CHARACTERISATION OF VIRTUAL POWER PLANTS

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# Table of Contents

Table of Contents .......................................................................................... 2
  List of Figures ............................................................................................ 4
  List of Tables ............................................................................................ 6
Abstract ........................................................................................................ 7
Declaration ..................................................................................................... 8
Copyright Statement .................................................................................... 8
Acknowledgements ....................................................................................... 9
List of Publications ....................................................................................... 9

Chapter 1 Introduction ................................................................................ 10
  1.1 Background .......................................................................................... 10
    1.1.1 The Virtual Power Plant (VPP) .................................................. 12
    1.1.2 Weather forecasting and the VPP ............................................. 14
    1.1.3 The VPP and electricity markets ............................................. 15
  1.2 Scope and Objectives of this Research .............................................. 17
  1.3 Main Achievements and contributions of this work .......................... 20
    1.3.1 Development of a Probabilistic, Domestic CHP Model .......... 20
    1.3.2 Development of Four Different VPP Prediction Models ........... 21
    1.3.3 Wide Area Support for VPP Power Prediction ....................... 22
    1.3.4 Network Effects Incorporated into the VPP Model ................. 23
    1.3.5 Modelling Network Security Impacts on VPP ....................... 23
  1.4 Chapter Summary .............................................................................. 24

Chapter 2 Overview of the Virtual Power Plant ....................................... 26
  2.1 Introduction ....................................................................................... 26
  2.2 The Virtual Power Plant ................................................................... 27
  2.3 Wind Turbines .................................................................................. 31
  2.4 Photovoltaic Arrays ......................................................................... 33
  2.5 Micro Combined Heat & Power ...................................................... 34

Chapter 3 Predicting the VPP Power Output .............................................. 36
  3.1 Introduction ....................................................................................... 36
  3.2 Uncertainty in Wind Power Forecasting ........................................... 40
    3.2.1 Air Density .............................................................................. 43
  3.3 PV Basics ......................................................................................... 44
    3.3.1 Clearness and Diffusion Index ............................................... 50
  3.4 Micro Combined Heat & Power Basics .......................................... 50
  3.5 Aggregating Generator Outputs ...................................................... 58

Chapter 4 Improving the VPP Prediction Model ....................................... 63
  4.1 Introduction ....................................................................................... 63
  4.2 The 5 Point Forecast Approach ...................................................... 66
  4.3 Raw NWP Data Approach .............................................................. 71
  4.4 Technology Model Improvements .................................................. 73

Chapter 5 Modelling Networks Effects in VPP ....................................... 81
  5.1 Introduction ....................................................................................... 81
  5.2 Modelling the Network .................................................................... 85
  5.3 Incorporation of Tap changers ......................................................... 90
  5.4 Changes to the Model to Allow the Network .................................. 97
  5.5 Network Security Assessment ....................................................... 99
    5.5.1 N-1 Analysis ........................................................................... 100
## Index

Chapter 6  Implementation and validation of the VPP Models .................................102
  6.1  Model Validation ..........................................................................................102
  6.1.1  Wind Turbine Model Verification ...........................................................102
  6.1.2  PV Array Model Verification ..................................................................103
  6.1.3  MicroCHP .................................................................................................104
  6.2  Basic Uncertainty Results ..........................................................................104
  6.3  Results from the Advanced Uncertainty Work ...........................................116
     6.3.1  Drawbacks and Advantages of the Broader Models ............................118
     6.3.2  Technology Profile Improvements ......................................................119
  6.4  Financial Analysis .......................................................................................121
     6.4.1  Financial Impact of the Different Prediction Methods .......................122
     6.4.2  Optimising Revenue for the VPP .........................................................123
     6.4.3  ROCs and FITs .....................................................................................128
  6.5  Network Analysis .......................................................................................129
     6.5.1  Voltage Limits .......................................................................................129
     6.5.2  Line Limits .............................................................................................132
     6.5.3  N-1 Analysis .........................................................................................133
Chapter 7  Conclusion and Further Work .............................................................137
  7.1  Main conclusions .........................................................................................137
  7.2  Suggestions for Further Work ......................................................................140
References ........................................................................................................142
Appendix A  Building the Toolset .......................................................................151
The Basic Power Aggregator Tool .....................................................................151
  Inputting Data ....................................................................................................152
  Outputting Data ................................................................................................153
  Augmentation of the Basic Process ..................................................................155
  Optimization of the Basic Process ..................................................................156
The Load-Flow Tool with Aggregation ...............................................................160
  Scripting ............................................................................................................163
  Populating the Network ....................................................................................166
  N-1 in the Network ..........................................................................................168
Appendix B  Publications ......................................................................................171
Introduction ........................................................................................................171
Characterising Virtual Power Plants .................................................................172
Characterising the VPP ......................................................................................188
  Abstract ............................................................................................................188
  Introduction .......................................................................................................188
  Technology breakdown ......................................................................................188
  Long period power ............................................................................................192
  Combining Technologies ...................................................................................193
  Examples ..........................................................................................................193
  Conclusion .........................................................................................................196
  References .........................................................................................................196
Financial Risk Associated with the Commercial Virtual Power Plant ................197
  Abstract ............................................................................................................197
  Introduction .......................................................................................................197
  Case Study .........................................................................................................198
  Conclusion .........................................................................................................204
  References .........................................................................................................204
Word Count: 56,921
List of Figures

Figure 3.1: Van der Hoven’s Spectral Gap [] ....................................................... 38
Figure 3.2: Normal and Uniform Distribution ..................................................... 41
Figure 3.3: Wind Turbine Power Output Curve .................................................. 42
Figure 3.4: Example Turbine Power Profile ....................................................... 42
Figure 3.5: Example Power Output Graph ......................................................... 43
Figure 3.6: Turbine Power Curve and Power Coefficient .................................... 44
Figure 3.7: Solar Angles Diagram ........................................................................ 47
Figure 3.8: Solar Cell Example ............................................................................. 48
Figure 3.9: MicroCHP Diagram .......................................................................... 51
Figure 3.10: CHP Periodic Cycle ......................................................................... 55
Figure 3.11: CHP Non-periodic Cycle ................................................................. 55
Figure 3.12: Four CHP Conditions ...................................................................... 56
Figure 3.13: Cumulative CHP Power Output ..................................................... 58
Figure 3.14: Combining Graphs Process ............................................................. 60
Figure 3.15: Diagram of the VPP Power Output Process .................................... 62
Figure 4.1: NWP Meteograms ........................................................................... 64
Figure 4.2: Example of NWP smoothing changes ............................................. 65
Figure 4.3: Incorrect 5 Point Assumption ......................................................... 68
Figure 4.4: Correct Five Point Aggregation ....................................................... 70
Figure 4.5: Incorrect and Correct Long Period Power ....................................... 71
Figure 4.6: Comparing Wind Power Curves ...................................................... 74
Figure 4.7: Inverter Efficiency ........................................................................... 75
Figure 4.8: Old Method for Turbine Output Power ........................................... 76
Figure 4.9: New Technique for Turbine Output Power ...................................... 78
Figure 4.10: Derived Inverter Power Curve ...................................................... 79
Figure 4.11: DC and AC Power Output against Insolation ................................ 80
Figure 5.1: Three Terminal Transformer ............................................................ 88
Figure 6.1: Middelgrunden Wind Turbines .......................................................... 102
Figure 6.2: Power Curve Adjustment ................................................................. 103
Figure 6.3: Measured PV Array Data ................................................................. 104
Figure 6.4: Adoption of the Normal Distribution .............................................. 106
Figure 6.5: Calculated and Estimated Probability Distribution Polygon .......... 107
Figure 6.6: Calculated and Estimated Cumulative Probability Curves ............ 108
Figure 6.7: Uniform vs. Gaussian distribution .................................................. 110
Figure 6.8: Rayleigh Comparison Curves ........................................................... 111
Figure 6.10: Hourly Data Sample 1 ................................................................... 114
Figure 6.11: Hourly Data Sample 2 ................................................................... 115
Figure 6.12: Ensemble Forecast ....................................................................... 117
Figure 6.13: NWP vs. 5 Point output ............................................................... 117
Figure 6.14: Wind Profile Changes ................................................................... 120
Figure 6.15: PV Profile Changes ...................................................................... 121
Figure 6.16: LPPO for Financial Analysis ........................................................... 123
Figure 6.17: Potential Profit Curves for the Forecast Types .............................. 125
Figure 6.18: Distinguishing the effects of the broad energy spread .................. 127
Figure 6.19: Power Dropped Through Line Unreliability ................................. 135
Figure 6.20: 77 bus Test Network .................................................................... 135
Figure A.1: Main DG Window ........................................................................... 152
Figure A.2: Add DG Window ........................................................................... 152
<table>
<thead>
<tr>
<th>Figure A.3: Build Output Parameters</th>
<th>154</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure A.4: Build List Parameters</td>
<td>159</td>
</tr>
<tr>
<td>Figure A.5: Load Flow Main Window</td>
<td>160</td>
</tr>
<tr>
<td>Figure A.6: Load-Flow Bus Attachment Window</td>
<td>161</td>
</tr>
<tr>
<td>Figure A.7: Single Load-Flow Window</td>
<td>162</td>
</tr>
<tr>
<td>Figure A.8: Load-Flow Output Window</td>
<td>163</td>
</tr>
<tr>
<td>Figure A.9: Load-Flow Scripting Window</td>
<td>164</td>
</tr>
<tr>
<td>Figure A.10: Simple Script Program</td>
<td>165</td>
</tr>
<tr>
<td>Figure A.11: Automatic DG Populating of the Network</td>
<td>167</td>
</tr>
<tr>
<td>Figure A.12: Accurately Distributing DG in the Network (Stage 1)</td>
<td>168</td>
</tr>
<tr>
<td>Figure A.13: Accurately Distributing DG in the Network (Stage 2)</td>
<td>168</td>
</tr>
<tr>
<td>Figure A.14: Grouped Data View</td>
<td>170</td>
</tr>
<tr>
<td>Figure B.1: Example 1 Output</td>
<td>194</td>
</tr>
<tr>
<td>Figure B.2: Example 2 Output</td>
<td>195</td>
</tr>
<tr>
<td>Figure B.3: The SEDG Network</td>
<td>199</td>
</tr>
<tr>
<td>Figure B.4: The Output Power Curve</td>
<td>200</td>
</tr>
<tr>
<td>Figure B.5: The Income vs. the Bid Placement</td>
<td>200</td>
</tr>
<tr>
<td>Figure B.6: The Cumulative Hours per year vs. the p/c Power Dropped</td>
<td>203</td>
</tr>
</tbody>
</table>
List of Tables

Table 1: Typical Roughness Lengths ................................................................. 40
Table 2: Power Variance by Generator Numbers ............................................. 105
Table 3: The Weather Ensembles ................................................................. 122
Table 4: 5 Point Forecast from the Ensembles ................................................. 122
Table 5: FIT Rates in Great Britain ............................................................... 128
Table 6: Micro Wind’s Effect on Network Voltages ..................................... 130
Table 7: PV’s Effect on Network Voltages .................................................... 131
Table 8: MicroCHP’s Effect on Network Voltages ....................................... 131
Table 9: Micro Wind Line Limit Check ......................................................... 132
Table 10: PV Arrays Line Limit Test ............................................................ 133
Table 11: Micro CHP Line Limits Test .......................................................... 133
Table 12: Scripting Data Types ................................................................. 164
Table 13: Scripting Commands ................................................................. 165
Abstract

The growing number of micro generation devices in the electrical network is leading many to consider that these devices can no longer be considered as fit and forget, but should instead be considered as having a demonstrable network impact which should be predicted and utilised. One of the techniques for considering the impacts of these devices is the Virtual Power Plant (VPP).

The VPP is the aggregation of all the Distributed Generation (DG) connected into the network up to and including the connection voltage of the VPP, such that the cumulative power up the voltage levels can be seen in the single VPP unit, rather than across a broad spread of devices.

One of the crucial tasks in characterising the VPP, developed in this work, is the ability to correctly predict and then aggregate the behaviour of several technology types which are weather driven, as a large proportion of DG is weather driven. Of this weather driven DG, some can only typically be dispatched with modification and the rest cannot be dispatched at all. The aggregation of the VPP as part of the electrical network is also developed, as the constraints of the network and the reliability of the network cannot be overlooked when considering the aggregation of the VPP.

From a distribution network operator’s (DNO) perspective, these characterisation models can be used to highlight problems in the network introduced by the addition of DG, but are also generally utilitarian in their role of predicting the power output (or negative load) found throughout the network due to DG. For a commercial agent interested in selling energy, these models allow for accurate predictions of energy to be determined for the trading period.

A VPP agent would also be adversely affected by line failure in the network, leading to the development of an N-1 analysis based upon reliability rates of the network, which is used as the basis for a discussion on the impacts of single line failure and the mitigation available through feedback from the DNO.
**Declaration**

I declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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List of Publications

The publications created during the course of this thesis are included in the Appendix, and are briefly described below.


The second paper, entitled “Characterising the VPP”, was published as conference paper number 814 of CIRED 2009, as part of Session 4 of the 20th International Conference on Electricity Distribution, June 2009. It details some of the mathematical aspects of the modelling process, including the long period power, and the aggregation of disparate units into the Virtual Power Plant.

The third paper, entitled “Financial Risk Analysis Associated with the Commercial Virtual Power Plant”, is currently unpublished, and details the financial risk associated with the probabilistic power output of the virtual power plant and the impact that a single line failure can have on an agent’s expected revenues.
Chapter 1 Introduction

This chapter introduces the Virtual Power Plant concept and identifies the challenges involved in their power prediction. Using this information, a list of objectives is drawn up for the body of work, followed by the novel contributions to scientific knowledge and achievements of the thesis. The thesis structure and chapter summaries are also presented.

1.1 Background

After a century of cheap energy from coal and oil fired sources, CO$_2$, one of the gaseous waste products, is thought to be one of the chief causes of the global warming effect. The Kyoto agreement, ratified by 37 industrialized nations (signed and ratified by a total of 187 countries) [1], states that emission of key greenhouse gases (and both hydrofluorocarbons and perfluorocarbons) should be reduced to a level which is 5% below the emission levels in 1990. A recent European Union agreement states that all EU member states should make “a firm commitment to achieve at least a 20% reduction of greenhouse gas emissions by 2020 compared to 1990”. This is in support of the desire to “stabilise greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system”. It is stressed that “in order to meet this objective, the overall global annual mean surface temperature increase should not exceed 2 °C above pre-industrial levels, which implies that global greenhouse gas emissions should be reduced to at least 50% below 1990 levels by 2050”[2]. These imperatives are leading to a change in the way energy is produced and used. As 66% of the world’s electrical energy production is from fossil fuels [3], alternative methods for generating energy are being investigated, as well as techniques for capturing CO$_2$. At the time of writing many possible solutions and techniques are showing promise, although no single one is capable of solving the problem alone. Thus, a portfolio of different ideas is being considered.

One of the solutions which has gained popularity in recent years is Distributed Generation (DG), whereby multiple small-scale electrical generators are installed singularly or as part of a farm, often over a large electrical area. They can use several methods of generating energy through a number of small generators, which are situated across a large area in comparison with a traditional power plant. In this
manner DG is often referred to as decentralized generation, as the power generation has moved away from a central generation plant towards multiple satellite generators. As a generation scheme DG has the benefits that its decentralization allows for a lower loss of energy through transmission, that many of the DG technologies do not require fossil fuels as a primary energy source, and that it is possible that money can be made (or saved) by utilising these local resources.

A key disadvantage of these DG resources is that they are currently invisible to the transmission (TNO) and distribution network (DNO) operators. This is for several reasons. At the present time there are only a small amount of DG units installed, so there is very little pressure (economic, political, or other) to take notice of these units as they have no significant effect on the load pattern. In order to generate electricity without reliance on fossil fuels as a fuel source, many DG units use the energy provided by weather driven sources (for example solar and wind) or utilise waste energy which would otherwise be lost, one form of which is Combined Heat and Power generation (CHP). As heat demand primarily drives CHP, and not electricity output or electrical demand (without additional control schema or heat sinks/sources), CHP units are also fundamentally driven by the weather.

When discussing DG, the difference between on-grid and off-grid applications must be mentioned. On-grid DG is generation which is connected to centralised generation, and is hence on the electricity grid; power balance and stability is maintained by this connection to the grid. Off-grid DG is generation which does not maintain a connection to centralised generation, and is self maintaining. Off-grid DG is typically found in remote areas, where connection to the grid would be either too expensive or difficult or both. For off-grid applications, some form of energy storage device is connected to store energy when generation is high, and supply energy when generation is low (compared to loading). This body of work is designed to be used with on-grid DG, which is also to say an on-grid VPP. Smart-grids [4] and islands are not strictly covered by the work, although many ideas are transferable.

The reliance upon the weather by some DG technologies carries the disadvantage that they are difficult to predict accurately, and when this is considered with their low network penetration, it is evident that they are an unattractive generation method for
the DNO and electricity suppliers. Consequently, the supplier must arrange for other sources of generation to meet his network load, even if the installed DG can meet some of it. Unnecessary generation and reserve generation will be scheduled, and as the price paid for electricity from a generator tends to be exponential it is important to not over-estimate usage. If the DG resources were visible and predictable to the DNO, the DNO and suppliers could reduce the amount of required generation and this reduction would come where the electricity is most expensive. This utilisation of resources improves the efficiency of the network, which can help lower the price of electricity and also promotes the use of green technologies.

1.1.1 The Virtual Power Plant (VPP)

One of the ways in which the DG installed in a network can be made visible to the DNO is through the use of a Virtual Power Plant (VPP). The VPP is a term which first came into use in the early 2000s, and indicates that a group of generating units have been amalgamated into a single construct which represents their combined outputs and effects. The VPP is more thoroughly described in Chapter 2, although a concise description is provided here. Its role is to simplify the electrical network, by amalgamating all the DG units into one Virtual box which is easier to work with than many hundred, or thousand, small units. It is similar in this regard to a microgrid, although the microgrid has the ability to run itself autonomously in an islanded state [5], whereas the VPP does not necessarily have this functionality. As a construct to manage DG units, the VPP can also be broken down into two separate pieces; a technical VPP and a commercial VPP [6].

The technical VPP (TVPP) deals with the physical presence of the DG within the network, and is contained within an electrical area. Its purpose is to serve the DNO, providing information in relation to the network to achieve successful network management and balancing operation. The TVPP requires detailed knowledge of the local network in order to provide accurate results, and connects to the distribution-transmission interface as a single unit with relevant power generation profile. The TVPP is connected to but also separate from the commercial VPP (CVPP).
One of the key issues addressed by the TVPP is the power output of the plant, although this is not the only characteristic feature. As will be discussed in Chapter 2, this is an area which still requires work, and is the focus of this body of work above any other characteristic of the VPP. The VPP, as will also be mentioned in Chapter 2, is not well suited to provide services other than energy, which can be sold on the market using the CVPP concept. This is not to say that ancillary services are impossible to provide, as evidenced in Chapter 2, only that the currently installed logistic framework does not support it.

The CVPP is different to the TVPP in that it has no point of connection, and does not have to be limited to one electrical area. The CVPP is used as a trading entity, and is built up from the portfolio of technologies and resources it encompasses. This amalgam has the advantage of reducing the imbalance risk associated with lone operation, and this feature will be covered later in greater detail. The CVPP provides the information which can be used by an agent to trade the power generated by the VPP. An individual unit, for instance, may be too small to participate alone, whereas the CVPP as a group can be large enough to trade energy. This allows the agent (and the DG owner) the ability to maximize revenues from their generation.

The CVPP can be constrained in some markets to be tied to a geographical area, although this is not strictly necessary. The TVPP and the CVPP define the two key aspects of the VPP and both are dependent on each other, which is to say that concerns within the TVPP can force a change in the CVPP, and concerns or obligations within the CVPP can force a change within the operation of the TVPP. Crucial to the operation of both is that the power generation is determinable.

As mentioned previously, the prevalence of weather driven DG presents a problem to the determination of generation output. The power output of a VPP is not easily definable although it is not random. Several important DG technologies are weather driven and are commonly referred to as intermittent generation. These technologies are often inherently variable, although they are predictable statistically. The key equations of power generation for the technologies involved have been solved to the point at which power output curves can be deduced. These intermittent generators’ power output can fluctuate randomly due to the variability of the prevalent weather
conditions, although if the weather conditions can be predicted accurately, the power generation and thus the VPP’s power output can also be predicted accurately.

1.1.2 Weather forecasting and the VPP

The uncertainty encountered whilst predicting the output for these weather driven generators is a feature of the limited amount of data available to predict the weather. The Earth’s atmosphere is in a constant state of change, and is an enormous, three dimensional problem. Even trying to solve this problem with a low resolution requires a vast amount of information and computational power, and very often the data set available comes with inherent error and is limited in its size. This leads to difficulty in prediction. The current solution to this problem is to solve this meteorological problem many times, for the full range of input data inclusive of the inherent error. This is known as numerical weather prediction (NWP), and produces a number of theoretical weather forecasts. Whilst it may be true that one of the numerous output scenarios is a very solid match to what eventually happens, there is no certain way to decide which of the outputs this is. Instead of randomly or arbitrarily choosing from the output data, the outputs are combined into an ensemble forecast which highlights the more likely forecasts.

Localised variations to the expected weather are also encountered when trying to predict VPP power output. Current NWP have a horizontal resolution which is graded depending on the scale of the model. The UK Met Office uses a grid size of around 40×40km for global predictions, and 12.5×12.5km for more detailed forecasts, which is small enough to provide generic data for the area, but too large to take into account smaller obstacles, which can add to the uncertainty of the weather forecast. Several techniques have been developed to solve this problem, and will be discussed below.

Arguably, wind forecasting has been researched the most when compared to solar insolation or temperature forecasting, and still remains a topic on which further improvements can be made. The papers by Nørgaard and Holttinen, and Lange and Focken [7,8], give a good overview and understanding of contemporary methods, but generally speaking these methods begin with the output from NWP and then refine the meteorological data, adapting it to the particular terrain under study (using
techniques such as WAsP[71]). Wind farm parameters are added, if required, finally producing a power output curve using the turbine parameters. Using measured data along with the forecast data, statistical adjustments are entered into the method as a form of feedback.

Solar insolation forecasting is less developed, and relies heavily on satellite data [9]. Applying NWP techniques to satellite data provides a likely insolation distribution, which can be applied directly to the solar modules. Module degradation, shadowing and deposit corrections can be made to the solar modules, but the uncertainty associated with the forecast pixels (1km$^2$ for the Meteosat 8 satellite [9]) leads to an inherent statistical spread which must be present in the modelling. This is discussed in greater detail below.

Temperature is one of the inherent variables that are forecasted using standard NWP and is as old as weather forecasting itself. Primarily used for predicting the output of combined heat and power (CHP) generators, temperature forecasting is also used for calculating the efficiency of PV modules. Presented in Chapter 3 is an overview of how to model CHP generators, using several determinable parameters.

### 1.1.3 The VPP and electricity markets

The market in which the VPP operates is not a constant. There are several different market schemes in which the VPP can operate, the key markets being the bilateral market, pooling, and the spot market [10]. In the UK, at least 95% of electricity trading takes place in bilateral trading [11]. The bilateral market is arranged through a broker and matches (usually anonymously) generation and loading bids, such that generators with high prices per MW are typically chosen after generators with lower prices per MW, and loads with higher revenues per MW are chosen before those with a lower revenue. All this is of course subject to constraints. Contrast this to a pool system, whereby all generators that are selected into the generation mix are paid the system marginal price, regardless of their actual bid. The third option is the managed spot market, which is used in the UK as the Balancing Mechanism. Loads and generators which are short or long must compensate for their deviation by selling or purchasing power from the network.
The CVPP system is designed in order to generate as much revenue for the individual members of the VPP. As the VPP has a low marginal cost because it has very few running costs, thus in the pool system (such as is used in California), the VPP can adopt a very low bid price to guarantee its selection for use and will be paid the system marginal cost. In the bilateral market (such as is used in the UK) the VPP must try to balance the very low running costs against the desire for profit, by artificially inflating the power price from the VPP. If the VPP bids too high, however, its bid will not be chosen and it will be forced to sell its power on the spot market.

The markets for the countries studied for the MASSIG project (Market Access for Smaller Size Intelligent electricity Generation), a study aimed at integrating DG and renewable energy resources (RES) into the market structure through VPPs rather than using flat-rates, are all bilateral enabled markets (Denmark, Poland, Germany and the UK) [12]. Concerning the services which are feasible for DG or RES to supply, the report identifies energy trading and reactive power management as attractive, whilst other services such as reserve and black start capability are impractical due to technical or legislative reasons.

Clearly, the volume of revenue generated by the VPP depends on which market it operates within. The work will analyse the profitability of the VPP in and of itself, and also compared against traditional generation to determine the financial viability of the VPP, as financial viability will act as a driving factor towards implementing more DG.

Distributed Energy Resources (DER) must also be mentioned briefly. DER is a term for not only DG but also energy storage as well as demand response (intelligent loading of devices). For on-grid applications, energy storage is an expensive addition which is not current necessary, although it has several benefits. The most important advantage of energy storage is the ability to manage peaks and troughs in energy usage – rapid fluctuations. Balancing these rapid changes in energy use is expensive because it relies on expensive fast acting generation plant [13, p321]. Decentralised load management through energy storage is one way of dealing with this problem. Energy storage can also be used to make the ‘intermittent’ generators more attractive
as their power outputs can be smoothed to a more constant level. The downside to energy storage is that the energy density for these devices is low, and their cost is large [14], although research continues to improve these figures. Petrol (gasoline) has an energy density of 46.4MJ/kg [15], whilst a relatively good battery has only an energy density of 1.26MJ/kg [16], leading to either very large batteries in urban environments, or very heavy batteries for vehicle power delivery. As this work focuses on on-grid applications and energy storage is currently unfeasibly expensive, only DG (and not DER) is considered in the work.

Responsive Loads (RL) are also not considered as part of the work. Responsive loads are able to reduce their loading in response to external factors, such as during peak load times, and/or increase their loading during load minimums. This durational load decrease (or increase) adds another layer of complexity to the model which can be approximated by adjusting the static load conditions if the RL penetration is high enough.

1.2 Scope and Objectives of this Research

The aims and objectives of this work are to provide a framework and set of models by which a VPP can be characterised. More specifically:

- To undertake a critical review of developments in VPP and their modelling and characterisation.
  It is important to identify the key research which has been undertaken in the area of the VPP and its prediction in order to determine the research questions which yet remain to be answered. A critical review of the literature will provide a firm basis from which new contributions may be added to the knowledge of modelling the VPP.

- To develop a power prediction scheme applicable to a Technical or Commercial VPP with the combined technologies as chosen for the work
  The logistically simplest and most basic service provided by the VPP is the production of power. The DG technology types which are the most common type of domestic generator are driven by the prevalent weather conditions, and do not have a precisely determinable power output for the purposes of prediction. Prediction of DG resources is not a new idea. The Risø Institute [8]
has researched the methods necessary to provide accurate modelling of wind
turbine clusters, and [9] provides work details on predicting individual PV
arrays. To the author’s knowledge, no model exists which can predict all the
technologies of this work at the same time, in the same VPP.

- To provide a novel power prediction scheme applicable to wide area
  prediction, which is to say amalgamating DG into a VPP over a very large
  geographical area.

One of the inherent drawbacks to the DG technologies of the work is that their
power outputs fluctuate, due to the uncertainty contained in their driving
factors; therefore their prediction. On a wider scale, the low loading factors
combined with the uncertainty in their individual outputs leads to an excess of
generation from centralized sources, as the VPP power is ignored from the
power scheduling. The ability to build a VPP over areas larger than a few km²,
or to determine the power output from VPPs some considerable distance apart,
removes the size restrictions present in the VPP from the forecast grid size,
and allows an accurate power prediction to be obtained over a region or
country. This wide area output provides the ability to consider all the DG in
the area through the VPP vehicle, allowing centralized generation to run on
lower power outputs, which improves the efficiency and running cost of the
network.

- To incorporate the electrical network into the prediction schemes, including
  line current and bus voltage constraints, such that the impacts of the network
can be determined.

The design of most networks does not consider the impact of a reverse of
power flow, which is possible when DG penetration levels are high. As
discussed in [39], at every level of the network constraints exist which must be
adhered to and which are possible to violate because of this reversal of power.
The VPP power prediction models must therefore incorporate the network data
into their process, in order to observe the limitations of the network and
determine if the VPP is likely to violate them.
• To compare the effects of the electrical network on the Technical and Commercial VPP in comparison to an infinite bus characterisations (a model containing no network implementation or characteristics).

Whilst the VPP operates in a dynamic network, we are considering the VPP in a static situation (no transient behaviour). The effects of the network upon the ability of the VPP to produce and sell power is directly impinged upon by any constraints which are violated, as these must cause the VPP to curtail or shutdown units which most adversely affect the violated voltage or line current; failure to self-manage this curtailment will force the DNO to intervene and reduce the generation capacity of the VPP. It is important, therefore, to ascertain the conditions which precipitate this behaviour from the VPP and compare this to the base case with no network to determine the magnitude of the network’s impact.

• To investigate the effects and magnitude of network reliability (single line outages) within the Commercial VPP in comparison the infinite bus characterisations.

Another issue involved with the network on the VPP is the problems arising with line reliability issues. Lines have a finite chance to fail during their service lifetimes for several reasons, of which some reliability issues are more serious and time consuming than others. The disconnection of a line affects all the connected loads and generators that have no alternative connection path, possibly reducing the power output and thus the revenue for the VPP during the disconnection period. The effects and magnitude of single line reliability must therefore be modelled and measured and then compared to the perfectly reliable network, to measure the overall impact that these issues have on the VPP output.

• To evaluate the developed models in their function, speed, complexity, and accuracy.

The models developed to predict the future power output of the VPP will have differences that affect the quality and accuracy of the predicted power output. Each model must therefore be verified against a measured data set and against
Fault conditions and dynamic operation are not evaluated; [17,18,19] discuss the effects of introducing DG on fault conditions well, and there are many other papers in the field. These papers are not specific to the VPP problem, but they can be used with the network model with reduction techniques to obtain the fault characteristic of the VPP at an observed bus. This is, however, outside the body of this work.

### 1.3 Main Achievements and contributions of this work

By the end of the thesis, it will be shown that several different, novel prediction schemes are available for forecasting the power output of a VPP using the technologies chosen for the work. The prediction methods are able to use a variety of input data styles, ranging from a single point of data to a stochastic approach. Each scheme provides a different degree of accuracy, and has its own benefits and drawbacks. In the development of these models and the results obtained from them, the following achievements and contributions have been attained and made.

#### 1.3.1 Development of a Probabilistic, Domestic CHP Model

Throughout the papers and publications which discuss CHP resources, there is a lack of a prediction model for the CHP plant. CHP generators are typically assigned an efficiency of the thermal production of the plant, as in [20], which can be used with measured data but is of little use for determining future outputs.

A probabilistic model of the domestic CHP based upon a household which runs their CHP boiler as dictated by a thermostat is developed. By determining methodically or estimating the domestic properties thermal resistance and heat capacity, and by knowing the CHP boiler’s electrical to thermal power output ratio, the probability of the boiler being on or off in any period of observation, and in what ratio, can be determined provided that the thermostat set points and the forecast temperature can be provided.

This model is vital for adequately predicting the CHP units in a probabilistic environment, as the CHP unit has a pronounced comb effect on the VPP power.
output, which is not adequately modelled by a simple averaging of the CHP power for the period.

### 1.3.2 Development of Four Different VPP Prediction Models

Using the models developed by others, and the CHP model developed, all three technologies were combined in the VPP model in a basic approach, which required only a single forecast parameter for wind speed, solar insolation and direction, and temperature, to produce an output. The model utilises accurate technology models for the wind turbines and PV arrays, using measured power transfer curves for the wind turbines and the PV array inverters, and incorporates site features such as roughness length, nominal operating cell temperature (NOCT) for PV arrays, and inverter shut-off.

The model is able to predict the discrete probabilistic power output for the VPP using the provided data for the generators and the weather conditions, in two separate formats. The first format is the so-called instantaneous power from the VPP, which accurately describes the likely power output for any given point of the forecast period, and can be used as the basis for future dynamic behaviour work. The second format is the long period power output, which is the discrete probabilistic power output as an average over the forecast period. This provides a much more meaningful data set for the purposes of energy trading, as the total power generated for the period is more important than the individual breakdown of how power was generated during the period.

The second and third models are advancements upon this basic model. The 5 point forecast model uses the style of data input which can be found on meteograms – this style of data presentation typically uses 5 of the percentage points from the cumulative distribution frequency of the forecast data, such as the 2.5%, 25%, 50%, 75%, and 97.5% points. Using these data points, a stochastic approach is taken to perform a more accurate prediction of the power output for the VPP, creating a stochastic discrete power output in both instantaneous and long period power formats.

The third model uses the raw numerical weather prediction (NWP) data points and treats them as a series of equally likely single forecast point events (as [7], applied to
all the technologies. By superimposing the power output graphs for each NWP point, the overall power prediction for the forecast period can be built quickly and easily. This approach has the additional advantage that because it uses the individual NWP data points, coincident data points for different forecast regions can be used to provide wide-area support, which will be mentioned below.

The fourth model is a simplified model based upon the principle of central limit theory. As the number of generators in the VPP increases, it becomes increasingly likely that the distribution of power will tend towards the normal distribution. Instead of using a convolution procedure to determine the power output of the VPP under these conditions, it is faster to estimate the power output by determining the mean power generation and standard deviation for each generator and then producing a fitted normal distribution using this data. As the number of generators in the VPP increases, this model increasingly becomes faster than the other models, and becomes more well fitted to the slower models.

1.3.3 Wide Area Support for VPP Power Prediction

The introduction of Wide Area support is immensely useful for determining the power output of a VPP. This is useful from a planning point of view because this removes the restriction on the VPP to lie within a single forecast region. Without this support, if a VPP has generators in 2 regions which were different grid squares in terms of the forecast, they would have to be regarded separately, and their outputs could not be combined with certainty, as will be discussed below. The wide area support also enables an accurate estimation of the overall VPP contribution of power for the prediction period to be determined. Both the Single point forecast model and the NWP forecast model support the wide area prediction.

This accurate determination of a large volume, and importantly aggregation, of DG enables the scheduling of the network to reduce the amount of central generation which is running, as currently all DG is covered by centralized generation because there is no guarantee of generation. If an accurate and overall prediction of DG power output can be produced, the generators which are forced to remain in operation because of DG can be shut-down for the periods where overall, DG can be reliably predicted to be producing power.
1.3.4 Network Effects Incorporated into the VPP Model

There have been several papers reporting the limits upon the network, and therefore the VPP, at the lowest to the highest network voltages of concern for the VPP. This work has found that the limitations reported by others are reliable, but has also found that the quantity of DG required in the network in order to meet these constraints has been very large.

In the papers [36] and [39], the limitations in a test network are discussed and [39] places the lowest network limit at 76% penetration rate due to line thermal limits. In the steady state analysis of the network limits, the work reaches a similar conclusion that the line thermal limits are the limiting factor, although the non-dynamic nature of the analysis produces a higher value.

This work determines that the network constraints are difficult to reach. In the test network under adverse network and weather conditions, the generation penetration rate to achieve the power generation levels necessary to place the network under threat of constraint violation was over 100%. Whilst the work does not deny that these constraints exist, it is suggested that due to the low loading factor typically found in DG, the limits inside the VPP are in no considerable danger of being violated more often due to the introduction of DG on the network.

1.3.5 Modelling Network Security Impacts on VPP

This work determines that the effects of a single line failure incorporating reliability rates on the power output, and therefore revenue, of the VPP is negligible.

In the event of the single line failure contingency, the VPP will lose all generation in the VPP which does not have an alterative connection path. It is important, therefore, to be aware of how badly this will affect the power output of the VPP. An unexpected loss of power will have a detrimental affect on the revenue of the VPP, as the VPP agent will place a bid in accordance with the predicted power output from the plant. If some of this is lost, then even under favourable conditions the agent will be forced to accept that he or she must purchase electricity from the market to account for the shortfall; if the shortfall is large enough, a loss can even occur. It is the findings of
this work that in the test network studied, the loss of power and revenue from the VPP under a contingent scenario was very small.

The short line length and the quantity of lines which comprise the VPP enable the VPP to only drop a small fraction of power when a contingency arises, as the likelihood of a key line being taken out of service is very small. Over the course of a year, the total loss of generating hours was found to be less than 0.1%, which could be reduced to less than 0.0001% by the introduction of adequate communications between the DNO and the VPP agent.

The shortfall faced by the VPP agent is similarly very small, and it is the opinion of the author that the agent would almost certainly incorporate the communication between themselves and the DNO discussed in this work to reduce the lost hours down from 0.1% to 0.0001%.

1.4 Chapter Summary

The body of the thesis is broken down into 8 chapters, these being:

- Chapter 1 – Introduction. This chapter places the work in a greater context, and introduces the work as a whole. The Objectives of the work and the Achievements of the work are detailed here.
- Chapter 2 – Overview of the Virtual Power Plant. This chapter describes the VPP and places it in a research context, and introduces the 3 generator technologies that are used throughout the thesis, these being wind turbines, PV arrays and CHP generators.
- Chapter 3 – Predicting the VPP Power Output. This chapter introduces the use of uncertainty into the prediction of future events in order to attempt a basic prediction schema for the VPP with the technologies previously described.
- Chapter 4 – Improving the Prediction Model. This chapter advances the work of the previous chapter, and provides a more complex, but more accurate, method for using the uncertainty data provided in a weather forecast to obtain the likely VPP power output. Several different variations are proposed for increasing the accuracy of forecasts.
• Chapter 5 – Implementing the Distribution Network. This chapter focuses on the VPP as a physical component within a larger electrical network. The reasons for this are explained, and the modelling process chosen for the task are described.

• Chapter 6 – Results from the Models. This chapter examines the results from the above chapters, analysing the differences between the various prediction methods and the effects of changes, or lack thereof.

• Chapter 7 – Conclusion and Further Work. The final chapter concludes the thesis, and reiterates the contributions developed throughout the work, as well as detailing further work made apparent by the work involved in the thesis.

Finally, the references follow the last chapter, followed by the Appendices.
Chapter 2  Overview of the Virtual Power Plant

This chapter details the current and past work done on the VPP, discussing control and prediction schemes which have been applied to DG and the VPP. The review discusses topics from a wide-range of applications, and highlights the knowledge gap concerning adequate prediction schemes. Following this is a review of the technologies chosen for the work, discussing their merits and their suitability for this work.

2.1 Introduction

The technologies investigated in this work were chosen using several criteria. Firstly, the technologies are mature, in that they are all currently available to install with no major logistical problems. Fuel cells were ruled out because of this; although they continue to progress, most homes do not have a hydrogen supply installed. This would require a reservoir for hydrogen to be installed alongside the hydrogen fuel cell module. Similarly, tidal generation is not applicable to most homes. Secondly, the technologies must be so-called green technologies. The reason for this is that one of the most important driving factors for DG is the growing concern about climate change and hence DG units installed to mitigate effect of electricity generation on the environment must ideally be environmentally benign and sustainable.

The three technologies chosen for this work are wind turbines, PV arrays, and CHP boilers. For an urban or domestic characterisation, this is specifically narrowed down to micro wind turbines, PV arrays and micro CHP boilers; although the characterisation is also valid for larger versions of these technologies. This miniaturisation of technologies is done to represent the intended use of the characterisation work, as urban characterisation is rather different to large scale generation such wind and solar farms.

Before the three technologies are introduced, a more thorough detailed description of their host, the VPP, follows.
2.2 The Virtual Power Plant

The VPP is a newcomer to the field of electrical engineering and covers three distinct objects. The first is a model of a Power Plant used to study performance or efficiency [21]. The second is a politico-economic term originating from France, whereby a portion of a large power plant’s output is virtually detached from the parent plant, so that portions of its power production can be auctioned off for a price [22]; hence the physical power plant’s output is split into several Virtual portions. The third is an amalgamation of DER such as DG into a visible generation unit, which can be used in system planning, management, and can operate inside the electricity market – this is the VPP which is used throughout the thesis.

The drivers and justification for the VPP are both financial and regulatory. As explained in [23], the utilisation of heat driven units can improve the utilisation ratio of the network, and the local, fast acting nature of these units offers the advantage of peak load shaving. As services, this power export capability and load shaving mechanisms are capable of generating revenue for the unit owner, and can also displace installed capacity by their utilisation in a broader energy management system, which is beneficial to conventional plant owners.

Beyond the financial consideration, DG aggregation into a VPP for energy trading (as well as other ancillary services) is mandatory for small generators, if they wish to trade, as they are not large enough by themselves to operate inside the energy markets. This factor is examined in depth in [24], which is one of a number of papers to begin using the technical and commercial VPP as two separate constructs used to fulfil two different roles for the overall VPP structure. The VPP as a vehicle or platform to enhance DER visibility and control to systems operators is the key focus of the paper, and whilst the paper suggests Optimized Power Flow (OPF) as one method of optimising the VPP, the inclusion of other ancillary services, as discussed below, limits the use of OPF.

Alongside the concept of the VPP is the concept of a smart grid, which is so-called because the elements within the network seek to self manage and control the grid for internally optimised behaviour. Some of the smart grids on DG overlaps with the
concept of the VPP, and in this context the divide between the VPP and the smart grid is not solid. In particular, the use of active management using DG within the network for smart-grids is directly applicable to the VPP, offering solutions to problems which present themselves within the network. To the DNO, the ability to resolve harmonic, reactive and voltage problems at the load point is valuable, which is something the VPP operator must be aware of, and able to utilise.

The majority of smart grid solutions involve the use of Energy Storage devices, cogeneration, such as CHP, or tri-generation (cooling, heating and power) [25], although a plethora of different schemes exist to exploit the features common to DG units [26]. This range of smart solutions is broadly split into two categories, methods of voltage, power etc. control within the network, and methods of controlling the DER to implement the voltage, power etc. control schemes, with several papers straddling across the two.

Reactive power control is suggested by Braun [27], and provides evidence of cost reduction if DG devices such as wind turbines and PV are integrated in reactive control in addition to conventional DG units, such as battery storage or diesel generators. Braun also discusses in [28] the merit of reactive power control from wind energy converters, finding the scheme attractive but with significantly varying costs.

Leading on from this, voltage control is also considered on medium voltage distribution network by using the aggregation of DG units [29]. By creating a co-ordinator for the control area, DG units can be effectively used in conjunction with On-Line Tap Changing (OLTC) transformers to regulate the voltage to within nominal levels by adjusting the amount of reactive power produced by DG units, with limited interference from the VPP optimisation scheme. Such a service is, of course, marketable. Voltage control is considered in [30] in which it is found that the techniques are effective, and it is determined that getting the balance of control techniques optimal is the next step in implementing voltage control schemes using DG.

In addition to voltage control issues, Bertling and Soter assert that power quality issues can be addressed [31]. By active monitoring of current harmonics introduced
by solid-state power supplies in the network, a counter-injection of current can be introduced by DG units if directed by a quality controller. Whilst the adjustment made by a single unit may be small, by adopting the program over many DG units, the voltage and current waveforms can be adjusted to be almost sinusoidal.

More traditional problems are also discussed, and various papers examine the ability of a VPP to deal with peak load magnitude. Kok [32] examines the role of the VPP to provide near real-time balancing services, using the flexibility of heat based plant, whilst several researchers [33] used a specifically developed software agent [34] to try and alleviate peak loading conditions. During a field test, [33] found that peak loading could be cut by 30% during the summer, and predicted a cut of up to 50% during the winter, although the trials were not ready in time for actual testing of this claim.

The VPP is also studied in [35] focusing on peak load shaving activities and optimization of revenue for the VPP. It is found that the VPP can expect to place a higher value on its energy under peak load shaving conditions. Additionally, in [34] a software agent for the VPP was not only developed, but this demonstrated the feasibility of up-scaling the VPP past the small practical test of the software.

From a planning point of view, there are several papers detailing possible frameworks for operation for the VPP. Zhang lays down a framework for the operation of a smart grid [36], and identifies the problems introduced by the changing energy structure. The paper recommends the installation of Flexible Alternating Current Transmission (FACT) and other energy management devices as cost effective solutions for network stability, in a network not yet entirely suitable for the deregulated market. A paper produced by several authors by Siemens, agrees with this synopsis, suggesting large scale HVDC links and increased penetration of FACTs to help manage modern networks [37], whilst [38] introduces a method of dealing with DG islanding if the control strategies fail.

Focusing on the management of the VPP, work has been done on the planning and control, ranging from over-arching divisions of the VPP, to practical or theoretical control systems with market participation. [39] develops a VPP architectural structure divided into 3 aggregation echelons, starting at LV Loads, and moving up to virtual
LV/MV Substations, and finally the HV/MV Virtual Power Plant, and notes the smoothing effect of aggregating DG, which will be discussed below. As in [36], the paper finds the limiting factor in DG introduction as a combination of voltage rise at LV, thermal constraints at MV/LV, and transformer ratings at the VPP level.

As in [24], several papers discuss the structure of the VPP as a separate Commercial and Technical structure. Both types of VPP are explored in [40] where it is argued that with correct support and management, a range of ancillary services are available through VPPs, increasing the revenues for generators. Both [41] and [42] detail two case studies which use the pair classification of VPPs, determining the technical and economic feasibility of the schema.

When dealing with the commercial VPP, research tends towards an agent based approach, where each participant can freely negotiate participation within a broader marketable group, [43] and [44]. The disadvantage to this scheme is that agreed aggregations may not be large enough to participate in economic activity due to restricting policy barriers, as described in [45]. The later paper also determines that the price per kWh available through co-generation is more expensive than the grid price, although carbon credits are not taken into account by the study.

Aggregating microCHP has received perhaps the most interest due to its universal appeal and degree of controllability, and the bulk of the papers referenced above in which active management roles are considered, depend upon microCHP. The prediction of domestic heat load for use with microCHP is presented by several authors in [46], detailing a method by which the hour by hour usage can be determined. The authors determine that the model is in need of refinement in terms of accuracy and timescale.

The prediction methods for the other technologies under nominal conditions are well documented, as discussed below. What is evident is that the majority of papers discussed in section 2.2 require accurate operating conditions of the DG units in order to perform. The knowledge base for VPPs is lacking in terms of forecasting this information, both in accurate prediction using inaccurate data, and the changing face of these predictions as the forecast horizon narrows.
2.3 Wind Turbines

Wind turbines are not a new technology, and have been used over centuries as an attractive source of “free” work, such as in traditional Danish windmills. Their maximum operational efficiency has long been determined as 59% of the power of the wind speed, and this is recognised as Betz’ law, formulated in 1919 [47]. Despite this inbuilt inefficiency and whimsical nature of the wind, wind turbines have been recognized as a good source for clean power.

The advantage of wind power is that the primary energy source is the wind, a ubiquitous resource. This is beneficial as it leads to a reduction in CO₂ production when compared to conventional generation, and also as it reduces the cost of generation – the wind is essentially free. The fact that the wind surrounds us is another advantage, as it requires very little logistics; no pipes and little handling of it is required. This is also the main weakness for wind turbines. The wind is greatest where the wind is greatest, as determined by the landscape topography, and there is very little that can be done about that fact, short of environmental landscaping on an enormous scale. Wind turbines must be placed at sites of greatest wind speed in order to be maximally effective, and this is sometimes frowned upon both onshore and offshore, as wind turbines are thought of by some to be unsightly and disruptive to animals. The first point is a matter of opinion, although those who live near wind turbines are generally more inclined to be favourable, than those who do not [48]. The second claim regarding wildlife is generally unsupported by wind authorities, including the British Wind Energy Association and the Danish Wind Industry Association, to quote; “Birds are seldom bothered by wind turbines, however. Radar studies from Tjaereborg in the western part of Denmark, where a 2 megawatt wind turbine with 60 metre rotor diameter is installed, show that birds - by day or night - tend to change their flight route some 100-200 metres before the turbine and pass above the turbine at a safe distance,” [49] and “Experience and careful monitoring by independent experts shows that birds are unlikely to be damaged by the moving blades of wind turbines. More information about this can be found from BWEA Best Practice Guidelines and the Royal Society for the Protection of Birds” [50].
The remaining disadvantage of wind turbines is their cost, as they are currently around £3000 per kilowatt rating for small scale applications [51], which is much more expensive than centralized generation at £500-1000 per kW [52]. This is restrictive, as many people do not have this quantity of free-cash in which to indulge in a wind turbine. Combined with the low cost of buying back electricity generated, pay-back periods can be as high as 20 years; turbine life span is typically 20-25 years [53,54]. Whilst this effectively generates net revenue of 25% of the initial investment cost, this period is longer than most people are prepared to wait.

The technical specifications for small scale wind turbines can vary, depending on the generator technology involved, as can the wind collection method. A typical house-mounted small scale turbine is rated at 1.5 kilowatts, as turbines of larger sizes cannot generally be supported on normal roof-tops, and must be mounted on poles, or frames [55]. These turbines which could see large scale penetration in urban environments have rotor diameters of around 2 metres, although the larger size of small scale turbines have diameters of 11 metres.

The problem of placing wind turbines into a VPP is the problem of the random variation of wind speed due to turbulence. Ideally, the VPP can precisely define its power output instantaneously and over a given period. Due to the random variations of wind turbine power output, this is not possible; the VPP cannot schedule wind turbines just as much as it cannot schedule the wind speed, although ongoing research continues to drive towards the goal of more accurate wind forecast scenarios, using AI, fuzzy logic, hybrid forecasting, and statistical approaches [56][57]. The ability to accurately forecast the initial conditions is directly related to the accuracy of the wind power models, and is therefore crucial. The VPP is at the behest of the wind speed and natural turbulence for the purpose of determining the power output of wind turbines. The characterisation of the VPP must, therefore, take a probabilistic approach to incorporate wind turbines. This is not a new concept in power distribution, as reliability issues have been factored into the economics of power delivery for quite some time.
2.4 Photovoltaic Arrays

Photovoltaic arrays are, unlike wind turbines, a new technology. The earliest machines to harvest solar power were built during the industrial revolution to generate steam, and although the photovoltaic effect was discovered by Becquerel at around the same time, it was highly inefficient. The growth of photovoltaic generation was catalysed by the growth of semiconductor technology, where the photodiode could be used to generate direct current. With this understanding in place, photovoltaic generation continues to be a topic of great research, trying to produce semiconductors with high efficiencies, and photovoltaic generation has been used for many years.

Similar to wind, the greatest advantage of PV is the abundant nature of the generating fuel, light from Sun. This leads to CO$_2$ free generation, which is good for the environment, and utilises a free fuel source which can be found all around us, which is a sound economic start point. Again, similar to wind generation, the drawback to this technology are that light levels vary quite substantially over the longitude of the planet and may be especially affected by cloud levels; placement and angling of the PV array can substantially affect the output. It must not be overlooked, however obvious, that PV arrays can only produce electricity during the day. Another disadvantage of the technology is the low efficiency of the technology. Commercially available cells have an efficiency of around 20%, requiring a large area for power generation [58]. Coupled with the cost per kilowatt, currently standing at between £4000 and £9000 per kilowatt [59], it is obvious why research is continuing into more efficient and cheaper technologies. Despite this, PV is an attractive technology as it can be placed almost invisibly onto rooftops, which have the advantages of being a plentiful supply of square metres, and also has a less visual impact than wind turbines.

In the UK, the British Photovoltaic Organisation suggests that PV generates around 750kWh/year per kW installed, provided that the siting is not unnecessarily shaded or angled inclemently. Using a favourable feed-in tariff of 38p/kWh, the very cheapest arrays have a 14 year pay-back period. This is due to renewable generation such as wind and PV having a great deal of backing and sponsorship from governments, and grants are available. In the UK, for instance, a grant is available so that around 50% of a 2kW system may be claimed back [60]. It is believed that the price of PV systems is
set to fall [61] and as the price of electricity is rising [62], the pay-back period and the
grid parity point – the point at which the PV electricity is equal or cheaper than the
price of grid electricity – will become more favourable.

Characterisation for the VPP is made difficult for PV technology due to inherent
inaccuracies in forecasting ground irradiance values. Satellite based forecasts of
ground irradiance using albedos have a small margin of error (such as the Heliostat
satellites), as cloud movements are a complex, layered phenomena [63]. Again, like
windspeed forecasting, solar insolation forecasting is an area of ongoing research,
with studies ongoing mainly focusing on artificial intelligence [64][65][66][67] as a
means of accurately predicting cloud movement and thus insolation levels. Once
again, uncertain nature of the forecast determines that the power output for the VPP
must be considered probabilistically, as it cannot be determined accurately enough
using current prediction schema. PV arrays, like wind turbines, cannot be scheduled,
just as the weather cannot be; this is a feature which is shared amongst wind, PV and
micro CHP generation.

2.5 Micro Combined Heat & Power

Micro combined heat and power (micro CHP) is a new technology, based on larger
sized heat and power plants. The technology relies on harvesting waste energy from
other processes, thus the nomenclature. In micro CHP, the exhaust gasses from
domestic boilers have their exhaust energies lowered by placing an electrical
generator onto the output. This process can increase the efficiency of boilers up to
90%, a remarkably high value. Of course, this is under ideal conditions, but it still
emphasizes the value of this type of energy recovery.

The primary advantage of combined heat and power generators is that they utilize an
existing application and extend its function. In this way, the micro CHP boiler can be
installed in a home as a replacement to an existing boiler and duplicate its primary
purpose whilst also generating electricity. This electricity itself can be thought of as
requiring no fuel, as the primary energy source for the generator is the exhaust gasses
from the boiler, which is present during periods of operation for the boiler. It cannot
be said that no fuel is required, or that no fuel is burnt to produce the electricity, but
the electrical generation is from scavenging and this cannot simply be dismissed or overlooked.

The cost of micro CHP and their predictability are the two problems associated with them. The cost affects the pay-back period, although the high initial investment has a fast payback time, reportedly 4 years [68], which would be due to the high power rating of boilers. Given the lifespan of a boiler, typically 15 years, and the initial investment (as above) of £3000, the boiler would generate £8250 net, assuming the generation characteristics remained constant over the 15 years.

The second problem, mentioned above, relates to the characterisation of the generator in the VPP. By their nature, micro CHP generators are slaves to thermal power, so cannot be dispatched for their electricity without external control. Larger CHP generation can be fitted with thermal storage, although this is less common in micro CHP and is not considered as part of this work. As the exact temperature of every house is unknown, what remains is uncertainty, as the generator's output through thermal production cannot be directly predicted. What can be predicted, however, is the likelihood of the generator being used if the ambient temperature is known along with some basic housing characteristics. Similar to the previous technologies, the micro CHP generator must rely on probabilistic techniques to portray its power output.
Chapter 3  Predicting the VPP Power Output

This chapter introduces the concept of uncertainty into the prediction of the power output of the VPP. Starting from techniques already utilised and developed by others, the chapter lays down the method by which wind and PV arrays can have their power outputs amalgamated. The chapter also develops a mathematical model of the CHP boiler from which the electrical power can be predicted, completing the technology amalgamation. Finally, the chapter discusses the difference between the instantaneous power output from the VPP and the ‘long period’ power output.

3.1 Introduction

The introduction of dependence upon the weather brings with it the problems of predicting the weather. The weather itself is very simple, as it obeys many of the older laws of physics, pertaining to gasses and their pressure, and their movement, etc. This would lead us to believe that predicting the weather itself would be a menial task; however, there is a fundamental barrier which we may not overcome. That barrier is that we have insufficient data with which to predict the weather, i.e. an ill-conditioned problem.

Weather systems extend upwards for kilometres, and even past what most people would describe as ‘weather’, the upper levels of the atmosphere interact to produce changes which are tangible. As we cannot discern the data regarding the pressures, densities and velocities of all the gasses involved in the weather we must acknowledge that a degree of error is introduced when the weather is forecasted – to the extent that the further ahead we try to forecast (in terms of time), the greater is the uncertainty of the prediction.

Weather prediction is getting better, however, and complicated models and measurement systems now allow a greater volume and density of information to be collected. Forecasting techniques rely on computer models, where the missing data is often treated such that a number of possible cases can be produced from a single set of data. By taking the outcomes and finding correlations between them, modern forecasting is able to determine the most likely course of the weather. Using this
technique, a direct product of uncertainty is produced in the numerous unique outputs from the common set of input data.

One solution to the forecast problem is the persistence model. This model measures the weather data for one prediction period, and then maps these conditions onto the next prediction period on the assumption that the weather conditions will persist. The use of data which has been measured is advantageous, but trying to apply it to the next prediction period on the basis of a close time horizon is not so advantageous. Robinson discusses this technique in greater detail in [69], but finds that whilst the technique is not invalid, this technique is poor in contrast with the use of correctly utilised forecasted data – p190 “a persistence forecast can easily be off by 20° (F) or even 40° if there is an overnight change in airmass” and “the (persistence) forecast, if we say it every day for a year, we should be right about 67 percent of the time. The NWS (National Weather Service) had better be (and certainly is) right more often.” This work, therefore, does not use the persistence model.

The reliance upon the weather brings about a certain uncertainty for several reasons. The first of these is the resolution of the weather forecasts, both in terms of distance, and in terms of time. The UK Met Office gives a spatial resolution of 12.5×12.5km for their general predictions [70], which is large enough to contain an entire VPP. The disadvantage of having such a large spatial size is that the spatial resolution is low, so geographical obstacles which are smaller than this size are averaged out, in the same manner in which details are difficult to make out or completely removed from low resolution pictures. Continuing the metaphor, the forecast is a low resolution picture, and in order to predict the weather across the VPP to the highest accuracy, a high resolution picture is required.

One way to resolve this spatial resolution problem is to use the initial prediction data in a second forecast which has a much higher spatial resolution, using the initial prediction as the boundary conditions. Adapting to the local terrain, the second forecast is more likely to expose the details that were hidden with the lower resolution forecast. Programs such as WAsP [71] are employed to expose the hidden details for use in wind speed (and direction) for wind turbines.
As mentioned above, the temporal resolution for the forecasts also plays a role in the uncertainty. In [72], a typical forecast data resolution at 15 minutes is given, but it would be unwise to assume that the forecast was a constant through the entire period, switching instantly to the next forecast when that point arrived. The forecast changes in accordance with the weather systems which are driving it, which move slowly, taking days to change. Beneath this are the fronts, which can be predicted over many hours. Beneath this is the weather seen at ground level, which fluctuates rapidly over the course of a minute or so. Van der Hoven used this information and found that when predicting wind speeds, there is a trough of minimum deviation between 10 and 60 minutes, named the spectral gap [73], Figure 3.1. Periods shorter than this suffer from the rapid low level mixing at ground level (peaking at around 1 minute), and periods after this are affected by the movement of weather fronts (peaking at about 12 hours). A further peak was found at 4 days, which represents the movement of weather system.

![Figure 3.1: Van der Hoven's Spectral Gap [74]]

Therefore, when trying to predict wind speed, it is useful to have a resolution of between 10 and 60 minutes. Solar insolation, on the other hand, involves the movement of many layers of clouds, which may be on a low level, a front level, or a system level. As the deviation at ground level shows peaks at points which represent the movement of the three major components which make up the changing weather, of which clouds are a party to, it is safe to conclude that the prediction of solar
insolation will also trough between 10 to 60 minutes because the clouds which vary the solar insolation levels are driven by the wind.

With this in mind, the temporal resolution of the forecasts given above is fairly ideal, sitting as it does inside of the spectral gap. This is to be expected, as meteorologists should know exactly what does and what does not constitute a reliable weather forecast in terms of both spatial and temporal resolution. The ideal weather forecast would have a very high spatial resolution, maintaining the good temporal resolution available at present. Developmental models have a spatial resolution of 1.5×1.5 km, with a time-frame of 15 minutes [70], which is an important improvement to current forecasts.

The second aspect which adds uncertainty to weather forecasts is something which was mentioned above, and that is that certain features can be beneath the detail level of the prediction – or outside of it. Weather forecasts aim to provide the mean value over their prediction area and time period, and a single prediction value does not indicate any amount of variation, although it is likely that variation will occur. When forecasting wind speed, mechanical mixing at low levels will cause the wind speed to fluctuate (as mentioned above, this variation peaks at about 1 minute) as the wind manoeuvres around obstacles and drags along the rough surface of the Earth. The transition of clouds over the sun causes temporary drops and rises in the level of solar insolation when compared to the average for the period. Generally speaking, the variation of wind speed can be defined by the height to be determined and a term known as the roughness length, which is an indicator of how much turbulence the obstacles in the path of the wind generate. The variation through cloud transition is less well defined, although the root mean squared error of the insolation levels provided by the Meteosat 8 against numerical weather prediction is seldom above 20% [6, 75], which can be substituted for this value until a better definition is found.

There are also two different power outputs which need to be considered. The instantaneous power output for each generator gives a measure of the variation which can be found over the course of the measurement time period. This is useful for determining possible swings of voltage and stability within the network, but is less useful in terms of energy trading, where a net volume of energy is more important.
Therefore, alongside the instantaneous power output, the VPP must also provide a measure of the average power that will be produced over the measurement period, which can be used for energy trading and system management over a longer time period.

### 3.2 Uncertainty in Wind Power Forecasting

As mentioned earlier, when dealing with wind speed variation, we deal with a term known as the roughness length. It is the measure of the drag imposed on the wind by the friction of the obstacles on the ground, and has units of metres. Table 1 below lists typical roughness lengths for several types of terrain [76].

<table>
<thead>
<tr>
<th>Types of Terrain</th>
<th>Roughness Length (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cities, forests</td>
<td>0.7</td>
</tr>
<tr>
<td>Suburbs, wooded countryside</td>
<td>0.3</td>
</tr>
<tr>
<td>Villages, countryside with trees and hedges</td>
<td>0.1</td>
</tr>
<tr>
<td>Open farmland, few trees and buildings</td>
<td>0.03</td>
</tr>
<tr>
<td>Flat grassy plains</td>
<td>0.01</td>
</tr>
<tr>
<td>Flat desert, rough seas</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Using this measure, it is possible to determine the turbulence value \( I_u \) for the wind speed at a site, using the following formula [77].

\[
I_u(z) = \frac{1}{\ln \left( \frac{z}{z_0} \right)} \quad (3.1)
\]

\( z \) is the height at which the wind speed is required (usually the wind turbine hub height), and \( z_0 \) is the roughness length.

The relationship between the turbulence value and the wind speed is that this value is the standard deviation of the wind distribution divided by the mean wind speed for the distribution. Mathematically speaking, it has the following form.

\[
I_u = \frac{\sigma}{\bar{U}} \quad (3.2)
\]

Sigma (\( \sigma \)) is the standard deviation, and \( \bar{U} \) is the mean wind speed.
If the forecasted wind speed is the mean wind speed, (3.1) and (3.2) can be combined to define the standard deviation for the forecast.

\[
I_u(z) = \frac{1}{\ln \left( \frac{z}{z_0} \right)}
\]

\[
\sigma = I_u \times \bar{U}
\]

\[
\sigma = \frac{\bar{U}}{\ln \left( \frac{z}{z_0} \right)}
\]  

(3.3)

This information provides 2 of the 3 pieces of information required to build the wind speed distribution for the site; the mean wind speed and the standard deviation of the wind speed. The missing piece of information, at a basic statistical level, is the distribution type. The Weibull distribution is commonly used [78] to describe the distribution of wind speeds over the course of a year, although there is little reason to assume that the same would be true over a shorter period of time. The normal distribution and the uniform distribution (Figure 3.2) were used initially during this work; the normal distribution is usually found representing natural phenomena, hence is the obvious choice as the distribution for this natural phenomena, whilst the uniform distribution is mathematically much simpler. The normal distribution was abandoned for the more advanced work, as will be discussed later.

Figure 3.2: Normal and Uniform Distribution
With the wind speed distribution found using either of the above distribution choices, the power output from the wind turbine can be evaluated provided that the power output curve for the turbine is known. This curve is a measurement of the amount of power generated by the turbine against the input wind speed. It commonly has a shape similar to the one shown in Figure 3.3.

As the probability for each wind speed is described statistically, and the power output from each wind speed is also known, the two graphs may be combined to yield the turbine power output.

For example, the upcoming forecast predicts that the wind distribution will be uniform, and will be between $3.0 \text{ms}^{-1}$ and $6.0 \text{ms}^{-1}$. The wind turbine has the profile shown in Figure 3.4:
By inspection, it is clear that no generation occurs beneath 4ms\(^{-1}\); therefore a third of the probable wind will produce no generation. The remaining wind, between 4 and 6ms\(^{-1}\), lies on the straight slope, starting at 4ms\(^{-1}\) and 0kW, and terminating at 6ms\(^{-1}\) and 0.25kW. The remaining two thirds of the probable windspeeds will therefore fall evenly distributed between 0kW and 0.25kW, leading to the final output graph, Figure 3.5:

![Figure 3.5: Example Power Output Graph](image_url)

In this most basic setup, the long period power output is simply the average of the instantaneous power output.

### 3.2.1 Air Density

A known assumption to the wind uncertainty work of this chapter, and the next, is a constant air density, leading to the standard power curve. In reality, the air density adjusts the power output from the generator terminals. The changes introduced by considering air density are discussed here briefly, so as not to be noticeably absent from the work.

The power in the wind is known to be:

\[
P(v) = \frac{1}{2} \rho A v^3
\]  

(3.4)

Where \(v\) is the wind speed velocity, \(\rho\) is the air density, and \(A\) is the cross-sectional area of flow [7].

A wind turbine converts wind power to electrical power with a conversion efficiency that varies with the wind speed. This conversion curve is known as the power coefficient, and can be derived from the power curve provided that the rotor swept
area is known (standard test conditions are at 15 °C and sea level). It typically has the shape shown in Figure 3.6.

![Figure 3.6: Turbine Power Curve and Power Coefficient](image)

By using the power coefficient with the forecast air density, a more accurate power curve can be produced for each forecast, thereby adjusting the power accordingly. The air density can also be determined theoretically if it is not listed, using the altitude of the turbine, the barometric pressure, and the temperature.

### 3.3 PV Basics

The uncertainty involved with photo-voltaic generation is constituent to the problem of forecasting insolation levels. Predicting the movement of clouds has inherent problems of the value forecasted, and the spatial resolution can lead to good accuracies on clear days and large errors on days where the clouds are more dispersed. Short-term forecasted data, called nowcasted data, is only as accurate as the satellite data which is used as the basis for prediction. Meteosat 8, a Heliosat, has a spatial resolution of 1km², a temporal resolution of 15 minutes and an relative root mean squared error of 20% [9].

Co-existing with this problem is the fact that solar irradiance comes in two categories, direct and diffuse irradiance. For the purpose of the model it is assumed that all irradiance is received directly. Unless the tilt on the PV array is sufficient to obfuscate a large portion of the sky, this should not impinge greatly on the array.
PV arrays do not have a power curve which directly converts between irradiance and power output. The power data provided with a PV array is measured under standard test conditions, which is a spectral intensity of airmass 1.5 at 1000W/m\(^2\). The airmass figure is not explained here further, other than that it is a measure of the relative length of atmosphere which sun-light must pass through and by which, due to atmospheric absorption and scattering, certain frequencies of light become greatly attenuated. The figures are useful as an indicator of efficiency and power output, however.

It is known that the power controller of a PV array seeks to maintain the cells at the maximum power point; hence the equation for the array power is greatly simplified, as the power output is proportional to the incident light power. Given a standard test condition to measure power of 1000W/m\(^2\) at 25 °C, it can be written that [20],

\[
P = P_{STC} \times \frac{G}{1000}
\]  

(3.5)

Where \(G\) is the incident array radiation, and provided that the temperature remains at 25 °C. Power output is known to vary linearly with the cell temperature, and the temperature co-efficient of the cell is given along with the power data. Therefore:

\[
P = P_{STC} \times \frac{G}{1000} \times [1 - b(T - 25\, ^\circ C)]
\]  

(3.6)

Where \(b\) is the temperature coefficient and \(T\) is the temperature in Celsius.

The temperature on the PV array is normally above the ambient temperature, as they have a high level of absorption and a low level of emission. The cell temperature can be given using the NOCT method,

\[
T_{Cell} = T_{amb} + \left(\frac{NOCT - 20^\circ}{0.8}\right) . G
\]  

(3.7)

Where \(T_{Cell}\) is the cell temperature, \(T_{amb}\) is the ambient air temperature in Celsius, NOCT is the nominal open circuit temperature in Celsius, and \(G\) is the solar insolation in kWm\(^{-2}\). The NOCT method for estimating cell temperature is based upon a test at 0.8kWm\(^{-2}\) with a windspeed of 1ms\(^{-1}\) and an ambient temperature of 20 °C, and is more realistic than assuming the temperature to be equivalent to ambient conditions, as:
“Since only a small fraction of the insolation hitting a module is converted to electricity and carried away, most of the incident energy is absorbed and converted to heat.”, p 476 [79].

Although this is the formula used in the model, it is a slight simplification. Assuming a maximum power point tracker, as we have done, a more accurate series of equations are [80],

\[
I_{pv} = I_{sc} \cdot \left(1 - C_1 \cdot \exp \left[ \frac{V_{pv} - \Delta V}{C_2 \cdot V_{oc}} - 1 \right] \right) + \Delta I \]  

(3.8)

Where

\[
C_1 = (1 - I_{mp} / I_{SC}) \cdot \exp \left[ -\frac{V_{mp}}{C_2 \cdot V_{OC}} \right] \]  

(3.9)

\[
C_2 = \frac{V_{mp}}{V_{OC}} \cdot \frac{1}{\ln \left(1 - I_{mp} / I_{SC} \right)} \]  

(3.10)

\[
V_{pv} = V_{mp} \cdot \left[1 + 0.0539 \cdot \log \left( \frac{E_{nt}}{E_{st}} \right) \right] + \beta_0 \cdot \Delta T \]  

(3.11)

\[
\Delta V = V_{pv} - V_{mp} \]  

(3.12)

\[
\Delta I = \alpha_0 \cdot \left( \frac{E_{nt}}{E_{st}} \right) \cdot \Delta T + \left( \frac{E_{nt}}{E_{st}} - 1 \right) \cdot I_{SC} \]  

(3.13)

\[
\Delta T = T_{cell} - T_{st} \cdot \frac{T_{cell}}{T_A} = T_A + 0.02 \cdot E_{nt} \]  

(3.14)

Where \( I_{mp} \) is the module maximum power current (A), \( I_{SC} \) is the module short-circuit current (A), \( V_{mp} \) is the module maximum power voltage (V), \( V_{OC} \) is the module open-circuit voltage (V), \( V_{PV} \) is the module maximum operating point voltage under arbitrary conditions, \( E_{nt} \) is the total irradiance incident to the module plane (W/m\(^2\)), \( E_{st} \) is standard light intensity (1000W/m\(^2\) at AM 1.5), \( \alpha_0 \) is the module current temperature coefficient (A°C), \( \beta_0 \) is the module voltage temperature coefficient (V°C), \( T_{SC} \) is the standard temperature (25 °C) and \( T_A \) is the ambient temperature (°C).

Note that these equations are for a single module, thus for the overall power produced by the array,

\[
P = N_p \cdot N_S \cdot V_{PV} \cdot I_{PV} \cdot F_C \cdot F_\theta \]  

(3.15)
Where \( N_P \) and \( N_S \) are the number of modules in parallel and series, respectively, and the power loss through connection and other detrimental effects are \( F_C \) and \( F_O \) respectively.

Regardless of the PV cell model chosen, the PV power formula does not relate the nowcasted irradiance value to the irradiance seen by the area of the PV array, however, unless the array is installed flat to the ground. The irradiance per square meter must be adjusted to account for the angles of the solar cells and the angles of the sun. The situation is easily explained using a diagram, Figure 3.7.

\[
G = G_n (\sin \beta \cos \phi + \cos \beta \cos \alpha \sin \phi)
\]  

(3.16)

Provided \( G_n \) is the direct beam intensity. Using the nowcasted value of \( G \), it can be seen that the direct irradiance value \( G_n \) can be obtained and this value used to determine the irradiance falling on the solar cell. This may then be used as per the formulae above to determine the power output.

As an illustrated example, a solar array rated at 3.5kW at 1000W/m\(^2\) at 25 °C is installed. The array is tilted 5° from the horizontal, and faces due south (180°). The

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{diagram.png}
\caption{Solar Angles Diagram}
\end{figure}
sun’s altitude is 30°, with an azimuth of 190°. The predicted irradiance for 15 minutes is 150W/m². This information is shown in Figure 3.8.

![Figure 3.8: Solar Cell Example](image)

We know that (3.16):

$$G = G_n (\sin \beta \cos \phi + \cos \beta \cos \alpha \sin \phi)$$

Therefore:

$$150\text{W/m}^2 = G_n(\sin 30^\circ \cos 0^\circ + \cos 30^\circ \cos 10^\circ \sin 0^\circ)$$

$$150\text{W/m}^2/0.5 = G_n$$

$$300\text{W/m}^2 = G_n$$

This value is the intensity of the beam, and must not be mapped to the solar array, which is not coplanar with the ground. Hence:

$$G = 300\text{W/m}^2 \times (\sin 30^\circ \cos 5^\circ + \cos 30^\circ \cos 10^\circ \sin 5^\circ)$$

$$G = 300\text{W/m}^2 \times (0.498 + 0.074)$$

$$G = 171\text{W/m}^2$$

This value is greater than the forecasted irradiance due to the tilt of the array. The array produces 600W at 25 °C. The temperature coefficient of the array is 0.5%, with a NOCT of 50 °C, and the temperature is given as 15 °C, hence,

$$T_{Cell} = 15 + 6.4125 = 21.4^\circ\text{C}$$

$$P = 600\text{W} \times [1 - 0.005 \times (21.4^\circ\text{C} - 25^\circ\text{C})]$$

The generation for this array at 15 °C is 610.8W.

With the basic working principles in place, it is then possible to come to terms with the uncertainty associated with the nowcasted irradiance data. Studies [9][81] have shown that the sky models used to predict direct and beam irradiance have a root mean square error of approximately 20%, although this varies according to the
particular model for the conditions. Once again, though, the studies do not offer a
distribution of their results, although in [9] the graphs are shown with error lines of
twice the standard distribution, above and below.

To build the Long Period power model requires the solution of many of the same
problems found for the wind model. The mean solar irradiance predictions, like the
mean wind speed predictions, are assumed to be 100% accurate. The movement and
shadow of clouds is the parallel of the wind’s turbulence for the PV model, therefore
the power generation will approach the mean value if a suitable period is chosen to be
measured. This, of course, relies on the assumption that irradiance values also have a
spectral gap, whereby the deviation from the prediction is at a minimum.

Considering the resolution of solar predictions, approximately 1km × 1km,
meteorologically speaking the turbulence in the irradiance data should be caused by
microscale events. These are meteorological events whose sizes are usually less than a
kilometre square, such as puffs of cloud. Mesoscale or synoptic scale events, such as
large cloud formations or weather fronts are much easier to predict and follow natural
laws; these form the basis of weather forecasting, and are considered accurate.

Therefore it is the microscale clouds which are the greatest contributor to irradiance
errors. Considering the size of these objects and their speed, it is possible to assume
that over the course of a period of about 15 minutes a great deal could pass through
the kilometre square of interest. As none of these objects is deep enough or large
enough to greatly affect the diffuse of beam irradiance it may also be assumed that
during this time period the change in total irradiance is not great. When these two
pieces of information are combined it becomes apparent that the small deviation due
to the microscale events is shrunk over the time period due to their frequency.

It may seem strange to choose this period as it is only 5 minutes longer than the
minimum period required for wind prediction; however, insolation data is forecastable
at 15 minute intervals using current technology. With this technology placing an
effective limit of 15 minutes before the next prediction is available to work with, there
seems to be little reason to attempt to shorten the period.
Similar to the basic wind turbine method, the long period power output is the average power of the PV array’s instantaneous power output.

### 3.3.1 Clearness and Diffusion Index

Although the work herein does not utilise the clearness index for the PV model, it would be remiss to not include it.

The clearness or clarity index, $K$, is a measure of the ratio between the light hitting the top of the atmosphere (at Air Mass 0) and the light hitting the ground plane. Although the exact ratio is dependant on the latitude and the scattering encountered in the light path, attenuation of 20-40% is normal for a clear day, whilst 70-90% can be experienced on a cloudy day.

Further to this, the diffusion index $K_D$, is the ratio of the diffuse light and the ground plane light. Assuming a negligible amount of reflected light, the beam fraction, which is the ratio of beam insolation to the total insolation on the ground plane, is $1 - K_D$, as the total insolation is,

$$I_{\text{ground}} = I_{\text{beam}} + I_{\text{diffuse}}$$

Using the clearness index, the diffusion index, and the tilt of the PV array, it is possible to determine the value of insolation falling on the PV array’s incident plane using the insolation at Air Mass 0, although theoretical data measured against real data can be not well fitted and have a large degree of scatter [82].

### 3.4 Micro Combined Heat & Power Basics

The micro CHP generator is somewhat different to the other technologies, as its main purpose is not the generation of electricity. Its primary purpose is to produce heat, therefore in order to characterise the micro CHP generator the periods where it is generating heat must be determined. Let us assume that the whole system may be modelled as a house which has a temperature, a heat capacity and a thermal resistance. The house loses heat through the insulation due to a difference of temperature between the domestic and ambient temperature. The house gains thermal energy, and thus temperature, through the boiler. This may be represented by its electrical equivalence.
The heat capacity of the building acts like a capacitor, storing heat instead of electrical charge. In this way, the boiler can be represented by a current source, as it charges up the capacitor (increases the building temperature) when it is engaged, as shown in Figure 3.9.

![Figure 3.9: MicroCHP Diagram](image)

With this information it is possible to represent and solve the system mathematically provided that the thermostat range for the house is known, provided that two conditions are met. The first condition is that the ambient temperature falls beneath the cut-in point for the boiler. If the temperature does not fall to this level, the whole process may be simplified by assuming that the boiler is not engaged during the period of observation. The second condition is that the temperature difference is not too great for the boiler to be able to support. If the temperature cannot rise above the cut-out point for the boiler once the boiler has been engaged, it can be assumed that the boiler will remain engaged for the entire period of observation.

The assumption that the only use of the boiler is to heat the house is not entirely correct. The use of hot water for washing and other purposes requires that the boiler be engaged, and electrical power produced as a by-product. This alternative use of the boiler is fractionally only a small use per year [83], indicating that this assumption is acceptable as it is being applied over many generation units. If the usage of boilers for hot water is measured and reduced to a probabilistic event, this should be included in the on-time for the boiler for the period to improve accuracy, and the assumption can be removed.

Under the proviso of the two conditions, 2 equations are available from the data. The first is a function which provides the temperature rise from the point at which the boiler is engaged. The second is the antagonist to this, the function which provides the temperature fall from the point at which the boiler is disengaged. Thus the first has a
starting temperature of the cut-in point, and the second has a starting temperature of the cut-out point.

From each of these may be derived a time period. The time period deduced from the 1\textsuperscript{st} equation is the time taken to reach the cut-out point; this is the ‘on time’ for the boiler. The time period deduced from the 2\textsuperscript{nd} equation is the time taken to reach the cut-in point; this is the ‘off time’ for the boiler. By taking the ratio of the length of ‘on time’ against the total cyclical period, the duty cycle for a set of conditions may be obtained. The following worked example demonstrates this, defining both of these equations algebraically.

A house is known to have a thermal resistance between the inside and outside of 0.005K/W, and a heat capacity of 1000kJ\textsuperscript{-1}. The house boiler is rated at 10kW heat with 3kW of electrical cogeneration. The building thermostat has a cut-in temperature of 19 °C and a cut-out temperature of 22 °C. The boiler is set to maximum and the ambient air temperature is 6 °C.

The instantaneous power loss is given by,

\[ p = \frac{6°C - t}{0.005 K/W} \]  (3.17)

Where \( t \) is the instantaneous temperature. It is known that,

\[ E = 1000 kJ/K \times t \]

\[ \therefore t' = \frac{E'}{10^6} \]  (3.18)

Given that power is the derivative of energy against time, by substitution,

\[ t' = \frac{p}{10^6} = \frac{6°C - t}{0.005 K/W} \times \frac{1}{10^6} = \frac{6 \times 10^{-6}}{0.005} - \frac{10^{-6} t}{0.005} \]

\[ t' = 1.2 \times 10^{-3} - \frac{1}{5000} \times t \]  (3.19)

By taking the Laplace transform of (3.19), the output may be resolved.
Chapter 3  Predicting the VPP Power Output

\[ sF(s) - t_0 = \frac{1.2 \times 10^{-3}}{s} - \frac{1}{5000} \times F(s) \]
\[ sF(s) + \frac{1}{5000} \times F(s) = \frac{1.2 \times 10^{-3}}{s} + t_0 \]
\[ F(s)(s + \frac{1}{5000}) = \frac{1.2 \times 10^{-3}}{s} + t_0 \]
\[ F(s) = \frac{1.2 \times 10^{-3}}{s(s + \frac{1}{5000})} + \frac{t_0}{s + \frac{1}{5000}} \]

And by taking partial fractions,
\[ F(s) = \frac{6}{s} - \frac{6}{s + \frac{1}{5000}} + \frac{t_0}{s + \frac{1}{5000}} = \frac{t_0 - 6}{s} + \frac{6}{s} \]
\[ \text{temp}(\text{time}) = (t_0 - 6)\exp\left(-\frac{\text{time}}{5000}\right) + 6 \]
\[ \therefore \text{temp}(\text{time}) = 16\times\exp\left(-\frac{\text{time}}{5000}\right) + 6 \quad (3.20) \]

From this expression, the ‘off time’ may be determined. More importantly, the general expression for the ‘off time’ can be evaluated as,

\[ \text{temp}(\text{time}) = (t_0 - t_{\text{ambient}})\exp\left(-\frac{\text{time}}{RC}\right) + t_{\text{ambient}} \quad (3.21) \]

Where \( t_0 \) is the start temperature - the boiler cut-out temperature, \( t_{\text{ambient}} \) is the ambient air temperature, \( R \) is the building thermal resistance, \( C \) is the building heat capacity and \( t \) is now the time. In this example, the ‘off time’ works out to be,

\[ 19 = 16\times\exp\left(-\frac{t}{5000}\right) + 6 \]
\[ \frac{13}{16} = \exp\left(-\frac{t}{5000}\right) \]
\[ \ln\left(\frac{13}{16}\right) = -\frac{t}{5000} \]
\[ -5000 \times \ln\left(\frac{13}{16}\right) = t = 1038.2s \]

Similarly, the ‘on time’ may be determined by adjusting the instantaneous power function to,

\[ p = \frac{6-t}{0.005} + P_{\text{boiler}} \]

Following through,
Leading to an ‘on time’ of 422.8 seconds. More importantly, the general expression for the ‘on time’ can be given as,

$$temp(t) = (t_0 - \frac{P_{boiler} \times R - t_{ambient}}{RC}) \exp\left(\frac{-t}{RC}\right) + P_{boiler} \times R + t_{ambient}$$ (3.22)

This leads to an overall cycle length of 1461.0s, or 24 minutes and 21 seconds, and a duty cycle of 28.9%. It is easy to assume that the statistical split is, therefore, a 0.289 probability at 3kW, and a 0.711 probability at 0kW, all other generation values having a probability of 0.0. This assumption is accurate for the purposes of the instantaneous CHP power model, as it deals with the instantaneous quantities, of which there are only two – the boiler having only 2 operational states.

For the long period power model, this would be an incorrect assumption, however. Assuming a measurement period of between 15 and 20 minutes, it is clear that the measurement period will be of equal length (if not shorter) than the cycle length of the boiler under working conditions.

If the measurement period is a multiple of the boiler cycle length (as in Figure 3.10), only a single probability can be obtained for the period – any translation of the $t_0$ point will still include the same amount of generation for the period. If the measurement period is not a multiple of the boiler cycle length, it is necessary to determine how much of the on and off periods will by caught by the measurement period, inclusive of any possible translation of the $t_0$ point. Illustrated,
No matter where the measurement period is moved to along the axis, or how many multiples of the cycle length it becomes, the fact that the frequency of the line above is fundamentally the same as the CHP cycle means that it will always produce a probability graph with a single generation value. This value will be at the power point $P_{On} \times \text{Duty-Cycle}$, and will have a probability of 1. Extending the measurement period past this length slightly,

The measurement period is now an integer multiple of the CHP cycle length, plus a constant factor (in Figure 3.11, 1 whole integer section, and 0.4 partial sections). Translation of the integer section of the measurement period will not affect its contribution to the power distribution; as it is a multiple of the boiler duty cycle it will always contain the same amount of on time and off time, regardless of translation. Translation of the remaining section of the measurement period can sample a variety of different on and off periods, and will produce many different probabilities depending upon where it is translated to. In the figure, the partial section measures a period where the generator is mostly on, although a translation could easily move the partial section into the substantial off period.

In essence, there are 4 different measurement conditions for the partial section, which are illustrated in Figure 3.12. In the illustration, $t$ represents the constant of the measurement period less the integer, or whole sections, $t_{on}$ the on-time of the cycle, and $t_{CHP}$ the cycle length. Thus,
Figure 3.12: Four CHP Conditions

In condition 1, $t_{on}$ is less than $t$, and $t_{CHP} - t_{on} (t_{off})$ is greater than $t$, whilst in condition 2 $t_{off}$ is less than or equal to $t$. In condition 3, $t_{on}$ is greater than or equal to $t$ and $t_{off}$ is less than $t$, whereas in condition 4 $t_{off}$ is greater than or equal to $t$.

Each of these conditions evaluates to a different graph, which is then used in conjunction with the ‘multiple part’ graph to produce the long period power generation probability graph. In order to build this, it is only necessary to weight the graphs according to their relative likelihood. If the integer sections of the measurement represents 80% of the total measurement period, it should be weighted as 80% of the final graph. Similarly, when determining the equations for each of the conditions, a value which occurs for x% of the time, for instance, should have a probability of x%. The equations, then, are,

\[
P_{Max} = P_{on} \times \frac{t_{on}}{t}
\]

\[
P_{Min} = 0
\]

\[
P(x) = \frac{2 \times t_{on}}{t_{CHP}} \cdot \frac{1}{P_{Max}}, x > 0, x < P_{Max}
\]
Chapter 3  
Predicting the VPP Power Output

Condition 2: \( t_{on} > t, t_{off} \leq t \)

\[
P_{\text{Max}} = P_{On} \times \frac{t_{on}}{t} \tag{3.28}
\]

\[
P_{\text{Min}} = \frac{t_{on} + t - t_{CHP}}{t} \cdot P_{\text{Max}} \tag{3.30}
\]

\[
P(x) = \frac{2 \times (t_{CHP} - t)}{t_{CHP}} \cdot \frac{1}{P_{\text{Max}} - P_{\text{Min}}} \cdot \frac{1}{x > P_{\text{Min}}, x < P_{\text{Max}}} \tag{3.32}
\]

\[
P(x) = \frac{2 \times (t_{CHP} - t_{on})}{t_{CHP}} \cdot \frac{1}{P_{Max} - P_{Min}} \cdot \frac{1}{x > P_{Min}, x < P_{Max}} \tag{3.37}
\]

Condition 3: \( t_{on} > t, t_{off} < t \)

\[
P_{Max} = P_{On} \tag{3.33}
\]

\[
P_{Min} = \frac{t_{on} + t - t_{CHP}}{t} \cdot P_{Max} \tag{3.35}
\]

\[
P(x) = \frac{2 \times (t_{CHP} - t_{on})}{t_{CHP}} \cdot \frac{1}{P_{Max} - P_{Min}} \cdot \frac{1}{x > P_{Min}, x < P_{Max}} \tag{3.37}
\]

Condition 4: \( t_{on} > t, t_{off} \geq t \)

\[
P_{Max} = P_{On} \tag{3.38}
\]

\[
P_{Min} = 0 \tag{3.40}
\]

\[
P(x) = \frac{2 \times t}{t_{CHP}} \cdot \frac{1}{P_{Max}} \cdot \frac{1}{x > 0, x < P_{Max}} \tag{3.42}
\]

Continuing the previous example, the conditions may be further explained by selecting a period for measurement, or for prediction, of 15 minutes (900.0 seconds). This is a total of 0 integer multiples of 1461.0 seconds, with a remainder constant of 900.0 seconds. With an on-time of 422.8 seconds, it is clear that the correct condition is 1, as \( t_{on} \) is less than \( t \), and \( t_{off} > t_{CHP} \). Using the condition 1 formulae,
$P_{on} = 3000W$

$P_{Max} = P_{on} \times \frac{t_{on}}{t} = 3000 \times \frac{422.8}{900.0} = 1409.3W$

$P(P_{Max}) = \frac{t - t_{on}}{t_{CHP}} = \frac{900.0 - 422.8}{1461.0} = 32.7\%$

$P(0) = \frac{t_{CHP} - t - t_{on}}{t_{CHP}} = \frac{1461.0 - 900.0 - 422.8}{1461.0} = 9.5\%$

$P(x) = \frac{2 \times t_{on}}{t_{CHP}} \times \frac{1}{P_{Max}} = \frac{2 \times 422.8}{1461} \times \frac{1}{1409.3} = 0.041\%$

At first the value for $P(x)$ (provided $x$ is within the conditions specified above) may be seen to be very low, but it is to be remembered that the integral of this value over the length of 0 to $P_{Max}$ must fill in the remaining probabilities to cause the graph to sum to unity. A quick multiplication verifies that this value is correct, leading to a cumulative distribution function seen in Figure 3.13,

![Figure 3.13: Cumulative CHP Power Output](image)

These steps build the distribution profile for the microCHP generator, removing the temporal quantities from the output, as these are values which are simply not known to us; this is why statistical methods must be used.

### 3.5 Aggregating Generator Outputs

With the models above for the three technology types it is possible to build the power output graphs for the instantaneous or long period averaged cases for each generator by simply passing the relevant data to each function. The power output graphs for each generator must then be amalgamated to form the output for the VPP, a process
which is straight-forward. It is convenient if all the graphs are built according to the same discrete quanta, or divisor, such as 50W, although this is not a strict requirement.

It is known that each generator in the VPP acts independently, which is to say that at any instant of time there is no correlation between the output power of one generator and the output power of another generator. This independence of output indicates that at any instant of time, the generators which make up the VPP can be generating any power output described by their power output graph, in proportion to the figure listed by the relevant power output. Therefore, all possible permutations of the system must be evaluated in order to determine the power output for the entire VPP.

Mathematically, this process is a convolution operation for all the graphs which make up the individual power outputs, for all the data points of interest. The power values which are physically unattainable by the system do not need to be considered by the convolution operation, which provides two natural boundaries for the operation. The lower boundary is at zero, as it is impossible to produce less than zero power, and the upper boundary falls at the sum of the maximum for both generators, as it is impossible to produce more than this amount. All values falling on or between these boundaries must be considered.

At the method level, convolutions are normally done on data which has undergone a Fourier transform to turn it into frequency domain data [84]. Whilst this is an option, it is also possible to perform a manual convolution on the discrete data, starting with the first 2 generator power outputs. By starting with the first two points, their probabilities are multiplied and the result placed into the sum of the two power values under consideration. As the first point in both graphs is likely at 0 Watts, this product is usually placed at 0 Watts in the convolved power output. The next power value in the first graph is then chosen, its probability being multiplied by the power value’s probability from the second graph, and the result placed appropriately. This process continues until all the values of the first graph have been considered, at which point the second power value from the second graph is chosen, and the process repeats itself until finally every probability from the first graph has been multiplied by every probability from the second graph and suitably placed in the final convolved output.
Throughout the process, if a probability is to be placed in a power point which already contains a probability, the two are added together; the later product does not overwrite the previous product. Once the first two generators have had their outputs aggregated, the next generator’s power output is aggregated into the power output aggregate using the same technique as above.

An example of the process is illustrated in Figure 3.14 below, with the text describing the graphs.

In Figure 3.14 the upper pair of graphs show two parent graphs whose convolutions are in varying stages of being built in the lower child graph. The first stage convolves the 2nd parent by the first up to the marker 1, 20% of Parent 1. This is shown in the child graph as the trapezium marked 1, where the plateau of the convoluted shape is formed where all previous convolutions have overlapped, and where the sloping leading and trailing edge are caused where fewer of the combinations have overlapped. In the second shape (also encompassing the first shape), 60% of the first parent has been included in the convolution, the leading slope peaking where the most convolutions have overlapped. In the third shape (also encompassing the first two) the entire of both parents has been included in the convolutions, leading to the triangular shape seen, whose width is the sum of the non-zero portion of both parents and whose peak is central.
It is crucial to note that this method of aggregating only applies so long as the generators are independent of one another. The generators’ power outputs must also not be mutually exclusive. If one set of conditions is used to determine the power output of one generator, and another set of mutually exclusive conditions is used to determine the power output of another generator, one cannot aggregate these generators unless one or both of them is re-evaluated using mutually inclusive conditions. If two PV modules are operated in an area where the average solar insolation is identical over a half hour period, they may not be aggregated if they operate using different average insolation values over that half hour period. Both PV modules may still see local variations (which are independent random fluctuations and, therefore the PV modules can be aggregated), but the average insolation must be the same or else they will be mutually exclusive, and cannot be aggregated in this fashion. Although this point seems obvious in the very simple cases (it cannot be two different averages in the same region at the same time), it becomes a more involved topic when many stochastic power output graphs are to be combined to form a more detailed output, as will be discussed in Chapter 4.

Combining the long period power into an aggregate is very straightforward using the single data point forecasts. Each generator will have a power output graph from which the average power, thus the average power for the measurement period, can be determined. For wind turbines and PV modules, these averages can then be added together, as only a single value is available for each turbine and no complicated series of convolutions are necessary. The micro CHP boilers in the VPP have a long period power output graph which is described by one of 4 sets of equations, as noted above. The long period power graphs for the micro CHP boilers are aggregated using the convolution technique, which is then convolved with the single value for average power obtained from the wind turbine and PV modules (whose probability is only non-zero at one position); in other words, the micro CHP output is translated by the average value of long period power obtained from the other two technologies. In this fashion, the long period power output for the VPP can be determined.

The aggregation process is shown below, in Figure 3.15.
In order to build both types of output power graph, each generator is first passed the relevant forecast data. The micro wind turbines are passed the mean windspeed, the PV arrays are passed the solar insolation, insolation RMSE and temperature, and the micro CHP boilers are passed the temperature. Using the methods explained above, each type of generator can then produce a discrete output power graph for the instantaneous power using the generator characteristics provided for each generator. If any generator was to be considered by itself as a standalone plant, this graph would be the final result, but the entire VPPs output is to be characterised. Hence, by the process of a series of convolutions described above, the instantaneous power output graph is built. The long period power output graph is built according to the aggregation rules described above using the average power from the micro wind turbines and the PV arrays, and the long period power graphs from the micro CHP boilers.
Chapter 4  Improving the VPP Prediction Model

This chapter improves upon the models proposed in Chapter 3, through the use of updated technology models, as well as alternative weather parameter entry methods. Inverter efficiency curves and measured wind power curves are added to the methods, enhancing the accuracy of the wind and PV array models, whilst the weather data entry is updated to incorporate a stochastic set of data points or a meteogram data set for the time period, the merits of which are discussed here and in Chapter 1.

4.1 Introduction

Chapter 3 laid down the basic principles which are used in order to build the instantaneous and long period power output graphs for a single generator or a group of generators. In practice the techniques laid down in chapter 3 form only part of the process, as weather forecasts are not given as single points, but rather as a set of possible data points, or as a statistical distribution.

Using the single point technique, the output to the VPP can be determined using 4 pieces of forecast information; the mean windspeed, the mean insolation, the insolation RMSE, and the temperature. By passing this information through the transfer functions for every generator and convolving independent outputs, the final output for both instantaneous, and long period power, may be determined.

Weather forecasts are found using NWP, which produce a series of forecast points using a slight variation in the input data [85]. Using this data instead of a single point is more likely to be accurate to the weather forecast, as it is a more inclusive set of data, containing all the possible outcomes, instead of just one.

NWP forecasts can be interpreted or displayed in several ways. The first is to divide each forecast point into statistical buckets, which can be used to determine a discrete distribution of the forecast. From this, or alongside this, the cumulative distribution function (CDF) can be built, determining 5 data points. The 5 points vary according to the source, but the Met Office gives the pair of points which contain 95% of the distribution about the median, the pair of points containing 50% of the distribution
about the median, and the median value. These points can be easily read from graphs (known as Meteograms), hence their usage, as shown in Figure 4.1.

![Figure 4.1: NWP Meteograms](image)

The second way to interpret each forecast is to weight each forecast as equally likely to happen, and to use each forecast point from the NWP. If equal consideration is given to every point that makes up the NWP, the outputs may be superimposed according to their equal weighting, and this can be used to produce the results.

Both methods have their advantages and disadvantages. The raw NWP predictions are very buckshot in their prediction – using many attempts to determine the weather in
the hope that the reflected image will converge towards the point which best indicates future events. Statistically speaking this is a stochastic approach, taking many discrete events to build the overall outcome, and is disadvantaged in its choice due to occasional lone outriders – points which fall considerably outside the majority. It is possible to have several outriders, but it is clear that the small permutations in the initial setup used to build the forecasts should produce a continuous trend of data, even if several regions are troughs. Hence, the five point forecast takes a slightly (mathematically) smoother look at the NWP output, being built using data from the CDF. This smoothing action removes the discrete jumps contained in the data, but also has the potential to smooth over areas of the output which may require rather more detail.

A good example of this is a statistical twin peak, in which two distinct peaks are observable in the output. Consider the following graph, Figure 4.2, built as a hypothetical NWP.

Both graphs have exactly the same windspeed at each of the 5 points used to build the meteogram data, the missing data from the CDF being filled by straight lines. This smoothing operation results in a forecast which is similar in many ways, but details which are obvious in the original are no longer present. Of particular interest is the peak after the meteogram has been produced which falls exactly in between the 2 peaks of the original – exactly where a trough lies in the original NWP output.
The above is a worst case example, but should be considered when using 5 point meteogram forecasts. It is not part of this work to discuss the suitability of the data presentation methods used by meteorologists.

With that caveat dealt with, there are two methods of advancing the uncertainty work which was presented in the previous chapter. The raw NWP data can be used, or the 5 point data can be used. Both of these methods constitute a change to a stochastic method of operation, as compared to a deterministic modus operandi in the previous chapter. The 5 point data method offers a smooth transition, as mentioned above, which is useful in determining a long period power output which does not contain any sudden discontinuities.

### 4.2 The 5 Point Forecast Approach

The five point forecast technique offers a level of continuity which is otherwise unavailable, as mentioned above, but is missing two key points of interest from a statistical point of view. Those two points are the 0% and the 100% points, and this poses a problem because these points are required. For windspeed and solar insolation, the 0% point can be assumed to be at 0 (either ms\(^{-1}\) or Wm\(^{-2}\)), as these are both scalar values, and it is certain that the wind speed or insolation cannot go any lower than this. In order to determine the 100% point, some degree of symmetry of ratios is assumed. This is by no means a certainty, but in this case an arbitrary value is being inserted, so the known data is simply extrapolated as a method of reducing introduced error. If we know the ratio of distances from the 0% and 2.5% point to the 50% point, and it is assumed that the ratio is similar for the upper end points, the ratio from 97.5% and 100% point to the 50% point will be the same. This is not ideal as these two points are chosen rather arbitrarily, but it is a certainty that the maximum error introduced into the forecast is 5%, as this is the sum of 0%-2.5% and 97.5%-100%. The error will be smaller than this, if not much smaller.

When dealing with temperature forecasts, the assumption made above that the lower limitation is 0 °C must be removed, as the temperature can fall below this point. A new assumption must be made to determine the 0% point for temperature forecasts. An assumption is made at this point that the temperature distribution can be described
using 2 uniform distributions; one for all values less than the median, and one for all values above the median. Using this assumption, the 0% point has its position determined by calculating the ratio of temperature change per % between 2.5% and 50%, and then using this ratio to determine how much the temperature will change over the entire 50%. Once this figure has been subtracted from the median temperature, this final value will be the temperature at 0%. For instance, if the 5 data points were 0.0 °C, 5.0 °C, 10.0 °C, 15.0 °C, 20.0 °C, the ratio between the 0% and 2.5% point to 50% is (50% / 47.5% = ) 1.05. Multiplying this by the respective temperature difference gives (-10 °C × 1.05 =) -10.5 °C, which when added to the 50% point gives a 0% point at -0.5 °C. The same process is used to determine the 100% point, adjusting the inputs accordingly to deduce a maximum temperature of 20.5 °C for the example points above. These assumptions on temperature are less solid than the assumptions above on windspeed and solar insolation, so it is likely that the error introduced is higher, whilst retaining the 5% error cap.

When the 5 data points have been supplemented with the two end points to complete the set up to 100%, the points can be converted into a probability distribution, which can then be used to obtain the power output from the generation units. The power output determination operation is made more difficult when more than 1 data point is used, as is discussed below.

When a single forecast point is used to determine the power output in a VPP, it is a straightforward task to apply a standard deviation and then determine the power output from a generator. Combining/aggregating the output powers of the generators is similarly uncomplicated, as explained in the previous chapter. As an example, in order to combine several wind turbines we need to make sure that the mean windspeed at a reference height is identical for each unit. If one unit had a different mean windspeed, then we could not combine this with the other turbines because it is using a different forecast to all the others – these are mutually exclusive events. This is intuitive, and due to the fact that only a single data point for each forecast type is used in the basic forecast, it can be assumed that this is a certainty; all the wind turbines will have the same mean windspeed at the reference height, all the PV modules will have the same mean solar insolation before adjustments for tilt, etc. The windspeed, for instance, can then be adjusted for localised variations for each
generator, and the power output curves may be derived from this. The certainty that the mean windspeed is exactly the same, regardless of unpredictable local variations, allows the curves to be combined using a convolution.

When the forecast data set is increased to 5 and then to 7 points, it is incorrect to assume that the VPP’s power output can be determined by passing the forecast data to the correct transfer method or function with the generator’s parameters, and then amalgamating once all the generators have had their power outputs determined. The simple aggregation and the incorrect aggregation approach used for 5 point forecasts are illustrated in Figure 4.3.

![Figure 4.3: Incorrect 5 Point Assumption](image)

Both methods share a similar approach, but it can be observed that by passing the 5 point forecast through the same process as was used for a single point invalidates the mutual exclusivity of the process. Two wind turbines, for instance, using this approach can have their outputs aggregated despite the fact that more than 1 average windspeed is present to derive the output. This is not problematic by itself, as more than 1 average windspeed must go into producing the VPP’s power output if the forecast dictates it; what is problematic is that the basic aggregation process insists that these conditions co-exist at the same time - and this is physically impossible.
This co-existence of forecasts is a property of the convolution process, when applied initially to the forecast. Once the forecast has been put through the convolution process to determine local fluctuations, the initial forecast conditions are no longer discernable. The local fluctuations act to conceal the true origin of any point after the process has been completed, so it cannot be said that any of the forecast points can be used in the characterisation because they have almost all broken the principle of mutual exclusivity.

It should be noted that the rule that there can only be a single mean windspeed (or any forecast condition) is valid provided that the generators operate inside the area which has been forecasted. A generator which lies outside the forecasted region must have its output determined by using the forecast which is appropriate to it. This is the only occasion whereby there may be more than 1 mean windspeed. The mechanism of linkage between the two forecasts is not included in the 5 point forecast data, thus there is no support for this in the models, although the alternative NWP prediction models discussed below make use of this. The linkage data is required to determine which forecast conditions are related between regions: if one region is forecast 20% greater values than its neighbour, the correlation between the regions will show only that the distribution has shifted by 20%, and will not show which forecast conditions coincide (in this case, this is the +20% point). This linkage mechanism is required so that coincident weather conditions are considered at the same time, so that the power output curves are built accurately; if two (or more) possible weather conditions never occur at the same time, we should exclude them from our solution in exactly the same way as we cannot allow two (or more) mean windspeeds in the same region.

The other reason why the basic aggregation method cannot be applied, and is incorrect, is that it does not produce a valid long period power output for the VPP. In the basic uncertainty model, the long period power output for wind turbines and PV arrays could be determined by averaging the instantaneous prediction. The same mutual exclusivity problem exists when trying to assess the average; there is more than one average value for the measurement period once the forecast becomes more complex, but it is impossible to discern which of the generator’s output power probabilities are from which input forecast value. With no method for distinguishing how much of any given probability is from the correct initial forecast value, it is
impossible to use the average power to form a weighted average power graph, which is the long period power graph.

The correct method to build the power output with 2 or more forecast points is to consider each mean value by itself, combining the power output graphs in the usual manner. By considering all the forecast values in this fashion, a series of aggregated power outputs can be built, each one started using a slightly different forecast value. Each of this series can be placed into a final power output graph by weighting each of the series by its forecast probability and then superimposing the graphs upon each other. This process is illustrated below (Figure 4.4). This weighting and superimposition poses a challenge in terms of keeping the output purely probabilistic, as each mean forecast value must be considered and aggregated alone, and there are an infinite number of values that a mean forecast value can take between any points which are not equal.

![Figure 4.4: Correct Five Point Aggregation](image)

The necessary ramification of this process is that a stochastic output must be produced. Whilst it is impossible to calculate an infinite number of sections to the forecast, it is feasible to calculate a large, but finite number of sections. The drawback to this method is that it introduces error into the output, depending on the quantity of sections taken, in a similar way in which the raw NWP forecast slices the data. This will be discussed in further detail below.
Briefly mentioned above, the long period power output and its relationship with the chosen aggregation practise is critically affected by choosing the correct technique. This is due to the chorus affect of the generation units. When the forecast value changes slightly to increase the generation, let us say of PV arrays, all PV arrays inside the VPP will have their outputs increase. Therefore the long period power output will increase slightly, and the generators can be said to be acting in chorus, or unison. Continuing with the example, consider that a single PV array has a long period power output which is uniformly distributed due to a roughly uniform solar insolation forecast. To build the aggregated long period power for a group of these PV arrays, the shape of the long period power graph remains the same, because the generators are all acting in unison; when the single generator is at its lowest power output, all the generators are at their lowest power output, and this theme continues up to the maximum power generation. If the long period power graphs were built for each generator and then aggregated using the convolution technique, the mutual exclusivity so much aforementioned would come into effect once again, resulting in an incorrect result. The difference between the two techniques is shown in Figure 4.5, assuming the uniform long period power output example as discussed above.

![Incorrect and Correct Long Period Power](image)

**Figure 4.5: Incorrect and Correct Long Period Power**

### 4.3 Raw NWP Data Approach

The alternative to working with the 5 point forecast is to use the raw NWP output forecasts. Each one of these is produced by accounting for the slight error in the
measurements that go into building the initial state of the weather for the prediction model, leading to multiple similar outputs from the same initial conditions over the first 15 minute forecast. Of course, the divergence produced after the first 15 minutes becomes the initial conditions for the next 15 minute increment, leading to forecasts that are totally divergent after 14-20 days [86]. [87] uses this raw NWP technique (solely with wind turbines) as part of the Risø model with good results.

As mentioned above when discussing the 5 point forecast method, there are advantages to working with the raw forecasts. The smoothing inherent to the 5 point technique, as illustrated in Figure 4.2 is not present; allowing the smoothed details to become more prominent in the power output. The stochastic nature of the power output is also more apparent, as an ensemble of forecasts is being used to build an ensemble power output; no slicing of the distribution is necessary to build the output. Effectively, this has already been done by the ensemble process.

The disadvantage to using the ensemble NWP forecasts is that the long period power can contain power gaps. As discussed above, the continuous increase of the output from a single generator will, for the long period power output, scale in size in accordance with the number of similar generators. As the ensemble method does not increment the input forecast regularly using many sampling points, the long period power output will be limited to a probability resolution of \( \frac{1}{n} \), where \( n \) is the number of ensembles used to build the VPP power output. This is not without its advantages, however, as the smaller number of ensemble forecasts used to build the power output reduces the amount of computational power, and therefore time, which must be used to build it.

Besides the other advantages of the use of this technique, perhaps the most important feature of using ensembles is that multiple different forecast regions can be used to build a single VPP power output; technical or commercial. The five point forecast technique cannot predict the power output unless the generators all fall within the same forecast grid square, as the relationship between the 2 (or more) regions is unknown, whilst the forecast for 2 or more grid squares can be obtained by choosing the two (or more) forecasts with the same initial state from the NWP output.
The multiregional approach is important for the TVPP, because it removes the forecast area limitation on where the TVPP is bounded, and therefore how many generators can be placed within it. Of course, the network still bounds the TVPP, but that is the correct boundary for the TVPP. The multiregional approach is also important for the CVPP, because it allows an agent on the small scale to correctly estimate the power output of the VPP. Without the multiregional approach, the agent would have to deal with several sub-areas of the CVPP, whose power relationship was not understood. On a larger scale, the agent who overlooks several VPPs in several different geographical regions can predict the power forecast for his or her entire portfolio of generators, allowing additional levels of knowledge which can be used to adjust the selling volume, and the selling price, accordingly.

The method to produce the ensemble power output closely resembles the method used for the basic uncertainty work, with adjustments made to utilise the ensemble forecast. For the basic operation, a single forecast value was passed to each generator, which obliged by producing an instantaneous power output, and the average of this was the long period power output. The micro CHP boiler produced a variation on this process for the long period power output, but the concept remained the same. Both types of power output graphs from the generators were then aggregated using a series of convolutions, leading to a final result. For the ensemble forecast approach, the generators are passed a single forecast, but its value is determined by the forecast region. The rest of the process remains the same, with an introduced final step at the end. Once the instantaneous power and the long period power output has been determined for each of the $n$ forecast points, the instantaneous graphs for every forecast are superimposed, and the long period power output graphs are superimposed. The total probability in each type of graph will then be equal to $n$, thus all the probabilities in the graphs are divided by $n$ to normalise the probabilities. These two normalised graphs are then considered to be the output.

### 4.4 Technology Model Improvements

Aside from the methodological changes introduced by either of the NWP methods, improvements to the initial technology models are possible. The transfer functions used in the basic uncertainty work were simplistic, but function to prove that the technique works at a low level. Any advancement to the models will produce more
accurate transfer functions, and therefore more accurate power output forecasts for the VPP.

The two technologies which benefit from this advancement are wind turbines and PV arrays, because they have a dynamic range of output power and efficiency, whereas the micro CHP boiler is on or off, and has a relatively static range of power output.

The basic wind power profile used in the model is built using a total of 3 points: the cut-in point, the rated power point, and the cut-out speed. It is analogous to Figure 3.3, but that is only a theoretical power curve. A more realistic power curve is determined by measurement of an example of the wind turbine in question under test conditions, resulting in a curve which accurately maps the input speed to the power output. Compare and contrast the two curves in the figure below (Figure 4.6).

![Figure 4.6: Comparing Wind Power Curves](Image)

Clearly, there are key differences between the two, but the most apparent difference is the generation area that is cut-out between 20ms\(^{-1}\) and 25ms\(^{-1}\) by the early cut-out point for this turbine. The full ramifications of this difference will be discussed later, but it is apparent that the turbine will not achieve maximum power generation nearly as often as the basic model would indicate.
Chapter 4  Improving the VPP Prediction Model

The basic PV array model has a similar inherent problem, because it assumes that the DC power produced by the array is converted perfectly into AC power. This is a false assumption, as the inverter electronics which govern the conversion are not perfect, and the conversion efficiency falls as the amount of DC power produced by the PV array falls; this can be thought of as a semi-fixed amount of power that is lost to the conversion process, which has a greater impact on efficiency. Figure 4.7, below, gives an example of a more realistic inverter efficiency curve.

![Figure 4.7: Inverter Efficiency](image)

If the basic inverter efficiency curve were to be shown on the same graph, it would lie at 100%, and the margin between the two curves is what introduces the error between the two methods.

In order to incorporate the more complicated power profiles (either power output curves, or inverter efficiency curves), changes are necessary in the methodology of the models. If the basic profiles are used, using the basic power curve for wind turbines and a flat inverter profile for PV arrays, the determination of the output value for each and every point is achievable using only a few logic tests.

Under basic operation, when determining the output power for the micro wind turbines the windspeed distribution is built first, using the mean windspeed data adjusted for height and the roughness length for the turbine. The turbine data contains
3 windspeeds, forming 5 sections: the off section from 0\(\text{ms}^{-1}\) to the cut-in speed, the ramp section from the cut-in speed to the rated speed, the flat section at maximum power between the rated speed and the cut-out speed, the discontinuous section at the cut-out speed, and the off section after the cut-out speed, as shown in Figure 4.6. Of these 5 sections, the discontinuity can be ignored entirely as it cannot contain any quantity of probability. The 3 horizontal sections (at 0\%, 100\%, and 0\% power respectively) can have their probabilities calculated easily by inspection of the windspeed distribution. Bearing in mind that the power output graph is discrete in nature, the remaining ramping region of the curve between 0\% at the cut-in windspeed and 100\% power at the rated power windspeed can be evaluated by determining the intersection windspeeds for the required power (the upper and lower boundaries for the discrete power), and then using these values with the windspeed’s cumulative distribution to evaluate the quantity of probability bounded by the 2 windspeeds. This is shown in Figure 4.8.

![Figure 4.8: Old Method for Turbine Output Power](image)

Similarly, the flat inverter characteristic used in the basic model decreased the difficulty of building the output power graphs. The power output produced by the stated solar insolation condition is determined first, and then the output power distribution is built using the RMSE insolation value. This produces a continuous output power distribution. Each discrete power point in the output is determined using the cumulative distribution function of the output power, and any output power which
is greater than the inverter limit is assumed to have caused the inverter to shut-down to prevent overloading [88]. Thus the power regions which lie outside of the inverter limits are shifted respectively to produce 0 Watts AC power, as the inverter is shut-down in these regions.

Modifications are therefore necessary to accommodate the more accurate profiles. Of the two technologies, micro wind turbines are the more straightforward to modify. As has been discussed above, every discrete power point in the power output is evaluated to produce the output. The basic power curve requires an investigation into a single slope between the cut-in speed and the rated speed to determine the intersection points, whereas the more realistic power curve profile requires evaluation of every slope which makes up the power profile to determine the intersection points. The intersection points between the power and the windspeed are then used to lookup the probabilities from the CDF which are used to evaluate the probability for each discrete power point used in building the power output graph.

Each discrete power point in the power output refers to an output power which has an associated upper and lower boundary power. The basic technique requires that the two power points be checked against the single slope for intersection, and where these are found the corresponding probability can be read from the windspeed distribution. By checking against every slope instead of just one, the method can be expanded to cover the new turbine power curve, as shown in Figure 4.9, below. If more than one windspeed region is found to contribute to the power, the probabilities for each are added together to determine the probability, as in the example.
The PV inverter efficiency curve is more problematic to implement when contrasted to the micro wind turbine method, as they are implemented in slightly different ways. Referring back to the PV inverter efficiency curve, the inverter is more efficient at higher AC powers, and is 0% efficient at 0% AC power. The basic PV model does not contain inverter efficiency, however, and it is desirable to determine the power curve which will convert between the PV array’s DC power output and the inverter’s AC output, using the listed efficiency profile of the inverter. This power transfer curve can be produced by taking the reciprocal of the efficiency and multiplying by the AC power, but there is a small problem. The 0% efficiency value at 0% AC output power can take any value of DC power, as any value of input DC power multiplied by zero will give the correct result – that result also being zero.

By examining the points close to the 0% efficiency point the power curve can be seen to flatten vertically. Furthermore, in the efficiency region between 0% and the first efficiency point, it is easy to prove that the DC input power is a constant which can produce the power between 0 AC Watts and the power dictated by the first efficiency point. This forms a discontinuity in the power curve, at the end of which is the 0% efficient point. As this 0% efficiency point lies at the end of a discontinuity, it is no longer required to be determined, as no quantity of probability can be contained by a discontinuity. Placing this point at 0 output power is also the intuitive solution, as the
low efficiency is a result of diminishing input DC power from the PV array, hence the inverter output power will only rise above zero once the internal conversion losses have been overcome by rising input DC power. The power curve produced from the example inverter efficiency, Figure 4.7, is shown in Figure 4.10:

![Figure 4.10: Derived Inverter Power Curve](image)

This type of curve is of the same format as the wind turbine power curve, and the same techniques which are used in the building of the micro wind turbine power output, with the improved power curve, can be applied to the inverter power curve. The fundamental difference between the two power curves is that the inverter curve does not have insolation along the x-axis, instead it has the PV array DC power.

To use the inverter power curve, it is first necessary to convert both axis of the power curve into real power units instead of percentages. This is done using the power limit for the inverter, and produces a derived power output curve. If the PV array DC power equation, (3.6), is considered:

\[ P = P_{STC} \times \frac{G}{1000} \times [1-b(T-25)] \]

It can be seen that this can be rearranged to find the insolation on the PV array in terms of the DC output power as a quadratic equation, explicitly:
Using this expression, it is possible to determine the ratio between the insolation, $G$, and the DC output power, $P$, an example of which is shown in Figure 4.11. This relationship can be applied to the inverter power curve, adjusting the x-axis values to a corresponding insolation value. This derives a power curve which relates the insolation received by the PV array to the AC output power produced by the inverter. Thus, this new power curve is in the same format as the wind turbine power curve (relating the input forecast variable to a power output). With the power curve in a similar style to the wind turbine power curve, the more sophisticated output power graph building process defined for micro wind turbines can be applied to the PV array power curve in the same fashion (Figure 4.11).

![Figure 4.11: DC and AC Power Output against Insolation](image-url)
Chapter 5  Modelling Networks Effects in VPP

This chapter uses the prediction schemes developed in Chapter 3 and Chapter 4 as the generator data from which to perform a load flow operation in the network of the VPP. The load-flow model and supporting equations are developed in the chapter, culminating in the process used for the N-1 network security analysis. The load-flow tool developed with the prediction models is discussed in the Appendix.

5.1 Introduction

The transmission and distribution network plays a very important logistical role in the electricity business, as it allows the many devices used in domestic and light industrial processes to connect to a source of generation many miles away – centralised generation. This is how the network system has operated for many years, since Westinghouse [89], but the growth of DG threatens to unbalance this delicate system, particularly at the distribution level. The distribution network were designed with the purview of a unidirectional power system, which is to say that electrical energy was generated at the remote power plant and transmitted to where it would perform useful work at the load. The addition of DG and VPPs is set to upset this unidirectional balance by cancelling out load to the point at which a reversal of the flow of power can take place.

The power flowing through the transmission lines is modified by the physics of transmission through the lines, in accordance with power flow theory. The commonly described real and reactive power flow equations are given below [90]. It is unlikely that the installation of distributed generation will cause the lines close to the injection point to overload, as DG is usually located close to load centres [91], although there are knock-on effects due to the new steady state conditions. In particular, many transformers in the grid are configured such that the power flow across them is from the centralised generators to the load, and adjusts the voltage and phase accordingly.

The basic equations governing the flow of real and reactive power at a particular node in the power network is described by [90]:

81
In the equations above, \( P_i \) is the real power flowing into node \( i \) from all other nodes \( k \), whose total number is equal to \( n \). \( Q_i \) is the reactive power flow under the same conditions. \( V_i \) and \( V_k \) are the complex voltages at node \( i \) and \( k \) respectively, \( \theta_{ik} \) is the voltage phase difference between nodes \( i \) and \( k \), \( G_{ik} \) is the real admittance between nodes \( i \) and \( k \), and \( B_{ik} \) is the imaginary admittance between nodes \( i \) and \( k \).

As a substantial change of voltage and phase angle is incurred in the transmission of electricity, it is reasonable (from examination of the power flow equations) to assume that a reversal in power flow will cause the opposite conditions to occur around the DG sites. These changes can place distribution transformers outside of its operating limits, which represents a not insignificant problem to the distribution network owner.

The voltage in a network with DG connected is affected by the apparent load reduction, or complete negation or reversal, due to the power generation of the DG units. Typically, the grid network reduces down from EHV (supergrid) down to the sub-transmission network, then down to the distribution voltages, then down to the consumer level. At the lower voltage levels of the distribution network, overhead lines may have progressed into underground cables, which is typical in urban areas for planning reasons. The drawback to these underground distribution cables is that they have higher capacitance values compared to overhead lines, and thus they are a good producer of reactive power.

Their production of reactive power in both overhead lines and underground cables is determined by the voltage, which is nominally 1.00 p.u., to +10% -6% in the UK [92] for Low Voltages. The counterbalance to the reactive generation is the absorption caused by current flowing through the line. Under normal conditions, both absorption and generation of \( Q \) occurs. [93] suggests an active voltage management scheme to solve this problem, rather than an expensive replacement of transmission line.
As the amount of DG inside the network increases, an increasing amount of power is injected into the distribution network, therefore the overall apparent load for the network will reduce. Depending on the magnitude of the power injected, this will first cause a reduction in current, and then cause the current flow to reverse. The reduction in current will decrease the amount of Q absorption, leading to a net generation of Q within the distribution network.

In overhead lines, it is assumed that $X_L \gg R$ (where $X_L$ is the line reactance and $R$ is the line resistance), such that the voltage magnitude is largely affected by the reactive power flow, and the voltage angle is largely affected by the real power flow. The reduced flow of Q due to DG is therefore detrimental to the voltage profile. When dealing with low voltage transmission in underground cable, it cannot be assumed that $X_L \gg R$, thus the voltage magnitude and angle are affected by $X_L$ and $R$. Therefore, as $Q$ increases and $P$ decreases the voltage magnitude in the network increases and the transmission angle decreases; a situation which is exacerbated by the naturally high $Q$ production of the underground cables. If the network is unable to rectify the situation through tap changing or other mechanisms, and if the DG continues to increase output, the voltage level will become unacceptably high. Thus, the voltage problem introduced by DG is greater in urban environments than in rural environments, for equivalent penetration ratios.

Line overloading is another problem which can be introduced. This problem is caused in tie-lines, as the distribution lines should be capable of handling the generation attached to them, assuming no building has DG attached to it which has a greater rating than its primary grid connection (over-sized DG) [94]. Under the scenario presented above, the voltage magnitude and angle are adjusted by increasing the output from DG. If two regions are connected by a tie-line, the first may be affected by DG whereas the second may not due to economic constraints, political boundaries, or geographical differences. This leads to the problem where-by the first area is continually trying to tie the voltage of the first region to that of the second. This voltage difference across a tie-line, unless rectified, could lead to the line being overloaded. Here is a secondary affect of the increase of DG; a side-effect of the problem of keeping the VPP region within voltage limits.
Under normal operating conditions, the distribution regions are kept within voltage limits by a variety of mechanisms, and tap-changing transformers are routinely used when compared with newer semiconductor based methods [95]. These on-line tap changing transformers (OLTCs) have definite limits of tapping, and under design conditions they are well suited to their role. The voltage profiles projected by load negation and DG power generation do not always kindly suit the tap profiles of the OLTCs, therefore a major investment would need to take place to ensure that two-way power could be achieved by the grid infrastructure. This is certainly a problem which grid operators are keen to dissolve, or resolve. The double-edge to this sword is that DG can also be viewed as a mechanism of deferral to system investment, such as in [91].

The introduction of the network to this work aims to focus on these aspects of characterisation to determine where these problems present themselves, and when. Identifying key weak-areas in the distribution network using the aid of the characteristic models developed above should aid the network strengthening process. If, as it may turn out, the network does not play a significant role in the characterisation, in itself this is a valuable piece of information; it is likely that this will be true for smaller DG penetration, and finding the point at which it becomes necessary is important.

Another use for the information available by running constrained within the network is financial in nature. As discussed above, the end user for this work is likely to be a DNO operator or VPP agent, to whom the information provided, is highly useful. An agent must be kept abreast of any conditions which may adversely affect his or her ability to sell the power produced within the VPP. Lines which are over-voltage or over-rated and cannot be resolved will trip, disconnecting load and generation into an island. Although there are methods of running islands and smart microgrids, this work does not focus upon them and the generation (and load) is assumed lost once it is islanded, and will rapidly black out.
Chapter 5  Modelling Networks Effects in VPP

5.2 Modelling the Network

In order to model the VPP including the network parameters, a load-flow program was developed which accommodated the generation technologies which were discussed and modelled in Chapter 3 and Chapter 4. Incorporated into the program is a method of inputting weather scenarios using time series data, using the various techniques outlined above. In this way, comparisons can be drawn between the various methods of modelling, indicating the impact of the introduction of the network.

The load-flow technique utilized to build the program is the full Newton-Raphson algorithm. The full variety of Newton-Raphson (NR) was chosen over the fast decoupled NR as fast decoupled NR relies on the line reactance being much larger than the line resistance, which is not guaranteed in low voltage distribution networks (especially when using underground cabling). Comprehensive descriptions of the algorithm can be found in numerous sources, but a brief overview based on Weedy’s method in [96] will be presented here.

The Network-Raphson process for solving load-flow is in iterative procedure, building upon the previous steps to form a solution which converges with greater accuracy towards a solution. Mathematically, this is represented in (5.3):

\[ x^{p+1} = x^p - \frac{f(x^p)}{f'(x^p)} \]  

(5.3)

Where \( x^{p+1} \) is the solution for the next iteration, \( x^p \) is the current solution for iteration number \( p \), and \( f(x^p)/f'(x^p) \) is the function to be solved divided by the derivative of the function to be solved for the current value of \( x \). This can be extended to work on a vector solution, as shown in (5.4).

\[ x^{p+1} = x^{(p)} - J^{-1}(x^p) f(x^p) \]  

(5.4)

Where \( x^p \) and \( f(x^p) \) are column vectors and \( J^{-1}(x^p) \) is the inverse Jacobian matrix for the function \( f \). The Jacobian matrix from which it is formed is a partial derivative of the form:
The equations of complex power flow in the network is shown in (5.5).

\[ P_k + jQ_k = V_k^* I_k^* = V_k \sum_{j=1}^{n-1} (Y_{kj} V_j)^* \]  

(5.5)

If the complex voltage and admittance are broken down into real and imaginary portions,

\[ V_k = a_k + jb_k \quad \text{and} \quad Y_{kj} = G_{kj} - jB_{kj} \]

Then (5.5) can be rewritten as:

\[ P_k + jQ_k = (a_k + jb_k) \sum_{j=1}^{n-1} [(G_{kj} - jB_{kj})(a_j + jb_j)]^* \]

Breaking this down into real and reactive power flows obtains (5.6) and (5.7),

\[ P_k = \sum_{j=1}^{n-1} [a_k (a_j G_{kj} + b_j B_{kj}) + b_k (b_j G_{kj} - a_j B_{kj})] \]  

(5.6)

\[ Q_k = \sum_{j=1}^{n-1} [b_k (a_j G_{kj} + b_j B_{kj}) - a_k (b_j G_{kj} - a_j B_{kj})] \]  

(5.7)

Using these two non-linear simultaneous equations for each node \( f(x^0) \) except the slack bus leads to the change in \( P \) and \( Q \) according to the coefficients \( a \) and \( b \), which forms the basis for the Jacobian matrix described above.

A Jacobian converts a series of functions or values in one unit or measurement type to another series of functions or values with a different unit or measurement type, and in this case is used to convert the complex voltage at each node to the complex power flow at each node. The Jacobian may be thought of as having 4 distinct regions, the derivative real and reactive power numerator being separated horizontally down the middle of the Jacobian, and the derivative real and reactive voltage denominator being separated vertically down the middle of the Jacobian.
For each region of the Jacobian, the diagonal elements and non-diagonal elements may be algebraically determined, and by substituting in the numerical values to the algebraic equations, the Jacobian may be built. This is then inverted, as per the Newton-Raphson procedure. A power flow is performed using the equations listed as (5.6) and (5.8), which produces a degree of power mismatch at each node. Using the inverted Jacobian, the node voltages throughout the system may be adjusted; thus the Newton-Raphson algorithm is implemented. The algorithm ceases to run when the power mismatch at every node is beneath a ceiling value.

Descriptions of Slack, PV and PQ buses in the Newton-Raphson algorithm may be found externally to this work.

Prior to the algorithm, however, comes a great deal of preliminary network setup. Connecting components must have their admittance matrix built correctly, and nodes must assume the correct status: Slack, PV, or PQ. The components available for use in the load-flow program are Buses, Lines, Generators, Loads, Shunts, Two Terminal Transformers and Three Terminal Transformers. Of particular interest are the transformers, as the admittance is dependant on the magnitude and phase of the tap ratio, as well as the winding impedance and charging.

Two terminal transformers have already been studied, and the power flow equations for them, detailed. Although equations exist for three terminal transformers, the models for them are not in keeping with the model used for the two terminal transformers, so equations were developed for them. Consider the transformer shown in Figure 5.1:
The primary impedance is $Z_p$, the secondary impedance is $Z_s$ and the tertiary impedance is $Z_t$. The complex tap ratios are given by $t_1$ and $t_2$.

The following may be written about the above circuit:

\[
V_j' = V_i \times t_1, \quad I_j' = \frac{I_{0j}'}{I_i'}
\]

\[
V_k' = V_i \times t_2, \quad I_k' = \frac{I_{0k}'}{I_i'}
\]

\[
I_{i'} + I_{k'} + I_{0j'} = 0 \therefore I_{i'} + I_{k'} t_2 + I_{0j'} t_1 = 0
\]

Also, by substituting the above,

\[
I_{i'} = Y_p (V_i - V_i')
\]

\[
I_{j'} = Y_c (V_j - V_j') = (V_j - V_j' t_1) Y_s
\]

\[
I_{k'} = Y_c (V_k - V_k') = (V_k - V_k' t_2) Y_s
\]

Therefore,
By substituting this into (5.8), the admittance may be determined,

\[ I_i^* = Y_p \left( V_i - \frac{Y_p V_i + t_2^2 Y V_k + t_1^2 Y V_j}{Y_p + t_2^2 Y + t_1^2 Y} \right) \]

\[ \therefore I_j = \frac{Y_p Y t V_i}{Y_p + t_2^2 Y + t_1^2 Y} + \frac{Y Y t V_k}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p V_i \]

Similarly with \( I_j \) and \( I_k \),

\[ I_j = \frac{Y_p Y t V_i}{Y_p + t_2^2 Y + t_1^2 Y} + \frac{Y Y t V_k}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p V_i \]

\[ I_k = \frac{Y_p Y t V_i}{Y_p + t_2^2 Y + t_1^2 Y} + \frac{Y Y t V_k}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p V_i \]

Leading to the admittances:

\[ Y_{ii} = \frac{Y_p^2}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p \]

\[ Y_{ij} = \frac{Y_p Y t_1^*}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p \]

\[ Y_{ik} = \frac{Y_p Y t_2^*}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p \]

\[ Y_{ji} = \frac{Y_p Y t_1^*}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p \]

\[ Y_{jj} = \frac{Y_p Y t_2^*}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p \]

\[ Y_{jk} = \frac{Y_p Y t_2^*}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p \]

\[ Y_{ki} = \frac{Y_p Y t_1^*}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p \]

\[ Y_{kk} = \frac{Y_p Y t_2^*}{Y_p + t_2^2 Y + t_1^2 Y} - Y_p \]

Using the \( \Pi \)-line method for describing lines. The other components were modelled using classical representations, which may be found externally to this work.
5.3 Incorporation of Tap changers

One of the most important features of a power network, as mentioned above, is the ability to modify the voltage or phase angle through the use of OLTCs. This work takes the approach suggested in [97] and improves on it to function using parallel transformers, as are often encountered feeding distribution networks from the transmission network.

The taps of transformers during the most basic network modelling and testing of the load flow program were fixed to their initial values, and were not free to move, even if the primary or secondary side fell outside of their voltage limitations. For a first attempt at a load-flow analysis program for the VPP problem this was not a bold manoeuvre. Increasing accuracy in the analysis required that the problem, including the network problem, be translated from a ‘dummy’ case to a realistic network, either built from a extant network, or designed to mimic a real network (such as those available from the United Kingdom Generic Distribution System, (UKGDS) [98]).

One of the feature requirements for a real network is the ability to regulate voltages using automatic tap changers, which is to say that the tap changes are permitted to automatically and freely to try to keep the voltages within limits. The most common voltage regulation using OLTCs is on either of the local buses at the point of connection, either the primary or secondary side of the transformer, although remote regulation using transformers is possible.

Voltage regulation on the network buses is achieved by using data from the Jacobian matrix created by the normal operation of the load-flow, so-called Sensitivity Analysis. The adjustment of network voltages using tap changers is discussed by Dusko Nedic in his paper, ‘Tap Adjustment in AC Load Flow’ [97]. The starting point for this operation is the inverse Jacobian, (5.21).
\[
J^{-1} = \begin{bmatrix}
\frac{\partial V}{\partial P} & \cdots & \frac{\partial V}{\partial Q} \\
\vdots & \ddots & \vdots \\
\frac{\partial \theta}{\partial P} & \cdots & \frac{\partial \theta}{\partial Q}
\end{bmatrix}
\]

(5.21)

The inverse Jacobian contains the pair of derivatives, \( \frac{\partial V}{\partial P} \) and \( \frac{\partial V}{\partial Q} \) for the regulated transformer bus, \( V_j \), and for the unregulated transformer bus, \( V_i \), which is a total of 4 derivatives (\( V \) is the bus voltage magnitude, \( P \) is the Real Power transfer, and \( Q \) is the Reactive Power transfer).

The steady state conditions for the power network can be described by a series of nonlinear network equations, based on (5.22),

\[
g(x, y) = 0
\]

(5.22)

Where \( x \) is the vector of independent variables, and \( y \) is the vector of dependent variables of the bus. If the system is linearised about the operating point \( x_0 \) it can be expanded using the Taylor series expansion, from which the 2\(^{nd}\) order terms and higher are discarded. If the vector of dependent variables is split into controllable variables, \( u \), and fixed parameters, \( p \), this leads to (5.23),

\[
\begin{align*}
\frac{\partial g(x, u, p)}{\partial x} \bigg|_{x_0} \Delta x &= -\frac{\partial g(x, u, p)}{\partial u} \bigg|_{x_0} \Delta u \\
\end{align*}
\]

(5.23)

Provided that the required change is small about the operating point \( x_0 \), it can be written that the change in an arbitrary function \( f \) with respect to a change in one of the parameters in \( u, \Delta u_i \), can be written as,

\[
\Delta f = \left. \frac{\partial f(x,y)}{\partial x} \right|_{x_0} \Delta x + \left. \frac{\partial f(x,y)}{\partial u} \right|_{x_0} \Delta y
\]

If \( \Delta x \) from (5.23) is substituted into the above equation and it is rearranged:

\[
\Delta f = \left. \frac{\partial f(x,u,p)}{\partial x} \right|_{x_0} \left[ \left. \frac{\partial g(x,u,p)}{\partial x} \right|_{x_0} \right]^{-1} \left. \frac{\partial f(x,u,p)}{\partial u} \right|_{x_0} \Delta u_i + \left. \frac{\partial f(x,u,p)}{\partial u} \right|_{x_0} \Delta u_i
\]
Chapter 5  Modelling Networks Effects in VPP

The equation (5.24) can be used to determine the changes necessary in \( u_i \) to affect the desired change in \( f \), using the sensitivity values contained within the inverse Jacobian. The sensitivity matrix is built using the parameters which are intended to be changed, and can be related to the transformer tap values using the power flow equations for the transformers. As Nedic states, “In both cases, the controllable variable \( \Delta u_i \) is the tap changer value.”

The four steps listed to calculate the transformer tap change are given as: “

1. calculation of \( \frac{\partial f}{\partial x} \),
2. calculation of \( J^{-1} \),
3. calculation of \( \frac{\partial g}{\partial u_i} \) and
4. calculation of \( \frac{\partial f}{\partial u_i} \).”

The equations for \( \frac{\partial f}{\partial x} \) and \( \frac{\partial f}{\partial u_i} \) depend on the model of the transformer, and the function of the transformer (voltage control, reactive power control, etc.).

For voltage control based on sensitivity analysis, Nedic goes on to describe \( f = V_j \), with the control variable \( u_i = t_{ij} \), where \( t_{ij} \) is the tap between the regulated and unregulated bus. \( \frac{\partial f}{\partial x} = [0 \ 0 \ \ldots \ 1 \ 0] = e^T_j \), where the non-zero entry refers to the position of the voltage \( V_j \) in the state vector. For \( \frac{\partial g}{\partial u_i} \), Nedic uses the derivative of the vector of Power flow equations by the tap ratio, \( \frac{\partial P}{\partial t} \) and \( \frac{\partial Q}{\partial t} \).

The equations used to describe power flow by Nedic are subtly different to the ones used in the model. The model uses the equations:

\[
P_j = |V_i||V_j| \left( -g \cos \theta - b \sin \theta \cos \theta_j + g \sin \theta - b \cos \theta \sin \theta_j \right) + |V_i|^2 \ g \quad (5.25)
\]
Chapter 5  Modelling Networks Effects in VPP

\[ P_{ji} = \left| V_j \right| \left| V_i \right| \left( \frac{-g \cos \theta_i + b \sin \theta_i \cos \theta_{ji}}{\left| t \right|} - \frac{g \sin \theta_i + b \cos \theta_i \sin \theta_{ji}}{\left| t \right|} \right) + \left| V_i \right|^2 \frac{g}{\left| t \right|^2} \]  

(5.26)

\[ Q_{ji} = \left| V_j \right| \left| V_i \right| \left( \frac{-g \cos \theta_i - b \sin \theta_i \sin \theta_{ji}}{\left| t \right|} - \frac{g \sin \theta_i - b \cos \theta_i \cos \theta_{ji}}{\left| t \right|} \right) - \left| V_i \right|^2 b \]  

(5.27)

\[ Q_{ji} = \left| V_j \right| \left| V_i \right| \left( \frac{-g \cos \theta_i + b \sin \theta_i \sin \theta_{ji}}{\left| t \right|} + \frac{g \sin \theta_i + b \cos \theta_i \cos \theta_{ji}}{\left| t \right|} \right) + \frac{b\left| V_i \right|^2}{\left| t \right|^2} \]  

(5.28)

Where \( \theta_i \) is the phase shift of the transformer, \( \theta_{ji} \) is the voltage angle between buses \( j \) and \( i \), \( \theta_{ij} \) is the voltage angle between buses \( i \) and \( j \), \( g \) is the real part of the admittance between buses \( i \) and \( j \), and \( b \) is the imaginary part of the admittance between buses \( i \) and \( j \). Only the terms for buses \( i \) and \( j \) are shown, as the other terms are removed by the differentiation, giving:

\[ \frac{\partial P_j}{\partial t} = \left| V_j \right| \left| V_i \right| \left( \frac{g \cos \theta_i + b \sin \theta_i \cos \theta_{ji}}{\left| t \right|^2} - \frac{g \sin \theta_i - b \cos \theta_i \sin \theta_{ji}}{\left| t \right|^2} \right) \]  

(5.29)

\[ \frac{\partial P_j}{\partial t} = \left| V_j \right| \left| V_i \right| \left( \frac{g \cos \theta_i - b \sin \theta_i \cos \theta_{ji}}{\left| t \right|^2} + \frac{g \sin \theta_i + b \cos \theta_i \sin \theta_{ji}}{\left| t \right|^2} \right) - \frac{2g\left| V_i \right|^2}{\left| t \right|^3} \]  

(5.30)

\[ \frac{\partial Q_j}{\partial t} = \left| V_j \right| \left| V_i \right| \left( \frac{g \cos \theta_i + b \sin \theta_i \sin \theta_{ji}}{\left| t \right|^2} + \frac{g \sin \theta_i - b \cos \theta_i \cos \theta_{ji}}{\left| t \right|^2} \right) \]  

(5.31)

\[ \frac{\partial Q_j}{\partial t} = \left| V_j \right| \left| V_i \right| \left( \frac{g \cos \theta_i - b \sin \theta_i \sin \theta_{ji}}{\left| t \right|^2} - \frac{g \sin \theta_i + b \cos \theta_i \cos \theta_{ji}}{\left| t \right|^2} \right) + \frac{2b\left| V_i \right|^2}{\left| t \right|^3} \]  

(5.32)

The final variable, \( \partial f / \partial u \), Nedic states to be zero in this case.

Examination of the theory gives us:

\[ \frac{\Delta f}{\Delta u} = - \frac{\partial f}{\partial x} \bigg|_{\mu_0} J^{-1} \bigg|_{\mu_0} \frac{\partial g}{\partial u_{\mu_0}} \bigg|_{\mu_0} + \frac{\partial f}{\partial u_{\mu_0}} \bigg|_{\mu_0} \]

\[ \frac{\Delta V_j}{\Delta t_{ij}} = - \frac{\partial V_j}{\partial x} \bigg|_{\mu_0} J^{-1} \bigg|_{\mu_0} \frac{\partial S}{\partial t_{ij}} \bigg|_{\mu_0} + 0 \]

\[ \frac{\Delta V_j}{\Delta t_{ij}} = - \left( \frac{\partial V_j}{\partial P_i} \frac{\partial P_i}{\partial t_{ij}} + \frac{\partial V_j}{\partial Q_i} \frac{\partial Q_i}{\partial t_{ij}} + \frac{\partial V_j}{\partial P_j} \frac{\partial P_j}{\partial t_{ij}} + \frac{\partial V_j}{\partial Q_j} \frac{\partial Q_j}{\partial t_{ij}} \right) \]
This theory was implemented as a method to regulate bus voltage, but there are scenarios which are not covered by Nedic’s work.

The regulated bus is inherently not permitted to be a PV or Slack bus, as this removes the ability to adjust the voltage magnitude of the bus at all. However, the unregulated side of a transformer is free to be a Slack bus or a PV bus. Nedic does not cover this eventuality. Clearly, it is possible for the unregulated side of a transformer to be either Slack or PV, as test networks often have a transformer or pair of feeder transformers to connect the system to the grid connection point.

The Jacobian is missing the entries for the voltage at the unregulated bus, which leaves up to 2 of the 4 correction terms unevaluated. When the unregulated bus is the Slack bus, the voltage on the regulated bus cannot be controlled using data from the Slack side, because the real and reactive powers are set to move freely to pick-up the excess generation or load in the network, and are not set to change because of the change of only the transformer taps. Therefore:

\[ \frac{\partial P_i}{\partial t_{ij}} = 0 \]
\[ \frac{\partial Q_i}{\partial t_{ij}} = 0 \]

No amount of increase or decrease in real or reactive power will manage to adjust the voltage for this bus. The same is true for the power derivative on a PV bus, so only the first expression is used. In actuality, the Q limits for generators will force a PV bus to become PQ under certain conditions. Under these conditions, however, the bus is PQ and the Jacobian will contain the terms required.

For the Slack bus case:
Another option which is not covered in the work of Nedic is the inclusion of transformers operating in parallel. When parallel transformers are included in the network, the Jacobian is built using elements of both (or all the) parallel transformers. When the tap adjustment is to be determined, the Jacobian term is then multiplied through by $\frac{\partial P}{\partial t_{ij}}$ etc. This is fine provided that there is only 1 transformer. When 2 or more are used, the algorithm tries to implement the change in voltage for every transformer, for a net change of:

$$\Delta V = \Delta v \times p$$

Where $\Delta v$ is the actual change in voltage, $\Delta v_t$ is the desired change in voltage, and $p$ is the number of transformers in parallel. In a situation where there is only a single transformer controlling a bus’s voltage magnitude, this leads to an appropriate shift. When transformers act in parallel on a bus, their properties are grouped to form the Y-bus and thus the sensitivity matrix. When the algorithm attempts to address the voltage issue it uses the grouped properties, which leads to a voltage adjustments which are a factor of $p$ greater than required, due to the parallel nature of the problem. In turn, this overcompensation causes oscillations in the solution, leading to a divergence and solution failure.

The solution to this problem is to evaluate all the transformers on face value, assuming that each controls only 1 bus voltage. With the preliminary tap positions
determined, it is possible to evaluate an estimate of the regulated bus voltages after
the next iteration by considering all the tap changing transformers in the system. The
magnitude of the estimated changes can then be compared to the desired changes, to
determine a ratio of how over-effective or under-effective the changes have been. The
tap change associated with each transformer is then modified by the ratio of
effectiveness. This uses the assumption that the local transformers have the greatest
impact on the regulated voltage by tap changing, and that the changes imposed by
remote transformers can be ignored. This is not entirely true, but it serves as a
working simplification of the more advanced solution, incorporating remote
transformers into the workings.

The more advanced method of determination of transformer taps operates similarly to
begin with. First, the taps are determined assuming that they control only a single bus,
as above.

\[
\frac{\Delta V_j}{\Delta t_{ij}} = -\left( \frac{\partial V_j}{\partial P_i} \frac{\partial P_i}{\partial t_{ij}} + \frac{\partial V_j}{\partial Q_i} \frac{\partial Q_i}{\partial t_{ij}} + \frac{\partial V_j}{\partial P_j} \frac{\partial P_j}{\partial t_{ij}} + \frac{\partial V_j}{\partial Q_j} \frac{\partial Q_j}{\partial t_{ij}} \right)
\]

\[
\therefore \frac{\Delta t_{ij}}{\Delta V_j} = -\left( \frac{\partial P_i}{\partial V_j} \frac{\partial t_{ij}}{\partial P_i} + \frac{\partial Q_i}{\partial V_j} \frac{\partial t_{ij}}{\partial Q_i} + \frac{\partial P_j}{\partial V_j} \frac{\partial t_{ij}}{\partial P_j} + \frac{\partial Q_j}{\partial V_j} \frac{\partial t_{ij}}{\partial Q_j} \right) \times \Delta V_j \quad (5.36)
\]

The estimated change of voltage for every regulated bus is then determined using the
inverse Jacobian and the derivates for real and imaginary power across the
transformers.

\[
\frac{\Delta V_j}{\Delta t_{ij}} = -\left( \frac{\partial V_j}{\partial P_i} \frac{\partial P_i}{\partial t_{ij}} + \frac{\partial V_j}{\partial Q_i} \frac{\partial Q_i}{\partial t_{ij}} + \frac{\partial V_j}{\partial P_j} \frac{\partial P_j}{\partial t_{ij}} + \frac{\partial V_j}{\partial Q_j} \frac{\partial Q_j}{\partial t_{ij}} \right)
\]

\[
\therefore \Delta V_j = -\sum_{i=0}^{\infty} \left( \frac{\partial V_j}{\partial P_i} \frac{\partial P_i}{\partial t_{ij}} + \frac{\partial V_j}{\partial Q_i} \frac{\partial Q_i}{\partial t_{ij}} + \frac{\partial V_j}{\partial P_j} \frac{\partial P_j}{\partial t_{ij}} + \frac{\partial V_j}{\partial Q_j} \frac{\partial Q_j}{\partial t_{ij}} \right) \times \Delta t_{ij} \quad (5.37)
\]

The total estimated voltage change at each node, \(\Delta V_j\), and the estimated voltage
change at each node due to the other nodes, \(\Delta V_{ji}\), are then divided by the required
voltage change at node \(j\). This leaves both sets as a ratio.
The reciprocal of $V_{ij}$ is taken, in order to determine a number of parallel virtual transformers contributing towards the change in voltage attributed to the transformer between $ij$. The intended tap change for each transformer can be divided by the amount of virtual parallels to account for the effects of local and remote transformers. From the perspective of each transformer, it is responsible for $V_j / V_{ij}^{-1}$ of the voltage problem at node $j$, so must have its estimated tap change adjusted by:

$$a_j = \sum_{j=0}^{n} V_j / V_{ij}^{-1} / V_j$$

$$a_j = \sum_{j=0}^{n} V_j V_j / V_j$$

$$a_j = \sum_{j=0}^{n} V_j$$

(5.38)

The correction value, $a_{ij}$, is then subtracted from $\Delta t_{ij}$ to determine the final tap value that must be used for the iteration. The simplified version of this operation, noted above, removes the last step and the necessity to store $\Delta V_{ij}$, choosing the final value of $\Delta t_{ij}$ to be the product of the original $\Delta t_{ij}$ by $1/V_i$.

### 5.4 Changes to the Model to Allow the Network

In order to run the VPP network using the characteristic models presented above, it is necessary to change the characteristic models, with respect to the statistical data. The first change to the proceedings is that no aggregation be done between generators. Once the individual generators have their power output determined this information is passed directly into the network model for use, where the network will automatically combine their power outputs. The second change deals directly with this preliminary stage, as the long period power output for each generator is averaged in order to obtain the generator’s power output which will be used in the load flow.

This stage is done for several reasons. The first reason is that the load flow developed is not a probabilistic load flow, and is a deterministic load flow. Probabilistic load flow methods continues to be developed and used in short and long term planning as well as normal operation [99,100,101,102,103], although there are various methods for solution of the probabilistic load flow, concentrating on the Monte-Carlo approach, and the analytical approach. The Monte-Carlo approach requires a vast quantity of simulations to be performed to obtain the answer, which is time
consuming, whilst the analytical method requires complex computation and approximation of the problem, which can lead to inaccuracies in the solution [104]. Whilst a probabilistic load flow would be a useful advancement to the characterisation [105], time constraints would not allow it.

The second reason is that the load flow is a fairly static representation of the network problem – it is considered for periods not less than 15 minutes in this case. Over such periods the loads at each node will fluctuate, but the average load is the value which is used for load flow model. [106] takes a look at the second by second affects of loading with DG, suggesting that their test network is ill equipped to deal with the levels of DG which they hypothetically installed. Where many loads are attached to a multiple node, such as distribution level networks, this averaging approach is mathematically more reliable and accurate, as a consequence of central limit theorem [107]. Briefly explained, if something has a 30% chance of occurring and it is sampled a great many times, the final value obtained will converge towards 30% as the sample size increases, which accounts for many physical constants, such as the speed of propagation of light and sound through mediums.

As discussed above, when considering the two approaches towards NWP implementations there are two routes available for use. The five point forecast method, or the raw NWP data. When considering the network and the VPP, the raw NWP data is a more suitable approach, because it allows for a greater size of network to be considered, and also because the raw NWP data produces much more suitable long period power output graphs from the DG in the VPP. As mentioned earlier, the long period power output for micro wind turbines and PV arrays using raw NWP forecasts is a single value, as contrasted to the power curves which are obtained from the 5 point forecast method. These do not require any kind of averaging before being applicable for use in the load flow model. Only the micro CHP generators require averaging for their use in the load flow if the raw NWP data is used.

The other advantage with the use of the raw NWP data is that an element of probability is maintained, because it is possible to build an ensemble value for many of the variables used in the load flow. It is possible to build the ensemble voltage at every bus, or the ensemble power flow down each line, and check these ensemble
results for problems. This information is lost using the five point forecast, except for the average value, so it is impossible to place a probability value on any problem highlighted by these conditions – the problem could occur for all forecast values, or may only just have been averaged enough to fall into a problem criterion. Similarly, some voltages and lines will show no problem at the average point, whilst several forecasts may cause the line or bus to have problems. Hence, the use of raw NWP data for forecasting the VPP with a network is the best solution.

The placement of the DG within the network for the analysis presents a problem, because the spread of generation throughout a real network is not even. If the models presented in this body of work are used on a real network with DG added, it is expected that the modeller will place the DG at the correct positions. For theoretical test networks, it is assumed that the spread of DG is as even as possible (except when extreme cases are required). This works on a foundation that each customer at each load is identical to every other customer in every way except that they are different customers, at possibly different busses. In the real network, of course, every customer has a slightly different view on the environment, has different disposable income, and lives at different geographical sites, all of which dictate likelihood to buy and install some DG! Removing these factors leaves a safe assumption that the DG population will be equally spaced through the load.

In the load flow program, in order to easily and quickly populate the test networks with DG, an option is available to select busses in the network on which to install DG. Based on the DG density, the Watts per household and the technology ratio between micro wind, PV and micro CHP, the model automatically installs DG at the selected busses, using DG parameters selected by the operator. This function automatically builds a discrete distribution pattern to make sure that the technologies are equally distributed by technology ratio, and by bus loading.

### 5.5 Network Security Assessment

Contingencies happen. The electrical network is built using components which have a finite service life and which can fail during service; temporarily or completely. In order to ascertain the security of the network to these unplanned disconnections, an ‘N
minus X’ analysis can provide useful data by disconnecting X number of lines from a stable position and determining the outcome on the network.

### 5.5.1 N-1 Analysis

A common type of contingency within a power network is the single line failure [108], where accident, natural problems or inclement weather conditions cause a single line to be disconnected. Studying the effects of these disconnections is known as N-1 analysis, as N is used to indicate the nominal number of lines in a network.

The N-1 analysis was chosen over N-2, N-3 etc. analyses because it represents the most likely disconnection scheme within the VPP. It is possible that more than one fault can be present in the network at the same time, although the likelihood is that the first fault will have been cleared or the line will have been repaired by the time of the occurrence of the second fault. Of course, this chance is varied by the length of lines and cables in the network.

The N-1 contingency analysis is important for a system security analysis and is used for determining system behaviour after a line trips, assessing contingent switching of lines, and adjustment of taps, etc. For the VPP, the N-1 analysis has potential as it allows the VPP operator to know the effect that an N-1 scenario will have on the output power of the VPP. This is especially important behaviour because the VPP operator is likely to be energy trading with the power output that the VPP produces, and will have hedged the amount of power output sold so that the profit incoming to his and his clients, the DG owners, is maximized. A line failure will disconnect both load and generation in a VPP, and whilst keeping load disconnection minutes low is crucial for quality of service for power companies, keeping generation connection minutes high is crucial to the generation of revenue for the VPP. Provided that the N-1 analysis is included in the output power from the VPP, the disruption and loss of revenue due to a line disconnection can be balanced by the increase in revenue by consistently under-estimating, if slightly, the amount of power produced by the VPP.

The N-1 analysis process uses the following procedure [109]. Firstly, the network is solved with all lines present and correct. This gives the base case from which to start the N-1 load flows. The transformer taps are fixed in position, along with the load and
generation values, so that no increase or decrease in either P or Q is allowed. This gives the initial stable condition of the network after the line is disconnected, and provides the starting point for the correction of any system problems which present themselves. Beginning with the first line in the network, each line is switched out and the load flow solved under the new conditions, storing the results for each case. By examining each case for problems the DNO can identify problems within the contingency event. By examining the likelihood of each contingency with the associated drop of generation, the VPP agent can identify problems with his or her bid model.
Chapter 6 Implementation and validation of the VPP Models

This chapter examines the models and the processes mentioned above, and validates them against measured data. The financial implications of the model are addressed, detailing the key differences between the models.

6.1 Model Validation

The basic operational characteristics for micro wind turbines and PV arrays have been covered by others elsewhere in great detail (see [20], [78], [80] and [85]), therefore only a concise validation of these models is presented here.

6.1.1 Wind Turbine Model Verification

The validation of the wind turbine model was provided using data taken from the on-line measurement of the Middelgrunden off-shore wind farm. The wind farm contains 20 turbines (2 groups of 10), and is situated 3.5km outside of Copenhagen, Denmark [110]. The measured power curves of the wind turbines are shown below in Figure 6.1.

![Figure 6.1: Middelgrunden Wind Turbines](image)

The initial prediction values, using the nacelle windspeeds from the wind turbines, were poor, with the predicted power values being within a ±20% of the recorded power output. However, as [85] suggests, the power curve for the wind turbines was
rebuilt using the data recorded from turbine operation, leading to a prediction value with a standard deviation of only 3% against the measured power output for the period (see Figure 6.2). With fine tuning of the model, as suggested in [85], and the incorporation of air density into the model, the accuracy of the power output curve could be improved even further. Of course, discrepancy of the certified power curve and the measured power curve could, in this case, be due to using nacelle wind speeds, but the important point to note is the large errors that can be introduced by using an ill-fitting power curve, even if the curve is only very slightly mal-fitted.

![Figure 6.2: Power Curve Adjustment](image)

### 6.1.2 PV Array Model Verification

The PV model verification is provided using data from a location in the US (Shutesbury Elementary School PV Array). The site is fitted with data-logging, and consists of an array of 18 solar modules, rated for 115Watts DC each, connected to a Sunny Boy 2500U inverter. The cells have Normal Operating Cell Temperature of 44 °C and temperature degradation of 0.49% per degree Celsius. A sample of data was taken between the 3rd of March 2010 and 9th of March 2010, and compared against a prediction using the measured conditions. This tests the kernel of the model and also showcases the validity of incorporating the inverter efficiency into the model. The data is presented in Figure 6.3.
The predicted power output (incorporating the ambient temperature and insolation on the array plane) is plotted against the actual inverter output. The expected power output using a hypothetical unity efficiency inverter is shown along with the expected power output using the actual inverter’s efficiency curve. The accuracy of the fit of the inverter to the predicted and measured power data is indicative of the success of the model to predict the array’s DC power output and the success of the model to accurately map the array’s DC power to AC power through the inverter.

### 6.1.3 MicroCHP

Insufficient data was available to study the power equations derived for CHP boilers in Chapter 3. However, the building temperature equations were derived from basic principles and do not rely on major assumptions in order to provide a working model – and are routinely used throughout the sciences (exponential temperature curves). These were then combined with the operational equations for CHP boilers provided in [20], to produce the CHP output power model based off the building parameters.

### 6.2 Basic Uncertainty Results

The basic uncertainty model forms the starting point for the other models, and the data it produces forms a good starting point for comparison to the other models. Additionally, it has characteristics which are shared amongst the models, highlighting several points of the characteristics of the VPP. The first characteristic demonstrated...
by the basic model is the effect of adding more generators into the VPP, an example of the central limit theorem.

When adding generators to a VPP, the variation of the instantaneous power does not vary linearly with the number of generators added. Indeed, the greater the number of generators in the VPP, the smaller is the increase of the instantaneous variation. The table below shows the effect of adding more generators for wind turbines, PV arrays and micro CHP.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Average Power/W</th>
<th>Variance/W²</th>
<th>Std. Deviation/W</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Wind Turbine</td>
<td>291.48</td>
<td>1408.7</td>
<td>37.532</td>
</tr>
<tr>
<td>2 Wind Turbines</td>
<td>582.96</td>
<td>2817.4</td>
<td>53.079</td>
</tr>
<tr>
<td>5 Wind Turbines</td>
<td>1457.4</td>
<td>7043.4</td>
<td>83.925</td>
</tr>
<tr>
<td>50 Wind Turbines</td>
<td>14574</td>
<td>70434</td>
<td>265.39</td>
</tr>
<tr>
<td>1 PV Array</td>
<td>502.76</td>
<td>130.49</td>
<td>11.423</td>
</tr>
<tr>
<td>2 PV Arrays</td>
<td>1005.5</td>
<td>260.99</td>
<td>16.155</td>
</tr>
<tr>
<td>5 PV Arrays</td>
<td>2513.8</td>
<td>652.46</td>
<td>25.543</td>
</tr>
<tr>
<td>50 PV Arrays</td>
<td>25138</td>
<td>6524.6</td>
<td>80.775</td>
</tr>
<tr>
<td>1 CHP Unit</td>
<td>599.83</td>
<td>539950</td>
<td>734.81</td>
</tr>
<tr>
<td>2 CHP Units</td>
<td>1199.7</td>
<td>1079900</td>
<td>1039.2</td>
</tr>
<tr>
<td>5 CHP Units</td>
<td>2999.2</td>
<td>2699700</td>
<td>1643.1</td>
</tr>
<tr>
<td>50 CHP Units</td>
<td>29992</td>
<td>26997000</td>
<td>5195.9</td>
</tr>
</tbody>
</table>

Briefly examining Table 2, the average power increases as expected and is a multiple of the scenario containing only 1 relevant generator (5 wind turbines produces 1457.5W, which is 5 multiples of the power for 1 wind turbines, 291.48W).

The variance is also a multiple of the base case, determined by the number of generators included in the VPP. As the Standard Deviation is the square root of the variance, and it is known that the derivative of a square root function is reciprocal, it can be said that regardless of the generator type or size, by increasing the number of generators in the VPP the normalised standard deviation will decrease. Considering the wind turbines above, the base case has a normalised standard distribution of 12.9%, whilst increasing the number of generators to 50 lowered the normalised standard deviation to 1.8%.
Coincident with the reduction of the standard deviation is the alteration of the power curves’ distribution towards the normal distribution.

![Figure 6.4: Adoption of the Normal Distribution](image)

Figure 6.4: Adoption of the Normal Distribution

Figure 6.4 shows an example of this effect, by increasing the number of generators from 1 to 5. In each case, the mean power and the standard deviation were used as the parameters to the normal distribution, which are also shown on the graph. The single generator is on the primary axis, whilst the 5 generators are on the secondary axis, clearly demonstrating the trend towards the normal distribution even with relatively few generators in the system.

This characteristic can be used to effectively estimate the output of the VPP, provided that the number of generators in the system is large, and provided that a single weather forecast point is to be considered. Alternatively, if raw NWP data is to be used, a series of single weather forecast outputs can be superimposed on each other to produce the estimate. By calculating the mean power output and variance for each generator, or by grouping identically rated generators and applying the result for one of them across the group, it is possible to determine an estimated the power output by adding the variance of power and the mean power for each generator. The standard deviation can be determined from the variance, and the normal distribution can be used to obtain the estimated power output.
As an example and demonstration, a VPP was constructed using 150 generators, divided equally amongst the 3 technologies. The probability polygons are shown for both in Figure 6.5, with the cumulative frequency plots shown in Figure 6.6.

The most evident feature of both is the large oscillations in the calculated probability curve, leading to a slightly undulating cumulative frequency plot. This is due to the effect of the CHP generators, whose output is formed at the 0% and 100% points, leading to a ‘combing’ effect of the output. The combing effect is repeated every 1500W, which is the power expected from the CHP generator when engaged. The comb effect is diffused greatly due to the number of convolutions with other, non-combed graphs. Bearing this in mind, it is not easy to determine how good the fit is between the two graphs, so the cumulative frequency plot for both methods is given in Figure 6.6.
The estimated output follows the trend of the comb-affected calculated output precisely, indicating the validity of the estimation, giving an overall error area of 0.061% between the two cumulative frequency graphs (0.061% of the chart’s area is contained in the regions between the two plots). If the same example as above is re-run without the microCHP boilers in the system, the area error falls to 0.001%, indicating that the process is valid for a large number of generators, and also that the microCHP boilers were responsible for the largest portion of error due to their combing effect.

The output from the basic forecasting technique (with 1 forecast point) is not as good at forecasting as the methods whose results are to follow, but is very good for use with meteorological data which has been collected and needs evaluation. If a site has been surveyed for a year (or 4 years, as [111] suggests) the data is not in 5 point or NWP data output format, it is simply a series of single data points for each variable (nominally: temperature, windspeed and direction at 10m above ground level, and solar insolation). The basic technique is well suited to take this data and examine theoretical VPPs using real off-line data.

The overall design philosophy of intermittent renewable generation, such as wind turbines, is that there must be a back-up for every Watt of generation installed. Although this will be covered further below, it is evident that if penetration is high
and weather conditions are favourable, there is no reason why back-up generation needs to be kept in spinning reserve at all times. This is not to suggest that back-up generation does not need to be available – simply that it does not need to be kept in spinning reserve if the VPP model output suggests a large output of power in the characteristic bell-curve. In Figure 6.6, for instance, the likelihood of generating less than 58kW using the 150 generators is too small to be unreadable from the graph, suggesting that 58kW of reserve kept spinning to pick up unforeseen loss of generation in the VPP can be potentially spun down. Whilst this is only a small value, it must be remembered that this is from only 150 DG units.

A good examination of this principle, as well as observing the power output from the VPP, can be made using off-line data as suggested above. However, it would be prudent to evaluate the differences between the two distributions which can be selected for the method’s distributions, the Gaussian and uniform distribution, before evaluating the results from the time series data, as this choice affects the output subtly.

Overall, both of the distributions produce outputs which are very similar, especially as the number of generators is increased. The primary difference between the two distributions is that they each produce a different average power and standard deviation for a generator under otherwise identical conditions. The effect that this has upon building the VPP’s power output using many generators has been mentioned above. Five identical wind turbines were run under 6 different wind regimens, consisting of 3 different windspeeds, and the uniform and Gaussian (normal) distribution. The output is shown below, in Figure 6.7.
Figure 6.7: Uniform vs. Gaussian distribution

The uniform distributions utilise the primary axis, whilst the Gaussian distributions use the secondary axis. Scanning horizontally, the normal/uniform distributions form pairs as the windspeed is increased, 2 low power curves, 2 medium power curves, and 2 high power curves. The key difference between the two methods is that the Uniform distribution favours a small region about its central value, and has a power output which is largely distributed about this point; the Gaussian distribution, in contrast, favours a wider range of input windspeeds due to the long tails of the distribution, and thus produces a curve which is more dispersed. The end effect of this is that the Uniform distribution produces an output which gravitates towards the extremes, whilst the Gaussian distribution tends towards the generator average, due to the differences of spread associated with identical standard deviations; the Gaussian distribution is normally considered to be encompassed by 6 standard deviations – 3 about both sides of the mean – whilst the Uniform distribution’s spread is the square root of three times the variance (standard deviation squared), thus the Gaussian spread is always a factor of root 12 larger than the Uniform counterpart (approximately 3.5 times greater). This contrast is dependant upon the particular power curve for the generator under study, and the expected variation of the forecast (the contrast decreasing with diminishing input variation/turbulence).
The time series examination uses the uniform distribution. Whilst the distribution for the turbulence around the site is not known, consider the following set of curves (Figure 6.8).

![Rayleigh Comparison Curves](image)

**Figure 6.8: Rayleigh Comparison Curves**

The curves are built by choosing a yearly windspeed distribution (unaffected by turbulence), and then by convolving it with a second distribution, the turbulence distribution. It is known that at a site, the windspeeds over the course of a year will tend towards the Weibull distribution, notably the Rayleigh distribution. In the plot above, 4 artificial curves have been generated by choosing between the uniform and normal distribution for the initial and turbulence curve, and these are shown against the Rayleigh distribution.

The curve which matches the Rayleigh distribution best is the Gaussian yearly windspeed distribution, convolved with the turbulence which is uniformly spread. Whilst this is only a qualitative measurement, it suggests that the uniform distribution is not an inappropriate choice between the two distributions. The actual solution almost certainly consists of two very similar distributions which convolve to form the traditional Rayleigh distribution; the Kolmogorov spectrum is a likely candidate [112].

*Time Series Results*
The time-series data uses meteorological data taken from Williamstown, Massachusetts (USA), at co-ordinates 42° 42’ 40”N, 73° 12’ 14”W, for the period of 1st June 2006 to 31st May 2007. The climate is temperate, non-coastal, and has seasonal weather swings that are roughly equivalent to northern England during the winter, and southern England during the summer.

The graph below (Figure 6.9) represents the capacity factor for wind, PV, and micro CHP using the time series data. The total capacity factor is also displayed on the chart. The chart reveals the seasonal trends for each technology, as well as providing an insight into the usefulness of each technology.

The chart was built assuming a single generator of each type, using the mean time period data as a measure of generation output. The wind turbine had a cut-in speed of 4ms⁻¹, a rated speed of 12ms⁻¹ and a cut-out speed of 25ms⁻¹. The PV array was inclined 10° to the south, with a rating of 1kW at standard test conditions, with a temperature coefficient of 0.005. The CHP unit was installed with a boiler rated at 10kW with conversion efficiency of 0.3 (30%), in a building with specific heat capacity of 800kJ/°C, a thermal resistance of 0.005 W/°C and a thermostat range of 19 to 21 °C.

The capacity factor for wind shows increased values during autumn, winter, and spring, which is expected due to the seasons. The graph also indicates the limitation of wind generation; the highest capacity factor is just over 20%, during March. This is due to poor placement, and is unfortunately irresolvable without choosing a different location. The American Wind Energy Association places the wind capacity factor as commonly 25-40% [113], so the placement here is well below par, having an average capacity factor of just 15%. This is not a problem of characterisation, as the model is able to predict the output; the average windspeed for the duration is 5.3ms⁻¹ with a standard deviation of 2.8ms⁻¹, which is simply quite a low windspeed.

PV arrays and micro CHP have antagonistic capacity factors, as is expected; the Earth is heated by the sun, after all. Their capacity factors are also a product of the seasons, with their capacity factors oscillating in accordance with the colder and hotter months of the year. Based on its latitude [20], the PV array should produce a peak power of
Figure 6.9: Year Long Technology Efficiencies
around 800W, and this is in keeping with the model output. This peak power of 800W has been used to determine the capacity factor of the PV array, although it should be noted that a site can have a very low capacity factor even if it received perfect insolation conditions, due to its latitude.

The CHP is, as mentioned above, antagonistic to the PV when it comes to the capacity factor. What is more striking, however, is the degree of variation for the capacity factor. The yearly average is only 22%, but the seasonal variation sees changes from 2% to 44%. No other technology sees a swing of such magnitude, although it must be realized that this swing is a factor of the characteristics of the house (a small/medium sized brick house with a 10kW boiler) and the location temperature range.

Analysis of the power outputs on a smaller scale is also revealing. The chart below, Figure 6.10, is a week’s data from May 2007, and is a good example week. The wind power output has been removed from both of the week analyses graphs below for clarity, as they are random fluctuations.

![Figure 6.10: Hourly Data Sample 1](image)

The first observable characteristic is the antagonistic relationship noticed above, but paralleled on the small scale. The CHP and the PV are about 10 hours out of phase with each other. Omitting wind generation from the examination, this produces a trough of generation at just before mid-day, as CHP generation falls off and PV
generation continues to increase. This produces a second, larger trough in the evening, as there is a gap between the sun setting and the temperature falling to a point where the CHP output increases again.

Of course, this summer balance relies on generation being spread equally between micro CHP and PV arrays; during the winter months (Figure 6.11) the gap from midday to the evening reduces down to a single trough, as the CHP generation increases and the PV generation reduces, leading the combined micro CHP and PV array behaviour as a rather smooth output.

The wind characteristics, on the other hand, are less easily definable. They are largely random, although there is a tendency for higher wind speeds at night during the winter, and higher wind speed during the day during summer. This is likely to be adjusted by the site, however, and the differences between day and night speeds were only small. This measured result is in keeping with the spectral gap, but it is un-optimum from a characterisation perspective.

The point raised earlier, which must be addressed again, is the requirement for back-up generation of equal size to the installed DG. While this statement is generally true as shown in the graphs above, where the total generation often falls to 100W or less (out of a total of 5300W, or 1.8% capacity factor), it is by no means true all the time.
Earlier, it was shown that by increasing the number of DG units, the spread of the instantaneous power could be reduced to relatively low values. In the two sample weeks shown above (which are plots of long period power), if the irradiance, wind velocity and temperature are known in advance, it is possible to start generators to supply the shortfall. What is however important is the contribution of micro CHP generation to this problem, however. The micro CHP plays a pivotal role (in the scenario above, at least), in determining the overall output, and it is only when it falls low, that the total falls considerably. Considering the fact that micro CHP output is based on the temperature, which is quite predictable hours in advance, it can be seen that whilst generation should be installed to cover any potential shortfalls in the renewable generation, it does not need to be running at reserve status unless there is a potential for the micro CHP, and if present, PV arrays to drop their output significantly.

In the case of 6th January to 12th January (Figure 6.11), for example, the CHP has a fairly steady output, with 4 sudden falls. Each one of these is around mid-day, where the solar heating has raised the ambient temperature and where, as it is winter, the PV cannot fill in the generation trough. In the case of 2nd May to 9th May (Figure 6.10) the CHP has a predictable output with a mid-day fall on every day. There is an element of recovery due to PV generation, but this cannot entirely allay the fall due to CHP generation.

It is also worth mentioning that the peak PV output is around 800W, and the CHP peak output is 1.5kW. Both of these technologies show rather predictable outputs over the hourly analysis, and, if the sizes of the technologies were reversed the reserve problem would become apparent during the evening, as the CHP generation would fall around mid-day to be overtaken by PV generation, which would fall sharply as night approached.

6.3 Results from the Advanced Uncertainty Work

The difference between the basic forecast and either of the advanced techniques is large, and affects both the instantaneous power output and the long period power. Consider Figure 6.12, a set of ensembles not atypical to ensembles between 2-5 days in advance:
The ensemble produces a median forecast value of 8.13 ms$^{-1}$, and the other 4 points which form the 5 point analysis lie at 5.38 ms$^{-1}$, 7.38 ms$^{-1}$, 8.75 ms$^{-1}$ and 10.63 ms$^{-1}$. These values were run through the model with a turbine at 10m above ground level in an urban roughness, with the power profile taken from a real turbine. The long period power output for the NWP runs are shown against the five point runs in Figure 6.13, below.
The long period power output from the single (median value) forecast value is 656W, coinciding with the mode power output from the NWP power ensemble, but not with the 5 point forecast power output mode value. This single forecast’s median value is also very close to the median value for the NWP ensemble, but less accurate compared to the 5 point median, which are 658W and 682W respectively. The smoothing function performed to obtain the 5 point forecast, as mentioned in Chapter 4, also smoothes the power output considerably, as would be expected. Indeed, the smoothing operation has affected the cumulative power output probability considerably, introducing a 3.87% error between the two curves, by area.

The instantaneous power output curve is affected in a similar manner, smoothed akin to the input values. The effect is measurably less than in the long period power output, as the instantaneous power naturally smoothes the input values due to the turbulence which is part of the model. By area, the cumulative power output probability polygons for the instantaneous power have only a 1.79% error, less than half of the error incurred by the long period power output. The single point forecast also accrues a quantity of error when compared to the raw NWP prediction, amounting to 3.89% by area of the CDF. Naturally, if the internal smoothing applied by the model due to turbulence is reduced, the mitigation this has on the instantaneous power’s error is also reduced. Running the above scenario with a much smaller roughness length verifies this, as this alteration increases the error between the 5 point forecast and the raw NWP forecast from 1.79% to 2.28%, and increases the error between the 1 point forecast and the NWP forecast from 3.89% to 5.98%.

### 6.3.1 Drawbacks and Advantages of the Broader Models

The advanced forecasting models come with a degree of caveat emptor. The advantage of using multiple scenarios, or bets, on the outcome on an event is known as bet hedging, and is useful because it increases the number of events which can lead to a successful outcome. In gambling, this successful outcome is normally monetary based, whereas the NWP prediction uses this technique to determine which weather scenarios are likely to occur, hedging each ensemble member against the next. This hedging is beneficial as it can cover a much greater number of events, and therefore a more diverse set of power outputs; power outputs which would otherwise be overlooked.
The downside to this hedging is demonstrated in the differences in the long period power output between the NWP forecast and the single point forecast, shown above. The reality of the situation is that there will be a single forecast average for the area for the period of observation, meaning that the ensemble members which did not predict the actual result effectively failed predictions, or lost bets. If the model and the NWP forecast are well thought-out and skilful, the two values will be very close, whilst a poor prediction method will see the two values – reality and the prediction – diverge.

This is analogous to flipping a weighted coin, which is more likely to land on one side than the other, and betting on the result. The truth is that the outcome will either be heads, or tails, but hedging bets can help minimise the loss incurred from backing a losing outcome. Thus two of the golden rules of probability can be defined for gambling as well as for weather (and ergo power) forecasting. The first is that hedging scenarios helps minimise loss by providing more winning options, in this case providing more likely weather forecasts; and the second is that regardless of hedging scenarios, you only win if you pick the final outcome all the time using only a single guess; in both gambling and forecasting, this is almost always impossible.

### 6.3.2 Technology Profile Improvements

Discussed above was an improvement to the operational models used by the characterisation by using more accurate power curves for the micro wind turbines, and inverter efficiency curves for the PV arrays. Briefly examined below is the effect these changes have on the power output from the generators, including an example using on-line data.

The two figures below (Figure 6.14, Figure 6.15) show the results of running both the wind model and the PV model with the old, basic profiles, and the new profiles, under a range of conditions from low power output to high power output. As the single point model forms the working basis for all the other models, only a single point forecast was used to produce the outputs.
Chapter 6  Implementation and validation of the VPP Models

The wind model (Figure 6.14) shows the largest alteration at low speeds, which is as to be expected, although all of the outputs are different. The power profile chosen was as per Figure 4.6, which has a lower cut in speed than the simplified power curve and a shallower cut-off ramp, meaning that it is able to produce power at lower speeds, but is not able to produce maximum power as often. The figure shows the results from 4, 8 and 12ms\(^{-1}\), with the lowest and highest windspeeds associated with the lowest and highest power, respectively.

![Figure 6.14: Wind Profile Changes](image)

The PV power output (Figure 6.15) also shows heavy perturbation at low powers, reducing in magnitude as the PV array’s power output increases. Considering the inverter profile of the old and new setup (Figure 4.7), this is to be expected, as the inverter’s efficiency is lowest when the PV array’s power output is lowest, and almost unity at higher powers. The figure shows the results from 400, 800 and 1200Wm\(^{-2}\), with the lowest and highest insolation producing the lowest and highest power, respectively.
The correct choice of power profile is evidently important to the correct prediction of power output. The case can be highlighted using the data from Middelgrunden, demonstrated in Figure 6.2. The VPP forecast values began with an error margin of ±20%, using the certified power curve for the turbines. By adjusting the certified power curve using the data recorded from the site, it was possible to reduce the error down to ±3% - which is a significant reduction, considering the certified power curve was already a good fit to the power data, as should be expected. Needless to say, the basic simplified power curve is not a very accurate fit to either the certified power curve or the measured power curve, suggesting that its use to predict power output at the site would be very unwise.

### 6.4 Financial Analysis

The VPP output power data is for use by two groups, namely the DNO and the VPP agent. The DNO has remit over the structural integrity of the VPP network, whilst the agent is concerned with the acquisition of capital for themselves and their clients, the DG owners. In the results and analyses below, the feasibility of each method is measured in terms of whether the agent is able to generate more revenue, or less revenue, and in each case, what factors are associated with the loss or gain in revenue.
Chapter 6  Implementation and validation of the VPP Models

The test network is the 77 bus HV underground network available from [98], which is an 11kV urban network fed from a 33kV Grid Supply Point, supporting a nominal 24MW, 5MVAr load.

### 6.4.1 Financial Impact of the Different Prediction Methods

The weather conditions for the test period are to be a windspeed of 7\text{ms}^{-1}, an insolation level of 400\text{Wm}^{-2} with an RMSE of 10\%, and a temperature of 11 °C, which are not atypical values. An ensemble prediction was assembled about this data, predicting these conditions as the modal conditions. The windspeed was not correlated between ensembles, and the irradiance and temperature data were determined as to be correlated, as the time series data above, suggests. The affect of an ensemble mismatch is also discussed below, after the base case. The forecast data is given in Table 3 and Table 4 below.

<table>
<thead>
<tr>
<th>Ensemble</th>
<th>Windspeed in ms$^{-1}$</th>
<th>Insolation in Wm$^{-2}$</th>
<th>Temperature in °C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7</td>
<td>400</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
<td>7.4</td>
<td>360</td>
<td>10.4</td>
</tr>
<tr>
<td>3</td>
<td>6.2</td>
<td>380</td>
<td>10.6</td>
</tr>
<tr>
<td>4</td>
<td>7.2</td>
<td>370</td>
<td>10.5</td>
</tr>
<tr>
<td>5</td>
<td>7.2</td>
<td>390</td>
<td>10.8</td>
</tr>
<tr>
<td>6</td>
<td>5.8</td>
<td>390</td>
<td>10.9</td>
</tr>
<tr>
<td>7</td>
<td>7.8</td>
<td>410</td>
<td>11.3</td>
</tr>
<tr>
<td>8</td>
<td>6.8</td>
<td>420</td>
<td>11.4</td>
</tr>
<tr>
<td>9</td>
<td>7.4</td>
<td>430</td>
<td>11.5</td>
</tr>
<tr>
<td>10</td>
<td>7.2</td>
<td>450</td>
<td>11.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Percentage</th>
<th>Windspeed in ms$^{-1}$</th>
<th>Insolation in Wm$^{-2}$</th>
<th>Temperature in °C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5</td>
<td>5.8</td>
<td>360</td>
<td>10.4</td>
</tr>
<tr>
<td>25</td>
<td>6.2</td>
<td>380</td>
<td>10.6</td>
</tr>
<tr>
<td>50</td>
<td>7.2</td>
<td>395</td>
<td>10.95</td>
</tr>
<tr>
<td>75</td>
<td>7.4</td>
<td>420</td>
<td>11.4</td>
</tr>
<tr>
<td>97.5</td>
<td>7.8</td>
<td>450</td>
<td>11.6</td>
</tr>
</tbody>
</table>

The 3 forecasts types were run on a set of 60 equally rated DG units, 20 units of each of the 3 technology types, running with realistic power profiles, producing the following long period power output (Figure 6.16).
From a power perspective, the 5 point forecast and the ensemble both have very similar profiles, and both provide a good fit to the actual weather conditions. The financial analysis assumes the UK electricity market model, the BETTA pool system [10], although the old style pool system is a more ideal model for the DG agent (as the DG agent could set a very low price to ensure their inclusion into the schedule and then be paid the highest price). DG units which operate from variable sources, such as wind turbines, PV arrays, and to some extent micro CHP boilers, typically have a low running cost due to the free source of energy input.

It should be pointed out that the energy under the ‘actual’ weather conditions are still only a prediction, as the fluctuations caused by the variability of the generators allows for a degree of freedom within the conditions. It is recognised that the energy delivered for the period will not be a probabilistic function, simply that this is the most accurate energy prediction for the period.

### 6.4.2 Optimising Revenue for the VPP

In the UK BETTA market, bids and offers are collected and anonymously traded using bilateral trade. Understandably, those attempting to purchase power will buy the cheapest options available, and those attempting to sell power will set their price to balance profit against the likelihood of not being selected. Following gate closure, the
balance point is found for the network and successful bids-offer pairs are paid on face value, with adjustments according to the power imbalance taken from the system buy and the system sell price.

In order to maximise revenue the agent must try to guess in advance what they believe the system sell price will be and place their bid marginally beneath this value in order to maximise their revenue. If the agent bids lower than the system sell price (SSP), the difference between the two is missed profit; if the agent bids above the system sell price, the difference between the system sell price and the system buy price (SBP) is effective loss (as although they will not be included in the schedule, they will still receive the reduced rate for their energy production). Due to this, the optimum market for DG units is the market pool, where the system sell price is paid to all successful bids, as the VPP agent can place their power with a very low price – due to the low running costs – to make sure that their bid is always accepted. The drawback to this system is that it artificially inflates the price paid by the customer, hence the adoption of the BETTA market in the UK.

The financial analysis contains 3 essential variables: the System Buy Price, the System Sell Price, and the bid price. An adjustment to any of these variables alters the profit curve of the VPP. Using data from [114], a typical SSP and SBP is £41.18 and £19.91 respectively. The agent has chosen to sell power for 35.00£/MWh, and has high confidence that their bid is going to be accepted whilst still being profitable for them. The profit curves for the two forecast scenarios and the actual outcome for a half hour period are shown below (Figure 6.17), focused on the region of interest.
The actual predicted energy for the period generates maximum revenue at 19.225kWh, whilst the 5 point forecast shows maximum revenue at 19.3kWh, and the ensemble peaks at 19.025kWh. Both of the forecasts are good fits to the profit curve, as both peaks are within 2% of the expected power output. In monetary terms, the actual profit peaks at £0.621 for the period, which drops to £0.599 and £0.595 if the peak profit points for the 5 point forecast and the ensemble power curve are used, respectively. This equates to a loss of 3.5% and 4.2% of the maximum available revenue in this scenario, suggesting that the methods used are viable, and separated by a small margin.

Let us assume that the actual weather condition and variations of the generators produce the most likely energy conditions, the mode average energy, producing an energy output of 17.7kWh. The agent will place a bid in accordance with the predictions, selecting the ensemble prediction suggestion of 19.025kWh for the bid. The price paid for the half hour period, 61.0 pence, is equivalent to 3.2p/kWh, which is a rather low value when compared to feed-in tariffs available [115]. Not included in this revenue, however, is revenue generated through sale of Renewable Obligation Certificates (ROC), which can also be sold; the price is determined on the source of energy, with certificates for wind and PV trading as a more expensive commodity
than microCHP ROC. [116] gives a figure of around 7p/kWh for the technology mix used in the test case, increasing the revenue dramatically.

Any energy which the VPP produces can sell these ROCs, and this increases the price per kWh by 7p. In the example above, 17.7kWh worth of ROCs can be sold, increasing the total revenue to 184.9 pence, leading to a final price of 9.7p/kWh, a good value to be achieving for selling electricity through bilateral trade. If the VPP had simply provided balance support by selling power at the SBP, the agent would have achieved 1.9p/kWh, increased to 8.9p/kWh using ROC trading. The choice or ability to trade on the bilateral market increases the base revenue by an additional 68%, a 9% increase if the ROC trading is considered.

The next case examines the same VPP when the weather forecast has been less accurate, in that the final outcome is not about the mode weather forecast, and is one of the less likely cases (shown as the Outlier on the graphs above). The forecast used has an average windspeed of 7.4ms\(^{-1}\), an insolation of 360Wm\(^{-2}\), and a temperature of 10.4 °C (ensemble 2).

The outlier power output and profit curve are shown respectively in Figure 6.16 and Figure 6.17. The maximum projected profit available in this situation is at 20.3kWh, with revenue of £0.654 for the period. The same 5 point and ensemble power forecasts apply from the example above, with their peak profit points lying at 19.3kWh and 19.025kWh, which are 5% and 6% smaller than the outlier scenario suggests. If the mode outlier energy is produced, 18.725kWh, and the same bid position is used, the base revenue for the period is 65.4p, an increase of 4.4p over the actual weather conditions (a 7.2% increase above the 61.0p determined above). This is to be expected, however, as the weighting towards overestimating or underestimating the maximum projected revenue point is related to the bid price and the system prices. In this example, the bid price was much closer to the System Sell Price than the System Buy Price, so the predicted energy profile for the period provided allowed for a slight shift towards a higher energy output.

Based on this data, it is observable that the mismatch of forecast energy compared to the actual weather data affects the revenue by a similar order of magnitude to the
mismatch itself, although the specifics are determined by the bid and system prices. This is not immediately apparent from inspecting only the predicted revenue, but it must be remembered that these predictions have a broader energy spread than the real outcome. Using the actual energy value of 17.7kWh and comparing this to the actual energy prediction illustrates both the maximum revenue shift, and the effects of the broader energy spread, Figure 6.18.

![Figure 6.18: Distinguishing the effects of the broad energy spread](image)

Indeed, looking from the maximum revenue point, the maximum fall-off rate towards the origin is the Bid Price less the System Sell Price, and the maximum fall-off rate extending towards infinity is the System Buy Price less the Bid Price. In the first example, the peak profit point lay at 19.225kWh, with revenue of £0.621. The System Sell Price, the System Buy Price, and the Bid Price are also given, leading to the 2 fall-off rates:

\[
\begin{align*}
  f_1 &= P_{\text{Bid}} - P_{\text{Sell}} = 3.5 - 1.991 = 1.509 \text{p/kWh} \\
  f_2 &= P_{\text{Buy}} - P_{\text{Bid}} = 4.118 - 3.5 = 0.618 \text{p/kWh}
\end{align*}
\]  

(6.1)

By dividing these values by the maximum revenue price, the % fall-off rate in either direction can be determined, per kWh.

\[
\begin{align*}
  r_1 &= 1.509 \text{p/kWh} / 62.1 \text{p} = 2.4\% / \text{kWh} \\
  r_2 &= 0.618 \text{p/kWh} / 62.1 \text{p} = 1.0\% / \text{kWh}
\end{align*}
\]  

(6.2)
These equations provide an easy way to determine the maximum fall off rates, which are only useful as a rule of thumb method of determining the changes in revenue due to changing the bid position towards or away from the maximum.

### 6.4.3 ROCs and FITs

Great Britain introduced a feed-in tariff scheme for small scale electricity generation from April 2010 [117]. The scheme covers PV, wind turbines, and microCHP less than 5 MW, as well as other generation technologies, so is directly applicable to this work.

The tariff rates available up to the end of March 2012 are listed in Table 5, below.

<table>
<thead>
<tr>
<th>Technology</th>
<th>Scale</th>
<th>Tariff Level (p/kWh)</th>
<th>Tariff Lifetime (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar PV</td>
<td>≤4kW (retro fit)</td>
<td>41.3</td>
<td>25</td>
</tr>
<tr>
<td>Solar PV</td>
<td>≤4kW (new build)</td>
<td>36.1</td>
<td>25</td>
</tr>
<tr>
<td>Wind</td>
<td>≤1.5kW</td>
<td>34.5</td>
<td>20</td>
</tr>
<tr>
<td>Wind</td>
<td>&gt;1.5-15kW</td>
<td>26.7</td>
<td>20</td>
</tr>
<tr>
<td>MicroCHP</td>
<td>≤2kW</td>
<td>10.0</td>
<td>10</td>
</tr>
<tr>
<td>Hydro</td>
<td>≤15kW</td>
<td>19.9</td>
<td>20</td>
</tr>
</tbody>
</table>

These prices are much higher than the prices available to the VPP agent by the sale of energy and ROCs. As discussed above, the VPP agent could expect to produce around 10p/kWh for the VPP energy and trading of ROCs, whilst a similar technology mix would produce an average tariff rate of 29.8p/kWh – almost 3 times as large. Clearly, it is in the interest of the DG owners to pursue this higher rate if possible, although it is limited by the accreditation of installer, the energy supplier, and other factors.

With this in mind, the VPP agent is at a great disadvantage to compete because the FITs scheme is not operating inside the scope of the market, and is able to trade with artificially inflated prices. The data available from these metered FITs installations moves the state of play towards the managed VPP by providing a more accurate electrical model, although the VPP as an entity is not realized by this scheme.
6.5 **Network Analysis**

6.5.1 **Voltage Limits**

The first network analysis determines the maximum amount of DG which could be connected whilst remaining within the voltage limits. Infield and Thompson, [106], state that (p.38) “BS EN 50160 … states that, under normal operating conditions, all 10 minutes mean rms values of the supply voltage shall be within the range of $U_n +10%/-15\%$, where $U_n$ is the nominal voltage.” These limits are used in the analysis; the initial operating condition of the network does not invalidate these conditions, as the lowest bus voltage is 0.949p.u.

The limits on the penetration of DG into the VPP by voltage limits is extremely sensitive to the weather conditions. A great quantity of microCHP can be installed, for instance, with no affect on the network if they never switch on. Each technology is examined individually, and then in conjunction with the other technologies, to see how the limits change, according to the technology mix.

For micro wind turbines, the largest power output and worst case scenario for voltage limits occurs when the mean windspeed is in-between the rated speed and the cut-out speed. This occurs around $15\text{ms}^{-1}$, which is well within the feasible forecast in the UK. As the test aims to stress the network, the single forecast point at this position is used to ensure a maximal generation condition.

The worst case scenario also takes account of load patterns in the network. The United Kingdom Generic Distribution System (UKGDS) provides resources for modelling and the analysis of distributed generation, and their 77 bus network was used for the network analysis. The UKGDS load profiles for the 77bus case is for a domestic economy load, with a maximum load of 101% the base case, and a minimum load of 18.8% the base case. The worst case scenario for voltage rise will occur with the largest flow reversal, when the loading is at its lowest.

This test network is representative of a typical distribution level network, and has a radial topography. This topography is an important factor in the safety of the network, as the radial nature of the flow leads to propagation of network safety issues ‘down
stream’ from the problem component, a problem which meshing, more common in higher voltage networks, seeks to address. Although lower voltage networks, typically urban networks, are becoming meshed as a means to defer costlier investment, this analysis presents the most common base case scenario where there is no meshing in the network.

The penetration rate as defined by the number of DG in the system divided by the number of houses in the network. A typical average loading for a house is 500W, and the average load on the network is 51.9% of the base case. Thus, with a total load of 24.274MW, the network contains:

\[
\text{Houses} = 24,274,000 \times 0.519 \times \frac{1}{500}
\]

Houses = 25,196

The table below lists the penetration of microwind turbines on the ‘worst case scenario’ half-hour, alongside the maximum and minimum bus voltage, not including the slack bus. Each microwind turbine is rated at 1.5kW maximum.

<table>
<thead>
<tr>
<th>Penetration</th>
<th>Minimum Voltage</th>
<th>Maximum Voltage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 in 500</td>
<td>0.986</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 350</td>
<td>0.986</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 200</td>
<td>0.986</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 100</td>
<td>0.989</td>
<td>0.996</td>
</tr>
<tr>
<td>1 in 50</td>
<td>0.991</td>
<td>0.996</td>
</tr>
<tr>
<td>1 in 10</td>
<td>0.994</td>
<td>0.997</td>
</tr>
<tr>
<td>1 in 5</td>
<td>0.996</td>
<td>0.998</td>
</tr>
<tr>
<td>1 in 1</td>
<td>0.998</td>
<td>1.047</td>
</tr>
</tbody>
</table>

For PV arrays, the largest power output and worst case scenario for voltage limits occurs when the mean insolation is large, but not large enough to go over the inverter limit, and when the insolation is large, such as summer mornings. The insolation for the example is 1000Wm\(^2\), with a RMSE of 10%. 
The table below lists the penetration of PV arrays on the ‘worst case scenario’ half-hour, alongside the maximum and minimum bus voltage, not including the slack bus. Each PV array has a $P_{STC}$ of 1kW, a NOCT of 50C, and an inverter limit of 1.5kW.

<table>
<thead>
<tr>
<th>Penetration</th>
<th>Minimum Voltage</th>
<th>Maximum Voltage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 in 500</td>
<td>0.985</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 350</td>
<td>0.985</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 200</td>
<td>0.986</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 100</td>
<td>0.986</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 50</td>
<td>0.988</td>
<td>0.996</td>
</tr>
<tr>
<td>1 in 10</td>
<td>0.990</td>
<td>0.996</td>
</tr>
<tr>
<td>1 in 5</td>
<td>0.994</td>
<td>0.996</td>
</tr>
<tr>
<td>1 in 1</td>
<td>0.998</td>
<td>1.024</td>
</tr>
</tbody>
</table>

For microCHP, the largest power output and worst case scenario for voltage limits occurs when the mean temperature is low. In the UK, a cold, winter night around dawn provides the maximum power output.

Table 8 below lists the penetration of microCHP boilers on the ‘worst case scenario’ half-hour, alongside the maximum and minimum bus voltage, not including the slack bus. Each CHP boiler has a boiler power of 10kW and a conversion rate of 30%.

<table>
<thead>
<tr>
<th>Penetration</th>
<th>Minimum Voltage</th>
<th>Maximum Voltage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 in 500</td>
<td>0.985</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 350</td>
<td>0.985</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 200</td>
<td>0.986</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 100</td>
<td>0.986</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 50</td>
<td>0.987</td>
<td>0.995</td>
</tr>
<tr>
<td>1 in 10</td>
<td>0.993</td>
<td>0.996</td>
</tr>
<tr>
<td>1 in 5</td>
<td>0.997</td>
<td>1.001</td>
</tr>
<tr>
<td>1 in 1</td>
<td>0.997</td>
<td>1.05</td>
</tr>
</tbody>
</table>
From examination of the results, it can be seen that this network is very well suited to the incorporation of DG. The network did not violate voltage limits under the test conditions, which saw a maximum voltage rise of 0.1pu from 0.995 to 1.05pu.

The network can handle a total of 63MW of dispersed generation without violating voltage constraints, which is approximately 2.5kW generation per home, using the worst case loading conditions for the network. It must be remembered that the likelihood of the lowest loading point coinciding with an ideal forecast for generation is very slim, so there is a degree of lenience in this figure; the lowest loading conditions are typically throughout summer/autumn nights, when PV arrays aren’t receiving insolation, micro CHP boilers aren’t generating due to high temperatures, and micro wind turbines aren’t generating a great amount of power as wind conditions are mild.

### 6.5.2 Line Limits

To test the network’s suitably by line limits, the limits provided along with the network data were used. Differing quantities of DG were installed into the VPP using the same conditions as were used for the voltage limit tests. The results for micro wind, PV arrays and micro CHP are shown in the tables below.

<table>
<thead>
<tr>
<th>Penetration</th>
<th>Lines Over-ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 in 500</td>
<td>0</td>
</tr>
<tr>
<td>1 in 350</td>
<td>0</td>
</tr>
<tr>
<td>1 in 200</td>
<td>0</td>
</tr>
<tr>
<td>1 in 100</td>
<td>0</td>
</tr>
<tr>
<td>1 in 50</td>
<td>0</td>
</tr>
<tr>
<td>1 in 10</td>
<td>0</td>
</tr>
<tr>
<td>1 in 5</td>
<td>0</td>
</tr>
<tr>
<td>1 in 1</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 10: PV Arrays Line Limit Test

<table>
<thead>
<tr>
<th>Penetration</th>
<th>Lines Over-ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 in 500</td>
<td>0</td>
</tr>
<tr>
<td>1 in 350</td>
<td>0</td>
</tr>
<tr>
<td>1 in 200</td>
<td>0</td>
</tr>
<tr>
<td>1 in 100</td>
<td>0</td>
</tr>
<tr>
<td>1 in 50</td>
<td>0</td>
</tr>
<tr>
<td>1 in 10</td>
<td>0</td>
</tr>
<tr>
<td>1 in 5</td>
<td>0</td>
</tr>
<tr>
<td>1 in 1</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 11: Micro CHP Line Limits Test

<table>
<thead>
<tr>
<th>Penetration</th>
<th>Lines Over-ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 in 500</td>
<td>0</td>
</tr>
<tr>
<td>1 in 350</td>
<td>0</td>
</tr>
<tr>
<td>1 in 200</td>
<td>0</td>
</tr>
<tr>
<td>1 in 100</td>
<td>0</td>
</tr>
<tr>
<td>1 in 50</td>
<td>0</td>
</tr>
<tr>
<td>1 in 10</td>
<td>0</td>
</tr>
<tr>
<td>1 in 5</td>
<td>0</td>
</tr>
<tr>
<td>1 in 1</td>
<td>0</td>
</tr>
</tbody>
</table>

Clearly, the network can handle a large quantity of DG, violating the network’s line limits above a total of 31.5MW distributed generation, equivalent to 1.25kW per household. This figure is under half of the power limitation associated by voltage problems in this urban network, and is also lower than the rated power for all three technology types. The fact that only micro-wind turbines managed to exceed the line limits, when on paper it is indicated that they all should have, denotes that it is difficult to achieve maximum generation with these devices, something which has already been discussed above when discussing the technologies.

6.5.3 N-1 Analysis

In the UK, the legislation regarding unplanned interruptions [118] guarantees a rebate if a fault condition is unresolved for a defined length of time. There is no standard
rebate for VPP operators, although it is described in [6] that the technical VPP is monitored and controlled by the local DNO, enabling the transfer of network information to the commercial VPP, preventing and protecting the agent from placing unrealistic bids once a known fault condition has arisen. This does not help the agent if the fault condition occurs after gate-closure, however, and the agent must be able to ride-through any financial risk which may be associated with these scenarios.

The reliability rates and repair times for various lines are given in [119], which were used with the line lengths in the network model. The worst cast scenario for a VPP operator is a network which provides no feedback, so line outages are not reported to the VPP operator. Provided that the DNO provides this information to the VPP operator, it is reasonable to assume that only line outages which occur after gate closure can adversely affect the VPPs contracted output.

Figure 6.19 shows the Cumulative hours in a year against the percentage power dropped under a setup with no DNO feedback, and with DNO feedback (using half hour periods with a full hour gate closure). Clearly, the feedback provided by the DNO is essential to minimising unnecessary loss on the part of the VPP operator. The lost area for these cases is 4 minutes 32 seconds per year with feedback, and 6 hours 24 minutes and 30 seconds per year without any feedback, or 0.00086% and 0.073% respectively for yearly power output.

Half of the power drops lose 6% or less power, and are caused by the relatively short line lengths and the short line length between load busses. In Figure 6.20, the leg marked 1 contains 3 busses and 3 lines, and is configured in the same way as the termination of almost all the other legs of the network. The longer network legs, starting with the leg marked 2, provide the configurations which account for the next 30% of the drops, as they contain lines which transfer larger accumulations of power. This leg configuration can also be seen as the termination to leg 3. Finally, the last 10% of the power drops are from the start of leg 3, as these lines support the largest volume of power transfer. In Figure 6.19, the short sections similar to leg 1 are observed up to 8720 hours, the starting sections of legs similar to leg 2 are observed up to 8750 hours, and the starting sections of leg 3 completes the year’s duration to 8760 hours.
Whilst the yearly power loss is small, the maximum power drop in a trading period is 31.6% in this network. The effect of this drop is to reduce the revenue of the VPP operator, and under non-ideal bid placement the VPP operator can operate at a loss; the maximum revenue fall-off rates are discussed above. Networks with a single connection point, for instance, have a small chance of total power disconnection, which could be disadvantageous for the VPP operator if contingent plans, such as some form of financial security, were not in place.
Once again it must be mentioned that the radial topology of the network is typical for distribution level networks. Limited amounts of network meshing can be installed and left open in radial networks to switch in during fault or disconnection periods in order to circumvent the problem device and maintain the grid. This grid does not have any meshing lines installed, and acts as a worse case scenario because almost all of the disconnections have unavoidable knock on disconnections further down the radial topology. Meshing lines between the type 2 lines and the type 3 line in Figure 6.20, for instance, would reduce the maximum drop by approximately 10%. The introduction of meshing into the distribution network is however a problem made more difficult by the actual geographical distance between the lines (and the associated obstacles along the route), which are not necessarily described on the one-line diagram, and the associated cost incurred by the shoring of the network.

Using the data from earlier as an example, the ensemble prediction suggested that maximum revenue would occur at 19.025kWh for the analysis period. The actual energy output for the period was 17.7kWh. Under normal conditions this would produce revenue of 61.0p for the agent, but a drop of 31.6% of the generation capacity, and thus energy to 12.1kWh, reduces this to only 38.0p – a reduction of revenue by 37.7%. This magnitude of energy loss is large enough to be impossible using the actual energy prediction, as 12.1kWh has a probability and cumulative distribution of 0, and has only a 0.5% probability and a 2.5% cumulative probability using the broader ensemble prediction. It is therefore important to perform these analyses in order to determine the effects of these energy drops, as they have only a very slight chance of occurring under normal operating and prediction conditions.
Chapter 7    Conclusion and Further Work

This Chapter concludes the work by discussing the original aims and objectives of the work, and how these were met. The achievements and contributions of the work are highlighted as part of this discussion, followed by the areas of work and knowledge which could not be completed and filled during the time available, which are suggestions for further work in this area.

7.1 Main conclusions

To repeat the scope and objectives in this work, as laid down in Chapter 1, were:

- To undertake a critical review of developments in VPP and their modelling and characterisation.
- To develop a power prediction scheme applicable to a Technical or Commercial VPP with the combined technologies as chosen for the work
- To provide a novel power prediction scheme applicable to wide area prediction, which is to say amalgamating DG into a VPP over a very large geographical area.
- To incorporate the electrical network into the prediction schemes, including line current and bus voltage constraints, such that the impacts of the network can be determined.
- To compare the effects of the electrical network on the Technical and Commercial VPP in comparison to an infinite bus characterisations (a model containing no network implementation or characteristics).
- To investigate the effects and magnitude of network reliability (single line outages) within the Commercial VPP in comparison to the infinite bus characterisations.
- To evaluate the developed models with regard to their function, speed, complexity, and accuracy.

The development of the models of the work required the formation of two distinct types of power outputs predictions for the VPP: the Instantaneous and Long Period Power predictions. The instantaneous power output can be thought of as a second by second measurement of the VPP output, and the long period power output, which is
the mean power output value for the entire length of the measurement period. The difference between the two is that first is more suited to observing power swings and dynamic behaviour with its associated voltage and line power changes, than for use in power trading, whilst the second has these properties reversed.

Working with these two routes to mapping power output, four separate models were developed to estimate the power output for a VPP during a measurement period. The first of these was developed using a single forecast point for each variable, and can be inaccurate in its prediction because of this. In its favour, this technique can be used to reggressively look at collected meteorological data to examine theoretical VPPs, or to determine the appropriate parameters for the VPP generators, such as the correct roughness lengths, or power profiles.

To develop the first model also required the development of a method by which micro CHP generators could have their output determined. This method is based upon thermal data for the site, and boiler data, which can be read from the faceplate. The simplest power output is the instantaneous power output, which gives rise to the long period power output, which must account for the cycle length of the boiler, and the measurement period. Indeed, if the measurement period is brought towards zero, the long period power output becomes the instantaneous power output, which is exactly as should be expected.

The second technique developed uses the data provided by NWP meteogram to form a 5 point weather forecast, from which the power output can be determined. This technique has the advantage of a spread of predictions, as determined by the NWP, which cannot be feasibly estimated by using a single forecast alone. It has the disadvantage that it works from a basis of smoothing the raw NWP ensemble members, which obfuscates the subtle changes found within the NWP data. It is also, like the next 2 techniques, a stochastic technique, whilst the single forecast technique is deterministic.

The third technique developed uses the raw NWP ensemble members as a series of weather forecasts as the input to the VPP characterisation process. By treating each member as a single forecast point, a series a power outputs can be built and then
superimposed to form an output. This technique has the advantage of using the NWP data, which is the most accurate prediction of the weather for the forecast period, and thus is the most accurate prediction for the power output; as verified in the results section.

The third technique is also very useful because it allows the wide area characterisation of VPPs which are either contained in an area which is greater than a single forecast zone, or not geo-electrically close at all, which is an immensely valuable contribution as it allows for a very accurate large-scale map of DG power production for the time-period under study through the VPP concept. As each ensemble member covers a very large area with a grid of forecasts, it is possible to pick the forecast for a number of individual forecast areas for each ensemble member. By determining the power output for the generation subsets for the ensemble and then amalgamating them, the third technique can encompass large areas, and create VPPs which are enormous in scale.

The fourth technique is a simplification technique, which is able to estimate the power output of the VPP using central limit theorem. This is especially useful when there are a large number of generators present in the system, as the convolution method used to produce the output of the models becomes very slow as the number of data points involved increases. Instead, the power output for each generator is determined, as per the starting step to the other techniques, and the statistical data for each generator is used to produce an estimate of what the power output should be. This technique can be thought of as an alternative to the first technique, and can be used in the second and third technique as a replacement to the first technique. Its advantage, as mentioned above, is a reduction of the time taken for a reduction is model accuracy. As noted in the results chapter, provided that the number of generators is large, the loss of model accuracy is very small.

Several core programs were written to apply the techniques described during the work, primarily a program to model the generators onto an infinite bus-bar, and a load-flow program which incorporated the techniques, making it possible to inspect the network of the VPP.
The introduction of the network to the VPP also provides a glimpse into some of the problems associated with VPPs. In an urban environment it was found that the amount of permissible DG in a VPP is quite different depending on whether the line limits, or the voltage limits, are considered. In reality, of course, the lower limit must be used, although the limit is a function of the amount of DG penetration and also the network load. The limits found in the work are a conservative limit, as they insist upon a worst case scenario which has a limited but finite probability of occurring. Even so, it was found that a large penetration of DG could be permitted even in this worst case scenario.

The financial aspect of the VPP, the CVPP, was also considered in the context of an agent, trying to generate revenue from the VPP. The maximum revenue fall-off rates were determined for cases where the bid and the actual power generation were not identical, and the fiscal accuracy of the application of the modelling techniques were discussed, suggesting that the ensemble power output curve is best suited to the application, although there is a degree of uncertainty even with a perfect weather prediction. The work also indicated that revenue above the current feed-in tariffs available was possible through the joint sale of power and Renewable Obligation Certificates.

The network and the CVPP were considered in the case of contingencies, where an unplanned line outage had a detrimental affect upon the amount of power available to the DNO and the agent, leading to a detrimental effect on the revenue available. If the DNO is able to feedback network outages to the agent before gate closure, the affect on the revenue is very minimal, although the affect without feedback is 2 orders of magnitude larger. Whilst the precise figures are network specific, the orders of magnitude between the 2 values are not.

### 7.2 Suggestions for Further Work

During the course of the work, several avenues were explored which later had to be curtailed, and they are presented here as possible further work. The first of these is a temporal look at the instantaneous power output, and a look at how this affects the long period power output. During the models it was assumed that the generators, no-matter how closely placed, were independent of each other. In truth, the generators are
not entirely independent, and this is a function of the placement of the generators and the time. It would be very good to get this investigated.

Another avenue which had to be curtailed is the distributions used to describe the windspeed and insolation variations. The work above suggests either a Gaussian or a uniform distribution, but acknowledges that neither of these is a true fit, but both are close. Work by others suggests the Kolmogorov spectrum is an accurate fit to the wind spectra, and the accuracy of the predictions of the models contained within would be improved by using more fitting distributions, whichever distributions they may be.

A form of probabilistic load-flow would also be very useful for this DG work, as the outputs from the DG units are probabilistic. This would eliminate the simplification used to apply the models to the network, and provide useful data for both the instantaneous power flow, and the long period power flow.

As well as these avenues, model improvements such as park effects, wind shading, solar shading, temperature troughs, and a whole host of other effects produced by introducing complex terrain would benefit the models accuracy. The question, when introducing complex terrain, is whether or not the benefits in accuracy are greater or outweighed by the model complexity (in terms of computing power), and the ease of creation and use of the models. The programs created using the models are fast to execute and easy to add to or modify, but the introduction of terrain, buildings, and landscape features adjusts not only the operational speed of the programs, but also the difficulty of use.
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Appendix A Building the Toolset

In order to apply the methods developed above, a toolset was developed. This chapter gives a brief overview of the tools, their function, and a little of the background functions, as a means to explain the tools and their usage and an aid to those trying to reproduce the methods.

The Basic Power Aggregator Tool

The basic aggregator tool is the most simplistic of the tools, as it runs without any attachment to a network. The DG may be thought of as being attached to an infinite bus for this tool. Onto this bus, the DG is added, and the VPP output is determined by inputting weather forecast conditions. This begins with the input stage.

The input for the process is the parameter data for the DG technologies. The output data is statistical data (to be built into a graph) recording the probability for power generation. Working through the process, the flow of information is as follows,

- User action to begin the output process,
- Output parameters chosen by means of a parameter input window,
- Output parameters read in and temporarily saved,
- Output data for individual generators compiled using appropriate data,
- Output data compiled by combining each data set for each individual generator,
- Output data written to screen.

This cycle is completed by adding the steps:

- User action to add a new type of generator, of user selected technology,
- Input data chosen by means of a parameters window,
- Input data read in for the generator(s),
- Input data stored within the program under the correct DG technology.

This may be considered to be an un-optimized flow, but this is the most basic flow of information which will produce the output. The flow may be analysed from start to finish, starting with the first window the user is presented with.
Inputting Data

The window shown above is the first window the user is presented with. Contained within this window are the means by which to add new generators of the user selected type, means by which to start the process of the compilation of DG data and the power output, means by which to view and edit the input data, and means by which to view the output data. The saving and loading of DG parameter lists is also available. The entire process is laid out logically, from left to right. Adding a new generator is done by pressing one of the buttons in the bottom left of the screen, labelled functionally as ‘Add Wind’, ‘Add PV’ and ‘Add CHP’.

Pressing any one of these buttons opens up a new window, which contains parameters specific to the technology, and moves the process along to the next step - choosing the input parameters. The window shown to the left, for instance, is specific to micro wind turbines, and is not the same as the window shown for PV and microCHP. All the required generator parameters are inputted here; none of them need to
be added elsewhere in the process.

Also visible in Figure A.2 is a numeric entry box labelled ‘Number’, which allows the generator with parameters as selected to be added into the model multiple times. This is a feature to facilitate fast data entry; if a scenario has 100 identically specified generators it is tedious to go through this process 100 times.

When the user presses the ‘Done’ button the window is closed and the user is returned to the previous window (Figure A.1). This moves the process along to the next 2 steps, reading the data, and saving the data. The data chosen by the user to be the DG parameters is saved temporarily, along with the number required. The correct DG list is then found in memory according to the DG technology selected. The program then appends generators to the list with the chosen parameters, stored temporarily, until the number of generators appended is equal to the number of generators chosen. The temporary parameters are then deleted.

The user can, however, always press the X in the top right-hand of the window to stop the input process. No changes are made to the stored generator parameters until the user chooses to be ‘Done’ inputting. There are, therefore, two paths for each technology type for the input of data. One results in new data, the other does not. Both lead back to the primary window.

**Outputting Data**

Moving right along the primary window there are 5 buttons, reading ‘Build Graph Modal…’, ‘Build Optimised Modal’, ‘Build List’, ‘Build List’ and ‘MC Analysis’. The first button, ‘Build Graph Modal…’, moves the process along to choosing the output parameters. The window is shown below, and contains all the parameters for building the wind, PV and micro CHP outputs. Currently the box marked ‘Wind Direction’ has no functionality within the program.
Figure A.3: Build Output Parameters

The check box labelled ‘Uniform Distribution’ selects between the use of the Normal distribution, and the Uniform distribution. The other entry points are self-explanatory. Once the user presses the ‘Build’ button, the build parameters are read in and saved temporarily, moving the process along to compiling the output for each individual generator. The parameters window (Figure A.3) is then closed. If the user desires to run the model using a sole data point for each forecast, such as a single NWP forecast, only the 50% input entry needs to be completed (the program automatically detects this as a single NWP run).

To compile the output data for each generator, the program iterates through each technology type and compiles both the instantaneous power and the long period power using the forecast data and the DG parameters. This is done by passing the relevant build parameters to a function contained within each generator, which builds the power output data using the equations and formulae laid-out in Chapter 3 and Chapter 4, above. Once the entire of a DG technology type has had its generators’ power outputs built, the program moves onto the next technology. This process is maintained until every DG unit has had its output data compiled. The program then moves on to the next step, aggregating/combining all the generators’ power outputs together.
This is a straight-forwards series of additions and multiplications to perform the necessary convolutions. A temporary output data set is constructed which contains a single probability of no generation (0 Watts), probability 1. A technology type is chosen, and the first generator within that type is considered. For every possible unique combination of the temporary output and the generator output, the sum total of generation is determined, the probability multiplied out, and the probability added to a new temporary output. Once the process has been completed for the generator, the old temporary power output is replaced by the new temporary power output. The next generator within the technology type is then considered, or should there be no further generators, the next technology type is considered. Once every technology type has been considered, the final output power graph is the extant temporary output power data set. The process may then move onto the next step, outputting the data to the screen.

Coinciding with this process, the long period results are generated. For wind and PV technologies this is a very simply process consisting of averaging the power output, and only for CHP does the process follow a similar course to the process above. The results are then combined in a data set ready to be written to the screen.

On the primary window (Figure A.1: Main DG Window) to the far right may be seen a large text box. This is the destination terminal for the output data. The data is formatted as a tabulated vertical list, and with the generation value placed to the left of the probability that accompanies it. The first probability is the instantaneous probability, and the second is the accompanying long period data. At the bottom of the list is written the length of time taken to build the data. This data is then set as the text of the text box, and the process is completed. The user is, of course, returned to the primary window, where the data may be selected and copied for further use.

**Augmentation of the Basic Process**

Just as it is necessary that the user can inspect the output data, it is necessary that the user can view or edit the generator parameters. This may be for a variety of reasons, but it is important that this input data can be surveyed. For this purpose, there are two large regions on the primary window (Figure A.1) that have not been discussed thus
far. The first region, to the upper left of the window, contains the list on technology types, and the generators held under each technology type. The second region, to the upper centre of the primary window, displays generator parameters. In order to inspect a generator’s parameters it is only necessary to locate it in the list and click on it, whereby the parameters will be displayed, fully editable, in the parameters box.

**Optimization of the Basic Process**

From the description above it may be apparent that a great deal of processing power is required to build the output data; each new generator added to the output increases the size of the output by its own size, and filling the new output is a process of the size (in data points) of the new generator multiplied by the size (in data points) of the old output data. There must, surely, exist a way to reduce the number of computations while retaining output accuracy.

The method developed for this is entirely simple in its operation, leaning heavily on the natural organisation within computing. Before the method can be explained, it is necessary to examine some probability theory.

When the output data is built, the generator’s data is taken and combined, each generator having a potentially different set of data. The statistical output of one generator is not linked to the statistical output of another by anything other than by the laws which govern its electrical output; the outputs are not dependant on each other. This allows the combination of these generators in any order, as their outputs are exclusive, from the point of view of probability. Further to this, it is possible to combine several generators and then add to them, as is done here, with no detrimental effect. Expanding this, it is possible to compile several groups of generators and then combine the groups, provided that every generator is considered once, and once only.

If it were possible to build a group which contained several different sets of generator parameters which were, although not made up of every generator, representative of the overall parameter choices, it would be possible to combine this group with itself to build the overall probability set. This can be better understood through an example.
In a situation involving 9 identical generators, 3 different but identical generators, and 27 different but identical generators, it is clear that a factor of 3 is shared. Therefore, by building a group with 3 of the first, 1 of the second, and 9 of the third, a group has been built which is representative of the overall parameter choices. By combining the output of this group with itself, twice, the output for the situation is determined. All generators are numerically accounted for, as the grouped generators total the correct number of each when multiplied out. The fact that 6 of the first, 2 of the second and 18 of the third were never considered individually is not a problem, as the multiples of the grouped generators, generators which are identical and equivalent to them, automatically takes them into account. Therefore the number of mathematical operations is reduced to 15 from the original 39.

The savings within the 24 omitted steps due to data set size reductions is also important, but it is suffice to say that this method is faster than the original method.

The method used within the program is highly similar to the method outlined above. The program identifies all identical generators in each technology type, storing each identity and the number of generators which share it. The first identity is chosen, and the output data built for it. A binary bit-test is then performed on the number of generators associated with the identity, for the following reason.

Given that the order of generators is irrelevant (indeed, even the exact generator is irrelevant if the output is identical), and that groups can be built up and added to achieve the final output, it makes sense to build the output along the easiest route of grouping. When the group is added to itself, the number of generators (in this case) will double. Therefore, the easiest grouping is to determine the groups which are required in the $2^n$ series. The binary representation of the number is this test, already done for us. Thus a bit-test for each bit will resolve the groups which both require compilation and require combination.

The sub-groups for the $2^n$ series are then built and added according to the binary representation, to build the finished group for the identity. The program then moves on to the next group’s identity and repeats this process. This is done until all identities...
have been accounted for, whereupon the identities’ groups are combined to produce the output data.

156 identical wind turbines, for instance, each producing an output set of 50 points, requires a total of \( n^2(\chi^2-x)/2 \) calculations, where \( n \) is the number of data points, and \( x \) is the number of turbines. In this case there are 30,225,000 calculations. The binary value for 156 is 10011100, requiring 4 groups to be built, \( 2^7 \) (128) being the highest group. This takes 637,500 calculations\(^1\), and the combination requires a further 9,520,000 calculations\(^2\) for a combined total of 10,157,500. Obviously, this value is greatly below the under optimised value of 30,225,000.

Looking back to the primary window (Figure A.1), there is a button labelled ‘Build Optimized Modal’, underneath the button to run the un-optimized output process. This button runs the optimized process discussed above, and is placed beneath the other output button for this reason.

The topic of time-series data is mentioned above, as a modelling aid, the results of which may be utilized for further study. The possibility to enter time series data, therefore, becomes important. The ability to view time series outputs becomes equally important. A method of entrance and exit must be added to the program for time series data. The remainder of the process remains unchanged.

The process list for the input and output of time series data, then, is,

- User action to begin the input of time series data,
- Collection of time series data (the build parameters),
- Reading and temporary storage of all the build parameters,
- Execution of the build function using the 1\(^{st} \) set of build parameters,
- The user selected build process (optimized or non-optimized) is completed during this segment,
- Storage of the build process output data in correct time series placement (1\(^{st} \)),
- Repetition of the above 3 steps, moving through all the time series data aptly,

\(^1\) The calculation is based on the addition of \( n^2+4n^2+8n^2\ldots2^Hn^2 \), i.e. \( (2^{H+1}-1)n^2 \), where \( H \) is the highest group built.

\(^2\) \( 128n\times16n+144n\times8n+152n\times4n=3808n^2=9520000 \)
- Formatting of the output data, with the exception of additional tabulated results on a single line, and tabulated ‘Identifiers’ as column headers.

On the primary form, 2 buttons can be seen to the right of the non-optimized and optimized process buttons, labelled ‘Build List’. Both of these are the entry point for the time series data, as this opens a new window that allows the collection of time series data. The window appears as follows,

![Figure A.4: Build List Parameters](image)

The parameters available for modification are identical to the build parameters under single run, with the addition of an ‘Identifier’, which is included to allow easy identification of results, as the nomenclature implies. The data grid can add or remove time series points using the ‘Add’ and ‘Del’ buttons, as well as Load and Save the data to file. The data files are tab delimited, including a tab at the end of each line, in the data order shown in the window – they are nothing fancy, designed for ease of authorship; they may be edited in any text editor. The data can be selected and copied from the grid conventionally, but no data may be pasted into the grid. Upon pressing the ‘Cancel’ button the time-series entrance is abandoned and the window is closed, with the loss of any unsaved data. Pressing ‘Ok’ closes the window and proceeds to the next step in the entrance point, reading and temporary storage of all build parameters.

The program then creates a series of objects to store the results in, proceeding as listed above. Each set of parameters is processed and the output saved. Once every parameter configuration has been processed, the results are displayed in the primary window.
The Load-Flow Tool with Aggregation

This program is a very complicated piece of software, but it can be reduced down to its component procedures and methods. The software runs and presents the user with the main window to begin with, as below. The component types are listed, along with various other buttons and lists.

![Load Flow Main Window](image)

The first procedure in the load-flow is the input and gathering of information. This can be done by either clicking on ‘Network’ and then ‘Open’, or by inputting the network data. This second option is done using the component list and the “Add” button, shown on the window. First, the user selects a component type by clicking it in the list, and then clicks the Add button. A generic, unconnected component of the selected type is added into the component list, and is shown in the component list (shown empty in the picture), found beneath the component type list. By selecting the component in the list, its properties are displayed in the large property box to the right of the window. The component properties are also editable in the box.
Once the components have been added, it is necessary to connect them together. This is done by selecting the component and then pressing the Attach button shown on the main window. This opens up a new window in which the bus list is presented. The user may then select the connection busses for the component, from 1 connection to 3 connections, dependant on the component type. The connection window is shown below.

**Figure A.6: Load-Flow Bus Attachment Window**

In the connection window above, there are 2 buses in the network, and these have been selected as the points of connection.

This process effectively builds the network without the use of a one-line diagram. There is a massive amount of behind the scenes programming which allows this process of inputting data to automatically build the component y-bus matrix, as well as automatic network islanding. In this way, by the time the network is desired to be solved, all the preliminary setup work has already been done.

In order to run the load-flow, the user must click on the ‘LoadFlow’ menu item in the main window, and then select ‘Single’. This opens a new window which allows the user to select the load-flow preferences. The Tolerance value is the tolerance according to the network MVA base. Using the standard 100MVA, the default tolerance is 1MW, although the user can select a tolerance as high as 100W. The iterations count is the maximum allowed number of iterations before the algorithm exits. If the algorithm is forced to exit because it has hit this limit, something is amiss. The other parameters are the same format as the previous tool, where there was no
network consideration. On clicking the Ok button, the load-flow is commenced for the 1st island in the network and the window is closed. Under usual conditions, this is the only island.

![Figure A.7: Single Load-Flow Window](image)

The process for performing a load-flow is well documented, such as in [90], and is also available from many internet websites, so it will not be overly laboured here. The basic process is to determine the power flows, and then compute the new bus voltages using the inverted Jacobian, then to determine the power flows again. When the power flows are beneath the ceiling tolerance value, the algorithm exits successfully. This may not even require the main body of the algorithm to run, dependant on the initial conditions of the network. Once completed, the result data for lines, buses, and generators are stored, and the user is returned to the main window. The text console to the bottom of the main window indicates how the process performed, indication convergence or divergence and the iteration count.

The user may view the normal output data by selecting ‘View’ in the menu and then any of the options in the menu, those being ‘Bus Data’, ‘Line data’, and ‘Generator Data’. Grouped Data viewing is also available for N-1 analysis. The following window is presented.
The user may change between bus, line, and generator data by selecting the appropriate tab on the window. Displayed in a grid are the results data for the case last run.

**Scripting**

A feature of the load-flow program which is useful for the verification of the probabilistic model, as well as for other purposes, is the scripting feature. This allows a network to be solved under different conditions without the user having to continuously change network variables. In order to begin a scripted solution, the user must press the ‘LoadFlow’ menu item, then the ‘Scripted…’ option. This opens a new window which is used solely for writing, loading, saving and running scripts on the open network. The window is as follows.
The text area which forms the majority of the window displays the current script. This may be cleared, loaded, or saved by selecting the ‘Scripts’ menu item and then the appropriate option from the list. When the script is written, it must first be parsed by the program, to check for errors, and then executed. This is done by selecting the ‘Run’ menu item and then the ‘Parse’ option in the list. The program scans the script for any unrecognized commands and alerts the user of them, before validating the script as Ok. To run the script, the user must select the ‘Run’ menu item and then the Run item from the list. The script is then executed according to the commands contained within it, and is parsed for safety reasons. The scripting commands available are Declare, CloneNetwork, ResultsDimension, Run3PLF, CreateDistribution, UpdateDistribution, UpdateNetworkWind, LoadsSet, GensSet, Mul, Add, BeginLoop, EndLoop, Set and ResultText. The scripter recognises the phrase BaseNetwork to be the loaded network, and recognized the following data types, Network, Deci, Distribution, Int and Curve. The commands and data types are explained below.

Table 12: Scripting Data Types

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network</td>
<td>A power system network</td>
</tr>
<tr>
<td>Deci</td>
<td>A decimal value, equivalent to a double precision number</td>
</tr>
<tr>
<td>Distribution</td>
<td>A distribution provider object</td>
</tr>
<tr>
<td>Int</td>
<td>An integer value</td>
</tr>
<tr>
<td>Curve</td>
<td>A curve type, of type Flat, Normal, or Rayleigh</td>
</tr>
</tbody>
</table>
Table 13: Scripting Commands

<table>
<thead>
<tr>
<th>Command</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Declare sName sType</strong></td>
<td>Declares an object of type sType with a name sName</td>
</tr>
<tr>
<td><strong>CloneNetwork sName1 sName2</strong></td>
<td>Creates a clone of network sName1 into the network sName2</td>
</tr>
<tr>
<td><strong>ResultsDimension &lt;iInt&gt;</strong></td>
<td>Declares the results object to have &lt;iInt&gt; result sets</td>
</tr>
<tr>
<td><strong>Run3PLF psName &lt;iIsland&gt; &lt;iIteration&gt; &lt;dTolerance&gt; &lt;iIndex&gt;</strong></td>
<td>Runs the network named psName and saves it in the results object at index iIndex, using the tolerance and number of iterations given in iIteration and dTolerance.</td>
</tr>
<tr>
<td><strong>CreateDistribution sName CurveName dMean dSigma bAuxEnable CurveName dAuxSigma</strong></td>
<td>Creates a distribution object. Legacy command.</td>
</tr>
<tr>
<td><strong>UpdateDistribution sName</strong></td>
<td>Legacy command.</td>
</tr>
<tr>
<td><strong>UpdateNetworkWind sName1 sName2</strong></td>
<td>Updates the network sName1 using distribution sName2. Legacy command.</td>
</tr>
<tr>
<td><strong>LoadsSet sName &lt;dPercent&gt;</strong></td>
<td>Adjusts all loads to be at dPercent% of their original value</td>
</tr>
<tr>
<td><strong>GensSet sName &lt;dPercent&gt;</strong></td>
<td>Adjusts all generators to be at dPercent% of their original value</td>
</tr>
<tr>
<td><strong>Mul &lt;sName1&gt; &lt;sName2&gt; sName3</strong></td>
<td>Multiplies sName2 by sName3 and stores it in sName1</td>
</tr>
<tr>
<td><strong>Add &lt;sName1&gt; &lt;sName2&gt; sName3</strong></td>
<td>Adds sName2 to sName3 and stores it in sName1</td>
</tr>
<tr>
<td><strong>BeginLoop sName &lt;dCount&gt;</strong></td>
<td>Begins the loop entitled sName</td>
</tr>
<tr>
<td><strong>EndLoop sName</strong></td>
<td>Ends the loop entitled sName</td>
</tr>
<tr>
<td><strong>Set sName &lt;sValue&gt;</strong></td>
<td>Sets the data object sName to be sValue.</td>
</tr>
<tr>
<td><strong>ResultText &lt;iInt&gt; sText</strong></td>
<td>Appends text sText to the result object name at index iInt.</td>
</tr>
</tbody>
</table>

The table above lists all the commands available. Some operands may be noted as being in triangular brackets, this indicates that the operand may be a declared variable,
or the specific value, i.e. “Mul 5.0 10.0 temp”, and “Mul temp1 temp2 temp” are equal provided that temp1 and temp2 are declared and set to 5.0 and 10.0. Below is a worked example of a script.

```plaintext
Declare MyNetwork Network
Declare iInt1 Int
Declare iInt2 Int
Set iInt1 10
Set iInt2 0
ResultsDimension 10
BeginLoop Loop1 10
CloneNetwork BaseNetwork MyNetwork
LoadsSet MyNetwork iInt1
Run3PLF MyNetwork 0 30 0.0001 iInt2
ResultText iInt2 Loads at
ResultText iInt2 iInt1
ResultText iInt2 Percent
Add iInt1 iInt1 10
Add iInt2 iInt2 1
EndLoop Loop1
```

Figure A.10: Simple Script Program

The script begins by declaring 3 objects, a network and two integers. The integers are set to 10 and 0. The results object is dimensioned to contain 10 sets of results, and a loop is started. Once inside the loop, the network object is filled from the base network, and the loads set to 10%, using iInt1. The load-flow is run using a tolerance of 0.0001 and 30 iterations maximum, saved in position 0, using iInt2. The results text is set to “Loads at 10 Percent” using iInt2 and iInt1. iInt1 and iInt2 are then incremented, and the loop end is reached. The loop then continues until it has been executed 10 times. The end result of this is to run the load-flow with loads at 10%, 20%, 30%, etc. up to 100%. The script is then completed.

The results from scripting may be viewed in exactly the same way as for non-scripted results. The only addition is that in the results window, the “Results Name” is filled using the result text provided by the script, and the horizontal slider at the bottom of the results form can be used to move between the result sets. The “Export” button in the results window is currently unconfigured, however, the data in the results grid may be copied and pasted out of the application.

**Populating the Network**

Adding the DG individually into the network is a time consuming task, especially as thousands of units can be required. In order to expedite the process, a process was developed to add a quantity of units automatically to the network.
The user can select a number of buses and then add DG to them in the ratios they choose by assuming that the loads on the buses are domestic only. By choosing the amount of load (in Watts) per home, the process determines the numbers of homes attached to the bus. When combined with the percentage of DG penetration and the ratios of microwind to PV arrays to microCHP, the process automatically attaches DG to the requested buses:

The user is then presented with 3 windows, requesting information for the micro wind turbines, the PV arrays, and the microCHP to be added, similar to Figure A.2. The process can be repeated for the addition of more generators with different parameters, until the correct number of units has been added.

The population of the VPP network with the DG poses a challenge in that the DG must be equally spaced throughout the network. It is not sufficient to simply add micro wind until its quota is full, and then move onto PV arrays.
To overcome this, the process first begins with only 2 technologies, such as wind and PV. The process builds a list and fills it entirely with wind turbines, the size of which is equal to the ratio of wind turbines and the ratio of PV Arrays. Provided that the ratio of PV arrays is not equal to zero, the process determines how frequently PV arrays are scattered, by dividing the length by the PV ratio. The PV arrays are then placed within the list (see below).

![Wind Turbine Wind Turbine Wind Turbine Wind Turbine](2:2 ratio of wind:PV PV Frequency: 2 in 4)

![PV Array Wind Turbine PV Array Wind Turbine](2:4 ratio of CHP:PV + Wind Wind + PV Frequency: 4 in 6)

Figure A.12: Accurately Distributing DG in the Network (Stage 1)

The same procedure is followed for adding in the correct ratio of CHP, using a starting list filled entirely with CHP, and the previously created list as the values to distribute amongst it.

![CHP CHP CHP CHP CHP CHP](2:4 ratio of CHP:PV + Wind Wind + PV Frequency: 4 in 6)

Figure A.13: Accurately Distributing DG in the Network (Stage 2)

**N-1 in the Network**

The N-1 analysis is implemented as a new routine in the model, which removes a line or transformer one at a time and run a simulation to solution (failure or success). Whilst viewing the results of the N-1 analysis using the basic results viewer allows the inspection, copying of results, etc., it is limited in that only a single case can be viewed at any time. One of the key functions of the N-1 analysis is the ability to
watch the line flows, or voltage magnitude on a single line or bus for each N-1 scenario. For the energy trading purpose, the volume of DG power attached is important, and this was difficult to find using the previously implemented result inspector.

A new result inspector window was designed to overcome this problem (Figure A.14). The window sorts the results according to the specified manner. The user can select to view the results by type, or by contingency. If the user views the results by type, a network property is given alongside the list of contingencies, such as the voltage magnitude at bus 0 for each contingency. If the user views the results by contingency, a list of network properties is listed for the contingency selected, such as all line P losses for contingency 5. In the screen capture below, the user has selected to sort by Contingency, and is looking at the Primary Real Power flow of the lines, whilst Line 3 is disconnected.

The network summary can also be viewed for each contingency, and in this case it does not matter whether the user sorts by type or contingency. The user can select a network property from a list, such as DG Real Generation, and the window will sort these against each contingency. This is useful for determining the amount of power produced by the DG, as line disconnection will alter the load and generation values.
Figure A.14: Grouped Data View
Appendix B Publications

Introduction


The second paper below, entitled “Characterising the VPP”, was published as conference paper number 814 of CIRED 2009, as part of Session 4 of the 20th International Conference on Electricity Distribution, June 2009. It details some of the mathematical aspects of the modelling process, including the long period power, and the aggregation of disparate units into the Virtual Power Plant.

The third paper below, entitled “Financial Risk Analysis Associated with the Commercial Virtual Power Plant”, is currently unpublished, and details the financial risk associated with the probabilistic power output of the virtual power plant and the impact of single line failures.
Characterising Virtual Power Plants

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Abstract The use of small-scale generation based on disparate new and renewable technologies is becoming more prevalent due to the imperative to reduce greenhouse gas emissions that are thought to be the chief cause of climate change. As penetration of these distributed elements increases, displacing central generation, there is growing need to understand the composite behaviour of groups of Distributed Generation (DG) devices, also known as Virtual Power Plants (VPPs). This paper presents an overview of the mathematical modelling of the VPP leading to the development of a user friendly tool that can be used as a power system engineering teaching aid to demonstrate the characteristics of VPPs.

Keywords virtual power plant, distributed generation, combining, modelling

Introduction
The growth of environmental awareness in society is putting pressure on the electric power generation business to reduce CO₂ emissions, thought to be the chief cause of climate change. This is leading to new methods to generate power. Some of these methods build upon existing green technologies and expand their size, such as new large scale offshore wind farms, while other methods employ newer technologies such as fuel cells. The shift is driven by a combination of factors ranging from increased awareness of climate change due to power generation from fossil fuels through to concerns about long term security of oil supplies. Aside from energy trading companies, small scale Distributed Generation (DG) technologies are available for commercial and residential buildings, which can offer similar green credentials for a smaller scale of power generation. Of course, small scale conventional fossil fuel based generation can also be installed for back-up purposes.
Environmentally, the installation of green technologies such as photovoltaic (PV), wind and micro combined heat and power (µCHP) is beneficial in that it reduces the electric power drawn from the grid, thus reducing the carbon dioxide released from conventional electricity generation. If installed in large enough quantities, the annual electrical power produced by these technologies can equal or become greater than the annual power usage of the building, or site. For a building with this quantity of DG installed it would be logical to suggest that the site could be removed from the grid entirely and become self-sustaining, if it were not for the intermittency of the technologies involved. PV arrays are dormant at night, wind turbines are a slave to the wind speed, and microCHP is a slave to the site heating requirements. To become truly off-grid requires the installation of energy storage devices, which is costly, so many sites simply feed power back into the grid when they produce more than they consume, and take power out of the grid when they consume more than they produce. The reliance on fossil fuels (for conventional generation) is, therefore, maintained.

The approach to modelling power networks with DG has been to assume the DG as a load offset\(^1\). This assumption is acceptable to a point; however the assumption fails if the small scale generation outstrips the load, and leads to a reduction of controllability of the network. At this point the flow of power through the distribution network can alter significantly, affecting bus voltages within the power network. Most importantly, the physical hardware of the network is installed to control power flowing for a range of conditions, but these conditions are usually entirely unidirectional, from the remote power station to the consumer. The reversal of power flow is beyond the scope of the hardware to control, so the hardware must be changed or modified to enable bidirectional power flow. On a smaller scale, the flow of power within the low voltage (LV) network is adjusted by the reversal of power, affecting the line voltage profile. Zero transfer of power from the distribution network to the LV network does not guarantee that the LV lines are not carrying power, anymore.

The virtual power plant (VPP) is an artificial layer placed between the system operator and the DG user. It is formed out of individual DG units, and co-ordinates the actions of the units as a whole (where this is technologically possible), rather than leaving units to govern themselves individually. In this way it acts as a facilitator, as the network operator can instruct the VPP operator to control the output of the plant,
requiring more or less power output. It also acts to amalgamate the power output from
the component generators. This is useful for owners of intermittent DG, as the
amalgamation of devices acts to reduce the complexity of their output power, which is
stochastic in nature to predict.

**Challenge of predicting the output of a VPP**
The primary problem with predicting the output power from DG is that these devices
are driven by unpredictable sources. Accurate prediction schemes for wind speed,
solar irradiance and temperature are all advanced topics in meteorological studies, but
they are complex problems. In addition to the problems of accurate forecasting, there
are local variations which are beneath the scale of the forecast. Overall, the problem is
of sizeable magnitude. In this work we focus on three DG technologies namely, wind,
microCHP and solar power. In order to derive aggregate models for these
technologies in the form of a VPP, it is first necessary to understand the
characteristics of each technology.

**Wind power basics**
The wind speed at ground level is, as mentioned above, characterized by a degree of
uncertainty in the large scale forecasting and also by localized turbulence beneath the
scale of the forecasted data. It is assumed in the following work that there is no
forecasting error, although this is not the case. This assumption is made to simplify
the mathematics of the operation, as the model changes from being probabilistic to
stochastic due to the integrations which must occur to remove this assumption. The
remaining uncertainty in the wind speed is dependant on localized variations, and this
can be modelled. Masters (2004)\(^2\), gives the average wind speed for a given altitude in
equation (1). The standard deviation due to the geometry of the landscape is
determined from equation (2)\(^2\). Broadly speaking, the higher the measurement point,
the greater and smoother the wind speed will be. Equations (1) and (2) provide the
mean speed, and the standard deviation of the wind speed respectively.

\[
\bar{U}(z) = \ln \left( \frac{z}{z_0} \right) \times \bar{U}(h) \\
\ln \left( \frac{h}{z_0} \right)
\]  

(1)
where $z$ is the height of interest, $z_0$ is the roughness length, $h$ is the measurement height, and $U$ is the wind speed.

$$\sigma = \frac{\bar{U}}{\ln\left(\frac{z}{z_0}\right)}$$  \hspace{1cm} (2)

where $\sigma$ is the standard deviation.

No distribution function is noted for accurately representing small time period measurements, so the Uniform distribution was chosen for use with the data, as this assumes no bias of distribution. With the uniform distribution, the mean wind speed and the standard deviation, the wind speed probability distribution can be evaluated. This distribution must be combined with the turbine power curve in order to produce a useful output. An ideal power curve is shown in figure 1. Using statistical theory, it is possible to combine the two curves to produce a single probabilistic power output. Although this can be done for a single unit, it is impractical to manage the generator outputs this way, as they must be combined into a single output for the VPP. Using continuous data is possible, but it is more convenient for the process to use discrete data. Therefore the probabilistic output is stored in a discrete form; for the wind turbines, PV arrays, µCHP generators and the VPP.

**Solar power basics**

The solar irradiance at ground level is also characterized by a degree of uncertainty. For irradiance, the largest uncertainty is due to the variable nature of clouds, although some structural shadowing may be involved, depending on the placement of the PV array. Whilst the larger cloud formations are visible from space and can be predicted, smaller cloud formations are less easily noticed and introduce a degree of error into forecasted irradiance. E. Lorenz et Al.\textsuperscript{3} give the Meteostat 8 satellite a resolution of 1km$^2$ and 15 minutes, with an RMS error of 20% at 15 minutes. Although no probability distribution is mentioned in their work as being particularly well fitted, they use the uniform distribution in their work and for consistency with the wind model, the Uniform distribution is chosen to represent this error. With this information, the power output for a PV array can be determined using models from B. Ai et Al. (2002)\textsuperscript{4}. Once again, this output is discrete in nature for ease of manipulation and combination.
MicroCHP basics
MicroCHP is more difficult to predict, as it requires more general data in order to produce its output. The boiler in a microCHP unit is fired to heat a building, and the waste heat is converted at some efficiency into electrical energy. The building then heats up until the thermostat is above the upper threshold, turning off the boiler for heating purposes. Once the building has lost enough energy to fall beneath the lower threshold of the thermostat, the boiler is turned on again.

Given that forecasted data contains ambient temperature it is possible to determine the likely duty cycle of the boiler provided that an educated prediction can be made of the building’s thermal parameters, such as its overall thermal resistance from exterior to interior and heat capacity. By choosing appropriate values for the building’s heat capacity and thermal resistance, and knowing other boiler parameters such as thermal power rating and conversion efficiency, it is possible to determine the duty cycle and consequently determine the instantaneous stochastic output power of microCHP.

Instantaneous and Long term Power
While it is important to determine the instantaneous power, as above, it must not be forgotten that another important quantity is the average power over the prediction period. The instantaneous power provides the likely power generation for the VPP at any point during the prediction time frame, which is different to the average power throughout the prediction time frame, described as being the long term power. Whilst the instantaneous power is useful for determining flows in the network during the time frame, the more static long term power is a more useful guide of the available power for the time frame, and will show the overall predicted flow of power.

The wind turbine long term power output can be generated using a simple mean function. Although this is a simplification, the period length chosen plays a key role in determining how inaccurate this method is. By choosing lengths which fall between 10-60 minutes, the variance in the wind speeds is minimized (Masters). Whilst this is no guarantee that the speeds will exactly fit the distribution, it maximizes the chance that it will.
The PV long term power output can also be generated using a simple averaging function, due to the cloud formations which cause the initial inaccuracy. Whilst the larger cloud formations which form the baseline forecast irradiance are easier to predict, the smaller, fleeting clouds cause inaccuracies which can be averaged out. Due to their size and speed, they produce fluctuations which are of a similar nature to duty cycle. Whilst this produces errors in the instantaneous power, this behaviour is smoothed out over longer time periods to produce a relatively accurate mean result.

MicroCHP is more difficult to characterize. Due to the polarised on-or-off behaviour of the generator, the output appears as a pulsed cycle. The probabilistic long term power output obtained from this is entirely dependent on the boiler cycle frequency and the observation period. Whilst the governing equations are lengthy to derive, they are not at all complicated, resolving into four distinct cases.

**Combining the DG Units**

The combination of the probabilistic power output graphs to form an overall probabilistic power output graph is, as mentioned above, greatly accelerated by using discrete data. To add the probabilistic power outputs of two DG units using continuous data involves the use of a great many integrations, and whilst the process also has to be done using discrete data, the discrete case resolves to simple multiplication and addition for each data point. This is done for each data point in the output data, repeating for each generator under consideration until every DG unit has been included in the two varieties of power output, the instantaneous power output and the long term power. Due to the probabilistic process, it does not matter in which order the DG units are considered.\(^5\)

**VPP Implementation**

To generate the program capable of performing the calculations and combinations automatically requires careful organisation of the program structure accompanied by an overview of how the program should interact and communicate data with the user.

The end user for this application is the manager of the VPP, who should be able to perform the aggregation of the output power with as little effort as possible; this is the
most frequently repeated task. Additionally, the manager should be able to add or remove generators from the system without difficulty. Furthermore, the manager should be able to process multiple scenarios in one sitting by either manually repeating the aggregation process, or by loading a list of forecasts for the program to work with.

The data input from the system operator comes in two places; the distributed generators’ unit parameter entry, and the forecast parameters entry. The unit parameters are required before the forecast parameters can be used and the forecast parameters are required to execute the program models. However, while the second input is required whenever the program models are run, the input of the unit data is required only during the VPP setup, i.e. once, unless the configuration of the VPP is modified. This generation unit setup is time consuming, governed by the number of generators within the system. Consequently, the VPP generator setup should be able to be saved and loaded to ensure swift progress to the main portion of the program.

The statistical output from the program takes the form of data sets against output power. Each forecast input set produces two sets of data, the instantaneous power output and the long term average power output. This is the final terminal for the flow of information within the program, as the program is not and does not try to be a graphical display or spreadsheet type application. Others have already done very well at creating these types of programs, so the data should be expressed to the user in such a manner that it can be transferred from the program into a graphical display package easily.

**The GUI**

In accordance with keeping the user traffic of the program to a minimum, the basic interface is built incorporating the specifications noted above. The input of data, both generation and forecast data, can be accomplished from the interface (Figure 2), as well as the loading and saving of VPP configurations mentioned above.

Additionally, it is possible to edit the generator parameters entered or loaded through the interface, using the leftmost two of the large boxes on the window. The leftmost box is able to select generators in the VPP, and the box to its right displays the
parameters of the selected generator. Changing any of the generator’s parameters through this manner is accomplished by simply editing the relevant value. Of course, these new values are not automatically saved to file, but this allows for minor or major modifications to the VPP without having to entirely delete a generator in order to re-enter it with different parameters.

Other than the aforementioned boxes, the flow within the program is from left to right. The leftmost six buttons allow for the input of new generators, deletion of generators, and the saving and loading of generator configurations. This group of buttons form the setup of the VPP, and once the VPP has been setup the user need not use them again. The next stages of the process are completed using the middle four buttons.

The middle four buttons allow for the input of the forecast data to complete the primary purpose of the program. They are split into two and then into two again. They are first split according to whether the user requires to run a single forecast or whether the user wishes to run a series of forecasts. This split is vertical, the leftmost buttons processing only a single forecast. The second split is whether the user wishes to run an optimized or non-optimized version of the process, which is useful as a demonstrative tool to show the time saved in running the optimized process; the outputs from both are otherwise identical. This split is horizontal, the non-optimized process being the top-most two buttons. The optimization itself will be discussed later.

The final portion of the window is the output text box. Upon completion of the main process, the text box is filled with the data sets using tab delimitation so that it can be copied and pasted directly into a spreadsheet application. In itself it cannot be edited, as it is not intended for user input, only output.

**Data Input**

Once the user selects to add a generator to the VPP, they are presented with a very easy to follow pop-up (Figure 3). It presents the user with a series of parameters for the generator which they are able to change. Also, to improve efficacy with entering identical generators numerous times, the user can choose to enter any number of
generators with the given parameters. Once the user is satisfied with the parameters, the generators are added by clicking the ‘Done’ button. Pressing the close button for the window exits the pop-up window to no effect.

If the user decides to process a single forecast data, they are presented with another pop-up window (Figure 4). Using the displayed parameters they can enter the forecast data. When the user is satisfied with the entered data, pressing the ‘Build’ button progresses the program through the aggregation process, then displays the results to the user.

If the user selects to run a series of forecasts, they are presented with a table pop-up window. The same build parameters seen in Figure 4 are available for edit, and the user can add and remove rows from the table. Should the data be stored in a text file list, the user can opt to load or save the data to file. Once the user is satisfied with the data list, pressing the ‘Build’ button reads the data from the table and processes each forecast in series. The entire results table is then displayed to the user.

The Back-End

Whilst the front-end is very straightforward, it builds entirely on the correct structuring of the back-end, and its processes. Including the GUI interfacing, the back-end is a single layer. The lay-out of the back-end can be seen in Figure 5. The functionality can be split into two categories, data management and data processing. Whilst the data processing naturally involves active data management, it is necessary to differentiate between the two so that code reuse can be accomplished. Although the data processing is more complicated, it is built upon the correct management of the data.

The data management functions are the first routines to be run as part of the back-end, where the data structures required are initialized. The management also handles the addition of generators, the deletion of generators, the selection of generators, and the loading and saving of VPP configurations. With regard to the forecast data, the management functions read in this data including the series data table, which itself includes the loading and saving of forecast data. On a final note, the data management function displays the output data to the screen.
The management functions do not do anything other than organize the data however. Bridging between the management and processing are the entry points to the data processing functions, which passes the data collections to the processing functions and collects the output data.

The data processing functions work with the data that the entry routine gives to it. This data is not without form however, and beside the processing functions are a collection of data classes which the data management manages, and the data processor utilizes. There is a class for each generator type, and the class holds the parameters for the relevant generator once it has been initialized. Furthermore, the classes have built in functionality. Each class can build its own output power graph, both for instantaneous and long term powers. The more complicated mathematical aspects of building these graphs is accomplished by yet another class which sits beside them, a class which can provide the output of the cumulative distribution at the requested point.

With these useful classes, the simplest route for data processing is to let each generator build its output power graphs, and then to combine the generators’ graphs into two complete output graphs. Whilst the simplest route, it is clear that the length of time required for processing the data is related to the number of generators, and is in fact quadratic in nature. Optimization is useful here in reducing the length of time required, as the number of generators can potentially be large.

**Process Optimization**
The process can be optimized by reducing the effective number of generators in the system. In our favour, many generators share identical parameters, and it is these generators which can be easily reduced.

The reduction is based on the theory that the order of aggregation is not important, only that each generator is aggregated into the total, and this is true for us. Working with this datum, identical generators produce identical output graphs. Therefore by combining 2 generators and then combining the output with itself, 4 generators can be effectively aggregated – provided that they are identical. Continuing with this trend,
the binary sequence of numbers of generators can be achieved with relatively few
calculations.

By identifying all identical generators and counting their number, the optimization
can come to fruition. As the number is stored on computer, it is naturally stored in
binary format, so examination of each bit of their number identifies which
combinations of this doubling process are required to build their outputs. Selecting
only the bits which are required, it is possible to build output graphs with far fewer
calculations. In a system of 156 identical generators with 50 points to their discrete
output each, the reduction in number of calculations is 66%.

The Model Outputs
The models and the program produce some observable characteristics, some of which
are more intuitive than others. In general, however, it can be stated that increasing the
number of units in the VPP is conducive to reducing the relative variation of the
instantaneous power from the mean. This is very good for the system operator, as it
improves their reliability to provide power.

Each technology also has associated output patterns. PV modules, for instance, show
the expected output of operating only during the day, whilst μCHP displays an
opposing behaviour to PV generation, operating during the cooler portions of the day.
Seasonally, these technologies generate power as they would be expected, PV being
prominent during the summer months, and μCHP being more prominent during the
winter months. Wind turbines display the least predictable output, showing peaks of
generation throughout the day – depending on which day is being studied.

The models used for the program do have their limits, however. The models assume
that the forecasted data is entirely accurate, which introduces problems of its own
making when predicting periods which do not have entirely accurate forecast data.
The system operator cannot gain useful insight into near-future forecasts as the
models do not take into account this uncertainty. The model will still produce an
approximate representation for the forecast data used, but will provide no degree of
variation due to the inaccuracies, as they have not been modelled yet.
Case Study
The case study presented is a setup of 3 generators, one of each type (wind, PV and CHP). The wind turbine is rated at 1.5kW at a height of 10m, with cut-in speed of 4ms\(^{-1}\), rated speed of 12ms\(^{-1}\), cut-out speed of 25ms\(^{-1}\) and a site roughness length of 0.7. The PV array is rated at 1.5kW maximum, \(P_{STC}\) of 1.0kW, surface azimuth of 180°, a temperature coefficient of 0.005 and a tilt angle of 10°. The CHP boiler is rated at 10kW, with a heat-electrical power conversion ratio of 0.3, with thermostat points of 19-21C, installed in a building of heat capacity 800JK\(^{-1}\) and thermal resistance of 0.005KW\(^{-1}\).

First, the generators were isolated. The instantaneous wind, PV and CHP were tested individually against a weather forecast of wind speed 15ms\(^{-1}\), irradiance 800WM\(^{-2}\), RMSE irradiance 20%, solar azimuth 160°, solar altitude 60°, and temperature 8C, over a period of 900seconds. A Monte Carlo simulation, using the same generators and weather parameters, was run alongside the tests to verify the validity of the models. Using a million stochastic samples, the mean errors for wind, PV and CHP were 0.010%, 0.008% and 0.002% respectively compared to the probabilistic graphs.

The generators were then operated as a group, using the same conditions as above. A Monte Carlo simulation was run using 10 million stochastic points and compared against the prediction, giving a mean error of 0.002% for the combination model. The combined output from all three generators produces a probabilistic output and stochastic output shown in Figure 6.

Conclusions
The paper set out to provide an overview of the modelling of the virtual power plant with a view to demonstrating how a user-friendly tool could be written to apply the models. Progress has been made in building probabilistic models for the three technologies discussed, wind, PV, and microCHP, and a tool has been developed with these models, placing emphasis on being fast, easy to grasp and easy to use. The limitations of the current model are its inability to incorporate the inaccuracies in the forecast data. Future work on the topic is the need to incorporate forecasts which are
further into the future, incorporating forecast inaccuracy not only for this purpose, but also for present-time forecasting inaccuracies.

References


Figure 1

Figure 2

Figure 3
Appendix B

186

Figure 4

Front-End
- Main GUI
- Add Generator Pop-Up
- Process Forecast Pop-Up
- Process Series Forecast Pop-Up

Data Management
- Generator Addition & Removal
- Output Display
- VPP Loading & Saving
- Series Forecast Loading & Saving
- Processing Entry

Data Processing
- Optimized and Non-Optimized Process

Mathematics Functions
- Generator Classes

Figure 5
Figure 6
Characterising the VPP

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Abstract
The use of small-scale generation of disparate technologies is becoming more prevalent due to the imperative to reduce greenhouse gas emissions that are thought to be the chief cause of climate change, as well as the desire to improve system flexibility and security. As penetration of these distributed resources increases, displacing central generation, there is growing need to understand the composite behaviour of groups of Distributed Generation (DG) devices, also known as Virtual Power Plants (VPPs). This paper presents the methodology for the mathematical modelling of the uncertain elements of the VPP. In this paper the VPP is defined from the standpoint of electrical and geographical proximity of DG devices typified, for example, by location in the same distribution area supplied from the one grid supply point.

Introduction
Small scale Distributed Generation (DG) devices are becoming more common in electricity networks, but their affect on the network are still under investigation. As their popularity increases, their effect on the network will be greater, so it is desirable to be able to predict with some accuracy their impact on the network, from their power output.

Three technologies currently in use as small scale DG are micro wind turbines, photovoltaic arrays (PV), and micro combined heat and power (MicroCHP), and these are the focus of the characterisation work.

Technology breakdown
Micro Wind Turbines
Wind turbines have been utilised for many years, and are well known to derive their power output from the wind. Typically, a wind turbine will have an associated power curve, which graphs the output power against the input wind speed. This graph can be used to determine the output power from any given input windspeed, whether this is a single windspeed, or a probability distribution of windspeeds.

In any given geographical area which is small in size, it can be said that the average wind speed predicted for that region is roughly constant throughout the geographical region. In meteorological terms, the area can be described as mesoscale, atmospheric phenomena usually defined as smaller than 1km – although the precise size of microscale varies from 1-5km. Whilst the average windspeed may remain fairly fixed throughout the area, the local windspeeds found at the turbine blades are not even, and must be adjust to account for the height and the environment of the turbine.

The easiest weather prediction to characterise starts with a single prediction of a windspeed. This must be adjusted for wind sheer by height, according to the wind shear calculation:

\[
\bar{U}(z) = \bar{U}(h) \times \ln \left( \frac{z}{z_0} \right) / \ln \left( \frac{h}{z_0} \right)
\]

Equation B.1

Where \( z \) is the turbine height, \( h \) is the prediction height (normally 10m), \( z_0 \) is the roughness length for the environment, and \( \bar{U}(x) \) is the mean windspeed \( U \) at height \( x \).

The standard deviation for the area can be calculated using the gustiness value for the area, by the re-arrangement of the following equation [1]:

\[
\sigma = \frac{1}{\bar{U}} \ln \left( \frac{z}{z_0} \right)
\]

Equation B.2

Where \( \sigma \) is the standard deviation. With these two equations, it is a simple process to convert the simple case of a single predicted speed to the likely power output. First, the predicted speed is adjusted to the correct speed at the correct height using Equation 1. The distribution of speeds produced from ground turbulence is produced using Equation 2. This distribution of speeds can be used with the power output curve to produce the final spread of the power output. The equations do not provide a
distribution profile, so the uniform distribution is used to equally weight all possibilities.

**PV**

Photovoltaic cells are also an old technology, but have only become viable for electricity production with the recent increase of semiconductor conversion efficiencies. PV generators derive their power output from solar irradiance over the area of the array.

Insolation, the amount of solar irradiance falling on the array’s area, is broken down into two components; direct and diffuse irradiation. Atmospheric scattering by aerosols, airborne particles and the atmosphere acts to break up the direction of the irradiance into a region greater than the area which the sun takes up in the sky. The insolation from the solar portion is called direct irradiation, and the scattered light which falls elsewhere is nominated diffuse irradiation. Whilst diffuse irradiation can contribute up to 20% of the total insolation on the solar array, it is assumed in this model that the entire contribution of insolation is from a direct source.

The insolation on the PV array can be determined using the following equation [2]:

\[ G = G_n (\sin \beta \cos \phi + \cos \beta \cos \alpha \sin \phi) \]

Equation B.3

Where \( G \) is the surface irradiance, \( G_n \) is the direct beam irradiance, \( \beta \) is the solar altitude (or 90° - solar zenith), \( \Phi \) is the surface tilt angle (where 0° is flat to the ground), and \( \alpha \) is the surface facing (relative to North). Using the predicted insolation on the ground plane the direct insolation can be obtain \( (G_n) \), which can then be used to find the overall insolation to the PV array.

The solar energy is then converted to heat and electrical energy. The heating extent on the cell is given by the Nominal operating cell temperature (NOCT) equation for the array [3]:

\[ T = T_{\text{amb}} + \left( \frac{T_{\text{NOCT}} - 20^\circ C}{1000 \text{Wm}^{-2}} \right) \times \left( \frac{G_n}{1000 \text{Wm}^{-2}} \right) \]

Equation B.4

Where \( T \) is the array temperature, \( T_{\text{amb}} \) is the ambient air temperature, and \( T_{\text{NOCT}} \) is the NOCT. With this, the power output can be determined using:
\[ P = \frac{P_{STC} \times G_s}{1000\text{Wm}^{-2}} \times \left[ 1 - b(T - 25^\circ\text{C}) \right] \] 

**Equation B.5**

Where \( P \) is the power output, \( P_{STC} \) is the power under standard test conditions and \( b \) is the temperature coefficient for the array.

In a similar fashion to the wind turbines mentioned above, the insolation is not guaranteed to be steady, and variations occur due to cloud movement. This uncertainty is more difficult to accurately affix a value to, although errors of 20% are listed for the Meteostat 8 [4], which can be used as a worst case value. Determination of the power output then follows the trend set down with the turbines above.

**MicroCHP**

Combined heat and power (CHP), or cogeneration, plants are not uncommon throughout Europe, and form district heating schemes. The principle power output from CHP is in thermal output, the electrical energy being a secondary part of the process. MicroCHP is a more secluded form of traditional CHP, where the CHP plant is large enough only for a single home. In this way a microCHP plant is usually a home boiler, which is of course, heat driven.

The largest demand on the home boiler is heating. Other uses for hot water become more dominant during the warmer months when hot water for heating is required less, yet remain small over the course of a year. The model provided assumes that the microCHP system is used only for home heating; other uses of hot water are neglected at the present time.

The electrical output from a CHP boiler is given as a conversion ratio between thermal and electrical power[5], i.e.:

\[ P_e = k \times P_t \] 

**Equation B.6**

In order to determine how long the boiler is on for, for a given period of time, it is necessary to estimate the thermal parameters of the house; the thermal resistance to the ambient outside air temperature, and the heat capacity of the building. Assuming that the heating is controlled thermostatically, which is not uncommon, the temperature fall and rise governed by the ambient outside temperature and boiler output can be derived to be:


\[ \text{temperature} = (t_0 - t_{\text{ambient}}) \exp\left(-\frac{t}{HR}\right) + t_{\text{ambient}} \]

\[ \text{temperature} = (t_0 - P_{\text{boiler}} \times R - t_{\text{ambient}}) \exp\left(-\frac{t}{HR}\right) + P_{\text{boiler}} \times R + t_{\text{ambient}} \]

**Equation B.7 & B.8**

By solving these equations for the time at which the thermostat upper and lower boundaries are crossed, the durations of the boiler being on and off can be found, leading to a duty cycle. If the instantaneous output power is to be determined, it is simply the electrical output power multiplied by the duty cycle.

If an average power over a longer duration is to be characterised, the particular lengths involved make the process more complex; the initial placement along the heating cycle is random, therefore the simple duty cycle behaviour is not guaranteed to be seen.

**Long period power**

The technologies above may also be described by their long period power. Whilst instantaneous power distributions are useful for predicting network behaviour, such as predicting line overloading or potential voltage problems, they are not ideal for use in models which require the average power over a longer period. Energy trading, for instance, usually takes place in half hour periods. For these type of purposes, it is useful to be able to predict the likely average power.

At first glance this seems straightforward. In the example generators above, there is a single input point. Over the course of the averaging period, the turbulent swings in windspeed or the temporary reduction in insolation will average out to produce a single datum.

Complexities are introduced by using more realistic meteorological forecasts. Typically, this will also be a distribution for the period, but we can only have 1 average value. Thus for any given weather condition, when the generators are to be aggregated to find their combined output, the generators may be convolved (as will be discussed below), but they may not be convolved for differing weather conditions, i.e., it is impossible to have an average windspeed of 10ms\(^{-1}\) and 12ms\(^{-1}\) at the same
time. The exception to this is if the generators are in two different forecast areas, but as discussed above, in a small geographical area the weather is roughly constant. Therefore these separate conditions (10 and 12ms$^{-1}$) must be evaluated individually, and then combined according to the weighting provided by the weather forecast.

At this point the characterisation becomes stochastic, rather than probabilistic. Up until this point, it is possible to generate probabilistic output distributions, which is to say that they can be described precisely. The non-linearity of the power output against input weather requires that every weather point in the input weather distribution be considered (when a weather distribution is used). Given that this problem has infinite size, it is necessary to segment it into many points which can then be added together to form a stochastic output.

**Combining Technologies**

The combination of DG plants in the simplest case takes place on a single busbar, which is to say that the network connections are overlooked. The generators must first have their power outputs calculated, using the methods given above. Once these have been determined it is possible to combine them using a convolution function, provided that the generators are all independent of one another. Central limit theorem dictates that under these circumstances, the power output will be the sum of the average powers of each generator, the standard deviation will tend towards the square root of the sum of the variances, and the power output will tend towards the normal distribution.

**Examples**

The first example (instantaneous power only) shows the both the simplest case featuring only a single forecast and the effects of a forecast distribution. The impact of the convergence introduced by increasing the number of generators (wind turbines) from 1 to 10 is also shown.
Cases A and B are shown on the left axis, and contain only 1 generator each. Cases C and D are shown on the right axis, and contain 10 generators each. Cases A and C use only a single data point for the prediction, whilst cases B and D use a forecast distribution. The difference between the axis scale is accounted for by the number of points used to build the output graphs.

The increase of generators from Case A to Case C shows the convergence towards a normal distribution mentioned above, but the difference between case B and case D, also with increased generators, does not show this. This is due to the number of samples which are taken to build the stochastic output, which act to conceal the convergences by superimposing them on top of each other.

The second example uses the same cases from the 1st example, but show the impacts associated with the long period power, which are more useful for power regulation and energy market purposes.
All 4 cases show a peak around 32%, with corresponding peaks seen in case A and C, which have been omitted for clarity. They are both located at the same point, 32%, and both have a 100% probability, as is expected. The remaining 2 cases, B and D, have the same profile, and demonstrate that increasing the number of generators has only a marginal affect on the power output when observed over a length of time.

The fluctuations seen in case D are artefacts of the stochastic process which builds the output data, as a very high resolution is required for the number of samples to be large enough to smooth out these fluctuations. The impact of these fluctuations looks dramatic, although their affect on the cumulative frequency distribution for the power output is very small. Increasing the number of samples to resolve this, then, is inconvenient in terms of the massively increased processing time which would be required, since it would fix a problem which is simply aesthetic.
Conclusion

The characterisation of the VPP allows power forecasts to be made which are useful for investigating the internal effects of the two-way power on the network and also for investigating energy trading, which has knock-on effects on other areas of the grid, such as the level of spinning reserve.

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Financial Risk Associated with the Commercial Virtual Power Plant

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Abstract

The virtual power plant (VPP) is a vehicle on which the carriage of small scale distributed energy resources (DER) can be brought to the attention and visibility of a system operator. Normally a “fit and forget” technology, DER can be amalgamated and handled as a single virtual unit, allowing the installed resources to be utilised as a visible and useful part of the system. Amongst several benefits, this allows the VPP to operate in the energy market through the use of an agent. This paper examines the risk associated to the agent from VPP power uncertainty and under contingent situations.

Introduction

The growing drive towards green economies has focused on the key areas of electricity generation and transportation. Whilst these two sectors are inextricably linked, especially through recent research and technological breakthroughs in hydrogen fuel-cells, the hydrogen economy is still far from fruition. Pressure is mounting within the electrical energy sector to find sources of reliable energy which produce as little CO₂ as possible, thought to be one is the primary gases which are causing climate change. One of the many approaches in the electrical energy sector is decentralized energy – energy production from homes, schools and businesses instead of from remote power stations, from energy sources which would otherwise become wasted.

Amongst the technologies available for decentralized energy are wind turbines, solar cells (PV) and combined heat and power boilers (CHP). Small generation plants inside the VPP are called distributed generation (DG) and collectively with energy storage devices are known as distributed energy resources (DER). This paper deals with DG and not DER, as cheap, long-lasting and space efficient energy storage systems are still under development and are frequently fitted on DG which is not
connected to the grid, so-called off grid applications, where unreliable wind speeds and solar insolation would cause a site to be without power otherwise.

The VPP can be conceptualized as two separate entities; the commercial VPP (CVPP) and the technical VPP (TVPP), as described by [1]. In brief, the commercial VPP is the ensemble unit from which energy transactions may be completed, and is built from the portfolio of generation connected inside its boundaries. The commercial VPP does not need a physical boundary; although in some trading systems a physical placement is required, enforcing a boundary. Further details of the European Union regulations are discussed in [2]. The technical VPP consists of the network models which allow the VPP to be visible to the system operator, providing information which can be used to manage to network. The technical VPP is located within definite electric-geographical boundaries, with information available for low, medium and high voltage aggregation.

Aggregation of DG is the fundamental tool behind both the CVPP and the TVPP, although this work focuses on the CVPP. Accurate aggregating of the DG can be completed provided that accurate models and input data can be obtained for the generation technologies, and the author has chosen wind turbines, PV and micro CHP. Previous research by the author has shown that by using input data from meteorological predictions a dual set of power aggregation is possible, one of which shows the distribution of VPP power over the course of the analysis period, and another which shows the average distribution of VPP power over the course of the analysis period. The immediate distribution of VPP power is useful for investigating possible network problems, as the distribution is much broader, whilst the average distribution of VPP power is more useful for energy trading, which will average out the swings of power seen in a second-by-second prediction of the VPP. The market for the CVPP is assumed to be trading in energy only for this paper, and no other services.

**Case Study**

The case study is formed in two halves. The first half examines the effect of the uncertainty inherent in the DG which aggregates to form the VPP and how these
effect the bid position of the agent. The second half examines the effect of a contingent scenario for the same agent.

The case study uses the 77 bus HV Underground network available from [3], an 11kV radial urban network fed from a 33kV feed, supporting 24MW and 5MVAr of load (Figure 1). DG units have been spread proportionally through the network according to the real power component of the loads connected in the network. The network does not contain transformation from distribution voltages to low voltages, which are bulked together as part of the load.

120kW of DG sources were connected into the network, with even ratios of wind turbines, PV arrays and micro CHP units. Un-exceptional expected weather conditions over a half hour (30 minute) period were chosen as the model input, and the network load-flow solved with no voltage or line problems. The likely power output under the weather conditions is shown in Figure 2. The agent responsible for the VPP clearly requires further information before a bid can be made. The model assumes that the agent can operate in a bilateral trade market, with a managed spot market arrangement for balancing, as discussed in [4].

The mode average energy output is at 20.550kWh, with a median energy output of 21.100kWh. The agent stands to be long if the weather is more favourable and short if the weather is unfavourable against the predictions. Using typical values for the system buy price [5], the system sell price, and a reasonable bid in the UK (41.18,
19.91 and 35.00 £/MWh respectively) the revenue delivered to the agent will vary according to the amount of energy the agent promises, as any excess or insufficiency of energy will need to be balanced through the spot market. The revenue curve against energy quantity, Figure 3, shows that the agent can maximize income at 24.775kWh, well above the mode value. This is due to the slight skew of the energy output, and the agent must consider this (and the opposite-skew, which can also occur) when placing a bid.

Figure B.4: The Output Power Curve

Figure B.5: The Income vs. the Bid Placement
This is an income of 69p for the half hour period, which equates to a price of 2.7p/kWh, lower than the typical price paid for electricity sold back into the grid [6]. This does not include Renewable Obligation Certificates, which the agent should also trade to boost the profit; a typical electricity supplier would pay 84p over the same period for the same volume of electricity including these certificates. [7] gives a figure of around 7p/kWh for the technology mix in the example, which provides an increase of revenue by 147p for the half hour period (assuming the median power value), taking the total revenue to 216p and increasing the price to 8.7p/kWh (or 87£/MWh). This final value is a much more competitive value, indicating the viability of this method.

The system sell price and the system buy price are factors which are normally outside of an agent’s control, but are semi-determinable. The agent’s own bid, however, must be set at such a level that the bid is accepted, which forms an inherent problem for VPPs. The utilisation of DG improves the efficiency of the network only if it is included, and as a weather driven resource it is only logical to utilise it when it is available. Bids that are too high will cut the VPP out of the bilateral market and will cost the VPP money (in lost revenue), yet the dichotomy is that in order to always include the VPP as a resource it must sell electricity at very low cost, which will cost the VPP money in lost revenue. Clearly, these two are not reconcilable.

The agent has the responsibility of ensuring that the models of the VPP are kept accurate, and that the input data is as accurate as possible. As can be seen in the revenue versus energy bid curve, there are no critical turning points, although deviations from the most accurate methods introduced by poor weather forecasts, technology modelling, or long gate closure times each incur a penalty when maintaining the maximum revenue for the VPP.

As an example, if the agent had placed a bid of 24.775kWh at 35.00 £/kWh and the VPP had generated the mode energy of 20.550kWh, the revenue would be 87p less the 17p of bought electricity; 70p total. A shift of 10% from the mode value (from 46.5% to 36.5% on the CDF) drops the energy output to 18.900kWh, increasing the deficit cost to 24p, reducing the total revenue to 63p – a drop of 10%. Had the original bid been 25£/MWh instead of 35£/MWh, the maximal predicted revenue bid position
falls to 16,300kWh. Assuming that the mode energy is produced in this scenario, the initial revenue becomes 41p plus the 8p from the surplus energy – 49p total. The same probability drop of 10% reduces the revenue from the surplus energy to 5p, taking the total to 46p, a drop of 6%.

Clearly, the unpredicted drop in energy affects the first case more strongly than the second, although the initial bid for the second case is much lower than the first, and the revenues are lower overall because of this. Had the agent not adjusted the energy of the bid to reflect the lower bid price in the second scenario, the agent would have generated 45p normally, falling to 38p under the 10% probability drop conditions, a decrease of 15.6%. Managing to secure a high bid price is an excellent way of mitigating the potential reductions of revenue which are incurred when energy must be bought from the spot market to make up for shortfalls. This also ensures maximum revenue, and should therefore be strived towards at all times.

The second aspect which an agent must consider is a sudden fault condition of a line which can cause an unplanned interruption to all or part of the DG units which make up the VPP. In the UK, the legislation regarding unplanned interruptions (The Electricity (Standards of Performance) Regulations 2005) guarantees a rebate if a fault condition if present for an unreasonable length of time. There is no standard rebate for VPP operators, although it is described in [1] that the technical VPP is monitored and controlled by the local DNO, enabling the transfer of network information to the commercial VPP, preventing and protecting the agent from placing unrealistic bids once a known fault condition has arisen. This does not help the agent if the fault condition occurs after gate-closure, however, and the agent must be able to ride-through any financial risk which may be associated with this phenomenon.

The failure rates and repair times for various lines are given in [8], which were used with the line lengths in the network model. The worst cast scenario for a VPP operator is a network which provides no feedback, so line outages are not reported to the VPP operator. Provided the DNO passes this information to the VPP operator, it is reasonable to assume that only line outages which occur after gate closure can adversely affect the VPPs bid scheme. Figure 4 shows the Cumulative hours in a year against the percentage power dropped under a setup with no DNO feedback, and with
DNO feedback (using half hour periods with a full hour gate closure) for the test network. Clearly, the feedback provided by the DNO is essential to minimising unnecessary loss on the part of the VPP operator. By multiplying the percentage loss by the duration for each interruption and totalling this lost time, the lost ‘100% generation time’ in a year for these cases is 4 minutes 32 seconds with feedback per year, and 6 hours 24 minutes and 30 seconds without any feedback per year, or 0.00086% and 0.073% respectively for yearly power output.

![Figure B.6: The Cumulative Hours per year vs. the p/c Power Dropped](image)

**Figure B.6: The Cumulative Hours per year vs. the p/c Power Dropped**

Whilst the yearly power drop is small, the maximum power drop in a trading period is 31.6% for the radial case study. The effect of this drop is to reduce the profit of the VPP operator, and under non-ideal bid placement the VPP operator can operate at a loss. If the agent had placed a bid at 24.775kWh at 35.00 £/kWh and the VPP had generated the mode energy of 20.925kWh, the revenue would be 87p less the 16p of bought electricity; 71p total. The drop of energy to 14.312kWh generates 87p less the 43p of bought electricity; 44p total, a drop of 38.0% of the revenue for the period. Depending on the particular configuration of the VPP and the market conditions, it is important to ensure that the VPP can place a financially secure bid such that sudden line disconnection does not compromise the future of the VPP operator. Networks with a single connection point for instance have a small chance of total power

203
disconnection, which could be catastrophic for the VPP operator if contingencies were not in place.

**Conclusion**

This paper concludes that with the incorporation of adequate financial planning, weather prediction techniques and with accurate network feedback, the VPP is an effective and competitive method for trading electrical energy on the market; the Renewable Obligation Certificates scheme must also be utilized fully by the VPP, however, in order to boost the profit of the VPP to its full potential. Contingent loss of generation is detrimental to the VPP agent, but if a high degree of communication exists between the VPP agent and the DNO, the amount of loss of generated energy can be mitigated to a very small value. Provided the VPP agent has enough financial backing to ride through these rare if difficult periods, he or she should be able to run a profitable plant.

**References**


[6] UK Electricity Suppliers that will buy back solar generated electricity, [http://www.totalsolarenergy.co.uk/electricity-suppliers.html](http://www.totalsolarenergy.co.uk/electricity-suppliers.html), accessed 01-08-2009
