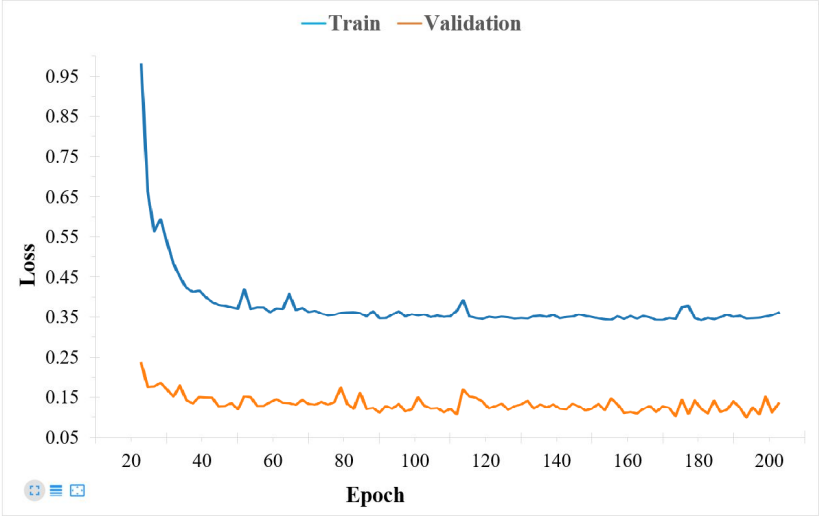


Figure 6-14 Unrepresentative Validation dataset Loss Curve

The RNN models used for the research were evaluated so that the problems related to underfitting, overfit, and also unrepresentative datasets are addressed through a research framework. The models are analysed using "Loss" and "Accuracy" metrics for training and validation dataset.

6.6 Bias (Fairness) in RNN and Bias Types

Bias (Fairness) is a measure of whether the decision making developed with the RNN algorithm is free from discrimination. Bias is "unconscious" and could result in in-accurate results from algorithms [175, 183]. Bias in recent years has become an increasingly critical factor in predictive and prescriptive analytics as RNN are used in high-risk decision-making

applications [175, 184]. Bias is often treated as a complex and multi-faceted concept that depends on the context of the application. For the DP-RI research study, there are possibilities of various biases caused either by humans, data, or technology. To effectively address the biases, a two-step approach is used in this research. In the first step, the types of biases for the DP-RI application are identified, and in the second step, the biases are addressed by using the concept of the fit/transform/predict paradigm through the AIF360 source toolkit [175].

For the DP-RI application, the types of biases are categorised into two groups [176, 185]:

- **Human Related:** Stereotyping, prejudice, or favouritism towards certain sensors, components, or sub-systems over others. These biases can affect the collection and interpretation of data, the design of a system, and how users interact with a system.
    - automation bias
    - confirmation bias
    - experimenter's bias
    - group attribution bias
    - Implicit / in-group bias
    - out-group homogeneity bias
- **Data Related:** Systematic errors introduced by a data sampling or reporting procedure.
    - coverage bias
    - non-response bias
    - participation bias
    - reporting bias
    - sampling bias
    - selection bias

6.7 Bias Mitigation Framework

In this section, methods are presented to show how the different types of bias were addressed systematically to ensure that the prediction results from the models are accurate and can be validated against real-life scenarios. The accuracy of predictions/performance of the models could be affected by bias and uncertainties if not appropriately addressed. All the different types of biases identified in Section 6.6 are grouped and addressed by the following fairness terms [186, 185]:

- Sample Fairness
- Label Fairness
- Model Fairness
- Observer Fairness
- Measurement Fairness

A systematic framework with bias mitigation algorithms, bias metrics, and bias explanatory was implemented at different stages to address problems associated with biases, as shown in Figure 6-15. Bias mitigation algorithms attempt to improve the fairness metrics by modifying the training data, the RNN algorithm, or the predictions. The bias mitigation algorithm inspects discrimination in the overall logic, ensures that the biasing is addressed, and assures model fairness and fosters trust. The framework steps for bias mitigation are as follows [175, 184]:

- Import Data
- Check bias at Pre-Processing, In-Processing and Post-Processing stages
    - Identify Protected attributes
    - Determine the Privileged and Unprivileged groups
    - Evaluate the bias against unprivileged groups detected in the metrics from thresholds
- Mitigate Bias
- Compare original and mitigated results

All of the algorithms are implemented by inheriting from the Transformer class. Transformers are an abstraction for any process that acts on an instance of Dataset class and returns a new, modified Dataset object [175, 187]. The different bias mitigation in AIF360 is as below [175].

- Pre-Processing
    - Disparate Impact Remover
    - Learning Fair Representations
    - Optimized Pre-processing
    - Reweighing
- In-Processing
    - Adversarial Debiasing
    - Meta-Algorithm for Fair Classification

- Prejudice Remover Regularizer
- Rich Subgroup Fairness

- Post-Processing
  - Equalized Odds Postprocessing
  - Reject Option Classification
  - Calibrated Equalized Odds Postprocessing

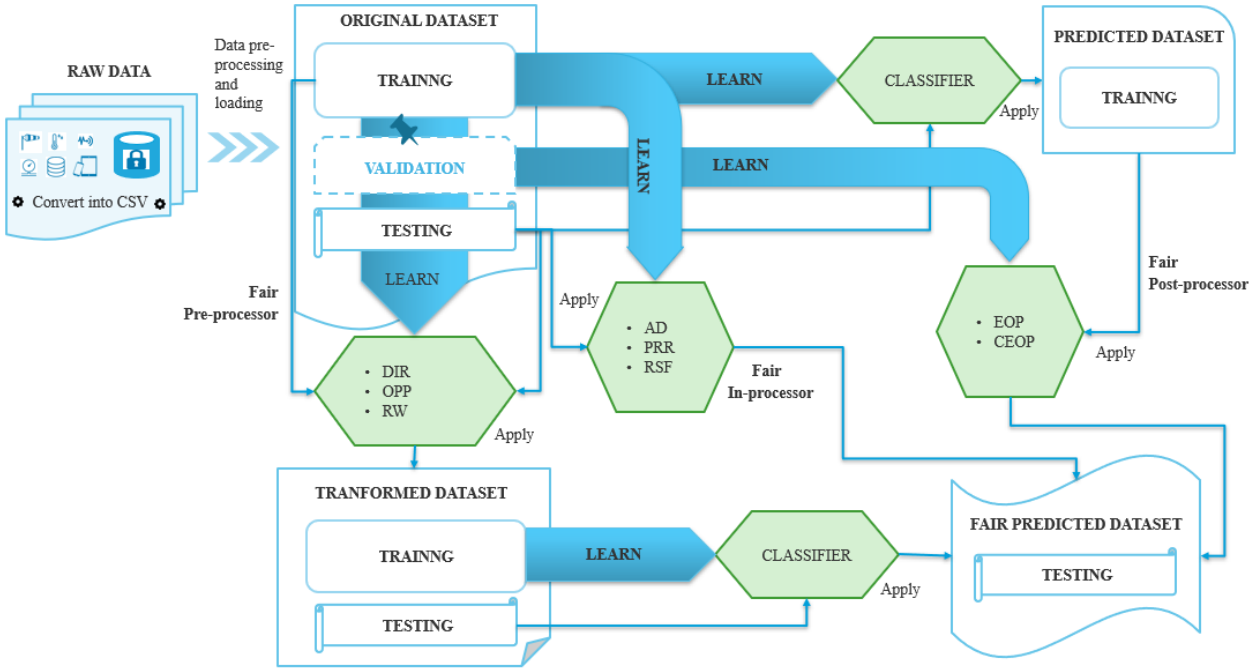


Figure 6-15 Addressing Bias for DP-RI RNN algorithm

The adoption of a particular bias mitigation algorithm is based on the requirements if the RNN models are found to have biased results. Few biases were identified at the beginning of the research study. However, some biases were identified during model development and a few after the implementation. Therefore, the mitigation algorithm has acted as an effective method to address the bias issues relevant to the DP-RI context.

6.7.1 Sample Fairness

The real-time dataset collected from the DP-3 vessel did not cover all of the possible scenarios of failure across DP sub-systems. Therefore, during data pre-processing, a distribution of failures across the sub-systems was ensured for different failure scenarios to cover the full spectrum. In this way, it was assured that the research would be based on unbiased data, which

is neutral, accurate, well balanced, and evenly distributed [176, 188]. The sample fairness ensured that the relevant biases in Section 6.6 were appropriately addressed. The pre-processing algorithms used to manage the sample biases for the DP-RI application are [189, 190, 191]:

- Disparate Impact Remover (DIR)
- Optimized Pre-processing (OPP)
- Reweighing (RW)

6.7.2 Label Fairness

The biases related to the mathematical model developed for the DP-RI were evaluated for performance against the DP-Capability plot and DP vendor control system output [58, 177, 192]. The semi-qualitative results of the models were matched with the field status during commissioning and sea trials. The targets for the algorithm were fixed with proper boundaries considering uncertainty and defining the operational envelope [175]. The label fairness ensured that relevant biases in Section 6.6 were appropriately addressed. The in-processing algorithms used to manage the label biases for the DP-RI application are [193, 194, 195]:

- Adversarial Debiasing (AD)
- Prejudice Remover Regularizer (PRR)
- Rich Subgroup Fairness (RSF)

6.7.3 Model Fairness

Model bias was eliminated by splitting the 67% training dataset into two sets (Training + Validation) and obtaining the learning curve to evaluate the performance. From the learning curves, it was ensured that over-fitting and under-fitting were eliminated [196, 197, 187]. The results proved to be of good-fit as the loss decreased to the point of stability with a minimal gap between the two final loss values of the training and validation. The model fairness ensured that the biases highlighted in Section 6.6 were appropriately addressed. The post-processing algorithms used to manage the model biases for the DP-RI application are [198, 199]:

- Equalized Odds Postprocessing (EOP)
- Calibrated Equalized Odds Postprocessing (CEOP)

6.7.4 Observer Fairness

During the programming and result evaluation, there is a tendency to see what one expects to see or wants to see. Therefore, it was ensured that the experiments were conducted by well-trained persons and without any potential biases. This resulted in the avoidance of Observer bias [200, 188]. The observer fairness ensured that the relevant biases in Section 6.6 were addressed. The pre-processing algorithms used to manage the sample biases for the DP-RI application are [193, 194, 195]:

- Adversarial Debiasing
- Prejudice Remover Regularizer
- Rich Subgroup Fairness

6.7.5 Measurement Fairness

Measurement bias will occur when there is an issue with a device resulting in systematic value distortion. It will tend to skew the data in a particular direction. When one sensor failed, and the other senor was working, the software was programmed to freeze the value of the failed sensor through constant comparison with the redundant sensors [201]. Therefore, measurement bias was addressed with due diligence during data collection to prevent any bias during the run-time of the algorithm. The measurement fairness ensured that relevant biases highlighted in Section 6.6 were addressed. The pre-processing algorithms are used to manage the sample biases for the DP-RI application [189, 190, 191]:

- Disparate Impact Remover
- Optimized Pre-processing
- Reweighing

6.8 Performance Results

In this section, the application of the RNN models to the DP-RI prediction from offline and real-time data are discussed and compared. The data represents the maximum extreme scenarios that the DP system could go through in its lifetime generated through field data and test data (un-accelerated and accelerated tests). All of the different test cases were performed with the various possible combinations to test the performance of the tool. In general, the four RNN models took similar amounts of time (approximately 16-18 hours) for two sets of sample

predictions (150,000 and 300,0000 samples), and the third (450,000 samples) took close to twice as long, at approximately 30-32 hours for each time prediction. The standard evaluation metrics, along with the learning curve method, were used to assess the prediction accuracy, speed of prediction, and ability to scale to different types of vessel data. The methods used for evaluating the performance of the RNN are divided into:

- Learning Curve Metrics
- Mathematical Evaluation Metrics

6.8.1 Model Comparison Using Learning Curves

Especially with the development of RNN, learning curves have become widely adopted for models that learn incrementally over time to optimise their internal parameters [202]. Learning curves help in evaluating model performance using multiple metrics and aid the user in selecting the model that is suitable for a particular application.

For the DP-RI application, where predicting the reliability is critical, two metrics have been used to classify the learning curve for selecting the models. One of the metrics is "Accuracy," which is used to measure the model performance, and the other is "Cross-entropy Loss," which is used for model optimisation [202]. The learning curve can be classified into one of two types [179, 182].

- **Performance Learning Curves:** Learning curves calculated on the metric by which the model will be evaluated and selected, e.g., accuracy.
- **Optimization Learning Curves:** Learning curves calculated on the metric by which the parameters of the model are being optimised, e.g., loss.

It is common to create dual learning curves during training. The training dataset is typically split into training and validation datasets as per Table 6-1. The models are evaluated on the training datasets to give an idea of how well the model is "Learning" [202]. The validation dataset provides a method to assess how well the model is "Generalising" [202].

Table 6-2, Figure 6-16, and Figure 6-17 shows the performance of the MLP RNN model.

Table 6-2 Learning Curve Table – MLP

EPOCHS	TRAIN - LOSS	VALID - LOSS	TRAIN - ACC	VALID -ACC
20	0.98	0.85	0.35	0.4
40	0.72	0.70	0.50	0.55
60	0.70	0.68	0.55	0.60
80	0.69	0.68	0.58	0.60
100	0.68	0.67	0.59	0.62
120	0.67	0.65	0.62	0.64
140	0.66	0.655	0.65	0.66
160	0.65	0.64	0.65	0.66
180	0.65	0.64	0.65	0.66
200	0.64	0.64	0.66	0.66

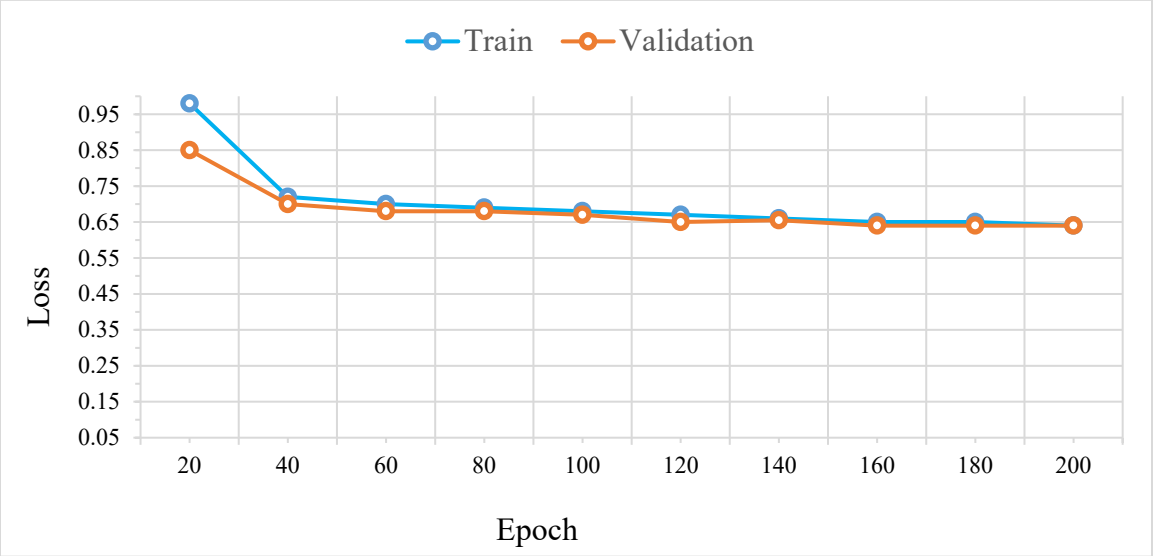


Figure 6-16 Training and Validation Learning Curves (Loss) – MLP Model

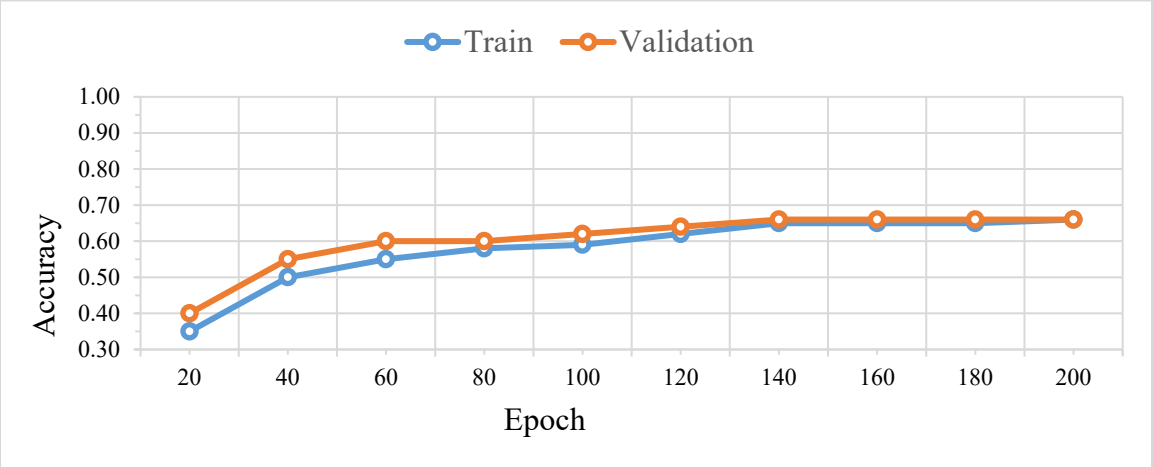


Figure 6-17 Training and Validation Learning Curves (Accuracy) – MLP Model

Table 6-3, Figure 6-18, and Figure 6-19 shows the performance of the SRNN RNN model.

Table 6-3 Learning Curve Table - SRNN

EPOCHS	TRAIN - LOSS	VALID - LOSS	TRAIN - ACC	VALID -ACC
20	0.96	0.90	0.60	0.61
40	0.61	0.55	0.64	0.66
60	0.48	0.45	0.68	0.70
80	0.44	0.38	0.70	0.72
100	0.38	0.38	0.73	0.76
120	0.35	0.38	0.77	0.81
140	0.35	0.34	0.81	0.82
160	0.33	0.32	0.82	0.84
180	0.32	0.31	0.83	0.84
200	0.32	0.31	0.85	0.85

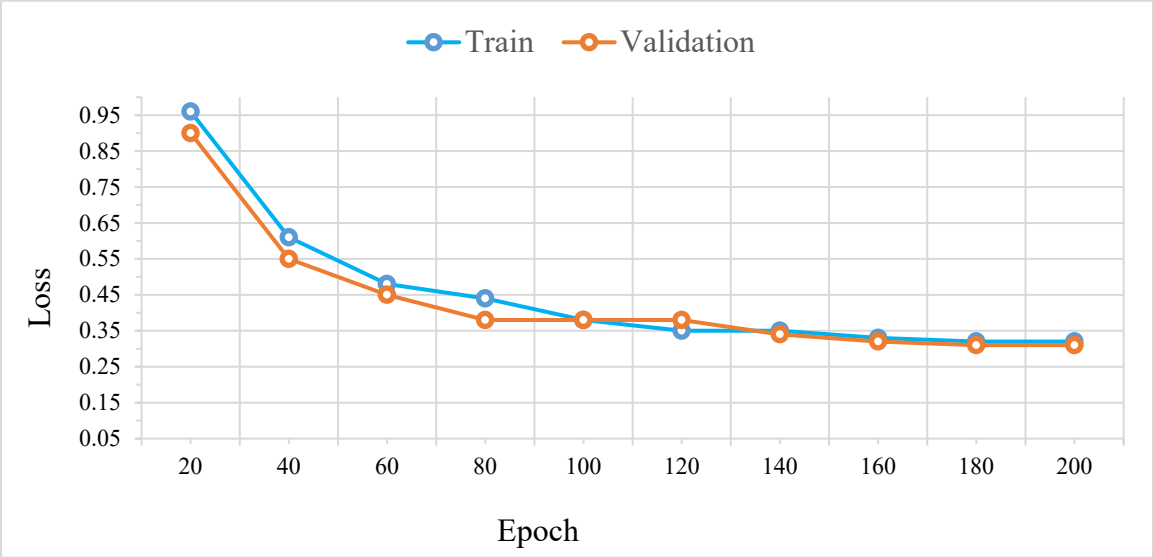


Figure 6-18 Training and Validation Learning Curves (Loss) – SRNN Model

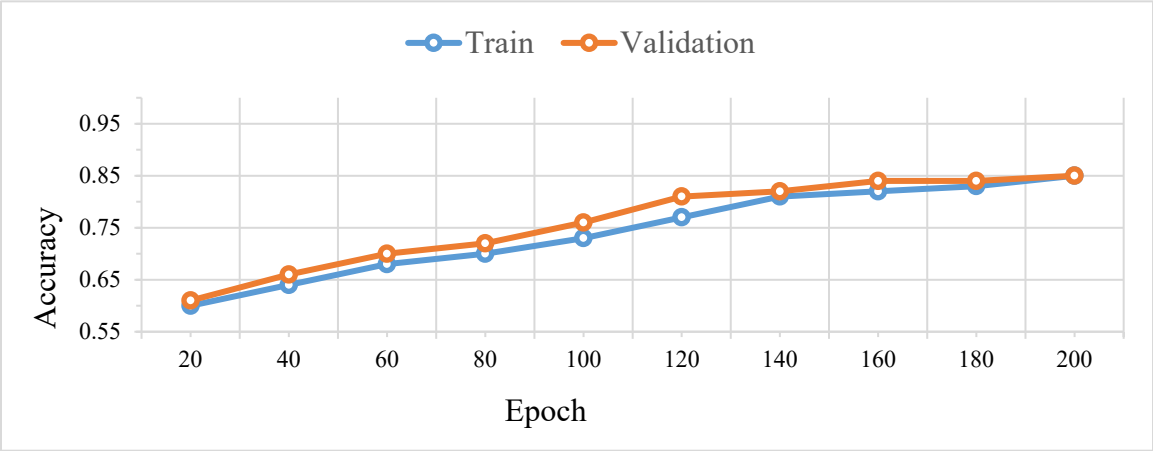


Figure 6-19 Training and Validation Learning Curves (Accuracy) – SRNN Model

Table 6-4, Figure 6-20, and Figure 6-21 shows the performance of the GRU RNN model.

Table 6-4 Learning Curve Table – GRU

EPOCHS	TRAIN - LOSS	VALID - LOSS	TRAIN - ACC	VALID -ACC
20	0.92	0.90	0.78	0.79
40	0.45	0.50	0.82	0.84
60	0.38	0.40	0.90	0.91
80	0.33	0.35	0.91	0.91
100	0.3	0.27	0.93	0.92
120	0.28	0.22	0.93	0.94
140	0.25	0.22	0.95	0.95
160	0.22	0.20	0.95	0.95
180	0.20	0.20	0.95	0.955
200	0.20	0.19	0.95	0.955

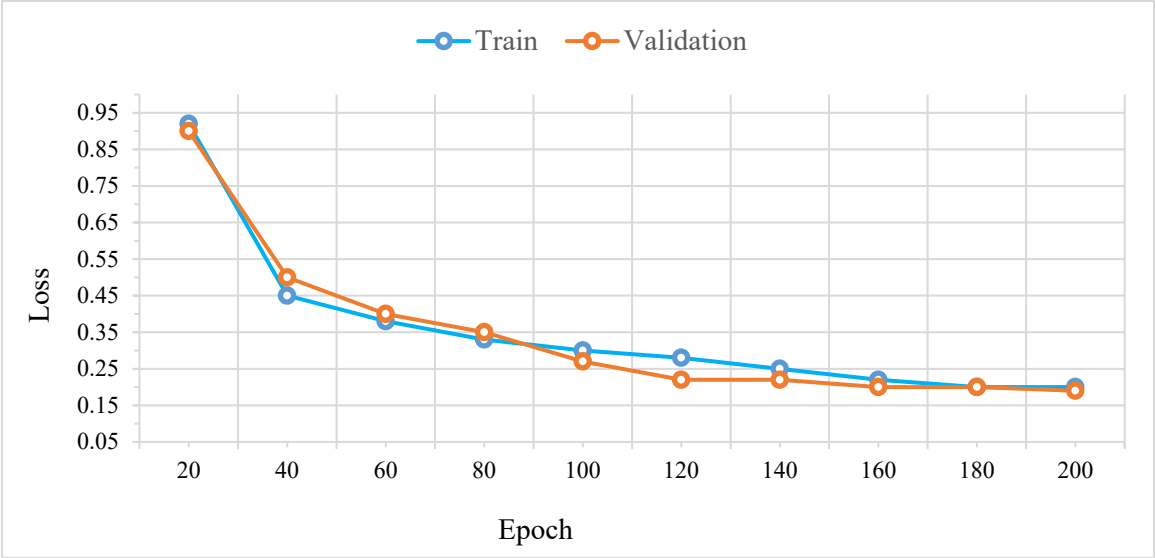


Figure 6-20 Training and Validation Learning Curves (Loss) – GRU Model

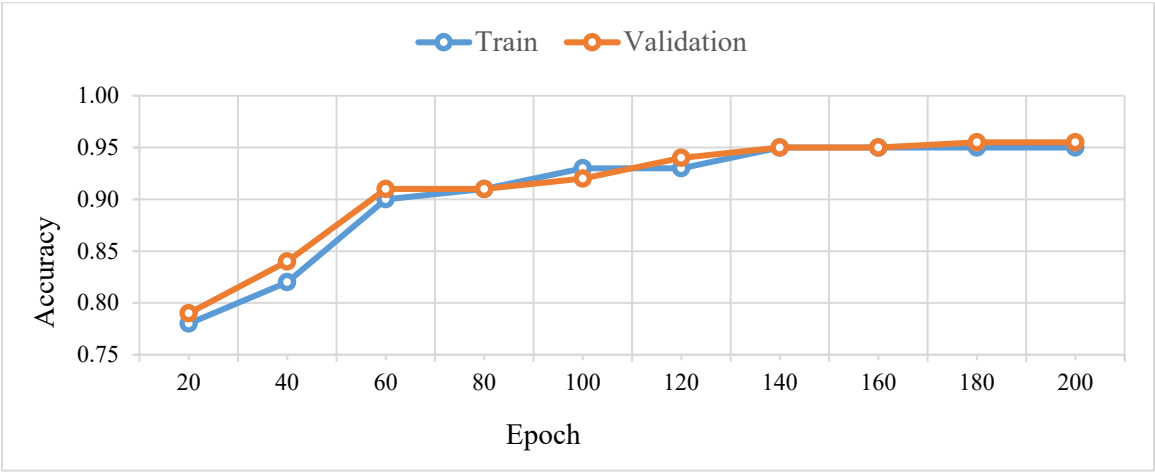


Figure 6-21 Training and Validation Learning Curves (Accuracy) – GRU Model

Table 6-5, Figure 6-22, and Figure 6-23 shows the performance of the LSTM RNN model.

Table 6-5 Learning Curve Table – LSTM

EPOCHS	TRAIN - LOSS	VALID - LOSS	TRAIN - ACC	VALID -ACC
20	0.80	0.7	0.82	0.9
40	0.30	0.25	0.90	0.95
60	0.25	0.20	0.94	0.96
80	0.25	0.20	0.95	0.96
100	0.20	0.15	0.96	0.97
120	0.15	0.18	0.96	0.97
140	0.15	0.18	0.96	0.97
160	0.15	0.16	0.96	0.97
180	0.15	0.16	0.975	0.98
200	0.15	0.16	0.975	0.98

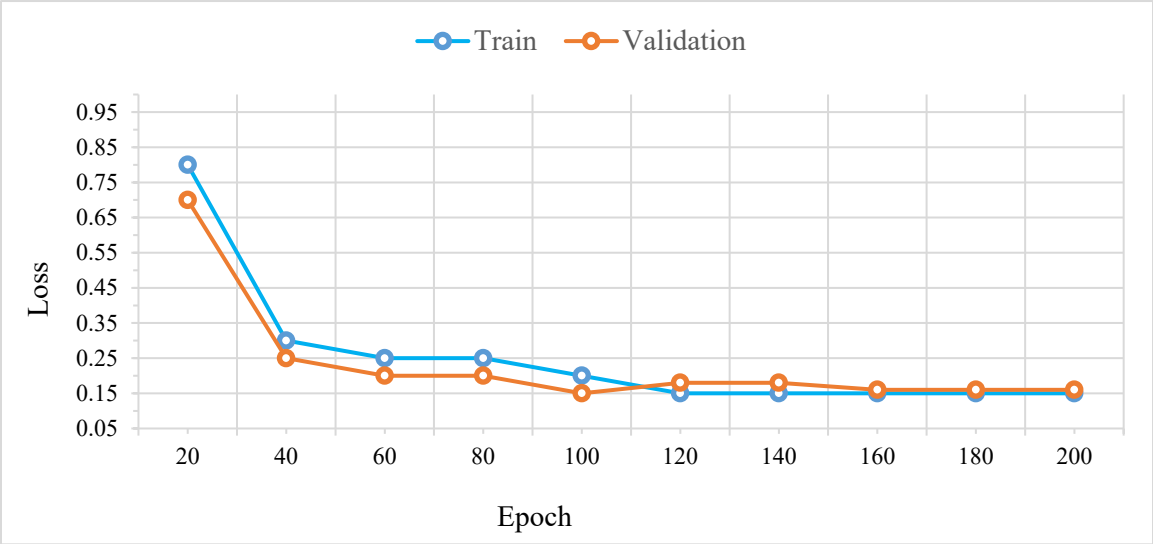


Figure 6-22 Training and Validation Learning Curves (Loss) – LSTM Model

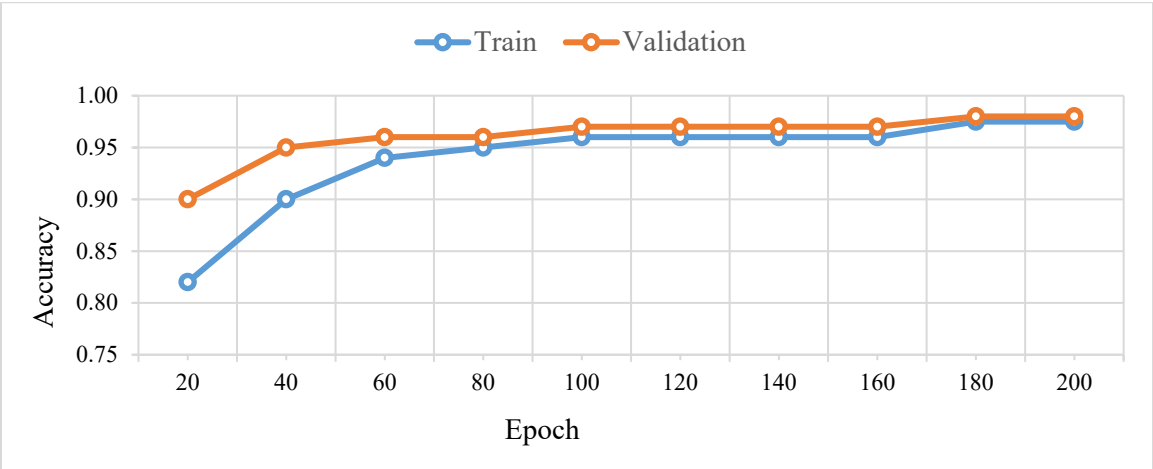


Figure 6-23 Training and Validation Learning Curves (Accuracy) –LSTM Model

In most of the cases, there was substantial evidence that LSTM outperformed the other models and was more suitable for the DP-RI application. The learning ability of LSTM adapts quickly and optimises the results for the validation datasets. Similarly, the forecast accuracy of LSTM proved superior to the other models. As the number of epochs was increased, the datasets were found to be learnable, and the accuracy improved for the models. In contrast to the other models, LSTM proved to be a good fit, and the accuracy was 3% better than GRU, 13% better than SRNN, and 32% better than MLP due to the LSTM attribute of constructing highly non-linear mapping between the input variable and the target variable. Therefore, during the comparison of RNN models using the learning curve, the results showed that LSTM is more accurate, fair, trusted, and easily understood, which makes it suitable for the DP-RI application.

6.8.2 Evaluation Metrics

Once the learning curves had been evaluated, the RNN models were compared based on the evaluation metrics, with the hyperparameters tuned to optimal values for performance analysis. The hyperparameter optimisation techniques are described in Section 6.9. The Root Mean Square Error (RMSE) evaluates how closely the predictions match the observations, as in Equation (6-25) [69, 79].

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(Y_j - \widetilde{Y}_j\right)^2} \tag{6-25}$$

The Mean Average Error (MAE) measures the difference between observed and modelled results, as in Equation (6-26) [69, 79].

$$\mathrm{MAE} = \frac{1}{N}\sum_{j=1}^{N}\left|Y_j - \widetilde{Y}_j\right| \tag{6-26}$$

where Y_j and $\widetilde{Y}_j$ are the actual and predicted values, respectively, and N is the number of samples. The values usually range from 0 (perfect fit) to ∞ (no fit) based on the relative range of the data. The test data sets, which were independent of the training datasets (Training + Validation), were used to evaluate the performance of the models against the evaluation metrics. RMSE is more sensitive to large deviations between forecasts and actuals. MAE, on the other hand, is a suitable measure when forecast errors are proportional to energy costs.

Table 6-6 Optimised Hyperparameter for RNN models

DLNN MODEL	HIDDEN LAYERS	NUMBER OF NEURONS	LEARNING RATE	REGULARIZATION	REGULAR / DROPOUT RATE	ACTIVATION FUNCTION	OPTIMIZER	RMSE	MAE
MLP	7	210	0.7	L2	0.001	ReLU	Adam	0.0121	0.00031
SRNN	7	210	0.6	L2	0.001	ReLU	Adam	0.0031	0.00054
GRU	7	175	0.4	Dropout	0.5	ReLU	Adam	0.0021	0.00141
LSTM	7	175	0.4	Dropout	0.5	ReLU	Adam	0.0010	0.01001

Table 6-7 RMSE for different RNN Models

EPOCHS	LSTM	GRU	SRNN	MLP
20	0.00510	0.00329	0.00967	0.01408
40	0.00210	0.00364	0.00708	0.01378
60	0.00163	0.00256	0.00352	0.01335
80	0.00154	0.00202	0.00310	0.01304
100	0.00132	0.00248	0.00290	0.01276
120	0.00121	0.00190	0.00230	0.01254
140	0.00115	0.00178	0.00257	0.01241
160	0.00113	0.00169	0.00297	0.01235
180	0.00102	0.00210	0.00312	0.01225
200	0.00100	0.00210	0.00318	0.01211

Table 6-8 MAE for different RNN Models

EPOCHS	LSTM	GRU	SRNN	MLP
20	0.00365	0.00551	0.00612	0.01154
40	0.00216	0.00432	0.00562	0.01122
60	0.00185	0.00347	0.00491	0.01092
80	0.00137	0.00224	0.00291	0.01072
100	0.00112	0.00174	0.00210	0.01046
120	0.00089	0.00143	0.00192	0.01019
140	0.00069	0.00122	0.00214	0.01004
160	0.00041	0.00086	0.00152	0.01003
180	0.00033	0.00058	0.00149	0.01002
200	0.00031	0.00054	0.00141	0.01001

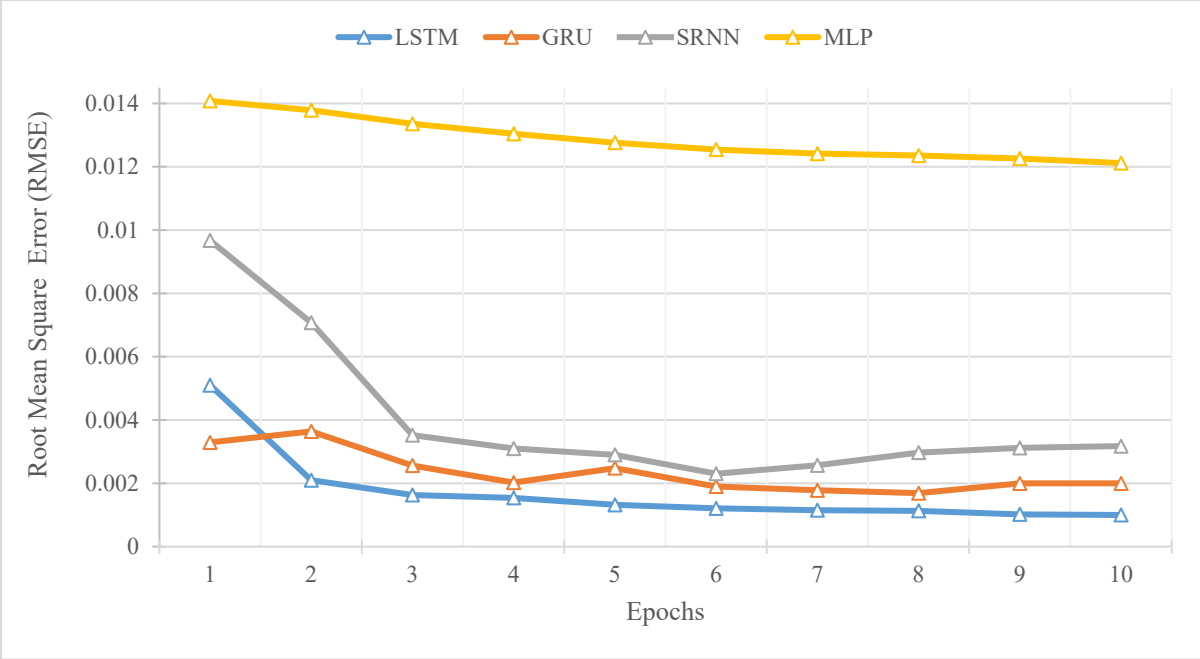


Figure 6-24 RMSE curve of different RNN models with optimised hyperparameters

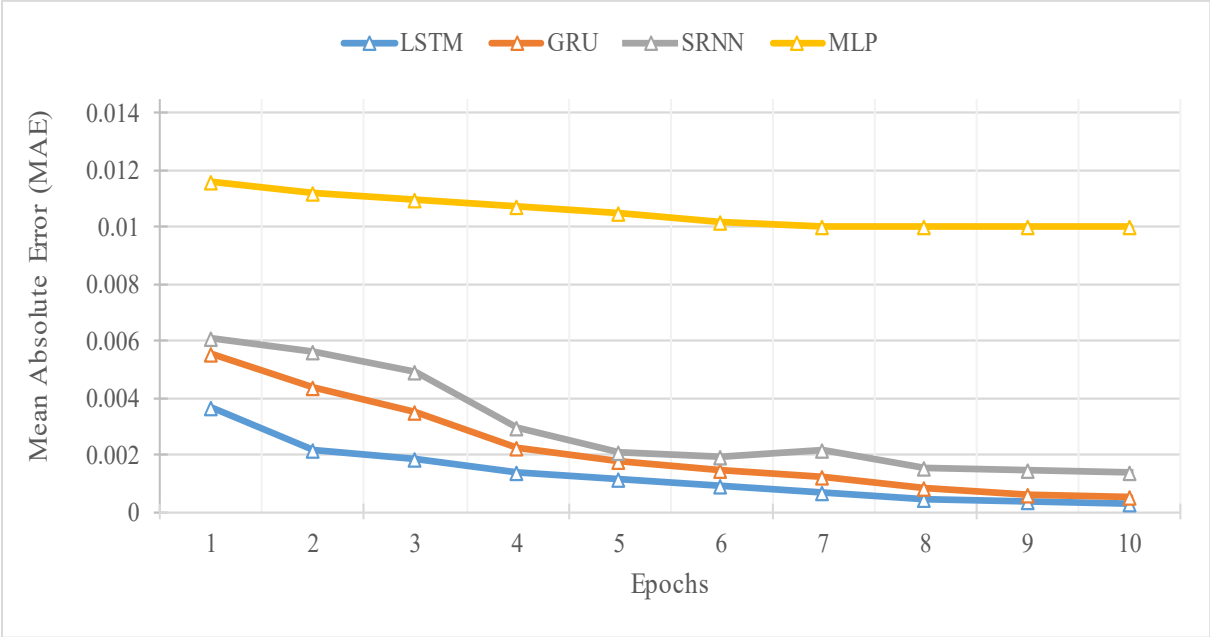


Figure 6-25 MAE curve of different RNN models with optimised hyperparameters

Table 6-7, Table 6-8, Figure 6-24 and Figure 6-25 clearly show that the LSTM outperformed the other models. In the majority of cases, the best performance for MAE and RMSE was shown by the LSTM model. The performance results justify the statement that LSTM is the best-suited model for the DP-RI tool application.

6.9 Hyperparameters for RNN Model Comparison.

Hyperparameters are the variables of RNN models that govern the training process and the topology of a model. The hyperparameters were kept constant during the training process of the RNN models and tuned in successive runs of the training of a model. These variables are different from the RNN model parameters. The variables in the model that are determined using the training dataset are termed the model parameters. The model parameters in the research are the weights and biases. Hyperparameters are adjusted to obtain the optimised weights to maximise model prediction accuracy. The hyperparameters are categorised into two groups as below [176, 203, 204, 185]:

- Model hyperparameters
    - Number of Hidden Layer
    - Number of Neurons
    - Activation Function
- Algorithm hyperparameters
    - Batch Size
    - Epochs
    - Split between the training and testing datasets
    - Optimizer
    - Learning Rate
    - Regularisation
    - Regularisation rate

In the next section, the key hyperparameters are identified and tuned for optimised results and increased performance for each of the RNN models. The models are then evaluated as discussed in Section 6.8 to identify their suitability for the DP-RI application. It is vital to choose appropriate hyperparameters in the model to obtain optimised results and performance. The optimal hyperparameters are determined by analysing their influence on the accuracy of prediction and the convergence time. It is an empirical process to select the optimal hyperparameter, so the grid search method and Keras-tuner were used.

6.9.1 Model Hyperparameters

Model hyperparameters influence model selection. For the RNN models used in this research study, the model hyperparameters were tuned to get the optimal prediction.

Hidden Layer L:

The hidden layer is one or more layers between input and output layers where the neurons are arranged with a set of weighted inputs and produce an output through an activation function depending on the problem and the dataset [176, 205].

Hidden Layer Neurons N:

The neurons in the hidden layers do not have any direct connection with the problem, and their primary function is to perform the computation and transfer information from the input nodes to the output nodes [176, 205]. These parameters determine the data transfer between different neurons, which is kept constant across each layer for other RNN models. The ideal number of hidden layers and neurons depends on the problem and the dataset. The optimisation techniques determine the perfect number of hidden layer and neurons per layer through a systematic approach.

Activation Function:

The activation function introduces non-linearity into the output of a neuron to ensure that neurons learn non-linear representation [176, 179]. The activation function determines the output shape of each node in the layer. The following activation functions were used for determining the optimal function for the DP-RI application:

- Tanh
- Sigmoid
- SoftMax
- ReLU
- Linear

After conducting a series of in-house experiments, it was found that the ReLU activation function yields the best performance in terms of loss and accuracy. Thus, the ReLU activation function was used for all the models.

6.9.2 Algorithm Hyperparameters

Algorithm hyperparameters influence the speed and quality of the learning algorithm. For the RNN models used in this research study, the model hyperparameters below were tuned to get the optimal prediction.

Batch Size:

Batch size is the number of patterns shown to the network before the weights are updated. It defines how many patterns to read at a time and keep in memory [206]. Mini-batch gradient descent is described as the batch size is between "1" and "size of the training set."

Epochs:

Epochs are the number times that the learning algorithm will work through the entire training dataset. The ideal combination of batch size and epochs depends on the problem and the dataset [207, 202]. The two hyperparameters are tuned together.

Split between the training and testing datasets:

The split between the training (training + validation) and the testing dataset was performed to evaluate the gradient descent and the learning curve performance [180, 202]. The split was evaluated for different combinations as defined in Section 6.5.4 and Table 6-1.

Optimizer:

An optimizer is a hyperparameter used to minimise the loss function by applying the computed gradients to the model's variables, by iteratively calculating the loss and gradient for each batch and adjusting the model during training. Gradually, the model will find the best combination of weights and bias to minimise loss [208], where the lower the loss, the better the model's predictions. The following optimizers were investigated [176, 207]:

- SGD (Stochastic Gradient Descent)
- RMSprop (Divide the gradient by the running average of its recent magnitude)
- Adam (Adaptive Moment Estimation)
- Adadelta (An Adaptive Learning Rate Method)
- FTRL (Follow the Regularized Leader)

Learning rate η:

The Learning rate is referred to as the step size, which defines the amount that the weights are updated during the training of the models [180, 206]. The learning rate has a significant influence on the speed of model convergence and the training effect for RNN based models.

Regularization:

Regularization is a hyperparameter technique which penalises the co-efficient to perform slight modifications in the learning algorithm. Regularization in the RNN models penalises the weight matrices to address the overfitting problem so that the model generalizes. The following regularization methods were applied to determine the most suitable method [209].

- L1
- L2
- Dropout
- Early Stopping
- Regularization rate

The regularization updates the general cost function by adding a regularization term.

Cost function = Loss (e.g. mean square error, binary cross entropy) + Regularization term

Due to the addition of this regularization term, the values of weight matrices decrease because it assumes that a neural network with smaller weight matrices leads to simpler models. Therefore, it will also reduce overfitting to an extent.

6.9.3 Hyperparameter Optimisation

The technique of selecting the correct set of models and algorithm hyperparameters for the RNN model is generally referred to as "hyperparameter tuning or Optimisation" [210, 208]. It is considered as the most critical step, and it determines the success of the DP-RI tool. For the hyperparameter optimisation, two sophisticated and well-established methods were used as below [211, 212, 210] :

- Grid Search
- Keras Tuner – Hyperband

Grid Search:

Grid search is widely used for hyperparameter optimisation. It involves constructing and evaluating one model for each combination of the hyperparameters. Cross-validation is used to evaluate each model, and the default of 3-fold cross-validation has been implemented. The steps applied in a grid search are as follows [213, 208]:

- Define a grid on *n* dimensions
- For each dimension, define the range of possible values
- Search for all the possible configurations and wait for the best results

For a given set of hyperparameters and their potential assignments, the naive practice is to search through the entire grid of parameter assignments and pick the one that performed the best. There are numerous hyperparameters for the DP-RI application which makes grid search infeasible as the number of possible assignments increases exponentially. Grid search and cross-validation took an enormous amount of time for the optimisation as it involves searching through a manually specified subset of the hyperparameter space [213, 214].

Keras-Tuner:

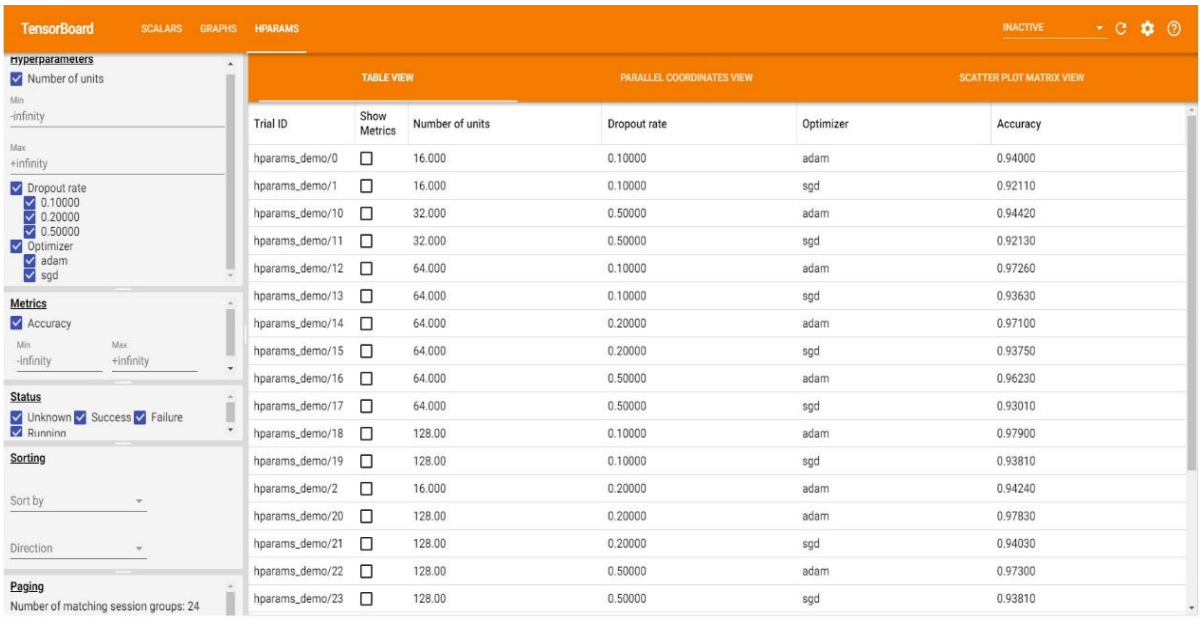
Later in the research work, it was found that there was a development in Tensorflow 2.0, which supported Keras-tuner. This was utilised, and the results obtained from both methods were the same. The Keras-tuner is a library that helps to pick the optimal set of hyperparameters. It is an easy-to-use, distributable hyperparameter optimisation framework that solves the problems associated with the traditional method of hyperparameter search [212]. Keras-tuner makes it easy to define a search space, and leverage included algorithms to find the best hyperparameter values. There are four methods in Keras-tuner for optimisation [176, 212]:

- Bayesian Optimisation
- Hyperband
- Random Search algorithms
- SKlearn

For this research study, the "Hyperband" method was implemented for hyperparameter optimisation. For fair comparisons between the different RNN models, the hyperparameters were tuned independently to achieve the best possible prediction. The Hyperband tuning algorithm uses adaptive resource allocation and early-stopping to quickly converge on a high-

performing model [211, 215]. The Tensorflow2.0 HParams dashboard provides historical information to determine the combination of the hyperparameters for better prediction and accuracy with faster convergence time. It consists of three different views to track and choose the best combination of hyperparameters, as shown in Figure 6-26 :

- Table view lists the runs, the hyperparameters, and the metrics.
- Parallel co-ordinates show each run going through an axis for each hyperparameter.
- Scatter plot view shows plots comparison of each hyperparameter with each metric.



Trial ID	Show Metrics	Number of units	Dropout rate	Optimizer	Accuracy
hparams_demo/0	☐	16.000	0.10000	adam	0.94000
hparams_demo/1	☐	16.000	0.10000	sgd	0.92110
hparams_demo/10	☐	32.000	0.50000	adam	0.94420
hparams_demo/11	☐	32.000	0.50000	sgd	0.92130
hparams_demo/12	☐	64.000	0.10000	adam	0.97260
hparams_demo/13	☐	64.000	0.10000	sgd	0.93630
hparams_demo/14	☐	64.000	0.20000	adam	0.97100
hparams_demo/15	☐	64.000	0.20000	sgd	0.93750
hparams_demo/16	☐	64.000	0.50000	adam	0.96230
hparams_demo/17	☐	64.000	0.50000	sgd	0.93010
hparams_demo/18	☐	128.00	0.10000	adam	0.97900
hparams_demo/19	☐	128.00	0.10000	sgd	0.93810
hparams_demo/2	☐	16.000	0.20000	adam	0.94240
hparams_demo/20	☐	128.00	0.20000	adam	0.97830
hparams_demo/21	☐	128.00	0.20000	sgd	0.94030
hparams_demo/22	☐	128.00	0.50000	adam	0.97300
hparams_demo/23	☐	128.00	0.50000	sgd	0.93810

Figure 6-26 Table view of HParams in Tensorboard

The results showed that all hyperparameters have a significant impact on the prediction accuracy of the models. The combination of the hyperparameters showed that there might be possible trade-offs between the prediction accuracy and convergence time, which needed an additional algorithm to find the right mix. The values shown in Table 6-9 were found to provide the highest prediction accuracy and, at the same time, have faster convergence time. Similarly, the optimised weights for the DP sub-systems with the best combination of hyperparameters are shown in Table 6-10.

Table 6-9 Keras-Tuner Hyperparameter tuned for RNN models

HYPERPARAMETERS	LSTM	GRU	SRNN	MLP
Hidden Layers	7	7	7	7
Number of Neurons	175	175	210	210
Number of Neurons in each layer	25	25	30	30
Activation Function	ReLU	ReLU	ReLU	ReLU
Alpha	0.5	0.5	0.5	0.5
Samples	450,000	450,000	450,000	450,000
Batch Size	10	10	10	10
Epochs	200	200	200	200
Training Dataset	67%	67%	67%	67%
Testing Dataset	33%	33%	33%	33%
Learning Rate	0.4	0.4	0.6	0.7
Regularization	Dropout	Dropout	L2	L2
Regularization Rate	-	-	0.001	0.001
Dropout rate for hidden layer	0.5	0.5	-	-
Dropout rate for input layer	1	1	-	-
Optimizer	Adam	Adam	Adam	Adam

Table 6-10 DP sub-system weighting for optimised hyperparameters

SNO	SUB-SYSTEM DESCRIPTION	WEIGHTING -WN
1	Reference System (W1)	20
2	DP Control System (W2)	14
3	Thruster/Propulsion System (W3)	10
4	Power System (W4)	10
5	Electrical System (W5)	06
6	Environment System (W6)	08
7	Operator / Human Error (W7)	32

6.10 Offline DP-RI prediction

The DP-RI application enables the DPO to prepare themselves in advance for complex offshore marine operations through offline simulation. The tool acts as an intelligent advisory-decision support element that will enhance the current process of check-list and preparation strategies. The time consuming and paper-based activities can be performed instead through the DP-RI tool with actual conditions from the DP system integrated into the tool. If any of the sub-systems is under repair, then the overall DP system and vessel performance can also be

calculated, and results are transparent to decisions on execution. The following are some of the critical applications for the offline DP-RI application:

- Preparation of the vessel for complex offshore operations
- Evaluation of the impact of failed sensors
- Evaluation of the performance of the DP system with reduced sub-system availability
- Foundation for the test cases and act as a foundation for prescriptive analytics
- Training of a new DPO

The offline prediction may be used as the first step for developing additional features such as real-time forecasting, prescriptive analytics, and evaluating suitability for different vessels. It also enables various stakeholders to assess the vessel performance with a different configuration to improve the system at the design stage and perform benchmarking between vessels.

6.11 Real-Time DP-RI Forecasting

Real-Time predictive analytics for the DP-RI application involves extracting useful information from the datasets received in real-time from the vessel through the vessel cloud infrastructure. The main feature of the real-time DP application is forecasting what might happen based on particular "if" scenarios rather than precisely predicting what will happen in the future. It enables and supports the decision-making process in real-time during complex offshore marine operations. The model is built through streaming offshore operation data at the sensor level involving rigorous experimentation, historical data, and iterative processes. As discussed in Chapter 3, the data collection for real-time is performed through an architectural set-up and ingested into the model after the data profiling to ensure it is structured data.

The real-time forecasting of the DP-RI tool would mainly be used for the following applications:

- Real-time visualisation of the reliability of the DP system
- Real-time visualisation of reliability of DP sub-systems
- Enhanced DPO experience
- Accurate profiling and status of the DP system
- Proactive action and prevention of the failure

- Demand sensing and data acquisition

The real-time feature, coupled with the suggestion from prescriptive analytics, makes DP-RI a complete holistic decision support tool for DP vessels. The semi-quantitative value of the DP-RI is used as the initial gauge to determine the reliability and plan for subsequent actions. For the research framework three categories are defined for the DP-RI as follows:

- DP-RI > 80, then the system is highly reliable and the DPO can take some time to evaluate the situation for any further actions
- 80 < DP-RI > 60, then the system is medium reliable and the DPO should react to implement the solution before the system reliability further reduces
- DP-RI < 60, then the system is low reliable and the DPO is required to immediately react and implement a solution to address the failure for safe operation.

6.12 Summary

The chapter provided a detailed description of the implementation of predictive analytics for semi-quantitative and quantitative reliability assessment of the DP system. A new research framework on the DP-RI concept was presented, which will be used for the decision making advisory support tool. Following this, a more straightforward method for the semi-quantitative representation of DP-RI was discussed, which used the optimised weights from the LSTM RNN models. Then the DP-RI framework internal architecture involved in the mathematical computation of reliability and prediction of reliability through RNN models was presented. For the mathematical calculation, the RBD method, system architecture, and component voting configuration acted as the basis for reliability computation. For the reliability prediction, the actual field data and test data are used for comparison on different RNN models to find the most suitable one. The datasets, machine specification, experimental set-up, including the data split, and learning curves were discussed in detail. The bias mitigation framework, which was used to make the system fair and trusted, was then presented. Finally, the performance results of the RNN models (MLP, SRNN, GRU, and LSTM) were evaluated using two methods. The results for both of the methods proved LSTM to be the most suitable model for the DP-RI application with the hyperparameters tuned for optimum results. In the last sections of the chapter, a brief description of the offline and real-time application of the DP-RI tool was presented.

7. Prescriptive Analytics for Resilience during DP Failure Incidents

7.1 Introduction

This Chapter describes stage 4 of the big data analytics, shown in Figure 3-1, involving prescriptive analytics for DP-RI application. The prescriptive analytics support in providing possible solutions to the DPO in the case of failure in the DP system to prevent failures leading to significant accidents. Section 7.2 of the chapter provides a high-level research framework for prescriptive analytics integrated into the DP-RI tool. The next section then presents the experimental set-up for the prescriptive analytics model implementation, which is used for the case studies. Following this section, the datasets prepared from the DP sub-system IMCA database with site-specific risk assessment documentation are presented and tailored for the model application. In the next section, the prescriptive analytics model execution is described. This starts with NLP suitability for the research framework and implementation of transformers in the DP-RI application context. The BERT model was then applied as a training strategy for prescriptive analytics through the Question and Answer system. Finally, the pre-trained model is fine-tuned with the datasets specific to the DP-RI concept, and the results are evaluated for accuracy and performance measurement.

7.2 Research Framework

The research framework for prescriptive analytics is an extension of the DP-RI application tool concept. The output of the DP-RI tool, which provides the qualitative and quantitative representation of the reliability of the DP system, is coupled with the DP control system alarm [2]. In this way, prescriptive analytics could analyse the exact situation and prescribe suggestions to the DPO, combining expert knowledge with existing risk assessment studies. The systematic approach of prescriptive analytics as a research framework is shown in Figure 7-1. The site-specific risk assessment, such as CAMO, TAM, ASOG, and WSOG, along with DP operation manuals, provides information for taking preventive and corrective action during emergencies [60, 63, 216, 217]. Therefore, in this research, prescriptive analytics uses the most advanced algorithm from Google, BERT, for handling the NLP task and prescribing possible solutions during failures in the DP system. The BERT model was applied as a Question and Answering system to provide the appropriate solutions to the DPO.

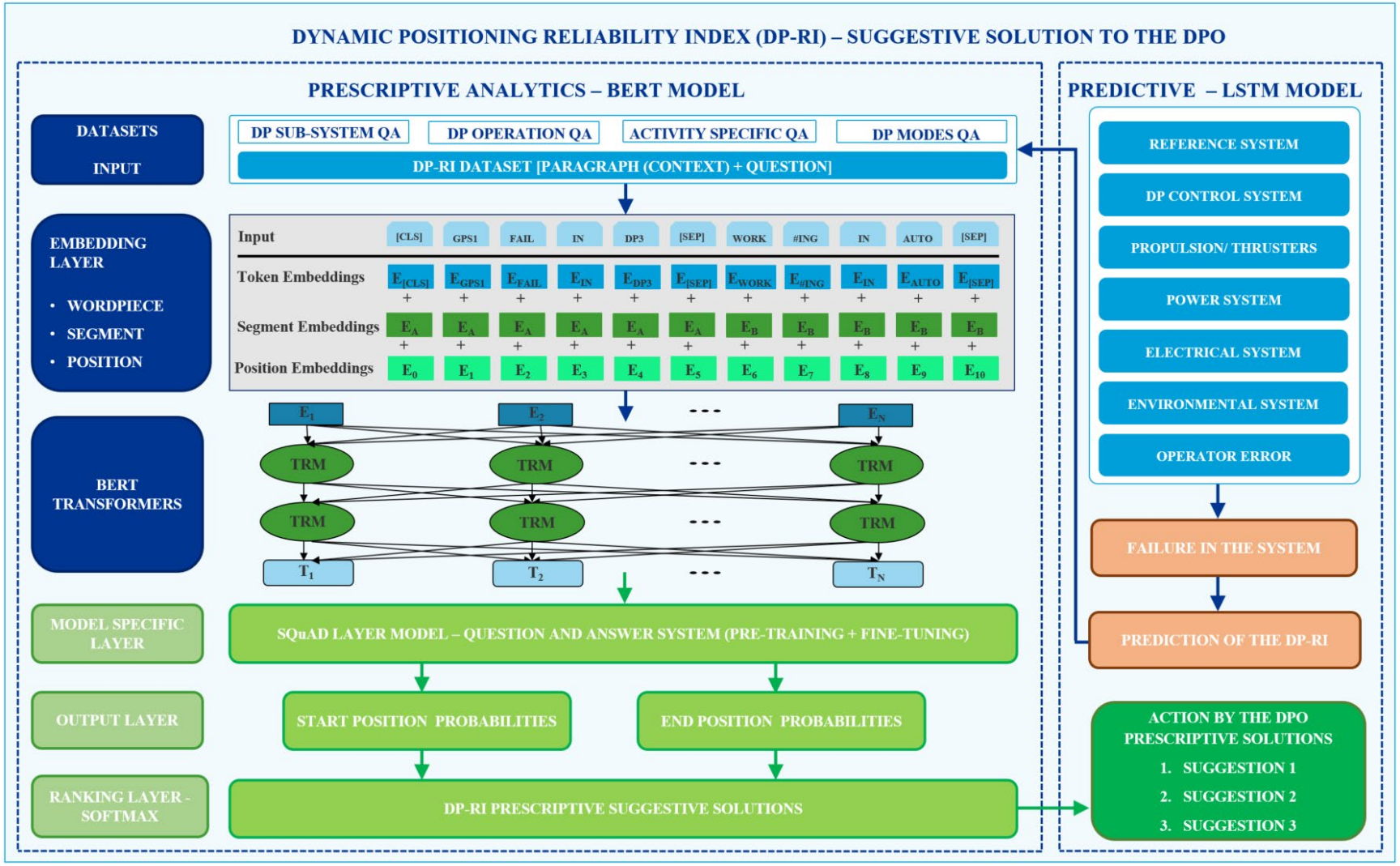


Figure 7-1 Research Framework of Prescriptive Analytics integrated with DP-RI

7.3 Experiment Set-up

In this section, the details of the experimental set-up related to the machine specification for cloud computing using BERT transformer models, programming language, API, platforms, libraries and debugging plugins for the implementation of the research are described [174, 175, 176]. K-Train library is an additional library that was used for prescriptive analytics, but not for predictive analytics.

Tensor Processing Units (TPUs) were used for suggestive solutions as part of the transformer models for the prescriptive aspect of the DP-RI application. They consist of Google's custom-developed application-specific integrated circuits (ASICs) used to accelerate machine learning workloads. The BERT model was trained with a large dataset, so it acts as a pre-trained model, and it demonstrated the ability to transfer learning. Thus only two additional steps of pre-training and fine-tuning needed to be done when addressing a specific NLP task [218]. The tools, platforms, and libraries used for the experiment related to prescriptive analytics are described in Section 8.2 of Chapter 8.

7.4 Data-Sets

In this research, the dataset for the prescriptive analytics is prepared based on the Stanford Question Answering Dataset (SQuAD) benchmarking format. The datasets meet the requirement of Question Answering (QA) capabilities [219, 220]. The data sources defined in section 3.4 of Chapter 3 consist of a massive amount of unstructured and semi-structured data. The BERT model, which has proven accuracy on SQuAD bench-marking, was tailor-made for pre-training and fine-tuning with DP-RI datasets. The DP-RI datasets are extracted from different data sources with distinct features, as shown in Table 7-1.

The individual datasets are carefully evaluated and combined to form the overall dataset. This dataset is used in fine-tuning and training of the BERT model as a QA system. The answers are predicted through the BERT model and evaluated by industry experts through a well-established method of data collection, as explained in Section 5.6.1 with criteria specific to failure scenarios taken from the data lake [221, 219]. As part of the research study, there were 250,000 datasets created from 2000 vessel data inputs (Design Document, FAT procedure, FMEA report, Proving Trial Report and DP operation manual, etc.).

Table 7-1 DP-RI datasets and distinct features for prescriptive analytics

Dataset	Question Sources	Answers	Number of Question	Documents
Reference System QA	System Alarms + Generated	Human Generated	600	10
DP Control System QA	System Alarms + Generated	Human Generated	600	10
Thruster System QA	System Alarms + Generated	Human Generated	600	10
Power System QA	System Alarms + Generated	Human Generated	600	10
Electrical System QA	System Alarms + Generated	Human Generated	600	10
Environment System QA	System Alarms + Generated	Human Generated	600	10
Operator / Human Error QA	System Alarms + Generated	Human Generated	600	10
DP operation QA	Expert Survey	Human Generated	20000	50
Activity Specific QA	Expert Survey	Span of words	600	10
DP Modes QA	Expert Survey	Multiple Choice	200	10

During the training and fine-tuning of the BERT model, the datasets were split as below:

1. Training dataset
2. Development (Dev) dataset
3. Test dataset

The DP-RI dataset consists of six critical parameters [221, 219, 222]:

Paragraph / Passage (Input):

A paragraph of text, consisting of a set of 5-10 passages, is used as input data which may contain an answer to the question. The passages are extracted from DP system related documents and annotated by experts. The passage without answers was indicated with selection "Zero." The fairness in the dataset for the answers is addressed by equal distribution among different sub-systems and its criticality according to vessel-specific DP operation manual [217].

Questions (Input):

The expert develops questions based on domain knowledge from the alarms generated in the system. A few questions were selected and filtered by another layer of experts to ensure whether they were answerable using the paragraph passed as input. Mapping of the problem (question) with the actual alarms from the existing DP control system is critical, therefore the site-specific risk assessment, which considers the operation scenarios was used as the basis for question formation.

Answers (Output- comparison):

Experts prepared answers for each question, and the dataset may contain zero or more solutions (answers). The experts synthesise the natural language answer with correct information in the passage for the prescriptive analytics to provide appropriate suggestions to the DPO. The output from the BERT model after the model-specific layer is compared against the answers annotated by experts.

Documents:

The paragraphs used are extracted from the documents. The "Title", " System", and the "Body text" of documents are included in the dataset. A total of 140 papers were indexed. The cross-reference is used for analysing the potential to extend research for different DP vessels.

Question Type:

The question in the dataset is automatically annotated using an internal algorithm to classify the question based on a segment label into either "Description", "System", "Sub-System", or "Person". The segment labels used for classification are "What", "Why", "Who", "How" etc.

Ranking:

Experts do the ranking of the sub-systems based on the weightings determined in Chapter 5. Based on the order, the possible solution priorities are determined and listed for the DPO operator to take action.

Table 7-2 shows the datasets indicating the Questions and Paragraph used for the training the BERT models. In this research, the alarms from the DP control system are transformed to questions manually and fed into BERT model to predict the answer from the relevant paragraph.

Table 7-2 Sample DP-RI datasets

SNO	DP ALARM	QUESTIONS	PARAGRAPH (PROVING TRIAL RESULTS & DP OPERATION MANUAL)
1	Wind Sensor 1 signal loss. Power Failure	What to do when wind sensor 1 fails in sub-system Environmental System (A6)?	Failure of one power supply will only fail one sensor and the DP system will use the data from another sensor. Choose Wind Sensor if it is disabled. Failure of a wind sensor signal or an erratic signal will cause the system to reject the wind sensor and use the information from another sensor. Check the connection points in IO module to identify common cause of failure. Selection of the best (preferred) wind sensor can be a matter of operator judgment. If only one sensor is active and back sensor is not enabled then operator should enable and make the sensor active. Wind sensor difference should not cause any position loss although some initial instability may result in harsh environmental operating conditions. All wind sensors should be enabled and hence available to the DP. If the back-up wind sensor cannot find the solution, change to joystick mode to take control of the DP vessel. The DPO to check the resultant force and error in the DP screen during manual control.
2	Main DP control system lost. Network Failure.	Why was the Main DP control system lost? What to do when sub-system DP	If a DPO is on watch during an emergency situation, the Master or Senior DPO may consider it necessary to take over at the DP operator station but should only do so if they are confident that their intervention will improve the situation. If the main DP control system fails, the immediate course of action may be for the DPO to change to the back-up DP control system at the emergency bridge or switch to the independent joystick, depending on the operational circumstances. The DPO

SNO	DP ALARM	QUESTIONS	PARAGRAPH (PROVING TRIAL RESULTS & DP OPERATION MANUAL)
		control System (A2) failed?	to check the power failure or check the network failure which caused the main DP system to fail. It should be noted that the independent joystick provides a single point of vessel control in all three axes so this will be a safer option than switching to manual control.
3	DG 1 Failure. Shutdown	What action to take when DG1(Online) fails with no standby in open bus configuration in Power System (A4)?	The power system is all of the components and systems necessary to supply the DP system with power and includes prime movers, generators, switchboards, power distribution system and all associated auxiliary systems / arrangements including piping, cables and routing etc. There are six modes of operation for the power generation system when the vessel is operating in DP. The operator can select any mode of operation once the required prerequisites are in place. Diesel Generator starting and stopping priority, 'Standby 1' to 'Standby 5' is selected by the operator. When the connected generator fails, then DPO should start the standby generator based on the configuration. The standby generator will reach rated speed and share the load with the connected generators. The DPO should identify and check the signal which resulted in the shutdown of the generator.
4	Thruster 2 Loss. Hydraulic Pressure Loss. Hydraulic Pump Failure.	What to do when failure occurs in Thruster System (A3)? How to	The thruster system is all of the components and systems necessary to supply the DP system with thrust force and direction. When one of the running thrusters fails, the DPO should start the standby thruster and connect to the DP system for automatic control allocation. The auxiliary system consist of the lube oil system for the thruster through hydraulic pumps in the thruster pumps. If there is a

SNO	DP ALARM	QUESTIONS	PARAGRAPH (PROVING TRIAL RESULTS & DP OPERATION MANUAL)
		respond to failure and resolve it?	pressure drop in the hydraulic line of the thruster it will be due to the pump failure. The failure will be treated as a hidden failure and could affect the thruster efficiency and not responding to command from DP system. Under such a situation when the vessel is in automatic mode, the DPO should check the thruster during pressure loss alarm. If the thruster doesn't respond to the command then the standby thruster should be connected, and faulty thruster should be deselected to resolve the issue offline. Check the pump failure which could be the result of power failure to the pump.
5	DGPS 2 Fail. Loss of Satellite signal	Who should ensure the proper selection of the source signal?	Operators must be aware that drift in GPS or GLONASS position data might be common when utilising two or more satellites of the same system due to failure with the respective satellites or correction data. In order to reduce the risk of such an occurrence, the use of both GPS and GLONASS satellites should be selected. Attention is also drawn to the fact that positioning errors may occur even though separate satellite systems have been selected due to failure of correction data. Alternative position reference systems should always therefore be available to the DP when possible. Good practice is to have the DGNSS systems using dual satellite beams as a situation where the DP system rejects a valid position reference system in favour of two common and incorrect DGNSS inputs. During operation the DPO should ensure at least two DGPS are online and operational.

7.5 Prescriptive Analytics – Possible Suggestive Solutions

7.5.1 Natural Language Processing

NLP is a collection of computational methodologies used for automatic analysis and representation of human languages [223]. The DP system has a lot of unstructured and semi-structured data contributing about 70% of the data, with only 30% being structured data. Recent advancements in technology have enabled NLP applications to be developed with higher accuracy, on a par with human capabilities, by allowing a deeper understanding of the text through neural network models [224, 225]. The other applications of NLP are syntactic information (e.g., part-of-speech tagging, chunking, and parsing) or semantic information (e.g., semantic role labelling, and named entity extraction) were defined in Chapter 3 [224]. NLP in this research has been implemented for text classification, sentiment analysis, and question and answering systems.

A simple neural network cannot easily handle the NLP problems as they are bag-of-words models leading to missing values. To address the issue, an RNN was used, which is a deep learning algorithm with multiple layers due to its recursive nature [84, 226]. However, the RNN has the problems of vanishing and exploding gradients and learning long term dependencies. LSTM addressed the issue of vanishing and exploding gradients [227]. However, LSTM models for NLP tasks are challenging to train, and transfer learning will not work efficiently. Besides, LSTM needs a specifically labelled dataset for every job. LSTM and RNN limitations for NLP applications can be summarised as follows [226]:

- Sequential computation inhibits parallelization
- No explicit modelling of long and short-range dependencies
- "Distance" between positions is linear
- Difficult to train and Transfer learning is not possible

The drawbacks are addressed through feed-forward network architectures, called Transformers using only attention mechanisms, dispensing with convolutions and recurrence entirely [226]. This has achieved state-of-the-art performance on several tasks and has been found to generalise very well to other NLP tasks, even with limited data.

7.5.2 Transformers

Transformers are a type of deep learning neural network architecture built with an attention mechanism to draw out global dependencies between the input and output. The model was developed to solve problems associated with sequence transduction or neural machine translation, which involve transforming an input sequence to an output sequence. The overall architecture of the transformer was built using an encoder-decoder stack with self-attention and a point-wise feed-forward network consisting of two fully connected layers, as shown in Figure 7-2 [226]. The attention mechanism allows the architecture to model dependencies without regard to their distance in the input or output sequences. The feed-forward nature and multi-head self-attention are critical aspects of transformers [226, 218]. The Transformer allows for significantly more parallelization and can reach a new state of the art in translation quality as the model is pre-trained with standard datasets.

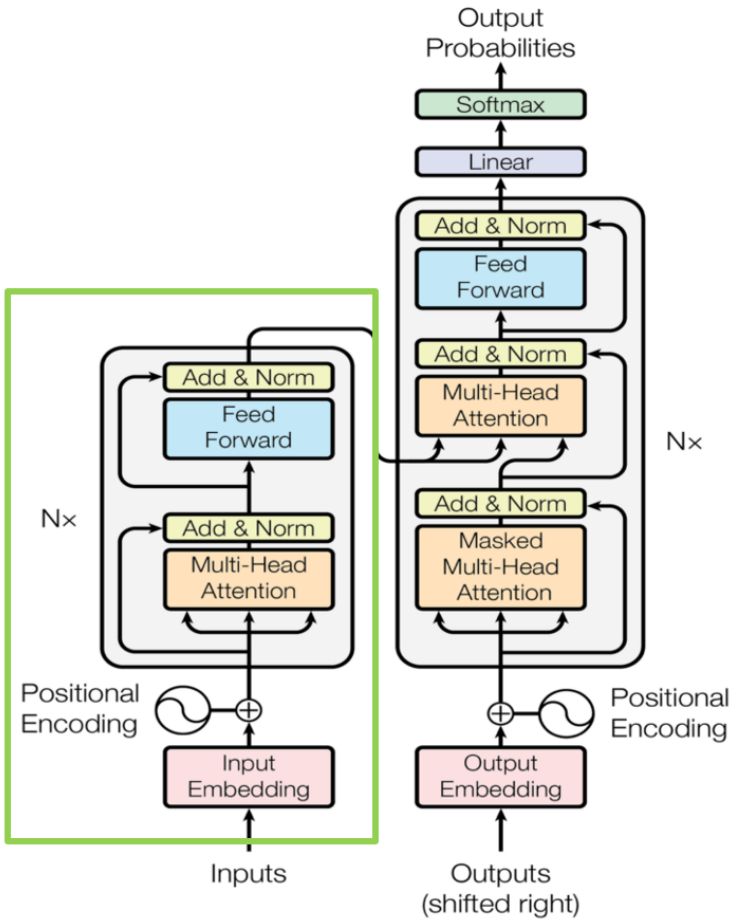


Figure 7-2 The Transformer - model architecture [226]

The transformer model architecture performs various tasks using the encoder and decoder that are stacked on top of each other multiple times, which is described by *Nx* in Figure 7-2. It uses the modules mainly consisting of Multi-Head Attention and Feed Forward layers. The inputs and outputs (target sentences) are first embedded into an n-dimensional space and changed to vector representation, as a string cannot be used directly in the model. The critical part of the model is the positional encoding of different words. These positions are added to the embedded representation (n-dimensional vector) of each word, which supports the model to interpret the context of the paragraph. The sequence of operations performed within transformer models are below [226]:

- Transformer Encoder
    - Scaled Dot-Product Attention
    - Multi-Head Attention
    - Skip connection & Layer normalization
    - Position-wise Feed-Forward Networks
    - Positional Encoding
- Transformer Decoder
    - Embedding and Softmax in Training
    - Inference
    - Encoder-decoder attention
    - Training
    - Soft Label

The main advantages of the Transformer model are that it accepts nonsequential inputs, which supports the research in that the model does not require that the input sequence be processed in the order. Transformers are parallelized and scaled much more quickly than previous NLP models with much higher accuracy and speed. Thus the transformer model is used for prescriptive analytics of this research with BERT using only the encoder part [226, 218].

7.5.3 Bidirectional Encoder Representations from Transformers (BERT)

BERT is a training strategy that uses the transformer model architecture; it is not a new architecture design [218]. However, in the transformer model, word embedding cannot explore the context of neighbouring words virtually. For this research, the steps included creating a

dense representation for NLP inputs, including those in the QA system, along with developing a representation model that is multi-purposed [218, 219]. BERT model architecture (Attention, Scaled Dot Product, Multi-head Attention, etc.) and IO representation were evaluated further to be implemented for DP-RI application.

BERT Model Architecture:

BERT uses the Transformer encoder to create vector representation. The critical aspect is that instead of focusing on the problem directionally, it discovers the context concurrently, making it different from other approaches. BERT's model architecture is a multi-layer bidirectional Transformer encoder, as shown in Figure 7-3, along with the internal structure of the encoder used for this research [226].

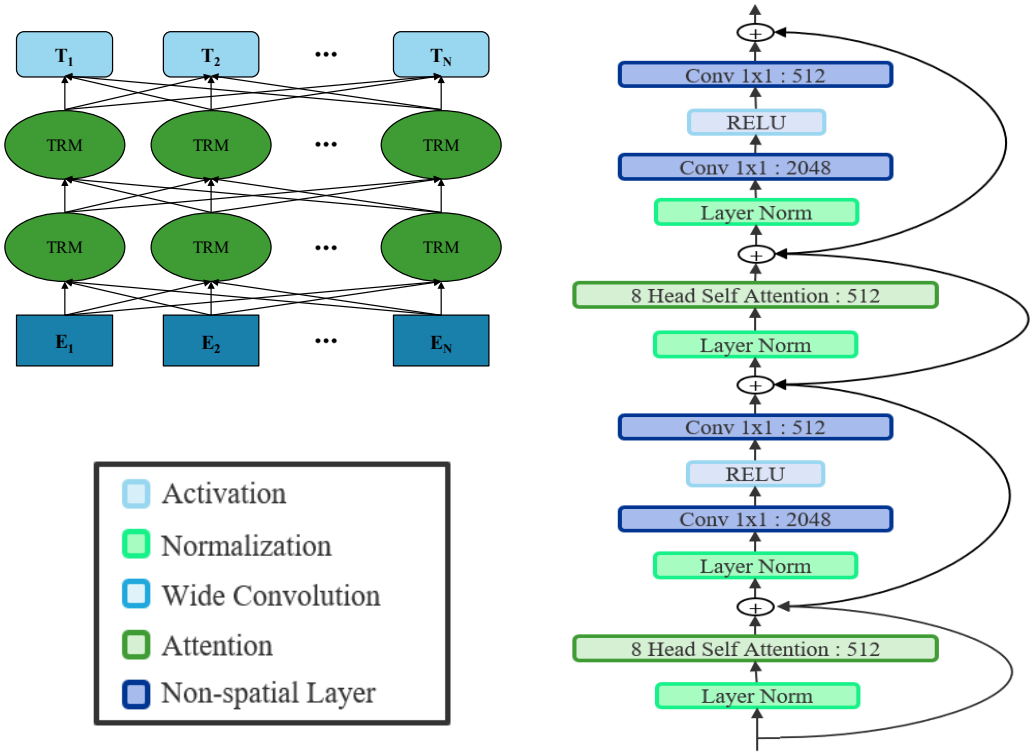


Figure 7-3 BERT Model architecture – Encoder Segmentation

There are two model sizes of BERT, which were used for this research study to determine their suitability for the DP-RI application along with LSTM. The two models used are $BERT_{BASE}$ and $BERT_{LARGE}$, which are different from the actual structure of the transformer model, as shown in Figure 7-4 [220, 228, 229]. The two model sizes are: $BERT_{BASE}$ (L=12, H=768,

A=12, Total Parameters=110M) and $BERT_{LARGE}$ (L=24, H=1024, A=16, Total Parameters=340M). The parameters are "L" encoder layers (Transformer blocks), "H" as the hidden size (embedding dimension), and "A" as the number of self-attention heads [218, 219, 220].

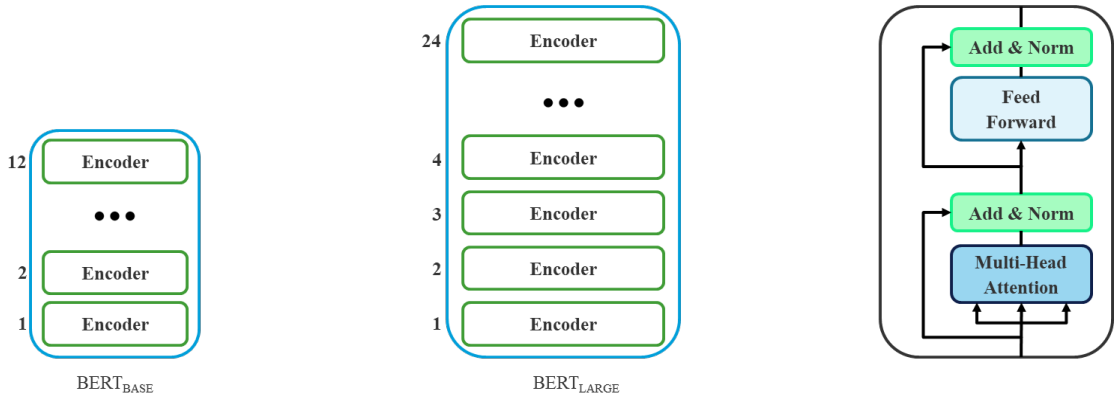


Figure 7-4 $BERT_{BASE}$ and $BERT_{LARGE}$ (Encoder stacking)

In the research, only the encoder part of the Transformer is used by the BERT model for DP-RI prescriptive analytics. Therefore, the section below will focus on the attention part of the encoder before applying it to the QA system.

Attention: An attention function supports mapping a query and a set of key-value pairs to an output, where the query, keys, values, and output are all vectors. The output of the model was computed as a weighted sum of the values, where a compatibility function of the query computes the weight assigned to each value with the corresponding key [226]. The attention in the transformer is of two types: self-attention and encoder-decoder attention. For the BERT model, only self-attention in the encoder is used.

Self-attention is an attention mechanism on the encoder side relating different positions of a single sequence to compute a representation of the sequence. It supports recomposing the sequence and understands how each of the elements is related to one another, grabbing global information/context about a sequence or sentence [226, 223]. Self-attention has been successfully applied for various NLP tasks, including Reading Comprehension, Question and Answer, abstractive summarisation, and learning task-independent sentence representations.

Scaled dot product:

The first part of each encoder performs the attention. Each word in the sentence serves as a single query. In this research, the context is considered as a query. The information is passed from the datasets prepared in Section 7.4. Q, K & V are matrices representing the sentences / sequences (after embedding) [226, 219]. All the attention can be computed concurrently with Q, K, and V packing all of the queries, keys, and values into matrices. The attention is computed through Equation (7-1) as below:

$$\text{Attention}\ (\mathrm{Q}, \mathrm{K}, \mathrm{V}) = \text{softmax}\ (\frac{QK^T}{\sqrt{\mathrm{d_k}}})\ \mathrm{V} \tag{7-1}$$

QK^T shows how Q is related to K, word by word. It also states V(=K) according to the attention mechanism. The attention has the same shape as Q. However, it is made up of elements from V concerning their correlation with Q, as shown in Figure 7-5.

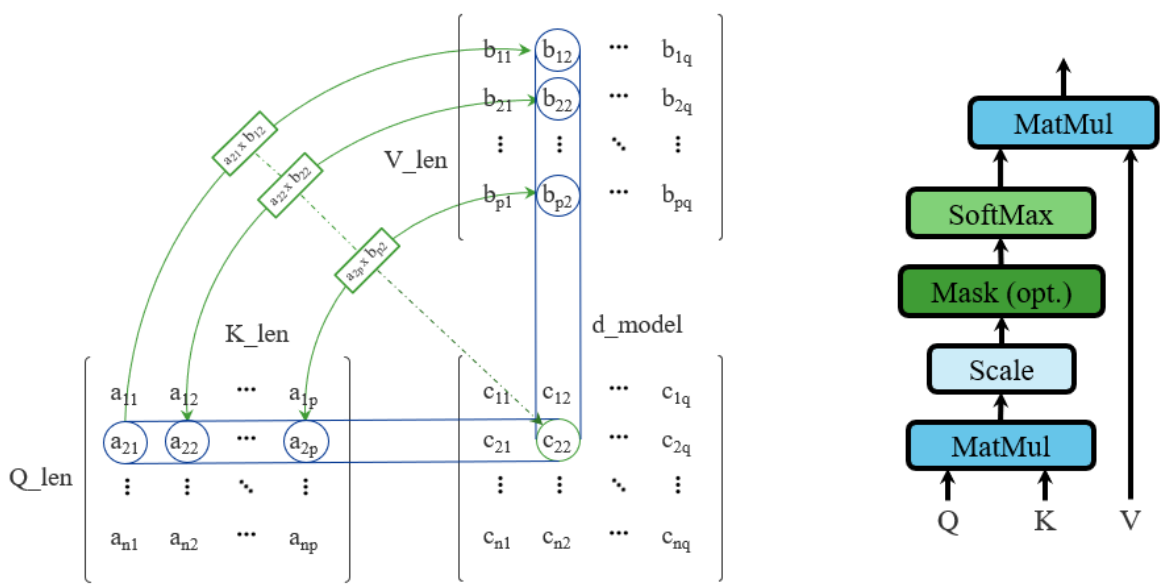


Figure 7-5 Scaled dot product – Encoder in BERT

Multi-head attention:

Multi-head attention allows the model to jointly read and analyse the information from different representation vector subspaces at a different position in the paragraph. Multi-head attention generates "h" attention per query. Conceptually, it packs h scaled dot-product attention together. For encoders, there are 12 attention heads for $\text{BERT}_{\text{BASE}}$ and 16 for

$BERT_{LARGE}$. Therefore, each transformation provides a different projection for *Q, K,* and *V*. The multi-head attention allow the model to view relevancy from 12 or 16 other "perspectives" based on $BERT_{BASE}$ and $BERT_{LARGE}$ models as in Equation (7-2). Thus, the overall accuracy increases. In each attention, the model will transform Q, K, V linearly with a different trainable matrix, respectively. As shown in Figure 7-6, the output vectors are concatenated, followed by a linear transformation and then processed by a model-specific layer [226, 223, 219].

$$\text{MultiHead}(\text{Q}, \text{K}, \text{V}) = \text{Concat}(\text{head}_1, \text{head}_2 \ldots \text{head}_h)W^o \tag{7-2}$$

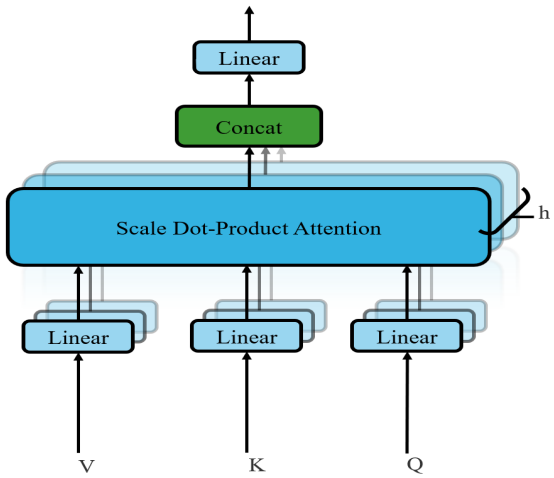


Figure 7-6 Multi-head attention

Input/Output representation:

To pre-train the model, the input assembly and expectation on the output had to be defined before pre-training BERT for the DP-RI QA system. The input for the encoder is converted to a token through the BERT tokenizer. Then tokens are converted to vectors through the word embedding process. The input consists of embedded words, an indication of 1st and 2nd words, and positional embedding [218, 219]. The input is composed of two sequences, a [SEP] token in between Sequence A and Sequence B, as in Figure 7-7 indicating the input and the context. The output is represented by two types: special output token to represent the NLP task [CLS] and the contextual representation token (Tk) as in Figure 7-7. As the NLP task involves QA, at the output, the token representations are fed into an output layer, which is a model-specific QA layer similar to SQuAD layer used in SQuAD benchmarking problems [228, 229].

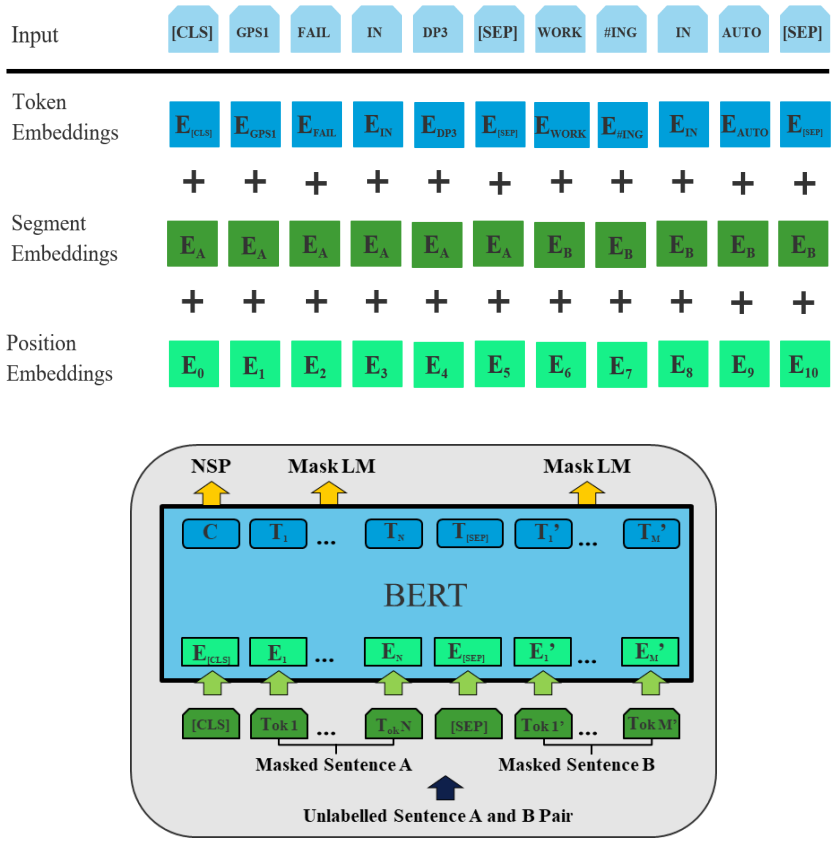


Figure 7-7 Input/Output representation for BERT model

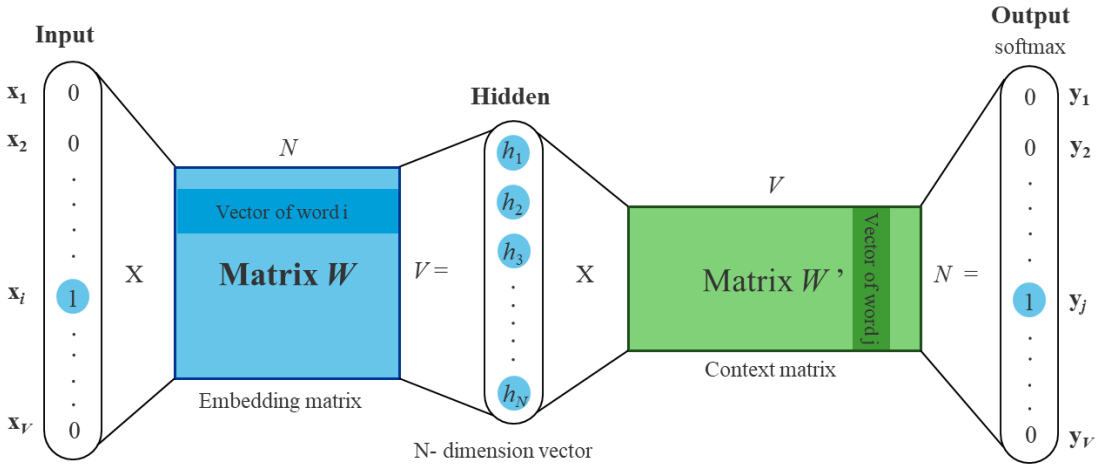


Figure 7-8 BERT model Input / Output with word and context matrix

For the QA NLP task, the outputs corresponding to the paragraph sequence will be used to derive the start and the end span of the answer. Instead of using every single word as a token, BERT breaks a word into word pieces to reduce the vocabulary size. The complete architecture for I/O representation for BERT is shown in Figure 7-8.

7.5.4 BERT Model as Question and Answer System for DP-RI

The BERT model has been widely used as a contextual representation of input question – passage pairs by using experience from SQuAD benchmarking problems [220, 228, 229]. For this research study involving the DP system, when the failure occurs, the reliability of the DP system reduces, leading to potential accidents. Therefore, the BERT model is applied as a QA system to prescribe solutions from the widely available database. The datasets prepared in Section 7.4 use the question and context, separated by the [SEP] token as input. In the end, a single dense layer is applied to each vector/token with two neurons at the end, as shown in Figure 7-9. The first neuron is used as the score for "being the start of the answer". Similarly, the second neuron is used as the score for "being the end of the answer" [220].

In the BERT training strategy, the transformer model is first pre-trained with data that requires no human labelling. The output from the pre-trained model is a dense representation of the input. To suit the DP-RI prescriptive analytics, a QA system was implemented for which the BERT model is modified by simply adding a shallow, dense layer connecting to the output of the original BERT model. After this, the model is re-trained with a dataset defined in Section 7.4 with labels specific for the DP-RI application. The prescriptive analytics part of DP-RI was divided into three activities as below [218]:

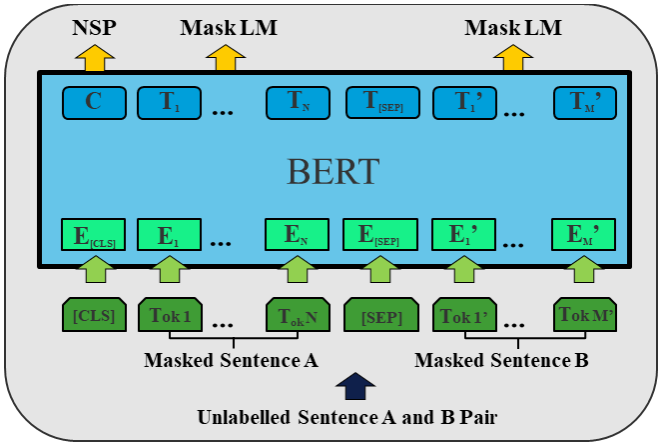
- **Pre-Training:** Creating a dense representation of the input
- **Fine-Tuning:** Fine-tuning the model to the QA system with DP-RI specific datasets for
- **Rating of suggestive solutions (Answers):** Rating the answers based on the weightings of the sub-systems using softmax activation through the logits score.

Pretraining:

The pre-training involves the training of the models with generalised prediction applications. The pre-training was performed on a text without any human labelling. BERT pre-trains the model for two specific NLP jobs. The two jobs are as follows [218, 220]:

- Masked Language Model: It enables the understanding of the sentence through approximation and supports vectors for each token. The Transformer encoder generates a vector representation of the input. Then BERT applies a shallow, deep decoder to reconstruct the word sequence(s).

- Next Sentence Prediction: It enables higher-level understanding from words to sentences and a single vector for the classification. The vector determines whether the model is used for the classification or other NLP tasks such as QA systems. The fundamental purpose is to create a representation in the output C that will encode the relations between Sequences A and B.



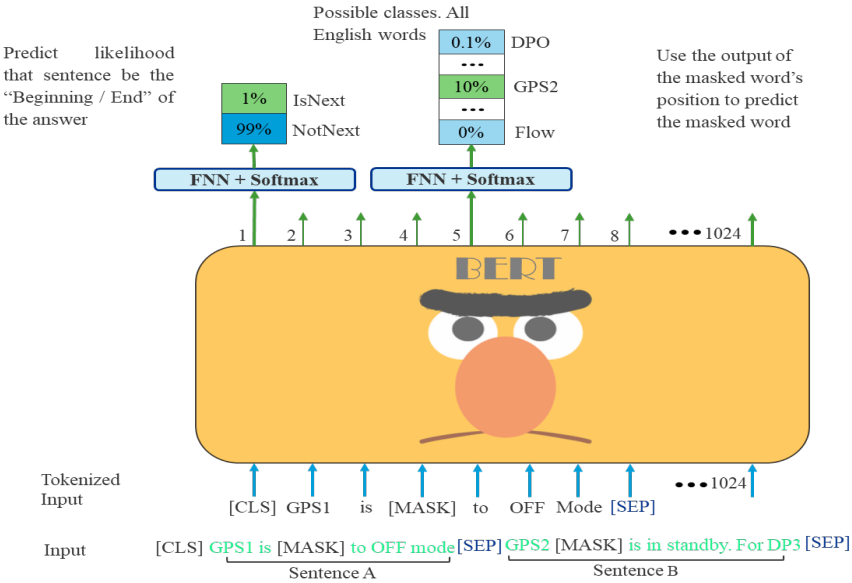


Figure 7-9 BERT pre-training phases

These two training tasks help BERT to train the vector representation of one or two word-sequences. Other than the context, pre-training discovers additional linguistics information, including semantics and coreference. Figure 7-9 shows the architecture for pre-training phases.

Fine-Tuning:

The next step after pre-training is fine-tuning involving fitting the task-related data and corresponding labels to refine the model parameters end-to-end. A shallow classifier layer is added for the QA system task to fine-tune the model output [218]. As BERT is more of a training strategy rather than a model architecture, the fine-tuning is straightforward. The self-attention VC mechanism allows swapping out the appropriate input and output and unifies two stages.

In the fine-tuning phase, as shown in Figure 7-10 for the question answering task, the input question and paragraph are represented as a single packed sequence. The question uses one embedding (A), and the paragraph uses another embedding (B). During fine-tuning, the start vector (S) and the end vector (E) are defined to identify the answer for the specific question. The probability of the word "i" being the start and the end of the answer span is computed as a dot product between T_i and S, T_i, and E. This is followed by a softmax over all of the words in the paragraph. It is presented by the Equations (7-3) and (7-4) [218, 219, 220].

$$P_i\,(S) = \frac{e^{S.T_i}}{\sum_j e^{S.T_j}} \tag{7-3}$$

$$P_i\,(E) = \frac{e^{E.T_i}}{\sum_j e^{E.T_j}} \tag{7-4}$$

The score of a candidate span from position i to position j is defined as $S.T_i + S.T_j$, and the maximum scoring span where j ≥ i is used as a prediction. The training objective is the sum of the log-likelihoods of the correct start and end positions. The maximum scoring for the start word and end word of the answer are used to determine the answer to the specific question. Finally, the model is fine-tuned with hyperparameters such as epochs, learning rate, and batch size to increase the performance and accuracy of the model. The details of the fine-tuning with the hyperparameters are presented in the experiment section 7.5.5.

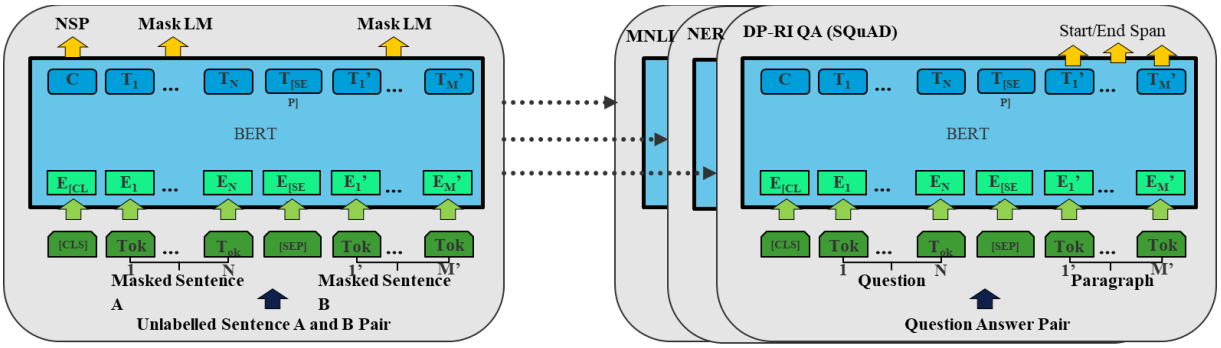


Figure 7-10 Fine-Tuning BERT for QA system

The fine-tuning instability of BERT was one of the critical issues in the research study during its application to DP-RI as a QA system [230]. The analysis showed that the instabilities were reported due to the smaller datasets of the DP-RI and catastrophic forgetting. The training was done on the TPU (POD and CHIPS). Table 7-3 presents the training time and fine-tuning time for the TPU and estimates of the GPU.

Table 7-3 BERT training time and DP-RI datasets fine-tuning time

MODELS	TPU POD	TPU CHIP	GPU
TRAINING TIME			
$BERT_{BASE}$	4 DAYS	8 DAYS	50-60 DAYS
$BERT_{LARGE}$	6 DAYS	12 DAYS	70-80 DAYS
FINE-TUNING TIME			
$BERT_{BASE}$	1 HOUR	4 HOURS	12-24 HOURS
$BERT_{LARGE}$	2 HOURS	6 HOURS	18-30 HOURS

The fine-tuning instability was addressed by using small learning rates combined with bias correction for avoiding vanishing gradients early in training. Another added feature was added by increasing the number of iterations and train to zero training loss by making use of early stopping [230]. The fine-tuning of the DP-RI dataset was performed on 100,000 labelled samples with DP-RI datasets. The research results revealed that the datasets above 20,000 showed robust performance for different hyperparameters. The optimised values of the hyperparameters are chosen for the testing on the testing/validation datasets which are shown in Table 7-4.

Rating of suggested solutions (Answers):

An additional layer is added for the model-specific application in which the answers are concatenated if multiple failures are leading to numerous questions as the input. For the DP-RI application, when there are numerous failures in the system, it leads to numerous alarms. Under such a situation, the mapping of alarms to the question leads to numerous questions and paragraphs fed into the BERT model [229]. The prediction of answers for the different questions provides the suggestion to the DPO to respond and take necessary steps. As shown in Figure 7-11, the softmax layer determines the rating for each answer based on the weighting of the sub-system and availability of redundancy during a particular mode of operation. The probability determination is represented by Equation (7-5) [176, 223].

$$S\,(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}} \tag{7-5}$$

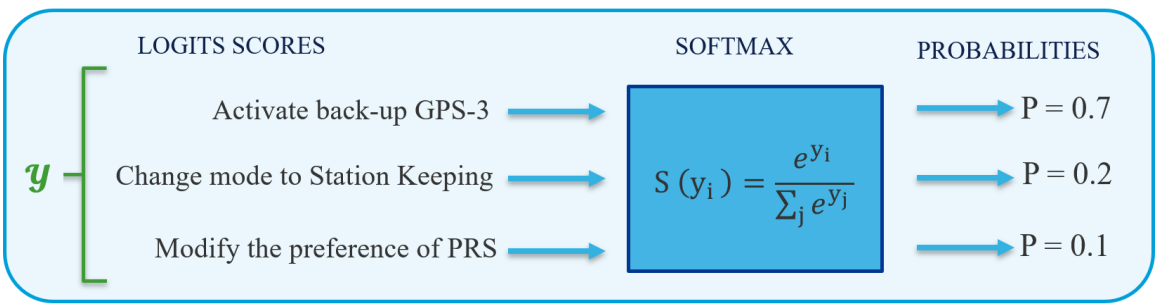


Figure 7-11 Rating of possible suggestive solutions

The dense fully connected softmax layer is used only in the case of multiple failures that need different actions from the DPO. If there is only one failure, the answers from the BERT model will be directly fed to the output with the softmax layer. The details of the rating on the actual application are explained in Chapter 8 with case-studies, and details of validation are presented in Appendix II as screenshots.

7.5.5 Experiment

The experiment was carried out in Colab using TensorFlow with TPU architecture. The details of the hardware, libraries, and software are presented in section 7.3 and Chapter 8. The datasets defined in Section 7.3 were used in the experiment for training, development (validation), and testing (evaluation). The investigation was carried out in the following steps:

- Creating dependencies and Bias Mitigation
- Data Pre-Processing
- Loading Dataset
- Creating the training and test datasets
- Building the model
- Training the model
- Evaluating Results

Creating Dependencies and Bias Mitigation:

The dependencies between the datasets were identified to create a single overall data set for the DP-RI application. The DP-RI dataset consists of dependencies between the sub-systems for various configurations and different modes of operation. Similarly, the dependencies between the software necessary for running the experiment in Colab were identified, and necessary libraries imported as packages. The next step is mitigating the biases in the dataset through a manual process that involves data pre-processing, splitting training, and test datasets and addressing the fairness through well-defined methodologies.

Data Pre-processing:

This involves creating the ".json" files for execution of the programming. The training data file and the vocabulary files are imported into the system. Then the metadata is created for the input training dataset. Finally, the training dataset is created similar to the SQuAD dataset using the Batch Size =4, and metadata sequence length = 450, and it is ensured that the training information is passed on to the program [228, 229].

Loading Data set:

The dataset is loaded to the Colab through the Keras library, which is part of Tensorflow 2.0. The dataset is stored in the ".json" format on Google drive. The three files training dataset, evaluation dataset, and vocabulary are loaded into the program. Then the root directory is created with the association for computational linguistics to ensure that the dataset is accessible for the BERT model and the output is created in the same location.

Creating the training and test datasets:

The data are loaded to the model and further split as below:

- Training dataset
- Testing dataset (development/validation and testing / evaluation)

Different classes of data within the datasets are identified with unique data labels, and the distribution is maintained between the datasets. The Keras K-train algorithm is used for the split, thus ensuring the fairness in the process.

Building the Model:

The model building process involves two steps. The first step is building the task-specific QA system layer (similar to the SQuAD layer) to train the BERT model. A dense layer is created representing the BERT QA layer using custom layers in Tensor from Keras using Tensorflow 2.0. The number of units is defined as "2," indicating the position of the score for the start of the answer and position of the score for the end of the answer. "Truncated Normal," which is a standard initializer used by Google, is adopted with "Standard deviation = 0.02". The logits are defined to get the input from the QA system layer and unstack the logits to get "logit [0] and "logit [1]," which represents the score to identify the "Answer."[220, 228, 229]

The second step is building the whole model structure, in which the additional dense layer is added to the model. In this step, it is ensured that the model is trainable, ahead of the next step. It takes in the sequence of inputs and produces the sequence of outputs [231]. The BERT layer call is in three-dimensions for the input, which are "Input_Word_Id," "Input_mask," and "Input_Segement_Id." Finally, the model returns the "Start_logits" and "End_logits." Thus, the BERT model is ready for the QA system, and the training can be performed on the model.

Training the Model:

Once the dataset is ready, and the model has been created, then the AI needs to be compiled for training the model. The hyperparameters are defined at the initial stages to determine the model performance, and the optimised values are obtained by iteration. The value of the hyperparameters is shown in Table 7-4. The critical item is the optimizer, which is a modified version of "Adam" preferred by Google [176, 218, 225, 229]. The optimizer uses the initial learning rate, number of training steps, and several warm-up steps. The scores are calculated through the loss function using classification to determine the start position and end position.

The sparse categorical cross-entropy is applied to both the outputs. The losses are computed separately, and then the total is obtained using both losses.

Table 7-4 Hyperparameter optimisation (Hyperparameters used for fine-tuning)

MODEL	$BERT_{BASE}$	$BERT_{LARGE}$
No of Encoder Layer	12	24
Embedding Size	768	1024
No of Self-Attention head	12	16
Parameters	100M	340M
Input Sequence length	450	450
Optimizers	"nlp.optimization. create_optimizer" "nlp.optimization. AdamWeightDecay"	"nlp.optimization. create_optimizer" "nlp.optimization. AdamWeightDecay"
Training Data Size	20000	20000
No of Batches train	500	500
Batch Size	4	4
Number of Epochs	3	3
Learning Rate	5e-5	5e-5
Learning Rate Schedule	Warmup-linear	Warm-up-linear
Warm-up steps	50	50
Warmup Ratio	0.1	0.1
Adam ε	1e−06	1e−06
Adam β1	0.9	09
Adam β2	0.999	0.999
Adam bias correction	True	True
Dropout	0.1	0.1
Weight decay	0.001	0.01
Loss computation	sparse_categorical_crossentropy	sparse_categorical_crossentropy

The next step is creating the custom training loop to keep track of losses and measure metrics to evaluate the performance of the QA system BERT models [231]. The custom training loop is used in the research to provide more flexibility and train the model with more control. It is performed with the support of Epochs. Training loss of each epoch is calculated for the complete training datasets. The "gradienttape" is used to record the operation, which is executed within the context manager [231]. It supports evaluating the weights to compute the loss function and gradients. The optimizer is applied to the model to decrease the gradient loss.

The model is trained for each epoch for pre-defined batch sizes, and the results are stored in the checkpoint manager [231]. Then time taken for each epoch run is saved; it took more than 4-6 hours for execution due to connectivity with the Colab server and the TPU accessibility. In this research experiment, the number of epochs is set to "3". The results are stored for every batch size of "50" through the training datasets. In the next section, the evaluation of the model performance is discussed.

7.5.6 Performance Evaluation – Testing and Results discussion

The BERT model implemented as a QA system for the DP-RI tool was evaluated using the testing dataset, and results are discussed with the metric evaluation parameters. The evaluation of the model performance is presented below in three steps.

Evaluation Preparation:

The evaluation preparation process is concept intensive, and thus diligent care was used to split the datasets into validation and test datasets. The dev dataset is imported, and the features are identified. After this, the tokenizer is used to token the dataset in the vocabulary and change it to lowercase.

Evaluation Creation:

A dictionary is created for evaluation, which defines types of unique field collection. "Namedtuple" is used to determine the output with field names to extract the output in a defined format. The fields are "unique_id," "start_logits," and "end_logits."

Evaluation Result:

The model performance and accuracy are evaluated through two metrics "F1" score and "Exact Match (EM)" score [219, 229, 232]. Metrics ignore the articles and punctuation for performance measurement. F1 score conveys the balance between the precision and the recall, and it is represented by equation (7-6). It measures the average overlap between the prediction and ground truth answers.

$$F1 = 2 * \frac{(\text{Precision} - \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{7-6}$$

Exact match measures the percentage of predictions that match any one of the ground truths answers precisely. Table 7-5 shows the F1 and EM score values for LSTM, $BERT_{BASE}$, and $BERT_{LARGE}$. The evaluation results clearly show that the $BERT_{LARGE}$ model outperforms the other models and algorithms. When comparing the training period, $BERT_{LARGE}$ took more time and capacity, leading to a high cost due to TPU usage. However, in terms of validation and testing, the accuracy was higher, and the response time was faster. Therefore, for the DP-RI application, $BERT_{LARGE}$ would be recommended for the prescriptive analytics part of the state-of-the-art advisory tool.

Table 7-5 Model Performance Evaluation

MODEL	DEV		TESTING	
	F1	EM SCORE	F1	EM SCORE
LSTM	66.07	64.76	64.82	62.91
$BERT_{BASE}$	85.64	84.57	84.40	82.89
$BERT_{LARGE}$	89.45	88.32	88.18	87.02

The model performance on the prediction of the answers was measured through the "F1" score, and the results analysis is shown in Table 7-6. The output answers from the DP-RI tool are compared with the available documentation and experts' judgements. Similarly, the rating of the solutions suggested are evaluated using "EM" score, and the analysis of the results are shown in Table 7-7. The rating/ranking order of the solutions suggestion are compared with the actual implementation steps onboard by the DPO during real scenarios based on the system availability. The scenarios from Table 7-2 are used for the detailed analysis of "F1" and "EM" scores.

Table 7-6 Answer evaluation for DP alarms and Question (F1 score analysis)

SNO	DP ALARMS	DP-RI TOOL ANSWER	EXPERT'S ANSWER	F1 SCORE ANALYSIS
1	Wind Sensor 1 signal loss. Power Failure	1. Choose Wind sensor 2 if it is disabled 2. Check the connection points in the IO 3. Change to Joystick mode 4. Check the resultant force and error in the DP screen	1. Enable and set Wind sensor 2 as preferred 2. Change to Joystick mode 3. Check the resultant force and error in the DP screen 4. Check for proper action to resolve failure	The possible solutions from DP-RI tool matches with the expert's judgement. The accuracy of the solution for the case is 90% considering the deviation in the solution suggested.
2	Main DP control system lost. Network Failure.	1. Change to back-up DP control 2. Change to Joystick mode 3. Check the network failure	1. Automatic changeover to back-up DP control 2. Change to Manual DP control 3. Change to Joystick mode 4. Check for proper action to resolve network failure	The possible solutions from the DP-RI tool to some extend matches with the expert's judgement and action taken during the actual scenario. The performance of the model prediction is 93%.
3	DG 1 Failure. Shutdown	1. Start the standby generator based on configuration 2. Check the signal led to DG shutdown	1. Automatic start of 1st or consecutive standby generator 2. Enable Power management system 3. Start the standby generator if not started automatically 4. Check for proper action to resolve shutdown of DG	The performance of the model prediction against the expert judgement has an "F1" score of 79%. The system did not consider the automatic operation from PMS, and therefore the automatic start of the Generator was not provided as a suggestion.

SNO	DP ALARMS	DP-RI TOOL ANSWER	EXPERT'S ANSWER	F1 SCORE ANALYSIS
4	Thruster 2 Loss. Hydraulic Pressure Loss. Hydraulic Pump Failure.	1. Start the standby thruster and connect to DP system 2. Check the hydraulic pump failure 3. Check the power to the hydraulic pump and drive	1. Check whether vessel could remain in the set position. 2. Next available thruster will start automatically and connect to DP mode 3. Check for proper action to resolve the issue with hydraulic pump 4. Check issue with the pressure transmitter	The "F1" score for the prediction from the DP-RI tool is 82%. The passage from the DP manual doesn't include the automatic feature of the thruster when in DP mode. Therefore, the possible solutions suggested by DP-RI tool is not in line with the actual steps by the DPO. If the appropriate passage was provided to the DP-RI tool, the prediction could have been better.
5	DGPS 2 Fail. Loss of Satellite signal	1. The other DGPS signal should be online 2. Check whether DPGSs shares the same satellite signal 3. Check for other alternative position reference system signal.	1. The DGPS signal independent of the failed DGPS should take over automatically 2. Check for the satellite signals to different DGPS 3. Ensure that DP is still able to operate with available reference signal 4. Check for other alternative position reference system signal.	The "F1 score" is 86% for the prediction from DP-RI tool. The automatic change-over between the DGPSs are not considered in the passage from the DP operation manual and proving trial procedure results. Similarly, the satellite interface to different DGPS was not indicated in the passage Therefore, the possible suggestions from the DP-RI deviated from the experts' judgement.

Table 7-7 Rating of solutions suggested (EM results analysis)

SNO	DP ALARMS	DP-RI TOOL ANSWER	EXPERT'S ANSWER	EM ANALYSIS
1	Wind Sensor 1 signal loss. Power Failure.	1. Choose Wind sensor 2 if it is disabled 2. Check the connection points in the IO 3. Change to Joystick mode 4. Check the resultant force and error in the DP screen	1. Enable and set Wind sensor 2 as preferred 2. Change to Joystick mode 3. Check the resultant force and error in the DP screen 4. Check for proper action to resolve failure	The EM score was 89%, when order and the probability ratings of possible solutions suggested from DP-RI tool and experts' judgement are evaluated. The main reason for difference was that the Wind sensor and Joystick are grouped under different sub-systems in DP-RI tool.
2	Main DP control system lost. Network Failure.	1. Change to back-up DP control 2. Change to Joystick mode 3. Check the network failure	1. Automatic changeover to back-up DP control 2. Change to Manual DP control 3. Change to Joystick mode 4. Check for proper action to resolve network failure	The evaluation revealed that the EM score was 82% due to the reason that the passage included did not have the automatic changeover and the manual control mode description.
3	DG 1 Failure. Shutdown of DG.	1. Start the standby generator based on configuration 2. Check the signal led to DG shutdown	1. Automatic start of 1st or consecutive standby generator 2. Enable Power management system 3. Start the standby generator if not started automatically 4. Check for proper action to resolve shutdown of DG	The PMS information for the automatic start of standby DG when the connected DG fails was not indicated in the passage extracted. Thus, the EM score was 83% for the scenario.

SNO	DP ALARMS	DP-RI TOOL ANSWER	EXPERT'S ANSWER	EM ANALYSIS
4	Thruster 2 Loss. Hydraulic Pressure Loss. Hydraulic Pump Failure.	1. Start the standby thruster and connect to DP system 2. Check the hydraulic pump failure 3. Check the power to the hydraulic pump and drive	1. Check whether vessel could remain in the set position. 2. Next available thruster will be start automatically and connect to DP mode 3. Check for proper action to resolve the issue with hydraulic pump 4. Check issue with the pressure transmitter	The DP-RI suggested the start of standby thruster as there was failure. However, the check on the ability to maintain the position was not provided as the suggestion. The reason for this is mainly the DP-RI tool is trained to provide possible solutions when there is a failure. Similarly, the automatic start of the standby thruster was not included in the passage used for prediction. Thus, the EM score is 78%.
5	DGPS 2 Fail. Loss of Satellite signal	1. Check whether other DGPS signal is online 2. Check whether DPGSs shares the same satellite signal 3. Check for other alternative position reference system signal.	1. The DGPS signal independent of the failed DGPS should take over automatically 2. Check for the satellite signals to different DGPS 3. Ensure that DP is still able to operate with available reference signal 4. Check for other alternative position reference system signal.	The architectural and connection information of the DGPS was not included in the passage. The rating of the possible solutions suggested by DP-RI is more or less related to the experts' judgement with little deviation of the rating ranking leading to EM score of 83%.

7.6 Summary

The prescriptive analytics to address the failure related to the DP system was presented with a state-of-the-art BERT model from Google. The research framework proposed in this chapter for prescribing possible solutions in the case of failure using the BERT model in the QA system acts as a basis for other applications. It will reduce the time required for solution generation by the DPO as it avoids referencing a massive number of documents or seeking expert advice during critical situations. During the training phases, once the alarm is simulated the question is created and fed to the model to prescribe solutions. This step acted as a "human-in-the-loop" prescriptive analytics methodology. Once the model is trained the human part is removed, and the process is automated to have fully functional AI system for the prescriptive analytics part in DP-RI tool. The possible solutions suggested, along with the actual reliability condition indicated in the DP-RI tool, will support the DPO to take quick action and prevent the failures leading to accidents. In this chapter, the experimental set-up and TPU details used for running the model are described. The datasets collection and pre-processing was presented followed by which methods of aligning data to suit the need for the QA system was defined. The bias mitigation methods were briefly described. Various NLP models and their suitability for DP-RI application was evaluated and the reason for choosing the BERT model was presented along with the evaluation results. Finally, the hyperparameter optimisation and application of the prescriptive analytics solution for other DP3 vessels are highlighted. In the next chapter, the case studies of predictive and prescriptive analytics are verified and validated using traditional risk assessment methodologies.

8. Verification and Validation of Predictive and Prescriptive Analytics Results

8.1 Introduction

This chapter describes the experimental set-up and case studies for verification and validation of results from the DP-RI tool with proven risk assessment methods. Section 8.2 describes the architecture of the DP-RI tool and network topology of the interfaces. The offshore set-up for the DPO and the onshore set-up for the SME used to validate DP-RI are described in detail. The data management, user access, and the security for information sharing with the on-board DP control system and DP-RI were identified and appropriate steps to mitigate the spurious control trips were addressed. In the next section, the programming language and libraries for the DP-RI tool are listed. The machine specification of the GPU used for the predictive analytics and the machine specification of the TPU used for the prescriptive analytics are presented. The experimental set-up for the case studies, along with the research boundaries and limitations, are presented to define the operation envelope for the DP-RI tool. The DP 3 vessel configuration is shown, which is used for the case studies. The set-up for the case studies was extracted from the IMCA accident database, and some of the case studies were based on the FAT / CAT procedure to test the effectiveness and robustness of the DP-RI tool. The verification and validation of the case study results were evaluated to confirm, through objective evidence, that the specified requirements of the DP-RI tool are fulfilled [233]. The final section of the chapter describes the summary of the results and improvement in the test cases.

8.2 DP-RI Tool Architecture and Network Topology

The DP-RI tool architecture and network topology are shown in Figure 8-1, depicting its interface with the DP control system on-board the vessel, whilst offshore, and transmission of data onshore for real-time monitoring. The interface was independent of the process network and secured through a router and firewall settings. The prediction and prescription algorithm runs on the DP-RI computer, and it reads the field data through the DP control system via read-only access. Based on the field information, the algorithm predicts the near future reliability of the DP system. In the case of failure in a sub-system, the DP-RI provides possible suggestions to the DPO for faster response action.

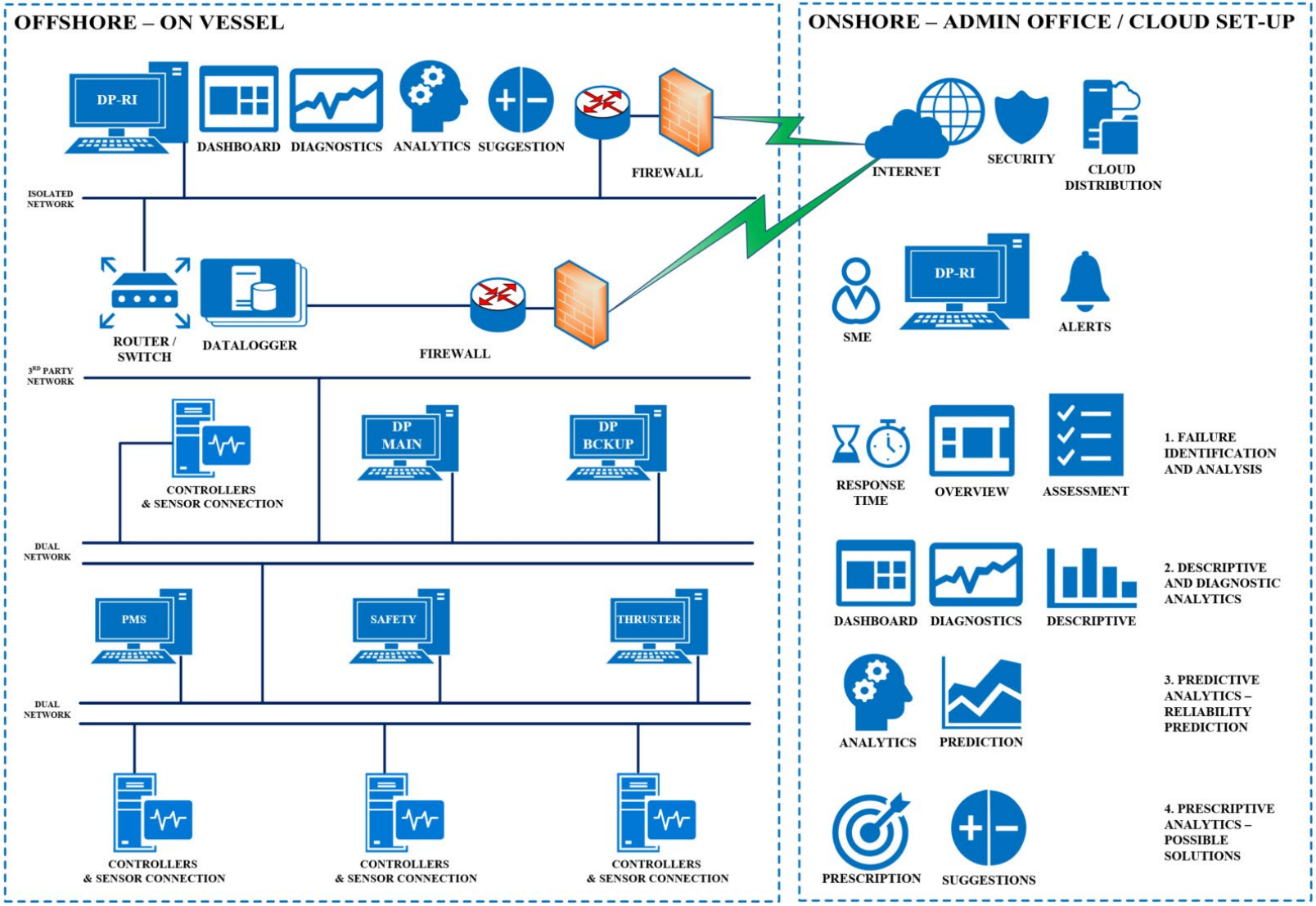


Figure 8-1 DP-RI System Topology

8.2.1 Data Management

One significant feature of the DP-RI tool is to interface and share data and information from the DP control system (including sub-systems) for safe and efficient operation. The data is collected from multiple sources, and the ability to manage all of the information seamlessly enables a new level of possibility to analyse and monitor situations, critical operations, and installation conditions. The DP-RI tool is provided with dynamic visualisation to handle the massive amount of data and assist the DPO to be efficient in critical operations.

Data Server

Data will be collected from the DP control system through a historical database protected via the router. The time-series defined sensor data are transferred through the OPC server configured as a master-slave configuration. The algorithm uses only the alarms and the events of the sensor tags, and there will be a delay of fewer than 3 seconds.

Data Collection and Storage

The time-series data will be recorded and stored as it changes. The capacity of the system is provided such that the time-series data can be stored for 30 days. The data features are 0.2% of range as dead-band compression and 0.1% of range as vector-based compression. The data are stored locally in the DP-RI computer, and there is a provision to store to the cloud for simulation of different configurations.

Data transfer time

Data transfer time for the information from the sensor to the controller to the data-logger and finally to the DP-RI application was less than 60 seconds. The time-series data are aggregated and stored in the datalogger. The time delay from the sensor to the DP-RI tool was due to transfer of data from the controller to the datalogger.

8.2.2 Security and Integrity

The DP-RI tool requires a username with a log-on password to perform simulations. Access rights were provided to different users with specific roles and sets of rights to set-up the applications. The DP-RI tool application does not affect the DP control system performance and integrity.

8.3 Programming Language

The Google Colaboratory (Colab), which is an open-source web application, was used to create and share documents that contain live code, equations, visualisations, and narrative text. The experiments were run using the codes which were developed using Colab, which is an executable document written and run within Google Drive using Python programming [174]. Python was used due to its efficiency in providing high-level data structures, and because it is a practical approach for object-oriented programming, which was required for handling the massive amounts of data for this application. Besides, Python was used for data cleaning and transformation, statistical modelling, data visualisation, and machine learning [234].

Tensorflow 2.0 is an end-to-end open-source platform for machine learning, including RNN. The features are used to build and deploy RNN-powered applications quickly by using a comprehensive, flexible ecosystem of tools, libraries, and community resources. Tensorboard provides the visualisation and tooling needed for machine learning experimentation to track and visualise metrics such as loss and accuracy. It also aids in visualising the model graph (operation and layers) and viewing histograms of weights, biases, or other tensors as they change over time. The Keras Functional API enabled the implementation of a wide range of different deep learning models so that suitable models for the DP-RI application could be identified [176]. Other libraries, such as Tensor graph, seaborn, pandas, NumPy, random, and Matplotlib, were used for various functions during the comparison of the models and evaluating the metrics [234]. The main advantages of using the Python programming language, Keras API, and libraries were that it helped in providing the following features [174, 176, 186]:

(i) Interface with GPUs in the Google Cloud Platform for increased performance
(ii) Data cleaning and comparison of the models during the validation stage, making it possible to check the loss and accuracy metrics
(iii) Debugging was faster due to the availability of Tensorboard, where the scalar/hyperparameters can be varied to find the optimal performance of the models
(iv) Running different complex deep learning algorithms for prediction and validating with the test data set for time series data was made possible due to the capability of the GPUs available in GCP through Recurrent Neural Networks.
(v) Tuning Hyperparameters and comparing the performance over-time.

8.4 Machine Specification

The sections below describe the machine specification of GPU and TPU used for predictive and prescriptive analytics.

8.4.1 Predictive Analytics

The GCP uses the Google Cloud Engine (GCE), which provides GPUs that can be used as virtual machines for running deep learning models. The GCP's Computing Engine with GPUs is used in efficient ML models to provide faster execution for real-time data interface. The GCP Infrastructure as a Service (IaaS) was used for the experimental evaluation of the research [235]. For the DP-RI application, as shown in Table 8-1, a high number of GPU and vCPU devices were selected from the various models available on the GCP as the DP-RI tool has a high computation requirement [234]. A GPU accelerates the specific workloads such as machine learning and data processing for optimised execution of the programming [234]. This particular model provided the capability to run a vast number of data-sets, and it can be readily applied to data from different vessels for further research evaluation.

Table 8-1 GCP GPU specification for predictive analytics

GPU model	No of GPUs	GPU memory	Available vCPUs	Available memory
NVIDIA® Tesla® K80	8 GPUs	96 GB GDDR5	1 - 64 vCPUs	1 - 416 GB

8.4.2 Prescriptive Analytics

TPUs were designed from the ground up with the benefit of Google's deep experience and leadership in machine learning [176]. Figure 8-2 shows the TPU architecture, and Table 8-2 specified the machine specification on the GCE.

Table 8-2 DP sub-system weighting for optimised hyperparameters

TPU model	TPU Cores	TPU memory	Processing Power	Network
Cloud TPU v2 Pod	512	4 TB High Bandwidth Memory (HBM)	11.5 petaflops	2-D toroidal mesh network

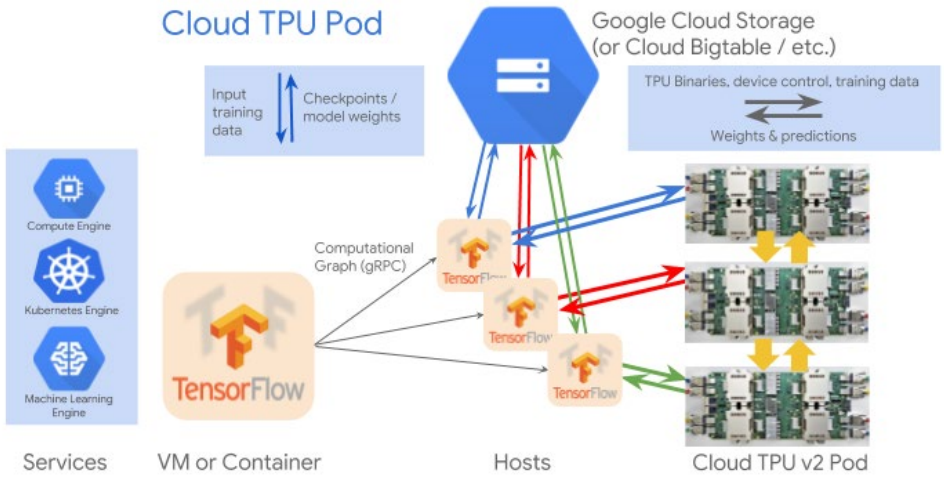


Figure 8-2 TPU architecture for BERT model fine-tuning [176]

TPUs are used for the NLP to speed up the prescriptive analytics as the time to prescribe suggestive solutions is limited, and action needs to be instantaneous.

8.5 Research Assumptions and Boundaries

8.5.1 Assumptions

The following are the assumptions for this research study:

- The two DP vessel models (DP3 Semi-submersible Drilling Rig and DP3 Drillship) used for the research had the same configuration as below:
    - 8 Diesel Engine (Rolls Royce)
    - 4 Switchboards (Siemens) Open and Close Bus-Tie Configurations
    - 8 Azimuth thrusters (Wartsila)
    - VFD drives (Siemens)
    - DP3 Control System (Kongsberg)
    - Reference System Sensors (Kongsberg)
    - Environmental Sensors (Kongsberg)
    - DPO (Seadrill, Transocean, Heerema, Floatel Etc)
- The DPOs working on the vessels are assumed to meet the competency requirements of the nautical institute, regulators, classification societies, and the Company.
- The weighting of the DP sub-systems is based on the AHP methodology presented in Chapter 4 and the opinions of industry experts.

- The probability of two or more failures occurring in a sub-system simultaneously is low.
- The DP-RI tool is used to make safety-critical decisions in real-time. Therefore, the artificial intelligence systems with deep learning algorithms needed to be designed with a high quality algorithm.
- The DP-RI tool was used to test vessels with different applications (Drilling rig, floating accommodation, PSV, etc.), class (DP3 / DP2), configuration (8/ 6 thruster and 4/3 switchboards), and sub-system vendors for specific cases to ensure the scalability.
- The inherent biases of the RNN model are appropriately addressed through necessary precautions and uncertainty in the forecasting was kept to a minimum.
- The data extracted from the two vessels are used to train the model with different scenarios as much as possible, and the model is assumed to deal with new situations and failures for which it was not explicitly trained.
- The data used for the thesis are knowledge-based data collected from industry databases and real-time data collected directly from sensors through the DP control system.
- The research is assumed to have a focus on the following criteria to ensure that the application to real vessels is possible shortly.
    - High-risk scenarios with low probability were evaluated to ensure that the decision should not have catastrophic consequences due to inaccurate prediction.
    - Critical consequences are often related to tail events – for which data are naturally scarce. As the data is insufficient, the uncertainty associated with prediction is high. This scenario is assumed to be addressed through training scenarios by testing with available case studies with high-risk ranking.
- The research was executed in the GCP and assumed to have the same efficiency when migrated to other IaaS platforms such as Azure or Amazon Web Services (AWS).

8.5.2 Boundaries

The following are the limitations of this research:

- The below databases were used for the big data analytics which are part of DNV GL Datawarehouse and publicly available data source.
    - IMCA Accident Database (Publicly available)
    - FMEA database (DNV GL)
    - HIL Database (DNV GL)
    - DP-Capability (DNV GL)
    - OREDA (Publicly available)
- Possible suggestive solutions to the operator during failure are generated based on the limited available databases and SME judgment. Therefore, the tool needs to be tested with as many scenarios as possible with available confidential databases before application into a real DP vessel.
- The DP-RI tool was integrated with onboard DP control systems through secured connection for monitoring pre-defined set of signals. The isolated sub-systems was not directly interfaced with DP-RI tool.
- Numerical simulations were performed, but physical model tests were not performed.
- Case studies from IMCA and hypothetical cases were used for evaluating the effectiveness of the DP-RI tool, and specific operation envelopes were considered to define the uncertainties.

8.6 Experimental Set-Up: Semi-Submersible Drilling Rig – DP 3 (DP AUTRO)

The semi-submersible drilling rig of DP-3 class was used for numerical simulations in the experimental set-up for the verification and validation of the DP-RI tool. Similarly, the results are validated on one Drillship DP-3 class during proving trials for some of the actual and hypothetical case studies. Figure 8-3 shows the configuration of the semi-submersible drilling rig used for the numerical simulations. In Section 8.7 and Section 8.8, different case studies are presented, and the effectiveness of the DP-RI tool is discussed along with verification and validation with existing methodologies. The simulation and run-time screenshots of the overall DP system, seven sub-systems and the limit set-up are shown in the Appendix II section of the thesis.

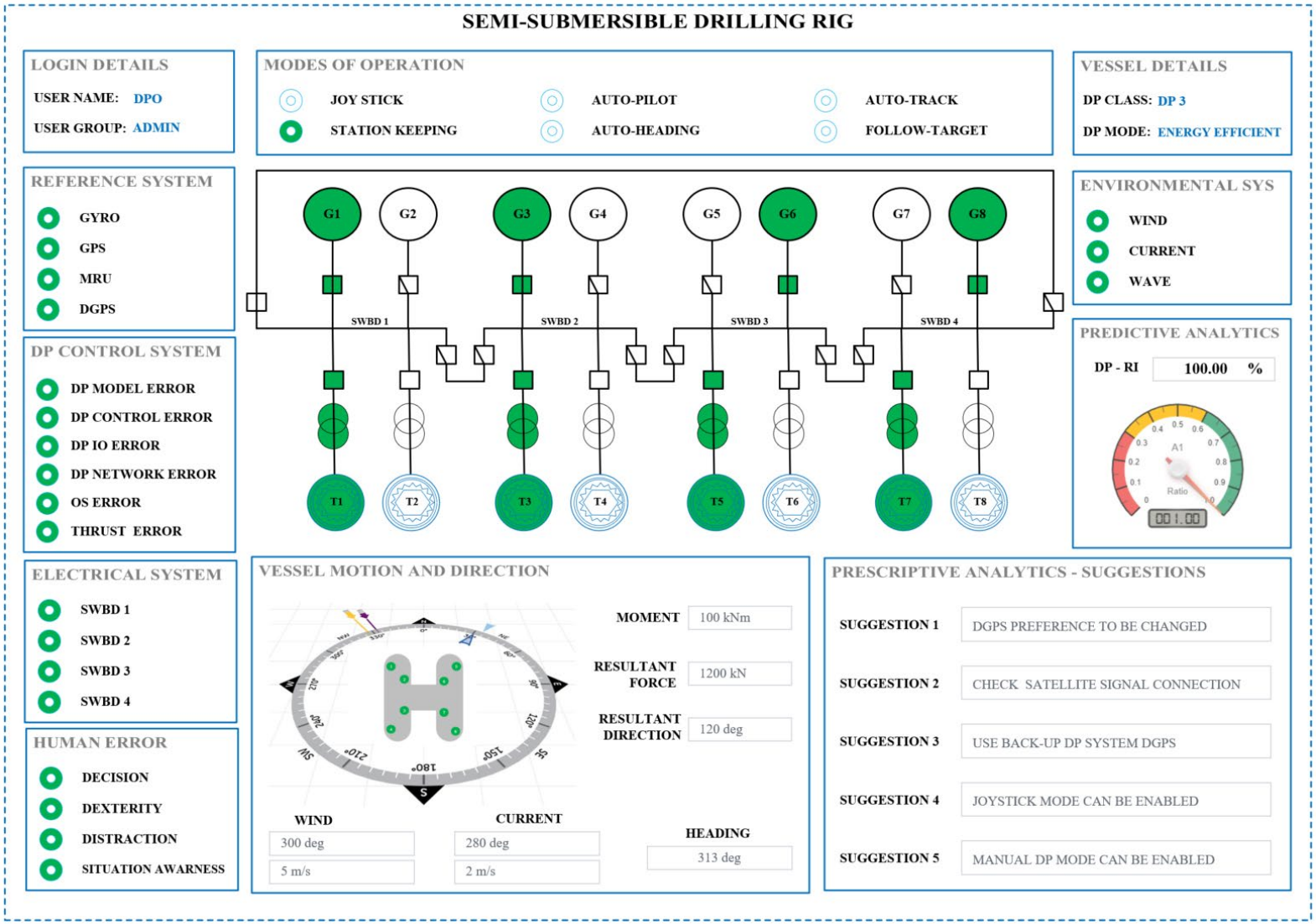


Figure 8-3 Semi-Submersible Drilling Rig Configuration for DP-RI experiment

8.7 Verification and Validation - Actual Case Studies from IMCA database

Case studies (1-4) are extracted from the IMCA database, and comparison is made between the actual events and simulation in the DP-RI. The flow of the case studies explained in the next section is defined in the flowchart as shown in Figure 8-4.

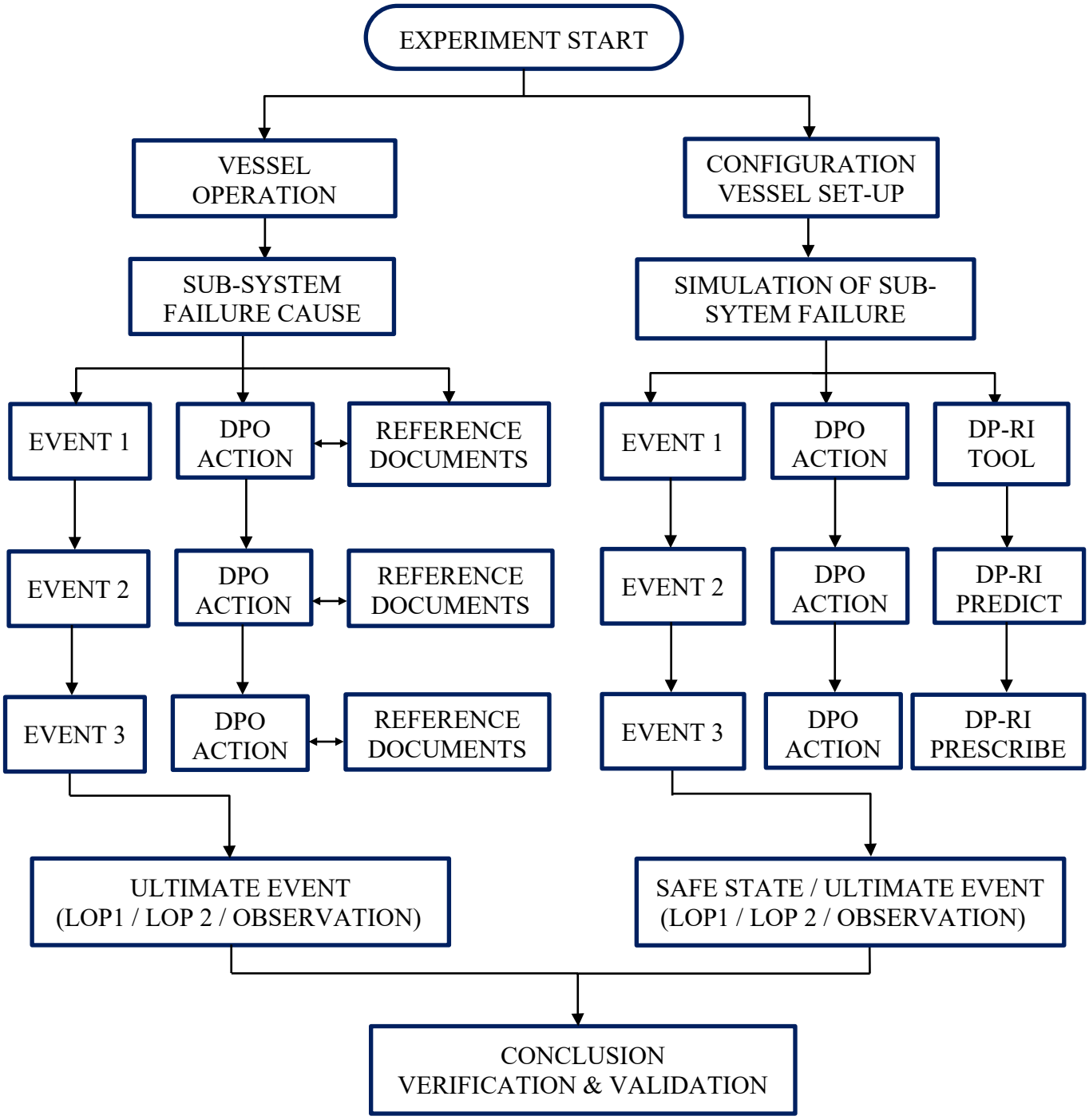


Figure 8-4 Flowchart – Experiments on case studies from IMCA database

Case Study 1:
IMCA Dynamic Positioning Station Keeping Review DPSI 29 -2019 (Event 3).

Description of the Case study and detailed analysis of simulation:
Case study 1 was extracted from the DP review event reported in 2019. The reported Event 3 resulted in a DP incident (LOP 1) on the actual vessel. Table 8-3 shows the comparison of the vessel set-up, failure in the sub-system, and successive events between the real scenario and the numerical simulations on the DP-RI tool. The experimental simulation of the existing scenarios was replicated in a controlled environment with a defined operational envelope. The DP-RI tool was not trained with this particular scenario so it could be used to evaluate the performance and accuracy. The vessel is a DP 3 drilling rig with System A, System B, System C, and System D connected in an open bus with one generator in each system running and connected online. There was a failure of the Automatic Voltage Regulator (AVR) in system A which led to drilling operation interruption. The DPO investigated the loss and used reference documents to rectify the failure. As there was no guidance on the precautionary steps, it led to network failures (Net A and B). This resulted in complete loss of DP control, and the vessel drifted 100 meters resulting in the DP incident.

The experimental simulation of the same scenario on the DP-RI tool showed different results as the tool provides information instantaneously to the DPO. When AVR failure was simulated in the electrical system, reliability was predicted as 75%, and the overall reliability of the DP system was predicted as 88%, indicating that the vessel can maintain position. The DP-RI tool also prescribed possible solutions and precautionary steps which could help the DPO to isolate the system during the rectification of failure. Therefore, it does not result in a network failure, and the system was restored for the drilling operation. From the results in Table 8-3, it is evident that the DP-RI tool could prevent the DP incident through its predictive and prescriptive functionalities. During the incident analysis of the actual case by IMCA experts, it was revealed that the vessel drifted after the network loss of DP control. The LOP 1 could have been prevented if the DPO has taken preventive steps to act on this. The response time was limited by the DPO's time to react and take corrective action to prevent a DP incident. Also, the same scenario was tested on a drillship during sea-trials with integration between the control system and DP-RI. The failure was simulated, and the DP-RI tool was able to predict the reliability value instantaneously and prescribe solutions to the DPO for further actions.

Table 8-3 Case Study 1 - Actual and Experimental results summary

VESSEL SET-UP	VESSEL CONFIGURATION	FAILURE CAUSE	SUCCESSIVE EVENTS	REFERENCE DOCUMENTS	DP-RI PREDICT	DP-RI PRESCRIBE	DPO ACTION
ACTUAL VESSEL (DP 3)	4 Generators Online 4 Generators Standby 4 Thrusters Online 4 Thrusters Standby 3 Gyros, 3 MRU and 2 Wind Sensors Online 2 DGNSS and 2 HPR Online Wind Speed = 46 Knots (251°) Current Speed = 3.9 Knots (217°) Wave Height = 6 metre Visibility = Good	AVR Failure in System A. Repair lead to failure of System B was lost, and the vessel drifted, leading to DP incident (LOP 1)	**EVENT1:** AVR fault Drilling Stopped	Site-Specific documents. FMEA and Operation Manual.			Refer to the procedure and stop drilling operation
			EVENT 2: Network lost A&B DP Control Fail	Alarm in DP control System. Site-specific documents.			Refer to alarms and check for appropriate steps in DP operation manuals.
			EVENT 3: Vessel Drifted Excursion 100 m resulting in LOP 1.	Knowledge of the DPO.			Visual Identification and DPO intervention after the actual incident.
SET-UP FOR DP-RI (DP3)	4 Generators Online 4 Generators Stand-by 4 Thrusters Online 4 Thrusters Standby 3 Gyros, 3 MRU and 2 Wind Sensors Online 2 DGNSS and 2 HPR Online Wind Speed = 46 Knots (251°) Current Speed = 3.9 Knots (217°)	AVR Failure in System A.	**EVENT1:** AVR fault Drilling Stopped		The reliability of the electrical system is predicted as 75%. The overall DP reliability is 88.5%	Prescribes the possible suggestion and one suggestion is to isolate the systems	DPO follows the suggestion and isolates the system
			EVENT 2: DP Control Isolated system restored		Reliability real-time remains at 75%. The overall DP reliability is 88.5%	Prescribes possible suggestions if the system network fails. Suggestion Joystick or TCS	Rectification was performed as per the DP-RI tool suggestion.
			EVENT 3: Vessel – Safe State Drilling Resumed		The reliability of the overall DP system is 100%	No suggestion when no failures in the system.	DPO performs normal monitoring duty during the drilling operation

The suggestion was based on the inputs provided to the tool during the prescriptive analytics training. Although the training was performed for each scenario separately, the DP-RI proved its performance when a sequence of events happened. It demonstrates the capability to scale for other failures.

Failure in sub-systems:
Electrical System (A5) → Primary cause

Human / Operator Error (A7) → Secondary cause

Actual Vessel Final Event:
DP Incident (LOP 1)

Experimental Set-Up (DP-RI) Final Event:
The vessel in a safe state

Risk Studies and documents used for verification and validation:

- FMEA results
- DP simulators
- DP Capability Plots
- Site-Specific Risk Analysis
- DP operation Manual

Conclusion - Verification, and Validation:
The DP-RI tool was able to bring together information from the different studies and present it instantaneously to the DPO with the possible suggestions to select and implement. This feature significantly reduces the reaction time, addressing the root cause of the problem without a single failure leading to catastrophic losses. As discussed in the table, the reliability of the overall system was 88%, and prescribing possible suggestions is the most novel feature integrated with the DP system to ensure safe operation. Thus, for this specific case, the DPO was alerted to potential consequences and able to take preventive action. In a case where it led to successive events, the DP-RI would have suggested corrective actions to the DPO.

Case Study 2:
IMCA Dynamic Positioning Station Keeping Review DPSI 23 -2012 (ID 1242).

Description of the Case study and detailed analysis of simulation:
Case study 2 was extracted from the DP review event reported in 2012. The reported accident, ID 1242, resulted in a DP undesired event (LOP 2) on the actual vessel. Table 8-4 shows the comparison of the vessel set-up, failure in the sub-system, and successive events between the real scenario and the numerical simulations on the DP-RI tool. The case study involves loss in the sub-system DP control system (A2) as the primary cause and human/operator error (A7) as the secondary cause. The DP-RI tool was never trained with this particular scenario so it can be used to evaluate the performance and accuracy. The vessel is DP 3 class with System A, System B, and System C connected in an open bus with four generators online and two generators on standby. All the thrusters in the Thruster System (A3) are online and connected. The failure of the DP control system led the thrusters to react erratically, and the vessel started drifting away from the set position. The DPO did not have sufficient time to prevent the subsequent event as there was no readily available solution from the current system set-up. The final event was a minor loss of position resulting in a DP undesired event (LOP 2).

The experimental simulation of the same scenario in the DP-RI tool showed different results, and the vessel was in a safe state throughout the fault condition. When a failure in the DP control system was simulated, the DP-RI tool predicted the reliability of the DP control System (A2) as 50% and the overall reliability of the DP vessel as 83%. The DP-RI tool prescribed possible suggestions to take control of the DP back-up control station to avoid excursion from the set-position. The DPO was able to react in time and take control and keep the vessel in a safe state. If the DPO did not react due to human error, then the DP-RI predicted the reliability of Human / Operator error (A7) as 50% and the overall DP vessel reliability as 54%. At this stage, the DP-RI tool would have provided possible suggestions to take control through Joystick or Manual operation. Then the DPO would have reacted to prevent the DP incident and keep the vessel in a safe state. Then the failures could be fixed, bringing the overall reliability of the DP vessel back to 100%.

Failure in sub-systems:
DP control System (A2) → Primary cause
Human / Operator Error (A7) → Secondary cause

Table 8-4 Case Study 2 - Actual and Experimental results summary

VESSEL SET-UP	VESSEL CONFIG	FAILURE CAUSE	SUCCESSIVE EVENTS	REFERENCE DOCUMENTS	DP-RI PREDICT	DP-RI PRESCRIBE	DPO ACTION
ACTUAL VESSEL	4 Generators Online 2 Generators Standby 6 Thrusters Online 0 Thrusters Standby 3 Gyros, 2 MRU and 3 Wind Sensors Online 3 DGNSS and 2 HPR Online Wind Speed = 0.7 Knots (280°) Wave Height = 0.1 metre Visibility = Good	DP control system failure. Operator error acting as secondary causes led to the thruster system to react erratically, leading to excursion resulting DP undesired event (LOP2)	**EVENT1:** DP control system failed, and operation stopped	Site-Specific documents. DP Operation Manual.			Refer to the procedure and stop operation
			EVENT 2: Thruster reacts erratically due to a lack of allocation algorithm.	DP capability plots.			Refer to alarms and check for appropriate steps in DP operation manuals.
			EVENT 3: Vessel drifted resulting LOP 2	Knowledge of the DPO.			Visual Identification and DPO intervention after actual incident.
SET-UP FOR DP-RI	4 Generators Online 2 Generators Standby 6 Thrusters Online 0 Thrusters Standby 3 Gyros, 2 MRU and 3 Wind Sensors Online 3 DGNSS and 2 HPR Online Wind Speed = 0.7 Knots (280°) Wave Height = 0.1 metre	DP control system failure	**EVENT1:** DP control system failed, and the operation stopped.		The reliability of the DP control is predicted as 50%. The overall DP reliability is 83%	Prescribes the possible suggestion 1. Use Back-up DP 2. Use Joystick	DPO follows the suggestion and transfers control to the back-up DP system.
			EVENT 2: Back-up DP control activated		Reliability real-time remains at 50%. The overall DP reliability is 83%	Prescribes possible suggestions 1. Manual DP 2. TCS	Rectification was performed as per the DP-RI tool suggestion.
			EVENT 3: Vessel – Safe State		The reliability of the overall DP system is 100%	No suggestion when no failures in the system.	DPO performs normal monitoring duty during the operation

Actual vessel's final event:
DP undesired event (LOP 2)

Experimental Set-up (DP-RI) final event:
The vessel in a safe state

Risk Studies and documents used for verification and validation:

- Site-Specific Risk Analysis
- DP operation Manual
- Investigation reports
- DP Capability Plots

Conclusion - Verification, and Validation:
The DP-RI tool showed the timely intervention of the DPO could prevent the failure in a sub-system leading excursion from the set-position . As the analysis showed the initial loss in the DP control system (A2) had only reduced the reliability of the overall DP system to 83%, and the secondary cause was the main reason resulting in the minor loss of position. Thus, for this specific case, the DPO was alerted to the possible consequences and could take preventive action without Human/operator error (A7) acting as a secondary cause. In the case where it led to successive events, the DP-RI would have suggested additional corrective actions to the DPO based on the circumstances.

Case Study 3:
IMCA Dynamic Positioning Station Keeping Review DPSI 29 -2018 (ID 18121).

Description of the Case study and detailed analysis of simulation:
Case study 3 was extracted from the DP review document reported in 2018. The reported accident, ID 18121, resulted in a DP incident (LOP 1) on the actual vessel. Table 8-5 shows the comparison of the vessel set-up, failure in the sub-system, and successive events between the real scenario and the numerical simulations on the DP-RI tool. The case study involves a failure in the Thruster System (A3) as the primary cause and the power system (A4) as the secondary cause. The DP-RI tool was not trained for this particular scenario and so can be used to evaluate the model's ability to predict new techniques. The vessel is DP 3 class drilling vessel with System A, System B, System C, and System D connected in a closed bus with four generators online and four generators on standby. Four of the eight thrusters in the Thruster

Table 8-5 Case Study 3 - Actual and Experimental results summary

VESSEL SET-UP	VESSEL CONFIGURATION	FAILURE	SUCCESSIVE EVENTS	REFERENCE DOCUMENTS	DP-RI PREDICT	DP-RI PRESCRIBE	DPO ACTION
ACTUAL VESSEL	4 Generators Online 4 Generators Standby 4 Thrusters Online 4 Thrusters Standby 3 Gyros, 3 MRU and 2 Wind Sensors Online 4 DGNSS, 1 HPR and 1 taut wire Online. 1 Laser system standby Wind Speed = 16 Knots (233°) Current Speed = 31.2 Knots (12°) Wave Height = 2.2 metre Visibility = Good	DG8 failure	**EVENT1:** DG8 failure and Thruster T1, T2, T3 & T 4 tripped.	Site Specific documents. FMEA and Operation Manual.			Refer to procedure and stop drilling operation
			EVENT 2: Drilling Stopped and vessel drifted	Alarm in DP control System. Site specific documents.			Refer to alarms and check for appropriate steps in DP operation manuals.
			EVENT 3: Vessel excursion leading to LOP1	Knowledge of the DPO.			Visual Identification and DPO intervention after actual incident.
SET-UP FOR DP-RI	4 Generators Online 4 Generators Standby 4 Thrusters Online 4 Thrusters Standby 3 Gyros, 3 MRU and 2 Wind Sensors Online 4 DGNSS, 1 HPR and 1 taut wire Online. 1 Laser system standby Wind Speed = 16 Knots (233°) Current Speed = 31.2 Knots (12°) Wave Height = 2.2 metre	DG 8 failure	**EVENT1:** DG8 failure and Thruster T1, T2, T3 & T 4 tripped.		The reliability of the Power System 50% and Thruster System as 0%. The overall DP reliability is 68%.	Prescribes the possible suggestion 1. Change to "Open" bus and Isolate DG 8 2. Start standby thrusters	DPO follows the suggestion and changes configuration to "OPEN" bus.
			EVENT 2: Drilling stopped and vessel excursion leading to LOP 2		The overall DP reliability is 68%.	Prescribes possible suggestions 1. Set auto for DGs and Thrusters 2. Rectify failures	Troubleshoot DG8 and rectify failures with T1, T2, T3 and T4 if any.
			EVENT 3: Vessel – Safe State Drilling Resumed		The reliability of the overall DP system is 100%.	No suggestion when no failures in the system.	DPO performs normal monitoring duty during the operation.

System (A3) are online and connected. The failure in one generator DG8 tripped four thrusters (T1, T2, T3, and T4), and the vessel was drifted from the set-position leading to a significant loss of position resulting in the DP incident (LOP 1). The DPO was not expecting multiple failures, and the time to prevent it was minimal, which led to stopping drilling operation.

The experimentation simulation of the scenario in the DP-RI tool was similar for the initial events as the multiple failures were instantaneous. When a failure was simulated in DG8 which tripped thrusters T1, T2, T3, T4, the DP-RI tool predicted reliability of the Power System (A4) as 75% and the Thruster System (A3) as 0%. This resulted in the overall reliability of the DP vessel prediction as 68%. The vessel started drifting, and the drilling operation stopped. The DP-RI tool prescribed possible suggestions as to create the remaining thrusters and isolate DG8 by arranging the system configuration to the "OPEN" bus. However, in the meantime, the vessel drifted from set-position / heading, which led to a minor loss of position leading to the DP undesired event (LOP 2). The DPO was able to take the necessary action in time, however, could not prevent LOP 2 as this failure was the result of multiple failures (two losses in two different sub-systems instantaneously). By proper action from the DPO based on the DP-RI tool suggestion, LOP 1 was prevented, and the DPO was able to bring the vessel back to operate with the reliability of the overall DP vessel at 100% with minimum downtime.

Failure in sub-systems:
Power System (A4) → Primary cause
Thruster System (A3) → Secondary cause

Actual Vessel Final Event:
DP Incident (LOP 1)

Experimental Set-Up (DP-RI) Final Event:
DP undesired event (LOP2) and Vessel to a safe state.

Risk Studies and documents used for verification and validation:

- DP Capability Plots
- DP simulator and FMEA report
- Site-Specific Risk Analysis
- DP operation Manual
- Investigation reports

Conclusion – Verification and Validation:
The DP-RI tool was able to perform well even when multiple failures happened in the system instantaneously. During the analysis, it revealed that initial losses in the Power System (A4) and the Thruster System (A3) had reduced the reliability of the overall DP system to 68% resulting in the minor loss of position (LOP 2). However, in the actual vessel, the result was a significant loss of position (LOP 1). Thus, for this specific case, the DPO was provided with possible suggestions promptly to take preventive action without Human/operator error (A7) acting as another layer of failure. Therefore, the DP-RI prevented the DP incident and reduced downtime by a considerable amount.

Case Study 4:
IMCA Dynamic Positioning Station Keeping Review DPSI 27 -2016 (ID 1665).

Description of the Case study and detailed analysis of simulation:
Case study 4 was extracted from the DP review document reported in 2016. The reported accident, ID 1665, resulted in a DP incident (LOP 1) on the actual vessel. Table 8-6 shows the comparison of the vessel set-up, failure in the sub-system, and successive events between an actual scenario and the numerical simulations on the DP-RI tool. In this case study, failure happens in the DGNSS due to loss/interruption of signal from the satellite. It leads to the loss of the DGNSS signal to the DP control system. The failure in Reference System (A1) was considered as the primary cause and the Human / Operator error (A7) as a secondary cause. The DPO was tired due to working long hours, which is considered as a reduced capability to perform the duty resulting in an error in the sub-system. The vessel is DP 2 class with System A, System B, and System C connected in an open bus with three generators online and three generators on standby. Three thrusters in the Thruster System (A3) are online, and three thrusters on standby. The failure of the DP control system led the thrusters to react erratically, and the vessel started drifting away from the set position. The DPO did not have sufficient time to prevent the subsequent event as there was no readily available solution from the current system set-up. The final event was a significant loss of position resulting in a DP incident (LOP 1) with the vessel drifting 400 m from the set position.

The experimental simulation of the ID 1665 scenario in the DP-RI tool showed different results for the final event, although the vessel experienced a minor loss of position.

Table 8-6 Case Study 4 - Actual and Experimental results summary

VESSEL SET-UP	VESSEL CONFIG	FAILURE	SUCCESSIVE EVENTS	REFERENCE DOCUMENTS	DP-RI PREDICT	DP-RI PRESCRIBE	DPO ACTION
ACTUAL VESSEL	3 Generators Online 3 Generators Standby 3 Thrusters Online 3 Thrusters Standby 3 Gyros, 2 MRU and 2 Wind Sensors Online 2 DGNSS, 1 laser system and 1 radar system Online Wind Speed = 10 Knots (250º) Current Speed = 0.8 Knots (285º) Wave Height = 1 metre	DGNSS signal lost. Interruptions in the service	**EVENT1:** DGNSS signal loss. Vessel stopped operation.	Site Specific documents. FMEA and Operation Manual.			Refer to system and procedure to stop operation
			EVENT 2: DP control system lost signal and started drifting	Alarm in DP control System. Site specific documents.			Refer to alarms and check for appropriate steps in DP operation manuals.
			EVENT 3: Vessel drifted 400m on DP leading to LOP 1.	Knowledge of the DPO.			Visual Identification and DPO intervention after actual incident.
SET-UP FOR DP-RI	3 Generators Online 3 Generators Standby 3 Thrusters Online 3 Thrusters Standby 3 Gyros, 2 MRU and 2 Wind Sensors Online 2 DGNSS, 1 laser and 1 radar system Online Wind Speed = 10 Knots (250º) Current Speed = 0.8 Knots (285º) Wave Height = 1 metre	DGNSS signal lost. Interruptions in the service	**EVENT1:** DGNSS signal loss. Vessel stopped operation.		The reliability of the Reference System predicted ad 75%. The overall DP reliability is 72%.	Prescribes the possible suggestion 1. Change to other satellite signal 2. Set manual value to DP control	DPO follows the suggestion and changes the satellite signal and manual value in DP control for model to operate.
			EVENT 2: Manual Operation to bring vessel to set position		Due to shift change the operator error predicted as 25% The overall DP reliability is 54%.	Prescribes possible suggestions 1. DPO SA to be increased by changing shift earlier 2. Rectify failures	DPO shift change and fix DGNSS issue
			EVENT 3: Vessel – Safe State Operation resumed		The reliability of the overall DP system is 100%.	No suggestion when no failures in the system.	DPO performs normal monitoring duty during the operation.

When the failure in the Reference System (A1) was simulated, the DP-RI tool predicted the reliability of A1 as 75% and the overall reliability of the DP vessel as 72%. The DP-RI tool prescribes the possible solution as to change the satellite signal due to interruption in the DGNSS or set the manual value in the DP control system to ensure that the model performs the allocation algorithm to keep the vessel in set-position. As it was a long shift for the DPO, the fatigue was taken into account. The DP-RI tool predicted the reliability of human/operator error (A7) as 25% and the overall reliability as 54%. The tool has provided a suggestion to change the shift of the DPO in duty. The new DPO rectified the failure with the DGNSS to ensure that the vessel is safe, and the overall reliability of the DP vessel is returned to 100%.

Failure in sub-systems:
Reference System (A1) → Primary cause
Human / Operator Error (A7) → Secondary cause

Actual Vessel Final Event:
DP Incident (LOP 1)

Experimental Set-Up (DP-RI) Final Event:
DP undesired event (LOP2) and Vessel to safe state.

Risk Studies and documents used for verification and validation:

- DP operation Manual
- DP Capability Plots
- Site-Specific Risk Analysis

Conclusion - Verification, and Validation:
The DP-RI tool was able to predict the reliability of failures in the sub-system and the human error effectively and advise on the allocation of the right resource to execute the operation efficiently. During the analysis, it revealed that initial failures in the Reference System (A1) and the Human / Operator error (A7) had reduced the reliability of the overall DP system to 54% with the vessel still in position compared to the actual vessel, which resulted in a significant loss of position (LOP 1). Thus, for this specific case, the DPO was provided with possible suggestions promptly to take preventive action without Human/operator error (A7) acting as another layer of failure. Based on the swift action from the DPO, the DP incident was prevented, and the vessel was able to perform its operation without any interruption.

8.8 Verification and Validation - Hypothetical Case Studies from FMEA and Test Procedures

Case studies (5-8) are extracted from FMEA reports with a common cause failure (CCF) identified as low probability and high consequences. The proving trial procedures were used as a reference to build the case study descriptions for simulation in the DP-RI tool. The flowchart in Figure 8-5 provides a better understanding of the case studies.

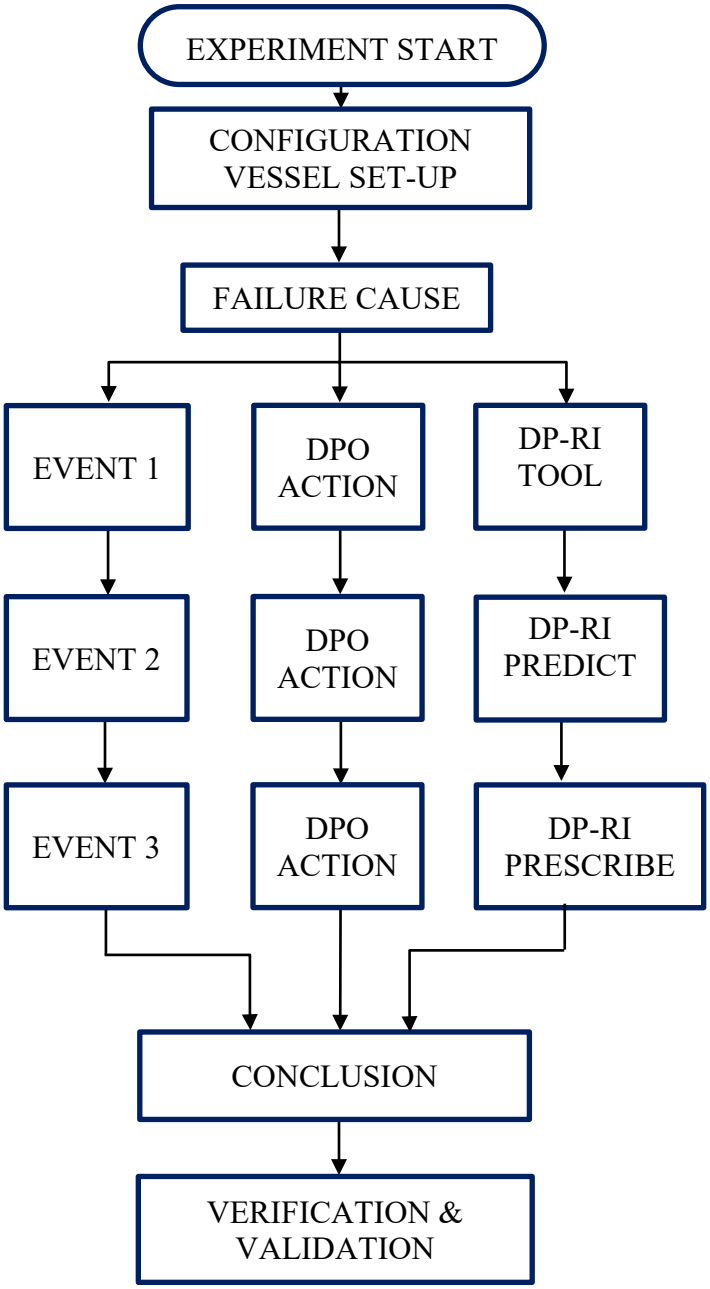


Figure 8-5 Semi-Submersible Drilling Rig Configuration for DP-RI experiment

Case Study 5:
Multiple failures due to CCF– From FMEA and SAT Procedure

Description of the Case study and detailed analysis of simulation:
The experimental simulation of the hypothetical scenarios was executed on the DP-RI to evaluate its performance when such failures occur during operational scenarios. As shown in Table 8-7, when there are multiple failures due to CCF, it affects two systems out of three. The first CCF affects the information related to Power Generation and the Power Management System (PMS), and complete control is lost on System A. At this point, the DP-RI tool predicts the reliability of the power system (A4) as 66.66% and the reliability of the overall DP-system as 82% indicating that the vessel can maintain its position with systems B and C online. DP-RI prescribes possible solutions to the DPO to take appropriate action to fix the system A failure. The prescribed suggestions are as follows:

1. Fix one network (A or B) to the field station/cabinets.
2. CCF leading to power supply failure, so isolate power at the power source or field stations.
3. Power supply modules interface, which could lead to CCF.
4. Restore system A through by-pass.

The DPO could select one of the possible suggestions and implement it to see whether the failure is fixed, and system A is restored. If one suggestion does not solve it, then the next could be tried to resolve the issue. As all the possible failures are shown, the DPO could react quickly and bring the vessel to regular operation by addressing the CCF in the power system.

In the meantime, another failure happens in the thruster system (A3) in system B. The DP-RI tool predicts the reliability of the thruster system (A3) as 66% and the overall reliability of the DP system as 64%. Now the DP vessel's overall reliability to maintain its position is “Medium,” and the vessel may start losing its position. DP-RI prescribes the following possible solutions to the DPO to take appropriate action to fix the system B failure.

1. Check for fire/flood in the pump room where thruster cabinets are located.
2. Fix one network (A or B) to the field station/cabinets.
3. CCF leading to power supply failure, so isolate power at the power source or field stations.
4. Power supply modules interface, which could lead to CCF.
5. Restore system A through by-pass.

Table 8-7 Case Study 5 - Hypothetical Experiment results summary

VESSEL SET-UP	VESSEL CONFIG	FAILURE CAUSE	SUCCESSIVE EVENTS	DP-RI PREDICT	DP-RI PRESCRIBE	DPO ACTIONS
SET-UP FOR DP-RI (DP-3) DRILLSHIP	3 Generators Online 3 Generators Stand-by 3 Thrusters Online 3 Thrusters Standby 3 Gyros, 3 MRU and 2 Wind Sensors Online 2 DGNSS and 2 HPR Online Wind Speed = 23 Knots (143°) Current Speed = 3.9 Knots (217°)	CCF lead to failure of power supply to controller and cabinet failure of power management (System A) and CCF failure of power supply to Thruster System (System C)	**EVENT1:** System A is lost and unable to monitor and control power system of group A.	The reliability of the Power system is predicted as 66.66%. The Overall DP system is 80% reliable	Prescribes the possible suggestions. 1. System B and System C able to maintain the position. 2. Rectify one net on System A. 3. Fix CCF and restore System A.	DPO follows the suggestion 1. Based on investigation, the vessel cannot maintain position. 2. Net A is fixed; one power supply is restored. 3. CCF found, and the system restored
			EVENT 2: System B is lost and unable to monitor and control thruster system in group B.	The reliability of the Thruster System is predicted as 33.33%. The Overall DP system is 64% reliable The reliability of the power system jumps to 66.66% as the failure with system A is fixed. The Overall DP system is 82% reliable	Prescribes the possible suggestions. 1. System A and System C able to maintain the position. 2. Rectify one net on System B. 3. Fix CCF and restore System B.	DPO follows the suggestion 1. Based on investigation, the vessel cannot maintain position. 2. One power supply was restored. System B online. 3. CCF found, and the system restored Meantime, System A comes online, and reliability increases to 66.66%
			EVENT 3: Vessel – Safe State Drilling Resumed	Reliability is 100%	No suggestion when no failures in the system.	DPO ensures both System A and System B is back in operation. The reliability of the DP system is 100%, so he continues the normal duty during the drilling operation.

As the error in the power system (A3) of system A was fixed during this time, the overall reliability of the DP system predicted as 82%. The DPO could select one of the possible suggestions and implement it to see whether the failure is fixed, and system B is restored. The error in the thruster system (A3) of system B could be fixed as the DPO could react quickly and bring the vessel back to regular operation by addressing the CCF in the thruster system in system B. The DP-RI tool predicts the reliability of the thruster system (A3) as 100% and the overall reliability DP system as 100%.

Such hypothetical scenarios have a low probability of occurrence and high consequences. Based on experience sharing sessions with Operators, Oil companies, independent consultants, and the DPO informed during similar situations in offshore it resulted in DP incident (LOP1) and operation was stopped. This was because there was a limited time for the DPO to react and fix the issue. However, with the advancement in technology, implementation of the DP-RI tool interfacing with the DP control system would be a much more efficient way of operating DP vessels offshore for complex operations.

Failure in sub-systems:
Power System (A4) → Primary cause
Propulsion System (A3) → Secondary cause

Risk Studies and documents used for verification and validation:

- FMEA results
- DP Capability Plots
- Site-Specific Risk Analysis

Conclusion – Verification, and Validation:
The DP-RI tool was able to bring together the best of different studies and present it instantaneously to the DPO with a possible suggestion to select and implement. The DPO would have found the solutions to address the problem without the DP-RI tool. However, it would have taken a long time. With multiple failure scenarios, it would most probably have led to a DP incident and resulted in the loss of position/property damage / environmental spill/downtime. The DP-RI tool predicted an accurate reliability value and prescribed suggestions for the DPO to react quickly, preventing a DP incident.

Case Study 6:
Multiple failures with Reference System and DP Control System– From DP capability Plot and DP proving trial test

Description of the Case study and detailed analysis of simulation:
The experimental simulation of the hypothetical scenario was simulated, as shown in Table 8-8. The failure was simulated in the DGNSS signal through power failure, and the signal to the DP control system was lost. At this point, the DP-RI tool predicts the reliability of the Reference System (A1) as 75% and the reliability of the overall DP-system as 83%, indicating that the vessel can maintain its position. DP-RI prescribes possible solutions to the DPO to take appropriate action to fix the system A failure. The prescribed suggestions are as follows:

1. Satellite signal needs to be corrected
2. Another reference signal can be used as a precision signal
3. Manual value can be set in the system

The DPO could select one of the possible suggestions and implement it to see whether the failure is fixed. If one suggestion does not solve it, then the next could be tried to fix the issue. As all the possible losses are shown, the DPO could react quickly and bring the vessel to regular operation by addressing the right failure.

In the meantime, another failure is simulated in the DP control system through loss of model reference. The DP-RI tool predicts the reliability of the DP control system(A3) as 25% and the overall reliability of the DP system as 40%. Now the DP vessel's overall reliability to maintain its position is “Low,” and the vessel may start losing its position. DP-RI prescribes the following possible solutions to the DPO to take appropriate action:

1. Use Back-Up DP control system
2. Set manual value if possible or change to other modes of operation

The DPO could select one of the possible suggestions and implement it to see whether the failure is fixed. The errors in the Reference system (A1) and the DP control system (A2) are fixed as the DPO could react quickly and bring the vessel to regular operation. The DP-RI tool predicts the reliability of the overall DP system as 100%.

Table 8-8 Case Study 6 - Hypothetical experiment results summary

VESSEL SET-UP	VESSEL CONFIG	FAILURE CASE	SUCCESSIVE EVENTS	DP-RI PREDICT	DP-RI PRESCRIBE	DPO ACTIONS
SET-UP FOR DP-RI (DP-3) Semi-submersible Heavy Lifting Crane Vessel	4 Generators Online 4 Generators Stand-by 4 Thrusters Online 4 Thrusters Standby 4 Gyros, 3 MRU and 4 Wind Sensors Online 2 DGNSS and 4 GPS, 2 HiPAP Online Wind Speed = 6 Knots 96°) Current Speed = 1.5 Knots (120°)	Reference System DGNSS power failure leading to loss of precision input resulting in vessel drifting.	**EVENT1:** DNGSS signal lost due to power failure	Reliability of Reference System (A1) predicted as 75% DP system is predicted as 83.33% reliable.	Prescribes the possible suggestions. 1. Satellite signal needs to be corrected 2. Other reference signal can be used as precision signal 3. Manual value can be set in the system	DPO follows the suggestion 1. Changes the reference to obtain precision 2. Forces the manual value to ensure DP control operates as intended
			EVENT 2: DP control system loss due to model reference failure leading to vessel drift	Reliability of DP control system (A2) is predicted as 25% DP system is predicted as 40% reliable.	Prescribes the possible suggestions. 1. Use Back-Up DP control system 2. Set manual value if possible or change to other modes of operation	DPO follows the suggestion 1. Based on suggestion the DP back-up control is used by DPO 2. If the back-up control also fails then the other possible modes of operation is chosen by the DPO to maintain the vessel in the set point (Position and Heading). The overall reliability of the DP system drop alarming the DPO for action.
			EVENT 3: Vessel – Safe State Due to appropriate action by the DPO	Reliability is 100%	No suggestion when no failures in the system.	DPO ensures multiple failures in Reference System (A1) and the DP control System (A2) are resolved on time ensuring that the vessel is in safe state to resume operation.

Failure in sub-systems:
Reference System (A1) → Primary cause

DP control system (A2) → Secondary cause

Risk Studies and documents used for verification and validation:

- DP Capability Plots
- Proving trial results
- Site-Specific Risk Analysis

Conclusion – Verification and Validation:
The DP-RI tool provided the appropriate solutions instantaneously to the DPO to take action and resolve the issue in the system. The failure, which would have resulted in the vessel experiencing a significant loss of position, was prevented with the help of DP-RI. The results are compared with the industry-proven risk studies such as CAMO and ASOG.

Case Study 7:
Multiple failures in different sub-systems – From FMEA and DP proving trial test

Description of the case study and detailed analysis of simulation:
The experimental simulation of the hypothetical scenarios was simulated, as shown in Table 8-9. The failure was simulated in the wind sensor signal through a power failure, which caused a communication failure from IAS to the DP control system. At this point, the DP-RI tool predicts the reliability of the Environmental System (A6) as 66.66% and the reliability of the overall DP-system as 86.66%, indicating that the vessel can maintain its position. DP-RI prescribes possible solutions to the DPO to take appropriate action to fix the system A failure. The prescribed suggestions are as follows:

1. Change to wind sensor signals from back-up DP control system
2. Isolate wind sensor 1 as it caused CCF of IO module
3. Fix CCF and restore the Main DP control system.

The DPO could select one of the possible suggestions for the initial failure and implement it to see whether the failure could be resolved. As all the possible suggestions are provided, the DPO could react quickly and bring the vessel to regular operation by addressing the leading cause for the event 1.

Table 8-9 Case Study 7- Hypothetical experiment results summary

VESSEL SET-UP	VESSEL CONFIG	FAILURE CASE	SUCCESSIVE EVENTS	DP-RI PREDICT	DP-RI PRESCRIBE	DPO ACTIONS
SET-UP FOR DP-RI (DP-2) PIPELAY VESSEL	3 Generators Online 2 Generators Stand-by 3 Thrusters Online 3 Thrusters Standby 3 Gyros, 3 MRU and 3 Wind Sensors Online 2 DGNSS and 1 HiPAP Wind Speed = 4 Knots (64°) Current Speed = 0.6 Knots (48°)	Wind Sensor failure in Environmental system leading to vessel drift.	**EVENT1:** Wind Sensor failure affect the vessel model information.	Reliability of environmental system (A6) predicted as 66.66%. The overall DP system is 86.66% reliable.	Prescribes the possible suggestions. 1. Wind sensor signals from back-up DP control system to be used 2. Isolate wind sensor 1 as it caused CCF of IO module 3. Fix CCF and restore Main DP control system.	DPO follows the suggestion 1. Based on investigation the vessel cannot maintain position. 2. Net A is fixed, one power supply restored. 3. CCF found and system restored
			EVENT 2: DP control lost and vessel start to drift. Operator involved in SIMOPS and lead to human error. The vessel drifted and let to LOP 2.	Reliability of DP control system (A2) predicted as 50% and the Human error (A7) as 50%. The overall DP system is 45.66% reliable.	Prescribes the possible suggestions. 1. Set to back-up DP control system 2. Perform shift change for the DPO 3. Take the DP to manual control if possible as per DP alert status	DPO follows the suggestion 1. Back-Up DP control system activated 2. Shift change performed with the new DPO on duty 3. The DPO has better decision making and situation Awareness. By this time the issue with the Reference System (A1), DP control System (A2) and Human error (A7) was fixed and DP reliability is 100%.
			EVENT 3: Vessel – Safe State Pipelay resumed after appropriate action from the DPO.	Reliability is 100%	No suggestion when no failures in the system.	DPO ensures all the system are without error and operating normal. The reliability of DP system is 100% so the DPO continues the normal duty during pipelay operation.

In the meantime, the failure causes loss of the IO module in the main DP control system leading to the unavailability of critical signals. The DPO capability for decision making and situation awareness reduces due to the end of the shift. The DP-RI tool predicts the reliability of the DP control system (A3) as 50% and Human / Operator error as 50%. Now the overall reliability of the DP system is 45.66%, the DP vessel's overall reliability to maintain its position is "Low", and the vessel may start to lose its position. DP-RI prescribes the following possible solutions to the DPO to take appropriate action:

1. Set to back-up DP control system
2. Perform shift change for the DPO
3. Take the DP to manual control if possible as per DP alert status

The DPO could select one of the possible suggestions and implement it to see whether the failure is resolved. The errors in the Environmental system (A6), the DP control system (A2), and the Human / Operator error (A7) are fixed as the DPO could react quickly and bring the vessel to a safe state. The DP-RI tool predicts the reliability of the overall DP system as 100%.

Failure in sub-systems:
Environment system (A6) → Primary cause
DP control system (A2) → Secondary cause
Human / Operator error (A7) → Indirect Secondary cause

Risk Studies and documents used for verification and validation:

- FMEA results
- Proving trial test procedure results
- DP simulator
- Site-Specific Risk Analysis

Conclusion – Verification and Validation:
The DP-RI tool was able to process the data continuously and instantaneously predict /prescribe the solution to the DPO. This enables the operators to focus on the issues correctly and promptly rather than checking the documents which would be time-consuming. More importantly, the differentiating factor the DP-RI tool is that for multiple failures, it provides solutions for the particular losses right way and prevents the failure leading to a DP incident.

Case Study 8:
Multiple failures due to CCF– From SAT, FMEA, and DP proving trial test procedure

Description of the case study and detailed analysis of simulation:
The experimental simulation of the hypothetical scenarios was executed, as shown in Table 8-10, with a sequence of failures simulated in different sub-systems. The first failure was simulated in SWBD B of the electrical system (A5) with loss of system B. At this point, the DP-RI tool predicts the reliability of the electrical system (A5) as 66.66%, and the reliability of the overall DP-system as 88% indicating that the vessel can maintain its position with systems A and C. DP-RI prescribes possible solutions to the DPO to take appropriate action to fix the system B failure. The prescribed suggestions are as follows:

1. Check System A and System C can maintain the position. If able to maintain within its capability start the necessary sub-system with System A and C.
2. Rectify the SWBD failure in System B
3. Ensure there is no CCF affecting other systems.

The DPO could select one of the possible suggestions and implement it to see whether the vessel able to main its position. If option 1 is not able to address the failure, then System B is restored. If one suggestion does not solve it, then the next could be tried to fix the issue. As all the possible failures are shown, the DPO could react quickly and bring the vessel to regular operation by addressing the loss in system B.

In the meantime, another failure was simulated in one of the direct factor parameters as shown in Figure 4-11, for the human/operator error (A7) sub-system affecting the performance of the overall DP vessel. This failure was simulated without clearing the loss in system B. The DP-RI tool predicts the reliability of the human / operator error (A7) as 25% and the overall reliability of the DP system as 68%. Now the DP vessel's overall reliability to maintain its position is “Medium,” and the vessel may start to lose its position. DP-RI prescribes the following possible solutions to the DPO to take appropriate action to fix the system B failure.

1. Change the shift of the DPO
2. Operate the vessel with maximum redundancy to ensure failure consequences are addressed through mitigation action
3. Ensure that system B is restored

Table 8-10 Case Study 8 - Hypothetical experiment results summary

VESSEL SET-UP	VESSEL CONFIG	FAILURE CASE	SUCCESSIVE EVENTS	DP-RI PREDICT	DP-RI PRESCRIBE	DPO ACTIONS
SET-UP FOR DP-RI (DP-3) DIVING VESSEL	3 Generators Online 3 Generators Stand-by 3 Thrusters Online 3 Thrusters Standby 3 Gyros, 3 MRU and 3 Wind Sensors Online 2 DGNSS and 3 GPS, 2 HiPAP Online Wind Speed = 2 Knots 30°) Current Speed = 0.5 Knots (45°)	Loss of System B due to SWBD failure.	**EVENT1:** SWBD B failure and system B loss.	Reliability of Power system (A3) is predicted as 66.66%. The overall DP system is 88% reliable.	Prescribes the possible suggestions. 1. Check System A and System C able to maintain the position. 2. Rectify the SWBD failure 3. Ensure there is no CCF affecting other systems.	DPO follows the suggestion 1. Confirms that System A and C can hold the set position. 2. SWB B was restored. 3. No CCF found and system restored
			EVENT 2: Human error due to unfamiliarity leading to DP vessel start to drift from set position resulting.	Reliability of Human Error is predicted as 25%. The overall DP system is 68% reliable. Once the System B failure is fixed the overall DP system reliability jumps	Prescribes the possible suggestions. 1. Change the shift of the DPO 2. Ensure the system B is restored	DPO follows the suggestion 1. The DPO changes the shift 2. Able to resolve the failure on time and main the vessel in safe position. Meantime System B comes online, and reliability increases to 100%
			EVENT 3: Vessel – Safe State Due to appropriate action by the DPO	Reliability is 100%	No suggestion when no failures in the system.	DPO ensures that the System B is back online, and Human error is resolved. The reliability of DP system is 100% so the vessel continues normal operation.

As the error in the electrical system (A5) of system B was fixed during this time, the overall reliability of the DP system is 82%. The DPO could select one of the possible suggestions and implement it to see whether the failure is fixed, and system B is restored. The loss in human/operator error (A7) could be fixed as the DPO could react quickly and bring it to regular operation. The DP-RI tool predicts the overall reliability DP system as 100%.

Failure in sub-systems:
Electrical System (A5) → Primary cause
Human / Operator Error (A7) → Secondary cause

Risk Studies and documents used for verification and validation:

- SAT procedure
- FMEA results
- Proving trial test procedure results
- Site-Specific Risk Analysis

Conclusion – Verification and Validation:
The specific case scenario was tested with an intention to see how the human factor plays a critical role during a failure in a sub-system. In conclusion, the procedure without the DP-RI could have resulted in a DP incident (LOP 1). The reason would be that the failure on the SWBD B was dormant (unnoticed), and the DPO was alerted only when the consequence resulted. There are multiple failures for the DPO to react and fix it within a limited time. In this scenario, the reliability of the sub-system Human / Operator error is 25%, and failure cannot be fixed in the time leading to a DP incident. The DP-RI tool results were verified and validated against the SAT procedure and proving trial results. Additionally, there was more information readily available qualitatively and quantitatively for the DPO to decide on the next steps with ease.

8.9 Summary of Verification and Validation – Test Results

In addition to the case studies presented above, numerous tests were performed with the DP-RI tool. The actual case studies were extracted from the IMCA and WOAD databases. The results were verified and validated against the detailed report prepared for each incident by experts. Similarly, the hypothetical case studies are extracted from the FAT, CAT, DP

operation manuals, and Proving trial procedures. The results are verified and validated against the expected results of the methods. The DP-RI tool was tested with different cases to ensure that it could perform its function as intended. Different DP-classes, configurations, vessel types, system providers, and DPO experiences were considered, and analysis was performed to identify the gaps. Necessary functionalities were added to implement it on the operational vessel. A summary of the test results is presented in Table 8-11 shows the number of actual cases and hypothetical cases, along with the accuracy of prediction.

Table 8-11 Summary of results – DP-RI tool

Case Studies	No of Test	DP Class			Accuracy (%)	
		DP 3	DP 2	DP 1	Trained	New or Unknown
Actual Case	600	300	200	100	99%	89%
Hypothetical Case	2200	1300	750	150	100%	93%

From the experimental results, it was evident that the DP-RI tool was able to predict and prescribe possible suggestions even for new scenarios on which it had not been trained. If it was tested for a particular case similar to training, then the accuracy was 100% and matches the exact results of the reference documentation and industry experts. For all the case studies, the prescribed possible suggestion was evaluated with the existing risk studies, and it was verified to match the real solutions to be implemented in the case of failures. The time taken by the DPO for implementing the solution and prevent the accident has reduced by half (50%) with the DP-RI without any reduction in accuracy. In fact, the accuracy has increased as the numerous expert's input were taken into consideration from the database for suggesting possible solutions to the DPO. Thus, the DP-RI tool is a novel advisory tool for the DP vessel to predict the reliability of the DP system and assist DPO during complex operations.

9. Conclusions and Recommendations

9.1 Summary of Research

The overall aim of this research was to develop an intelligent, state-of-the-art decision-making tool using artificial intelligence and data analytics. The decision-making tool, DP-RI, will be used for the prediction of offline and real-time reliability of DP systems (Quantitative and Qualitative) through predictive analytics. The functionality of the DP-RI tool also suggests possible solutions to the DPO during any failure in the DP system through prescriptive analytics. This ensures that the DPO is in complete control and has a clear over-view during complex marine operations to prevent DP related accidents in the case of failures. Detailed analysis of the limitations and entanglements of existing risk assessments, safety studies, numerical methods, and simulations for the reliability assessment of DP systems are presented.

This research work meets the main aim and objectives through a systematic approach, which is presented in different chapters of the thesis. The research resulted in a universal database for the DP systems created using DP System Level FMEA, DP Vendor FMEA, HIL and OREDA. It also consists of IMCA Station Keeping Accident Analysis Reports, DP capability plots, and Site-Specific Operational Risk Analysis. The critical information is transformed into structured data from semi-structured and unstructured data. This is the first significant break-through achieved in the research, which facilitated in carrying out various analytics on the DP context. Descriptive and Diagnostic Analytics are implemented on the database to identify the correlation between different sub-systems with the DP system. A new classification of sub-systems is determined, which played a vital role in DP system functionality, and this classification was completed based on big data concepts. The sub-system inter-dependencies were presented, which were used in developing suggestive solutions, and to provide a clear overview for the DPO; the lack if this was one of the limitations of existing studies. AHP was used to determine the weighting of each sub-system and this was validated through LSTM. A holistic research framework using predictive analytics was proposed for offline and real-time prediction of the reliability of the DP system through the LSTM model. In addition, prescriptive analytics were applied through Natural Language Processing using BERT as Question and Answering model to provide the suggestive solutions to the DPO.

9.2 Achievements of the Research and Innovative Work

To summarise the key achievement and innovation of research are as follows:

- A new method of classification of the DP system was introduced, which identified all the critical sub-systems, and which is different from the traditional way. It was based on the IMS consisting of other databases through descriptive and diagnostic analytics of big data concepts.
- An intuitive and systematic approach was proposed for the weighting of the sub-systems using AHP through input from various industry experts involved in different phases of the DP system life-cycle. This was in-line with the IMCA guidance of involving other discipline leads and, at the same time, expanding the study from FMEA to much more diverse applications.
- For the first time, a novel research framework was developed based on predictive analytics using LSTM. This was implemented in predicting the offline and real-time reliability of DP systems (Quantitative and Qualitative). The results were compared with proven risk assessment methodologies.
- State-of-the-art prescriptive analytics using the BERT model was instigated by using the model as a Question and Answering system in generating possible solutions to the DPO during failures to prevent DP incidents. The prescriptive analytics is combined with the predictive analytics part to function as a unified approach in providing possible solutions along with the ranking for the DPO to choose the best one for any particular situation.
- Numerical experiments with an actual DP system architecture were created for the verification and validation of the DP-RI tool. The interface between different DP systems through other protocols are established to ensure system integration of the DP-RI tool with the actual system onboard the vessel. The case studies were developed from the existing records on the IMCA accident database and complicated situations to evaluate the robustness of the DP-RI tool.

9.3 Future Research Work

This thesis provides a novel research framework for the prediction of the reliability of the DP system through state-of-the-art RNN models using universal databases. However, the prediction is based on the dataset collected for the research through DNV GL and research partners. So, there is a need for fine-tuning of the models based on the actual real-time data from numerous vessels.

The recent digital transformation in the marine, oil, and gas industries has enabled companies to create a digital ecosystem for technology and infrastructure to share data and integrate with more partners (Vendors, Operators, Classification Societies, etc.). Thus, in a few years from now, the real-time data from vessels will be accessible for research to fine-tune the model and increase the robustness of the DP-RI tool.

The DP-RI tool results were verified and validated against the existing risk assessment methods and safety studies. The mathematical model for the reliability of sub-systems is developed using the RBD for a different configuration. Further, the overall reliability of the DP system is calculated through traditional assurance methods. However, in the future, the digital twin representation of the actual physical model will become the norm for sub-systems assurance. Currently, due to a lack of standardisation and unavailability of guidance for the digital twin, the research on DP-RI cannot include this part. In the future, researchers will be able to focus on integrating the digital twin with DP-RI from the design stage to ensure that the sub-system physical models are kept updated throughout the DP lifecycle. The integration will support in estimating the accuracy of the prediction and, at the same time, help the model to learn new scenarios more quickly.

With all the future research improvements, it would be possible to develop a more advanced state-of-the-art real-time DP-RI tool application. The predicted information from the DP-RI could be integrated into the DP control system to rapidly indicate the reliability value and provide possible solutions to the DPO when the failure occurs. Thus, the integration would support in improving the robustness and closed-loop performance of the DP system to provide practical solutions over time, in turn leading to autonomy.

APPENDIX I: QUESTIONNAIRE TEMPLATE

DNV·GL

QUESTIONNAIRE: DYNAMIC POSITIONING RELIABILITY INDEX

QN REFERENCE NO	**DP-RI-QN-0012**	**REV**	**00**
PARTICIPANT NAME	**Mr. STOKKE HENNING**	**DATE**	**01/03/2016**
PROFILE	**CAPTAIN WORKING FOR VESSEL OPERATOR WITH 15+ EXP**		
SELECTION OF SUB-SYSTEMS	**BASED ON THE 20 SUB-SYSTEM PROVIDED 7 TO BE FILLED**		

DP SYSTEM EXPERIENCE - PHASE :

DESIGN ☐ **CONSTRCUTION** ☐ **PROVING TRIAL** ☐ **OPERATION** ☐

SUB-SYSTEM DESCRIPTION	NUMBER	WEIGHTAGE	LIKERT RATING
REFERENCE SYSTEM	A1	20	1
DP CONTROL SYSTEM	A2	15	2
THRUSTER / PROP SYSTEM	A3	10	3
POWER SYSTEM	A4	10	3
ELECTRICAL SYSTEM	A5	05	5
ENVIRONMENT	A6	10	4
HUMAN ERROR	A7	30	1

NOTE: RELATIVE RATING BETWEEN THE SUB-SYSTEMS ARE USED FOR THE AHP

GOAL – SAFE AND REALIABLE DYNAMIC POSITIONING SYSTEM

GOALS ARE DEFINIED FOR THE BOUNDARIES TO DETERMINE THE CRITICAL SUB-SYSTEM FOR DP SYSTEM FUCNTIONALITY

CRITERIA

CRITERIA NAME	*INTER-DEPENDENCIES*	*CURRENT METHOD*
STATION KEEPING CAPABILITY		DP-CAP
PREVENT LOSS OF POSITION		FMEA AND DP SIM
PREVENT LOSS OF REDUNDANCY		FMEA AND VENDOR FD
DP MODE OF OPERATION		DP SYSTEM
PREVENT SOURCE OF ACCIDENTS		OPERATION MANUAL
DP CLASS OF OPERATION		DP SYSTEM

QUERIES TO THE RESEARCH GROUP FROM PARTICIPANTS

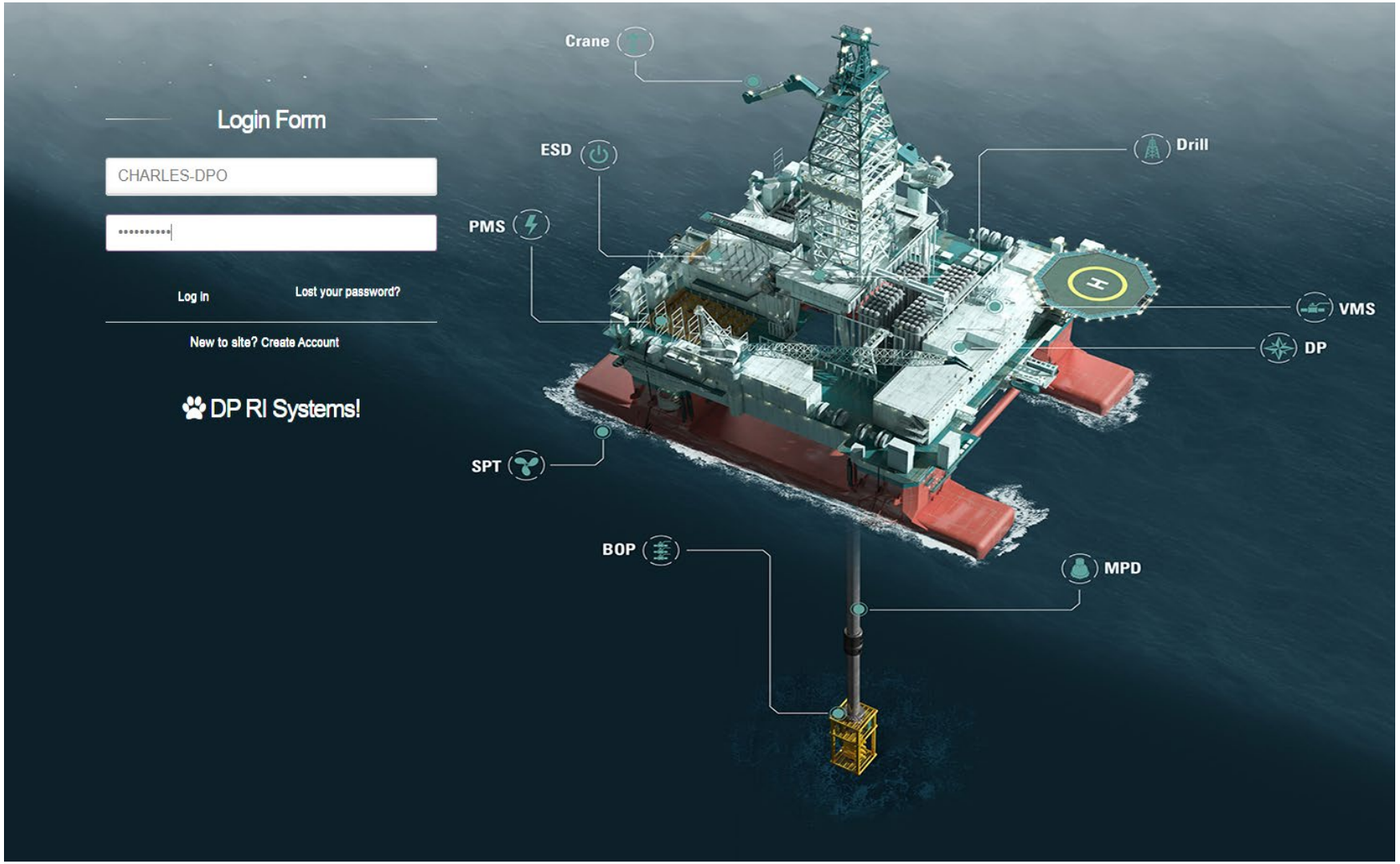
1.
2.
3.

REMARKS BY DNVGL BEFORE DATABASE UPDATE

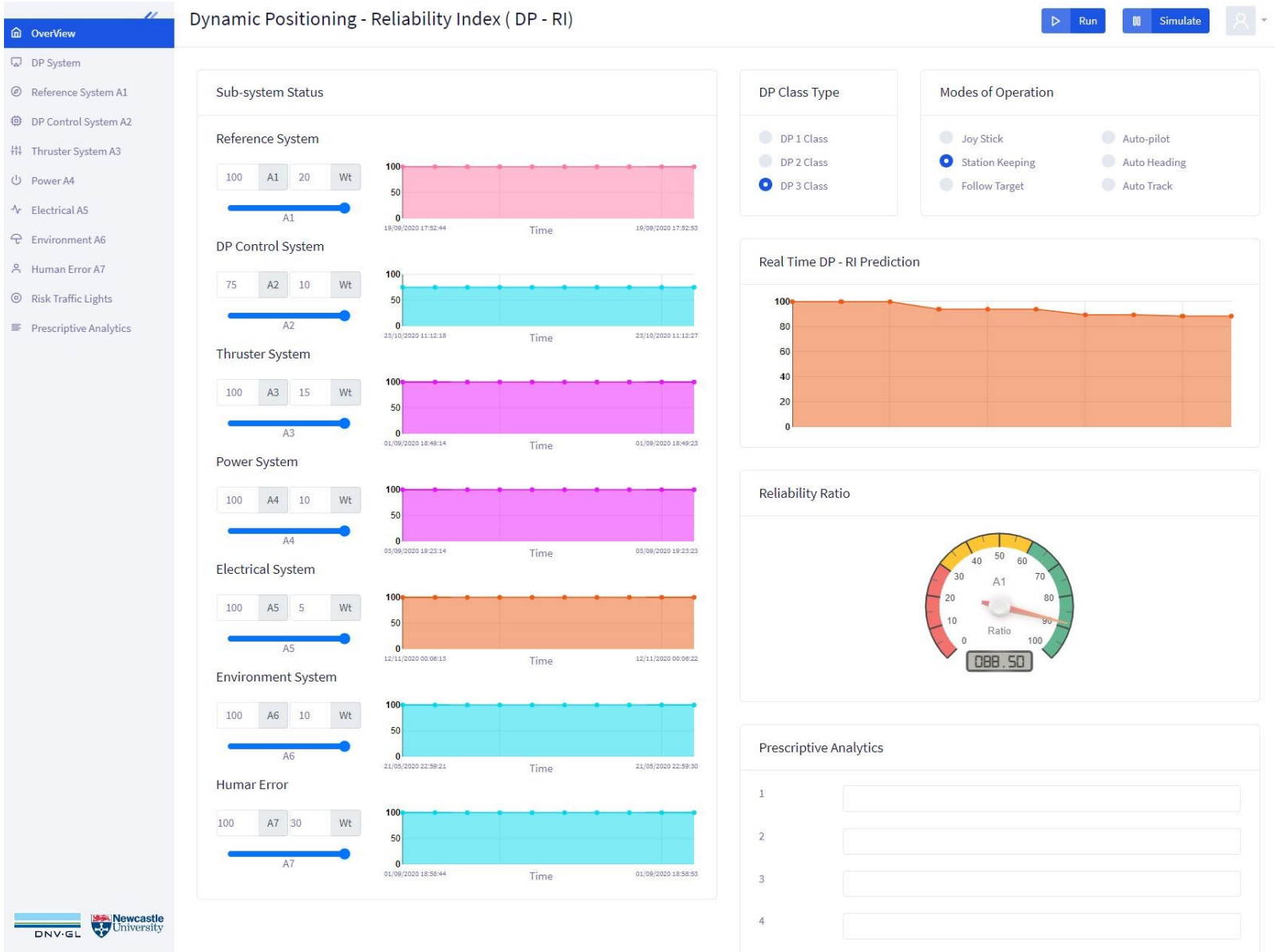
ISSUED BY	VERIFIED BY	REGISTERED BY
INTERN MULTIPLE STUDENTS DNV GL	RESEARCH STUDENT CHARLES FERNANDEZ DNV GL	SYSTEM ADMINISTRATOR IT CONSULTANTS DNV GL

APPENDIX II: VERIFICATION AND VALIDATION FOR DP-RI TOOL

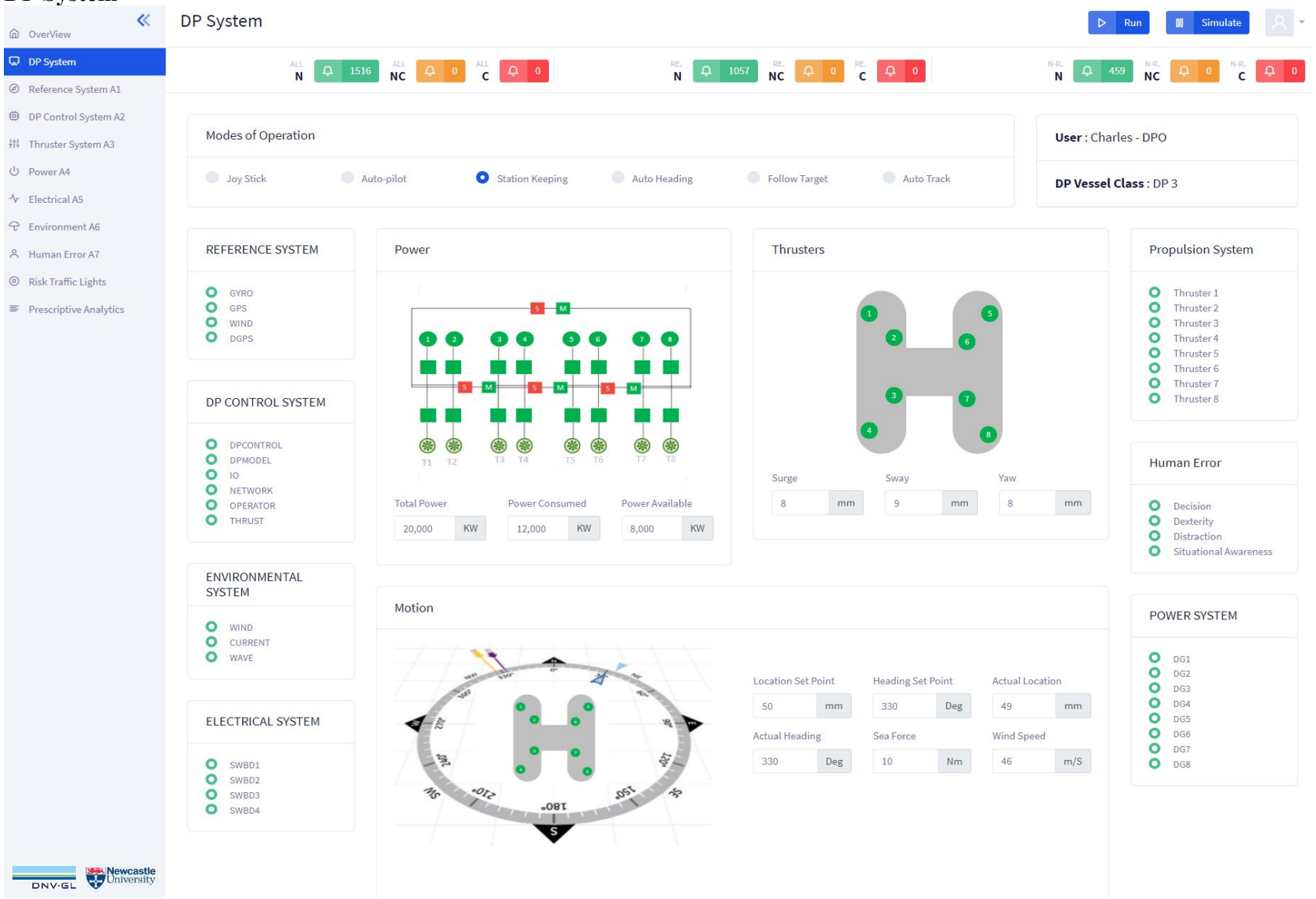
Case Study No. 1
Login Page: Credential to login to DP-RI Tool



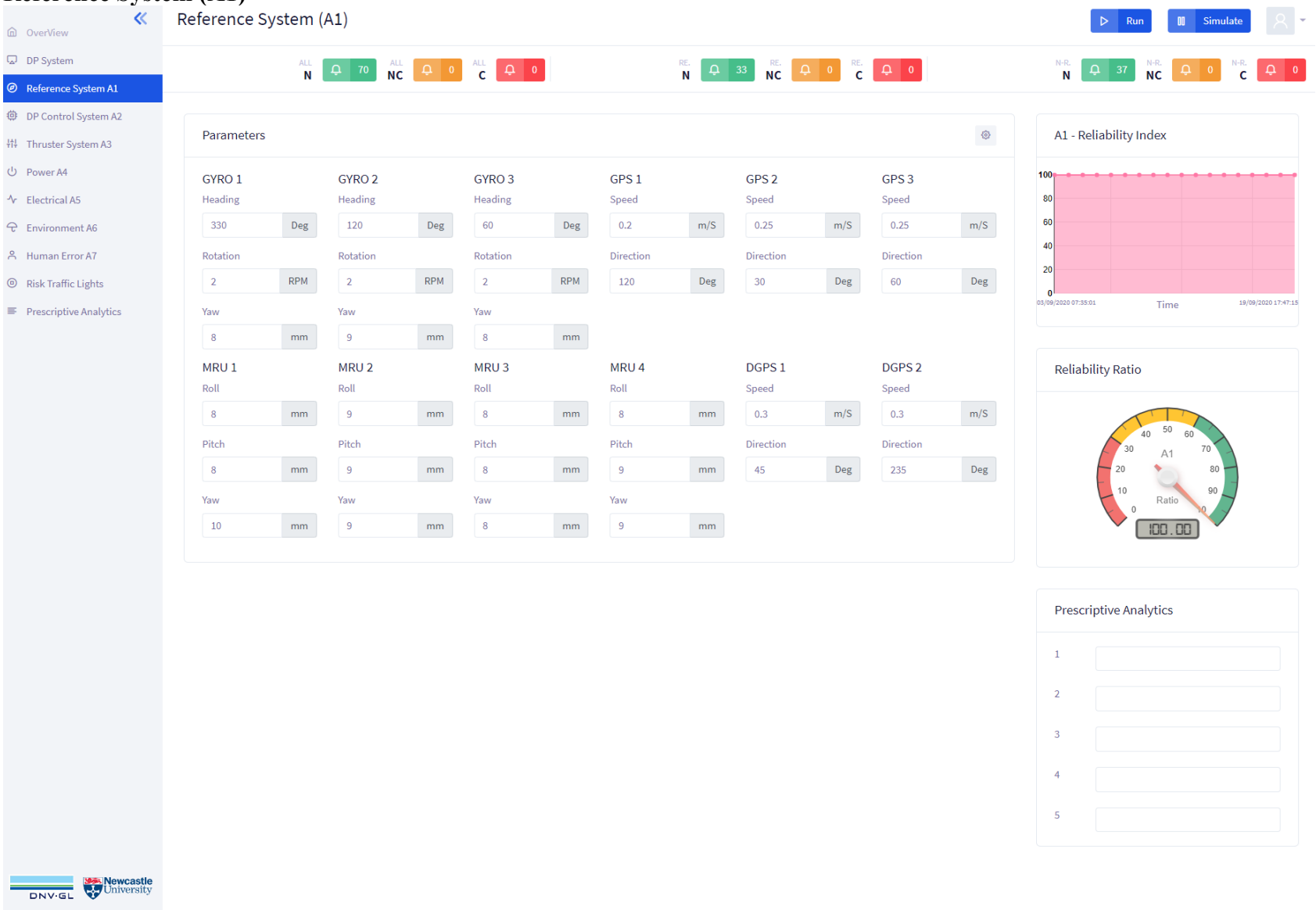
Overview Page


OverView
DP System
Reference System A1
DP Control System A2
Thruster System A3
Power A4
Electrical A5
Environment A6
Human Error A7
Risk Traffic Lights
Prescriptive Analytics
Dynamic Positioning - Reliability Index (DP - RI)
Run
Simulate
Sub-system Status
Reference System
100 A1 20 Wt
A1
DP Control System
75 A2 10 Wt
A2
Thruster System
100 A3 15 Wt
A3
Power System
100 A4 10 Wt
A4
Electrical System
100 A5 5 Wt
A5
Environment System
100 A6 10 Wt
A6
Humar Error
100 A7 30 Wt
A7
Time
DP Class Type
DP 1 Class
DP 2 Class
DP 3 Class
Modes of Operation
Joy Stick
Station Keeping
Follow Target
Auto-pilot
Auto Heading
Auto Track
Real Time DP - RI Prediction
Reliability Ratio
A1
Ratio
088.50
Prescriptive Analytics
1
2
3
4
DNV·GL
Newcastle University

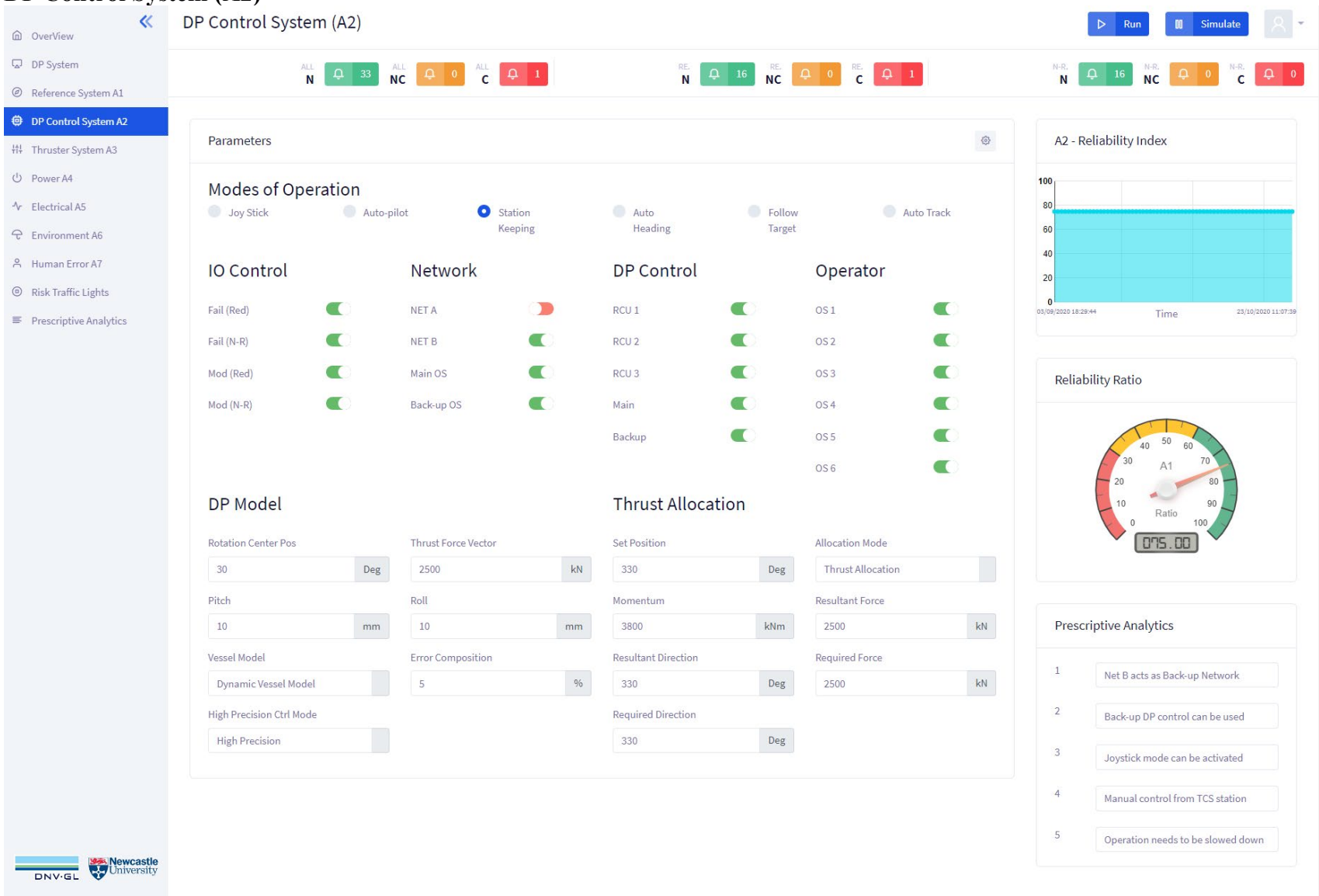
DP System


DP System
Run
Simulate
OverView
DP System
Reference System A1
DP Control System A2
Thruster System A3
Power A4
Electrical A5
Environment A6
Human Error A7
Risk Traffic Lights
Prescriptive Analytics
ALL N 1516
ALL NC 0
ALL C 0
RE. N 1057
RE. NC 0
RE. C 0
N-R. N 459
N-R. NC 0
N-R. C 0
Modes of Operation
Joy Stick
Auto-pilot
Station Keeping
Auto Heading
Follow Target
Auto Track
User : Charles - DPO
DP Vessel Class : DP 3
REFERENCE SYSTEM
GYRO
GPS
WIND
DGPS
DP CONTROL SYSTEM
DPCONTROL
DPMODEL
IO
NETWORK
OPERATOR
THRUST
ENVIRONMENTAL SYSTEM
WIND
CURRENT
WAVE
ELECTRICAL SYSTEM
SWBD1
SWBD2
SWBD3
SWBD4
Power
T1 T2 T3 T4 T5 T6 T7 T8
Total Power 20,000 KW
Power Consumed 12,000 KW
Power Available 8,000 KW
Thrusters
Surge 8 mm
Sway 9 mm
Yaw 8 mm
Propulsion System
Thruster 1
Thruster 2
Thruster 3
Thruster 4
Thruster 5
Thruster 6
Thruster 7
Thruster 8
Human Error
Decision
Dexterity
Distraction
Situational Awareness
Motion
Location Set Point 50 mm
Heading Set Point 330 Deg
Actual Location 49 mm
Actual Heading 330 Deg
Sea Force 10 Nm
Wind Speed 46 m/S
POWER SYSTEM
DG1
DG2
DG3
DG4
DG5
DG6
DG7
DG8
DNV·GL
Newcastle University

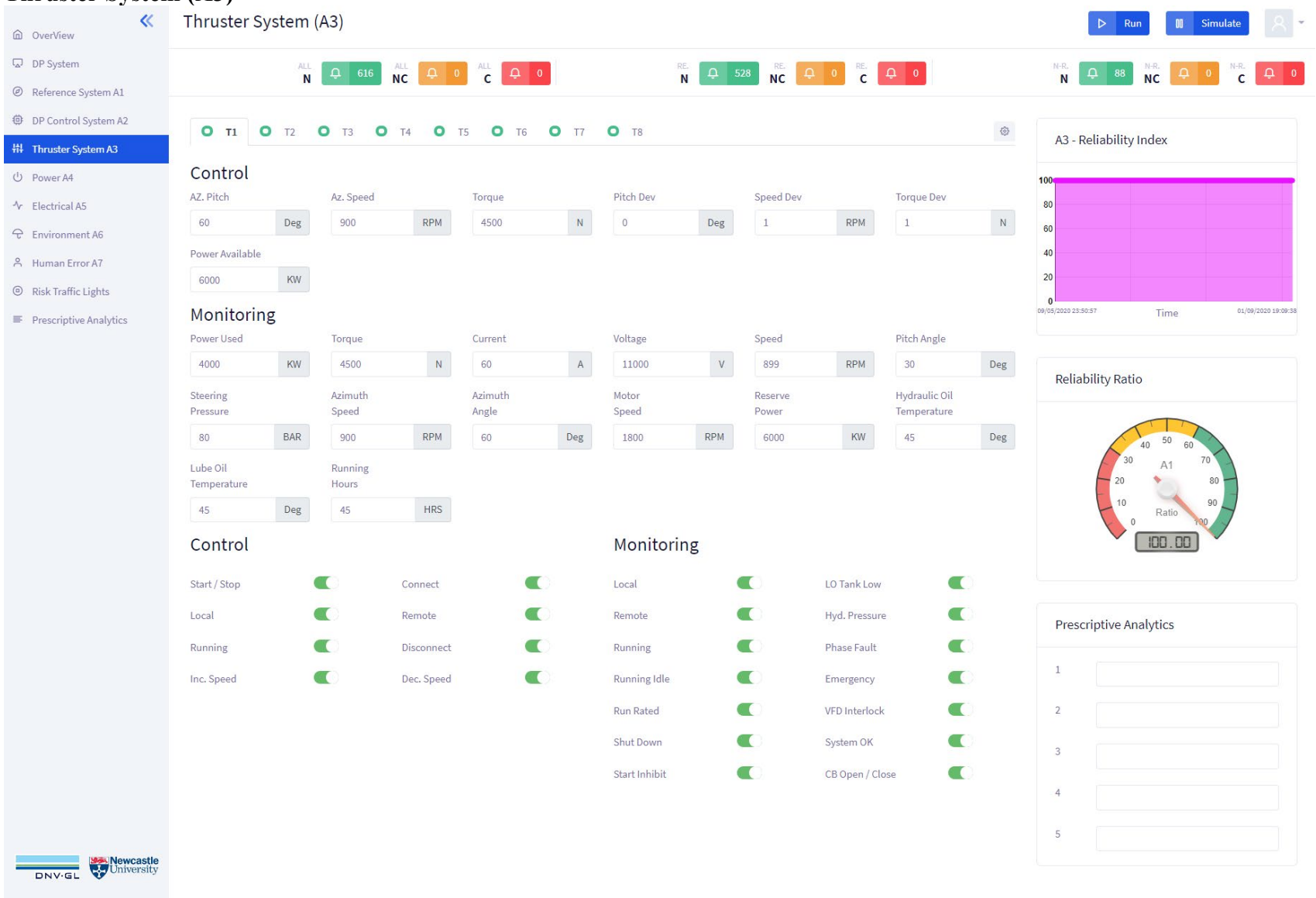
Reference System (A1)



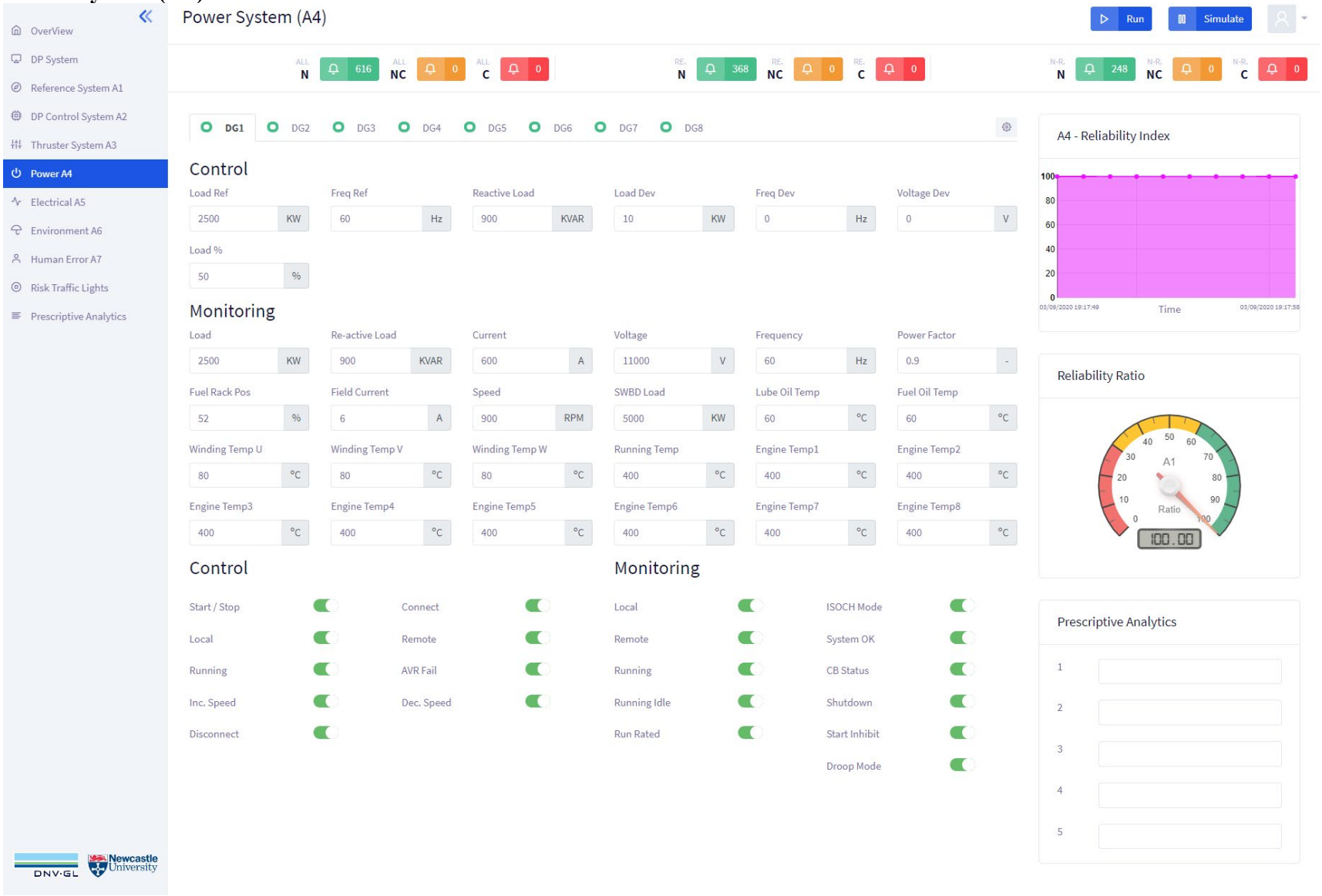
DP Control System (A2)



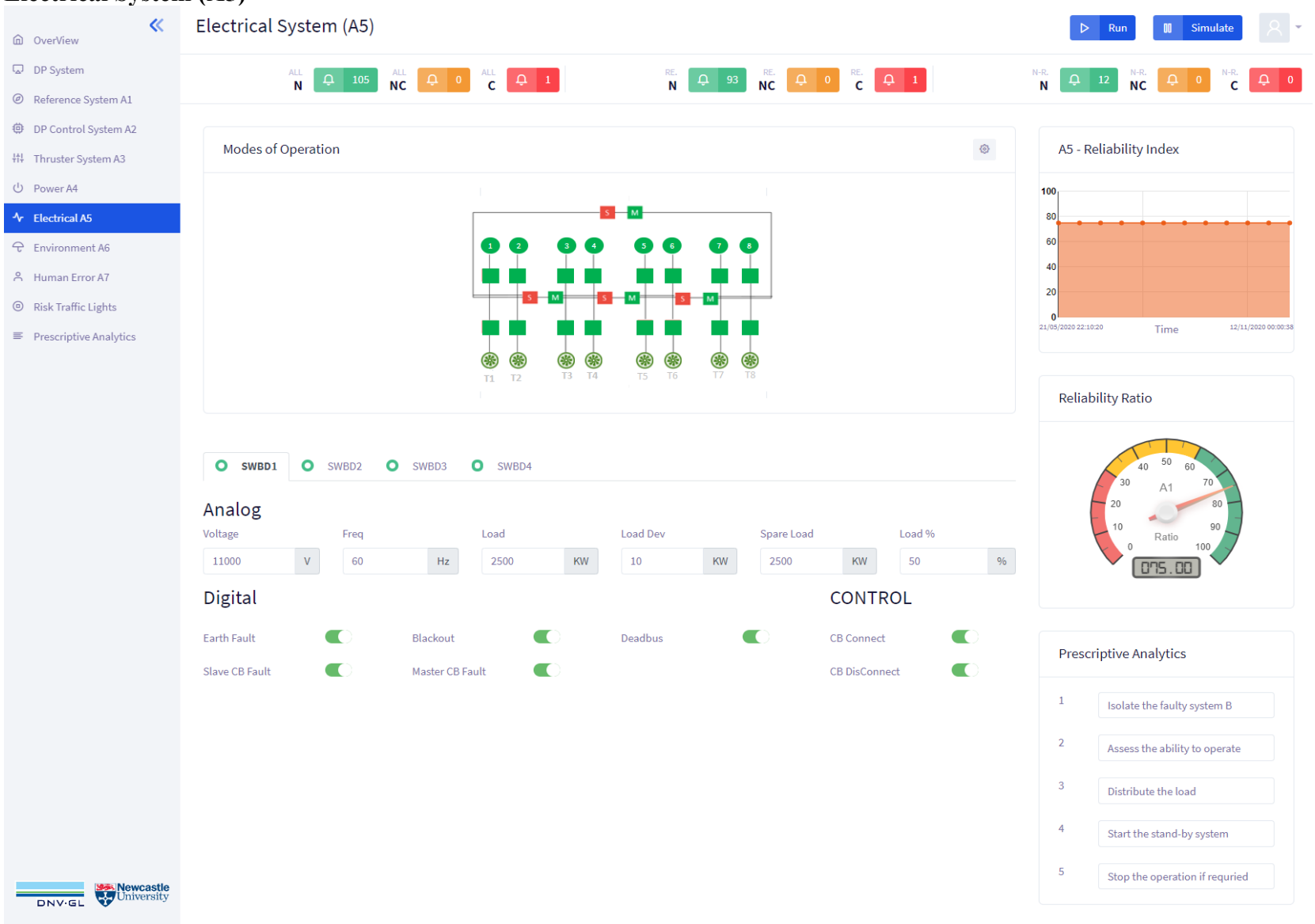
Thruster System (A3)



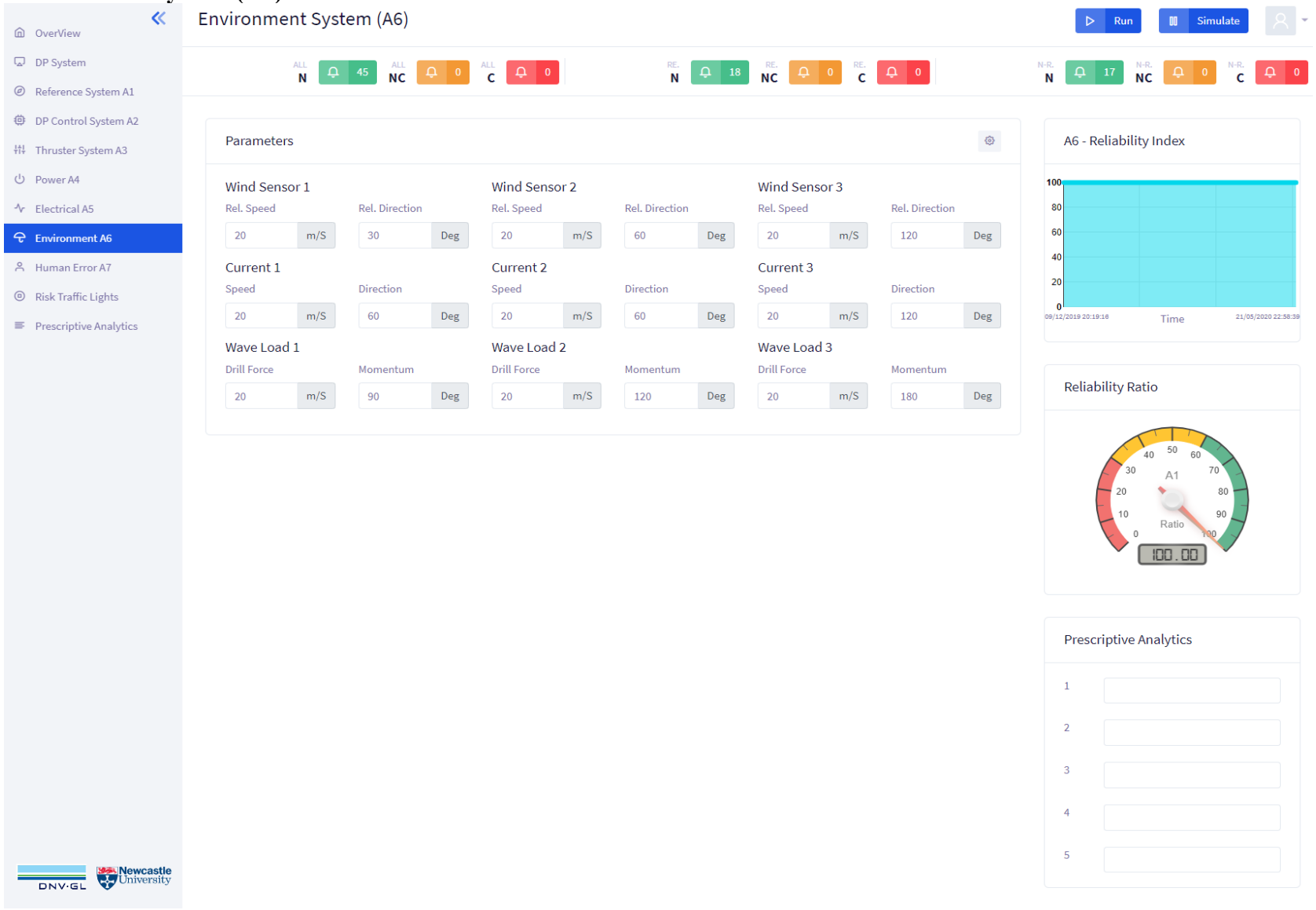
Power System (A4)



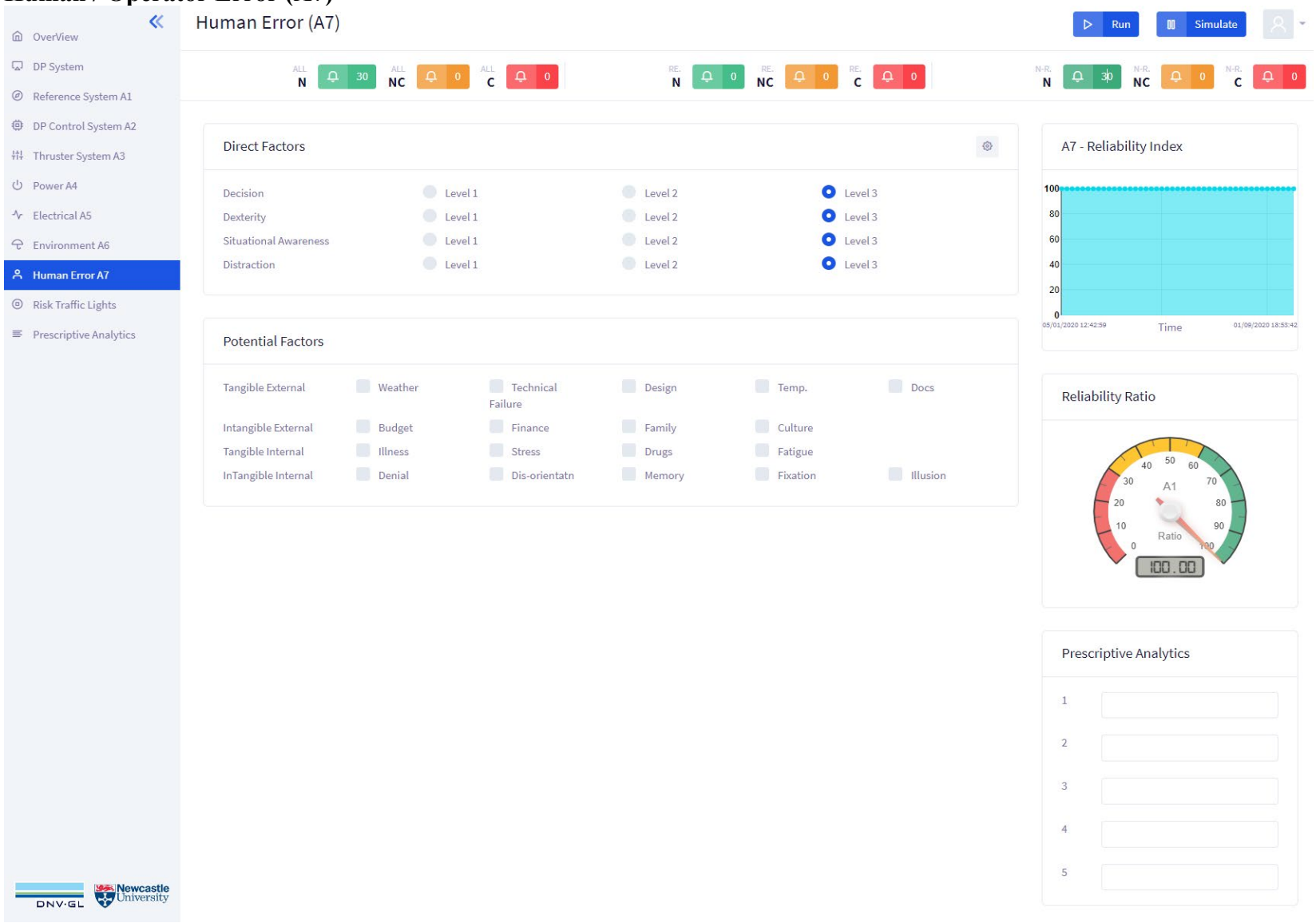
Electrical System (A5)



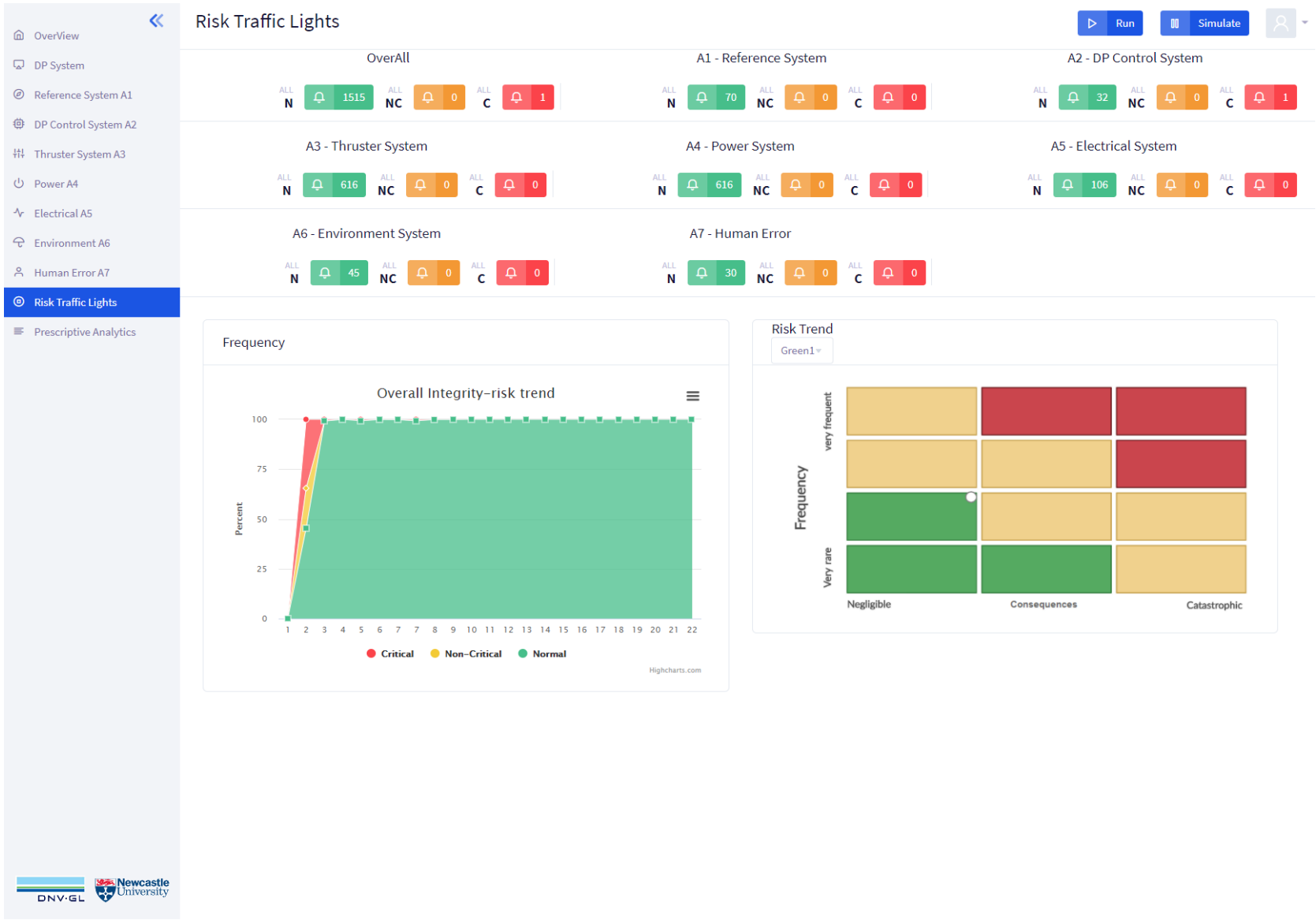
Environment System (A6)



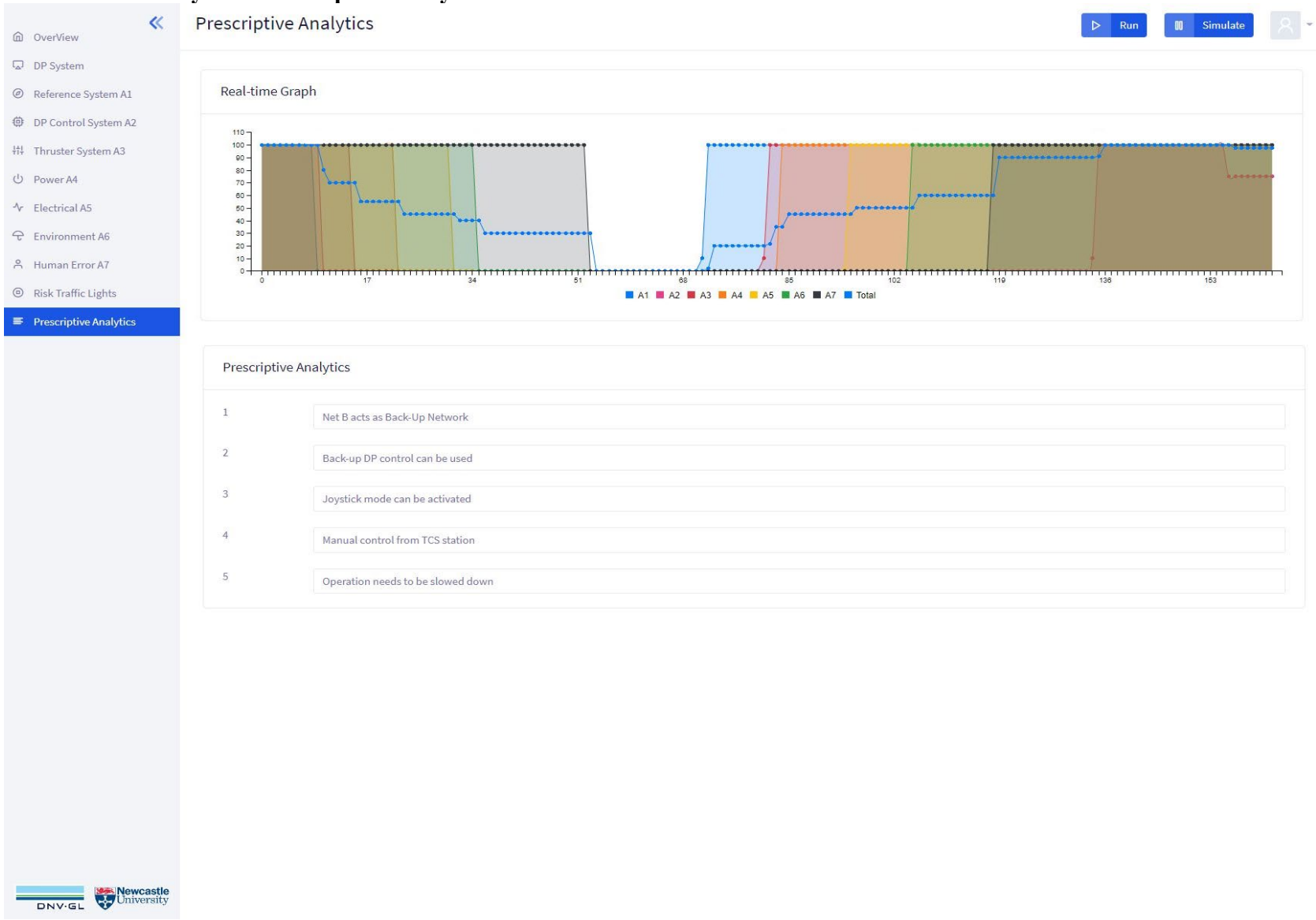
Human / Operator Error (A7)



Risk Profile



Overall Reliability and Prescriptive analytics



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