Optimisation of energy usage and carbon emissions for an advanced anaerobic digester plant

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Abstract

In this thesis Northumbrian Water Limited's (NWL) Advanced Anaerobic Digester (AAD) plant at Howdon was used to investigate modelling and optimisation opportunities based on energy prices, demands and their new greenhouse gas emissions pledge. It is believed this site is the first in the UK with a mixed operational strategy for biogas and biomethane produced on site: to burn in Combined Heat and Power (CHP) engines to create electricity, burn in Steam Boilers for onsite steam use or inject the biomethane into the national grid - Natural Gas can be imported to make up shortfalls in biomethane if required.

Initially, a realistic model for the gas distribution on site was developed using a novel mixed integer linear programming (MILP) approach. Retrospective Optimisation (RO) using historical plant data was performed, with results indicating the plant operated optimally within accepted tolerance 98% of the time. However, improving plant robustness (such as reducing unexpected breakdown incidents) could yield a significant increase in gas revenue of 7.8%.

Next, the gas distribution model is developed further as a realistic MILP model for energy and carbon management where operators are provided with a visual daily operational schedule based on varying tariffs. The results indicate that biomethane injection should be maximised for the highest financial gain, with the driving force for optimising the remaining operations being the site electricity demand and whether the electricity purchased from the grid generates carbon emissions, based on the new carbon performance commitment.

Using the developed energy and carbon model a sensitivity analysis was performed on electricity tariffs, natural gas prices, the volume of biogas production and the Biomethane Upgrade Plant (BUP) processing limits. The results reinforce the understanding that maximising biomethane injection into the national grid is the most cost-effective operational strategy. Second to this, the optimal operation of the CHP engines is subject to the available excess biogas available after BUP processing and the current daily energy prices. To ensure the site always maintains a positive revenue, operators should ensure that at least 20,000 Nm^3/day of raw biogas can be processed and injected into the national grid.

Finally, an investigation into the unique modelling problem regarding the three on site Anaerobic Digesters (ADs) was performed. A key parameter used in the current optimisation model is the amount of biogas that is produced on site each day, however currently an average daily value is used based on historical data. To improve the optimisation, it would be better to provide a more accurate prediction based on current state of the ADs and the expected sludge processing volumes into the ADs. The lack of individual gas flow data for each AD posed an interesting challenge in predicting the total biogas flow produced on site. Multiple linear models of the onsite AD's were investigated but were not accurate enough to be used on site. A NARX (Nonlinear autoregressive with external input) Neural Network was developed to model all three anaerobic digesters as a single process for the day ahead prediction of biogas production. The resulting optimal NARX model can accurately predict the biogas production on a day-ahead basis over 95% of the time.

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Table of Contents

List of Figures

List of Tables

Nomenclature

[Nm^3=Normalised Cubic Meter] [subscript ',i' represents parameter for multiple units, e.g. Boiler 1,2 or 3]

Abbreviations / Terms		
AAD	Advanced Anaerobic Digestion	
AD	Anaerobic Digester	
ADM1	Anaerobic Detester Model No. 1	
ANN	Artificial Neural Network	
ASP	Activated Sludge Process	
BSM1		
BUP	Biogas Upgrade Plant	
'Carbon Credits'	Kilograms of Carbon Dioxide emitted to atmosphere ($kg.CO_2e$) as a result of using a particular energy/fuel source.	$kg.CO_2e$
CHP	Combined Heat and Power (engine)	
CHPQA	Combined Heat and Power Quality Assurance	
COD	Chemical Oxygen Demand	
DO	Dissolved Oxygen	
DSS	Decision Support System	
GUI	Graphical User Interface	
MILP	Mixed Integer Linear Programming	
MPC	Model Predictive Control	
NARX	Non-linear Autoregressive Network with Exogenous inputs	
NWL	Northumbrian Water Limited	
OPEX	Operating Expenses	
PDS	Percent Dry Solids	
PIC	Public Interest Commitment	
PLC	Programmable Logic Controller	
RA	Retrospective Analysis	
RO	Retrospective Optimisation	
SCADA	Supervisory Control and Data Acquisition	
TDS	Total Dry Solids (in tonnes)	
VFA	Volatile Fatty Acids	
WWTP	Wastewater Treatment Plant	

Model Parameters		
$B_{I,t}$	Biogas flow to Grid Injection (*BUP*) at time ‘t’	Nm^3
$B_{CHP,i,t}$	Biogas flow to CHP Engine ‘i’ at time ‘t’	Nm^3
$B_{S,t}$	Biogas flow to Steam Boilers at time ‘t’	Nm^3
$B_{f,t}$	Biogas Flow to Flare Stack at time ‘t’	Nm^3
B_{Total}	Total Biogas Produced from Digesters	Nm^3
C_B	Biogas Cost to burn on site	£/Nm^3
C_{CO_2}	Cost of each Carbon Credit	£/ kg.CO_2e
C_E	Electricity Import Cost	£/kWh
C_N	Natural Gas Cost to burn on site	£/Nm^3
C_I	Biogas Injection Cost/Revenue	£/Nm^3
C_f	Flare ‘Costs’ for Biogas on site	£/Nm^3
C_P	Purchase cost of Propane	£/L
$E_{GEN,i,t}$	Electricity generated by CHP engine ‘i’ at time ‘t’	kWh
$E_{GEN,max}$	Maximum Electricity that could be generated by a CHP engine operating at full gas flow	kWh
$E_{IMP,i,t}$	Electricity Imported as a result of CHP Engine ‘i’ on reduced capacity at time ‘t’	kWh
G_{CO_2}	Total Carbon Credits Generated on site	kgCO_2e
K_{IMP}	Carbon Credits generated from Importing Electricity	kgCO_2e /kWh
K_{EXP}	Carbon Credits generated from Exporting Electricity	kgCO_2e/kWh
K_N	Carbon Credits generated from Importing Natural Gas	kgCO_2e/m^3
K_{EB}	Carbon Credits generated from Exporting Enriched Biomethane	kgCO_2e/m^3
K_P	Carbon Credits generated from Using Propane	kgCO_2e/L
K_{CHP}	Carbon Credits generated from using Biogas in the CHP Engines	kgCO_2e/m^3
K_R	Carbon Credits generated from using Biogas anywhere else on site (Boilers, Flare)	kgCO_2e/m^3
$N_{CHP,i,t}$	Natural Gas flow to CHP Engines at time ‘t’	Nm^3

$\boldsymbol{N_{S,i,t}}$	Natural Gas flow to Steam Boilers at time 't'	Nm^3
$\boldsymbol{P}$	Volume of Propane used to enrich Biogas	L
$\boldsymbol{S_{min/max}}$	Gas flow constraint for Boilers to ensure steam production	Nm^3
$\boldsymbol{T_c}$	Total Operational Cost	£
$\boldsymbol{T_{CO_2}}$	Total Cost of Carbon Credits	£
$\boldsymbol{T_B}$	Total cost of Biogas Usage	£
$\boldsymbol{T_N}$	Total cost of Natural Gas Usage	£
$\boldsymbol{T_P}$	Total cost of Penalty Terms	£

	MILP Binary Variables **(All variables are 1 or 0)**
$\boldsymbol{y_i}$	Used to ensure fuel selected with $\boldsymbol{z_{i,t}}$ (for CHP Engine 'i') remains the same throughout the day
$\boldsymbol{w_{Bi,t}}$ or $\boldsymbol{w_{Ni,t}}$	Used in conjunction with the binary variable $\boldsymbol{R_{i,t}}$ for the Dual Fuel CHP engines. When an engine is online ($\boldsymbol{R_{i,t}}$= 1), both $\boldsymbol{w_{Bi,t}}$ and $\boldsymbol{w_{Ni,t}}$ will be 0, otherwise one of them will be 1 (depending on the value of $\boldsymbol{z_{i,t}}$). Subscript 'B' denotes Biogas flow and subscript 'N' denotes Natural Gas flow.
$\boldsymbol{z_{i,t}}$	Used to determine fuel used in CHP Engine 'i' at time 't'. $\boldsymbol{z_{i,t}} = 1$ indicates running Biogas, and 0 indicates natural gas
$\boldsymbol{z_{j,t}}$	Used to determine fuel used in Steam Boiler 'i' at time 't' $\boldsymbol{z_{j,t}} = 1$ indicates running Biogas, and 0 indicates natural gas
$\boldsymbol{R_{i,t}}$	Used to track whether an engine 'i' (1-4) is operational ('**R**unning' or 'Online') at time point 't'. $\boldsymbol{R_{i,t}} = 1$ indicates an engine is operational.
$\boldsymbol{su_{i,t}}$	Used to track whether engine 'i' (1-4) is in start-up phase $\boldsymbol{su_{i,t}} = 1$ indicates an engine is in start-up mode
$\boldsymbol{su\_B_{i,t}}$	Used in parallel with $su_{i,t}$ for dual fuel engines only, to track whether engine 'i' (1-3) is in start up phase *and* using biogas as a fuel $su\_B_{i,t} = 1$ indicates an engine is in start-up on Biogas

$\boldsymbol{su\_N_{i,t}}$	Used in parallel with $su_{i,t}$ for dual fuel engines only, to track whether engine ‘i’ (1-3) is in start up phase *and* using natural gas as a fuel $\boldsymbol{su\_N_{i,t}} = 1$ indicates an engine is in start-up on natural gas	
$\boldsymbol{sd_{i,t}}$	Used to track whether engine ‘i’ (1-4) is in shut-down phase $\boldsymbol{sd_{i,t}} = 1$ indicates an engine is in shutdown	
$\boldsymbol{sd\_B_{i,t}}$	Used in parallel with $\boldsymbol{sd_{i,t}}$ for dual fuel engines only, to track whether engine ‘i’ (1-3) is in shut-down phase *and* using biogas as a fuel $\boldsymbol{sd\_B_{i,t}} = 1$ indicates an engine is in shutdown and was running Biogas	
$\boldsymbol{sd\_N_{i,t}}$	Used in parallel with $\boldsymbol{sd_{i,t}}$ for dual fuel engines only, to track whether engine ‘i’ (1-3) is in shut-down phase *and* using natural gas as a fuel $\boldsymbol{sd\_N_{i,t}}$ indicates an engine is in shutdown and was running natural gas	

	<u>Conversion Constants</u>	
$\boldsymbol{\alpha}$	Convert daily process limits to half hourly (each time period in model)	
$\boldsymbol{\beta}$	To convert kg to Nm^3 for Natural Gas	
$\boldsymbol{CV_B}$	‘Calorific Value’ of gas, to convert biogas flow volume to MWh	MWh/m^3
$\boldsymbol{CV_N}$	‘Calorific Value’ of gas, to convert natural gas flow volume to MWh	MWh/m^3
$\boldsymbol{\varepsilon_{CHP}}$	Heat recovery efficiency of CHP engines based on total energy input of fuel	
$\boldsymbol{\varepsilon_S}$	Heat recovery efficiency of steam boilers based on total energy input of fuel	
$\boldsymbol{\rho_{GEN,i,B}}$	Power Conversion Factor for engine ‘i’ – biogas volume to electricity	kWh/m^3

$\boldsymbol{\rho_{GEN,i,N}}$	Power Conversion Factor for engine 'i' – natural gas volume to electricity	kWh/m^3
$\boldsymbol{\mu_{su}}$	Adjustment constant to adjust the maximum and minimum gas flow when the engine enters start-up	
$\boldsymbol{\mu_{sd}}$	Adjustment constant to adjust the maximum and minimum gas flow when the engine enters start-up	

	General MILP Parameters
$\boldsymbol{A}$	Matrix containing parameters for inequality statements
$\boldsymbol{Aeq}$	Matrix containing parameters for equality statements
$\boldsymbol{b}$	Vector containing limits for inequality statements
$\boldsymbol{beq}$	Vector containing target for equality statements
$\boldsymbol{f}$	Vector of cost functions for each variable
$\boldsymbol{intcon}$	Vector stating which variables in $\boldsymbol{x}$ are integers
$\boldsymbol{lb}$	Vector containing lower bounds of all variables
$\boldsymbol{ub}$	Vector containing upper bounds of all variables
$\boldsymbol{x}$	Vector of Variables

Chapter 1 General Introduction

This Chapter provides an introduction to generic wastewater treatment and the scale of operations for the Northeast of England. The fundamental background knowledge of the Howdon treatment site that was used as a focus for this PhD is provided, and the complexity of sludge processing operations and the overall aims and objectives of the thesis are presented. A brief outline of how each chapter meets these aims is also given here.

1.1 Introduction to NWL

Northumbrian Water Limited (NWL) provides approximately 4.4 million people with water services and 2.7 million people with wastewater services [1] – they provide both clean and wastewater services in the north east of England, but only clean water services in the south east. Figure 1-1 shows the operating area for NWL in the Northeast.

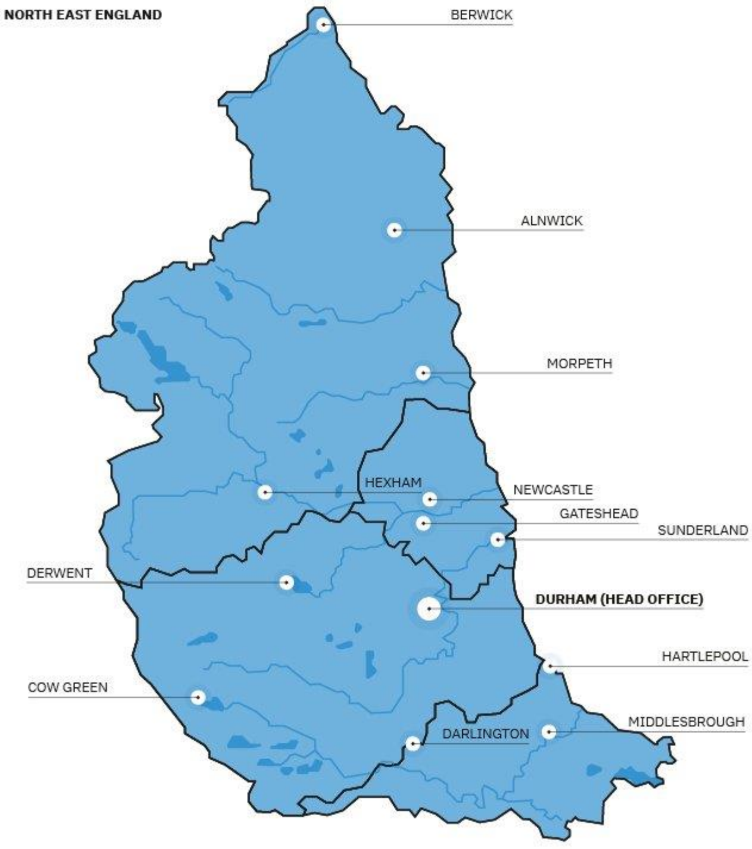

Figure 1-1 - NWL Northeast England operating area [1]

Their primary objective is the provision of clean drinking water and the treatment of wastewater. NWL has a duty to provide these services at a reasonable cost whilst also providing value for shareholders. Price reviews and regulations with the sector's regulator (Ofwat) ensure NWL maintains a commitment to customers, improving current operations and reducing their environmental impacts. It should be noted that, in the UK, the water sector is a heavily regulated, where water companies operate under monopolistic conditions and thus, benchmarking their performance using robust methods is fundamental for regulation [2]. As an example, unlike other sectors (such as energy), a resident in the Northeast can only purchase water and wastewater from NWL, or a resident of London must pay Thames Water, hence the need for regulations across the sector.

As part of the sector's Public Interest Commitment (PIC), the UK water industry has made an ambitious pledge to achieve net zero carbon emissions by 2030 [3]. NWL has reduced operational emissions by 46% since 2009, are the only UK water company to use 100% of the remaining sludge after sewage treatment to produce renewable power and have taken the decision to beat the PIC target by aiming for net zero carbon emissions by 2027 [4]. NWL has voluntarily agreed with the regulator a performance commitment on the company's carbon emissions, this commitment is linked to a financial penalty/reward. The performance of NWL based on this criteria *may* form part of Ofwat's future benchmarking for regulation, and with the link to financial penalty/rewards, meeting this pledge is no longer just an ethical commitment. This agreement was finalised during the PhD, and therefore is considered from Chapter 3 onwards.

The work presented in this thesis seeks to aid NWL in their operational decision making at the site level, using one of their larger WWTPs as a case study example for the methodologies explored, with a focus on improved site revenues or validating them (based on a validation of existing operational strategy decisions).

1.2 Introduction to Wastewater Treatment

NWL has over 400 sewage treatment works in the Northeast of England which treat around 800 million litres of wastewater every day [5]. However, not every site is equipped to process the solids (sludges) that are separated during the wastewater treatment process. Typically, the solids are separated from the bulk liquids in settlement tanks, and the remaining water is treated and cleaned before being released back into the environment (such as in a local river). All of the solids that are generated will ultimately be transported and processed at one of two processing plants: the Howdon plant in Tyneside (Newcastle) and the Bran Sands plant in Teesside (Middlesbrough). These plants are large, to meet processing demands, and therefore have high energy demands which results (or can result) in large CO_2 emissions.

1.2.1 Howdon WWTP - Introduction to site

NWL is the only wastewater company in the UK to use all sludge after wastewater treatment to produce renewable electricity [6]. NWL anaerobically digests (typically) up to 40,000 tonnes of sewage sludge (dry solids) annually across the business, and processes up to 12,000 L/s of raw sewage at its Howdon WWTP. An overview of the treatment process of the site is shown in Figure 1-2. The site is typical of a modern large scale WWTP, in that the raw sewage pumped into the site is screened and then the solids are separated from liquid in the clarifiers. Bulk water treatment comes in the form of aeration lanes and UV treatment before the clean water flows into the local river.

The solids removed during clarification are thickened (water is removed) to allow for increased storage capacity in the 'strategic storage tanks'. This sludge storage also receives sludge through lorries on site - all sludge or dry solids arising from NWLs over 400 wastewater treatment works are either processed at the Advanced Anaerobic Digestion (AAD) facility at Howdon or at the similar plant on Teesside. These plants are known as '*Advanced'* Anaerobic Digestion due to the thermal hydrolysis stage during sludge treatment. Howdon is critical to the company's (and the North East's) wastewater operations.

The AAD facility at Howdon was designed to achieve higher biogas (a combination of methane and CO2) volumes and lower retention times by pre-treating the sludge in a thermal hydrolysis plant (designed and installed by a company called CAMBI). This pre-treated sludge feed is fed into three large Anaerobic Digesters (ADs) on site, where a mesophilic reaction breaks down the solids into biogas.

Typical anaerobic digestion does not involve the use of thermal hydrolysis but uses a simpler pasteurisation technique for sludge pre-treatment. Studies have shown that typical anaerobic digestion requires retention times of 20-30 days, whereas AAD (with a thermal hydrolysis pre-treatment stage) can reduce retention time to 10-18 days [7,8]. Hydrolysis is known to be one of the key rate limiting steps in anaerobic digestion in the production of methane and breaking down of organic compounds [9,10], with studies showing the benefits and optimisation of thermal hydrolysis parameters for improved methane production [11].

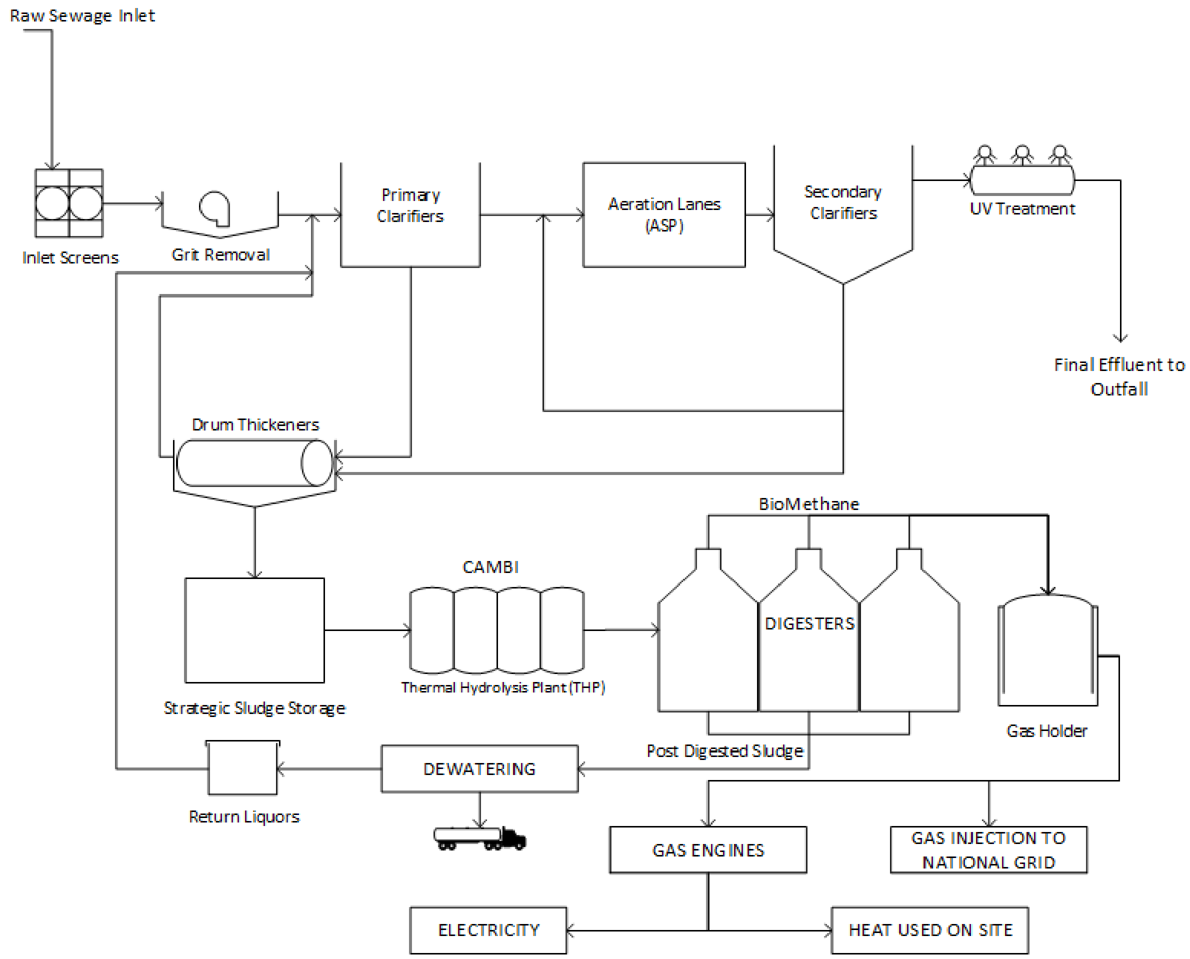

Figure 1-2 - Overview of the wastewater treatment processes at Howdon

The CAMBI plant consumes energy in the form of steam in order to further break down the composition of feedstock available to the anaerobic digestion process, but in doing so producing more net energy (i.e. producing more biogas than is needed to produce the steam required) and vastly reducing retention times of the ADs.

1.2.2 The AAD plant at Howdon

Typically, Biogas produced on a wastewater Anaerobic Digestion (AD) plant in the UK is used to generate electricity only. The AAD plant at Howdon is rare in that it has three possible uses for Biogas produced on site, shown in Figure 1-3: upgrade for injection into the national gas grid; burning it in Combined Heat and Power (CHP) Engines; or burning it in Steam Boilers for the thermal hydrolysis plant. There are currently four[1] CHP Engines, three Steam Boilers and one Gas Upgrade/Injection plant on site. If required, the plant may flare excess Biogas under emergency circumstances to safeguard the plant or for short periods during routine maintenance (under Environment Agency regulations), though operators must minimise this as much as possible. To ensure overall sludge processing remains unimpeded the plant may draw Natural Gas from the national gas grid to be used in the CHP Engines or Steam boilers. Nationally, many similar sites are looking to upgrade to produce Biomethane for injection into the National Gas grid to take advantage of the government's Renewable Heat Incentive [12]. The CHP engines and Steam Boilers can only utilise one fuel type at a time: Biogas or Natural Gas.

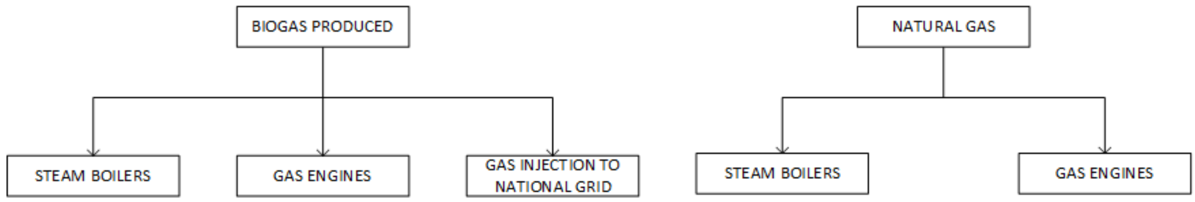

Figure 1-3 - Possible gas distribution across AAD plant

CHP electricity generation is an effective way to reduce energy costs and carbon emissions [13,14]; these systems typically take a fuel source and efficiently convert it into usable heat and energy [15] and in the case of the Howdon WWTP the CHP units are 'Gas Engines' provided by MWM [16] that burn the non-purified Biogas from the digesters to generate heat and electricity.

A later addition to the site added a Biomethane Upgrade Plant (BUP) where CO_2 is removed from the biogas via a stripping column and its quality (calorific value) is raised such that it is suitable for injection into the national gas grid [16]. The relatively new processing techniques (CAMBI and BUP) involved in the AAD plant results in significant operational challenges to maximise the economic performance.

[1] At the time of developing the Gas Distribution model in Chapter 2, the site only had three dual fuel CHP engines, but had finished installing a fourth Natural Gas engine by the time the model in Chapter 3 was developed.

WWTPs are continuously being driven towards increased efficiency of plant operation due to regulatory pressures [17,18], and it is widely thought that there is considerable room for improving the efficiency of WWTPs [19]. If companies are able to schedule their operations successfully around supply and demand of energy, there are opportunities for annual OPEX savings of 2-5% [20], and the use of energy recovery techniques and Biogas can reduce a WWTP carbon footprint by 10% [21]. WWTPs have an abundance of low-grade thermal energy and organic substances in sludge [22], which if harnessed can reduce carbon emissions and energy cost/consumption. In addition, low-carbon energy targets and policies are helping drive industries away from fossil fuels and more towards renewable energy sources for electricity generation [23].

Previous studies have investigated the flexible generation of electricity of a WWTP using controlled gas production and storage [24,25] however the WWTPs studied do not have the capability of Gas to Grid injection of renewable biomethane, nor considered the economic impact of varying electrical (or gas) tariffs. It is believed that the Howdon site is unique amongst most worldwide WWTPs due to the flexibility for gas processing.

1.3 Operational strategy and legal requirements

NWL must manage this plant so that it meets its two primary objectives: that of processing all necessary sludges so that they are capable of being re-cycled to land, and to optimise the revenues accruing to the plant whilst minimising the operating costs. In achieving this NWL must be able to schedule planned maintenance, accommodate unforeseen breakdown, work with the constraints of the capacity of the local gas grid, decide whether to buy gas back in order to generate electricity for the site and generate and make appropriate use of the waste-heat coming from its combined heat and power plant.

The plants inputs are variable, energy required on site is variable, and the subsidies available for gas injection high. Day to day operation of the plant is fully monitored, but its control relies on the experience, availability and knowledge of the operators. A supervisory control system taking current data input and validating operations choices would help in securing sludge processes, optimising net revenues, allowing greater use of the operators time and provide assurance to the leadership regarding plant operation. Such a system could also be deployed at the company’s other facilities, such as the Bran Sands WWTP in Teesside.

1.4 Aims and Objectives of each chapter

At the beginning, the PhD had a generic aim of investigating control and optimisation opportunities of the Howdon WWTP, with scope to take a more focussed direction after preliminary investigations and spending time on site. It was decided that the direction the PhD would take would be towards Energy and Gas management for the AAD plant, rather than on optimisation and control of wastewater operations – as the AAD plant is relatively new, and the technologies involved (such as the BUP grid injection) are also relatively new to the sector there was a clear gap in knowledge to be exploited. The overall aim of the PhD would be to model, validate and optimise process operations and operational strategies focused around the AAD plant on site.

The first objective was to develop a methodology to model and optimise the gas of the AAD plant. In Chapter 2, the gas use and distribution on site was modelled using Mixed Integer Linear Programming (MILP) techniques within MATLAB's optimisation toolbox, such that operators' decisions could be validated. This model was then used to perform Retrospective analysis (RO), to provide operators with said validation.

Whilst the model in Chapter 2 is useful for operators, there are limitations that required addressing. In addition, during this time a new carbon performance commitment was agreed between NWL and Ofwat, which was believed could be included with amendments to the gas distribution model. Thus, the second objective was to further develop and refine the Gas Distribution model outlined in Chapter 2.

In Chapter 3, the limitations of the gas distribution model were addressed, and the new carbon performance commitment was also included to provide operators with understanding of how the new agreement might affect site operations in the future, resulting in the development of the Energy and Carbon model.

The Energy and Carbon model can provide operators with fast solutions to a difficult optimisation. However, to receive appropriate feedback on the requirements of the model there was a need to provide operators with a more visual form of the model. Hence the fourth objective of the project, the need to create a visual user interface which operators can use. Chapter 3 also presents the app that was developed within the MATLAB environment.

The fifth objective was to use the developed Energy and Carbon model to investigate the impact of site operational strategies based on energy pricing. In Chapter 4, the model was used to perform a more in depth analysis of how fluctuating energy prices (using a range of historical UK natural gas prices and variations on the electricity tariff) and biogas production levels affects the optimal revenue achievable and also the optimum operational strategy that should be employed on site to achieve said revenue.

It is addressed in Chapter 2 and 3 that the developed models rely on at least a day-ahead prediction of how much biogas the on-site ADs will produce – something which is currently unavailable to NWL. The fourth objective was to address this lack of information through either the improved use of site data for data driven modelling, developing a mechanistic model of the AAD's or a combination of the two.

Chapter 5 begins investigations to remedy this, with the development of data driven prediction models for biogas production. This posed an interesting challenge, as typical data that would be used to create a mechanistic model of an AD is not readily available due to process equipment and monitoring limitations on site.

The final chapter of this thesis summarises the findings of the PhD, discusses limitations of the developed models and proposes the next steps that could be taken beyond that of the PhD. Additionally, the major academic contributions and key outcomes (statement of innovation) of this PhD are presented.

Chapter 2 Gas Distribution Model

In this Chapter, a Gas Distribution model was developed using novel Mixed Integer Linear Programming (MILP) techniques. The model parameters and equations are presented and is used to perform Retrospective Optimisation (RO) of historic plant operations to validate operators' previous operational strategies. Limitations of the developed model are also discussed and addressed in later chapters.

2.1 Introduction

At the time of developing the gas distribution model, the Howdon site had three dual fuel CHP engines, in addition to the BUP. A diagram of the AAD plant is shown in Figure 2-1. The three CHP engines are 'dual fuel' as they can use either biogas or natural gas, but not a blend. Similarly, the steam boilers may also use either fuel, one at a time. The Biogas produced from the on-site ADs may be sent to the BUP for processing and injection into the National Grid as a renewable energy source. The emergency flare stack is shown also. The process variables (gas flows) that are used throughout this chapter are also shown on the process diagram for reference.

The aim of this Chapter is to explore and address a key need within the AAD plant of NWL: improved control schemes and validation of operational strategies. Typically, in the water industry, advanced process control and data driven modelling is uncommon; standard control schemes use on-off control via PLC (Programmable Logic Controller) and SCADA (Supervisory Control and Data Acquisition) systems to control localised processes to within specified limits, without consideration of upstream plant behaviour [17]. Widespread use of SCADA-type system technology permits the exploitation of more advanced supervisory concepts and system control [26]. However, although SCADA based systems can store vast amounts of historical data regarding plant operations, they are typically underutilised (especially with the water sector), leaving companies in a 'data rich, information poor' state.

Such large amounts of data can be used for Retrospective Analysis (RA) and learning to make improvements to future operations. An example of the application of Retrospective Learning is in the aviation industry [27], where analysis and learning after incidents creates improved safety procedures. Typically, retrospective learning techniques are not used in regard of operational aspects of a process [28]. However, in work conducted by T. Cummings *et al* in 2017, Retrospective Optimisation (RO) and learning was used to develop improved scheduling procedures for multiple nitrogen liquefier units and the development of electricity spot pricing for a pricing predictor [28]. In the case of Howdon WWTP, site systems store several years of operational data which is not currently being used for any RO or analysis. To the author's knowledge, there has been no development of models of WWTPs based on RO in literature, though it should be noted that previous work has been done developing predictors or forecasts of energy pricing using grey prediction models [29].

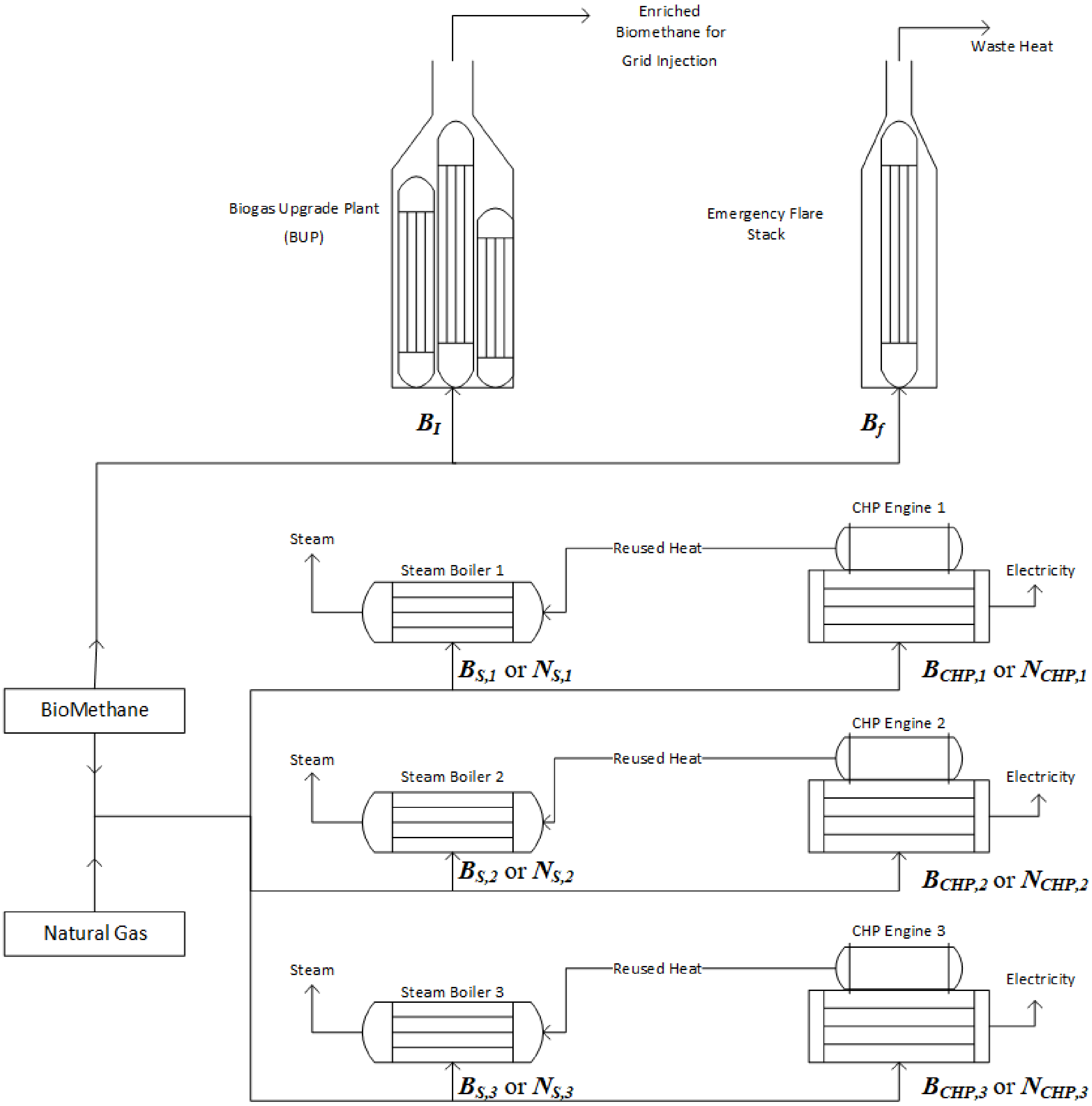

Figure 2-1 - Process diagram for gas distribution on site. Biomethane (aka Biogas) source is from Anaerobic Digestion on site, Natural Gas is from the National Grid.

To perform RO for this site, a model of the process was developed using Mixed Integer Linear Programming (MILP) to determine optimal historic performance that can be compared to actual historic operations. MILP takes a series of linear relationships made up of equalities, inequalities, integer defined parameters and upper and lower bound constraints to minimise a linear objective function. MILP is a fast and accurate way of achieving optimisation requirements, and "because of its rigorousness, flexibility and extensive modelling capability, has become one of the most widely explored methods for process scheduling problems" [30].

Some examples of various MILP applications include: scheduling of a polymerisation reactor where reductions in CPU processing time of over 98% were achieved using MILP scheduling techniques [31], multiproduct milk processing where complex plant scheduling with over 400 variables was achieved in just over 2 minutes [32], scheduling for an ice cream processing facility where multi-week ahead schedules were determined [33] and scheduling of a multiple cryogenic air separation unit and compressor plant where site operating costs could be improved by an average of 5% and reducing power consumption by up to 5% [34,35], where the latter was performed within a Microsoft Excel Spreadsheet. This highlights the effectiveness and ease of application of being able to model a process in a MILP form, if the problem can be posed in such a way to take advantage of MILP software.

There is a clear gap in literature of designing control schemes, optimisation techniques and models for gas distribution of AAD sections of WWTP, as literature-discussed here focuses on developing control strategies or models of the effluent treatment side of a WWTP. It should be noted that whilst there are many studies on improving the yield of biomethane produced from anaerobic digesters, such as using calcium or enzymatic pre-treatment of sewage [36,37], this chapter focuses on the optimal way to use the biomethane produced as an input variable to a MILP optimisation, not improving yield or developing a model of the anaerobic digesters.

Currently, there is no model on site to advise the optimal distribution of Biogas produced or how much Natural Gas must be used to ensure optimal cost and sludge processing performance, nor is there evidence of such a model in use at a WWTP internationally. Here, for the first time, the development and application of a realistic model and its solution using MILP is reported, which is used to advise the optimal daily operational strategy that will minimise of gas distribution costs. RO is performed using the model (and using historic data) to determine how optimal previous operational strategies were, on a cost minimisation basis.

The remainder of this chapter is structured as follows. Initially, a ‘proof of concept’ investigation into the use of MILP techniques on site is presented for a high-powered centrifuge on site in section 2.2. Next, in the Methods section (2.3) the site constraints, formulation of the gas distribution MILP model and development of the objective function for optimisation are presented. The results section (2.4) shows example optimisations from the optimiser model and shows the results of the RO performed, which also considers the importance of maintenance and improved breakdown robustness and discusses current model limitations. Finally, conclusions (section 2.5) are presented alongside proposals for further work and improvements to this model (section 2.4.6), which are explored in future chapters of this thesis.

2.2 Initial MILP Investigation – ‘proof of concept’ example

To ensure MILP techniques were applicable and used in the correct way, an initial ‘proof of concept’ investigation was performed as to the operating times of a centrifuge on site, based on electricity tariffs.

After sludge has been fed into the Anaerobic Digesters, the ‘post digested sludge’ waste is processed during the ‘Dewatering’ stage (see Figure 1-2). This waste has a high volume of water and would be costly to transport off site. Therefore, this sludge is thickened in the Final Cake Centrifuge to form a ‘Cake’, which is much more cost effective to transport off site. The cake is stored in the Cake Silo, which is emptied onto lorries for removal off site.

The only constraints that affect the operation of this centrifuge are as follows:

- If the Post Digested sludge storage tank is too full or empty;
- If the cake silo is full; or
- If the cake silo is empty, and there is a removal lorry inbound to remove cake.

With these constraints in mind, there are very few operation limitations to altering the operational schedule of this centrifuge, making it an ideal area to investigate first.

The centrifuge in question operates with a 160 kW motor, with two smaller assist drive motors. Figure 2-2 provides a visual representation of the system, with the electrical ratings and typical loads shown in Table 2-1. As such, during operation the machine consumes a high amount of electricity.

Table 2-1 - Electrical Units, Power Rating and Loads of Post Digested Sludge Processing (VSD = Variable Speed Drive)

Unit	**Power Rating (kW)**	**Estimated Load**
Centrifuge: Main drive (VSD)	160	80%
Centrifuge: Back drive	37	100%
Centrifuge: Oil drive	0.55	100%
Sludge pump (VSD)	22	70%
Screw from Centrifuge	7.5	100%
Conveyor belt to silo	5.5	100%
Poly Dosing pump (VSD)	4	50%

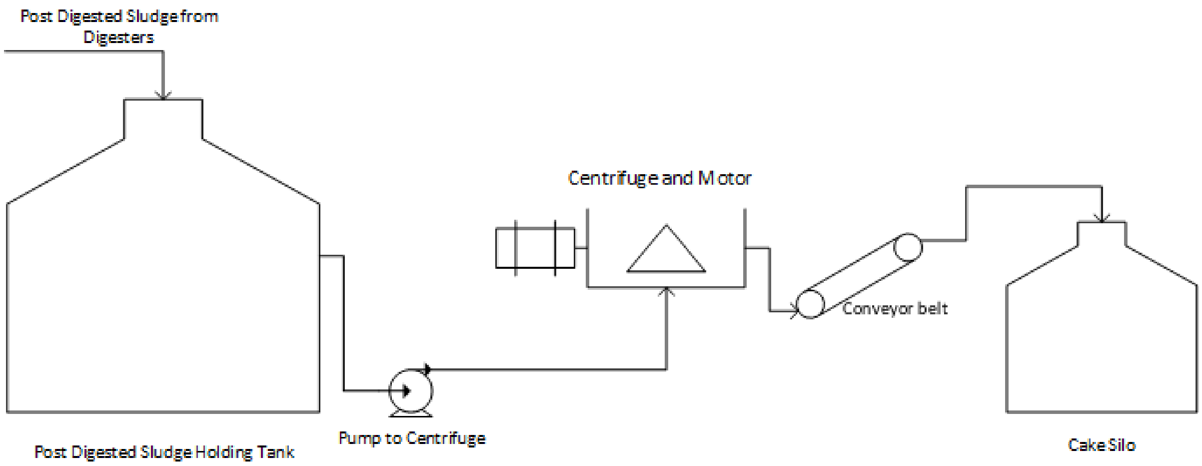

Figure 2-2 - Diagram of Area of Investigation (Post Digested Sludge Thickening)

To find out the best possible schedule of operation for the centrifuge, it was decided that Retrospective Optimisation (RO) through MILP would be the best course of action. Adapting previous work carried out by *Cummings et al.* [38], the operation time of the centrifuge was assigned to a binary variable w_t associated with a cost function of the tariff price c_t and the power usage P_t, such that Mixed Integer Linear Programming (MILP) could be used to minimise the Total Cost *Tc* subject to:

$$T_c = \sum_{t=1}^{N_t} c_t \, . \, P_t \, . \, w_t \qquad (2\text{-}1)$$

$$w_t \in \{0,1\},\ (\forall\ t = 1 \dots N_t)$$

Where N_t is the operation horizon, April 2016-April 2017, in 15-minute intervals. When the binary variable w_t is set to 1, it simulates the centrifuge running for 15 minutes at time interval t, and when 0 it simulates the centrifuge not in operation. The cost function T_c is calculated by summating each 15-minute interval cost of operating the centrifuge where w_t is 1.

However, to better represent historical operations the MILP model was also constrained such that the centrifuge operates for the same amount of time over the annual period, which was 4563.5 hours. As w_t represents a 15-minute operational time period, the total number of operational time periods must be 18,254. This constraint is given by Equation (2-2):

$$\sum_{t=1}^{N_t} w_t \quad = 18{,}254 \tag{2-2}$$

The MILP optimisation tool used was MATLAB's 'intlinprog' function, where the binary variables were optimised to produce the optimal operational schedule.

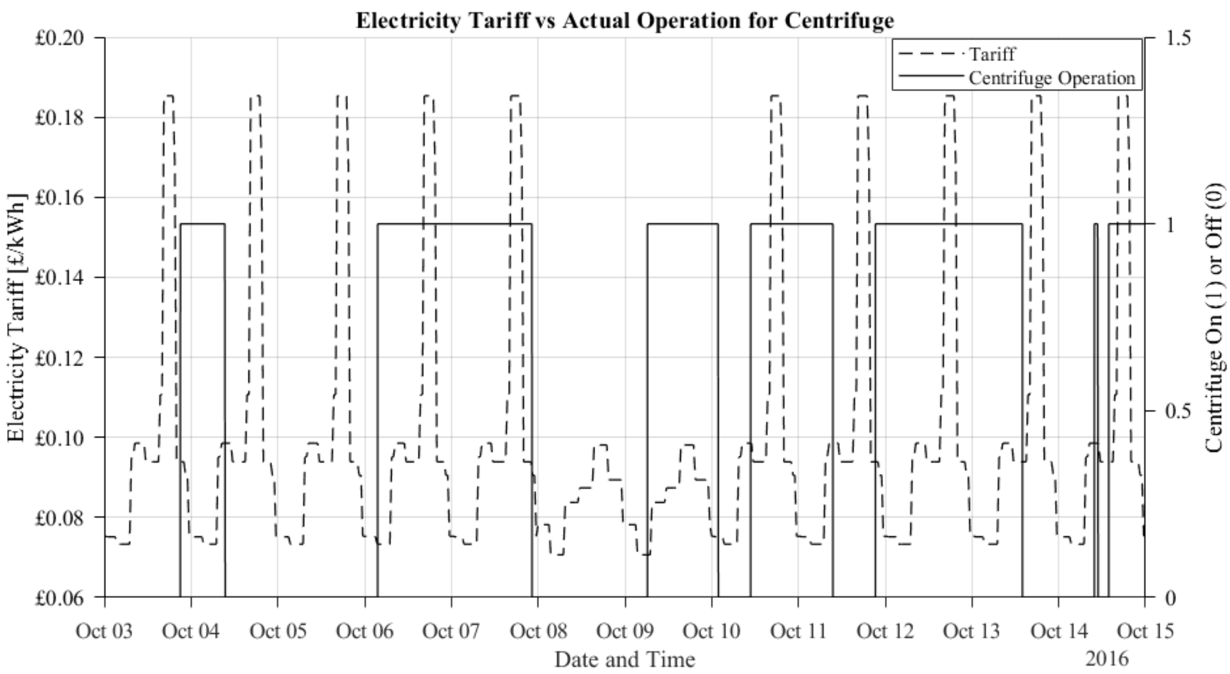

Figure 2-3 –Actual historical operation of Centrifuge, where 1 means 'On' and 0 means 'Off'. The electricity tariff for the site at the time is plotted for reference.

The actual operation for a ten-day period in October 2016 is shown in Figure 2-3, with the cost optimised schedule shown in Figure 2-4. During this time, the historical electricity tariff was a fixed variable tariff, whereby the price was fixed but varied throughout the day. In both figures, the historical site electricity tariff is shown alongside the operation of the centrifuge.

It should be noted here that, for this example 10-day period shown the historical operation of the centrifuge was approximately 140 hours, whilst the optimised schedule operates for just under 100 hours; the optimiser was constrained such that the total annual operational duration of the optimised schedule matched that of the historical annual operational duration, which was a total of 4563.5 hours, as shown by Equation (). Therefore, on a week-by-week comparison the operational hours may differ.

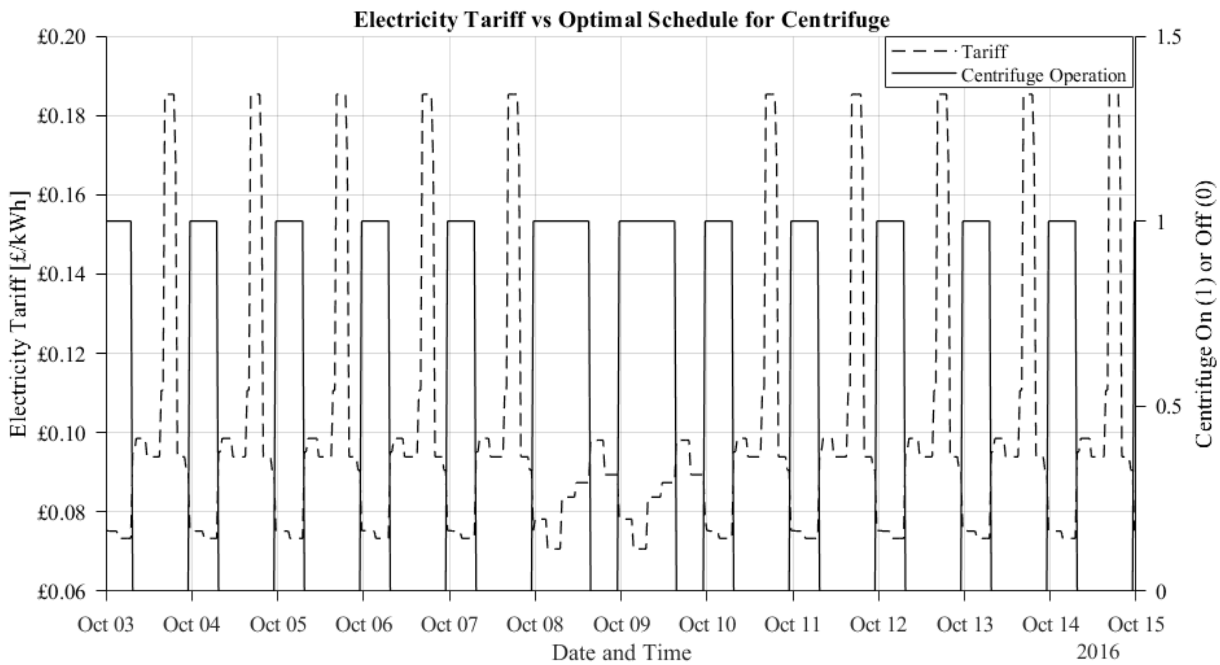

Figure 2-4 -Optimised operation of Centrifuge, where 1 means 'On' and 0 means 'Off'. The electricity tariff for the site at the time is plotted for reference.

The total cost of operating this optimal schedule is shown in Figure 2-5, and the total potential saving was £18,239.15 per annum. This initial investigation shows that MILP can be used on site to optimise process scheduling operations with differing tariffs and production values, with tangible benefits. The MILP techniques applied here were used to model the Gas Distribution on site in the reminder of this chapter.

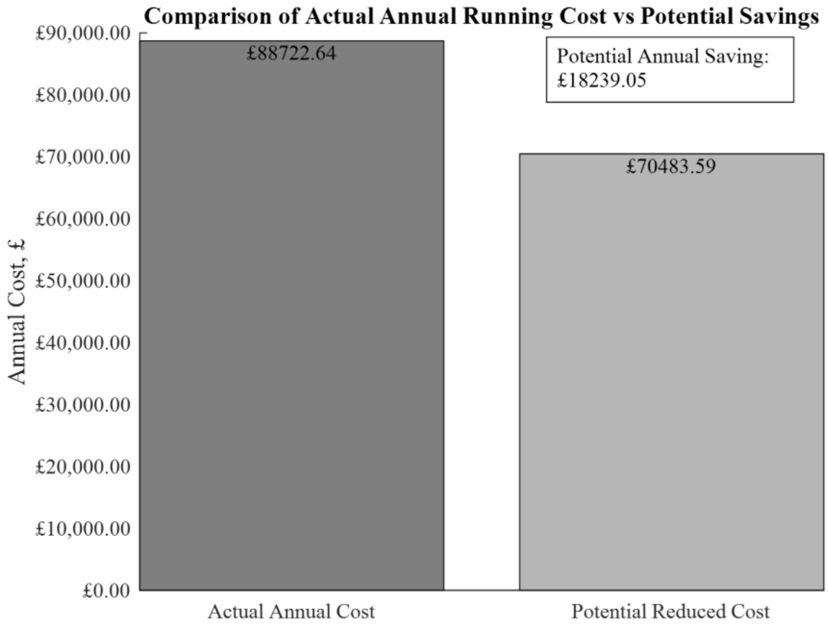

Figure 2-5 - Comparison of Actual Operation Cost and Optimal Schedule Cost

2.3 Methods – Gas Distribution Model development

In Section 2.2, an example ‘proof of concept’ MILP model is given for a centrifuge on site where the optimisation uses 15-minute time period intervals. The development of a Gas Distribution model for the AAD plant is outlined and used for analysis in the reminder of this Chapter. The notation used in Section 2.2 is separate to the reminder of this Chapter, and it should be noted that the optimisation for the Gas Distribution model takes place over a single 24-hour time period, rather than multiple time periods.

2.3.1 Unit processing limits

To model the site and perform RO, processing limitations of gas flow for each unit must be known. The daily processing limits [Table 2-2] were determined thorough retrospective analysis of historical plant operational data and through discussions with operational managers on site. Flow limits are different for Biogas and Natural Gas volumes. The minimum gas flow for an engine to operate is 50% the maximum flow. Currently, should there not be enough Biogas produced to satisfy operation of a CHP Engine, operators require that an engine run on Natural Gas and have the gas flow rate to that engine set to the maximum.

Table 2-2 - Operational constraints for units on site

Limiting Parameters	Operational Constraints
$\boldsymbol{B_{I,max}}$	Max flow: 40,000 Nm^3 / day
$\boldsymbol{B_{I,min}}$	Min flow: 0 Nm^3/ day
$\boldsymbol{B_{CHP,max}}$	Max Flow: 16,000 Nm^3 / day
$\boldsymbol{B_{CHP,min}}$	Min flow: 50% of max flow
$\boldsymbol{B_{S,max}}$	Max flow: 4000 Nm^3 / day
$\boldsymbol{B_{S,min}}$	Min: 200 Nm^3 / day
$\boldsymbol{B_{f,max}}$	No Max
$\boldsymbol{B_{f,min}}$	Min: 0 Nm^3 / day
$\boldsymbol{N_{CHP,max}}$	Max flow: 9000 Nm^3 / day
$\boldsymbol{N_{CHP,min}}$	Min flow: 9000 Nm^3 / day
$\boldsymbol{N_{S,max}}$	Max flow: 2500 Nm^3 / day
$\boldsymbol{N_{S,min}}$	Min flow: 200 Nm^3 / day
$\boldsymbol{S_{max}}$	Upper Limit: 5700 Nm^3/ day
$\boldsymbol{S_{min}}$	Lower Limit: 3300 Nm^3/ day

The gas holders on site that capture and intermediately store the Biogas produced are typically able to store up to an hour's production of biogas, should the Biogas flow downstream be interrupted. Therefore, for the purpose of this model the daily volume of biogas produced must all be utilised in the available units on site.

The cost parameters for each gas flow were taken from the OPEX (Operating Expenses) reporting features available on the onsite SCADA system. Costs tend to be in units of p/kWh or equivalent, so the cost parameters in the model are combined with standardised conversion factors to enable a simple cost in £/Nm^3 (GBP per Normalised cubic metre) of gas; gas flows on site are reported in Nm^3. For the purposes of confidentiality, the cost function parameters cannot be reported here.

2.3.2 MILP Equations/Parameters

2.3.2.1 Objective function

The simplified objective function is shown by Equation (2-3). The aim is the minimisation of the total costs of gas distribution use on site, subject to plant constraints:

$$T_c = T_B + T_N + T_P \tag{2-3}$$

The total cost for Biogas and Natural Gas use on site, T_B and T_N respectively, are defined by summating the gas flows to each CHP Engine or Steam Boiler and the Biogas flow to the Biogas Upgrade Plant (BUP). Here, B represents a Biogas flow (Nm^3, variable), N represents a Natural Gas flow (Nm^3, variable) and C represents the cost of using the associated gas (£/Nm^3, constant):

$$T_B = \sum_{i=1}^{3}\{B_{CHP,i} \cdot C_B\} + \sum_{j=1}^{3}\{B_{S,j} \cdot C_B\} + B_I \cdot C_I \tag{2-4}$$

$$T_N = \sum_{i=1}^{3}\{N_{CHP,i} \cdot C_N\} + \sum_{j=1}^{3}\{N_{S,j} \cdot C_N\} \tag{2-5}$$

For a realistic optimisation, both costs and revenues of gas streams on site are considered; injecting Biomethane into the National Grid through the BUP creates a revenue as the gas is sold (C_I), burning Biogas in the boilers and CHP engines has no associated cost (C_B) whilst purchasing Natural Gas for use anywhere has a cost associated (C_N).

Whilst there is no cost associated with burning Biogas on the flare under occasional emergency use, overuse is discouraged by regulatory bodies and is considered a waste. To prevent the optimiser from sending gas to the flare stack a penalty term, T_P, on flaring Biogas was applied to the objective function. By setting the cost function for flaring, C_f, high the optimiser would allow flaring only as a last resort. The site requires minimising flaring in order to satisfy its environmental and regulatory commitments.

$$T_P = B_f \cdot C_f \tag{2-6}$$

Therefore, the objective function is:

$$T_c = \sum_{i=1}^{3}\{C_b\, B_{CHP,i} + C_n N_{CHP,i}\} + \sum_{i=1}^{3}\{C_b\, B_{S,i} + C_n N_{S,i}\} + C_I B_I + C_f B_f \tag{2-7}$$

Should the optimiser advise that flaring gas should be done, it will affect the actual minimised cost; after optimisation when calculating the total daily operational cost on site, if required the penalty term is subtracted from the minimised cost to reflect actual operational costs, and for more accurate RO.

2.3.2.2 Mass Balance constraint – Model Input

Whilst individual process units have their own sets of constraints for gas usage, the overriding site constraint is given by the overall mass balance of Biogas distributed across the site: the volume of Biogas produced from the anaerobic digesters must equal that of Biogas distributed across site. There is no constraint of Natural Gas of this form, as Natural Gas is readily available if required. The total volume of Biogas produced, B_{Total}, is the only variable that is input into the model.

$$B_{Total} = \sum_{i=1}^{3}\{B_{CHP,i} + B_{S,i}\} + B_I + B_f \tag{2-8}$$

2.3.2.3 CHP Engines constraints

The CHP engines can only utilise one fuel type at a time: Biogas or Natural Gas. Therefore, the binary variable $z_i \in \{0,1\}$ is introduced to ensure only one of each gas type is used by each unit. The total gas flows to any engine, $B_{CHP,i}$ and $N_{CHP,i}$, is between the maximum and minimum flows:

$$B_{CHP,min} \cdot z_i \leq B_{CHP,i} \leq B_{CHP,max} \cdot z_i \tag{2-9}$$

$$N_{CHP,min} \cdot (1 - z_i) \leq N_{CHP,i} \leq N_{CHP,max} \cdot (1 - z_i) \tag{2-10}$$

Under these conditions, when z_i takes the value of 1 then only Biogas may flow to engine ‘i’, whereas a value of 0 denotes a Natural Gas flow. z_i is a variable determined by the model to optimise gas distribution. The binary variable z_i provides the gas selection functionality by allowing z_i to alter the upper and lower constraints of the inequalities.

2.3.2.4 Steam Boilers constraints

The steam boilers can also only have one fuel source at a time. Similarly to the CHP inequalities in the ‘CHP Engines constraints’ section above, the steam boiler parameters make use of a binary variable, $z_j \in \{0,1\}$ subject to:

$$B_{S,min} \cdot z_j \le B_{S,j} \le B_{S,max} \cdot z_j \tag{2-11}$$

$$N_{S,min} \cdot (1 - z_j) \le N_{S,j} \le N_{S,max} \cdot (1 - z_j) \tag{2-12}$$

There are additional constraints for the steam boilers that differ from the CHP engines. Unlike the CHP engines, the steam boilers must always be producing enough steam to satisfy site process requirements and therefore do not all have high gas flow or low gas flow at the same time. After retrospective analysis of historic data, for any given day the three boilers operate on a total daily flow where one operates near maximum, one near minimum and one in between. This is in order to supply enough steam for use on site. As such, the additional constraint on the boilers is:

$$S_{min} \le \sum_{j=1}^{3} \{B_{S,j} + N_{S,j}\} \le S_{max} \tag{2-13}$$

Retrospective analysis of the different fuel flows to the boilers also revealed no distinguishable difference in processed volume of Biogas or Natural Gas flows, hence each gas type has equal weighting in this constraint.

2.3.2.5 Gas to Grid injection (Biogas Upgrade Plant) constraint

The BUP takes the raw Biogas and enriches it such that the resulting biomethane can be injected into the national grid as a renewable energy source. As there is only one fuel source, the constraints of sending Biogas to the BUP are:

$$B_{I,min} \le B_I \le B_{I,max} \tag{2-14}$$

In an ideal setting there would be no limit to the volume of biomethane that can be injected into the national grid. However, the total volume that can be injected is subject to local demand and gas network pressures; if too much biomethane is injected too quickly the pressure in the grid could rise too high for continued injection, whereby Northern Gas

Networks (the local gas network operator) would shut off grid injection from the site; this is known as going into a 'reject' state. Operators have discovered that maximum daily volume of Biogas that can be processed through the BUP is currently around 40,000 Nm^3, which was validated through retrospective analysis of BUP processing volumes, grid injection volumes and 'reject' state instances.

2.3.2.6 Flare Stack constraint

Due to the volumes of biomethane produced on site and the safety considerations from site design, there is considered to be no upper limit for the total volume of Biogas the flare stack can take:

$$0 \leq B_f \tag{2-15}$$

2.3.3 Solver

The optimiser model was developed in MATLAB using the in-built function *intlinprog*, which is a MILP algorithm solver in the Optimisation Toolbox package. It is a standalone optimiser similar to other known optimisation packages such as CPLEX or Gurobi. The *intlinprog* package uses the following steps to perform optimisation, as outlined in the Mathworks documentation (*intlinprog* can solve the problem in any of the stages. If it solves the problem in a stage, *intlinprog* does not execute the later stages.) [39]:

1. Reduce the problem size using Linear Program Preprocessing.
2. Solve an initial relaxed (noninteger) problem using Linear Programming.
3. Perform Mixed-Integer Program Preprocessing to tighten the LP relaxation of the mixed-integer problem.
4. Try Cut Generation to further tighten the LP relaxation of the mixed-integer problem.
5. Try to find integer-feasible solutions using heuristics.
6. Use a Branch and Bound algorithm to search systematically for the optimal solution. This algorithm solves LP relaxations with restricted ranges of possible values of the integer variables. It attempts to generate a sequence of updated bounds on the optimal objective function value.

The optimiser model was implemented using this function and contains 24 constraints, 14 possible gas flows with 6 binary variables. The optimal gas flows and binary variable values are obtained through minimisation of the cost function to give optimal gas distribution on an economic basis, whilst maintaining site operability.

The total historic daily Biogas volume produced on site is the only historic value passed to the optimiser. The model then calculates the volumes of Biogas and Natural Gas that are required to be distributed to each unit to satisfy daily operation at the minimum cost, subject to the constraints outlined.

2.3.4 Displaying Optimisation Results

The function *intlinprog* will always aim to minimise the objective function. As such all revenue parameters are negative and cost parameters are positive inside the optimiser; a negative optimal value provided by the optimiser indicates a potential revenue, whilst a positive value a cost. After optimisation, the resulting ‘optimal value’ is multiplied by -1 so that a positive value represents revenue and negative a cost, as one would expect. When displaying results of optimisations visually, total daily revenue is used for a direct comparison to site operations.

2.3.5 Performing Retrospective Optimisation

To perform RO, historic plant operational data was used for the 12-month period. For a given date, the historic total daily production of Biogas on site is passed to the optimiser which then provides operators with an optimised minimum cost and the optimal daily strategy for operating the plant for that date. The optimal strategy provided can then be compared to actual gas distribution on site, using historic data. For each day in the 12-month data set, the optimised minimum cost for RO was compared to historical site operation (and the subsequent cost of operating using that strategy) to compare how the site has performed in the past.

During RO, the model constraints are adjusted to reflect planned site maintenance; for example, if a CHP Engine was offline on a specific date for annual safety inspections, then the upper and lower gas flow constraints for Biogas and Natural Gas for that engine would be set to 0 Nm^3. This allows the model to perform optimisation with the correctly available units on site.

2.4 Results and Discussion

2.4.1 Optimiser Visual Results

For a given daily volume of Biogas produced on site, the optimiser provides the operator with a visual operation strategy for the optimised minimum cost; Figure 2-6a shows the results to maximize cost reductions for a daily Biogas production of 40,000Nm^3 (a typical production level for the site). Figure 2-6b displays a version, provided by the optimiser, showing the percentage daily utilisation of each unit.

For a daily Biogas production of 40,000 Nm^3, the site should be operated according to the strategy in Figure 2-6 for optimal cost efficiency: to inject all biomethane into the national grid, use Natural Gas in the CHP engines at 100% load to generate electricity on site and use Natural Gas in the steam boilers to create steam as required. For a given daily volume of Biogas, the optimiser provides a fast and reliable result in a matter of seconds.

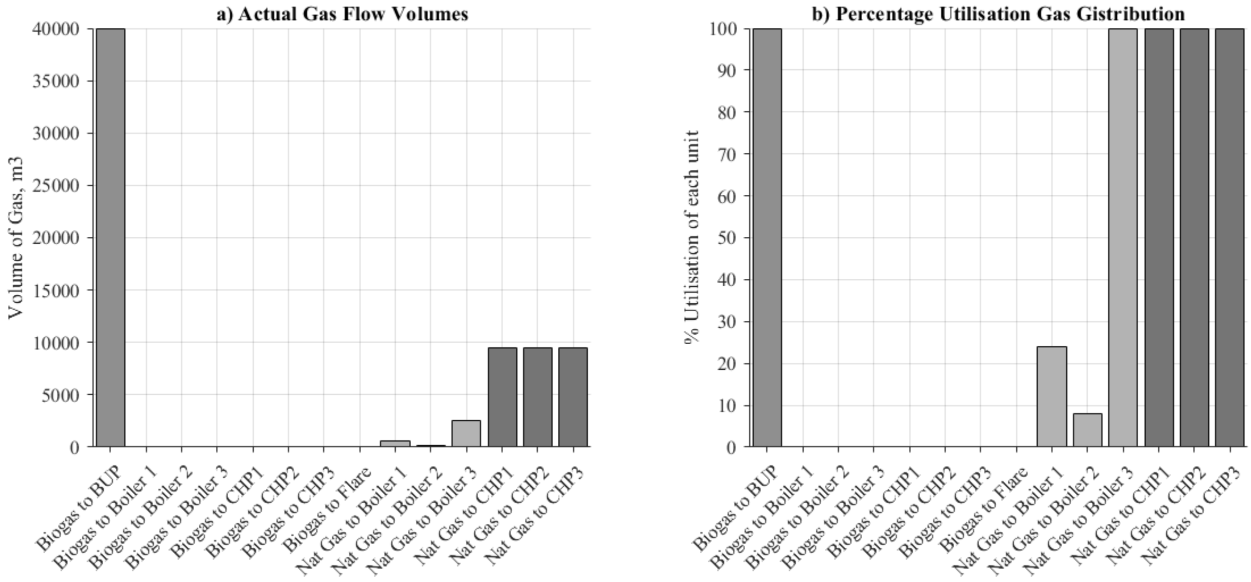

Figure 2-6 – Example Optimised Gas Distribution for daily total Biogas production of 40,000Nm^3.
a) Optimised Daily gas distribution (actual flow volumes),
b) Optimised Daily gas distribution Normalised (by percentage daily utilisation)

2.4.2 Retrospective Optimisation (RO)

Performing RO of the plant over multiple days is difficult to achieve if the operators must sift through multiple graphs for each day that is analysed. For an easier visual indication of how the optimiser suggests the plant should be operated with regards to fuel types for each unit, a Gantt chart showing the gas type selected for is presented – Figure 2-7 shows an example date range from the full RO and compares this to historical operation.

The colour of each block represents a particular fuel type for each unit, typically Biomethane or Natural Gas. However, in reality there may be times where both fuels were recorded historically, as shown in yellow. When switching an engine from Biomethane to Natural Gas, historical operations will show both fuel types were used but for clarity each fuel would have been combusted separately, not as a blend. For example, Figure 2-7 suggests both fuel types were used historically in the CHP Engines on some days, but for CHP Engines this actually show days where a gas type switchover took place.

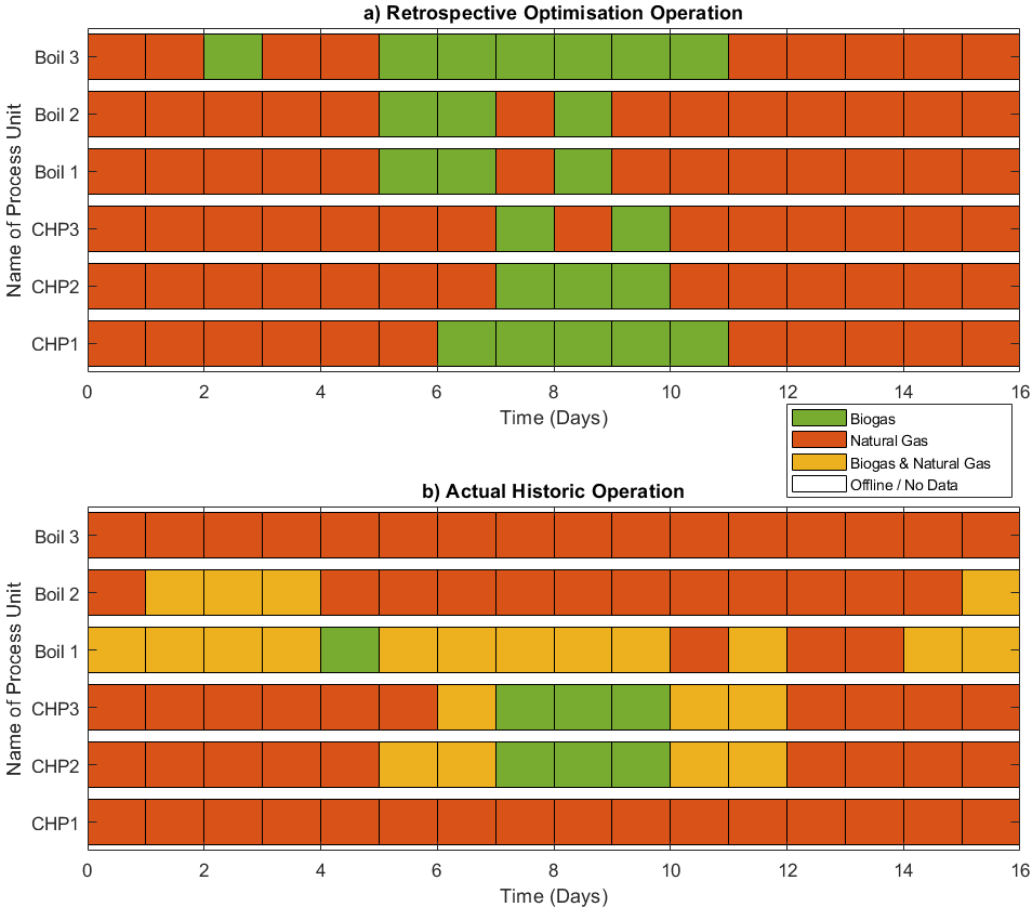

Figure 2-7 - Gantt Chart for an example period showing the type of gas used on site for each unit that can use either Biogas or Natural Gas. Results from Retrospective Optimisation (a) are presented alongside Historical Operation (b).

The historical fuel type shown in the boilers is inferred from historical gas flow data, and on occasion the flow meters indicate that two fuel types were used when this may not have been the case, hence the multiple “yellow” days for boilers. Specifically, in the case of Boiler 1 it may be an indication of an issue with the gas flow meters on site. It may also be an indication that fuel switchovers in the boilers happen more often.

In this figure, it may be seen that the optimiser advised that, between day 6-11, the plant should have swapped some CHP Engines and boilers to run on Biomethane, which the plant mostly managed to achieve with the exception of the boilers.

Each daily optimisation has an associated minimised operational cost, which is used to evaluate RO of plant operations. The minimum cost found by the optimiser is compared to the cost associated with actual historical distribution on site by plotting one against the other. The daily optimal operational cost was compared to the actual historical cost over the 12-month period Nov 2017 to Oct 2018, the historical plant data available, and is shown in Figure 2-8.

In order that RO is representative of site operations, planned site maintenance is included in the RO. Using site maintenance logs, if a unit was taken offline for a full day for scheduled repairs or safety inspections then the optimiser will not have that unit available for the given day of RO.

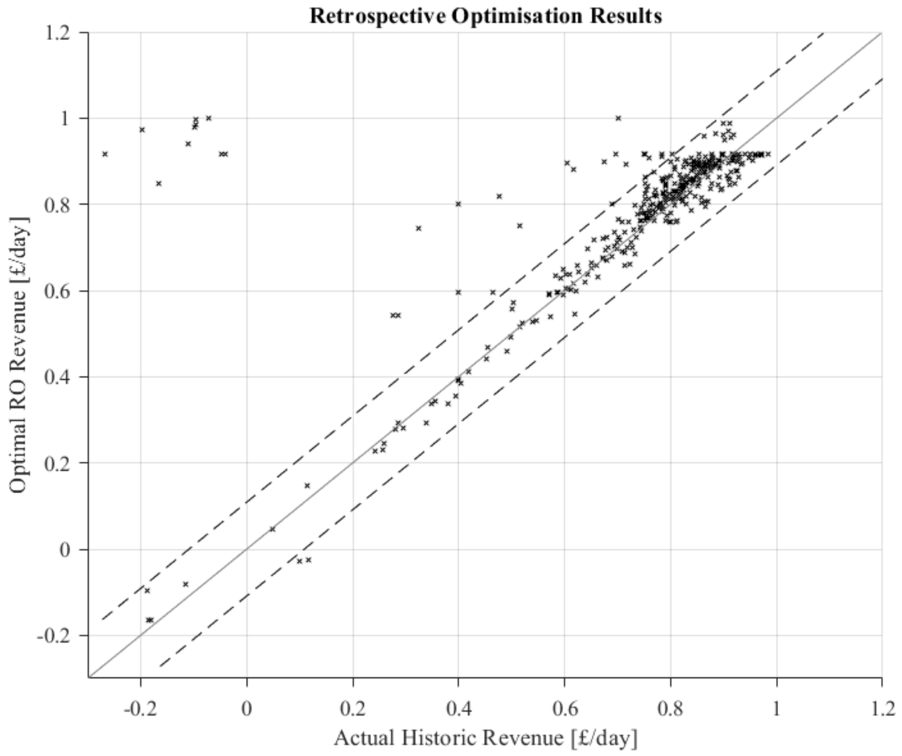

Figure 2-8 [2] - Actual Historic Gas Revenue vs Optimiser Gas Revenue, normalised. Solid line represents shows y=x, and the dashed lines represent the tolerance band (±10% of the max revenue)*

Whilst the parameters of the model are static, for each 3-month moving period, the average maximum gas flows to each unit (Biogas and Natural Gas) are recorded and compared to the gas flow parameters of the model. If the model parameters are more than 10% away from the 3-month average, a warning is displayed during RO such that the user can determine and select an improved parameter. As of yet, the warning parameters have not been triggered, indicating that the initial parameters are valid across the whole RO horizon. It is also why there is a 10% band on the RO graphs.

A band of 10% of the maximum revenue achieved was chosen as the tolerance for optimality as the model parameters do not deviate more than 10% from the historic use of the units on site. Of the 366 days analysed, based on a tolerance of ±10% of the highest revenue, RO indicates the plant operated to within tolerance 98% of the time (332 days). This provides some validation to operators that their historic operational strategy was optimal. However, the 2% non-optimal operational days have a potential lost revenue of almost £350,000

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[2] Note: Wherever noted with '*' in this chapter, the figures presented use the actual revenue in £/day for plotting but for confidentiality (at time of publication) the axis have been normalised based on the highest revenue and do not represent the actual financial figure.

(£349,291); if the site was optimally operated 100% of the time, there is the potential for an increase in revenue of 7.8%. The non-optimal operational days are likely due to unplanned breakdowns and maintenance on site, which can be investigated by comparison with site maintenance logs.

It should be noted that the Gas Distribution model described within this Chapter performs optimisation using daily processing values and does not consider the impacts of electricity demand on site – the potential increase in revenue described here may not be as high (or could possibly be higher) if the model were to consider these changes, or the granularity of optimisation were improved (such as the multi-time period optimisation performed in Chapter 3). The limitations of this model are described further in Section 2.4.6.

2.4.3 Importance of Maintenance Logs

It is paramount that planned shutdowns are logged and programmed into the optimiser to allow for the best comparison of RO and historic operation. However, unplanned shutdowns cannot be pre-configured in the model. RO will highlight non-optimal days and, typically, will highlight the severity (if any) of unplanned shutdowns across the site and will produce a monetary value attributed to each shutdown. However, should an operator wish to change the number of available units (e.g. CHP Engines) on site for scenario modelling, they are able to do so.

Figure 2-9 compares the historic gas distribution (Figure 2-9a) to the optimised distribution if planned shutdowns are ignored (Figure 2-9b), whereas Figure 2-10 compares the historic gas distribution (Figure 2-10a) with the optimised distribution if maintenance in included within the RO (Figure 2-10b). For the example date selected, the BUP was offline for planned maintenance. This demonstrates the importance of including planned shutdowns in the model; by not including them, the model would assume all units were available and thus it would appear the plant operated sub-optimally, yet this was not the case historically.

It should also be noted here that the model has no preference of which engine should be in operation. On the example shown on Figure 2-10b the optimiser selects CHP2 to be used for Biogas by coincidence – the actual engine used is not important to the model, and is an operator decision to maintain the health of the engines.

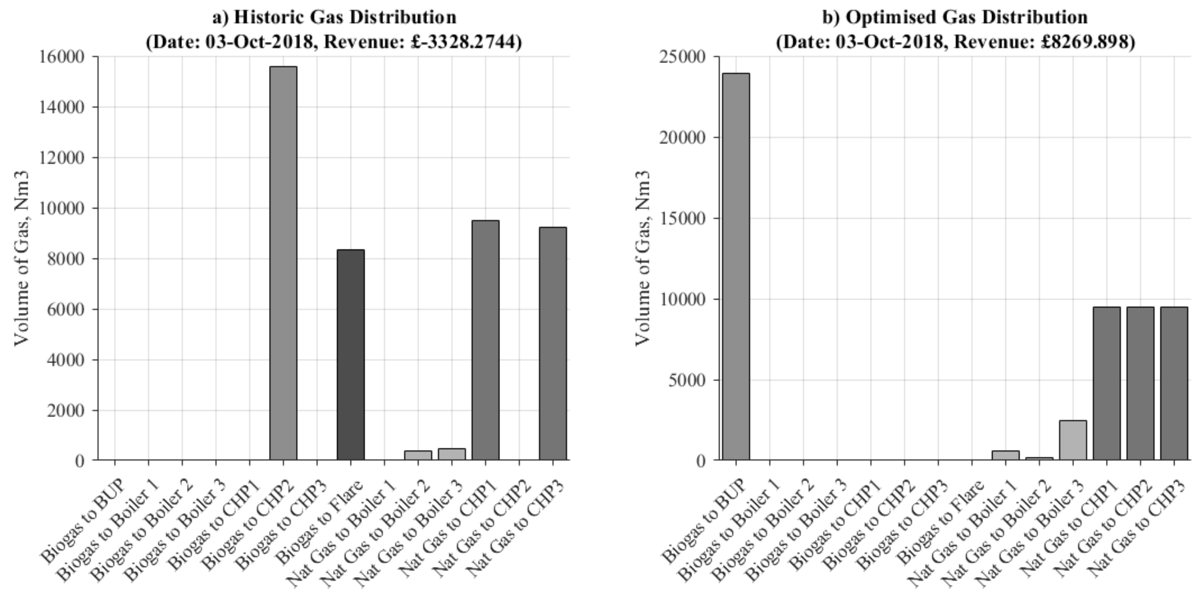

Figure 2-9 – Example comparison between: (a) historic site operations, and (b) Optimised gas distribution on site, for an example date. The optimised distribution assumes all units were available, but RA showed the BUP unit was actually offline for planned maintenance.
[Daily Biogas Production: 23,927 Nm^3]

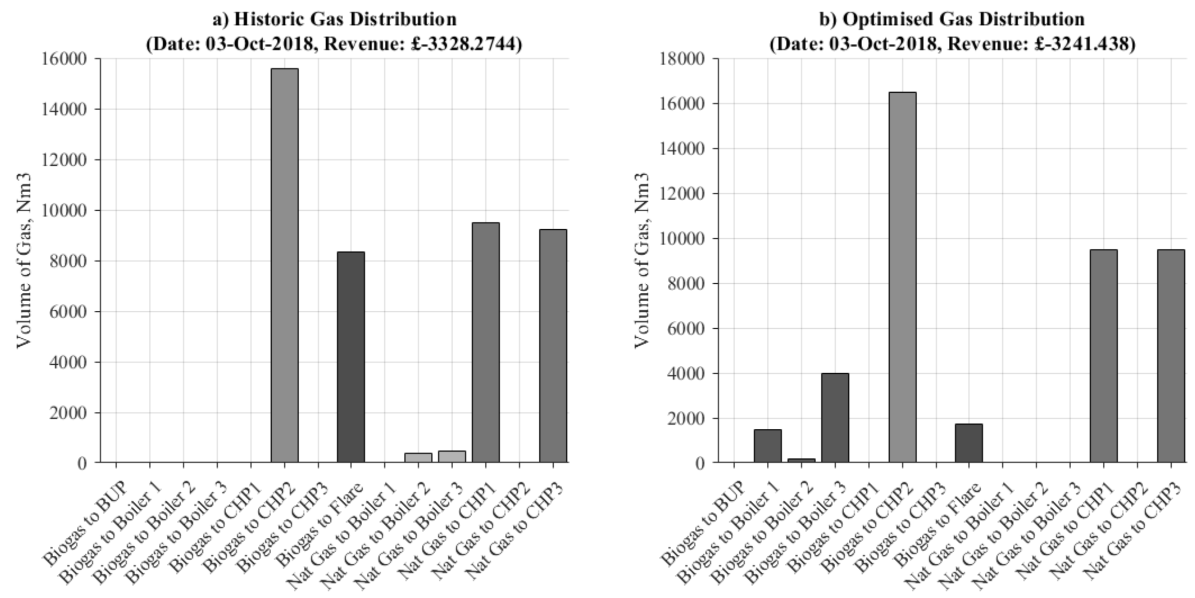

Figure 2-10 - Example comparison between: (a) historic site operations, and (b) Optimised gas distribution on site, for the same example date as Figure 2-9, but Optimiser model now accounts for the planned offline BUP unit.
[Daily Biogas Production: 23,927 Nm^3]

2.4.4 Investigating Unplanned Outages

Using the site maintenance log, planned and unplanned downtime of units on site can be shown on the Annual RO graph in Figure 2-8. The Boiler, CHP Engine and the BUP unplanned outages are plotted on Figure 2-11. Based on the distribution of outages on Figure 2-11, boiler downtime has no major impact on the historic operability of the site. The CHP Engines would appear to have more of an impact on site operations as more of the outliers are associated with unplanned outages.

However, almost every non-optimal outlier on Figure 2-8 is associated with an unplanned outage (full or part day) with the BUP shown on Figure 2-11. Gas injection into the grid is where the plant makes the majority of gas revenue, and the fluctuations of daily gas injection volumes account for most of the variation in the plant operation; whilst a maximum Biogas processing volume of 40,000 Nm^3 is typical, this limit is influenced by external factors and on occasion the site may be able to inject more Biomethane (and subsequently process more Biogas) than the model accounts. It also stands to reason that unplanned outages with this unit will likely cause the plant to operate sub-optimally.

Crucially, full day planned maintenance outages do not cause the site to operate sub-optimally – the plant operates within optimal tolerance on each of the Full Day planned maintenance plots on Figure 2-12. Currently, the model can only handle planned maintenance where a unit is due to be offline for the full day – planned maintenance taking less than a full day cannot accounted for in the current model. The potential shortfall in revenue of ~£350k is mostly due to unplanned breakdowns and planned maintenance that does not take a full day.

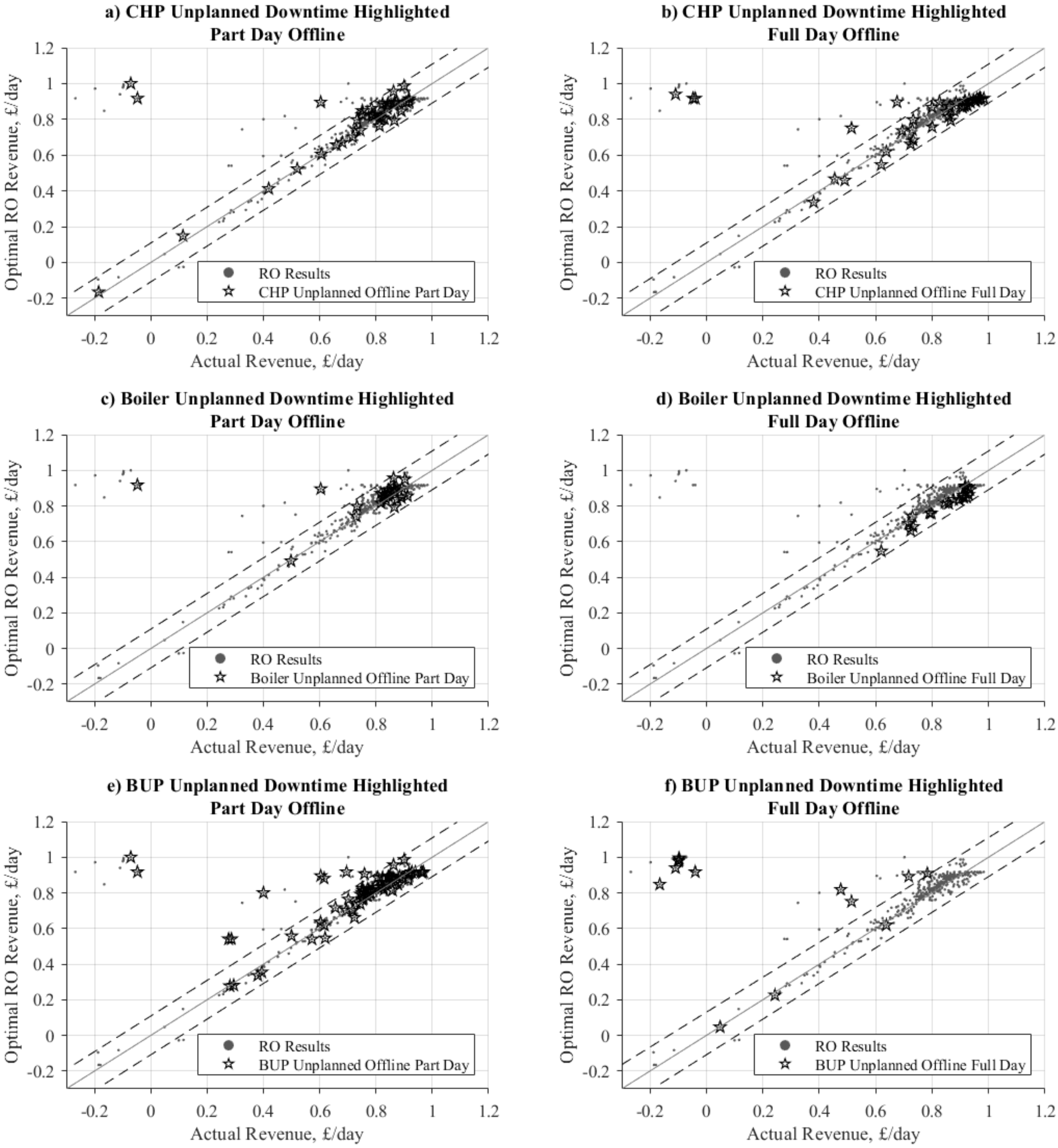

Figure 2-11[A] - Annual RO but days with Unplanned Downtime of units are highlighted.*
'Part Day' refers to a unit being available for less than the 24-hour optimisation period, and typically ranges from 1-6 hours. 'Full Day' refers to a unit being offline for use for the entire 24-hour period.
Solid line represents shows y=x, and the dashed lines represent the tolerance band (±10% of the max revenue)

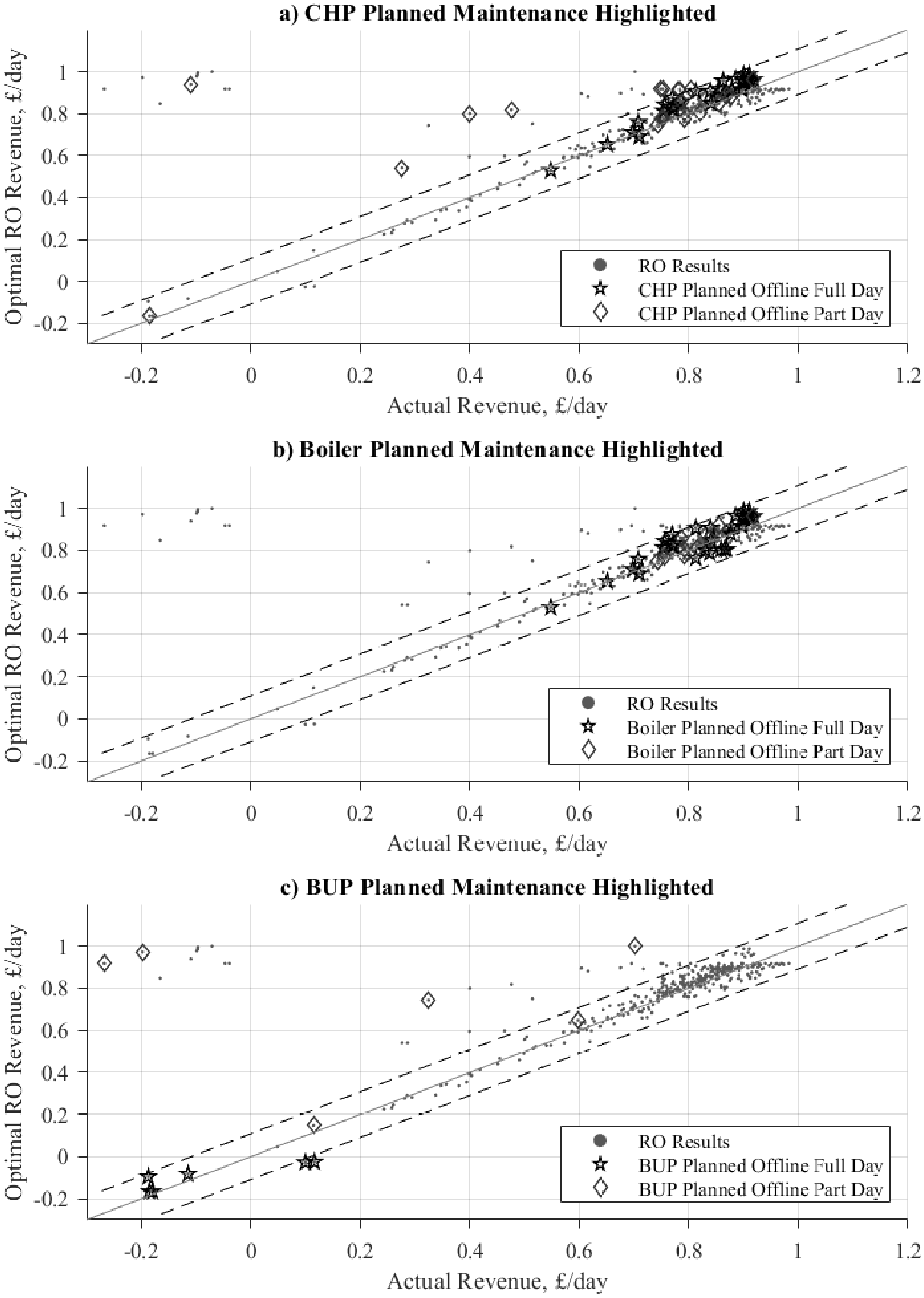

Figure 2-12[A] - Annual RO but days with Planned Maintenance of units are highlighted.*
'Part Day' refers to a unit being available for less than the 24-hour optimisation period, and typically ranges from 1-6 hours. 'Full Day' refers to a unit being offline for use for the entire 24-hour period.
Solid line represents shows y=x, and the dashed lines represent the tolerance band (±10% of the max revenue)

2.4.5 Achievable Increase in Revenue

A perfect process plant would always run optimally without any unexpected breakdowns or unforeseen circumstances preventing optimal operation. However, this is not the case and should be mentioned when considering the potential 7.8% increase in revenue available. If the plant operated to within optimal tolerance 98% of the time, then to what extent could this be practically increased further? Whilst undesirable it is expected that process plants will ultimately have unexpected downtimes, especially with new technologies and installations. Acceptable levels of lost revenue due to unexpected maintenance is a decision for site managers, the RO presented here is supporting investment decision making – allowing operational managers to quantify the benefit of maintenance expenditure

After investigating the possible cause of outliers from RO (Figure 2-8), it is clear the main focus for improvement should be the BUP. Each of these outliers corresponds to a day where the BUP failed (full day or part day, Figure 2-11) or whether the BUP was planned to be offline for maintenance for part of the day (Figure 2-12). Failures in the BUP could be mechanical (such as a component breaking) or 'gas-spec' failures; if the gas composition does not meet the correct standard for injection it will enter a 'failed' state and reject gas until the specification target is met.

It is worth noting that the BUP part of the AAD plant is a recent addition to the site, with installation completing late 2015. It is a new operation for operators and for the local gas network to manage correctly; the data used for RO is still within the BUP's early years on site, so a higher number of unexpected downtime would be anticipated due to the complexity and age of the technology. It is believed by operators that the BUP has operated more robustly in recent years, but RO has not been performed over a later date yet so this cannot be confirmed in this chapter.

The highlighted data on Figure 2-11 is also a good indicator of the number of unexpected instances on site, their origin and how impactful breakdowns of individual units are with regards to economic operations. As the number of planned part-day maintenance instances is low, RO of the plant using this model is a good indication of the potential improvement for plant robustness and could help provide justification for future investments.

2.4.6 Model Limitations

Currently, the Biogas Distribution Model is a retrospective optimiser only, as a future prediction of Biogas production is currently unavailable. In Chapter 5, initial investigations are carried out modelling the digesters to predict this Biogas production, to provide operators with a full sludge processing optimisation model to allow for improved operational forecasting.

In addition, the model does not consider electrical costs associated with the CHP Engines, electrical import tariffs or site load with regards to electricity and heat and assumes that CHP engines must be in operation provided they are not offline for maintenance. Electricity generated through the CHP Engines is used on site to reduce electrical consumption from the national grid and heat produced from them is reused to reduce gas requirements for the steam boilers on site (the steam is used as part of the Thermal Hydrolysis process). Clearly, shutting down a CHP Engine will increase the electrical demand on the National Grid, with site electrical costs increasing due to reduced CHP electrical output, as well as increasing the heat load on the Steam Boilers.

To incorporate electricity generation, it will require splitting the model into smaller optimisation steps. The model currently uses daily values for processing limits, however Electrical Import/Export costs on site are 'fixed-variable' (vary half hourly but are fixed and known) meaning that each half hour the CHP electricity generated on site will offset a different Import cost, thus will require its own optimisation step. This would present unique and interesting challenges, as each optimisation step would require linking together, to prevent excessive ramping (turning on and off) of CHP Engines, or fuel type switching every half hour – fuel types for CHP Engines cannot be switched over throughout the day.

2.5 Conclusions

This chapter proposes a MILP model for Gas Distribution and Optimisation of an AAD Plant with multiple options available for Biogas use on site. The optimisation model takes a single input of Daily Biogas volume produced, in m^3, by the Anaerobic Digesters to provide operators with an optimal daily operational strategy; the strategy is provided to the operators in visual form for each day, though weekly strategies are also possible if required. The model also includes a penalty term on the flare stack for preventing unnecessary use of the emergency flare.

RO techniques were performed with historical operational data to determine the economic effectiveness of previous operational strategies. The model proposed uses MILP optimisation techniques to perform RO across the historical data horizon (one year) in a matter of seconds, with individual daily optimisations taking far less computational time.

Comparing the summated daily gas revenues used for RO of the plant indicates a potential increase in revenue of 7.8% (~£0.35m) for the period optimised if the plant was run optimally all of the time. Upon discussion with operators and analysis of the Maintenance and Breakdown logs, the 'lost revenue' and non-optimal performing days (points on Figure 2-8 not within tolerance band) are mostly due to unit malfunctions, indicated on Figure 2-11, and are mostly due to the loss in revenue from lower Biomethane Injection due to BUP unplanned outages (Figure 2-11, graphs '*e'* and '*f*').

The potential increase in annual revenue from gas distribution could be achieved through improved operational strategies or (more importantly) improved plant robustness, such as reducing the number of incidents of unplanned outages, with a specific focus on the Biomethane Injection Plant. The potential increase in revenue could be used to justify future plant improvements: historically, the plant operates optimally most of the time with non-optimal performing days occurring mostly when unplanned downtime of process units occurs. Operators could categorise these outages as 'avoidable' or 'unavoidable', and then use the 'avoidable' outages and the expected increases in revenue as leverage to request plant improvements.

Finally, improving the proposed model to include electrical costs and heat loads, as discussed previously, would transform the model into a full Energy Management model for the AAD plant: a possible Decision Support System (DSS), that could be used for RO and to validate future operational strategies. In the current state the proposed Gas Distribution model is not detailed enough for implementation on site. In Chapter 3, the proposed model here was developed further to include these limitations for a more complex optimisation.

Chapter 3 Energy and Carbon Model

This chapter proposes an Energy Management Model for the AAD plant at Howdon, using MILP to perform day-ahead optimisation based on live day-ahead pricing and estimated future biomethane production levels. The previous gas distribution model created for the site was effective but too simple to meet the complex demands of the full site, performing the optimisation over multi-time period steps rather than over a single time step optimisation, and with the new Net Zero Carbon emissions pledge an improved approach was required.

3.1 Introduction

In the previous chapter, a realistic model for gas distribution of an advanced municipal wastewater treatment works was proposed, where Retrospective Optimisation (RO) is performed [40]. Whilst a good representation and optimisation tool for gas distribution, the proposed model had limitations regarding electricity use on site: the CHP engines produce electricity for consumption on site or for export to the electricity distribution network, which was not included in the previous model, nor was the new carbon performance commitment included.

Whilst RO is a useful tool for retrospective analysis to improve future operations such as optimal scheduling [38], it would be beneficial for the site to have an optimisation tool to aid in operational decision making. Although different wastewater processing techniques will have different degrees of carbon emissions (usually based on their various energy demands) [21], optimisation of current procedures is always useful to reduce emissions as far as possible. With the new challenge of net zero carbon emissions, it was decided to improve the previous model to address the limitations and, to aid in achieving the net zero emissions target, develop the model further to include new optimisation constraints regarding carbon emissions, heat and electricity generation and varying electrical import tariffs.

The model implemented in this chapter is formulated through MILP and is developed on the founding model described in the previous chapter. As has been previously stated (see Chapter 2.1) MILP has widely applicable industrial applications for optimisation. However, more specifically and more relevantly, MILP techniques have been used successfully in the optimisation of micro-grids [41–43].

Micro-grids are small power systems which utilise various energy generation units of different types (typically renewable sources) such as biomethane, solar, wind, and storage devices like batteries or thermal energy storage [44] sometimes in connection with the main power utility grid. Micro-grids tend to cater to the combined heat and power needs of the system, utilising waste heat to improve system efficiency [44,45]. The AAD plant at Howdon could be considered a localised microgrid on site, but without either heat or electricity storage capabilities [Figure 3-1], using the renewable energy biomethane produced on site or Natural Gas as an energy source (at the time of developing this mode, NWL has installed a new fourth gas engine on site, hance the different site layout compared to Figure 2-1).

The model formulated in this chapter requires 48 discrete time periods for the day-ahead optimisation, due to the half-hourly electricity tariffs the site is subject to (see Section 3.2.2). Discrete-time MILP formulations have been developed when considering renewable generation with an established demand [46] as well as using CHP systems in residential microgrids [47]; both MILP models implemented cover micro-grids comparable to the case of Howdon.

Whilst more complex solutions have been applied to the optimisation of micro-grids, such as Model Predictive Control (MPC) techniques [48] or combined MPC and MILP models [49], one of the major benefits of the application of MILP techniques to the process scheduling problems lies in the computational efficiency for the solution of the resulting MILP problem [30].

The updated version of the model in this chapter considers electricity import tariffs to determine whether a CHP Engine should be operating or not, using Biomethane processing demands and the new Carbon Emissions pledge to optimise operations. The model can be used to help managers see the impact the new Carbon Emissions performance criteria will have on revenues, as well as aid in managerial decision making in whether to change energy supplier for electricity.

The novelty of this work lies in the application of MILP optimisation techniques to a renewable biomethane energy plant at a wastewater treatment works, alongside the inclusion of a new Carbon Performance Commitment with associated Outcome delivery Incentive for the NWL. MILP techniques have been applied to the optimisation of clean water networks (see [50–52]) but the application has focused on clean water distribution, such as urban water supply chain optimisation. Currently there is no reported research on the application of MILP techniques to energy management of a wastewater AAD plant, and whilst the Howdon AAD plant is akin to a Micro-Grid as previously mentioned, it is believed there is a substantive gap in the reported literature in the application of MILP in this area.

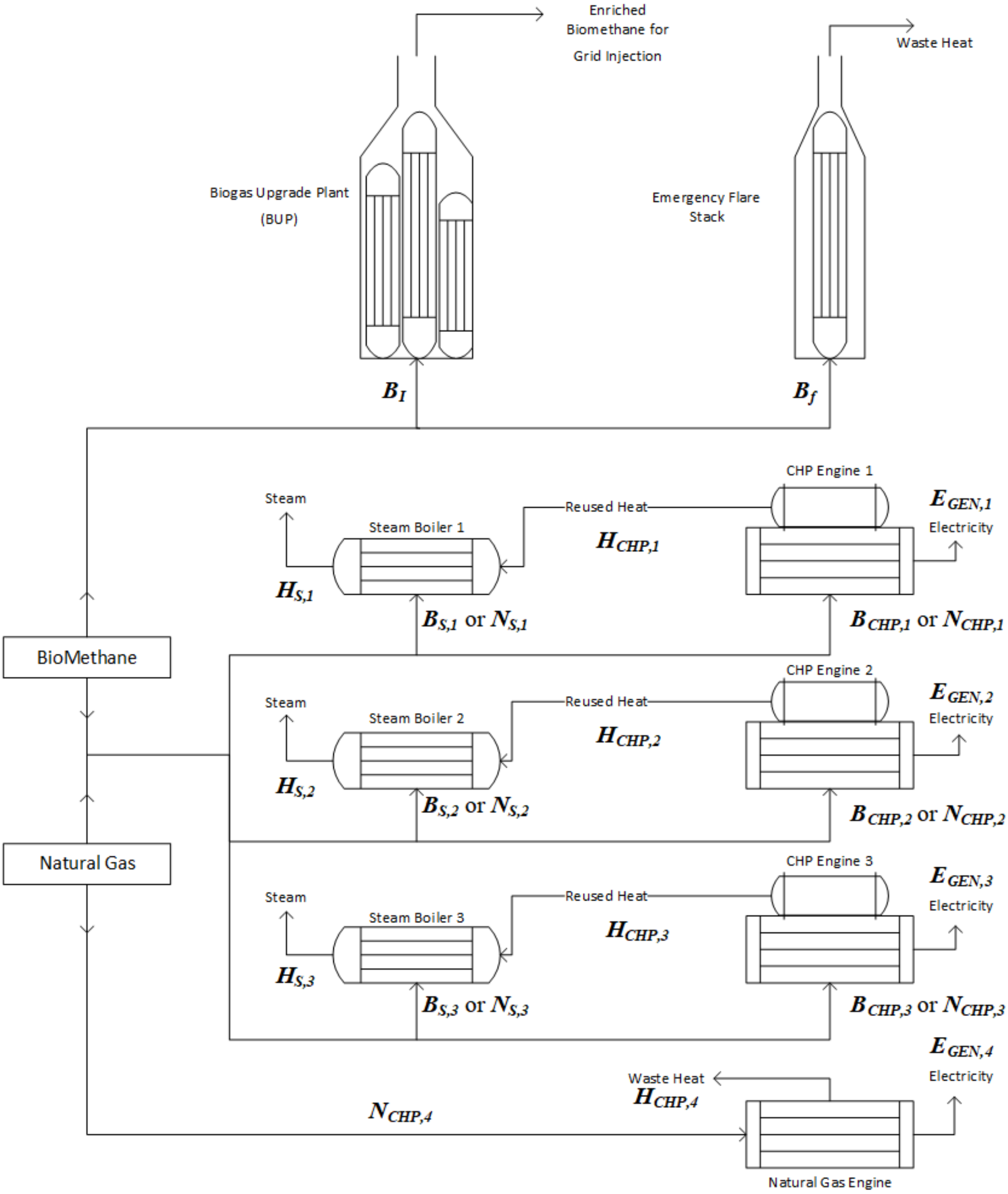

Figure 3-1 – Updated Process Diagram for Gas Distribution on site (originally presented in [40]*). Biomethane source is from Anaerobic Digestion on site, Natural Gas is from the gas distribution network. Diagram also shows heat production and electricity generation from CHP engines. At the time of developing the energy model, NWL had installed a fourth engine, hence why it is not present on Figure 2-1.*

An updated process diagram for the AAD plant (and the variables used in this chapter) are presented in Figure 3-1. Most notably, the difference between this updated process diagram and the one shown previously in Figure 2-1 is the inclusion of a fourth gas engine, heat recovery and generated by CHP engine and the boilers and the electricity generated by the gas engines. The improved processing constraints and limitations are explained throughout this chapter.

The remainder of this chapter is structured as follows. The site constraints, formulation of the MILP model and development the objective function for optimisation are outlined in the Methods section. The Results section shows example optimisation results from the Optimiser based on an example variable electricity tariff, investigates the managemental decision around Carbon Emissions and Electricity Imports and compares the advised optimal operational schedules with the current operational strategy. Finally, conclusions are presented alongside limitations and potential improvements to this model.

3.2 Methods

3.2.1 Unit Processing Limits

The gas processing limits for each unit in this model are shown in Table 3-1, with changes made from Chapter 2 to include updates to operational constraints and the new fourth engine.

Table 3-1 - Operational gas flow constraints for units on site [40].

Limiting Parameters	Operational Constraints
$\boldsymbol{B_{I,max}}$	Max flow: 40,000 Nm^3 / day
$\boldsymbol{B_{I,min}}$	Min flow: 0 Nm^3/ day
$\boldsymbol{B_{CHP,max}}$	Max Flow: 16,000 Nm^3 / day
$\boldsymbol{B_{CHP,min}}$	Min flow: 50% of max flow
$\boldsymbol{B_{S,max}}$	Max flow: 4000 Nm^3 / day
$\boldsymbol{B_{S,min}}$	Min: 200 Nm^3 / day
$\boldsymbol{B_{f,max}}$	No Max
$\boldsymbol{B_{f,min}}$	Min: 0 Nm^3 / day
$\boldsymbol{N_{CHP,1-3,max}}$	Max flow: 9000 Nm^3 / day
$\boldsymbol{N_{CHP,\ 4,max}}$	Max flow: 10000 Nm^3 / day
$\boldsymbol{N_{CHP,min}}$	Min flow: 50% of max flow
$\boldsymbol{N_{S,max}}$	Max flow: 2500 Nm^3 / day
$\boldsymbol{N_{S,min}}$	Min flow: 200 Nm^3 / day
$\boldsymbol{H_{Req}}$	70 MJ / day
$\boldsymbol{S_{min}}$	Lower Limit: 3300 Nm^3/ day

A site diagram showing the gas distribution, electrical production and heat generation on site is shown earlier in Figure 3-1. For clarity, throughout the chapter the fourth engine is referred to with the subscript $\boldsymbol{CHP, 4}$ but this engine is not CHP as it does not make use of the waste heat on site – it is a Natural Gas Engine for generating electricity only.

3.2.2 Electricity Import Tariffs

Understandably, switching a CHP engine off results in a lack of generation of electricity thus, assuming all electricity generated is also consumed on site, this lack of generated power is required to be imported from the electricity distribution network. It is therefore imperative that the electrical import tariff of the site is considered.

Unlike most modern home consumer energy tariffs, large businesses (such as NWL) tend to be subject to varying electricity tariffs depending on market conditions and regulatory charges. Howdon's electricity tariff is known for the following day. The price changes for each half hour period. This presents an opportunity to optimise the gas usage around the peaks and troughs in electricity prices (as biogas produced could be used for electricity generation rather than grid injection), provided this does not impact on site operation.

Although it has been noted in previous studies that day-ahead markets may be of limited value to a power system that relies highly on renewable energy [53] the renewable biogas produced is a consistent available resource in this case, thus day-ahead pricing can be taken advantage of to produce an optimal daily operational schedule.

Whilst tariffs like these can change annually, subject to contract agreements and regulatory changes, it is anticipated than in the near to mid-term UK industrial prices will continue to be delineated in 30-minute time bands known as settlement periods. The example fixed import tariff shown in Figure 3-2 (from April 2019 – April 2020) is a valid approximation for the typical tariff the site is subject to today and was the most up to date information at the time of the study performed within this Chapter.

Currently, site operators do not consider the varying cost of electricity imports during day-to-day operations – the focus is on the sludge processing requirements to satisfy the sites regulatory consents. By considering this price variance the optimal economic operational strategy may differ than the current strategy whilst still being able to meet the operational requirements.

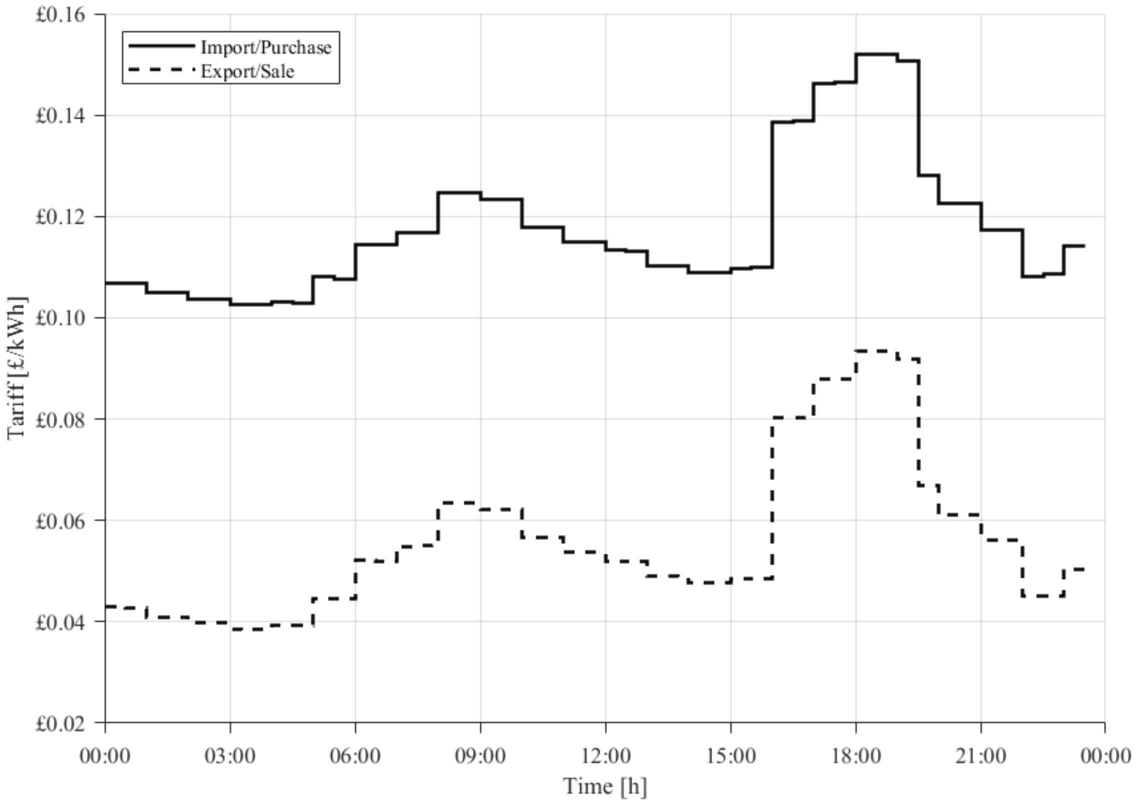

Figure 3-2 - Example daily electricity import tariff for Howdon STW in pence per kWh; 24 hour period (00:00-24:00) with changes to price every half hour. This is an actual historical price applied to the site during the Apr2019 – Apr 2020 period, and is a valid aproximation for todays tariffs.

3.2.3 Natural Gas Prices

Whilst it is recognised that Natural Gas prices do vary, analysis has shown a gradual increase in price from 18.5 pence/therm to 42.4 pence/therm over a 10 year period [54]. The price of Natural Gas in the UK tends to remain at a fixed cost throughout the day, thus for the purpose of this model can be assumed constant over the 24-hour operational horizon.

3.2.4 Electricity Generation

The three CHP engines are on site are each rated at 1750 kW and the Natural Gas Engine rated 2000 kW, producing this electrical power at full gas flows. Retrospective analysis of historical operations validates the ratings, however as Biogas and Natural Gas have different Calorific Values (CVs) the total volume of gas required is different to produce the same power. A Biogas fuel source will require a higher flow of gas to the engine than Natural Gas, reflected in the operational constraints (Table 3-1).

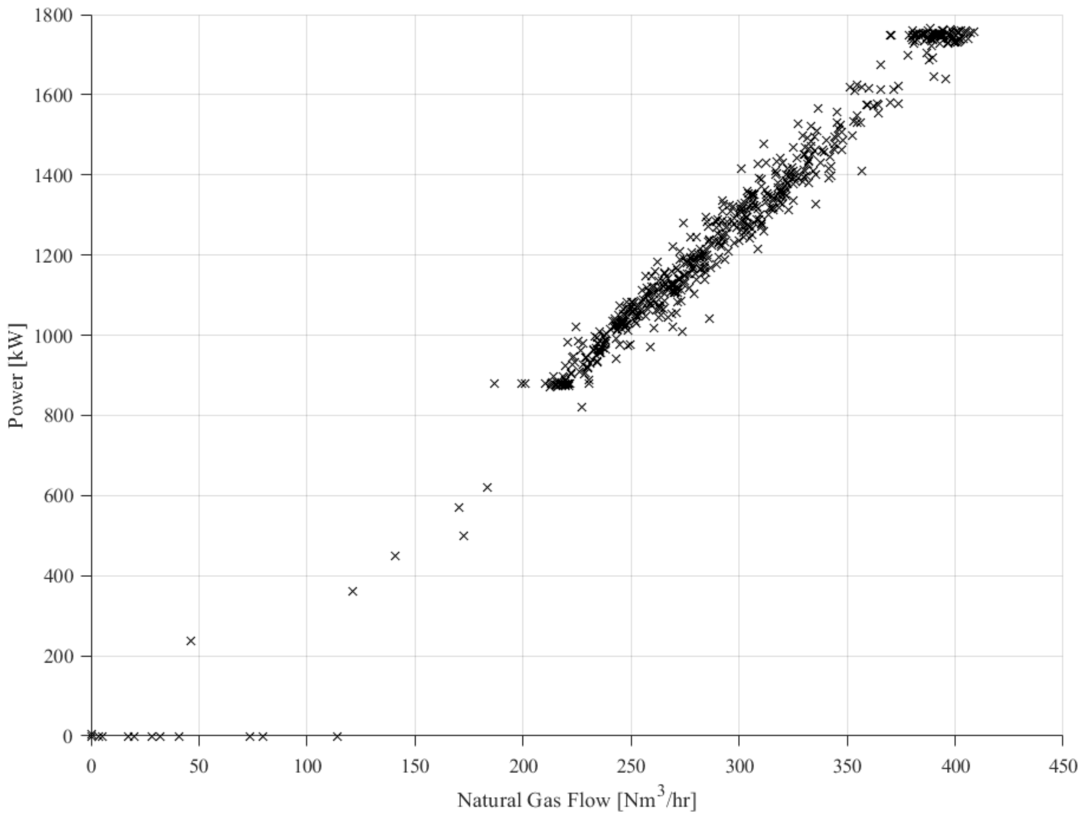

Figure 3-3 - Example Power Curve of CHP Engine 1 operating on Natural Gas for the month of October 2020

Further analysis of historic gas flow rates to power output shows the power curve of the gas engines can be reasonably assumed to be linear in the operating region (where the chosen fuel gas flow rate is between max flow and 50% max flow). As an example, Figure 3-3 shows the power curve for CHP Engine 1 operating on Natural Gas. Where the engine is fully operational (200-400 m^3/hr) the power curve can be seen to be linear. Where the engine is starting up (0-200 m^3/hr) the power curve is non-linear, however the model only considers the region when the engine is fully operational. As start-up times take approximately 15 minutes, for each time period within the model when the engine is switched on the engine is considered to be non-operational for 15 minutes, then fully operational thereafter. This is explained further under section 3.2.6.4 below.

3.2.5 Cost of Carbon Dioxide – ‘Carbon Credits’

To aid in achieving the net zero carbon emissions target, NWL has agreed with the UK water industry regulator cost parameters for CO_2 emissions. Additionally, the emissions parameters are defined by an industry-standard accounting process managed by UK Water Industry

Research. These parameters include various company-wide variables, such as natural gas purchased, or electricity generated. The variables that impact the Howdon AAD plant are recorded in Table 3-2 with their associated carbon emission factors. The amount of CO_2 emitted is noted as kg.CO_2e (kilograms of CO_2 equivalent emitted).

Table 3-2 - Carbon Emission Factors for the variables at Howdon AAD plant. [55] *– correct at time of writing but are subject to annual reviews.*
(All m^3 noted here refer to normalised cubic metres.)

Variable	Symbol	Factor	Units
Import Electricity [3]	K_{IMP}	0 or 0.31	kgCO_2e /kWh
Export Electricity [4]	K_{EXP}	-0.28307	kgCO_2e/kWh
Import Natural Gas	K_N	2.03053	kgCO_2e/m^3
Export Biomethane	K_{EB}	-2.04652	kgCO_2e/m^3
Propane	K_P	1.51906	kgCO_2e/L
Biogas CHP	K_{CHP}	0.0175	kgCO_2e/m^3
Biogas residual	K_R	0.16	kgCO_2e/m^3

The value of CO_2 emissions (kg.CO_2e) generated using these factors will be referred to as 'carbon credits' throughout this chapter. It should be noted that some factors are negative (they are seen as 'offsetting' other carbon emissions by the regulator Ofwat), therefore there is the theoretical possibility to generate an overall negative value of carbon credits given the right site operation, which NWL may claim against other areas of the business.

These carbon credits are new and applied across the entire business and will be applied in arrears of two years. Thus, when displaying optimisation results, the optimal daily revenue is shown both including and excluding carbon: the 'Excluding' carbon value is representative of the revenue the site will likely see in their books immediately, whilst the 'Including' carbon

[3] This factor was dependant on the original source of electricity (renewable or not) subject to contractual agreements between NWL and their energy provider and was not yet finalised at point of writing.
[4] Export Electricity factor only applies to electricity made using Biogas in the engines. There is no factor for Natural Gas electricity exports.

is the revenue the site will make in two years' time, once the performance commitment is applied.

The electricity factors surrounding CO_2 emissions shown in Table 3-2 are static parameters, however it should be noted that the CO_2 emissions resulting from electricity generation are not usually static. The National Grid ESO have developed a state of the art machine learning and power system modelling to forecast the carbon intensity and generation mix for electricity on a regional basis within the UK [56]. Whilst such a tool and model is relevant and would be useful for actual emissions monitoring, it is not applicable to this model due to current legislative agreements.

3.2.6 MILP Equations and Constraints

3.2.6.1 Objective Function

The simplified objective function is given by Equation (*3-1*). The aim is the minimisation of the total cost of site operations (including gas distribution, electricity import costs, and penalty terms as well as the 'cost of carbon'), subject to site constraints:

$$T_c = \sum_{t=1}^{48} \left(T_{B,t} + T_{N,t} + T_{P,t} + T_{E,t} + T_{CO_2,t} \right) \tag{3-1}$$

The total cost for Biogas and Natural Gas use on site, $T_{B,t}$ and $T_{N,t}$ respectively, are defined by summating the gas flows to each CHP Engine or Steam Boiler and the Biogas flow to the Biogas Upgrade Plant (BUP) during each time period. Small amounts of propane, P, are used in the enrichment process for upgrading Biogas into renewable Biomethane that can be injected into the gas distribution network and are included under the Biogas costs. Here, B represents a Biogas flow (Nm^3, variable), N represents a Natural Gas flow (Nm^3, variable) and C represents the cost of using the associated gas (£/Nm^3 for all except propane which is £/L, constant):

$$T_{B,t} = \sum_{i=1}^{4} \{ B_{CHP,i,t} \cdot C_B \} + \sum_{j=1}^{3} \{ B_{S,j,t} \cdot C_B \} + B_{I,t} \cdot C_I + P_t C_P \tag{3-2}$$

$$T_{N,t} = \sum_{i=1}^{4} \{ N_{CHP,i,t} \cdot C_N \} + \sum_{j=1}^{3} \{ N_{S,j,t} \cdot C_N \} \tag{3-3}$$

Both costs and revenues of gas streams on site are considered; injecting Biomethane into the gas distribution network through the BUP creates a revenue as the gas is sold (C_I), burning Biogas in the boilers and CHP engines has ‘usage’ cost (C_B) whilst purchasing Natural Gas for use anywhere has a cost associated (C_N).

To prevent the optimiser from sending gas to the flare stack a penalty term, $T_{P,t}$, on flaring Biogas was applied to the objective function. The cost function for flaring, C_f, was manually set high previously such that the optimiser would allow flaring only as a last resort. In this version, there is no direct cost of burning Biogas on the flare stack (C_f=0), however burning Biogas on site anywhere other than in the CHP Engines is subject to the carbon performance criteria (see Table 3-2 – Biogas Residual). Should operators require a direct penalty term be applied, C_f can be easily adjusted accordingly. The site is required to minimise flaring to satisfy its environmental and regulatory commitments.

$$T_{P,t} = B_{f,t} \cdot C_f \tag{3-4}$$

The total cost of electricity imported is given by summing each half hour operation and has its own associated variable cost (Figure 3-2) such that the total cost of electricity imports, T_E, is given by:

$$T_{E,t} = C_{E,t} \cdot E_{IMP,t} \tag{3-5}$$

Using Biogas and/or Natural Gas on site will affect the carbon credits accrued, as well as the use of Propane and Electricity. The total cost of Carbon Credits, T_{CO_2}, is found by summating the total credits generated from all sources, G_{CO_2}, and multiplying by the cost of each credit, C_{CO_2}. Using Natural Gas across the site has the same credit generating parameter, D_N, whereas using Biogas has a different parameter for use in BUP, CHP Engines and the Boilers / Flare.

$$T_{CO_{2,t}} = C_{CO_2} \cdot G_{CO_{2},t} \tag{3-6}$$

$$\begin{aligned} G_{CO_{2,t}} = {} & \sum_{i=1}^{4} \{ K_{CHP}\, B_{CHP,i,t} + K_N N_{CHP,i,t} \} + \sum_{i=1}^{3} \{ K_R\, B_{S,i,t} + K_N N_{S,i,t} \} + K_{EB} B_{I,t} \\ & + K_R B_{f,t} + K_P P_t \end{aligned} \tag{3-7}$$

Therefore, the objective function for a 24 hour horizon is given by:

$$\begin{aligned} T_c = \sum_{t=1}^{48}\Bigg(&\sum_{i=1}^{4}\{C_b\, B_{CHP,i,t} + C_n N_{CHP,i,t}\} + \sum_{i=1}^{3}\{C_b\, B_{S,i,t} + C_n N_{S,i,t}\} + C_I B_{I,t} \\ &+ C_f B_{f,t} + C_P P_t \\ &+ C_{CO_2}\Bigg[\sum_{i=1}^{4}\{K_{CHP}\, B_{CHP,i,t} + K_N N_{CHP,i,t}\} + \sum_{i=1}^{3}\{K_R\, B_{S,i,t} + K_N N_{S,i,t}\} \\ &+ K_{EB} B_{I,t} + K_R B_{f,t} + K_P P_t\Bigg] + \sum_{j=1}^{48}\left\{C_{E,j}\cdot\sum_{i=1}^{4} E_{GEN,i}\right\}\Bigg) \end{aligned} \tag{3-8}$$

3.2.6.2 Adjusting Process Limits

The proposed model requires the optimisation horizon of one day to be broken up into 48 half hourly intervals (time points) such that the half hourly electrical tariff, Figure 3-2, can be incorporated. The process limits outlined in Table 3-1 are adjusted from daily values to half-hourly using the constant $\boldsymbol{\alpha}$**.** The default model state assumes that all units are available for use, however should operators be aware of planned maintenance for a particular day then the process limits can be adjusted to accommodate planned offline units.

3.2.6.3 Mass Balance Constraint – Model Input

The overriding site constraint is given by the overall mass balance of Biogas distributed across the site: the volume of Biogas produced from the anaerobic digesters, B_{Total}, must equal that of Biogas distributed across site. There is no constraint of Natural Gas of this form, as Natural Gas is readily available if required. Other than up to date tariff information, the total volume of Biogas produced, B_{Total}, is the only variable that is input into the model on a daily basis.

$$B_{Total} = \sum_{t=1}^{48}\left\{\sum_{i=1}^{3}\{B_{CHP,i,t} + B_{S,i,t}\} + B_{I,t} + B_{f,t}\right\} \tag{3-9}$$

3.2.6.4 Gas Engines Constraints – Gas Flows and Operation Time Limits

The Engines have a minimum gas flow throughput to allow operation (50% of the maximum flow), and in addition each gas engine may either be in an 'On' of 'Off' state. To allow for a unit to be On or Off, $R_{i,t} \in \{0,1\}$ is introduced to allow the model do determine the overall state of each engine at each time point 't'. In addition, there is another binary variable implemented for biogas or natural gas flow to an engine, $w_{B,i,t}$, $w_{N,i,t} \in \{0,1\}$, used to aid in this endeavour due to the two possible fuels for the CHP engines. Essentially, $R_{i,t}$ determines whether an engine is online or offline, and $w_{B,i,t}$ *or* $w_{N,i,t}$ help maintain linear consistency to ensure only one fuel type is used.

There is significant inertia associated with the operation of the gas engines, meaning that once switched 'On' each engine has a minimum operating time, τ_{min}, and once switched 'Off' there is a shut down time. Once an engine has been switched off the engine must enter a rest state for a minimum time, τ_R, before it can be re-initialised. In the model, τ_{min} and τ_R are the number of time-periods an engine must remain operational or rest for.

Operators require engines to remain operational for at least 4 hours once switched on and must rest for at least 1 hour after shutting down, therefore in the model $\tau_{min} = 8$ and $\tau_R = 2$. The time-periods when an engine is switched on and off are tracked using the 'start-up' and 'shut-down' binary variables, $su_{i,t}$, $sd_{i,t} \in \{0,1\}$ respectively.

In their paper, Kelly and Zyngier [57] present new and improved methods for using MILP binary variables in sequence-dependant switchovers for discrete-time scheduling problems, using and tracking start-up, shut-down and operating time variables to ensure minimum operating times or rest times. Here, their proposed techniques are adapted for this model to the constraints on τ_{min} and τ_R, such that for each gas engine the minimum operating time and rest constraints are tracked and implemented.

In our model, when an engine is switched on $su_{i,t}$ and $R_{i,t}$ both take the value 1 at the same time, but an engine cannot be in start-up and shut-down simultaneously, and thus only one of $su_{i,t}$ and $sd_{i,t}$ may be active at a time, but they may both be 0. The model tracks previous time periods to determine whether an engine can be switched on, or is already operational and can be switched off by:

$$R_{i,t} - R_{i,t-1} - su_{i,t} + sd_{i,t} = 0 \text{ , } t \geq 2 \tag{3-10}$$

$$su_{i,t} + sd_{i,t} \leq 1 \tag{3-11}$$

To ensure an engine remains operational for the minimum operating time, at a given time-period ‘t’, the model tracks the previous τ_{min} time-periods (from the current time point t to $t - \tau_{min}$) to look for previous values of su_i that took the value 1, and if any of them did then it is forced that the current operational state is ‘On’, $R_{i,t} = 1$, given by:

$$\sum_{tt=1,\ t-tt>0}^{\tau_{\min}-1} (su_{i,t-tt}) - R_{i,t} \leq 0 \qquad (3\text{-}12)$$

If the minimum operating time has been achieved, the value of $R_{i,t}$ is not forced, and the model may use Equation (3-10) to determine whether the engine may still remain operational or can now be switched off.

Similarly to start-up and minimum operating time the model also forces the engine to remain offline by looking at previous time periods (t to $t - \tau_R$) of the shut-down variable, $sd_{i,t}$, and preventing the start-up variable from taking the value 1:

$$\sum_{tt=1,\ t-tt>0}^{\tau_{R-1}} (sd_{i,t-tt}) + su_{i,t} \leq 1 \qquad (3\text{-}13)$$

Due to the CHP engines having two options for fuels, the introduction of four more binary variables are necessary, $su\_B_{i,t}$, $su\_N_{i,t}$, $sd\_B_{i,t}$ and $sd\_N_{i,t}$, for the dual fuel engines. These are effectively the same as $su_{i,t}$ and $sd_{i,t}$ the start-up and shut-down variables, however a separate start-up and shut-down variable must be specified for both the Biogas flow (denoted by subscript ‘B’) and the Natural Gas flow (denoted by subscript ‘N’). To ensure no conflicts, a constraint is placed to ensure only one of the extra start-up or shut-down variables is active, depending on the fuel selected and whether $su_{i,t}$ or $sd_{i,t}$ is required:

$$su_{i,t} - su\_B_{i,t} - su\_N_{i,t} = 0 \qquad (3\text{-}14)$$

$$sd_{i,t} - sd\_B_{i,t} - sd\_N_{i,t} = 0 \qquad (3\text{-}15)$$

The introduction of another linear constraint is required to ensure that a dual fuel CHP engine cannot be both operational ($R_{i,t} = 1$) and in shut-down ($sd_{i,t} = 1$), as well as to ensure linear consistency with the $w_{B,i,t}$ and $w_{N,i,t}$ variables when an engine is offline:

$$sd_{i,t} + R_{i,t} + w_{B,i,t} + w_{N,i,t} = 1 \tag{3-16}$$

With regards to the natural gas engine, Equation (3-16) is not applicable because there is no $z_{i,t}$ term and only one $w_{i,t}$ term, therefore it requires two separate constraints of its own to perform the same function as Equation (3-16):

$$R_{i,t} - w_{N,i,t} = 0 \tag{3-17}$$

$$sd_{i,t} + R_{i,t} \leq 0 \tag{3-18}$$

When an engine is switched on at a given time point ‘t’, it enters the start-up phase, where each gas engine is assumed to be offline for the first 15 minutes of that time-period, and then fully operational thereafter. In actuality, engines are typically operational within 10-20 minutes. In the case of the current model, given the 30-minute time periods, a CHP engine in a start-up time-period would only generate electricity at full operation for 15 minutes. The model also assumes no heat is recovered in the first 15 minutes, and any gas used to start up the engine is ignored – the volume of gas used to ramp up to operational time is negligible over the course of a day, especially given the slight variation in start-up times. When switching off an engine, gas flows are ramped down slowly. To account for this, the model assumes, similar to start-up times, that during a shut-down time-period an engine is operational for 15 minutes then instantly offline. To account for this, μ_{su} and μ_{sd} are introduced, adjustment constants to adjust the maximum and minimum gas flow when the engine enters start-up or shut-down respectively.

The three CHP engines can only utilise one fuel type at a time: Biogas or Natural Gas. Therefore, the binary variable $z_{i,t} \in \{0,1\}$ is introduced to ensure only one of each gas type is used by each unit at each time point 't'. The total gas flows to any dual fuel CHP engine at time 't', $B_{CHP,i,t}$ and $N_{CHP,i,t}$, is between the maximum and minimum flows subject to:

$$\begin{aligned} B_{CHP,min} \cdot z_{i,t} - B_{CHP,min} \cdot w_{B,i,t} - B_{CHP,min} \cdot \mu_{su} \cdot su\_B_{i,t} - B_{CHP,min} \cdot \mu_{sd} \\ \cdot sd\_B_{i,t} \leq \boldsymbol{B_{CHP,i,t}} \\ \boldsymbol{B_{CHP,i,t}} \leq B_{CHP,max} \cdot z_{i,t} - B_{CHP,max} \cdot w_{B,i,t} - B_{CHP,max} \cdot \mu_{su} \cdot su\_B_{i,t} \\ - B_{CHP,max} \cdot \mu_{sd} \cdot sd\_B_{i,t} \end{aligned} \tag{3-19}$$

$$\begin{aligned} N_{CHP,min} \cdot (1 - z_{i,t}) - N_{CHP,min} \cdot w_{N,i,t} - N_{CHP,min} \cdot \mu_{su} \cdot su\_N_{i,t} - N_{CHP,min} \\ \cdot \mu_{sd} \cdot s\_dN_{i,t} \leq \boldsymbol{N_{CHP,i,t}} \\ \boldsymbol{N_{CHP,i,t}} \leq N_{CHP,max} \cdot (1 - z_{i,t}) - N_{CHP,max} \cdot \mu_{su} \cdot w_{N,i,t} - N_{CHP,max} \cdot \mu_{sd} \\ \cdot su\_N_{i,t} - N_{CHP,max} \cdot sd\_N_{i,t} \end{aligned} \tag{3-20}$$

Note that $z_{i,t}$ is shared across Equations (3-19) and (3-20), whereas $w_{B,i,t}$ and $w_{N,i,t}$ are separate for each fuel. Under these conditions, for any given time, when z_i takes the value of 1 then only Biogas may flow to engine 'i', whereas a value of 0 denotes a Natural Gas flow. z_i is a variable determined by the model to optimise gas distribution. The binary variable z_i provides the gas selection functionality by allowing z_i to alter the upper and lower constraints of the inequalities.

Similarly, once the model has determined the value of $z_{i,t}$, the corresponding value of $R_{i,t}$ is determined to ascertain whether a CHP Engine should be on or off. Depending on the value of $R_{i,t}$ and the value of $z_{i,t}$, the values of $w_{B,i,t}$ and $w_{N,i,t}$ are determined.

For example, assuming an engine was deemed to operate on biogas over a 24-hour period (when $z_i = 1$) but was scheduled to be offline during part of the day then $R_{i,t} = 0$ and $w_{B,i,t}$ and $w_{N,i,t}$ both equal 0. However, when the engine is switched back on (operational), $R_{i,t} = 1$ and $w_{B,i,t} = 1$ but $w_{N,i,t} = 0$. Figure 3-4a is a visual example of this binary variable interaction during start-up, shutdown, operational and offline time periods for a CHP Engine, where a single engine starts up and shuts down twice over a single 24-hour time period. An example for Natural Gas operation (when $z_i = 1$) is also shown on Figure 3-4b.

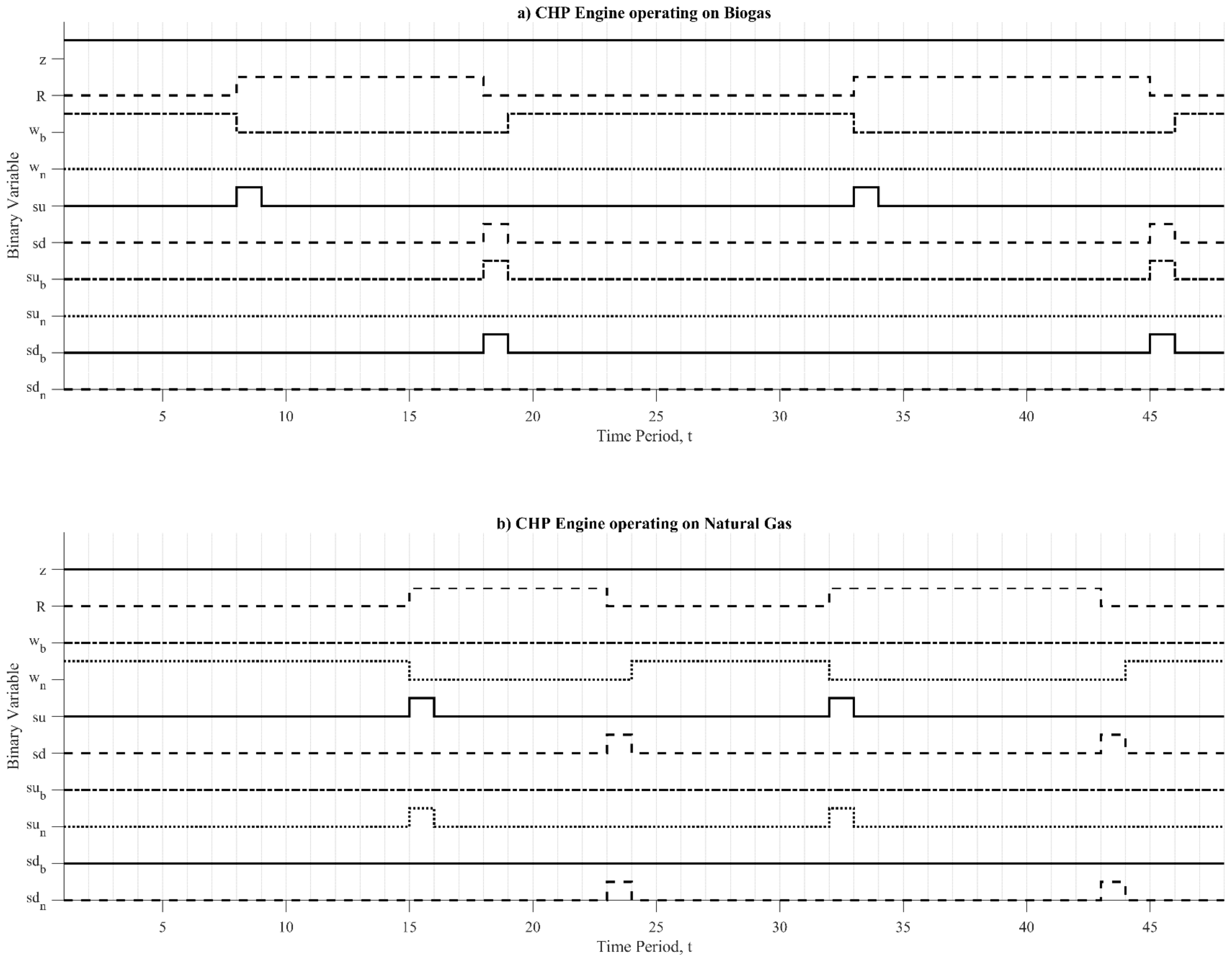

Figure 3-4 Visual representation of how the binary variables $R_{i,t}$, $z_{i,t}$, $w_{B,i,t}$, $w_{N,i,t}$, $su\_B_{i,t}$, $su\_N_{i,t}$, $sd\_B_{i,t}$ and $sd\_N_{i,t}$ interact to simulate operational behaviour of a CHP Engine. Two scenarios are given, for any dual fuel CHP engine over a 24-hour (48 half hourly) time-period, with two instances of the engine starting up and shutting down:
a) CHP Engine operating on Biogas
b) CHP Engine operating on Natural Gas

When an engine enters start-up or shutdown ($su_{i,t}$ or $sd_{i,t}$ = 1) the limits on the chosen fuel are adjusted (through $su\_B_{i,t}$, $su\_N_{i,t}$, $sd\_B_{i,t}$ and $sd\_N_{i,t}$) to reflect the limited availability or operational time of the engine.

The fourth Natural Gas engine can only have one fuel type, so the binary variable $z_{i,t}$ is not required and the flow to this engine is given by:

$$\begin{aligned} N_{CHP,min} \cdot w_{N,i,t} - N_{CHP,min} \cdot \mu_{su} \cdot su_{i,t} + N_{CHP,min} \cdot \mu_{sd} \cdot sd_{i,t} \leq \boldsymbol{N_{CHP,i,t}} \\ \boldsymbol{N_{CHP,i,t}} \leq N_{CHP,max} \cdot w_{N,i,t} - N_{CHP,max} \cdot \mu_{su} \cdot su_{i,t} + N_{CHP,max} \cdot \mu_{sd} \cdot sd_{i,t} \end{aligned} \tag{3-21}$$

3.2.6.5 Gas Engines Constraints – Electricity Generation

The CHP Engines burn Biogas or Natural Gas to generate electricity primarily for use on site. As would be expected, the power rating of the engines remains the same regardless of fuel type, but a higher biogas flow is required to obtain the same power output (due to the lower CV of Biogas compared to Natural Gas). Retrospective analysis of historical operations confirmed the power output of each CHP engine to be 1750 kW at maximum flow. The Natural Gas engine is rated higher at 2000kW, and the power output of the engines is assumed to be linear with the associated gas flow (Figure 3-3).

The electrical tariff is in kWh, thus for each half hour interval the total kWh of electricity that could be generated by any CHP Engine on Natural Gas or Biogas is $E_{GEN,1-3,max} = 875kWh$, and Engine 4 $E_{GEN,4,max} = 1000kWh$. The power conversion factor for Biogas and Natural Gas, $P_{GEN,i,B}$ and $P_{GEN,i,N}$, was determined from the maximum gas flows and maximum power output of each engine and used to convert gas flow in m^3 to kWh.

Therefore, the Electricity Generated in an engine, $E_{GEN,i}$, is given by:

$$\boldsymbol{E_{GEN,i,t}} = B_{CHP,i,t} \cdot \rho_{GEN,i,B} + N_{CHP,i,t} \cdot \rho_{GEN,i,N} \tag{3-22}$$

3.2.6.6 Electricity Import and Export Constraint

Currently when all four engines are operated at full power, the electricity generated can meet site parity and even overproduce at times. Any electricity generated is currently consumed on site by other wastewater treatment processes first before exporting any excess to the national grid. In this model, should an engine be operated at reduced gas flow, it is assumed that the reduction in power follows a linear relationship, as given by Equation 12 and shown in Figure 3-3.

The Electricity Imported or Exported for each time period is given by summating the generated kWh from all engines and then making up the difference to meet demand with electricity imports, $E_{IMP,t}$, or excess generation becomes exports, $E_{EXP,t}$,:

$$\sum_{i=1}^{4}(E_{GEN,i}) - E_{EXP,i,t} + E_{IMP,i,t} = E_{DEM,t} \tag{3-23}$$

An estimate for the electricity demand, $E_{DEM,t}$, is required in Equation (3-23) and is provided through retrospective analysis of typical total site power demands, shown in Figure 3-5.

At no point can the site simultaneously import and export electricity, as would be the case with Equation 13; the model requires an additional binary constraint on the variables for electricity imports, $E_{IMP,t}$, and exports, $E_{EXP,t}$, so at least one of these variables is always 0. The introduction of $x_{i,t} \in \{0,1\}$ ensures that the model only allows electricity imports or exports, subject to the constraints:

$$\boldsymbol{E_{EXP,i,t}} \leq x_{i,t}\left(\sum_{i=1}^{4}(E_{GEN,max}) - E_{DEM,t}\right) \tag{3-24}$$

$$\boldsymbol{E_{IMP,i,t}} \leq (1 - x_{i,t}) \cdot E_{DEM,t} \tag{3-25}$$

These two constraints limit the model to allow only one of the terms $E_{IMP,i,t}$ or $E_{EXP,i,t}$to be non-zero based on the value of $x_{i,t}$. When $x_{i,t}$ takes the value 1, Equation (3-25) forces the model to have no electrical imports ($E_{IMP,t}$ = 0) and Equation (3-24) would limit the value of electrical exports to be the difference between maximum generation possible and site demand. Conversely $x_{i,t}$ = 0 ensures Equation (3-24) forces the model to have no electrical exports ($E_{EXP,t}$ = 0) and limits the maximum electrical import to be that of total site demand. The value of $x_{i,t}$ is forced based on Equation (3-23), where the electrical generation of the engines determines whether electrical imports or exports are required to validate the expression.

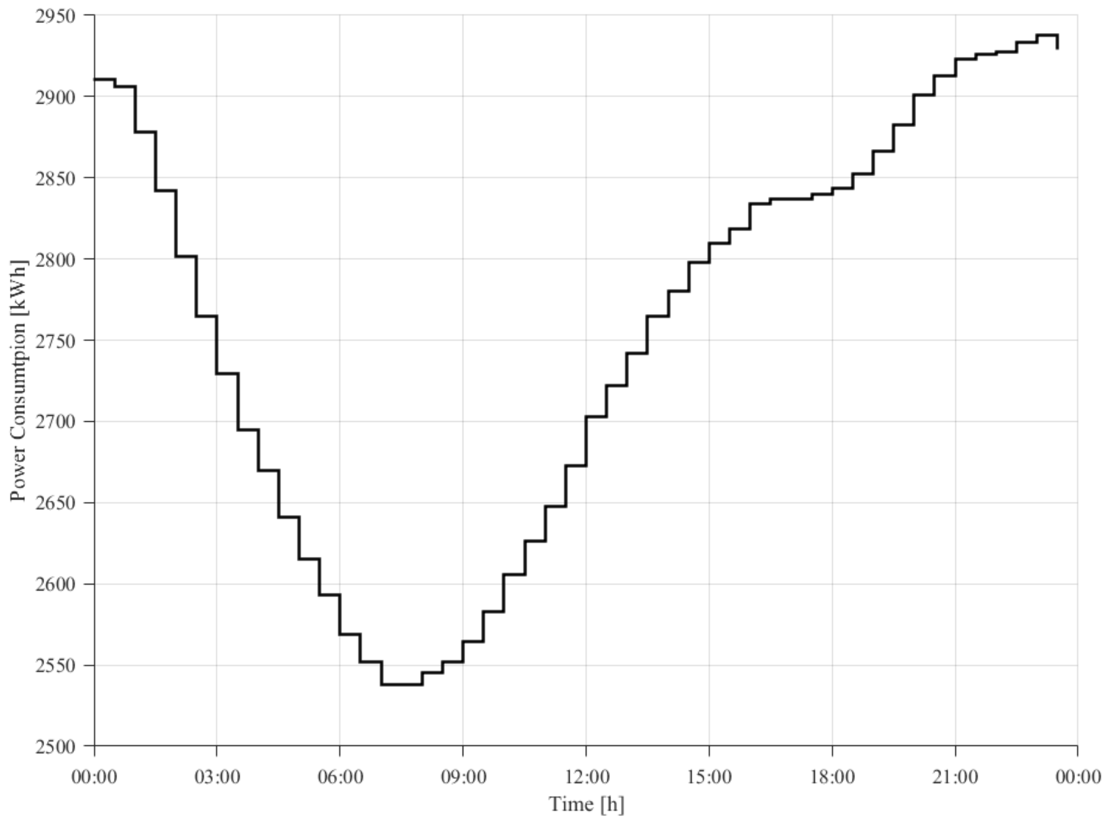

Figure 3-5 - Average Power Demand of the Howdon treatment site. The power demand is for the entire site, not just the AAD plant, and thus is seen to follow the typical diurnal flow pattern asociated with wastewater treatment sites, as expected.

3.2.6.7 Steam Boilers constraints

The steam boilers can also only have one fuel source at a time. Similarly to the CHP inequalities in the "*Gas Engines Constraints – Gas Flows*" section above, the steam boiler parameters make use of a binary variable, $z_j \in \{0,1\}$ to determine the fuel type, however as steam boilers must always be operational to provide steam there is no $w_{i,j}$ term:

$$B_{S,min} \cdot z_{j,t} \leq \boldsymbol{B_{S,j,t}} \leq B_{S,max} \cdot z_{j,t} \quad (3\text{-}26)$$

$$N_{S,min} \cdot (1 - z_{j,t}) \leq \boldsymbol{N_{S,j,t}} \leq N_{S,max} \cdot (1 - z_{j,t}) \quad (3\text{-}27)$$

Unlike the CHP Engines, there is no $w_{i,1}$ or $w_{i,2}$ term as the Steam Boilers should always be in operation to allow for enough steam to be generated as part of the sludge treatment process.

There are additional constraints for the steam boilers that differ from the CHP engines. Unlike the CHP engines, the steam boilers must always be producing enough steam to satisfy site process requirements and therefore may not all have high gas flow or low gas flow at the same time. The three boilers operate in tandem the CHP engines such that the heat recovered from CHP is used with the boilers to provide steam on site. After retrospective analysis of historic data, for a typical day the total energy required for steam generation on site is $H_{Req} = 70\ MWh$.

The steam boilers operate at 90% efficiency to obtain useful heat from a fuel source, with a further 10% of said useful heat used during the blowdown process, resulting in an 81% efficiency, $\varepsilon_S = 0.81$, in raw fuel energy to useful steam heat. The CHP engines recover 10% of the raw energy input from fuel as useful heat in the boilers, $\varepsilon_{CHP} = 0.1$.

The useful heat recovered from CHP ($H_{CHP,i,t}$) or generated by steam boilers ($H_{S,i,t}$) is given by:

$$\boldsymbol{H_{CHP,i,t}} = \left(B_{CHP,j,t} \cdot CV_B + N_{CHP,i,t} \cdot CV_N\right) \cdot \varepsilon_{CHP} \tag{3-28}$$

$$\boldsymbol{H_{S,i,t}} = \left(B_{S,j,t} \cdot CV_B + N_{S,i,t} \cdot CV_N\right) \cdot \varepsilon_S \tag{3-29}$$

where CV_B and CV_N is the calorific value of biogas and natural gas respectively, converting gas flows into MWh.

To ensure enough heat is produced for steam generation, the total sources of heat on site must match or be greater than the minimum required energy demand, H_{Req}:

$$\boldsymbol{H_{Req}} \leq \sum_{i=1}^{3}\{H_{CHP,i,t}\} + \sum_{j=1}^{3}\{H_{S,j,t}\} \tag{3-30}$$

Retrospective analysis of the different fuel flows to the boilers also revealed no distinguishable difference in processed volume of Biogas or Natural Gas flows, hence each gas type has equal weighting in this constraint.

3.2.6.8 Gas to Grid injection (Biogas Upgrade Plant) constraint

The BUP takes the raw Biogas and enriches it such that the resulting biomethane can be injected into the gas distribution network as a renewable energy source. As there is only one fuel source, the constraints of sending Biogas to the BUP are:

$$B_{I,min} \leq B_{I,t} \leq B_{I,max} \tag{3-31}$$

In an ideal setting there would be no limit to the volume of biomethane that can be injected into the gas distribution network. However, the total volume that can be injected is subject to local demand and gas network pressures; if too much biomethane is injected too quickly the pressure in the grid could rise too high for continued injection, whereby the distribution gas network operator may shut off grid injection from the site; this is known as going into a ‘reject’ state. Operators have discovered that maximum daily volume of Biogas that can be processed through the BUP is currently around 40,000 Nm^3, which was validated through retrospective analysis of BUP processing volumes, grid injection volumes and ‘reject’ state instances.

3.2.6.9 Flare Stack constraint

Due to the volumes of biomethane produced on site and the safety considerations from site design, there is considered to be no upper limit for the total volume of Biogas the flare stack can take:

$$0 \leq B_{f,t} \tag{3-32}$$

3.2.6.10 Preventing CHP Fuel Switching

There is the additional daily constraint that the fuel used in each CHP Engine must remain the same throughout the entire day. It is not currently possible to automate the switching of fuels. Therefore, as the model is broken up into 48 optimisation periods, the binary variable $z_{i,t}$ (used by the model to determine the fuel for engine ‘i’) must be the same at each time ‘t’; the binary variable y_i is used for each of the 48 time points to accommodate this.

$$z_{i,t} + y_i = 1, \forall, t = t_1, \ldots., t_{48} \tag{3-33}$$

With the addition of y_i, whether the model determines a CHP fuel of Biogas ($z_{i,t} = 1$) or Natural Gas ($z_{i,t} = 0$), the chosen value of $z_{i,t}$ will remain the same for each time point. For example, if the model decided that CHP Engine 1 should operate on Biogas, i.e. $z_{1,t_1} = 1$, this would force $y = 0$ to satisfy Equation (3-33), which in turn would force $z_{1,t_2} = 1$ to also satisfy Equation (3-33).

3.2.7 Constraints Matrix and Solver

The optimiser model was developed using MATLAB using function *intlinprog*, which is a MILP algorithm in the Optimisation Toolbox package. Further information on *intlinprog* can be found in Section 2.3.3. The optimal gas flows and binary variable values are obtained through minimisation of the cost function to give optimal gas distribution on an economic basis, whilst maintaining site operability.

The electrical import tariff changes every half hour, thus for a daily optimisation (24 hour horizon) the model requires breaking down into 48 'mini-optimisations' that are still linked into a single optimisation step. Each 48 half hourly optimisation consists of 2355 variables of which 1491 are integers, 1972 inequalities and 768 equalities.

3.3 Results/Discussion

For a given daily volume of Biogas produced on site, the optimiser provides the operator with a visual operation strategy for the optimised minimum cost; Figure 2-6 shows the results to maximise cost reductions for a daily Biogas production of 38,000Nm^3 (a typical approximate average production level for the site). The gas flow rates have been normalised, showing the percentage daily utilisation of each unit based on total daily maximum flow that could be processed. In this scenario $\boldsymbol{K_{IMP}} = 0$. The total daily revenue is shown both with and without consideration of the Carbon performance commitment. This is because the performance commitment will be applied after a two-year delay, hence the immediate revenue the site will see may not be the most optimal.

For a daily Biogas production of 38,000 Nm^3, the site should be operated according to the strategy in Figure 2-6 for optimal cost efficiency: to enrich all biogas and inject all biomethane into the gas distribution network, use Natural Gas in the CHP engines at reduced load to generate electricity on site and use Natural Gas in the steam boilers to create steam as required. For a given daily volume of Biogas, the optimiser provides a fast and reliable result in a matter of seconds.

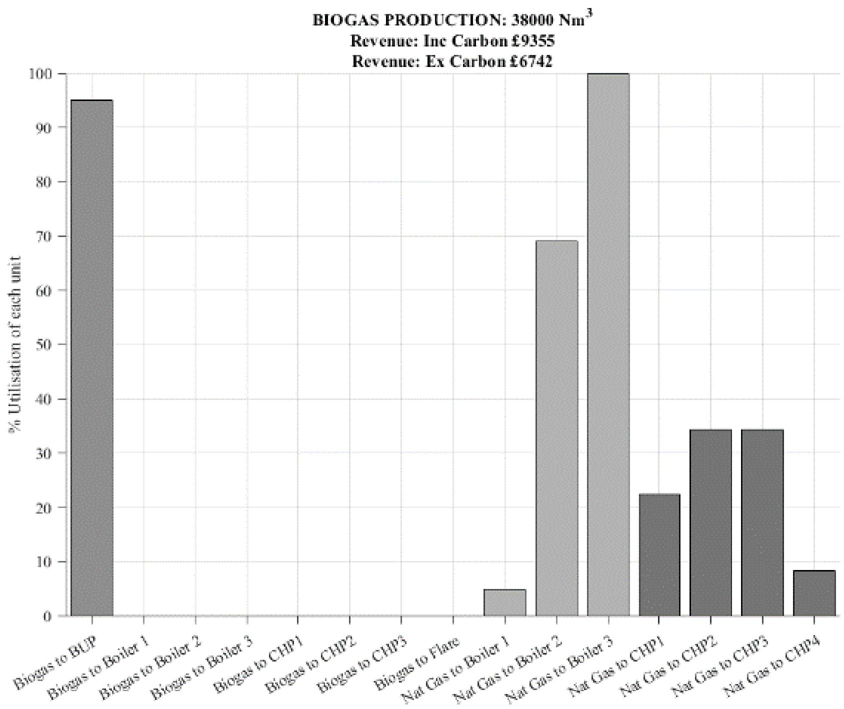

Figure 3-6 – Example Optimised Gas Distribution for daily total Biogas production of 38,000Nm³, $\boldsymbol{K_{IMP}} = 0$. Left: Optimised Daily Gas Flow Volumes, Right: Normalised Optimised Daily Utilisation of Each Unit [Inc = Including, Ex = Excluding.]

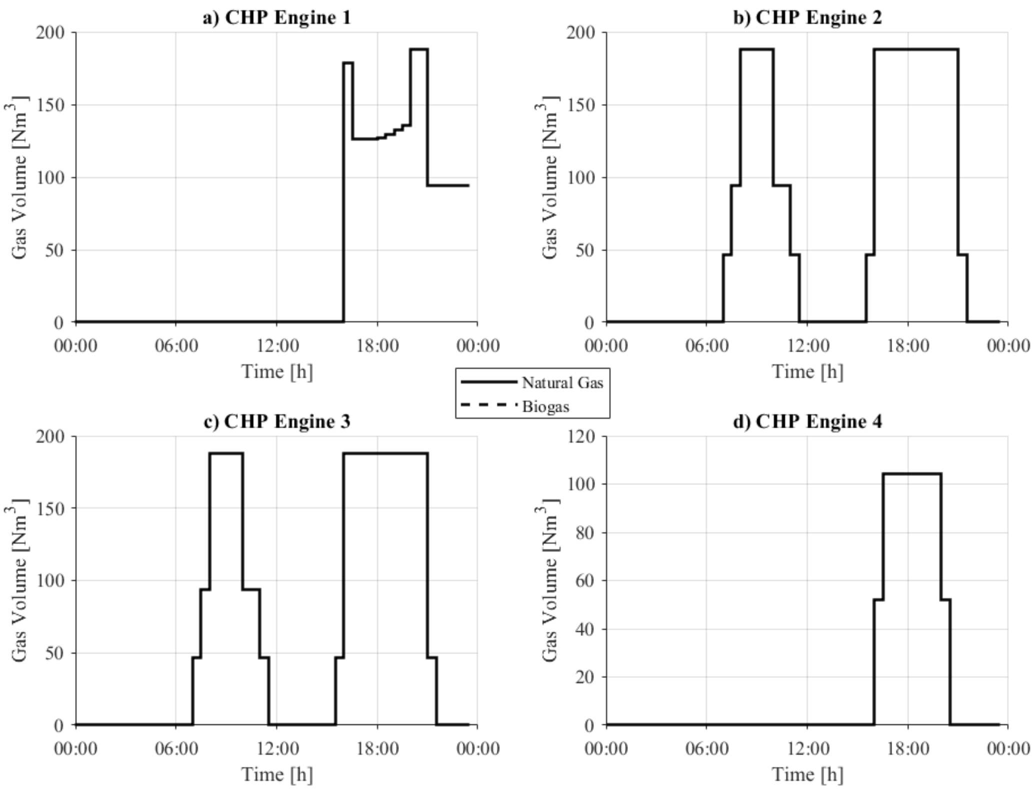

Figure 3-7 - Gas Flow to CHP Engines 1-4 (a, b, c, d) every half hour over the 24 hour operational horizon. [$\boldsymbol{K_{IMP}} = 0$, $\boldsymbol{B_{TOTAL}} = 38{,}000\ Nm^3$]

At first glance, it would appear the model has inaccuracies as the optimiser advises the use of CHP Engines at lower utilisation than actual operation would allow. However, the graph in Figure 2-6 shows the total daily utilisation, not the utilisation throughout the day. To better understand the advised operational behaviour, the gas flows to the CHP Engines are shown on Figure 3-7, where Figure 3-8 shows the total electricity Imported and Generated.

When the electricity import carbon parameter, $\boldsymbol{K_{IMP}}$, is set to 0 it is more cost effective to have the engines offline and import all electricity required from the electricity distribution network, except when the electricity tariff becomes high at 7-10am and 4.30-7.30pm. During 7-10am, electricity prices are high enough to be more cost effective to switch on two CHP engines, however (based on the site demand) it is not worth it to switch all engines on. During the 4.30-7.30pm peak it is more cost effective to switch all engines on to meet site parity rather than import electricity.

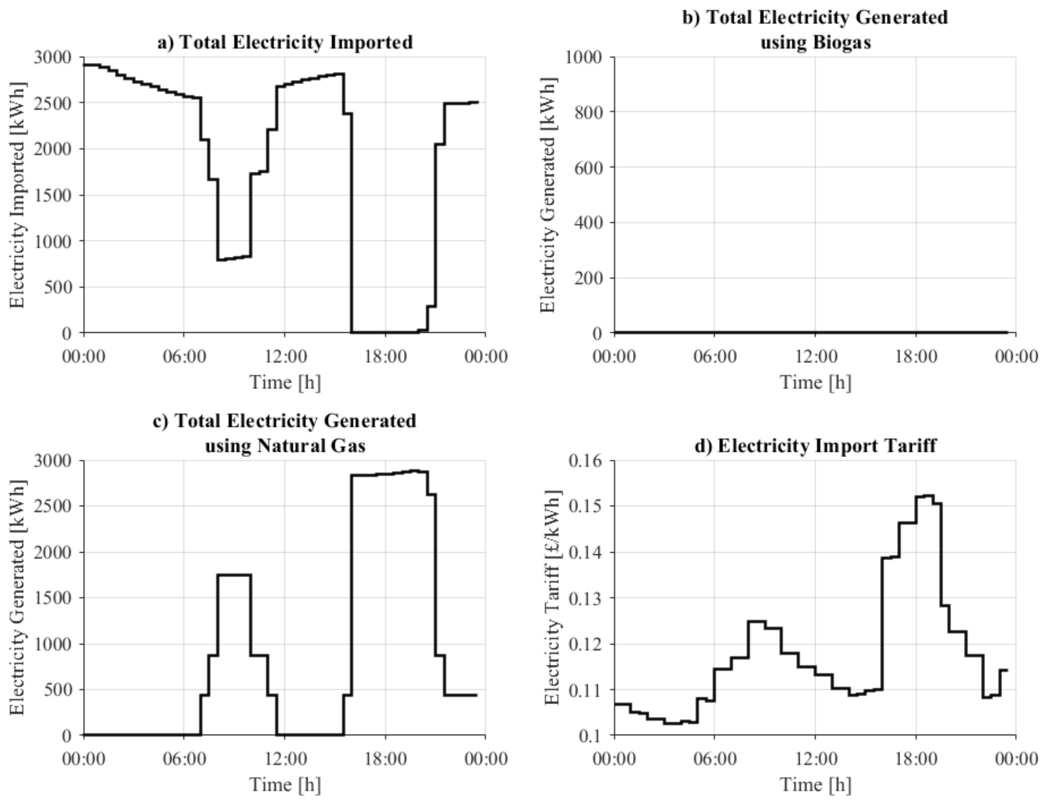

Figure 3-8 - Total Electricity generated or imported every half hour over a 24 hour operational horizon. Electrical Import Tariff is also shown for convenience.
[$\boldsymbol{K_{IMP}} = 0,\ \boldsymbol{B_{TOTAL}} = 38{,}000\ Nm^3$]

As can be seen from Figure 2-6, the immediate revenue the site will see (excluding Carbon, £6742) is lower than the actual revenue once Carbon is included (£9355). It is important to note the site revenue both including and excluding Carbon costs as the carbon costs will be applied with a two-year delay, therefore there will be an immediate site revenue and delayed site revenue. As the injection of Biomethane has a negative cost (Table 3-2), this operational strategy creates an overall negative number of Carbon Credits generated (Figure 3-9), which also demonstrated by the increase in revenue when considering carbon (Figure 2-6).

Whilst the cost of the Carbon Credits, C_{CO_2}, will remain constant over the coming years, NWL has the operational decision about their source of electricity for the Howdon site, which will impact $\boldsymbol{K_{IMP}}$. Figure 2-6 through Figure 3-9 show the optimal operational schedule for a typical daily biogas production when $\boldsymbol{K_{IMP}} = 0$ (renewable electricity imported only). However, should the decision be made such that electricity imports continue to be from non-renewable sources, the value of $\boldsymbol{K_{IMP}} = 0.31$ and the optimal operational schedule (for the same daily biogas production volume of 38,000 Nm^3) changes, as does the optimal revenue achievable.

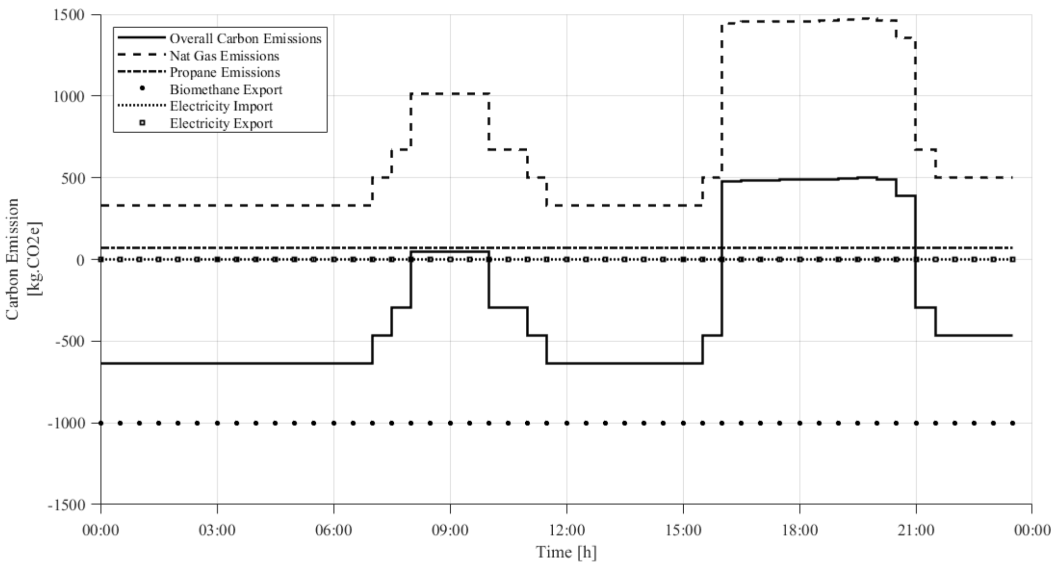

Figure 3-9 - Carbon Credits generated each half hour over the optimised 24 hour operational horizon. $[\boldsymbol{D_{IMP}} = 0,\ \boldsymbol{B_{TOTAL}} = 38{,}000\ Nm^3]$

Figure 3-10 shows that, with $\boldsymbol{K_{IMP}} = 0.31$ and no other factors changed, the total revenue achievable for $\boldsymbol{B_{TOTAL}} = 38{,}000\ Nm^3$ including carbon costs is over £1000 per day lower than with $\boldsymbol{K_{IMP}} = 0$, however the revenue excluding carbon is higher. This means that, in the short term, the site would see an initial revenue of around £12,000 per day, but in two years' time would receive a £4000 financial penalty as a result of the carbon performance commitment.

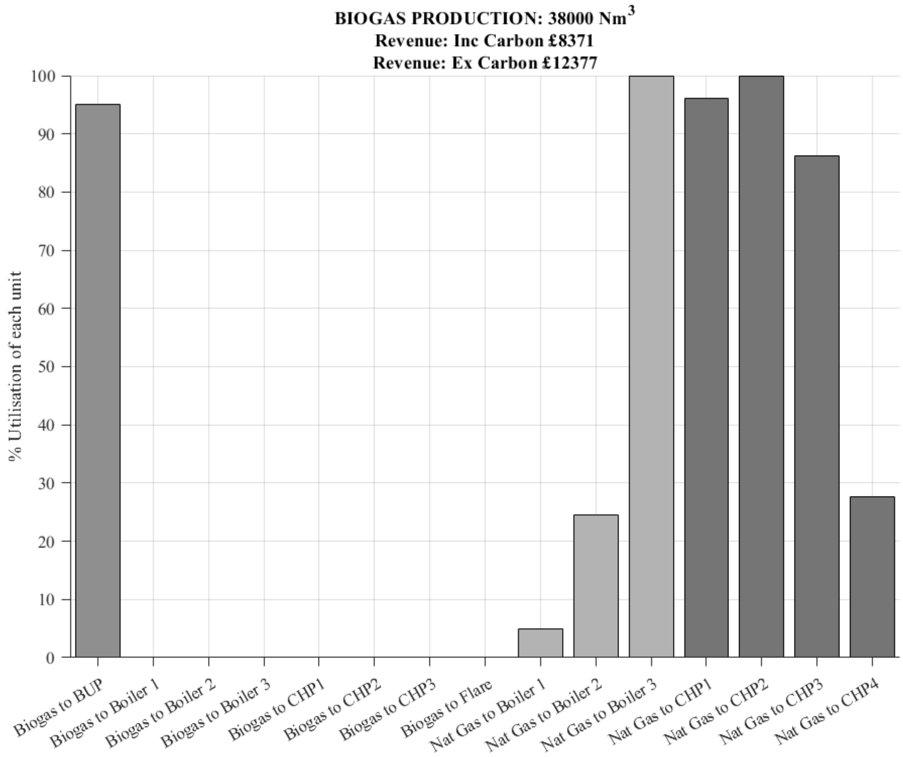

Figure 3-10 - Example Normalised Optimised Gas Distribution for daily total Biogas production of 38,000Nm3, $\boldsymbol{K_{IMP}} = 0.31$.
[Inc = Including, Ex = Excluding.]

The optimal operational schedule when $\boldsymbol{K_{IMP}} = 0.31$ is to almost generate electricity entirely on site by using Natural Gas in the CHP Engines, shown in Figure 3-11. Interestingly, the optimal strategy proposed when $\boldsymbol{K_{IMP}} = 0.31$ is almost identical the current operational strategy for the site. Currently, the operational strategy is to generate electricity on Natural Gas all day to meet site parity [Figure 3-13] and inject as much biogas produced into the gas distribution network. The current strategy would also see almost identical revenues on site [Figure 3-14], which are within the 10% error margin, thus implying that altering the current strategy would make negligible difference to site revenues. It should be noted that, as the current strategy does not rely on any electricity imports, the revenues shown in Figure 3-14 are identical for $\boldsymbol{K_{IMP}} = 0.31\ or\ 0$.

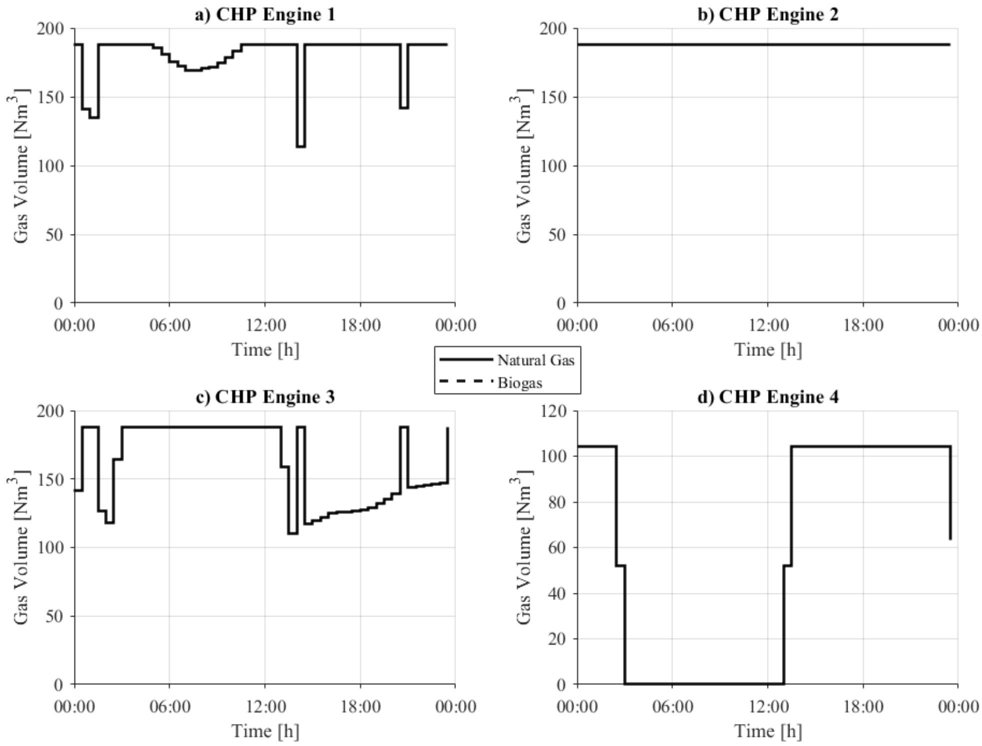

Figure 3-11 - Gas Flow to CHP Engines every half hour over the 24 hour operational horizon.
[$\boldsymbol{D_{IMP}} = 0.31$, $\boldsymbol{B_{TOTAL}} = 38{,}000\ Nm^3$]

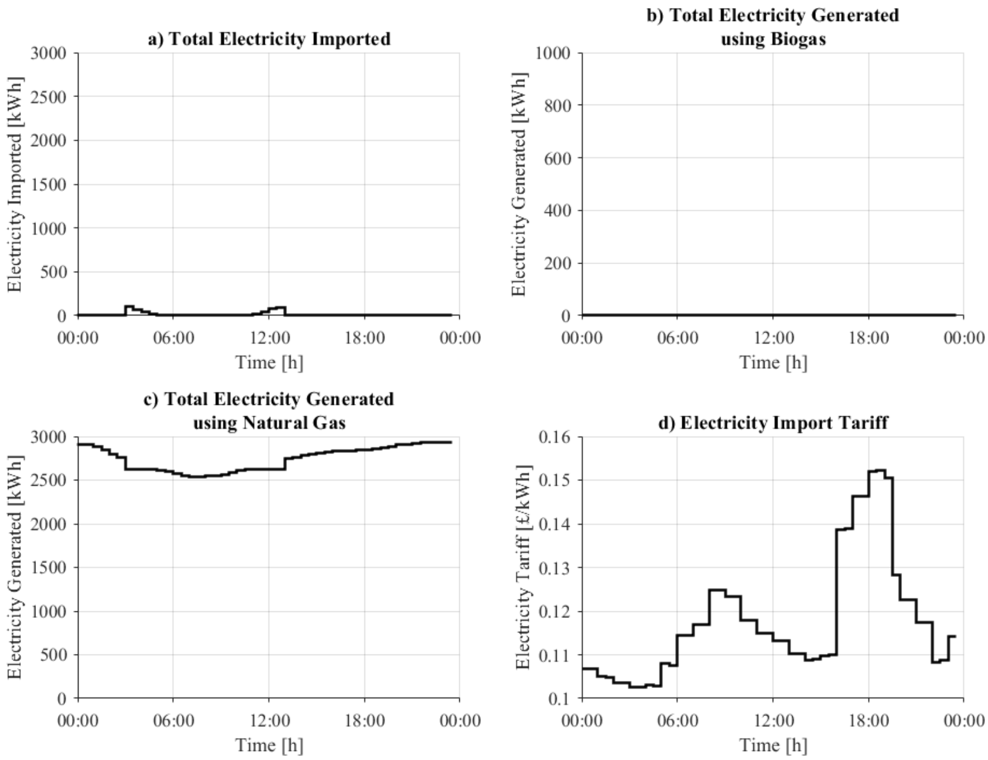

Figure 3-12 - Total Electricity generated or imported every half hour over a 24 hour operational horizon. Electrical Import Tariff is also shown for convenience.
[$\boldsymbol{D_{IMP}} = 0.31$, $\boldsymbol{B_{TOTAL}} = 38{,}000\ Nm^3$]

It is therefore evident that the main factor in the deciding the site operational strategy will be the decision regarding $\boldsymbol{K_{IMP}}$. A value of $\boldsymbol{K_{IMP}} = 0.31$ would suggest that the current operational strategy could remain employed without significant impact, given that electricity and gas prices remain similar to that of the current model. However, should $\boldsymbol{K_{IMP}} = 0$ operators could adjust the operational strategy and see revenues increase in the future; the immediate site revenue seen (excluding carbon) would drop almost 50% from ~£12,000/day to ~£7,000/day (comparing Figure 2-6 and Figure 3-14), however the total revenue in including carbon could increase by over 10% (from ~£8,000/day to ~£9,000/day, again comparing Figure 2-6 and Figure 3-14).

With both scenarios, operators would need to also consider any increased revenues with the potential of maintenance or wear and tear on equipment as a result of being switched on and off throughout the day, as well as any environmental obligations and benefits.

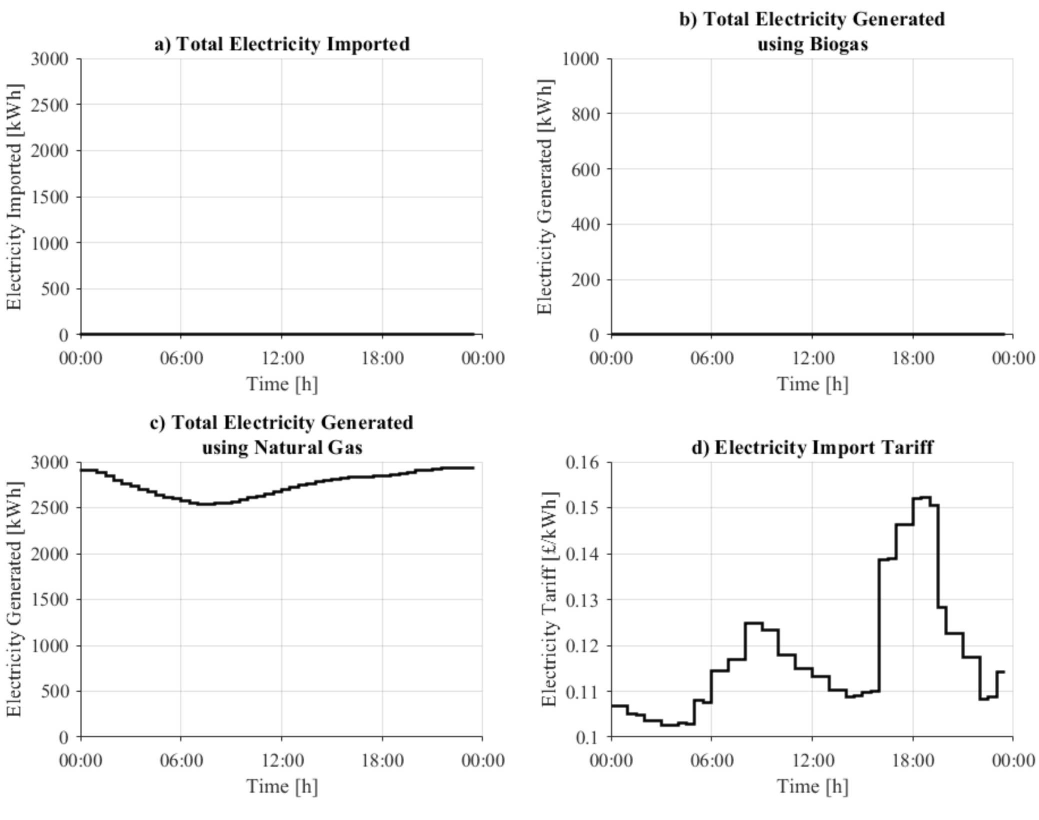

Figure 3-13 – Electricity generated and imported under the current operational strategy, for an example biogas production of 38,000 Nm³. Here there are no electricity imports

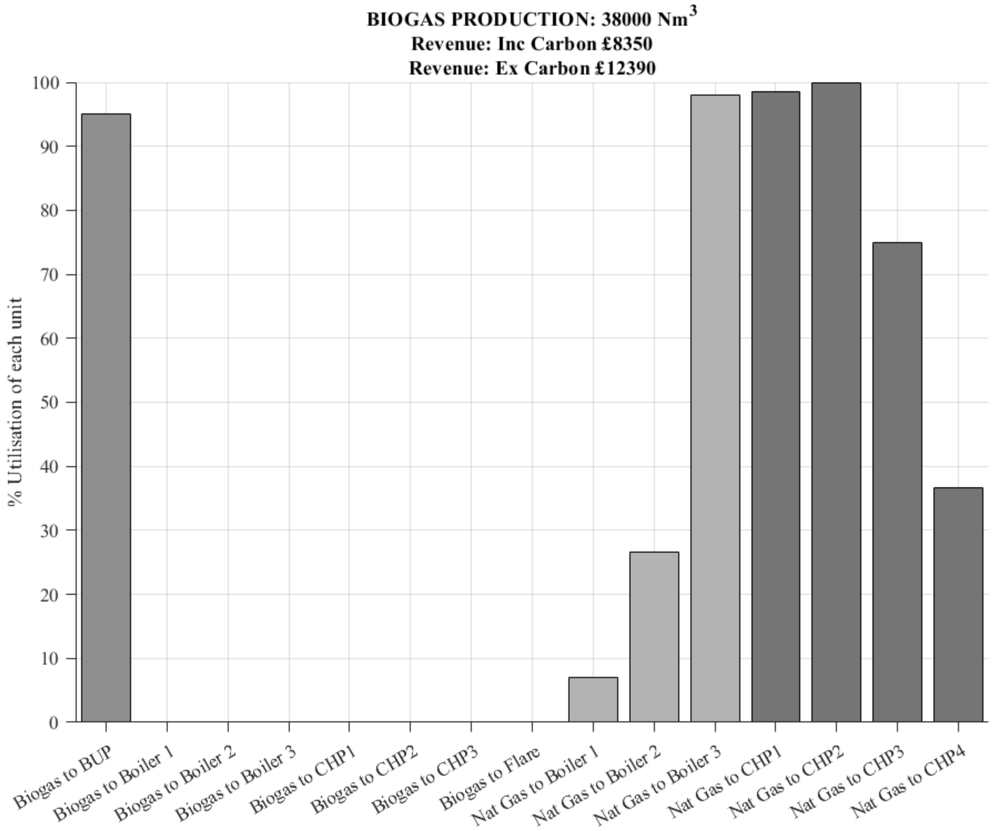

Figure 3-14 - Normalised daily utilisation of units under the current operational strategy (aiming for complete electricity generation to meet site demand), based on a daily biogas production of 38,000 Nm^3

3.3.1 Biomethane Injection

It is worth noting that for the two scenarios tested on electricity imports ($\boldsymbol{K_{IMP}} = 0\ or\ 0.31$), the model suggests that all biogas produced should be upgraded and injected into the national gas grid. This is to be expected, as the high revenues from biomethane injection and the 'negative' carbon emissions associated with the carbon performance criteria are the most beneficial (and the only source) in generating significant site revenues. One could argue that the model should be simplified such that biomethane injection is always maxed out first. Whilst this would simplify the model, there may be occasions where operators are not able to inject the full (or any) biomethane, and as such keeping the model in this form allows operators to investigate these scenarios.

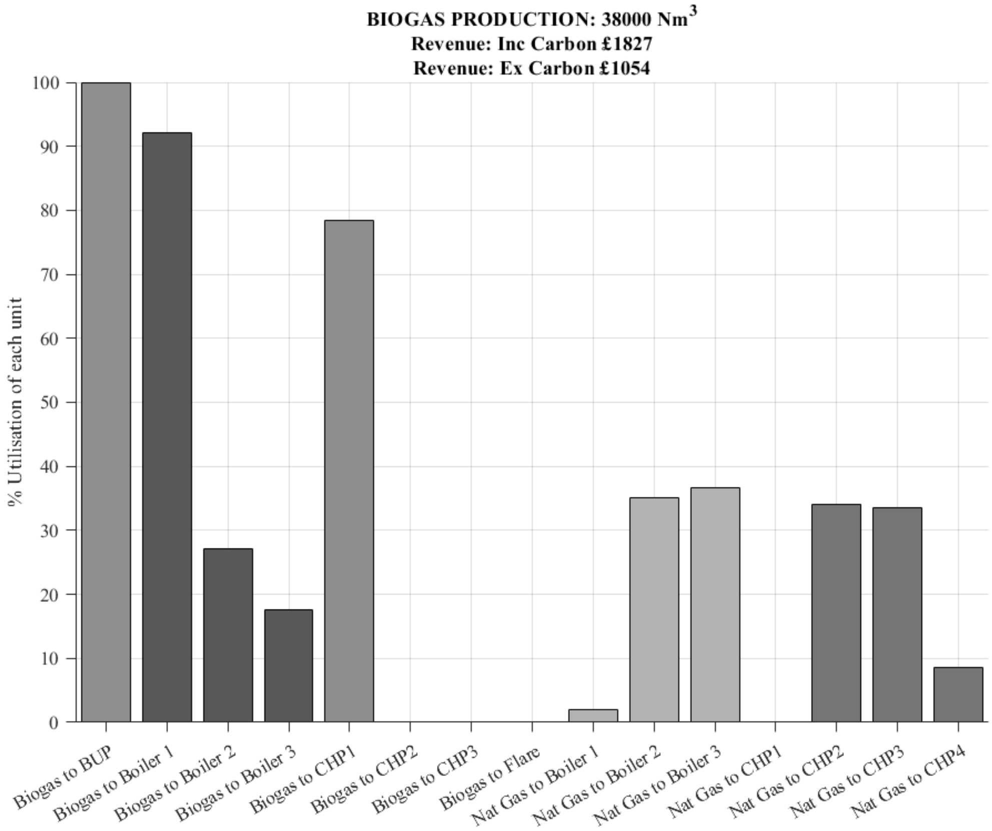

Figure 3-15 - Example Normalised Optimised Gas Distribution for daily total Biogas production of 38,000Nm3, $\boldsymbol{K_{IMP}} = 0$, *but the Biomethane Upgrade Plant may only operate half capacity (max throughput of 20,000 Nm^3). [Inc = Including, Ex = Excluding.]*

As a hypothetical scenario, the same parameters as shown in Figure 2-6 are used but only allowing the Biomethane Upgrade Plant to operate at half capacity, with the results of optimisation shown in Figure 3-15. Under this scenario, the site would see a significant reduction in revenue, however operators are able to understand how much biomethane they should and could process elsewhere on site, such as in the steam boilers (Figure 3-15) or CHP engines (Figure 3-16). It is therefore important to keep all parameters in the model, so operators may test and validate future operational scenarios.

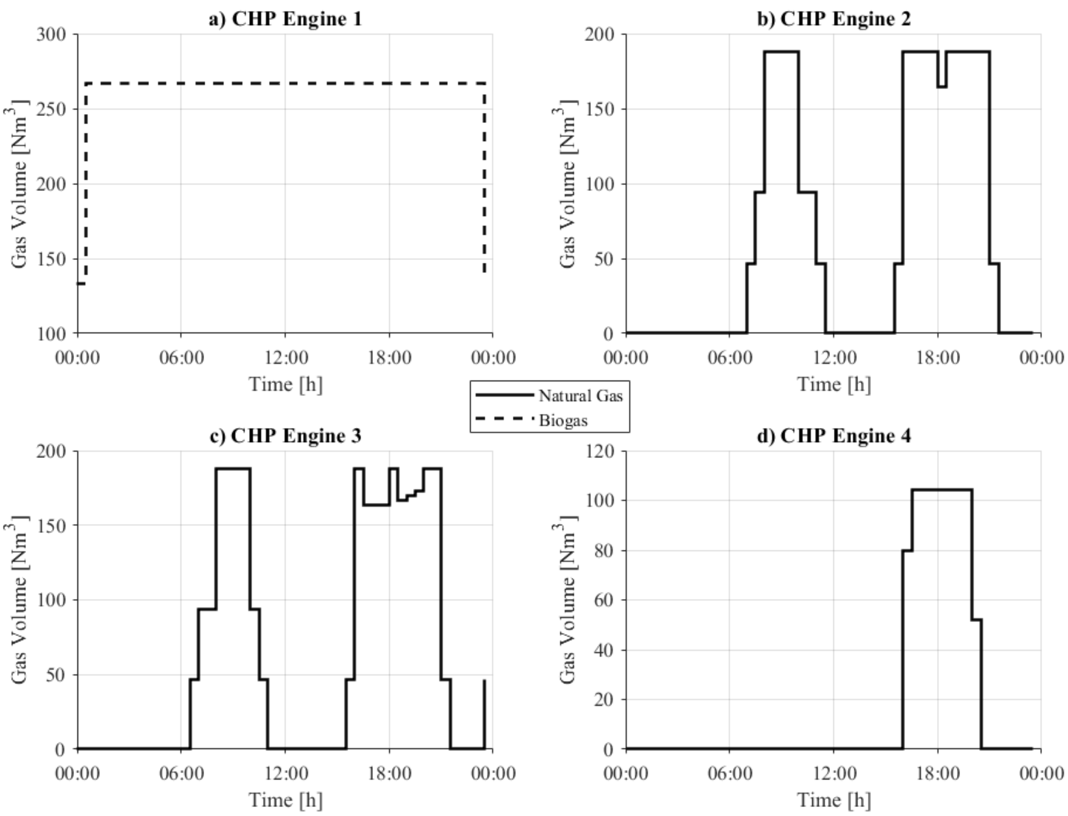

Figure 3-16 - Gas Flow to CHP Engines 1-4 (a, b, c, d) every half hour over the 24 hour operational horizon, biogas production of 38,000Nm3, $\boldsymbol{K_{IMP}} = 0$, but the Biomethane Upgrade Plant may only operate half capacity (max throughput of 20,000 Nm^3).

3.3.2 Model Tolerance / Error

Each piece of equipment on site has a typical maximum daily processing limit. However, the maximum limit does vary slightly from day to day. For example, whilst the CHP Engines may be rated to process a maximum daily biogas flow of 16,000 Nm^3, the actual recorded processed volume of gas will vary slightly. This variance may be due to a several of reasons, such as: instrumentation errors, variances in temperature or in gas compositions. Based on RO, when operating a unit at maximum capacity the recorded processed value does not deviate more than ±10% of the limit stated in Table 3-1. Therefore, the gas flows and optimal revenues stated in this model are all subject to a ±10% error.

3.4 Graphical User Interface for operators

To ensure the model developed throughout this chapter reflects actual plant behaviour and can provide meaningful and feasible solutions (such as making sure the engines are not switched on then off every half hour), it was imperative that site operators and managers be a part of the development process to provide feedback.

However, to achieve this the model must be presented in such a way that it is useable for operators to test. The Energy Management model was built into a GUI (Graphical User Interface) within the MATLAB app creation tool - when first loading the GUI the user is presented with the screen shown by Figure 3-17, which provides operators with an overview of the day ahead optimisation once one is performed.

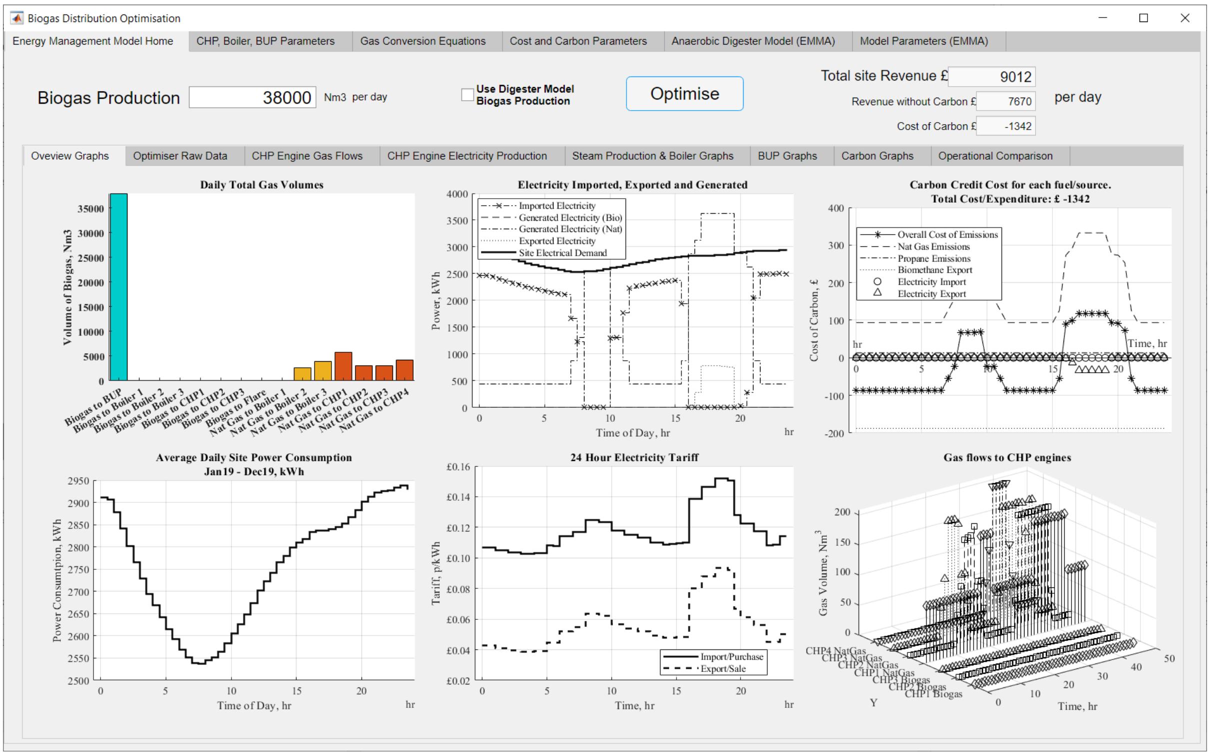

Figure 3-17 - Energy Management Model GUI homepage, where operators can see an overview of optimisation results once an optimisation is performed

However, operators may wish to investigate scenarios on site whereby the site is not operating based on typical operation (default parameters), for example if a CHP Engine is expected to be offline due to scheduled maintenance. The GUI allows operators to alter the process or cost parameters of the model on the appropriate page, such as the CHP Engine, Boiler and BUP parameters screen shown on Figure 3-18. Additionally, the GUI has separate screens for each process unit on site such that individual unit operations can be investigated, such as the CHP Engines shown on Figure 3-19.

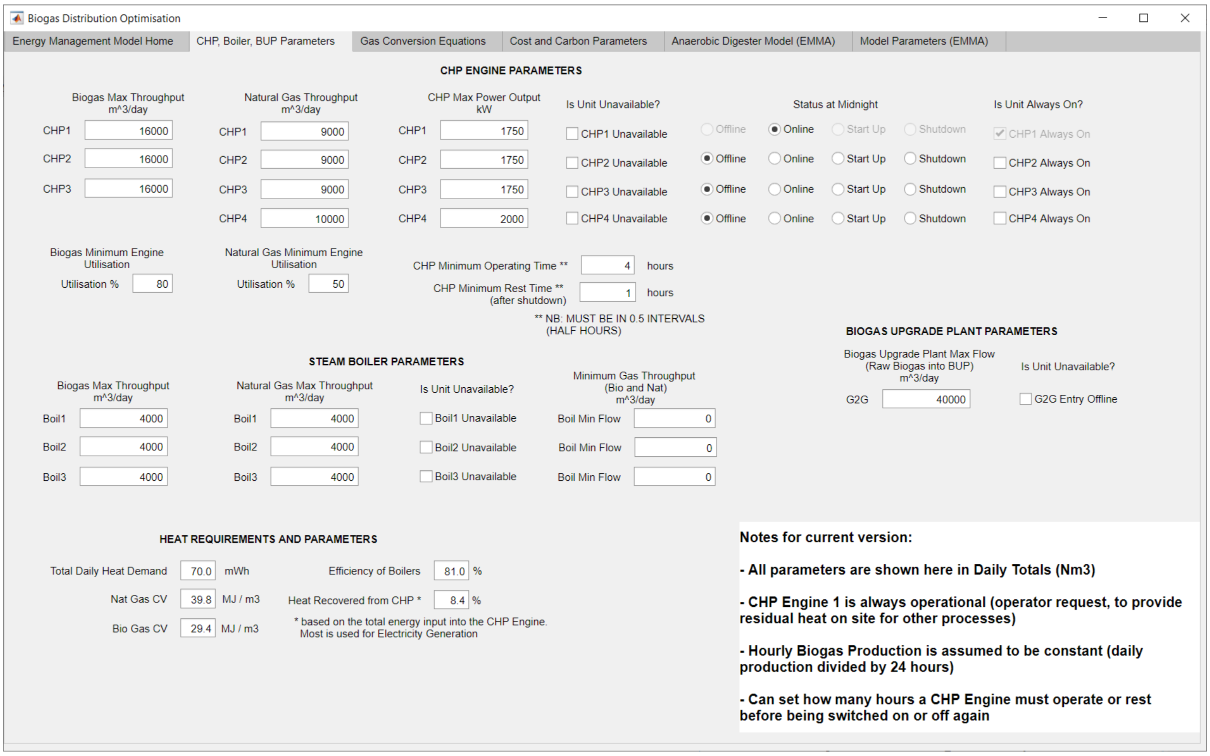

Figure 3-18 - Energy Management model GUI parameter selection and editing page

Whilst developing a GUI within the MATLAB app designer might not provide a long-term solution for implementation on site (due to licencing restrictions, for example), operators are able to easily investigate scenarios themselves and provide feedback on any extra features the model required to be more useful. One such example during development was the need to allow the CHP engines to be switched on and off during the day, but to incorporate a minimum operating time once switched on.

The GUI also highlights the importance of the new carbon legislation, whereby operators are shown the impacts it has on operations and are also shown the changes needed to operational strategy to both ensure the site maintains acceptable revenues and meets the carbon neutrality pledge. Operators are also able to validate their operational strategies themselves.

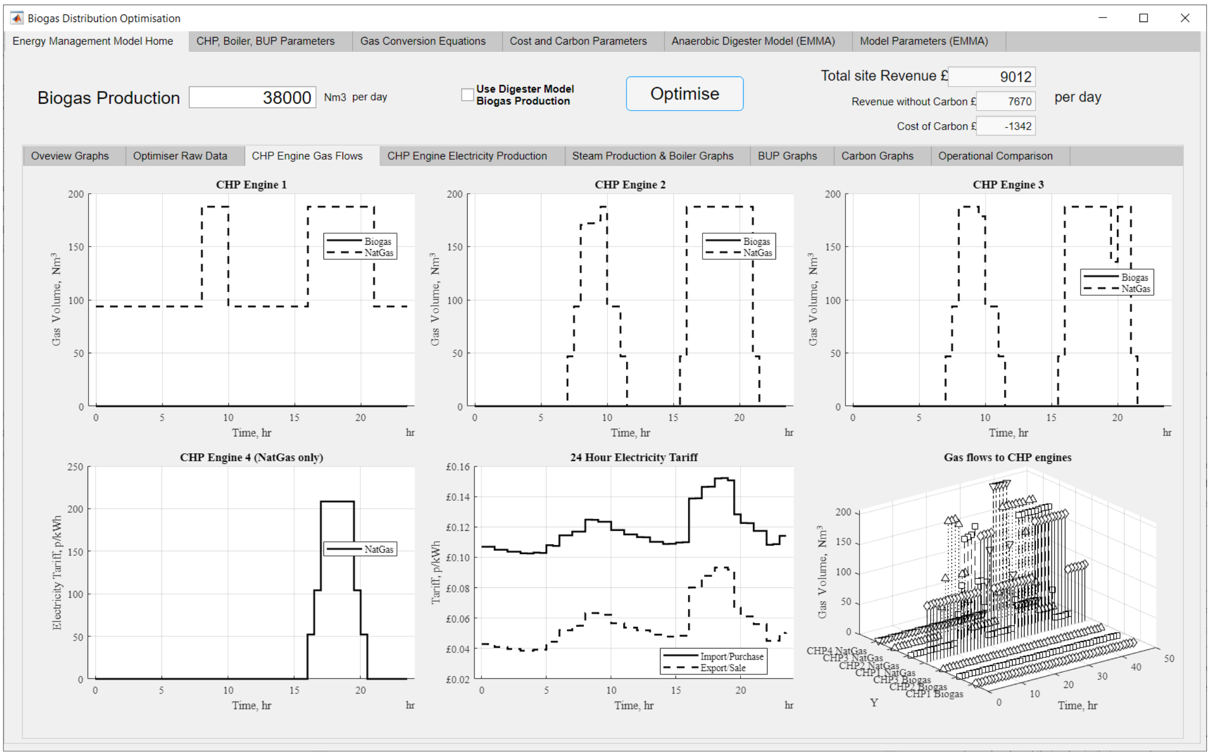

Figure 3-19 - Energy Management model GUI CHP Engine operational schedule screen

3.5 Limitations of Model

The proposed model in this chapter provides operators with a visual optimal operational schedule for a day-ahead electricity tariff. However, this is on the assumption that a day-ahead prediction of Biogas production is available. Currently, operators roughly estimate biogas prediction based on estimated sludge processing levels. As an improvement to this model, as previously mentioned in Chapter 2.3.6, investigations and development of a prediction model for Biogas production that could be fed into the optimisation is performed later in Chapter 5.

3.6 Conclusions

This chapter proposes a MILP Energy Management model for Optimisation of Gas Distribution and Electricity Imports/Generation of an AAD Plant with multiple options available for Biogas use on site whilst considering the environmental impacts regarding the new Carbon Emissions pledge. The optimisation model takes a single input of Daily Biogas volume produced, in m^3, by the Anaerobic Digesters to provide operators with an optimal daily operational strategy; the strategy is provided to the operators in visual form for each day, though weekly strategies are also possible if required.

The revenues achievable under the current operational strategy are within tolerance to those with the advised optimised strategy under the condition $\boldsymbol{K_{IMP}} = 0.31$, leading to the suggestion that keeping the current operational strategy in place would still be advisable if the business decides to not source renewable electricity. However, under the condition $\boldsymbol{K_{IMP}} = 0$, a change in operational strategy from the current strategy could yield an increase in site revenue of over £1000/day (12%).

Ultimately, based on initial investigations, the optimal operational strategy is mostly driven by the electricity imports and whether they are subject to the carbon performance emissions agreement; this is a decision for NWL energy managers based on the source of their electricity. However, any decision that might suggest the site should deviate from the currently operational strategy must also consider the potential increase in maintenance and costs from any new operational strategies.

In addition, operators and managers can use the developed model and tool to validate their operating strategies and test future scenarios, which will in turn ensure the plant is operated more effectively more often. The tool can also be used to aid in achieving the Carbon Neutrality pledge by monitoring and advising on expected carbon emissions based on operational strategies.

In the next Chapter, the Energy model developed here is used to perform a more in-depth analysis of the effect of changes to certain parameters (electricity prices, natural gas prices, biogas production volumes and BUP processing capabilities) will have on site revenues and operating strategies.

Chapter 4 Scenario and Sensitivity Analysis using the Energy Management Model

This chapter uses the model outlined in Chapter 3 to investigate how changes to energy prices, biomethane production and biogas processing limits effects the site revenues achievable and the operational strategies required. The optimum operating strategy for the CHP engines is also presented, which indicates that the biogas produced should be sent to the BUP for grid injection as much as possible.

4.1 Introduction

The electricity supply industry within the UK has undergone multiple reforms since the late 80’s that have transformed the way energy is priced and traded within the energy market [58]. Similarly, the UK natural gas market has undergone dramatic changes over the past 30 years, starting with the 1982 Oil and Gas Act [59]. Both markets have seen an increase in the number of companies participating in the trading and sale of energy, including strategic entities such as investment banks, resulting in increased exposure to price volatility [54].

With many market players and constant changing prices, understanding the impact of energy prices on site operations is likely to become more prevalent in the coming years. Models have been developed that indicate that aiming for net zero carbon emissions, and investing in alternative energy sources, can cause volatile responses in oil prices [60], or that general energy price changes could be affected by carbon emissions targets [61]. It is understood that there is a relationship between the market price for electricity and gas prices. Natural gas and greenhouse gas allowance prices have an increasing effect on electricity prices, whereas renewable sources (such as solar and wind) have a decreasing effect on electricity prices [62], with energy prices much more sensitive to changes in gas prices when demand is high [63].

In recent times, the world has been challenged with the impact of the global pandemic. Countries responses to the pandemic, such as nationwide lockdowns, have seen nationwide energy demand fall to unprecedented levels historically across multiple countries, including the UK [64], which has also seen the markets fluctuate abnormally, with no historic reference.

As demonstrated in Chapter 3, the optimal operational strategy for the AAD plant is complex to identify without the aid of modelling and optimisation tools, especially with the introduction of the new Carbon Emissions performance criteria that can have significant impacts on the optimal operational strategy.

In the previous chapter, a brief investigation was performed into site operations, using fixed energy tariffs and fixed biogas production levels. One of the main drivers that affects plant performance is the decision around the source of electricity imports on site and how they affect the carbon emissions performance criteria, $\boldsymbol{K_{IMP}}$, as discussed in Chapter 3.3. However, it is understood that NWL is to move towards using renewable electricity on site (i.e., $\boldsymbol{K_{IMP} = 0}$), to aid in meeting their carbon neutrality pledge. Additionally, the results shown in Chapter 3 assume a constant daily production of biogas (a typical site average of 38,000 Nm^3), which is not always the case for the site historically. Therefore, a more detailed analysis into site operability can be performed to understand the effects of energy prices and biogas production has on site operations and revenues.

In Chapters 2 and 4, it has been shown that MILP has a wide variety of applications and has been used extensively to model process operations. Such models have also been used to aid in the analysis and understanding of how specific process or cost variables can affect operations and revenues. In their paper, *Zhang et al.* design a MILP model to optimise the scheduling of a fuel gas system at a refinery. They use their model to investigate how changes to various process streams affects plant performance, optimisation results and therefore revenues, with results indicating one unit (the compressor) is the process bottleneck [65]. In this chapter, the aim is to perform a similar investigation on key process variables and the cost of energy for the Howdon AAD plant, to determine how the site could and should be operated under different criteria. The Energy Model developed in Chapter 3 was used to better understand plant management strategies by performing a sensitivity analysis on the highest impact variable external factors: biogas production, electricity tariffs, natural gas prices and biomethane injection throughput (BUP limits).

The remainder of this chapter is structured as follows: in the methods section, the various scenarios to be tested in the model are noted regarding electricity prices, natural gas prices, biogas production volumes and BUP processing volumes. Next, the results of varying both energy prices are displayed under two scenarios: with varying biogas production levels and varying BUP processing limits (with all other variables constant under both scenarios). Finally, the limitations and conclusions of the analysis are presented, with an introduction to the next phase of work in Chapter 5.

4.2 Methods

The effect of varying four key parameters was investigated as part of this chapter: the electricity tariff (import and export), natural gas price, biogas production volume and BUP processing limits.

Initially, varying energy prices were investigated whilst keeping the biogas production and BUP limits constant to determine how much these impact site revenues assuming typical production levels. This sensitivity analysis is then built upon with two further investigations: varying the Biogas production level (BUP limits constant) and then varying the BUP limits (biogas production constant). In each of the two further investigations, the varying energy tariffs outlined in Section 4.2.1 were used.

In addition, all revenue values shown here (as a result of testing each scenario in the model) are inclusive of the two-year delayed carbon tax. As previously mentioned in Chapter 3, the carbon performance criteria tax is payable for NWL after two years, so the immediate site revenue will be different to what is shown here, but it is important to include carbon in the revenue for future operations and analysis.

4.2.1 Varying energy prices only

The main parameters that NWL are unable to influence is the energy prices for electricity and natural gas. Therefore, the first investigation was to determine the impact these factors have on typical gas processing volumes. For this analysis, there were 17 different electricity tariffs and 12 different natural gas prices explored – an explanation as to what these are and how these are determined are explained in sections 4.2.1.1 and 4.2.1.2 below. These tariffs were input to the Energy Model, with a constant biogas production of 38,000 Nm^3 and constant BUP limits of 40,000 Nm^3, such that a direct comparison with the results from Chapter 3 could be drawn. This resulted in 204 simulations based on changing energy prices only.

4.2.1.1 Electricity Tariff

The electricity tariff shown in Figure 3-2 was used as a basis for the varying electrical tariff. The electrical import and export cost shown was varied between -3p/kWh and +5p/kWh, in steps of 0.5 p/kWh. Using the previous electrical tariff as a reference ensured the overall half hourly trend (shape) and the price difference between import and export remained consistent.

The main tariff and the upper and lower bounds used are shown in Figure 4-1 with the 17 tariffs used all within the shaded area. Additionally, the tariff was varied by -3p/kWh to ensure that at no point the electricity export tariff went negative, and was varied by up to +5p/kWh such that the highest peak of the tariff was comparable to historic prices the site has seen, as previously demonstrated on the example tariff shown on the centrifuge example in Chapter 2 (Figures 2-3 and 2-4).

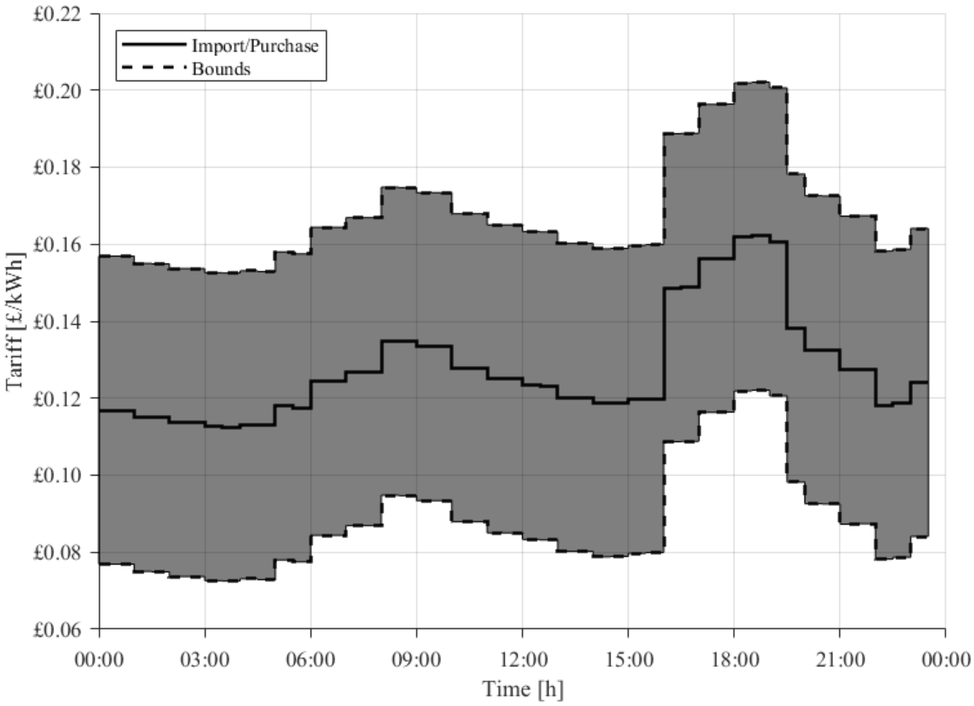

Figure 4-1 Electricity Import Tariff used for sensitivity analysis. Dashed lines show upper and lower tariffs, solid line shows the electrical import tariff from Chapter 3. All tariffs used follow the same shape and are within the shaded area.

4.2.1.2 Natural Gas Tariff

Typically in the UK, the price of gas has historically fluctuated between 20 p/therm and 80 p/therm [66]. However, the last time the price of gas went above 75p/therm was in 2013, with the most recent spike of 73p/therm in 2018. Therefore, the price of natural gas in this study was varied between 20-75 p/therm, in steps of 5p, resulting in the 12 different energy prices to be run. Per optimisation, the price of natural gas remains constant throughout the day.

4.2.2 Varying Biogas production

Based on historical site data, the AAD plant at Howdon has produced between 10,000 and 60,000 Nm^3 of raw biogas per day from the three anaerobic digesters. However, as shown in Figure 4-2 most of the time the digesters produce between 30,000 and 45,000 Nm^3 of biogas per day. It is for this reason that the volume of biogas produced that is passed to the model was ranged from 30,000 to 45,000 Nm^3, in steps of 500 Nm^3, resulting in 31 different production levels. This combined with the two varying energy tariffs resulted in a total of 6,324 simulations to be passed to the model. During this analysis, the limits on the BUP were kept constant, at the typically expected value of 40,000 Nm^3.

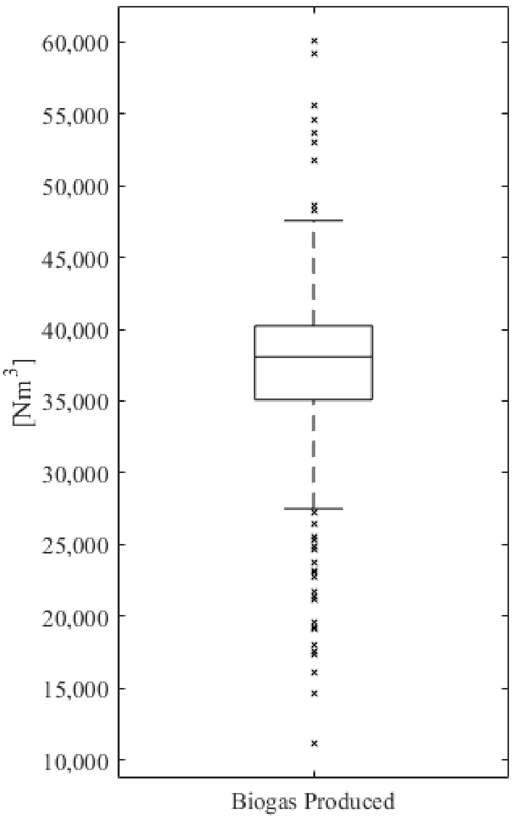

Figure 4-2 - Boxplot of annual historical daily biogas production volume from all three anaerobic digesters (Apr 2017 - Apr 2018).

4.2.3 Varying BUP limits

In Chapter 3.3.1 a brief investigation on how the processing limits of the BUP affect site revenue the most was performed. Currently, the BUP grid injection point is tightly controlled by the gas quality being injected and the local gas network, which is outside of NWL's control – should the pressure in the grid become too high then NWL may no longer be able to inject biomethane, hence the daily limit of injection. Should this daily limit be reduced in future, due to reduced gas demand or other external factors, operators would wish to know how this may affect site operations and revenues.

In general, it is accepted (on site) that the processing limit of the BUP is around 40,000 Nm^3 of raw biogas per day, however this does fluctuate slightly and is not always guaranteed. As this unit is key to overall site revenue streams, it was decided to investigate the limits of this particular unit and how changing the energy tariffs might affect site revenues depending on the availability of the BUP.

The maximum processing limit of the BUP was varied between 0 and 40,000 Nm^3 raw biogas per day in steps of 5000 Nm^3, resulting in 9 different processing levels (scenarios). This combined with the two varying energy tariffs resulted in a total of 1,836 simulations to be passed to the model. During this analysis, the daily biogas production level was kept constant at the typical value of 38,000 Nm^3.

Due to the system of linear equations set up within the model, MATLAB is always able to find a solution to the MILP problem. However, when the volume of biogas produced exceeds the volume that can be processed by the BUP, occasionally the solver finds multiple solutions and can take a while to converge on a single optimum. It is for this reason that a limit of up to 5 minutes per optimisation was employed for the analysis with the BUP limits (Section 4.2.3), although no single optimisation took the full 5 minutes to converge.

4.3 Results and Discussion

The results shown by varying the energy prices (section 4.3.1) took around an hour to achieve, with the 204 optimisations of the model using different energy prices. These 204 scenarios were then used with varying biogas production levels (section 4.3.2) where the 6,342 scenarios took ~18 hours to complete. The 204 energy scenarios were also used with varying BUP limits (section 4.3.3) where there were 1,836 scenarios in total to optimise, which took ~12 hours to complete. As stated in section 3.2.7, each daily scenario (48 half hourly) optimisation consists of 2355 variables of which 1491 are integers, 1972 inequalities and 768 equalities.

When plotting the results of the analysis, the trend of each varied electricity tariff remained the same, thus the daily average electricity price was calculated for each scenario and used for plotting.

4.3.1 Varying energy prices only

First, using the same model parameters outlined in Chapter 3 the electricity tariff was adjusted only, to determine the effect on revenues. The results of this analysis are shown in Figure 4-3.

As would be expected, as the price of electricity rises the overall site revenues would fall. However, once the average price reaches around 12 p/kWh the optimum achievable revenue stabilises. This is due to the price of natural gas which, at this point, becomes cheap enough to be useful to run in the CHP engines, either for all or part of the day. One must remember that the CHP engines have a minimum operating time once switched on, therefore the price of electricity must become expensive enough compared to that of natural gas to ensure a switch-on is cost effective.

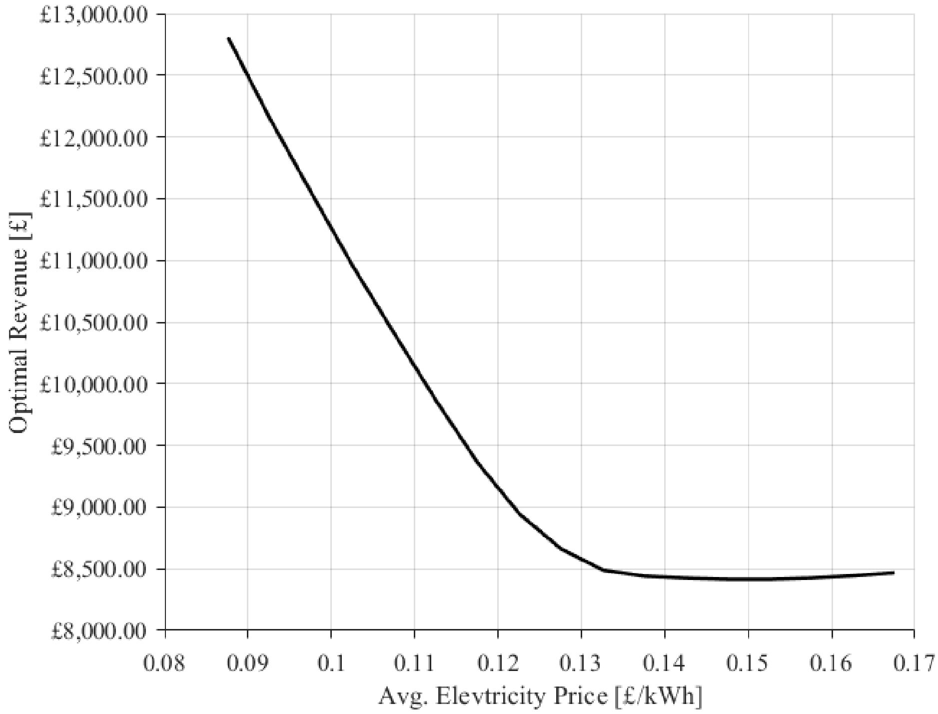

Figure 4-3 – Optimal Daily Revenues acheivabnle using model parameters from Chapter 3, but the electricity tariff was altered. Gas prices remains fixed at 65 p/therm, daily biogas production at 38,000 Nm^3.

Similarly, the price of natural gas was investigated by keeping the electricity tariff constant (the same as in Chapter 3.2.2, Figure 3-2) and changing the price of gas only. Unlike the electricity tariff, rising gas prices always results in a lower optimum achievable revenue. This is because natural gas is likely to be always required on site when the BUP is fully operational – energy is required on site in the form of steam, and due to the high revenues from the RHI scheme the raw biogas will almost always be used for grid injection before use in the boilers. In addition, it has already been demonstrated (Figure 3-6) when the gas price is 65 p/therm, based on the tariff in Figure 3-2, the CHP Engines should operate on natural gas during peak electricity price periods – thus it stands to reason that, when keeping this tariff the same, reducing the natural gas price would see an increase in potential revenue.

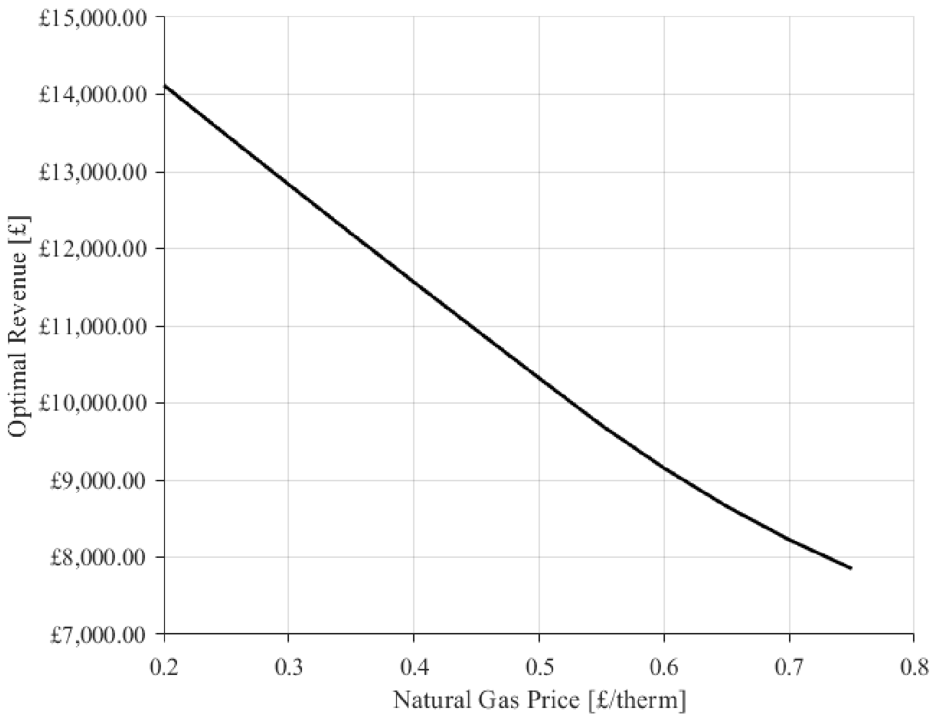

Figure 4-4 - Optimal Revenues achievable using model parameters from Chapter 3, but the natural gas price was altered. Electricity prices remained fixed as shown in Fig.3-2, daily biogas production at 38,000 Nm3

While Figure 4-3 and Figure 4-4 show interesting results, it is also true that the price of electricity and the price of natural gas could both change and affect revenues – the limited data shown does not give a full enough picture on how natural gas prices and electricity prices affect site revenues and operations.

Figure 4-5 demonstrates the impact changing both energy prices has on site revenues, assuming a constant typical biogas production of 38,000 Nm^3. As the price of natural gas decreases the impact electricity prices has on suite revenues becomes less and less, shown by the flattening of the plane along the electricity price axis. In addition, as the price of electricity increases above a daily average of roughly 12 p/kWh the daily site revenue is primarily dictated by the price of natural gas, shown by the straight plane when electricity price is greater than 12 p/kWh.

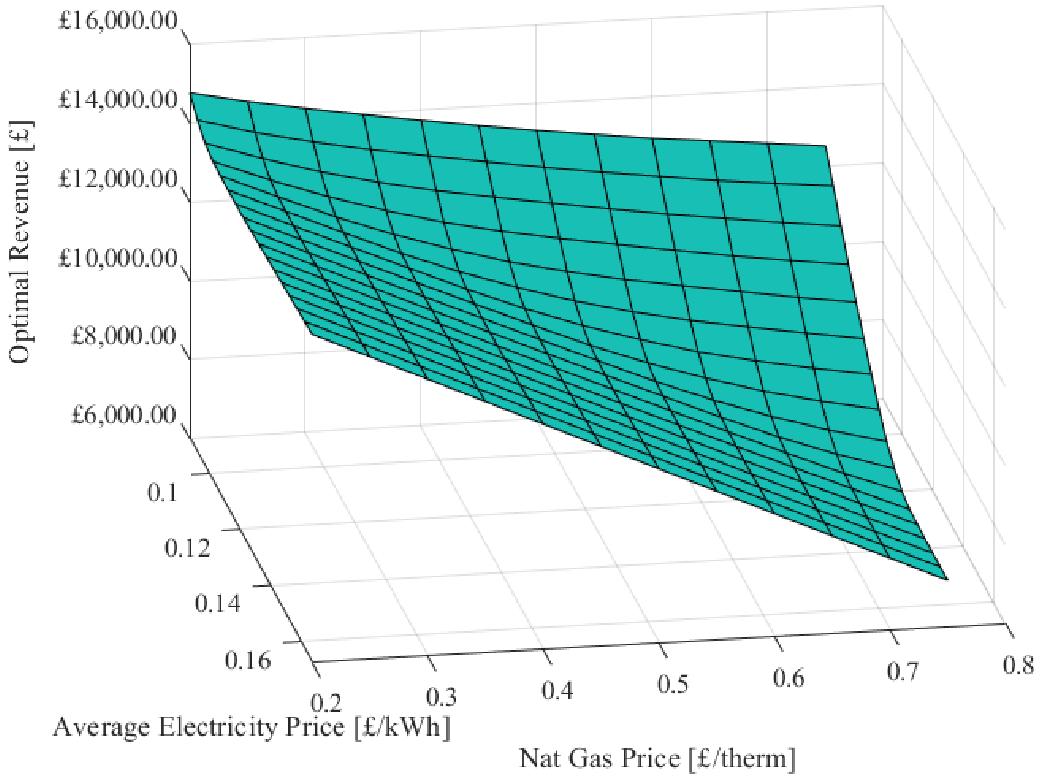

Figure 4-5 - Sensitivity Analysis of optimal daily site revenue by varying both Natural Gas and Electricity prices, assuming a constant biogas production of 38,000 Nm^3 and a constant BUP limit of 40,000Nm^3.
Note: the colour of the plane shown matches the biogas production colour scale shown on Figure 4-7 for consistency and comparison.

Under a worst-case scenario when natural gas and electricity prices are both highest, the site is still able to maintain a net positive revenue above £7000 per day, assuming that all biogas can be upgraded and injected into the national grid and the volume of biogas is around 38,000 Nm^3. When electricity is most expensive, for every 15p/therm the price of natural gas increases by, the optimum revenue the site can achieve reduces by ~£2,000 /day. When natural gas is most expensive, as the average price of electricity becomes less than 12p/kWh, for every 1p/kWh is lowers the optimum revenue increases by ~£1,100 per day.

Understandably, while site revenues are of interest to managers, operators will be more concerned with the actual operational strategy of the site – namely, how the CHP engines should be operated. The simulation results have been re-plotted on Figure 4-6, however the electricity generation of the CHP engines is shown instead of site revenues, and the colour of each simulation result shows which fuel type is used in the engines. Should operators wish they can view the specific individual daily strategies in the form of previous figures (such as Figure 3-15) but Figure 4-6 shows a more generic operational strategy such that multiple simulations can be compared.

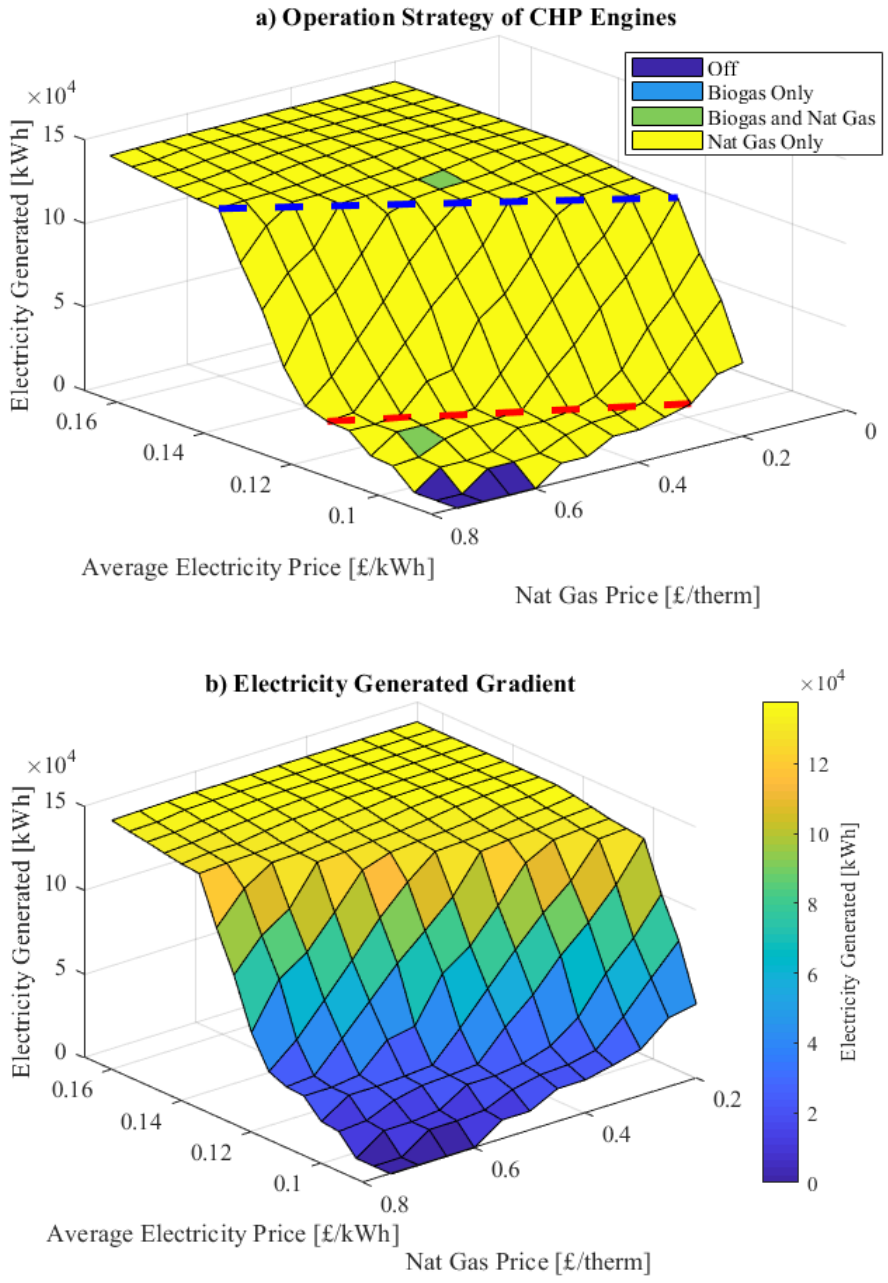

Figure 4-6 Sensitivity Analysis of CHP Engine operations by varying both Natural Gas and Electricity prices, assuming a constant biogas production of 38,000 Nm^3. The red and blue dashed lines indicate energy price boundaries where the operation of CHP engines changes significantly.

The results shown in Figure 4-6 are extremely useful for operators which suggests that, under the current biogas production and BUP assumptions, when electricity is cheap it is optimal to not use the CHP engines much for electricity generation, as shown by the area of the surface plot beneath the red dashed line (where the CHP engines are generally not used). Here, the engines should be switched on rarely during peaks in electricity price periods during the day (a strategy similar to that which was suggested in Chapter 3.3, Figure 3-6).

In the region between the red and blue dashed lines the CHP engines are not fully operational to meet site power demand but are used more in this region; the engines are operated for longer periods throughout the day, not just during peak electricity price spikes. The price of electricity is more expensive for longer periods, resulting in a more cost-effective strategy to rely more on natural gas to generate electricity, however there are times during the day when electricity remains cheap enough to warrant a switch off of the engines (subject to the minimum operating time constraints).

Above the blue dashed line energy prices are high enough for the engines to be operated all the time to meet site power demand, preventing any electrical import costs, shown by the flattening of the surface plot in this region. It should be noted here that under the current assumptions around biogas production and BUP processing limits, overall, the engines should not operate on biogas.

Whilst it is reassuring for operators and managers that the site can maintain net positive revenues even when energy prices become high (Figure 4-5), the underlying assumption made that biogas production or BUP processing capabilities are constant and high is not always going to be true. Thus, the generic operational strategy of the CHP engines suggested in Figure 4-6 may not hold true, specifically when limiting the BUP processing limits, which would require Biogas to be utilised elsewhere. In the following sections (4.2.2 and 4.2.3) the Biogas production volume and BUP limit variables were tested.

4.3.2 Varying energy prices and biogas production

The same energy price variations as 4.3.1 were used, however instead of assuming a constant biogas production level of 38,000 Nm^3, the production volume was adjusted (as stated in 4.2.2), with the results shown in Figure 4-7.

By increasing or decreasing the overall production level of biogas, the operational strategy regarding CHP engines remains unchanged within the bounds of the biogas productions used, only the revenue achievable is different – i.e., for each production level of biogas the optimal revenue surface plot shown in Figure 4-5 is shifted up or down in the z-axis. As has been previously stated (in Chapter 3.3.1) the gas to grid injection is the main revenue driving factor for site operations, which is reinforced with the simulation results shown in Figure 4-7 as the only change to site operations is revenue based. The operational strategy of the CHP engines remains unchanged from Figure 4-6 for each biogas production level, which is to be expected.

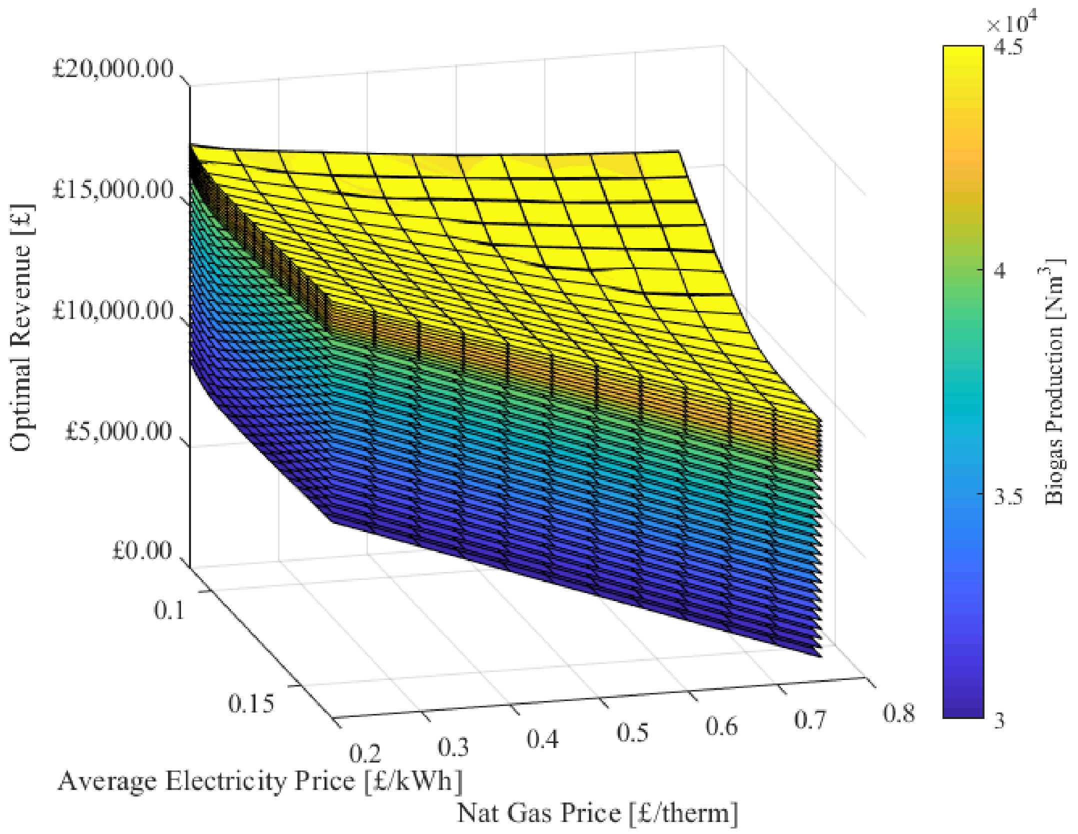

Figure 4-7 Sensitivity Analysis of optimal site revenue by varying biogas production level in addition to Natural Gas and Electricity prices.

If the BUP can process up to 40,000 Nm^3 (which is assumed under this scenario) then when biogas production levels exceed this capacity the biogas will be required to be used elsewhere on site, however one CHP engine requires a minimum of 8,000 Nm^3 of biogas per day to operate at only half capacity – therefore any excess biogas that is produced is consumed by the on-site steam boilers for heat purposes.

Given the current revenue levels of biomethane injection into the national gas grid, operators should therefore recognise that the level of biogas that is produced by the digesters has no impact on CHP operations, but any excess biogas produced that cannot be injected should have priority for steam production on site.

4.3.3 Varying energy prices and BUP processing limits

The same energy price variations as 4.3.1 were used, however instead of assuming a constant BUP processing limit of 40,000 Nm^3, the processing volume was adjusted (as stated in 4.2.3), with the results shown in Figure 4-8.

The simulations performed reinforce how important the gas to grid injection is for site revenues. Regardless of energy prices, for the site to maintain a positive revenue stream at all times the BUP must be able to process at least 20,000 Nm^3 of raw biogas for grid injection per day. If the BUP processing limit falls between 10,000 and 20,000 Nm^3 then the site can still break even or even make a profit, if energy costs are low – if energy costs are too high then the site will no longer become profitable and becomes a cost to operate.

Figure 4-9 shows the CHP engine operational strategy for each BUP processing limit simulated. As previously stated, the dual fuel CHP engines require a minimum volume of biogas per day for operations, and when the BUP is limited to 25,000 Nm^3 or less the dual fuel CHP engines can operate on biogas, shown on graphs ‘a’ though ‘f’. When one or more engines are required to be operated on biogas, the reliance on electricity imports becomes less and less, shown by the general increased generation of electricity on graph ‘a’ compared to ‘f’.

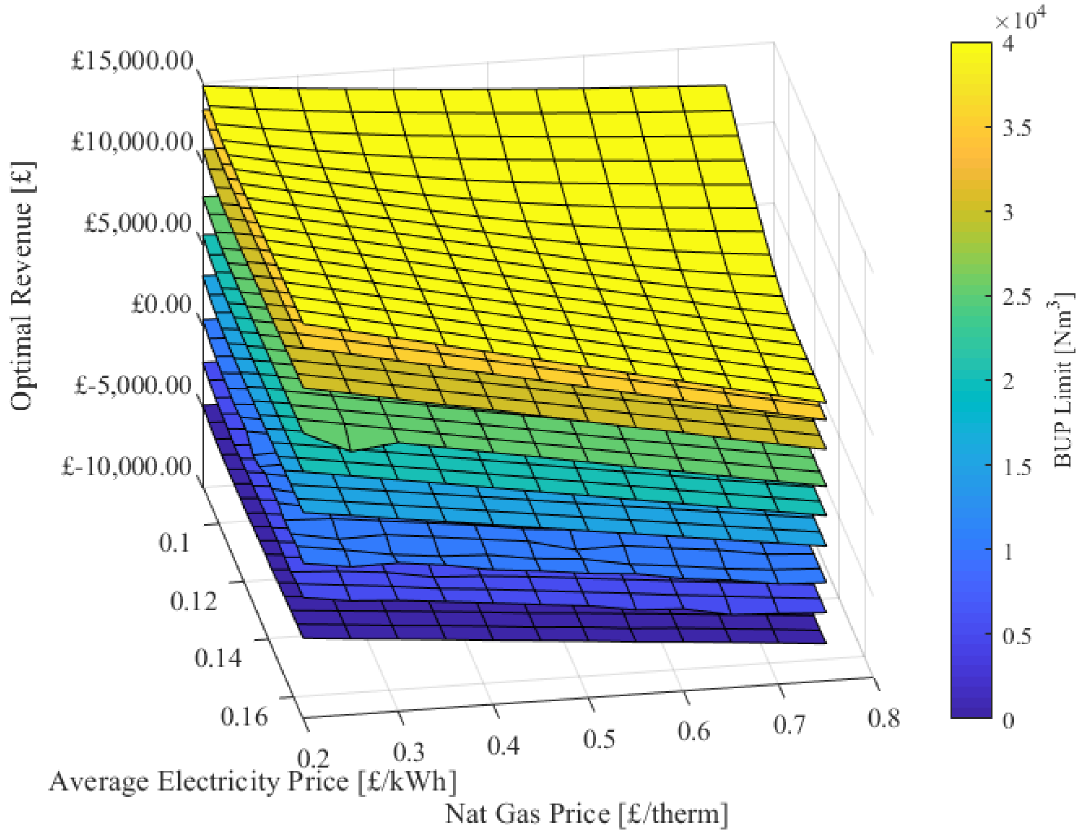

Figure 4-8 Sensitivity Analysis of optimal site revenue by varying BUP processing limits in addition to Natural Gas and Electricity prices

Interestingly, the ramping boundaries (based on energy prices) that were shown previously on Figure 4-6 still hold true for all graphs on Figure 4-9, and are most likely due to the fourth natural gas engine that is still affected by natural gas prices. Additionally, the lower the BUP processing value (and the more reliant on biogas the CHP engines are) the lower the impact the price of electricity has on site revenues, as shown by the flattening of the plot along the electricity axis on Figure 4-8. The data down on Figure 4-10 is the same as shown on Figure 4-9, however the fuel selection for each CHP Engine is not highlighted – the colour scheme for Figure 4-10 is used to help emphasise and show the steepness and gradients of the surface plots on Figure 4-9.

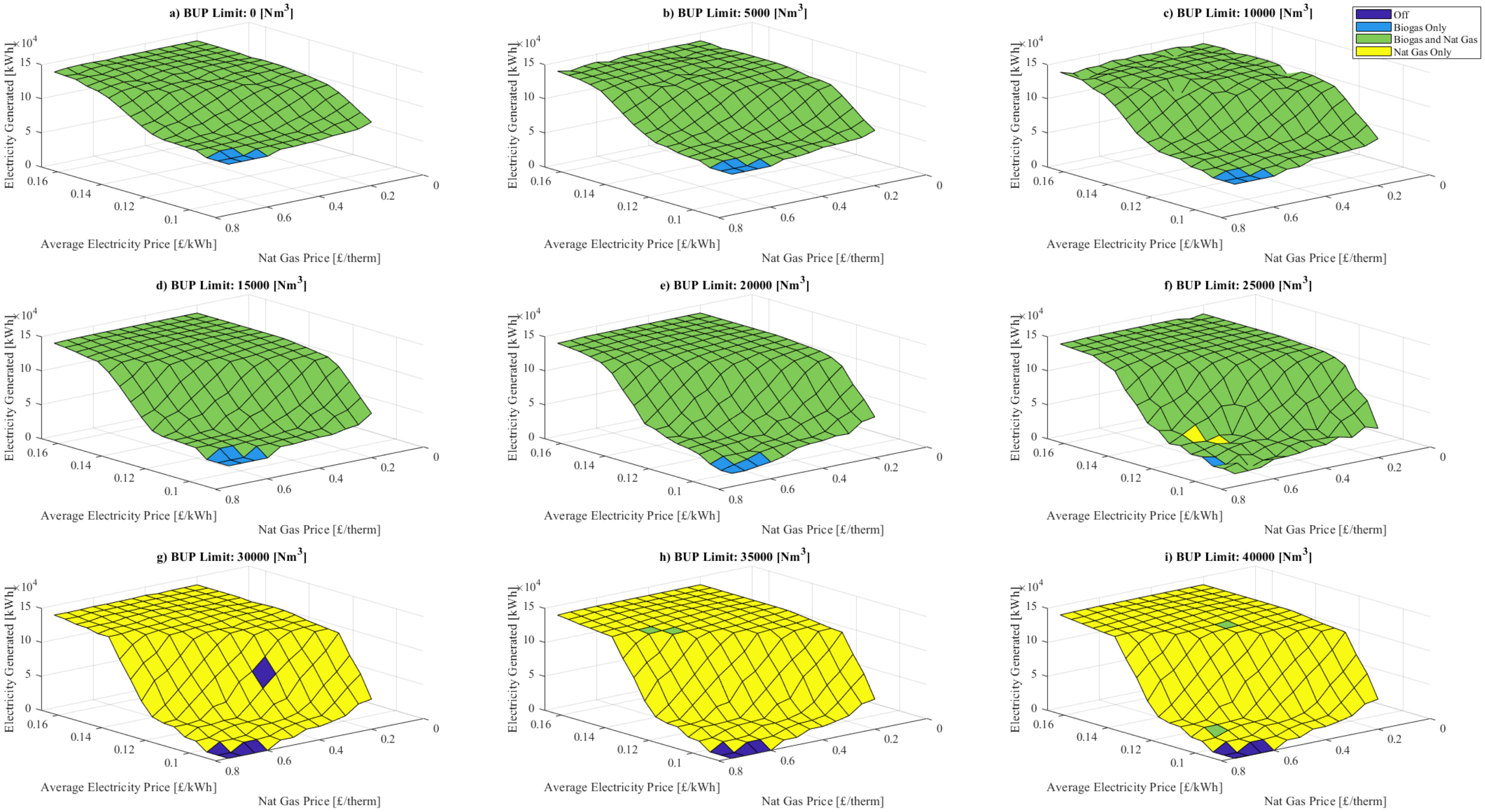

Figure 4-9 Sensitivity Analysis showing CHP Engine operational strategy by varying Natural Gas and Electricity prices for different processing levels of the BUP (a-i shows a different daily BUP processing volume), assuming a constant biogas production of 38,000 Nm3. The reader is reminded that gas engine 4 is natural gas only, and that only CHP engines 1-3 are dual fuel. Graph 'i' is the same plot as Figure 4-6.

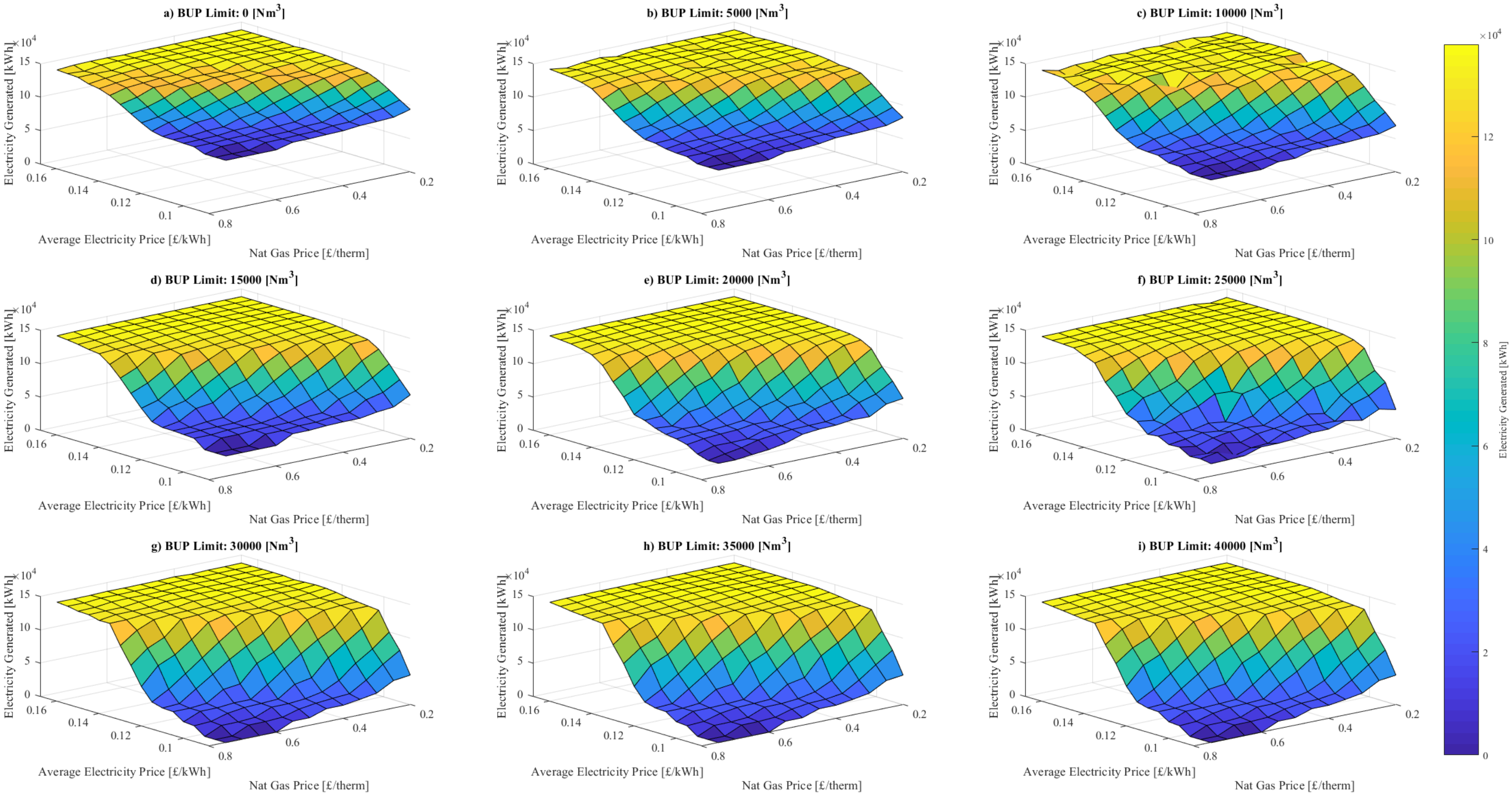

Figure 4-10 Sensitivity Analysis of CHP Engine operations by varying Natural Gas and Electricity prices for different processing levels of the BUP (a-i shows a different daily BUP processing volume), assuming a constant biogas production of 38,000 Nm3. The reader is reminded that gas engine 4 is natural gas only, and that only CHP engines 1-3 are dual fuel. Graph 'i' is the same plot as Figure 4-6. The data shown is the same as Figure 4-9, but the CHP operational strategy is not shown to highlight the gradients.

4.3.4 Validation of tariffs used

After the sensitivity analysis was performed using the hypothetical price variations stated above, the actual historic tariff information for gas and electricity prices for Howdon became available for the period of April 2020 – August 2021. Figure 4-11 shows this most recent historic electricity Import (Figure 4-11a) and Export (Figure 4-11b) tariff, whilst Figure 4-12 shows the historic gas prices over the period January 2020 to August 2021 – unlike the electricity data, there are periods where no data was available for the gas prices, however the general trend and variation in prices can still be observed.

In the study above, the price of gas was varied between 25 and 75 p/therm based on historic UK market prices. As can be seen on Figure 4-12, the price of natural gas has exceeded 80p/therm in July 2021, with prices reaching over £1.10 per therm at the time of submission (August/September 2021).

Based on the historical gas prices the site has seen over the past year, it is the authors belief that the gas prices used during this study remain valid for the expected prices the site will see in the near future as prices appear to be falling back into the expected region. However, managers could re-perform further sensitivity analysis on even higher prices, as the August 2021 peaks in gas price are unprecedented and were not predictable at the time of the study. Additionally, the peaks seen this August could become the new normal, where prices may remain exceptionally high for longer, thus performing further analysis at these higher prices would be advantageous.

Howdon STW is usually subject to two tariffs, one for ‘Summer’ months (April to November) and one for ‘Winter’ months (November to April), where winter tariffs are usually subject to additional levies and therefore increases in price. This general increase in tariff can be observed on Figure 4-11 during the ‘winter’ months. To validate the electricity tariff used as part of this study, the average site tariff was determined for three different date ranges:

- The entire data range shown on Figure 4-11,
- April 2020 (inclusive) to November 2020 (exclusive) and,
- November 2020 (inclusive) to April 2021 (exclusive).

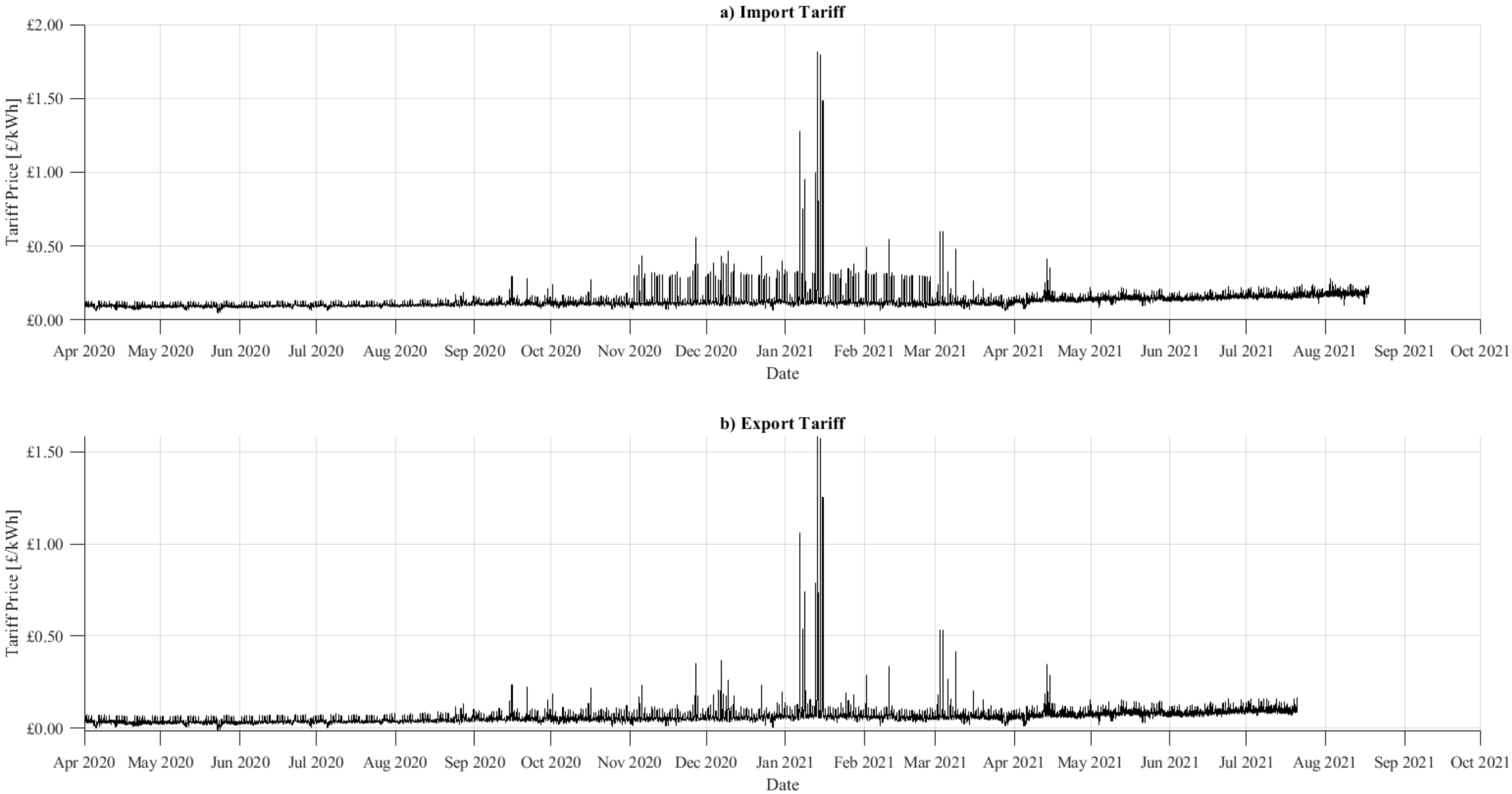

Figure 4-11 Historic Electricity Import and Export prices (half hourly) for Howdon STW during the period April 2020 to August 2021.

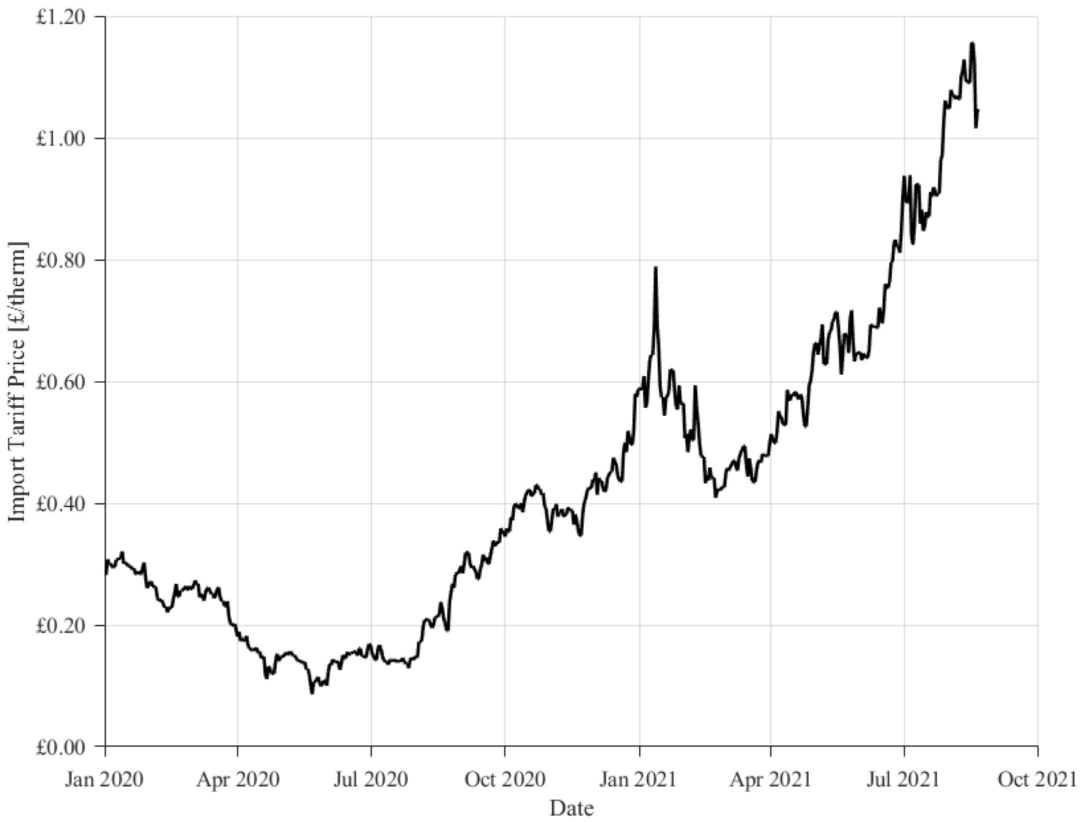

Figure 4-12 Historic Gas Import Tariff for Howdon over the April 2020 to August 2021 period. The Export tariff was always 0.56p/therm lower than the import, but is not shown to maintain clarity of the trend.

The mean for each half hourly tariff price was calculated, and the resulting 24-hour mean tariffs are plotted on Figure 4-13. It should ne noted that there are clear outliers from the mean tariffs (on Figure 4-11), which of course will be of interest for managers and operators to investigate. Now the historical tariff information is available, the Energy Management model could be used to perform RO (similar to that performed within Chapter 2.4.2), such that historical operations can be validated, such that operational strategies required for future spikes in price can be explored.

The overall mean tariff (Figure 4-13a) still shows the typical diurnal price trend across the 24-hour time period, however it is much closer to the higher bound of the hypothetical tariff used in the study (Figure 4-1), but still within the bounds itself. The 'Summer' tariff shown (Figure 4-13b) follows the diurnal trend and lies well within the bounds of the hypothetical tariff used, however the 'Winter' tariff shown (Figure 4-13c) shows much higher spikes in electricity prices during the 16:00-19:00 region, which are outside the bounds of the sensitivity analysis.

In general, the hypothetical electricity tariff used for this study is a valid approximation for the tariffs the site will experience today. The analysis is likely better suited to be an approximation of the 'Summer' tariffs the site will see, however should managers require they could re-perform the analysis using the higher tariffs that have been seen more recently.

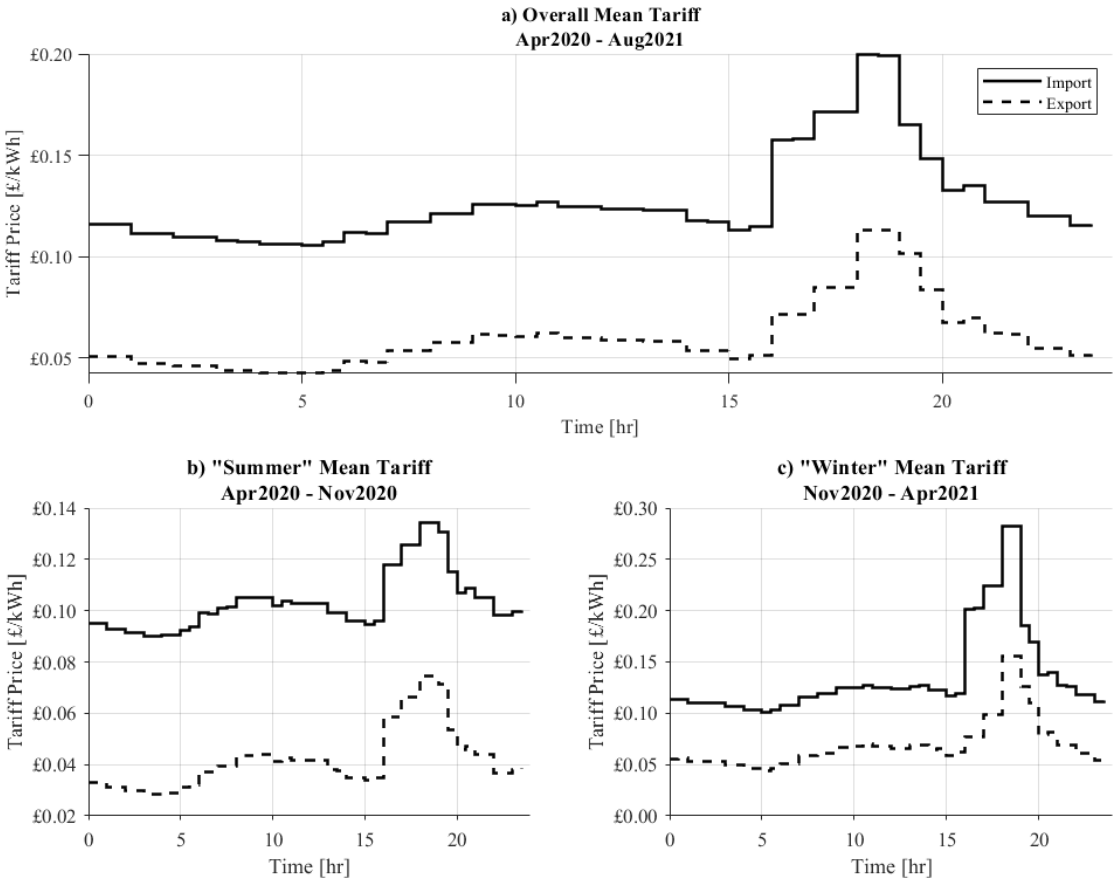

Figure 4-13 Average electricity import and export tariff costs, based on the date ranges selected from the dataset shown on Figure 4-11

There have been unprecedented prices that have never been seen on-site before, with spikes in electricity prices, both high and low. Some examples of erratic and unique electricity price behaviours are shown on Figure 4-14, where the daily tariffs with the highest and lowest peak or trough for electricity export and import are shown. Here, the search for the highest and lowest tariff prices was performed independently for Import and Export prices, therefore the fact that the dates shown for Import and Export costs are the same is coincidental (but somewhat expected as they are intrinsically linked).

First, exceptionally high spikes in electricity price have been observed, with import costs exceeding £1.75 per kWh (Figure 4-14a), an almost eightfold increase in the average tariff price for the same time of day shown on Figure 4-13a. Second, the export costs shown on Figure 4-14d suggests that there was an exceptionally unusual low demand for electricity (or vastly increased generation) across the sector as export costs were seen to be negative – a negative export cost infers that NWL would have to pay the National Grid if they were to generate and sell/export electricity during this time. As NWL do not currently use electricity exports as a main driver of revenues, such a rare occurrence may not be of high importance to managers, however should future operational priorities change it may become an important factor – if such events occur more frequently in the future, then self-generated electricity storage could be a potential solution and consideration.

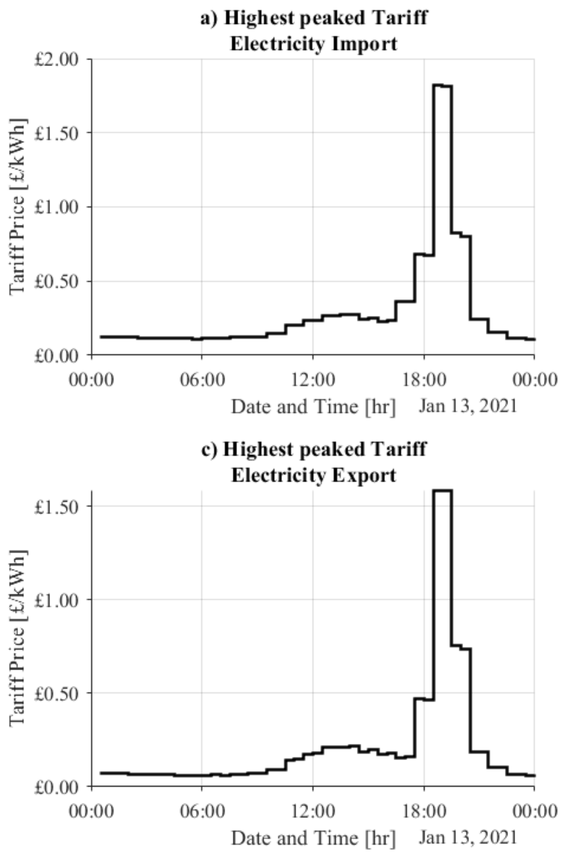

Figure 4-14 Selected historic electricity import and export tariff information, based on the singular highest and lowest price observed over the Apr2020-Aug2021 period. It is completley conicidental that the the dates on graphs 'a' and 'c' are the same, as well as the dates shown on graphs 'b' and 'd', as the search for highest and lowest prices were performed seperately for import and export prices.
Note: A positive Export price means revenue/sale price.

The general trends shown on Figure 4-14 also show increased volatility (more variance with peaks and troughs) during the 24-hour period. Such unusual behaviour with electricity prices and high spikes in gas prices could not have been anticipated at the start of this sensitivity analysis, therefore could not have been accounted for. However, managers could use the Energy Management model presented to investigate the opportunities and affects instances like this might have on site revenues and operations under future investigations.

The global pandemic (COVID-19) has caused a drastic shift in social and economic behaviours, which has led to increased volatility in energy prices due to unpredictable and varying demands. Historically, the price of electricity has remained consistent with small variations and occasional spikes, as is shown during the April 2020 to October 2020 period on Figure 4-11, and the price of gas (in the wholesale market) has historically not risen above 90 p/therm. However, since the easing of lockdown restrictions in the UK from around April 2021, the day-to-day variation in electricity prices has increased (less consistency and more volatility) with a general slow increase in daily price also observable from this date, and the price of natural gas rising unprecedently high – the reader is encouraged to visit the Ofgem website ‘Wholesale Market Indicators’ for historical data on UK energy prices (gas and electricity) [66]. These rises could be attributable to UK businesses starting back up after the easing of pandemic restrictions, or on wider socioeconomic impacts on energy markets.

4.3.5 Limitations

The sensitivity analysis shown here has focussed on key areas of the site as well as energy prices under the assumption that other price factors, such as biomethane injection revenues, remains constant. In the future, the current agreement NWL has regarding biomethane injection into the gas grid will need renewing, in which case the model used here would need updating to allow for any new agreements. Additionally, the model and analysis here does not include any other annual based agreements that could affect site revenues or operational strategies, such as the CHPQA (CHP Quality Assurance) programme.

In terms of unit operations on site, the analysis performed here has only considered the BUP and how limiting this affects site operations. This is because it is the most valuable asset on site regarding revenues. In the future, the model could be used to perform a similar analysis around the CHP engines and even the boilers (although when one boiler becomes unavailable the others are able to compensate). Operators would be able to see how site revenues could be affected by unit maintenance and downtime.

Furthermore, the model currently assumes CHP engines produce a set amount of electrical power when in operation, however it is not unreasonable to assume that the power produced by these engines may reduce over time due to wear and tear, albeit slightly (reduced power efficiency). The model could be used to analyse the impact of degradation in CHP performance, and possibly indicate to mangers increases or decreases in expected revenues based on this degradation.

4.4 Conclusions

In this study, the model derived in Chapter 3 was used for further analysis of the impact energy prices has on site revenues. The price of electricity imports and exports was varied using the example tariff (shown in Figure 3-2) as a reference, and the price of natural gas was used using historical UK gas prices as a reference. Since performing the analysis, the most recent historic energy prices were used to validate the hypothetical tariffs used as part of the study.

The analysis reinforces the understanding that maximising biogas injection into the national grid is the most cost-effective operational strategy. Second to this, the optimal operation of the CHP engines is subject to the available excess biogas available after BUP processing and the current daily energy prices.

As the natural gas price becomes more expensive the price of electricity has a higher impact on site revenues that are achievable. It is around the average price point of 12 p/kWh that operators and managers should be considerate of - when electricity prices go above this point the optimum revenue on site is dictated by natural gas prices.

The BUP limits were tested as a demonstrative example of variable process limits, which highlights the importance on maintaining this process as it is the main driver of revenues for the site. To ensure the site always maintains a positive revenue, regardless of how high energy costs may become, operators should ensure that at least 20,000 Nm^3 of raw biogas can be processed and injected into the national grid.

This study also demonstrates how operators and managers can use the model for scenario testing and operational strategy validation. The use of the Energy Management model presented here (analysing various scenarios) is a useful tool for managers as it can help provide evidence to aid in contractual agreements with regulatory bodies – the Energy Management model could also be used by the regulators themselves as a financial and site monitoring aid to ensure water companies are held to account for their agreements.

The main driver that can be controlled somewhat by NWL (that affects the operational strategy and revenue of the site) is the daily biogas produced by the anaerobic digesters. For NWL to make the most of the analysis performed in this section, better predictions and forecasts of biogas production levels based on current sludge processing levels would be advantageous. This would allow manager sand operators to truly see how the site should be operated, based on current prices and factors they are unable to control. In the next Chapter, an initial investigation into predicting this daily volume is presented, along with the site-specific complexities surrounding the anaerobic digesters and data recording capabilities.

Chapter 5 Biogas Prediction through Digester Modelling

To make better use of the already developed models, an accurate prediction of Biogas production volumes would be beneficial for operators and managers on site. However, modelling each individual digester is difficult as the gas flow sensor data for each digester is not usable. This chapter investigates data driven modelling approaches to predict the total biogas production of all three ADs based on the status and feed data for each individual AD.

5.1 Introduction

A model or tool for the prediction of Biogas production levels on site is something NWL currently does not have. For the Energy Management model to truly become a predictive optimisation tool, a prediction of biogas production is necessary, otherwise the Energy Management model can only reasonably remain useful for retrospective optimisation rather than prediction or advice.

The aim is to be able to predict the volume of biogas that will be produced by the Anaerobic Digesters (AD's) based on the sludge feed volume (and potentially use other parameters such as pH or temperature). The ability to predict biogas production will aid in future operational decisions to advise whether a change in plant state is required. There is plenty research focusing on optimisation of digester parameters or sludge feed for increased biogas production or on the accurate modelling of ADs [67–69], however for this to occur the data recorded by the plant must be high quality.

There are two possible methods of modelling and predicting the biogas production on site using historical data:

1. Create three individual models, one of each AD, and summate their predictions to calculate the overall biogas produced

2. Model the three ADs as a single 'entity' or digester, and aim to predict the volume of biogas produced in a single model

The most widely used mechanistic model for ADs is the Anaerobic Detester Model No. 1 (ADM1), presented by *Batstone et al* [70]. Many models that exist for ADs, including ADM1, are based on Chemical Oxygen Demand (COD) as a base reference unit [71]. Because of this, ADM1 is seldom applied directly in plant operation, with some making efforts to transform ADM1 into a mass-balance based model instead of COD [72]. Based on the non-linear fundamental differential equations required to model an AD, each AD would require a separate model that will require extensive testing and validation to determine digester-specific parameters for operation, including around 60+ parameters [73].

Furthermore, the microbial and physiochemical processes of AD are highly complicated; current understanding of these processes is not comprehensive and continuously being updated as new microbial processes are discovered [74]. Mechanistic models (such as ADM1) can face challenges due to the limited understanding of AD, thus digestion prediction is mostly inaccurate [75]. It is for this reason that novel methods, such as using machine learning algorithms, are being sought to accurately predict digestion performance without the need for a mechanistic model [76].

One of the difficulties of modelling the Digesters is that the relationship between sludge feed (TDS) and biogas produced is not linear, as previously mentioned. The relationship exhibits linear properties but if it is assumed only linear there is too much noise in the data to be able to draw accurate enough predictions. Figure 5-1 shows a simple scatter plot of daily TDS fed into the digester vs biogas production.

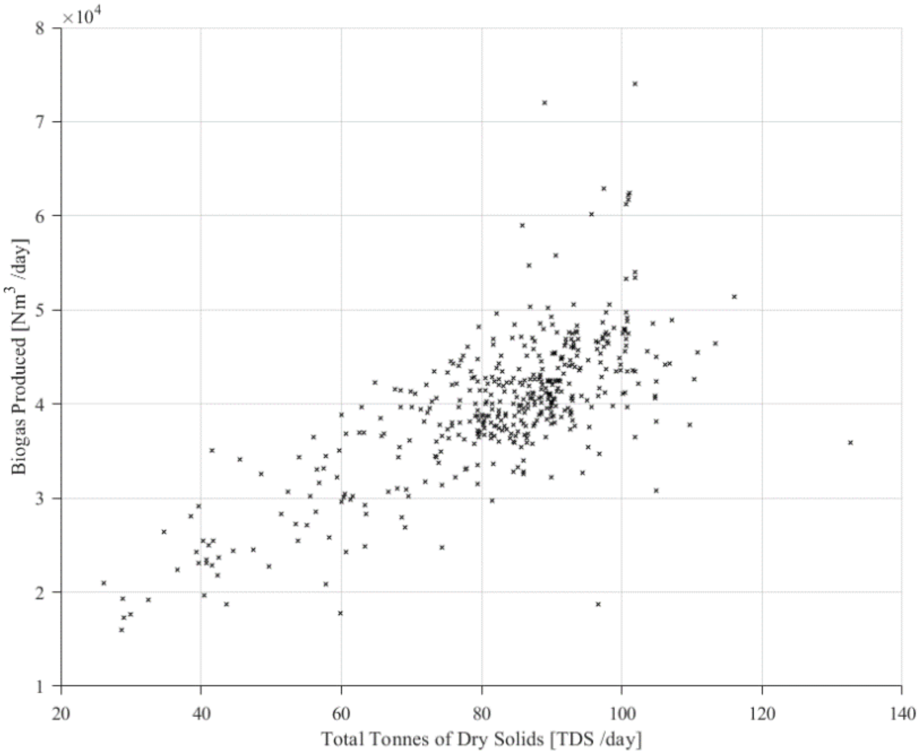

Figure 5-1 - Totalised Dry Solids fed into the ADs vs Totalised Biogas Produced (Daily totals over a 15-month period) [With two Lines of Best Fit]

Whilst there does exhibit a somewhat linear relationship between TDS and biogas production, using a simple linear relationship with these two values only would result in inaccurate biogas predictions and a very noisy fit. There are multiple studies of modelling anaerobic digesters using different feed stocks, many describe and model the system as non-linear [70,74,75,77–79]. Typically, this is due to the behaviour of the microorganisms changing depending on their environment, i.e. changes in temperature, pH, feed rate etc that affect growth rates.

Figure 5-1 exhibits a large amount of noise – i.e. the same mass of dry solids yields different biogas production volumes. This could be due to noisy data but is more likely to stem from the non-linear mechanistic relationship that also includes variables such as Temperature, pH and Volatile Fatty Acids (VFA's).

Each digester has separate data for sludge feed (in m^3) but sludge feed volume into the digesters is not a very useful variable to use on its own, as the mass of dry solids in the feed varies almost daily – during part of the separation process the sludge is dried, and these solids are then watered down slightly during the thermal hydrolysis stage before being fed into the digester. It would be advantageous to use TDS fed into the digesters in tandem with sludge feed volume. There is also data readily available for digester temperature, which is known to play a key role in the efficiency of sludge-to-biogas conversion.

Other variables such as COD and VFA's are known to affect biogas production within an anaerobic digester, but data for these are not recorded digitally (like sludge feeds or temperatures) and subsequently portions of this data is missing and unavailable to use for historical modelling. In addition, the historical data for AD pH has large sections of missing data. An attempt was made to include these terms within models, but attempts were also made to model the digesters without it, to determine whether the lack of data is substantial enough to be detrimental to any models created.

One could argue that developing a Grey Box model would be the optimal approach, whereby a data driven model can be aide with a mechanistic model. A grey prediction model is typically categorised by incompleteness of information for a model; grey models can be 'whitened' by inserting more messages effectively around the forecast origin [80]. Typically, models of actual plants or operations are known as Grey Box models where the model combines a hybrid of theoretical and 'prior knowledge' to form a more accurate model than theory or data driven models alone [81]. Lack of plant information has delayed the introduction of more complex control strategies and models in the water industry, however recent advances in technology have seen significant progress with respect to instrumentation for wastewater processes [17].

Fundamental knowledge of the system is required to create a model from first principles, often in the form of differential equations derived from mass and energy balances, whereas data-driven modelling uses process data to produce a model through an assortment of potential techniques [82].

If an accurate model for each digester could be made, it would be beneficial for the operators on site to understand and visualise the operational state of each digester. However, to create such a model accurate historical data on the biogas output for each individual AD is required, in addition to other parameters. Unfortunately, the biogas output data is not available for individual digesters, as the flow meters atop the AD's repeatedly provide inaccurate an unusable data, as agreed by operators on site and demonstrated by Figure 5-2. When the biogas volume produced by each individual AD is summated it provides a total biogas volume that is vastly inaccurate compared to the totalised flow at the pre-treatment plant ('SCADA total') or even the summated usage of biogas across all unit operations on site.

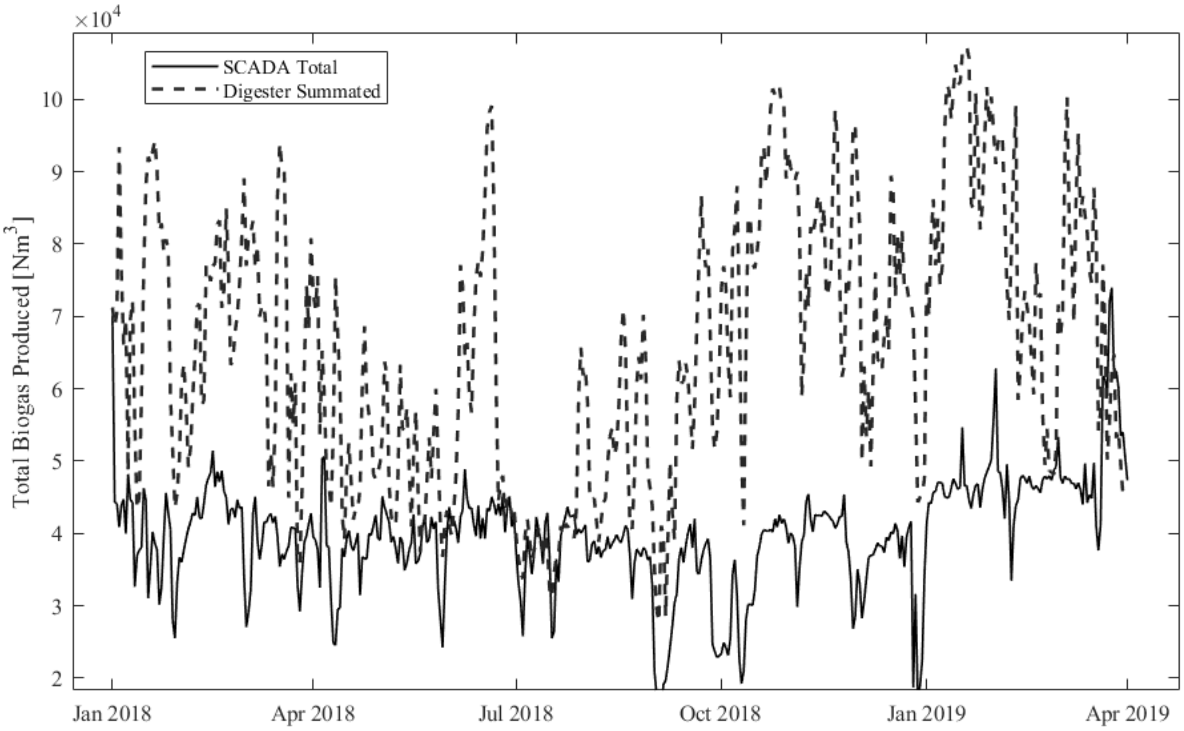

Figure 5-2 - Comparison of Total Biogas Produced from two sources: SCADA total value (summated flow recorded at the biogas pre-treatment plant taken from on site SCADA system) and summating the total volumes recorded out of each individual anaerobic digester. The summation demonstrates how innacurate the individual digester flow meters are.

It is an added difficulty that the totalised volume of biogas produced across all three AD's must be used to create a prediction tool for the summated flow. In addition, it would likely be problematic to create a mechanistic model for each digester without the gas production level for each digester. To model the anaerobic digesters and predict biogas production, historical data for each digester must be available for use, preferably in digital form so as not to rely on manual data gathering. It has already been established that biogas production levels are not available, however other input data is available such as individual Digester Feed volumes, Total Dry Solids (TDS), digester temperatures and digester pH. Some variables such as digester Volatile Fatty Acids (VFA's), Percentage Dry Solids (PDS) and Percentage Volatile Solids (PVS) are available but are not digitally collected, with large gaps in data sets. Hence the data required to successfully develop a mechanistic model of each AD was not available at the time of writing; developing a grey box model was not possible and an alternative data-driven approach was required using the data that was available.

It was decided to first attempt to predict the totalised biogas production levels based on input data for each digester in the form of a linear based relationship and determine whether it would be a useful or 'good enough' approach. Whilst it would be preferable to create a unique model for each digester (so the behaviour of each digester could be monitored and predicted better), it is believed that developing an individual model for each digester will not produce as accurate a tool for biogas production as the individual biogas production data is unusable to create a such a tool.

Non-linear processes exist frequently in industry, thus not all optimisation and modelling problems can be modelled as simple binary linear relationships like the previous models developed within this project. Within linear models, non-linearity is usually handled with techniques of piecewise linearization or transforming into polynomials then linearizing those polynomials [83]. Standard procedures for "linearizing" nonlinear integer problems (including those of piecewise approximation) typically involve a radical increase in the number of problem variables and constraints [83]. Hence, benefits through linear programming can be lost due to excessive increase in computational requirements and constraints compared to taking a non-linear approach initially.

If a linear model can be found to provide reasonable enough predications for total biogas production, then this could easily be applied to alternative sites within the business and not just the Tyneside WWTP that is the focus of this stud. It was not missed that a more complex data model may be required, using machine learning techniques for example, of which preliminary work designing a Neural Network was performed at the end of the study.

5.2 Linear Modelling

5.2.1 Methods

Linear Modelling is the fitting of observed data to fit a straight line on a curve, such that predictions on future values can be made assuming they follow the same trend. A linear regression model describes the relationship between a dependent variable, y, and one or more independent variables, X.

A multiple linear regression model is typically of the form:

$$y = b + b1.x1 + b2.x2 + b3.x3 \ldots \tag{5-1}$$

Essentially, each variable input into the model ('x' terms) is multiplied by a 'b' coefficient, and each coefficient-variable pair is added together. Variables may be interactions or powers of previous variables, such as:

$$y = b + b_1.x_1 + b_2.x_2 + b_3.x_1^2 + b_4.x_1.x_2 + b_5.x_2^2 \ldots \tag{5-2}$$

MATLAB's *regress* function allows for a linear equation of any form to be generated from any sized data sets. The *regress* function essentially determines the 'b' coefficients for any given linear equation of the form of Equation (5-2).

An attempt to use data from all three digesters to model a totalised biogas flow was performed, as individual gas flows from each digester are not available. Linear and Squared terms for each variable were used, and an interaction term between each of the 3 components within the digester was also used.

The first MLR model [Equation (5-3)] included many interaction and power terms, with the intention of removing them one or two at a time to find the best model:

$$\begin{gathered} y = b_0 + b_1.T_1 + b_2.T_2 + b_3.T_3 + b_4.T_1^2 + b_5.T_2^2 + b_6.T_3^2 \ldots \\ b_7.F_1 + b_8.F_2 + b_9.F_3 + b_{10}.F_1^2 + b_{11}.F_2^2 + b_{12}.F_3^2 \ldots \\ b_{13}.P_1 + b_{14}.P_2 + b_{15}.P_3 + b_{16}.P_1^2 + b_{17}.P_2^2 + b_{18}.P_3^2 \ldots \\ b_{19}.TDS + b_{20}.TDS^2 \ldots \end{gathered} \tag{5-3}$$

$$b_{21}.T_1.F_1 + b_{22}.T_2.F_2 + b_{23}.T_3.F_3 \dots$$
$$b_{24}.T_1.P_1 + b_{25}.T_2.P_2 + b_{26}.T_3.P_3 \dots$$
$$b_{27}.F_1.P_1 + b_{28}.F_2.P_2 + b_{29}.F_3.P_3 \dots$$
$$b_{30}.T_1.F_1.P_1 + b_{31}.T_2.F_2.P_2 + b_{32}.T_3.F_3.P_3$$

Where, in daily totals/averages:

y = Total Biogas Produced
T_i = Temperature (of digester 1,2,3)
F_i = Feed (of digester 1,2,3)
P_i = pH (of digester 1,2,3)
TDS = Total Dry Solids fed across all three digesters

However, it is often difficult and time consuming to identify which parameters and interaction terms should eliminated or kept to ensure a robust model is identified. After manually identifying multiple MLR models to attempt to predict biogas production of the ADs, to improve the performance and identification of key variables a LASSO regression approach was used (using the *lasso* function within MALTAB).

LASSO (Least Absolute Shrinkage and Selection Operator), proposed by R. Tibshirani, minimises the residual sum of squares subject to the absolute value of the coefficients being less than a constant [84]. The LASSO approach takes the same parameters used during the MLR modelling phase but can identify and remove any redundant predictor variables. It shrinks some coefficients and sets others to zero, hence attempting to retain the good features of both subset regression and ridge regression [84]. The general formula used by the LASSO approach is given by Equation (5-4).

$$\min_{\beta_0.\beta}\left(\frac{1}{2N}\sum_{i=1}^{N}(y_i - \beta_0 - x_i^T\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\right) \tag{5-4}$$

N = the number of observations.
y_i = the response at observation i.
x_i = data, a vector of length p at observation i.
λ = a nonnegative regularization parameter corresponding to one value of `Lambda`.
The parameters β_0 and β are a scalar and a vector of length p, respectively.

There were four linear regression models used to attempt to identify a suitable prediction model for biogas production; Table 5-1 outlines the predictor variables used in each of the modelling scenarios. Models 1, 2 and 4 use data that is automatically available due to the available sensors on site, however the data for pH has large gaps of missing data, hence why model 4 attempts to predict biogas production without this data. Model 3 also uses data that is generated manually in the onsite labs – as this data is not always available, model 3 was only performed to determine whether including this data would have substantial improvements to any predictions.

Table 5-1 Linear Regression models tested

Model No.	Predictor Variables Used
1	T_1, T_2, T_3, F_1, F_2, F_3, P_1, P_2, P_3, TDS, T_1^2, T_2^2, T_3^2, F_1^2, F_2^2, F_3^2, P_1^2, P_2^2, P_3^2, TDS^2, $T_1 \times F_1$, $T_2 \times F_2$, $T_3 \times F_3$, $T_1 \times P_1$, $T_2 \times P_2$, $T_3 \times P_3$, $P_1 \times F_1$, $P_2 \times F_2$, $P_3 \times F_3$, $T_1 \times F_1 \times P_1$, $T_2 \times F_2 \times P_3$, $T_3 \times F_3 \times P_3$
2	T_1, T_2, T_3, F_1, F_2, F_3, P_1, P_2, P_3, TDS
3	T_1, T_2, T_3, F_1, F_2, F_3, P_1, P_2, P_3, TDS, VFA_1, VFA_2, VFA_3, PVS_1, PVS_2, PVS_3, PDS_1, PDS_2, PDS_3
4	T_1, T_2, T_3, F_1, F_2, F_3, TDS

VFA_i = Volatile Fatty Acids (of Digester 1,2,3)
PVS_i = Percent Volatile Solids (of Digester 1,2,3)
PDS_i = Percent Dry Solids (of digester 1,2,3)

Each model shown in Table 5-1 was developed using both the *regress* or *lasso* functions within MATLAB, but the historical data used was separated into two parts: training data and validation (unseen) data. The testing data was passed to the functions to determine an appropriate linear fit – the resulting fit was then plotted against the historical biogas production, and the validation dataset was then used to also test the model. The Testing data was from the period January 2018 – April 2019, and the validation dataset is from April 2019 – August 2019.

5.2.2 Results

5.2.2.1 MLR

The modelling results are shown in Figure 5-3, where the fitted data (circles) does follow a linear pattern but with noisy results; a linear fit of training data is expected as the *regress* function (used to determine MLR models in MATLAB) forces a linear relationship as best as possible according to the provided variables. However, the fitted data remains too noisy to be used - this may be due to overfitting or again, just due to a noisy data set.

The model was then used to predict biogas production using unseen data (crosses on Figure 5-3) – this historical data set was not shown to the *regress* function when developing the models. This allows for testing of the robustness of the model.

Figure 5-3a shows that the predicted unseen data (crosses) is vastly inaccurate compared to the fitted data used for training. Using so many interaction terms early has likely led to overfitting within the model; overfitting a model is when a model has become too reliant on the original data set, that is it unable to adapt or allow for deviations in unseen data sets.

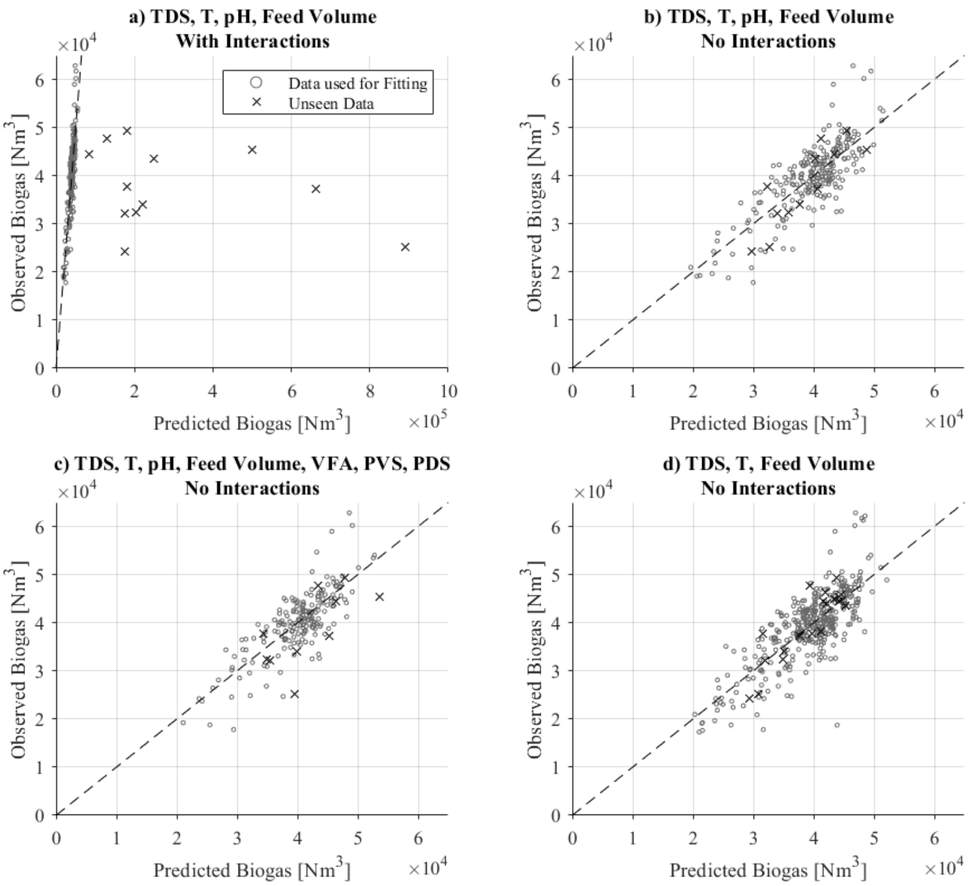

Figure 5-3 - MLR model results for biogas production. Graphs 'a' through 'd' use the predictor variables outlined in models 1-4 in Table 5-1. The dashed line is y=x, shown to aid in comparisons and demonstrate the accuracy of the regression fits.

Figure 5-3b uses the same initial dataset as Figure 5-3a, but all the additional interaction terms have been removed (see Table 5-1). The results of this reduced interaction fitting demonstrates that the linear fit is still noisy, thus is it expected that linear models are unlikely to be able to improve or reduce this level of noise. However, the unseen data fits are much more reasonable and do follow the general linear fit. It is believed that the data here is longer overfitted. The resulting model is still unusable onsite though; the predicted biogas volume varies too much from the actual production value, thus the prediction side of the optimiser will not be of use to operators.

An attempt to model the digester was made with extra data sets that are manually calculated by the lab technicians on site – the hypothesis was that better data (that is usually used to develop mechanistic models) might improve the noise of the resulting models. This data includes Percent Volatile Solids (PVS), Volatile Fatty Acids (VFA) and Percent Dry Solids (PDS) of each digester feed volume. The results from this modelling attempt, Figure 5-3c, also show the biogas predictions to be of linear form, however the predications appear equally as noisy as that of the previous modelling attempt. It is believed that the new data does not provide as much substantial influence on biogas production as initially thought. In addition, similar modelling results can be achieved with less data that is more readily available in the previous models (as the data is captured digitally).

As previously mentioned, some data sets are not complete, particularly the data that is manually generated and input into the database (PVS, VFA, PDS), however some of the automatically captured information has large gaps and missing information. The pH sensor data has many gaps; if a model relies on values of pH to predict biogas production, any gaps in data would likely mean the model is unusable and unable to predict productions (without estimating the pH of the AD). To this end, a model was created using only Feed Volumes, Temperatures and TDS, and included an interaction term between TDS and Feed Volume. The results of the mode with this interaction term are shown in Figure 5-3d.

The increase in the number of data points compared to Figure 5-3b is reflective on the increased data set that can be used for modelling and testing (i.e. as pH is no longer used, the dates where this data was missing can now be used for modelling). The test on unseen data also forms a tighter linear relationship. The fitted model shows a tighter prediction response for both the fitted and unseen data sets. However, there are still too many outlier cases where the model does not perform well.

In general, it is unreasonable to expect a model to predict more accurately (with less noise) on unseen data than with the initial training data. The current aim is to have predictions within 10% of the observed value, within tolerance acceptable by operators and managers. The trained models do not achieve this, so a more accurate model must be sought out.

5.2.2.2 LASSO

Using the same modelling scenarios for the MLR modelling approach, a LASSO regression was performed, such that (if required) any redundant terms provided for modelling could be automatically identified and removed during the modelling and training process. The resulting models are shown on Figure 5-4(a-d).

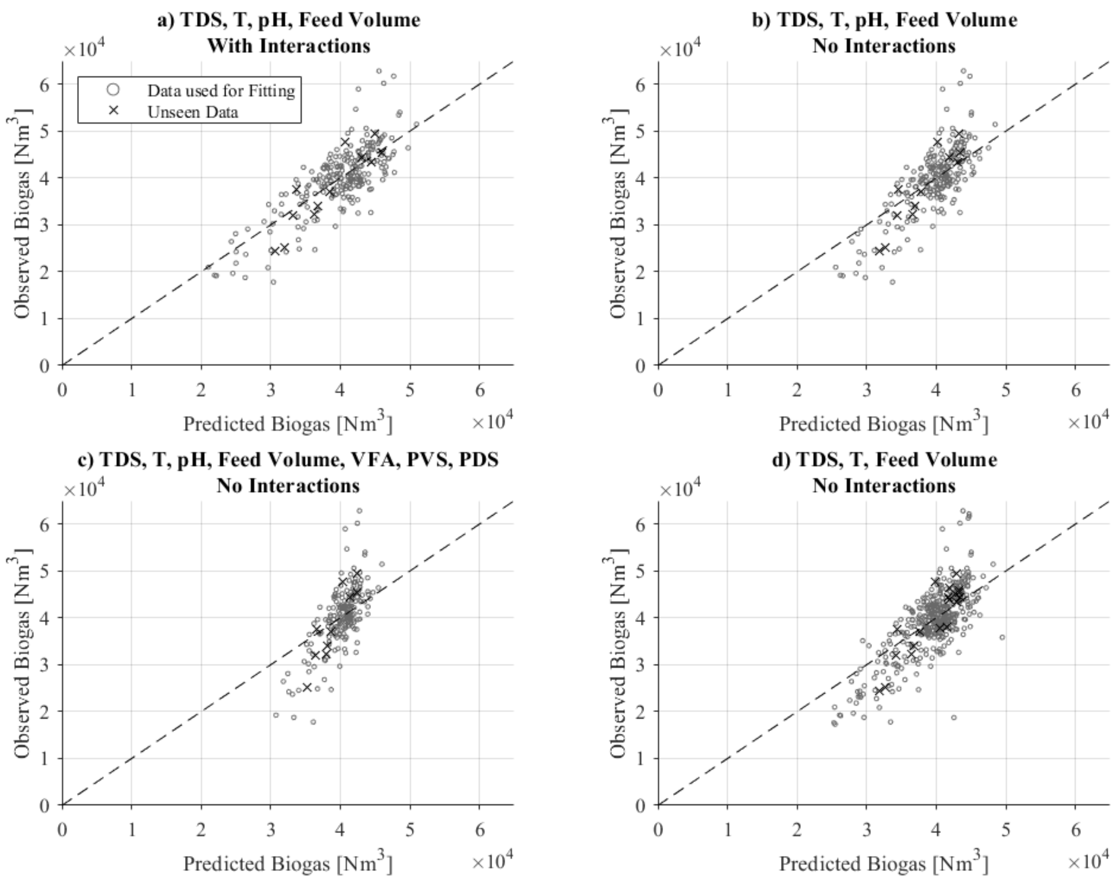

Figure 5-4 LASSO regression results for biogas production. Graphs 'a' through 'd' use the predictor variables outlined in models 1-4 in Table 5-1. The dashed line is y=x, shown to aid in comparisons and demonstrate the accuracy of the regression fits.

The resulting LASSO regression models presented do provide a tighter linear fit, but they also are slightly skewed away from the y=x line. The resulting fit for Model 1 and 2 (Graph ‘a’ and ‘b’) show almost identical results, which is expected due to the LASSO technique removing redundant predictor variables (and model 2 is a simpler version of model 1). Additionally, Model 4 (Graph ‘c’) also shows very similar results to model 1 and 2, again as it is a simpler version of Model 1, but there are more data points available due to the removal of pH (so there more dates will full datasets available for regression). Introducing the manually generated data (PVS, VFA, PDS) results in the worst fitting model (Figure 5-4c) – whilst this model shows the tightest response (least noise), the response of the fitted model is much more skewed away from y=x than the other fits.

When using cross-validation techniques within LASSO regression, the resulting models can identify key predictor variables, with redundant ones removed. Table 5-2 shows which predictor variables correspond with minimum cross-validated mean squared error (MSE) and which variables form the sparsest model within one standard error of the minimum MSE. For each model in Table 5-2, and missing predictor variables or interaction terms (from Table 5-1) can be assumed to be redundant and therefore removed from that model.

Table 5-2 LASSO Regression results, showing the predictor variables used to generate the predictions and graphs shown on Figure 5-4

Model No.	**Model Variables with minimum cross-validated mean squared error (MSE)**	**Model Variables of sparsest model within one standard error of the minimum MSE**
1	T_1, T_3, F_1, F_1^2, P_1^2, $P2^2$, TDS, TDS^2, $F_1\times TDS$, $F_3\times TDS$, $T_1\times F_1$, $T_2\times F_2$, $T_3\times F_3$, $T_1\times P_1$, $T_1\times F_1\times P_1$	TDS, $T_1\times F_1$
2	T_1, T_2, T_3, T_1^2, T_2^2, T_3^2, F_1, F_2, F_1^2	F_1, TDS
3	T_1^2, F_1^2	F_1, TDS
4	T_1, T_2, T_1^2, T_2^2, T_3^2, F_1	T_1, F_1, TDS

Interestingly, of all four models developed through the LASSO approach, each model suggests that pH is not a particularly important predictor in biogas production, with the most emphasis placed on Temperature and TDS, with some placed on the Feed volumes also. Also, the reduced parameter model (Model 4) is still able to predict biogas production as well as the other Models with more variables, albeit still not effectively enough to be used onsite.

It should be noted that, for each prediction to be made, a full set of variables is required to be input into the model. I.e., if there is a data point missing for one variable for a particular day, that data cannot be used for fitting or testing the model on predicting biogas volumes. It is for this reason that there is a different number of data points in graphs on the models.

The MLR and LASSO models are still too noisy with their fitted response and unseen data prediction responses for practical applications, hence a more advanced prediction and modelling approach was required.

5.3 Artificial Neural Network (ANN) Model

5.3.1 Introduction

As the previously calculated linear regression models are not accurate enough to be used on site, a preliminary investigation into the use of an Artificial Neural Network (ANN) weas performed to determine whether the approach could be used for the prediction of biogas with this unique challenge. An ANN is an advanced machine learning technique that can be used for modelling processes or phenomena where the relationships between the input variables and output variable(s) are difficult to identify. The training techniques provide a mathematical weighting to each input variable and to each node in each layer thereafter, which ultimately cause the output(s) to be calculated (Figure 5-5).

ANNs are able to approximate functions using universal approximation theorem, and the backpropagation algorithm enhances the efficiency in updating undetermined parameters [85]. Neural Networks are very much in the spotlight currently, however training a neural network is unique to each induvial problem and can be very time consuming and computationally expensive. The training time of an ANN can be sped up, however, through use of a sufficiently powerful CUDA enabled GPU [86].

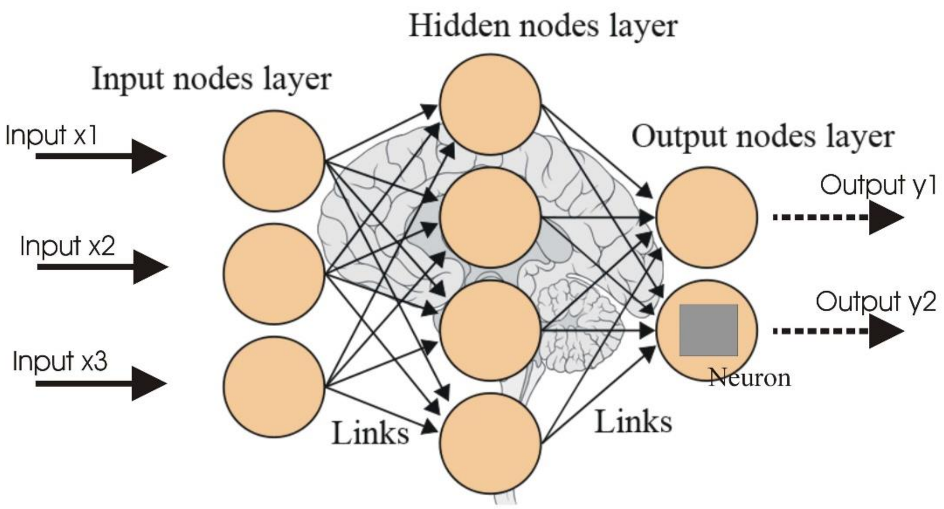

Figure 5-5 - Typical Neural Network layout. A Neural Network may have any number of hidden nodes layers, and any number of nodes. [This Photo by Unknown Author is licensed under CC BY-SA]

There are multiple forms of ANN, with different approaches possible to model time-series data (the historic biogas production data is a time-series dataset, as previous temperatures and pH values can influence future values). One of the more commonly used ANNs for time-series data is the Non-linear Autoregressive Network with Exogenous inputs (NARX), with feedback connections enclosing several layers of the network [39]. NARX models can be used as a predictor in time-series modelling, where it has been demonstrated that NARX recurrent networks have the ability to replicate the dynamics of complex non-linear systems [87].

5.3.2 Methods

One of the difficulties in designing an ANN is the selection of the number of layers and hidden neurons [88]. Neural Networks may have any number of neurons in each layer, and any number of hidden layers, although increasing the number of hidden layers and neurons can lead to increased computational time and overfitting problems [89]. In general, most systems can be sufficiently modelled with one hidden layer, and almost all problems should have less than five [90]. ANNs have been used to model ADs for non-municipal waste (typically cattle and agricultural) [91–94], with NARX models also used [95].

The defining equation for the NARX model is given by Equation (5-5):

$$y(t) = f\left(y(t-1), (yt-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u)\right) \quad (5\text{-}5)$$

where the next value of the dependent output signal *y(t)* is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal. Figure 5-6 shows the diagram of the resulting network, as shown on Mathworks.com [39].

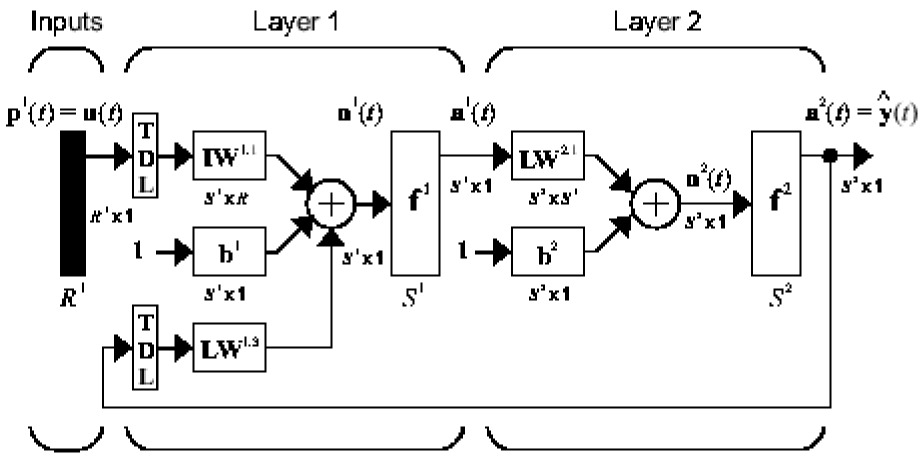

Figure 5-6 Diagram of NARX network, where a two layer feedforward network is used for approximation.[39]

When training a neural network within the MATLAB machine learning toolbox, users must decide the shape and size of the ANN, i.e. how many hidden layers and hidden neurons there are per hidden layer. The optimal shape and size are unique to each process and dataset. Figure 5-7 shows the NARX Net structure as depicted by the MATLAB environment, which is a simpler form of Figure 5-6.

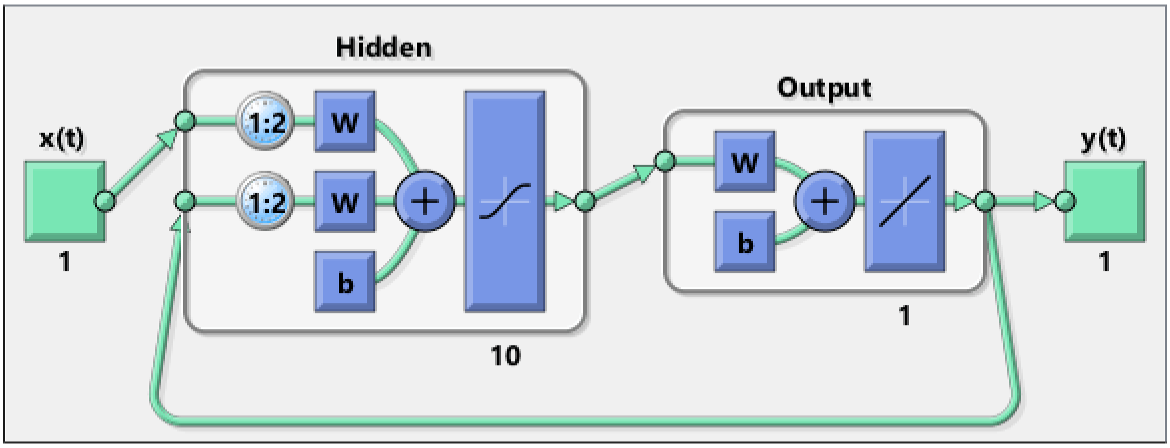

Figure 5-7 - A typical NARX Neural Network layout, as depicted within the MATLAB environment.

During training, MATLAB will randomly select which data within the dataset is to be used for training, validation, and testing. Therefore, each time a new ANN is trained the actual training dataset may vary, which in turn could lead to a sub-optimal trained network – re-training the same sized network on different randomisations of the same data can lead to different results. As such, during the training phase each neural network is trained using the same data 100 times, resulting in 100 random permutations of the entire dataset per training session. The resulting network that has the highest R^2 value was then chosen as the 'best' network out of the 100 trained networks and saved for comparison against other sized ANNs.

Using the previous data in the linear model fitting (AD Temperature and Feed Volume for each AD, and the TDS) several NARX ANNs are trained and the performance of them is investigated through R^2 values and by determining how well the ANN can fit data and trends to within 10% tolerance.

For a NARX Net, the number of feedback delays must also be decided, i.e. the number of previous data points used during the input layer, in this case the number of previous days' worth of data. For example, a feedback delay of 2 would mean that, to predict biogas production tomorrow, the previous two days' worth of data must be input into the ANN. In this study, multiple NARX ANNs are trained with one hidden layer containing 1-20 hidden neurons, and also between 1-5 feedback delays, resulting in the need to train 10,000 NARX ANNs (repeating each neuron:feedback pair 100 times, as stated).

5.3.3 Results

The overall optimum NARX Net was chosen based on the R^2 value (Figure 5-8) and also on how many predictions the network made that were within 10% of the historic biogas production (Figure 5-9), and is denoted with a red X on these figures.

Interestingly, increasing the number of neurons generally has a negative impact on the resulting R^2 value in most cases, as shown on Figure 5-8, particularly when the number of feedbacks is between 2 and 4 days. Between 1-10 neurons increasing the number of feedback increases the R^2 observed, however increasing the number of neurons beyond this region generally has a negative effect, suggesting that this creates some overfitting of the data.

It may be that, regarding R^2, certain combinations of neurons:feedbacks can encapsulate trends of data that otherwise cannot be done with less neurons or feedbacks, but cannot achieve accuracy. However, increasing the number of feedback delays has a clear benefit to the resulting predictions of the model, shown in Figure 5-9.

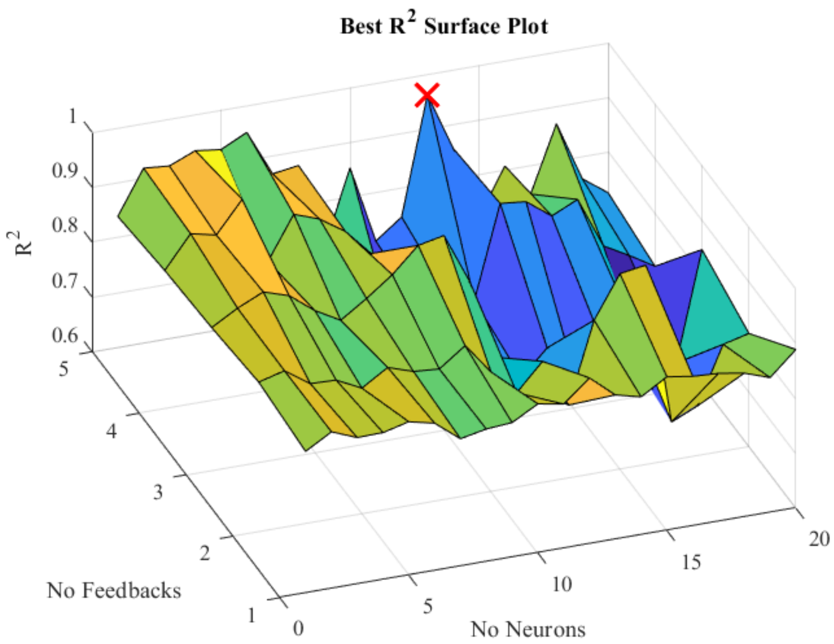

Figure 5-8 - R^2 of time-series response of trained neural networks, comparing neural network prediction to actual production of biogas. Optimum chosen model highlighted with a red cross (×).

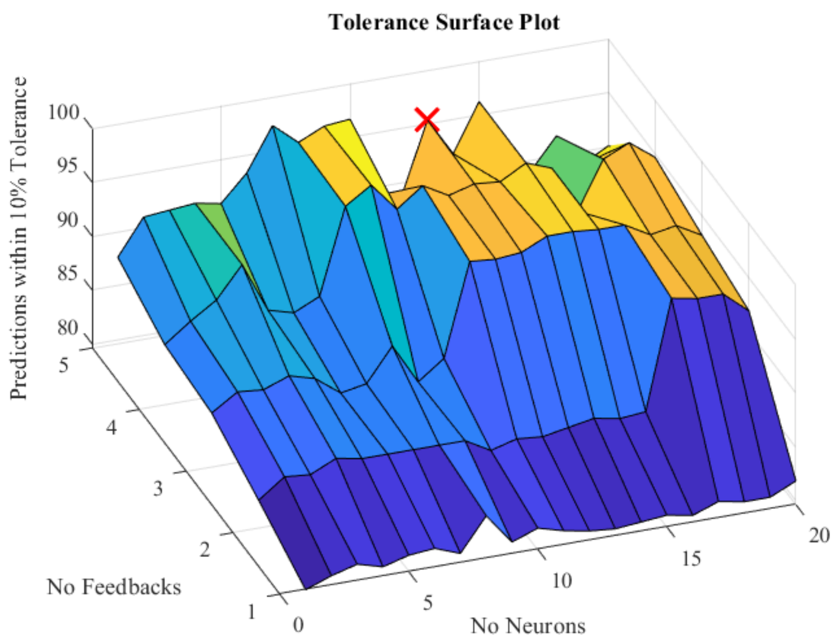

Figure 5-9 - Percentage of time-series predictions given by the trained neural network that were within 10% of the historic biogas production. Optimum chosen model highlighted with a red cross (×).

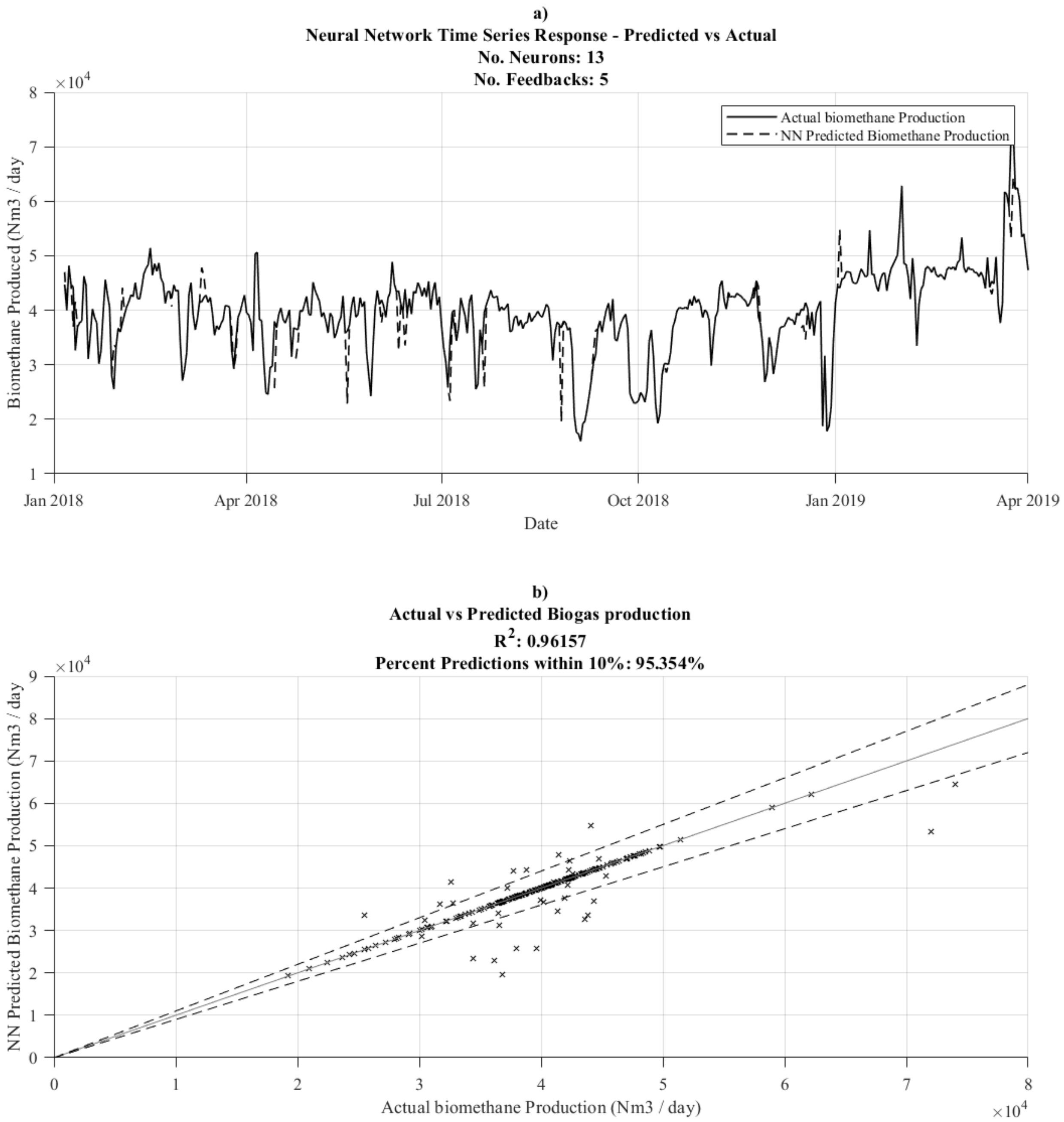

Figure 5-10 - Best performing NARX Neural Network trained, with 13 neurons in the hidden layer and 5 days feedback delay.
a) Time series day-ahead prediction response compared to historic production of biogas,
b) actual vs predicted biogas (a perfect fit would be y=x (solid grey line), and the dashed lines show a 10% tolerance).

The optimum neural network consisted of 13 neurons in the hidden layer, with a feedback delay of 5 days, with an R^2 of 0.96157 and percentage of predicting meeting tolerance of 95.3%. Whilst this combination does not have the highest R^2 or the highest tolerance achieved, it does have the highest pairing of the two. In their paper, Dhussa *et al* found an optimal NARX ANN consisting of two hidden layers with 10 neurons each and 18 days feedback [95], but the AD was for cattle waste not municipal waste. Our trained network could potentially be improved with the addition of another hidden layer, or even an increase in the number of feedback delays. With over 95% of biogas predictions within 10% of historic production, it is believed that this neural network is sufficient for use on site, although further validation against historic data should be performed before actual implementation.

Additionally, the data used for training was selected due to the high volume of available data. Should future improvements be made to digital monitoring and recording of data, sufficient data could be available for each AD such that more parameters could be used for modelling (such as pH, VFA or COD).

5.4 Conclusions

The AAD plant at Howdon poses a unique optimisation and modelling problem regarding the three on site ADs. The lack of individual gas flow data poses an interesting challenge in predicting the total biogas flow produced on site.

Multiple linear models of the onsite AD's were investigated. It has been shown that taking a linear approach to predicting biogas production of the anaerobic digesters is possible, but the resulting predictions are too noisy for implementation and not useful on site. Whilst quick to determine and easily transferable to alternative sites, the resulting models are just not accurate enough to be used.

A NARX Neural Network was also developed for the production of biogas. The resulting optimal NARX model consisted of one hidden layer with 13 neurons, and 5 days feedback delay. The model is able to accurately predict the biogas production on a day-ahead basis over 95% of the time (to within 10% of the actual biogas production), using the limited dataset of Temperature, Feed Volume and TDS. The resulting model could potentially be improved further with the training of additional ANNs, or by improved data recording on site, leading to a richer and better dataset to create models with.

Chapter 6 Summary and Future Work

This final chapter summarises the work presented and discusses the potential uses and adaptations that could be performed using the presented methodology. Potential improvements to the developed models are also presented, along with some suggestions for further investigations.

6.1 General Summary

The preliminary focus of this thesis was to investigate optimisation opportunities at the Howdon WWTP (owned and operated by NWL) with a broad investigation. The initial review concluded there was a significant opportunity to aid in managing the gas distribution at the AAD plant, as managers did not have a tool to aid in validating their operational strategies. A realistic and novel solution was initially developed, using MILP techniques, which was used to perform RO of historic operations. This initial investigation found that the plant operated optimally within accepted tolerance 98% of the time, and even considers planned maintenance.

At this point, the developed gas distribution model did not consider electricity demand on site or carbon emissions – it was intended to develop the model further to include electricity in later revisions, however the inclusion of carbon emissions came about due to the very new legislation (that was introduced in April 2020). Even though it does not consider carbon, the initial RO analysis results using the gas distribution model suggests that the total amount of annual biogas that is flared could be reduced by up to 2.4% through improved management, resulting in a reduction of approximately 24,000 kg.CO_2 emissions per annum.

The UK Water sector has pledged to become carbon neutral by 2030, with NWL aiming to beat the pledge by 2027. To achieve this, NWL has agreed with the regulatory bodies a ‘Carbon Performance Criteria’, whereby the overall carbon emissions of the business will be charged at £187 per tonne CO_2 emitted, but renewable generation (such as biomethane) will be seen as carbon reducing under this agreement. As the legislation introduced to aid in meeting the pledge is very new, including it within the optimisation framework has produced a truly novel technology – it is believed to be the first technology in the sector that deals with the combined optimisation of plant requirements and business legislation impacts.

The Energy Management model (an improved version of the Gas Distribution model that also considers electricity demand, electricity generated and carbon emissions) can be used to help managers see the impact the new Carbon Emissions performance criteria will have on revenues, as well as aid in managerial decision making, such as whether to change energy supplier for energy (i.e., price changes).

The studies shown in chapters 3 and 4 indicate that, to operate in the most cost optimal way, large changes to site operational strategy should be made (for example, relying more on electrical imports rather than generation through CHP Engines) under certain criteria. Not only will this have large impacts on site revenues, but the change to operations may also result in other legislative criteria being adversely affected, such as CHPQA (see Chapter 6.2.4). The main outcome of the analysis performed shows that, for the plant to maintain a positive revenue stream, operators should ensure that at least 20,000 Nm^3/day of raw biogas can be processed through the BUP and injected into the national grid – this is regardless of the price of energy that was simulated.

The Energy Management model developed requires a prediction of how much raw biogas the ADs will produce the next day. As such, it would be beneficial for operators to have a tool to provide this information, rather than rely on experience alone or historical data. However, developing a model of the individual ADs to provide a prediction of biogas production is challenging with the current equipment configuration, as the gas flow sensors do not provide accurate data that can be used. The initial study demonstrates how data-driven modelling techniques can be applied to create a model that is able to predict the combined biogas production volumes based on the individual feed and status data of the ADs. Using historic data for testing and development, the optimum NARX Neural Network model was able to predict the biogas production on a day-ahead basis over 95% of the time (to within 10% of the historical value).

It is hoped that the work presented here in this thesis will have tangible benefits for NWL, with the innovative approaches able to provide information that would otherwise be unavailable (such as the validation of operational strategies). However, the models presented provide solutions to just a few of the areas for optimisation that were identified during the initial review stages of this PhD and throughout the development phase of the models. To allow the research presented here to achieve its maximum impact, developments and additions to the presented models and other aeras for future investigations are discussed in the remainder of this chapter.

6.2 Future Investigations and Improvements

Though the proposed models in this thesis are highly valuable to NWL managers and operators, they are not in an easily usable form for implementation on site, nor do they currently cover all current legislative requirements. In addition to improving the proposed models to address the limitations discussed in this thesis, there are other avenues of research and improvement that have been identified for the AAD plant and the wider WWTP at Howdon, which are discussed in the sections below.

6.2.1 Embedding the Energy Management model into NWL systems

The models presented as part of this thesis are a proof of concept, thus direct implementation within NWL systems would be beneficial to enable them to be used appropriately by managers and operators alike. As such, the current optimisation models should be transferred over to NWL, with training provided to staff on how they can be used. To allow for continuous development and improvement, a specialist within the business should also be trained on the principles driving the model and its derivation, including understanding the source code, the fundamental equations of the models and how they are determined and how to apply/build new models for other sites using the existing models. Any deployment of a tool using the models developed here would also need to be able to handle changes to existing legislation or processes and incorporation of new ones – the development of the current Energy Management model has been a dynamic process, with many fundamental design changes made to include new regulations (such as the Carbon emissions pledge), thus the proposed model will likely not be effective for use if it remains static in the current form. .

Currently the optimisation framework is implemented in MATLAB as a standalone optimisation tool, thus further coding, collaboration, and adjustments are required to provide robust implementation of the model (potentially in a different coding language) that can draw upon data directly from within NWL's database. Should a change in coding language be required, open-source optimisation packages could prove beneficial, such as using the CPLEX or Gurobi optimisation packages in Python. There is also the potential to improve the Energy Management model further, with the addition or change to a multi-objective optimisation (instead of a single financial optimisation objective). Whilst a proof-of-concept model exists in MATLAB, there are significant challenges that must be addressed to ensure a robust implementation on site.

It is anticipated the methodologies that have been developed throughout this thesis are not just applicable across the entire wastewater treatment sector, but anywhere where biomethane is produced – it will be necessary to demonstrate the applicability of the model to different sites to Howdon if it is to be implemented to areas outside of NWL. Whilst all sites are different, there are generic features and similar processes such that the optimisation framework could be tailored to new sites. Any future projects should first aim to apply the transferred knowledge to other sites within the business at NWL, possibly producing a tool that can be used to roll out the developed models to other sites with ease, and once validated it could even be rolled out to sites external to NWL.

6.2.1.1 Application to the Brans Sands plant

NWL has a very similar plant to the Howdon WWTP in Teesside, known as Bran Sands. In terms of validating the approaches contained within this thesis to new sites, the Bran Sands site would be the best place to start; both sites provide wastewater treatment services, use AAD for sludge processing and are able to either generate electricity or inject renewable gas into the national grid with the biomethane they produce. Fundamentally the underlying equations for the optimisation framework should remain largely unchanged, save for changing the process limits specific to the new site. However, the challenge would be to design a tool whereby it is easy for non-experts in the optimisation framework to make said changes for applicability to new sites. This would require building a system that can automatically build the optimisation framework after being given the appropriate units and unit constraints. Identifying new model parameters requires data analysis of the site, and adding site-specific legislative requirements is also difficult – to be able to add these in an easy way for operators would be beneficial but non-trivial.

6.2.2 Improved Biogas Predictions

The advanced machine learning technique (Neural Network) applied as part of this study is an initial investigation into data-driven models that can be applied to the onsite ADs. As the initial modelling study shows promising results for the prediction of biogas production, further investigations (beyond that of this project) should be carried out modelling the digesters. This future work would likely see a deeper investigation into the shape and size of ANNs, as well as investigating using more AD parameters to improve biogas predictions. Depending on future data recording capabilities of the ADs gas production volumes (whether the placement and configuration of gas flow sensor issue is addressed), any future work could also include developing a grey-box model, taking advantage of a combined mechanistic and data-driven model to improve biogas predictions.

6.2.3 Energy Market Forecasting

Currently the agreement between NWL and its energy provider is to receive a 'fixed-variable' electricity tariff for each site, whereby their provider will let them know their electricity tariff (that varies over a 24-hour period) one day ahead. Whilst this allows for the current model to optimise on a day-ahead basis, predictions over a greater horizon are not possible due to lack of information regarding energy prices. It would be beneficial for NWL to be able to accurately forecast and optimise future plant operations further than a day-ahead basis.

The main drivers for energy market price fluctuations are demand on the grid (consumer and industry) and renewable energy penetration. The increasing penetration of unpredictable and intermittent renewables, such as wind and solar PV, has led to renewable generation recently becoming the main cause of variation in power prices [20].

A future investigation could utilise historical information for NWL's site-specific energy tariffs alongside historical weather patterns, seasonal and daily grid demand, and renewable energy generation to predict the electricity market and ultimately provide NWL with a prediction of future site energy tariffs. This work would likely build upon existing research into energy pricing forecasts based on renewable penetrations, such as Cummings et al [28].

6.2.4 Introducing new legislation – e.g. CHPQA

Investigations into legislation and environmental policies surrounding the site, and how they may influence site operations, has been ongoing throughout the development of the energy management model, with a view to implementing such policies into the optimisation framework. The framework requires specific enhancements to be made, such that the consideration of carbon emissions, environmental issues, new legislation, and year-long forecasting for biomethane processing can be included.

It was decided, at the time of development, not to include one particular piece of legislation, CHPQA (Combined Heat and Power Quality Assurance). CHPQA can be considered a 'tax relief' that is achieved assuming the CHP engines provide a certain amount of electrical power each year – NWL could potentially fail to meet the legislative requirements should the model (and suggested optimised strategy) work independently and without consideration of the cumulative running time of the engines.. The current model exists as a day-ahead optimisation only, which could have drastic impacts on non-process related criteria, such as the CHPQA legislation, if not also considered within the model. To effectively consider this, the model would have to be extended to be a year ahead optimisation framework. Adapting the energy management model to include these types of legislation will come with new academic challenges, such as interpreting the legislation criterion within the optimisation framework boundaries – for example, the CHPQA legislation is calculated using non-linear expressions, but the MILP framework is entirely linear.

6.2.5 Sludge Network Model

The current energy model optimises daily operations based on biomethane production levels, which is governed by sludge processing at the individual site level. The sludge processing levels of individual sites is often affected by factors external to the site's sludge processing demands – for example, unit maintenance at one site could see the processing requirements of another increase. NWL must, as a primary focus above all other ventures, meet it's legislative requirement to process the waste it receives within acceptable tolerances.

New investigations could take place to develop a model to analyse and predict companywide sludge processing requirements that could be used in tandem with the site-specific models. To develop such an oversight model, data gathering of historical production levels would be required to identify base sludge influent levels and potential relationships with weather or seasonality. Once any relationships are identified or ruled out, a prediction model for influent sludge levels across the business could be developed; this again may include advanced machine learning techniques to incorporate possible variations due to weather or seasonality. Such a model would aid in the logistics of sludge transport within the business.

In addition, understanding and predicting the business wide sludge levels will make the sludge processing requirements of each site more transparent, resulting in making prediction models for expected daily biomethane production more accurate, in turn making the energy management model even more useful.

6.2.6 Possible site adaptations – Smart Grid

Renewable electricity sources, such as solar, wind and ocean, are often inconsistent and fluctuate and therefore meeting the challenge of coordinating fluctuating and intermittent renewable energy production with energy system demand is essential as electricity systems depend on an exact balance between demand and supply at any time [96]. Often it is highlighted that the transition towards renewable energy sources requires large amounts of energy storage [97], in order to maintain a constant power supply during peak demand and production times. However, the AAD plant at Howdon is generally able to produce a consistent renewable energy resource (biogas).

One of the key assumptions about the AAD plant at Howdon is that any electricity generated on site must be either consumed immediately or excess generation is exported to the national grid – there is no storage capability for excess generation. Any excess generation would likely result in spikes in power production into the national electricity grid, which will in turn require extra management from the grid but also could be unbeneficial for site revenues. One could argue that adding electricity storage capabilities to the plant could aid in maintaining stability in the national grid, as well as power spikes on site, in turn preventing excessive ramping of CHP engines – the site could be turned into a localised Smart Grid. The site could also introduce more renewable sources of electricity, such as solar or wind turbines. For smaller household consumers, this type of hybrid energy storage technology has been widely investigated, but profitability remains questionable [98], but for larger sites where energy contacts are vastly different from household consumers such a solution could be an attractive option.

Whilst such improvements to the site could increase the complexity of managing site operations, the model developed as part of this thesis could be adapted to investigate such an opportunity, providing managers and operators with valuable information for potential future revenue streams, operating procedures, and scenario analysis.

6.2.7 Wider energy market considerations

The scenario analysis results shown in Chapter 4 suggest that, as a general theme, increasing gas prices leads to the reduction of use of natural gas to generate energy on site, subject to the electricity prices. This is an interesting (yet somewhat expected) observation, as it compliments existing research into energy price volatility the impact on consumption across the UK. N. Aminu discusses this trend and the impacts on the wider economic market implications in their paper, where modelling increasing gas prices in the UK by one standard deviation was found to cause up to “15 quarters [3 month periods] worth of economic decline due to reduced demand in the market” [99]. As a main consumer of gas in the Northeast, is it in the interest of NWL to monitor their gas usage in comparison with the wider sector? Could they be a driver for wider economic change with the decisions on plant operability? Whilst the answers to these questions are outside the scope of this thesis, they are interesting and noteworthy for senior management to consider when reviewing operating strategies. The modelling tools generated as part of this thesis could be used within possible future investigations to aid in answering some of these questions.

6.2.8 General Improved Process Control – A short review

Throughout the completion of this PhD, it was observed that the water industry lacks somewhat in the application of Advanced Process Control – investigations into improvements and opportunities in this field was originally a potential avenue the PhD could take.

Typically, in the water industry, Advanced Process Control is uncommon and standard control schemes use on-off control via PLC and SCADA systems to control localised processes to within specified limits, without consideration of upstream plant behaviour [17], which has been identified as directly applicable to the Howdon WWTP site. Widespread use of SCADA-type system technology permits the exploitation of total for more advanced supervisory concepts system control [26]. Advanced process control techniques could be implemented to take advantage of the varying loads and plant conditions, whilst still achieving high safety margins. According to M. Katebi et al, “The barrier to the successful implementation of the control system is not the control software or hardware, but rather the problem of designing control systems that are integrated with the plant operation and management and have a high degree of local autonomy, flexibility and reliability” [100].

A review by C. Martin et al questioned whether there is enough data available about the influent into WWTPs to develop accurate enough models of said influent. It was argued that the ability to generate hypothetical influent profiles will increase awareness and improve modelling robustness during future designs or improvements to WWTPs [101]. Regarding the operation of WWTPs, it is a valid point in that future models and improvements should be able to handle abnormal operating behaviours of the plant. An accurate model or simulator can be helpful for additional operator training [102], especially in the event of hazardous materials in the influent. The MILP model presented in this thesis could be used to aid in such an endeavour.

One of the most common operations for biological secondary treatment on modern WWTP is the Activated Sludge Process (ASP) (shown on Figure 1-1 as the Aeration Lanes), used to remove organic and nutrient pollutants [103,104]. The ASP requires a high amount of energy through the aeration of high volumes of liquid, to ensure high Dissolved Oxygen (DO) concentrations. Due to high energy reduction potentials, ASP has been the focus area of several researchers to develop accurate and reliable control schemes. O'Brien et al use Model Predictive Control (MPC) for aeration control on a WWTP in [17]. In their work, energy savings in excess of 25% were achieved.

C. Foscoliano et al. developed a recurrent neural network model for problem identification where a dynamic matrix control (DMC) was used as a predictive control algorithm; control strategies were applied to the BSM1 model, but the coefficients of the dynamic matrix used in the model predictive control were kept constant [105].

Improving on earlier work applying MPC control to a WWTP [106], W. Shen et al. proposed that feedforward control modifications to a feedback DMC scheme perform better at controlling the ASP than more complex Quadratic DMC or non-linear MPC [107], giving rise to the idea that MPC may not be the optimal or only control strategy that could be applied to Howdon STW.

Work has also been done to develop a smart buffer real time control (RTC) strategy to improve Storm Tank control and Primary Clarifier operations [108]. Primary clarifiers were optimised such that a reduced number of clarifiers were used for 94% of the time, storm discharges were reduced by 44% and discharge volume estimated at 33% lower [108]. Similarly, S. Kroll et al. looked at applying an RTC scheme to the pumping network for the WWTP influent, where limiting flows to the WWTP did not have an negative impact on the overall sewage network and helped reduce spills [109]. This could be directly applicable to the optimisation of Howdon STW, although the Howdon STW is considerably larger in scale and likely subject to different legal consents.

The control schemes discussed so far have mostly been applied to the BSM1 WWTP model as a simulation only, with few practical applications. The BSM1 model has become the standard simulation tool for performance assessment of control techniques applied to wastewater treatment plants (WWTP) [110], meaning different control strategies can be compared effectively. Upon review, BSM1 is a reasonable model to apply developed MPC for ASP, but it only projects the operation of a WWTP over one week and does not include any sludge processing; BSM2 was developed by K. Gernaey in [111], which includes sludge treatment and projects operation of a WWTP over a year's period [112].

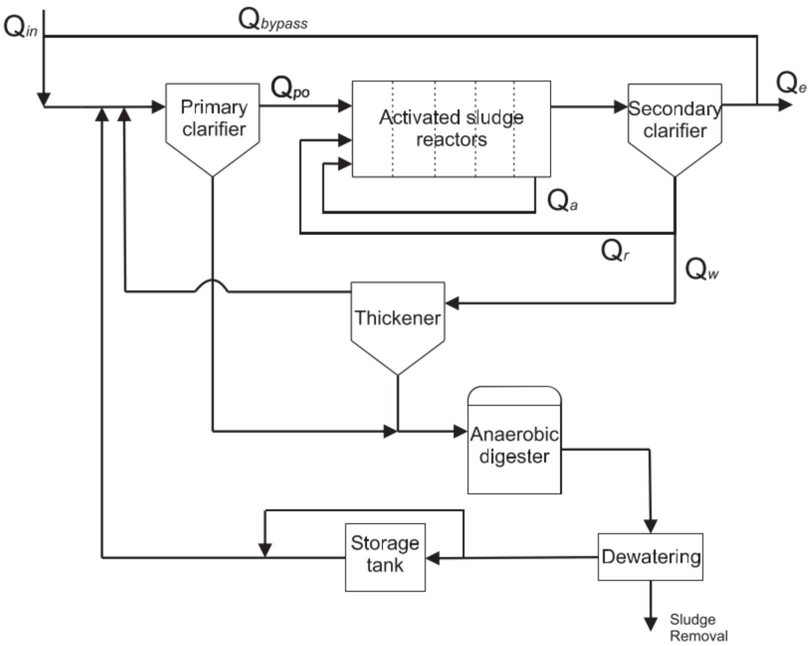

Figure 6-1 Overview of BSM2 plant, by I. Santin et al. [112]

An overview of BSM2 can be seen in Figure 6-1. BSM2 is a clear improvement over BSM1 with regards to controlling sludge treatment, yet by comparison Howdon STW is a much more complicated WWTP (please refer back to Figure 1-1); the inclusion of the AAD processing plant makes Howdon STW more advanced than the sludge processing model used in BSM2.

MPC has developed considerably over the past few decades [113], both in industry and within research, and appears to be rising in popularity in line with other more complex control algorithms. This is likely due to the ability of MPC to handle complex non-linearities that are common in industry [113]. However, complex non-linear optimisers can have high computational requirements.

Advanced Control schemes should be able to take advantage of new monitoring technologies for instantaneous information regarding plant status, removing the need for regular operator measuring and intervention.

The WWTP at Howdon treats both liquid effluent and 'sludge' solids (that make up Raw Sewage that flows into the site), therefore MPC or Neural Network models and controllers that have previously been developed could potentially be applied to the wider operation of the Howdon WWTP. However, there is a clear gap in literature of designing control schemes and optimisation techniques for AAD sections of WWTP, as literature discussed focuses on developing control strategies of the effluent treatment side of a WWTP. The MILP optimisation model developed in this thesis for the optimisation of energy and gas distribution on site could be used in tandem with a wider supervisory advanced control scheme for the entire WWTP, which could be developed as part of future endeavours by NWL for continuous improvement.

6.3 Major Contributions to Date

Presented here is a list of the major contributions to the scientific and academic community as a result of this PhD:

- Article Published in the 200th Edition of the Institute of Water's magazine [https://issuu.com/instituteofwater/docs/1118_iow_magazine_q4_interactive_v2]
- Wastewater Network Conference *Winner of Best Poster* (Nov 2018) [https://www.ncl.ac.uk/media/wwwnclacuk/engineering/files/stream/wastewater-network-conference-2018-harry-laing-poster-competion-winner.pdf]
- ECCE12 conference in Florence *Poster* (Sept 2019)
- IChemE Advances in Process Automation and Control Conference in Manchester *Poster* (Nov 2019)
- STREAM Annual Conference *Poster* (Jul 2019)
- Process Intensification Network (PIN) Conference *Poster* (Jun 2019)
- Research Paper (Published): "Development of a Biogas Distribution Model for a Wastewater Treatment Plant: A Mixed Integer Linear Programming Approach"

published with Institute of Water's 'Water Science and Technology' research journal. (Jun 2020) [https://doi.org/10.2166/wst.2020.363]

- Research Paper (Under Review): "An energy and carbon management model for an Advanced Anaerobic Digestion plant", currently under review with the research journal "Energy" (Jun 2021).
- IChemE Advances in Process Automation and Control Conference (Virtual) *Presentation - "Optimising Energy and Carbon management for an AAD plant at Northumbrian Water using Mixed Integer Linear Programming ".* (Oct 2021)

The majority of Chapter 2 of this thesis has been adapted from the research paper published with 'Water Science and Technology', whilst the content of Chapter 3 is currently under review with 'Energy' for potential publication.

6.4 Statement of Innovation

The outcomes of this thesis can be summarised in the following four main topics:

1. Development of an Energy Management model for operations optimisation:

   The model optimises gas distribution on site to maximise revenues, ensures electricity and heat demands for the site are met and integrates new legislation around carbon emissions. Use of the model allows for improved forecasting of operational strategies required to maximise revenues, and also validates operators' decision making.

2. Scenario analysis of site operations using the developed models:

   The Gas Distribution model was used to perform retrospective analysis of historical site operations, validating site performance and operational decision making. With the introduction of the new carbon emissions legislation, the improved Energy Management model was used to investigate potential future scenarios around energy pricing, biogas production and biomethane injection limits.

3. A methodology to predict biomethane production using data driven modelling

   Development of a mechanistic model for each of the on-site AAD's is difficult due to the data that is available for them (as discussed in Chapter 5). It was shown that a purely data driven model could be developed to reasonably predict biogas production volumes on a day ahead basis, which could be used in tandem with the Energy Management model to improve forecasting of operational strategies on site.

4. The GUI (app) for operators to use:

   The GUI developed demonstrates how the models presented in this thesis can be integrated into a visual format for site operators and managers to be able to make use of. Day ahead optimisations are presented in graphical form such that operators can see the impact new legislations and energy prices can have on optimal operational strategies, as well as. Operators were also able to provide valuable feedback throughout the development of the methodology of the presented models.

6.5 Final Notes

The main aim of the work presented in this thesis was to explore new control and/or optimisation opportunities at the Howdon WWTP. Through the application and development of novel MILP techniques, an optimisation tool (Energy Management Model) was created for the AAD plant at Howdon. This tool can be used by operators and managers to validate current or historic operating strategies and investigate future scenarios, such as maintenance schedules or future energy pricing, and once implemented on site could be used daily. The Energy Management Model also considers the new carbon emissions performance criteria, which will provide valuable outcomes to aid in NWL's carbon neutrality pledge.

Additionally, initial investigations have demonstrated that reasonably accurate predictions of biomethane production can be modelled though data driven techniques only, without the need for a mechanistic model of the ADs on site. This section of research should be continued further, exploring other modelling approaches over a prolonged period.

Finally, the future direction of the research presented within this thesis has been discussed. The main focus should be to embed the models presented directly within NWLs systems such that they can begin to be used on site by managers and operators, with continuous developments to the existing models in mind (such as the ability to include of CHPQA and future legislation that do not exist yet).

There are multiple avenues of future investigation that could be pursued that would be beneficial to the models presented or that could make use of said models (such as a sitewide Advanced Process Control supervisory scheme, or energy market forecasts) that have been identified. Process modelling and advanced control of WWTPs presents a real opportunity for improvement of the sector operates, and it is believed the work presented in this thesis helps to advance the water sector in this area.

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