MODELLING AND CONTROL OF BATTERY ENERGY RESOURCES IN LOW VOLTAGE DISTRIBUTION NETWORKS

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I would like to dedicate this thesis to my father; he has always stated that he wanted at least one of his children to follow his footsteps in the electric power industry.
Abstract

Over the last decade governments in Australia and around the globe have heavily promoted the installation of rooftop solar photovoltaics (PV) in residential low voltage (LV) distribution networks. While distributed solar PV offers a range of benefits, they have not significantly reduced distribution network demand during critical periods due to the incongruity between the residential load profile and the solar PV generation curve. The residential load profile has load demand in the morning, moderate demand during mid-morning, low demand during the middle of the day and peak demand in the evenings. In winter the mid-morning demand is greater than in summer leading to instances where there are two peak demand periods during the day. Solar PV generation is low during the morning and steadily increases until the middle of the day and then decreases until the evening. Peak solar PV generation typically occurs when demand in the network is low. This entails that solar PV resources are poorly utilised and high concentrations of solar PV generation in LV distribution networks can often lead to the degradation of power quality through overvoltage and instances of reverse power flow. Moreover, the addition of solar PV to existing LV networks with unbalanced phases can often exacerbate existing power quality issues in a particular overloaded phase. Corrective measures to address power quality issues may require costly augmentations to the electricity network.

The capacity of the electricity generation and supply system's infrastructure is dictated by the necessity to meet yearly peak demand. Peak demand only occurs for a small duration of time thus inferring that for the majority of the time the electricity network is underutilised. During such short periods, the load on subsections of the electricity network may come within reach of its operational capacity and trigger the need for network augmentations to ensure that outages do not occur in the future. Meeting an incremental increase in load incurs a high cost due to the capital works and labour required to service a small increase in load that only occurs for a small duration.

Battery energy storage (BES) installed in the residential distribution network presents an opportunity for electricity network operators to better manage peak demand and power quality issues while concurrently handling changed power conditions due to distributed solar PV. The increasing performance and reducing cost of BES means that it is becoming a feasible solution for electricity distribution network operators seeking to defer costly incremental network augmentations. However, BES can only deliver on such potential infrastructure deferrals if coupled with intelligent systems that can schedule the optimal storage and release of power to the grid. Presently, there are only a few network side BES with intelligent systems presented in the literature. The majority of the literature focuses
on the installation of BES in residential households. This PhD study sought to address this present gap in research through developing a three phase BES scheduling system for the residential LV distribution network.

The core operational objectives of the three-phase BES scheduling system are to reduce daily peak demand, balance loads, and charge during low demand periods or when solar PV is generating. The scheduling system comprises three components:

1. Pattern recognition based expert system that forecasts load profiles;
2. Scheduler that receives load profile forecasts and produces an initial schedule; and
3. Online real time operator (RTO) system that analyses load in real time and compares this with the provided schedule in order to mitigate scheduling error, and then dispatches the revised schedule to the BES system.

The development of these three main components was separated into four objectives. The first objective was to construct load profile property forecast models. The second was to formulate and develop the expert system. The third objective involved developing the scheduler. The forth and final objective integrated the outcomes of the first three objectives with the development of the RTO. The completion of the objectives were achieved using 14 months of load data (i.e. voltage, current and phase angle) provided by the local electricity distributor Energex for a residential LV network located in an inner northern suburb of Brisbane, Queensland, Australia which consisted of 128 residential customers connections.

Load property forecast models involve forecasting the magnitude of the morning peak (MP), evening peak (EP) and the amount of energy used in a day (TEU). The forecast models were developed using a time series modeling technique with exogenous variables such as temperature. The MP, EP and TEU forecasts are used as input variables in the expert system in the pattern recognition process. The expert system is composed of a correlation clustering algorithm to identify groups of repeating load profile patterns in the load data, a discrete classification artificial neural network (NN) to select a pattern that is most likely going to occur and post processing routines to adjust the selected pattern to the MP, EP and TEU forecasts. The expert system was developed to provide information for the scheduler to base schedule calculations on.

The scheduler was based on heuristics developed from an observation that the optimal schedule for a BES system that did not have a restrictive energy storage capacity was the peak demand minus the rated output of the system. The heuristic was then used to create an initial discharge schedule. From there, the system constrains the peak demand discharge according to the available energy at the state of each peak demand period. The
scheduler achieves load balancing through phase prioritised charging and discharging operations. Specifically, the scheduler charges more from the phases that are forecasted to have the lower loads and discharges more to the phases that are forecasted to have the higher loads. At the end of the scheduling operation the schedules are dispatched to the RTO.

For each time interval the RTO forecasts load using autoregressive time series models. The forecasted load allows for a recalculation of the discharge magnitude, if the schedule is set to discharge and rebalancing of how much each phase is charged from, if the schedule is set to charge. Through a positive and negative feedback system, based on the difference between the scheduler’s rate of energy use and the real rate of energy use, the RTO increases or decreases the discharge magnitude. After these routines have been completed, the RTO dispatches the schedule to the BES system.

Results displayed that the expert system can forecast load profiles with a high degree of accuracy with hindcast $R^2$ ranging from 0.86 to 0.88 and validation $R^2$ ranging from 0.81 to 0.84 across the three phases. The scheduler was able to receive the load profile forecasts and produce an initial schedule that optimally reduces daily peak demand, balances load and charges during low demand periods or when solar PV exhibits high generation. Similar to the scheduler, the scheduling system incorporating the RTO was able to achieve its operational objectives while mitigating scheduling error. The scheduler was repurposed to show that the system can also be used to size BES systems based on historical load data. This system will be able to provide network operators with the performance metrics of different BES systems with different capacities, allowing for complementary economic feasibility analysis to also be completed.

This research provides a robust foundation for future work to be undertaken, including:

- The development of a BES system sizing algorithm that simultaneously optimises LV network grid performance and economic feasibility goals;
- The integration of the scheduling system with a BES system for real world testing purposes; and
- The repurposing of the scheduling system to operate in commercial networks and the incorporation of electric vehicles used to support the grid.
Declaration

This word has not been previously submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Signed: __________________________________________

Date: ____________________________________________

Christopher Joseph Bennett

Griffith University
Acknowledgement of Published Papers

Section 9.1 of the Griffith University Code for the Responsible Conduct of Research (“Criteria for Authorship”), in accordance with Section 5 of the Australian Code for the Responsible Conduct of Research, states:

To be named as an author, a researcher must have made a substantial scholarly contribution to the creative or scholarly work that constitutes the research output, and be able to take public responsibility for at least that part of the work they contributed. Attribution of authorship depends to some extent on the discipline and publisher policies, but in all cases, authorship must be based on substantial contributions in a combination of one or more of:

- Conception and design of the research project
- Analysis and interpretation of research data
- Drafting or making significant parts of the creative or scholarly work or critically revising it so as to contribute significantly to the final output.

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- Include in the list of authors only those who have accepted authorship
- Appoint one author to be the executive author to record authorship and manage correspondence about the work with the publisher and other interested parties.
- Acknowledge all those who have contributed to the research, facilities or materials but who do not qualify as authors, such as research assistants, technical staff, and advisors on cultural or community knowledge. Obtain written consent to name individuals.
Included in this thesis are papers in Chapters 4, 5 and 6 which are co-authored with other researchers. My contribution to each co-authored paper is outlined at the front of the relevant chapter. The bibliographic details for these papers are:

Chapter 4:

Chapter 5:

Chapter 6:

Signed: ___________________________ Date: ____________
Christopher Joseph Bennett

Countersigned: ___________________________ Date: ____________
Principal Supervisor: Assoc. Prof. Rodney Stewart

Countersigned: ___________________________ Date: ____________
Associate Supervisor: Prof. Junwei Lu
List of Publications

The following papers were produced to disseminate some concepts and results from the work undertaken by the author during the course of this Ph.D. study.

Refereed journal publications


Refereed conference papers

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The PhD experience is a long journey of acquiring the skills required to become a capable and independent researcher. Throughout this journey there have been many people who have influenced its outcome that I would like to personally acknowledge. First and foremost, I would like to forward my most sincere gratitude to my principle supervisor Assoc. Prof. Rodney Stewart. He provided me with an opportunity to experience the academic engineering research environment through an honours research scholarship internship at the Smart Water Research Centre. After the internship I started the PhD candidature under his supervision. He was always an enthusiastic supervisor, had countless ideas about how various different problems can be solved and how these solutions can lead to avenues for future research. Assoc. Prof. Stewart’s greatest strength as a supervisor is being able to develop a keen insight and highlight the most important facets of problems in fields that are not necessarily his expertise.

My associate supervisor Prof. Junwei Lu set up the research group to investigate smart-grid and micro-grid technologies to ensure that Griffith University is at the forefront of this burgeoning industry. I am very thankful for Prof. Lu for giving me the opportunity to choose my own project within this research space. As a result I was able to research the topic I found most interesting which will enable me to pursue a research career in the same space. Prof. Lu was also an enthusiastic supervisor and always willing to provide the necessary resources to make this research possible.

At the start of my research, the research group’s industry partners (i.e. Energex and Elevare) generously provided resources, time and advice in order for the research to be made possible. Specifically, Bevan Holcombe, David Wise, Terese Milford and Aidan Roberts have made notable contributions to my research.

My friend Simon Biggs and my parents bore the brunt of my brain storming throughout my PhD candidature. Simon was able to provide valuable feedback on the use of different types of algorithms and aided the development of the replication software presented in different publications. My father aided my research by providing technical knowledge of power electronics and indicated what operations were feasible.

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# List of Acronyms and Units

**Acronyms:**

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<th>Definition</th>
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<tbody>
<tr>
<td>AR</td>
<td>Autoregressive</td>
</tr>
<tr>
<td>ARIMA</td>
<td>Autoregressive integrated moving average</td>
</tr>
<tr>
<td>ARIMAX</td>
<td>Autoregressive integrated moving average with exogenous variables</td>
</tr>
<tr>
<td>ARMA</td>
<td>Autoregressive moving average</td>
</tr>
<tr>
<td>BE</td>
<td>Battery efficiency</td>
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<tr>
<td>BES</td>
<td>Battery energy storage</td>
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<td>BESS</td>
<td>Battery energy storage system</td>
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<tr>
<td>C</td>
<td>Capacity</td>
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<td>CDP</td>
<td>Characteristic demand profile</td>
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<tr>
<td>CR</td>
<td>Charge rating</td>
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<tr>
<td>CV</td>
<td>Charge vector</td>
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<tr>
<td>DER</td>
<td>Distributed energy resources</td>
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<tr>
<td>DoD</td>
<td>Depth of discharge</td>
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<tr>
<td>DR</td>
<td>Discharge rating</td>
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<tr>
<td>DSS</td>
<td>Decision support system</td>
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<tr>
<td>DT</td>
<td>Discharge target</td>
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<tr>
<td>EP</td>
<td>Evening peak</td>
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<td>EV</td>
<td>Electric vehicles</td>
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<tr>
<td>$H_0$</td>
<td>Null hypothesis</td>
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<tr>
<td>$H_a$</td>
<td>Alternative hypothesis</td>
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<tr>
<td>IE</td>
<td>Inverter efficient</td>
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<tr>
<td>iCR</td>
<td>Inverter charge rating</td>
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<tr>
<td>iDR</td>
<td>Inverter discharge rating</td>
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<tr>
<td>LV</td>
<td>Low voltage</td>
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<td>MAE</td>
<td>Mean absolute error</td>
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<tr>
<td>Abbreviation</td>
<td>Definition</td>
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<tr>
<td>MAPE</td>
<td>Mean absolute percentage error</td>
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<td>MP</td>
<td>Morning peak</td>
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<td>MSE</td>
<td>Variance of model error</td>
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<td>MSE</td>
<td>Mean sum of squares</td>
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<tr>
<td>NDMP</td>
<td>Next day morning peak demand forecast model</td>
</tr>
<tr>
<td>NDPD</td>
<td>Next day evening peak demand forecast model</td>
</tr>
<tr>
<td>NDTEU</td>
<td>Next day total energy use forecast model</td>
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<td>NEM</td>
<td>National energy market</td>
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<tr>
<td>NN</td>
<td>Artificial neural network</td>
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<td>NOCS</td>
<td>Network operator control system</td>
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<td>PV</td>
<td>Photovoltaics</td>
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<tr>
<td>Q_e</td>
<td>Quantity evening</td>
</tr>
<tr>
<td>Q_m</td>
<td>Quantity morning</td>
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<tr>
<td>R²</td>
<td>Coefficient of determination</td>
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<tr>
<td>RET</td>
<td>Renewable energy target</td>
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<tr>
<td>RMSE</td>
<td>Root mean squared error or standard error</td>
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<td>SEQ</td>
<td>South East Queensland</td>
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<tr>
<td>SoC</td>
<td>State of charge</td>
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<tr>
<td>STATCOM</td>
<td>Static synchronous condenser</td>
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<tr>
<td>t</td>
<td>Time interval</td>
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<tr>
<td>TC</td>
<td>Total charge</td>
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<tr>
<td>TEU</td>
<td>Total energy use</td>
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**Units:**

- **kV**: Kilovolt
- **kW**: Kilowatt
- **GW**: Gigawatt
- **kWh**: Kilowatt hour
- **GWh**: Gigawatt hour
CHAPTER 1
Introduction

1.1 Research background
Over the last generation governments in Australia and around the globe have been promoting the research and installation of renewable energy technology through means of economic incentives, statutes and regulations. The main objective of this has been to reduce society’s dependence on conventional sources of electricity generation (i.e. coal and gas fired power stations) in order to reduce greenhouse gas emissions. Through the development of renewable energy technology and smart-grid technology ancillary benefits, such as increasing energy security, improving the electricity network reliability, and reducing the costs of supplying electricity.

Recent notable policy enactments in Australia have contributed to the research and installation of renewable energy technology, namely, the Renewable Energy Target (RET) through the Renewable Energy Act 2000 and the Clean Energy Act 2011. The RET is a government mandate stipulating that 20% of the electricity generation in Australia is to be generated by renewable energy sources, such as wind, solar, geothermal, etc. The objective of the Clean Energy Act 2011 was to reduce Australia’s greenhouse gas emissions, by 2050, to 80% below the 2000 levels, through the introduction of a market whereby participants can trade emission permits.

In conjunction with the Commonwealth Government, each state and territory within Australia incentivised the installation of residential rooftop solar photovoltaic (PV) arrays (Paltridge, 2010; Zahedi, 2010). The Commonwealth government instituted a rebate program providing participants with Renewable Energy Credits to be used to reduce the cost of purchasing and installing solar PV. The states and territories primarily incentivised the uptake of solar PV through the use of feed-in-tariffs. Feed-in-tariffs operate by
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providing owners with income for the energy their systems supply to the electricity network.

These policy enactments increased the amount of energy generated from renewable energy sources in Australia from 18.9 to 19.7 TWh from 2005/2006 to 2009/2010 (Bureau of Resource and Energy Economics, 2012). Over the same period the proportion of energy produced by wind sources increased from 1.7 to 4.8 TWh, while the energy generated from solar sources increased from 0.1 TWh to 0.3 TWh (Bureau of Resource and Energy Economics, 2012). The increase in energy generated from solar sources was primarily due to the uptake of rooftop solar PV. Seed Advisory (2011) reported that, from 2001 to 2011, there were 615,000 rooftop solar PV installations. In South East Queensland (SEQ), the number of installations increased from 2,000 to 221,000 over the period June 2009 to June 2013 with 33% of the installations taking place during the financial year 2012/2013 (Energex, 2013). As of the 2012-13 financial year, the combined capacity of rooftop solar PV was 2.3 TW (Australian Energy Regulator, 2013).

An efficient electricity generation and supply system is designed to produce a reliable supply, with minimal blackouts and disturbances, at a low marginal cost. To maintain an efficient system, the capacity must be such that it is able supply electricity when the demand for electricity is at its peak. When demand for electricity is at its peak it is referred to as 'peak demand' or 'peak load'. Peak demand is often defined according to different time periods such as yearly, monthly, weekly, etc. Different subsections of the electricity network experience peak demand at different times and magnitudes, reflecting when customer activity is highest. In commercial areas, daily peak demand typically occurs between the middle of the day and the early afternoon. Customers in residential areas are typically not at home during the middle of the day. Their activity is generally highest in the mornings and more so in the evenings causing the daily peak demand to occur in the evening. Augmenting or upgrading the network to meet peak demand is conducted on a subsection basis when the demand in a particular subsection is nearing or is at capacity. Peak demand only occurs for a small period of time entailing that for the majority of the time the capacity of the network in underutilized.

According to the Australian Energy Market Commission (2012), $11 billion of capital investment is made to meet 100 hours of peak demand. Meeting future peak demand growth will account for ~45% of capital investment in the distribution network and ~53% of capital investment in the transmission network (Australian Energy Market Commission, 2012). Peak demand is expected to grow at 2.6% per year until 2020 (National Energy Savings Initiative, 2011). It is estimated that this will require $39 billion in network infrastructure augmentation from 2011 to 2015 and $40 billion to $120 billion in
additional peak generation capacity (National Energy Savings Initiative, 2011). Future growth of base load (i.e. minimum load on the network) and peak demand is dependent on economic conditions. However, the investment costs related to operating the network can be reduced if the network augmentation required to meet peak demand growth is deferred to a future date. This is due to the time value of money effect.

The integration of renewable energy technology in the electricity grid does not necessarily archive the intended objectives and conform to the goals of an efficient electricity generation and supply system. The factors that may contribute to non-conformance include:

- Wind and solar generation technologies are intermittent; wind generators do not generate when wind speed is not within specific parameters; solar PV does not generate at night and there is a reduced output when the weather is overcast (Jewell & Unruh, 1990; Strbac et al., 2007).
- Due to the intermittency, conventional generators are required to keep a portion of spinning reserve to supply power in cases of fluctuations (Jewell & Unruh, 1990; Strbac et al., 2007). In turn, the need for conventional generators is not abated.
- Solar PV in residential low voltage (LV) distribution networks generates during periods when the load is low. This leads to power quality issues such as voltage-rise and does not contribute to reducing load during peak demand periods (Energex, 2013; Alam et al., 2013).

Western Power (a network operator for South West Western Australia) by Jones et al. (2012), and Ausgrid (2011) (a network operator for New South Wales) both conducted studies on the impact of solar PV on their electricity networks. Through the use of scenario forecasting, the proliferation of solar PV in South West Western Australia was found to reduce the network's peak by 1.2% to 1.72% (Jones et al., 2012). Analysis on of the impacts in residential distribution substations found that solar PV had negligible effects on peak demand reduction. In contrast, substations catering to a diversity of commercial and residential loads were found to have their peaks reduced due to the peak demand occurring earlier in the day. The study concluded that solar PV would have little effect on deferring network augmentation. The Ausgrid (2011) study found that the five substations with the highest solar PV penetration had an estimated peak demand reduction ranging from 0.1% to 2.9%. Similar to the findings of the Western Power study, solar PV installations had a minor effect on peak demand reduction, however, it was not substantial enough to defer network augmentation.

There has been an established trend of investing and installing renewable energy technologies which has led to an increase in the amount of energy generated from those
sources. In coincidence, there has been a vast proliferation of rooftop solar PV installations, primarily in the residential LV distribution network. Nonetheless, there have been notable discrepancies between the objectives of installing renewable energy technologies and the results. This is primarily due to the intermittency and the time of the generation of wind and solar based technologies. As a result, the dependence on conventional generators is not reduced and network augmentations, particularly in the residential distribution network, are not deferred. Consequently, at this time, the investments in renewable energy technology could potentially become a sunk cost or an economic loss. Accordingly, the costs of such investments will be represented in customers’ electricity bills without any associated benefit returning to customer.

There is an opportunity to created value out of the renewable energy technology investments by commingling them with other technologies such as energy storage. Energy storage technologies provide the opportunity to store energy generated from intermittent sources and release energy into the electricity network in a continuous and stable fashion. The most advantageous opportunity is the installation of energy storage technologies in areas of the residential LV distribution network where there are high penetrations of solar PV installations. The general concept behind this is that the energy storage system will be charged when solar PV is generating and discharged when demand is high, such as peak demand periods. This concept is known as ‘peak shaving and valley filling’, can prevent remedial measures such as tap changes and network augmentations in response to power quality degradations and reduce peak demand such to defer network augmentations.

The residential LV distribution network is characterised by a high variability in load, the occurrence of random “shocks”, and the load across the phases of the network is unbalanced (Bennett et al., 2014a). Across each phase and for each consecutive day, peak demand occurs at different times and is of varying magnitudes. The current study proposes the concept of peak shaving and valley filling through the use of energy storage for the residential LV distribution network. To achieve this, a comprehensive energy storage scheduling system is required. The goal of the scheduling system is to dictate to the energy storage system the times it should charge (i.e. when load is low and solar PV is generating) and discharge (i.e. during daily peak demand periods). An additional online component is required to continuously analyse the load data and adjust the scheduling decisions. The application of such a system has great potential due to the significant residential rooftop solar PV penetration across Australia.
Chapter 1 – Introduction

1.2 Problem statement
The diurnal pattern of the load (load profile) in residential LV distribution networks and the nature of the solar PV generation has led to an incongruity between the periods of highest demand for electricity and the electricity generated by solar PV. The high penetration of rooftop solar PV may lead to instances of power quality issues, such as voltage-rise, and may necessitate the triggering of remedial measures. The majority of the energy consumed in the residential networks during the day occurs during the peak demand periods, while the intermittency of solar PV generation requires conventional generators to maintain a portion of the spinning reserve, furthering the reliance on conventional generators. Therefore, the installation of solar PV does not appear to abate network augmentation to meet peak demand or reduce the costs associated with supplying electricity.

The current study has proposed that: energy storage, in areas of the residential LV distribution network with high penetrations of solar PV, will be able to store the energy generated by solar PV and discharge that energy into the electricity network during periods of peak demand. Benefits that may be accrued from the installation include improving power quality (e.g. voltage-rise and network balance) and reducing peak demand to defer network augmentation. To meet this outcome, an energy storage scheduling system is required to be developed.

1.3 Scope and objectives
The scope of the thesis was confined to the development of an energy storage scheduling system. This scheduling system is designed to be applied to three phase battery energy storage (BES) systems that can be retrofitted in residential LV distribution networks with rooftop solar PV installations. This entails the operation of the BES and scheduling system is independent of solar PV installations but utilizes the energy generated by solar PV.

Scheduling systems are generally composed of two main components: a scheduling component (that produces a schedule to dictate to the energy storage system) and an online component (that adjusts and dispatches the schedule). The scheduling component requires information that provides inferences about the future so that a schedule can be developed. The development of the energy storage system's two components forms the four objectives of the thesis. The first two objectives pertain to using historical load data to forecast future load, the third objective involved the development of the scheduler and the fourth objective was connected to the development of the online system to adjust and dispatch the schedule. These objectives can be summarised as follows:
Chapter 1 – Introduction

1. The construction of the load profile property forecast models for each phase of the LV distribution network (namely, the evening peak demand (EP), the morning peak demand (MP), and the total energy used (TEU)).

2. The creation of the pattern recognition based expert system to forecast load profiles for each phase of the LV distribution network to receive the forecasted load profile properties and to calculate the load profiles that are most likely to occur in the future.

3. The development of the scheduler component. The scheduler receives the load profile forecasts from the expert system and calculates the optimal charge and discharge schedule constrained by the properties of the BES system.

4. The development of an online system, known as the real time operator (RTO), that analyses the schedule and recent historical load data, and augments the schedule if necessary then dispatches the schedule to the BES system.

The data used to achieve the four objectives was generously supplied by Energex from an LV distribution transformer in their smart-grid trial area.

1.4 Research design and method

1.4.1 Overview

The main purpose of this research is to develop a residential LV distribution network three phase BES scheduling system, thus the implemented research design is that of a software development process. The development of software starts at the formulation or definition of its goals and purposes. With the definition in place, a series of problems or components that constitute the objectives of the development process can be identified and solved. The solution to each problem requires a different method due to the functions that the component is required to perform. The problems are solved in a sequential manner based on the dependencies of other problems.

1.4.2 Design summary

Figure 1—1 displays the overall flow chart for the BES scheduling system. The system initialises at the start of the day where time \( t \) equals one. At the start of the day the system acquires the weather forecast and historical load data. The weather forecast and historical load data are used by the load property forecast models in order to forecast TEU, MP and EP for each phase. The TEU, MP and EP forecasts along with the weather forecast are used by the expert system to forecast the day’s load profile for each phase. The load profile forecasts are then sent to the scheduler in order to calculate an initial charge and discharge schedule and the initial schedule is then passed to RTO. Throughout the day the RTO analyses historical load day against the initial schedule and makes adjustments to the
schedule to mitigate scheduling error and avoid dispatching inefficient charge or discharge commands.

Figure 1—1 BES scheduling system flow chart

The structure of the BES scheduling system necessitates a series of dependencies where information from the previous component is required for the next component to function. Table 1—1 highlights some of the dependencies that each component of the BES scheduling system has. The expert system is dependent on the load profile property forecasts. The scheduler is dependent on the expert system’s load profile forecasts and load profile property forecasts. The RTO is dependent on the initial schedule calculated by the scheduler. The series of dependencies determine the order by which solutions are to be provided for the research objectives.

Table 1—1 Component dependencies

<table>
<thead>
<tr>
<th>Component</th>
<th>Dependencies</th>
<th>Component Dependencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load profile property forecast models</td>
<td>• Weather forecast</td>
<td>• Load property forecast models</td>
</tr>
<tr>
<td></td>
<td>• Historical load</td>
<td></td>
</tr>
<tr>
<td>Pattern recognition expert system</td>
<td>• Weather forecast</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Historical load</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• TEU, MP and EP forecasts</td>
<td></td>
</tr>
<tr>
<td>Scheduler</td>
<td>• EP forecasts</td>
<td>• Load property forecast models</td>
</tr>
<tr>
<td></td>
<td>• Load profile forecasts</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Pattern recognition based expert system</td>
</tr>
<tr>
<td>Real time operator</td>
<td>• Historical load</td>
<td>• Scheduler</td>
</tr>
<tr>
<td></td>
<td>• Initial schedule</td>
<td></td>
</tr>
</tbody>
</table>

Figure 1—2 displays the order in which the research objectives are sequenced in order for the efficient development of the BES scheduling system. The load profile property forecast
models are constructed first due to other components of the BES scheduling system being dependent on TEU, MP and EP forecasts. The next stage in the process is development of the pattern recognition based expert system that uses the TEU, MP and EP forecasts to forecast load profiles and provide information to the scheduler about future load states. The third objective to be addressed is the scheduler. The scheduler uses the load profile forecasts and the EP forecasts as input information to calculate and initial schedule. The fourth objective is the development of the RTO and completion of the BES scheduling system. The RTO requires the initial schedule from the scheduler to coordinate the charge and discharge cycles of the BES.

Figure 1—2 Research objectives flow chart
1.4.3 Method summary

Objective 1 involved the use of time series analysis modelling techniques, exponential smoothing algorithm and regression modelling techniques. Time series analysis techniques included the use of the autocorrelation and partial autocorrelation algorithms to identify significant seasonalities in the TEU, MP and EP time series. An exponential smoothing algorithm is used to account for changes in the local means through the TEU, MP and EP time series. External or exogenous variables are selected by analysing their relationships with the dependent variables by means of graphical comparisons, f-test for regression and t-test for regression coefficients. Coefficients of the models are estimated by use of regression and half of the time series and the second half of the time series are used to evaluate model performance.

The pattern recognition based expert system is employed to forecast load profiles for each phase in order to avoid continuous increase in forecast error that accompanies recursive time series forecasting. Objective 2 involved the use of pattern recognition techniques. A correlation clustering algorithm was developed and used to identify repeating patterns within each phase’s load time series. A discrete classification neural network was used to map external variables and TEU, MP and EP forecasts to patterns identified in the load time series. A series of post-processing routines were used to adapt patterns selected by the discrete classification neural network to TEU, MP and EP forecasts in order to achieve the most accurate load profile forecasts. The expert system was trained using observed external variables, TEU, MP and EP time series. The performance of the expert system was evaluated using forecasted external variables, TEU, MP and EP time series.

Objective 3, the development of the initial scheduling system or scheduler, relies on both qualitative and quantitative approaches. The qualitative approach entails understanding the literature on BES scheduling systems and what processes or algorithms are used to calculate an optimal schedule. This allows for gaps in the literature to be identified and inferences to be made about the structure and subcomponents of the scheduler. The evaluation of the scheduler is quantitative in nature to allow for the determination of failure states and whether or not it is achieving its intended purpose.

Objective 4, the development of the RTO, employs a similar method to the previous objective. The qualitative approach involves reviewing the literature to identify scheduling failure states, mitigation routines and implemented solutions for real time operation of the BES scheduling system. This allows gaps in the literature to be identified and new solutions for this research’s BES scheduling system to be developed. The quantitative approach involves using metrics to identify failure states allowing for subcomponents to be improved upon. The development of short-term load forecast algorithms was
conducted according to a time series analysis modelling approach similar to the first objective.

1.5 Research novelty and significance

The novelty and significance of this research is observed in:

- The construction of load forecast models for the residential LV distribution network;
- The formulation of a pattern recognition based expert system for forecasting patterns in time series;
- The development of a complete and comprehensive BES scheduling system; and
- The demonstration that the BES scheduling system can be used for BES system sizing purposes.

The published literature on load forecasting primarily deal with the application of forecast modelling techniques to sections of the electricity network that service large numbers of customers such as the total system, substation and feeder levels. In comparison to these levels of the electricity network, the residential LV distribution network is more variable in nature and exhibits a greater frequency of random "shocks". The reason for this is that the residential LV distribution network has less diversity. This research adds to the literature on load forecasting due to the focus of developing for the LV residential distribution network. Thus through the process of constructing the load forecast models knowledge is gained in the following areas:

- The key variables that affect load;
- Prominent seasonalities in the load time series;
- Methods for accounting for the non-stationary load time series;
- How conventional modelling techniques can be applied; and
- How the greater variability affects forecast accuracy.

The pattern recognition based expert system was established to forecast load profiles with a high degree of accuracy. This method was employed due to its ability to avoid the use of the recursive time series forecasting due the high susceptibility the recursive technique has to increasing forecast error when applied to highly variable time series. Similar to time series modelling techniques, patterns are identified in the time series and are use as basis to forecast future states. It does so by combining correlation clustering, discrete classification neural network and post-processing routines. The pattern recognition bases expert system can be easily applied to other subsections of the electricity network and
achieve a high degree accuracy or other fields that involve time series modelling such as electricity price or water flow forecast modelling.

The complete BES scheduling system combines load forecasting, initial scheduling and online operations to form a comprehensive package. The current literature on BES scheduling systems primarily apply to single phase of the electricity network and rely on the use of optimisation routines to minimise cost functions. The BES scheduling system developed in this research advances the literature by applying BES scheduling to the three phases of the residential LV distribution network. By doing the BES scheduling system can perform additional functions beyond the standard peak shave and valley fill such as load balancing through charging and discharging operations. Automated load balancing in the network can provide financial benefits to network operators through minimising the frequency of tap changes and manual rebalancing of the network. The scheduler and the RTO were designed to be less complex than BES scheduling systems that rely on optimisation routines by the use of heuristics. Heuristics allow for features of optimal solutions to be programmed in the schedule calculation process. Value is provided to researchers and institutions through the reduced complexity by allowing replication and use of the BES scheduling system.

In this research it is demonstrated that the BES scheduling system can be repurposed for BES system sizing operations. For given load time series and BES system configuration, simulations of the BES scheduling system provide metrics to analyse its performance. Changes in BES system configurations will yield different performance metrics. From here, algorithms can be developed to find optimal BES system configurations for given performance targets. This allows network operators to perform financial analysis to determine whether or not installing a BES system is a feasible investment.

1.6 Thesis outline

The thesis is composed of seven chapters, with Chapter 1 being the introduction. Chapter 2 contains the background information for the study and a review of the literature. Chapter 3 presents the research methods used. Chapter 4 outlines the population of the load property forecast models. The development of the pattern recognition based expert system, used to forecast load profiles, is presented in Chapter 5. The scheduler, RTO and the completed scheduling system is presented in Chapter 6. Finally, Chapter 7 highlights the significance of the research and presents the conclusions and avenues for future research. This document comprises both traditional thesis chapters and reformatted peer reviewed publications. Chapter 1, 2, 3 and 7 are traditional thesis chapters, while Chapters 4, 5 and 6 are reformatted peer reviewed publications.
Chapter 1 – Introduction

Chapter 2 begins by outlining the structure of the conventional electricity generation and supply system and how the system is operated in SEQ region. The background information includes advances in the way electricity is supplied, namely: demand management, smart grids, micro grids and electric vehicles. A discussion provides an understanding of the operational environment to which the scheduling system is to be applied, that is, residential LV distribution networks and solar PV generation. Additionally, details of the theories that underpin load forecasting and energy storage scheduling systems are presented; they form the basis of the development of the scheduling system.

Chapter 3 synthesises the knowledge gained from Chapter 2 and outlines the formulated research method. The goals of the scheduling system are organised and placed in a hierarchy of importance; the information required to calculate the schedule is established; the method for developing the scheduling system is created; and how each objective is integrated within the overall method is outlined. The rest of the chapter is structured according to the objectives of the thesis, namely: a presentation of the method for constructing the load profile property forecast models; an outline of the integration of a correlation clustering algorithm, discrete classification artificial neural network (NN) and post processing routines; a definition of the scheduling heuristics; details of the scheduler’s operations; and concludes with the scheduling error mitigation processes of the RTO.

The construction of the load profile property forecast models are presented in greater detail in Chapter 4 (the first peer reviewed publication of the thesis). The chapter begins by stating why the development of these forecast models are necessary and then gives a detailed literature review of load forecast modelling. The research methods section outlines how the load profile forecast models are constructed according to two modelling techniques. The benefits and drawbacks are discussed in the results section, along with barriers to producing high accuracy forecast models for the residential LV distribution network.

The development of the pattern recognition based expert system is detailed in Chapter 5. Firstly, the necessity of a new modelling approach is outlined; secondly, the literature review highlights the forecast modelling theory, load profile forecasting techniques and what constitutes an expert system; thirdly, the methods section presents the expert system’s construction and operational flow charts, and discusses how the subcomponents of the expert system are integrated; fourthly, the results section details the accuracy of the load profile forecasts.

Chapter 6 focusses on developing the scheduler, the RTO and integrating the outcomes of all previous research objectives. One of the major goals is highlighted, namely, the
heuristics used to underpin the scheduling system and the differentiation of the scheduling system from the more complex alternatives. The charging, discharging and load balancing functions of the scheduler are presented. The chapter also presents the method used to develop the scheduler, how the RTO uses the calculated schedule and how the RTO performs analyses of the historical load data. Further details are given in relation to the short-term load forecast models and the error mitigation, charging and discharging routines. Next, the scheduling results for the scheduler and complete system are illustrated and discussed. The results section concludes with an explanation of how the scheduler can be repurposed to size BES systems.

Finally, Chapter 7 presents the findings of the research. Chapter 7 begins by summarising the goals and objectives that underpin this research. Each objective is highlighted in the detailed overview of the methods and results brief. The research’s contributions to the literature in the areas of load forecasting, scheduling (based on load profile forecast) and online operations are presented. Additionally, the limitations of the research are discussed and the avenues for future research are proposed. The chapter concludes with a final statement.
CHAPTER 2

Literature review

2.1 Introduction

A literature review was undertaken to establish the research background information upon which the three phase BES scheduling system for the residential LV distribution was to be based. This literature review began by investigating the conventional electricity generation and supply system to gain an overview of the part of the electricity network to which this research related. From there, other advances in electricity supply technologies and management strategies overlapping with energy storage technologies were identified. This was an important step due to the high potential that the future electricity supply system would incorporate a mixture of technologies and strategies. Next, knowledge of the residential LV distribution network and solar PV design environment research was gained. Finally, as the most important aspects of designing the scheduling system were the forecasting system, the scheduler, and the online dispatch system, the prominent forecast model and algorithms and energy storage scheduling algorithms were reviewed.

2.2 Electricity generation and supply system

2.2.1 Overview

The electricity generation and supply system comprises three major stages: generation, transmission network and distribution network. The generators in the network produce the power, while the transmission and distribution networks are structured according to a hierarchy of voltages to supply the power to the customers. Table 2—1 provides a brief overview of each stage of the generation and supply system.
Table 2—1 Electricity generation and supply system

<table>
<thead>
<tr>
<th>Stage</th>
<th>Overview</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>Power is produced at voltages between 11 to 21 kilovolts (kV). The voltage of the power produced is increased via a step-up transformer for the purpose of transmission (Willis, 2004).</td>
</tr>
<tr>
<td>Transmission</td>
<td>The transmission network comprises three phase lines which convey power, at voltages ranging from 115 to 1000 kV. The purpose of conveying power at such high voltages is to reduce systems losses relating to the $P=IR^2$ law. The transmission system connects to the switching stations that dictate the power flow routes. Some large industrial customers are connected to the transmission network (Willis, 2004).</td>
</tr>
<tr>
<td>Sub-transmission</td>
<td>The sub-transmission network transmits power from the transmission switching stations to the distribution substations at voltages ranging from 34 to 230 kV (Willis, 2004).</td>
</tr>
<tr>
<td>Distribution</td>
<td>The distribution network substations are the meeting points for the incoming transmission and sub-transmission lines, as well as outgoing distribution feeder lines. The substations maintain power quality and voltage levels (e.g. tap changes), control power flow through switching and stepping down the voltage from the transmission levels to the distribution feed levels. The feeder lines range in voltage from 4.2 to 34.5 kV. The primary customers connect directly to the feeders. In SEQ, the feeders are rated at 11 kV (Willis, 2004).</td>
</tr>
<tr>
<td>Sub-distribution</td>
<td>The lateral lines are short lines that branch off feeders and convey power to the secondary customers (e.g. residential and light commercial customers). Step-down LV distribution transformers reduce the voltage from 11 kV to 120 or 240 V. In SEQ, residential customers are supplied by three phase Y-connection lines at 240 V and 50 Hz. Typically residential customers are connected to a single phase of the network. Customers requiring more power have three phase connections (Willis, 2004).</td>
</tr>
</tbody>
</table>

2.2.2 South East Queensland

The electricity generation and supply system that supplies SEQ is part of Australia’s National Energy Market (NEM). The NEM is a wholesale electricity market for the supply of electricity to retailers and high demand customers such as smelters. These customers arrange contracts with the transmission and distribution network operators to incorporate the costs associated with the transmission and the distribution of electricity (Australian Energy Market Operator, 2010). The NEM interconnects Queensland, New South Wales, the Australia Capital Territory, Victoria, South Australia and Tasmania. It does not include Western Australia or the Northern Territory. The Australian Energy Market Operator is responsible for ensuring the reliability and stability of the NEM. This is achieved by coordinating the buy and sell orders in the short-term electricity market and by submitting the buy orders as a remedial measure in case of any anticipated shortfalls in supply.

Queensland has over 28 generators with a total generation capacity of 12.69 gigawatt (GW) (Australian Energy Regulator, 2011). The transmission network operator in Queensland is Powerlink, which holds over $4.1 billion in assets, with its network extending over 13500 km. Queensland has two distribution network operators, Ergon
Chapter 2 – Literature review

Energy and Energex. Ergon Energy operates the distribution network in rural and Northern Queensland. Its network line length is over 146000 km, while its assets are over $7.1 billion. Energex is the distribution network operator for SEQ. Its network is 54000 km in line length, while its assets are worth over $7.8 billion. Finally, Queensland has 27 licenced electricity retailers, 11 of which retail to small customers (Australian Energy Regulator, 2011).

Residential electricity bills in Queensland are composed of costs associated with the transmission and distribution of electricity, the wholesale and retail energy costs, as well as the carbon and green costs. According to the Australian Energy Regulator (2013), the transmission and distribution of electricity have the greatest influence on the cost of electricity, accounting for 52% of the total cost. The wholesale energy costs have the second greatest influence at 21%. The retail transaction fees account for 15%, while the carbon and green costs make up 12% of the bill.

2.3 Advances in electricity supply

2.3.1 Overview

Advances in the supply of electricity are being made through demand management programs and smart-grid and micro-grid concepts. The goal of such advances is to improve the reliability and efficiency of the electricity generation and supply systems, while also reducing costs. Demand management programs are programs that seek to alter customer behaviour to achieve goals (e.g. reducing the amount of energy being consumed and changing when energy is being consumed). The smart-grid concept exploits the continual reduction in the costs of communication, computation and data storage and integrates these technologies with the conventional electricity network to make the electricity network “smart”. In turn, the components of the electricity network can be intelligently managed to achieve different goals and objectives. The micro-grid concept incorporates the notion that the electricity supply system can be subdivided into smaller isolated or semi-isolated networks. For these networks to operate they are composed of distributed energy resources (DER), such as local generators and energy storage.

2.3.2 Demand management

Demand management programs primarily involve appliance efficiency mandates, providing information to customers so that they can make informed decisions and time-of-use tariffs. The energy efficiency standards mandate the minimum level of efficiency that a building or appliance must achieve (Harrington & Damnics, 2004). It is anticipated that energy usage will decline, especially as the older appliances are replaced with more efficient products. The energy efficient building standards incorporate both physical
design and positioning aspects and the use of insulating materials (e.g. double-glazed windows) and insulation to reduce building energy use. The current energy efficiency labels provide customers with information that promote the purchase of appliances that consume less energy (Mullaly, 1998; Harrington & Damnics, 2004). Mullaly (1998) observed that customer behaviour has a great influence over energy savings; hence, energy savings programs should focus on both promoting energy efficient appliance and changing customer behaviour. The impact of such informed choices and behaviour have been reflected, in part, in the reduction in residential energy consumption (Energex, 2013).

In Australia, half of the cost of electricity to customers is associated with its transmission and distribution (Australian Energy Regulator, 2013). A large portion of the cost of operating transmission and distribution networks is due to the requirement to meet peak demand, which occurs for only a short period of time. Therefore, the energy consumed during peak demand periods costs more to supply than at other periods, with the value or cost of electricity supplied to customers changing throughout the day. As the demand for electricity increases, its value or marginal cost also increases. Time-of-use tariffs seek to price electricity according to its value (Torriti, 2012). The price of electricity is set low when demand for electricity is low. Conversely, when demand for electricity is high (e.g. during peak demand periods) the price of electricity is set high.

The theory and effects of implementing time-of-use tariffs are summarised in Figure 2—1. Briefly, the two demand curves represent the propensity of customers to consume different quantities of energy at different prices. The demand curves represent the different values of electricity for the morning and evening usage. The diagram shows that in the evening period the consumers are more willing to purchase the same quantity of energy as the morning period but at a higher price. The supply curve represents the generators’ willingness to supply electricity at different prices. The original price of electricity, set at 59 price units, is calculated as the quantity consumed in the morning, \( Q_{m1} \), and the quantity consumed in the evening, \( Q_{e1} \). The time-of-use tariff sets the morning price at the intersection of the morning demand curve and the supply curve; similarly, the evening price is set at the intersection of the evening demand curve and the supply curve. The decreased price in the morning incentivises customers to consume more energy, such that the quantity consumed moves from \( Q_{m1} \) to \( Q_{m2} \). The increased price in the evening causes customers to consume less, and so reduce \( Q_{e1} \) to \( Q_{e2} \). The effective result of introducing time-of-use tariffs is to reduce peak demand and shift the load to periods of the day when demand was originally low (Torriti, 2012).
2.3.3 Smart and micro grids

Smart-grid technologies aim to increase the efficiency of operating electricity systems; the development of smart-grid technology is facilitated by the reduction in costs of communication, computation and data storage. The anticipated benefit of incorporating smart-grid technology into the electricity network is to reduce the costs associated with the operation, maintenance and infrastructure. Smart-grid technologies can include technology that facilitates demand management, power quality correction, fault detection and local generation and storage. Smart-grid technology and demand management programs are relied upon for the construction and operation of micro-grids.

The smart metering of the electricity network facilitates demand management programs by providing high resolution electricity meter data to customers, retailers and network operators. These programs include billing arrangements and highlight usage to customers to make them more aware of their electricity use. Smart meters generally record voltage, current and power in real time and more advanced meters are able to record phase angle and harmonics. Hence, they can be used for additional purposes such as power quality monitoring, identification of illegal connections and DER management, outlined in Table 2—2.

Speculations regarding the future of smart-grids and micro-grids include the integration or reliance on DER (an umbrella term for generators and energy storage to be distributed throughout the electricity network). DER are situated closer to customers or loads than conventional generators allowing for specific solutions to implemented in different areas.
Generators which fall under the DER category have a rated power output from one kW to one MW and cover generator technologies such as solar PV, wind turbines, gas turbines, microturbines and biomass to energy (Bayod-Rujula, 2009). Energy storage technologies used as DER include BES, ultra-capacitors, compressed air, fuel cells, flywheels and hydrogen (Mohd et al., 2008; Divya & Østergaard, 2009). The DER systems can fulfill a range of objectives, including storing energy generated from solar and wind generators and discharging energy when needed, such as during peak demand periods.

<table>
<thead>
<tr>
<th>Application</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information provision</td>
<td>Smart meters and display technology can inform customers of how much energy they are using and at what times. Customers can then use this data to determine the magnitude of their base load, how much energy different appliances use and whether or not the use of appliances should be adjusted. The provision of this information has led to an 11% to 17% reduction in electricity consumption (Gans et al., 2013).</td>
</tr>
<tr>
<td>Billing</td>
<td>The greater energy use data recording resolution allows for the efficient implementation of time-of-use tariffs and peak usage charges. With knowledge of previous electricity use and the time-of-use tariffs, customers will be able to better manage their electricity use and potentially reduce their electricity bills (Wang et al., 2011). Peak usage charges allow for customers to be charged an amount that reflects the cost of supplying the electricity and prevents other customers from subsidizing large users (Hledik, 2014).</td>
</tr>
<tr>
<td>Power quality</td>
<td>The role out of smart meters allow for the electricity network to be spatially monitored in real time. This allows for the network operator to identify power quality issues and faults in the network. In such cases, the network operator can engage in remedial measures and repair the fault (Kezunovic, 2011).</td>
</tr>
<tr>
<td>Illegal connections</td>
<td>The monitoring of the electricity network allows for illegal connections to be identified through the identification of power quality issues and losses. The network operator’s system identifies the losses through discrepancies between historical load data and metered data. An investigation or the activation of counter-measures can then take place such as injecting harmonics (Deb et al., 2011; Depuru et al., 2011).</td>
</tr>
<tr>
<td>DER management</td>
<td>Smart metering can play a role in DER management through the provision of information to control generators and energy storage systems. The information can be in the form of load forecasts or characterisations of historical loads. With this information the scheduling and online control of DER can be enacted. These systems are typically designed to be on the customer side of the connection.</td>
</tr>
</tbody>
</table>

The installation of the distributed generation and energy storage combined with controllable loads through smart metering, allow for the establishment of a micro-grid. Micro-grids are rated to supply electricity from a few kilowatts (kW) to a couple of GW (Bayod-Rujula, 2009). The grids can be applied to rural properties, commercial buildings, industrial uninterruptible power supplies and residential areas (Bayod-Rujula, 2009; Kriett & Salani, 2012). These applications operate in island conditions separate from the conventional electricity network.
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Micro-grid designs with a connection to the electricity network can reply on power from the electricity network in circumstances of insufficient power to meet demand. Advances in the control systems will allow such micro-grids to isolate themselves in the event of a discontinuation of supply or a degradation of power quality (Ackermann & Knyazkin, 2002; Bayod-Rujula, 2009). Consequently, the micro-grid will rely solely on the distributed generators and the energy storage for a power supply (Divya & Østergaard, 2009). Once the electricity network’s integrity has been restored, the micro-grid will then be able to resynchronise. However, for the grids to be completely isolated there needs to be sufficient generation, storage and management technologies to ensure a continuous supply of electricity.

The deviations from the electricity network operational standards, e.g. degradation in quality, are of concern for DER systems (Ackermann & Knyazkin, 2002; Enslin & Heskes, 2004). Power quality issues that arise with DER include:

- DER systems not coordinated with the load on the network can cause variations in voltage beyond the statutory limits (Ackermann & Knyazkin, 2002);
- Frequent activations and disengagements of DER systems and irregularities with the voltage controlling equipment can lead to voltage flickering (Ackermann & Knyazkin, 2002); and
- Inverters that are required to facilitate the integration of DER technologies into the grid, depending on the quality of the equipment, can cause injections of harmonics. Harmonics in the waveform lead to greater losses and potentially increase the voltage in the network above statutory limits (Ackermann & Knyazkin, 2002; Enslin & Heskes, 2004).

There is the potential for the widespread ownership of EV, which rely on the use of battery banks or fuel cells, and are charged at charging stations or wall-sockets at the owner’s residence. The energy storage faculties allow the EV to be treated as DER, to “support the grid” or provide ancillary services to the electricity network and will be an important aspect of the design of future smart and micro grids. Supporting the grid can involve the use of EV to peak shave and valley fill and to maintain power quality and stabilize the grid (Tomic & Kempton, 2007).

An integrated communications system is required for the EV to support the grid and to become an integral part of the smart and micro grids. The communication system will allow for the EV supporting the grid to be controlled and scheduled by the network operator or a power flow management system (Tomic & Kempton, 2007). Along with the necessity for communication with the network operator, the control systems supporting the grid services need to take into account the availability and reliability of the EV.
perform these services (Tomic & Kempton, 2007; Quinn et al., 2010). The availability and reliability concerns are related to the continuous stochastic process of the EV connecting and disconnecting to and from the electricity network (Quinn et al., 2010). The communications and control systems infrastructure must be designed to facilitate the support of the grid while under circumstances of uncertain supply. To some extent the availability and reliability of the EV to provide services can be estimated, especially as regularities in customer behaviour has been determined. The most common estimation method is the probability of the availability and reliability (Fluhr et al., 2010; Quinn et al., 2010; Al-Awami & Sortomme, 2012).

Additionally, the uncoordinated charging of the EV has the potential to cause power quality issues such as losses, voltage fluctuations and frequency and phase angle distortions (Taylor et al., 2010; Deilam et al., 2011; Xu et al., 2011). Taylor et al. (2010) and Xu et al. (2011) conducted analyses of the impact of the EV on the distribution network. They found that when owners arrived home from work during peak demand periods, the EV would be charged. This behaviour resulted in greater loads during peak demand periods and, in some circumstances, the distribution transformers became overloaded. As a solution to this problem, Deilami et al. (2011) proposed the real time coordination of the charging and discharging of the EV, which involves incorporating time varying costs of electricity and the owner’s preferences to prioritise the charging of the EV.

2.4 Residential LV distribution network and solar PV

Unlike subsections of the electricity generation and supply system that service a greater number of customers, the residential LV distribution network has numerous power quality issues relating to the greater relative influence of the individual customers. Moreover, the residential LV distribution networks tend to have unbalanced phases and exhibit a high degree of variance and volatility which can result in voltage fluctuations, and phase angle and frequency distortions. The phenomenon of unbalanced phases contributes to power quality degradation, power losses and potential overloading of singular phases (Chindris et al., 2007; Sathiskumar et al., 2011). Networks with a high degree of power quality issues can lead to customers’ appliances being damaged or destroyed.

The load in residential LV distribution networks is influenced by external conditions such as weather, day of the week, time of the year and specific events (e.g. popular television shows) (Bennett et al., 2014a). These external factors influence the amount of electricity consumed and when it is consumed. Throughout the year the nature of the daily load profile changes primarily in response to the change in average daily temperatures. Two
distinct load profiles occur in the network for summer and winter. Figure 2—2 displays the summer and winter load profiles. The summer load profile is characterised by a low load in the early morning, with increasing load throughout the day and a peak demand occurring in the evening between six pm and nine pm. The winter load profile has a low load in the early morning, a peak demand period in the morning between six am and ten am, a low load during the middle of the day to early afternoon and a peak demand period in the evening between six pm and nine pm. The morning peak in the winter profile occurs due to the customers’ use of heating appliances.

![Graph showing summer and winter load profiles](image)

Figure 2—2 Summer and winter load profiles

The load on a residential LV distribution transformer for each phase, over a 24 hour period, is presented in Figure 2—3. The phases are unbalanced and throughout the day the phases experience different loads. The pattern of each phase’s load is a reflection of the activity of the customers. For example, phases 1 and 3 experience higher loads than phase 2. Either more customers are connected to phases 1 and 3 or the behaviour of the customers during these phases differ from phase 2. During the peak demand period phases 1 and 3 have greater peaks with longer durations than phase 2. To prevent the further unbalance of the network and to mitigate the associated power quality issues, the control algorithms for DER need to be designed to promote load balancing.
Residential rooftop solar PV has the ability to reduce consumption of electricity from conventional sources. The ability to reduce consumption is hampered by the misalignment of the solar PV generation curve and the residential load profiles. Figure 2—4 presents a comparison of the solar PV generation curve with the summer and winter load profiles. The solar PV generation curve is representative of the output of a single six kW system on a clear day. In the early morning there is little or no generation. As the sun’s inclination, relative to the earth, increases the system’s generation increases. The system reaches its peak output during the middle of the day and the early afternoon. Then the generation decreases until sundown. The solar PV’s generation curve does not overlap for the Summer and Winter evening peak demand periods; however, it partially overlaps for the Winter morning peak demand period. This misalignment results in a reduction of the base load during the day measured at the transformer.

Ali and Putrus (2012) and Alam et al. (2012) investigated the impact of residential rooftop PV on power quality. In the first instance, Ali and Putrus (2012) simulated a LV distribution network with a summer load profile and altered the amount of rooftop solar PV in the network. The result showed the greater the penetration of solar PV, the higher the voltage rose during the day. At the 25% penetration level the voltage remained within the statutory limits, while at the 50% level the voltage neared the statutory limit. Then the voltage exceeded the statutory limit at very high penetration levels. Alam et al. (2012) also analysed the change in network behaviour for an unbalanced network. The investigation noted that solar PV output during the middle of the day caused a voltage rise beyond the statutory limits, contributed to load unbalance and reversed the power flow.
2.5 Load forecasting in the electricity system

2.5.1 Overview
Forecasting future load states is an integral part of the management of the electricity generation and supply system. These load forecasts are classified into three forecasting horizons (short, medium, and long-term), which are used for different management purposes. The short-term horizon, ranging from one minute ahead up to one week ahead, are used to ensure generators have enough supply and spinning reserve to meet the demands and to estimate the prices of electricity in the near term. The medium-term horizon, ranging from a week ahead up to several months ahead, are used to schedule maintenance, network augmentation and remedial measure operations. Long-term horizons, ranging from 6 months ahead to many years, are used for strategic goal planning and for ensuring system capacity into the future to accommodate growth in demand or alterations to energy usage patterns.

The most common modelling techniques used to develop load forecast models include multivariate regression, time series techniques (e.g. autoregressive integrated moving average (ARIMA)) and machine learning algorithms (e.g. support vector machines, fuzzy inference networks, artificial neural networks, etc.). These modelling techniques aim to find relationships between dependent variables and independent variables. Dependent variables are the variables being forecast (e.g. load, price, voltage, current, phase angle, etc.). Depending on the modelling technique, dependent variables can be exogenous or time-lagged permutations of the dependent variable. Exogenous variables include
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economic statistics, weather, behavioural events and time based parameters (e.g. day of the week). Multivariate regression assumes a deterministic arrangement between the model’s dependent and independent variables. Capturing specific relationships involves the use of prior statistical analyses. ARIMA (p,d,q) is the general format of time series models. The ‘p’ represents the number of lagged parameters of the dependent variable, the number of autoregressive terms; the ‘d’ conveys the number of discrete differences, the degree of integration; and the ‘q’ is the number of the lagged error terms, the moving average component. Machine learning algorithms are self-learning algorithms which excel at mapping non-linear relationships; they have many applications including pattern recognition, control systems and optimisation. One example is the neural network (NN), which mimics how biological neural networks behave by storing information in artificial synapses and neurons and are altered by feedbacks from external stimuli.

To effectively schedule a BES system short-term load forecasts are required for two reasons. The first is the high cost of BES, which meets the requirements of the operation in an electricity network, namely, suitable depth of discharge (DoD), number of cycles and voltage and current ratings. The high cost per kilowatt hour (kWh) constrains the size of the battery bank which, in turn, curtails the period that the energy resource usage can be optimised. The second is the need to anticipate the near-term load conditions such to optimally operate the BES system and avoid failures. Failures can be attributed to incorrectly anticipating the magnitude and timing of a peak, as well as the network’s load balance. In both circumstances the energy resources are misallocated.

2.5.2 Theory

2.5.2.1 Regression and time series models

Equation 2.1 outlines a general linear model. Variables in the model include the predicted dependent variable (\(\hat{y}\)), the independent variables (\(x\)) and the constant (\(c\) or \(\beta_0\)). Independent variable coefficients (\(\beta\)) are multiplied with the independent variables. There are \(n\) number of independent variables and coefficients, while the error in the statistical model is represented by \(\varepsilon\). Additionally, the model assumes that there are relationships between the dependent and independent variables.

\[
\hat{y} = \sum_{i=1}^{n} \beta_i x_i + c + \varepsilon
\] (2.1)

The general linear autoregressive (AR) model is presented in Equation 2.2. The model assumes that previous states of the system provide information about the future state of the system. The difference between the general linear model and the AR model is that the
independent variables are replaced by time lags of the dependent variable $y$. In this circumstance, $t$ is the time interval, $i$ denotes the lag and there are $p$ number of lagged variables. AR models can be combined with external variables (e.g. weather in load forecast models) to better emulate the system.

$$\hat{y}_t = \sum_{i=1}^{p} \beta_i y_{t-i} + c + \varepsilon \quad (2.2)$$

There are a number of ways to estimate or calculate the coefficients of linear and linearized models. The most common method used is the least mean squared regression algorithm (see Equations 2.3-2.6):

$$\hat{\beta} = (X^TX)^{-1}X^TY \quad (2.3)$$

where,

$$\hat{\beta} = [\beta_0, \beta_1, \beta_2, ..., \beta_n]^T \quad (2.4)$$

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{m,1} & \cdots & x_{m,n} \end{bmatrix} \quad (2.5)$$

$$Y = [y_1, y_2, ..., y_m]^T \quad (2.6)$$

$\hat{\beta}$ is a vector containing the constant ($\beta_0$) and the coefficients of $x$; $X$ is an matrix with each row pertaining to an independent observation, and each column denotes a separate variable, $Y$ is a vector containing the dependent variable with each element pertaining to an independent observation, $n$ is the number of variables and coefficients, $m$ is the number of observations and $T$ is the transpose. Equations 2.7 and 2.8 present the linear algebra form of the general linear model:

$$\hat{Y} = X\hat{\beta} + \varepsilon \quad (2.7)$$

where $\hat{Y}$ is the vector of predicted values:

$$\hat{Y} = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_m]^T \quad (2.8)$$

To capture a non-linear relationship between the dependent variable and an independent variable, the independent variable needs to be adjusted according to the type of relationship. As an example, an independent variable observation matrix, with a parabolic relationship, is presented in Equation 2.9. The observations for variable $n$ are squared before the estimation of the model coefficients.
\[
X = \begin{bmatrix}
    x_1 & \cdots & x_{1,n} \\
    \vdots & \ddots & \vdots \\
    x_{m,1} & \cdots & x_{m,n}
\end{bmatrix}
\] (2.9)

In the model development process, to determine whether or not the estimated coefficients have an effect, the calculation of the statistical significance must be undertaken. The first statistical significance test is the f-test for regression; the second test is the t-test for regression coefficients. The f-test for regression establishes a null hypothesis \((H_0)\) that states that the model coefficients are equivalent to zero, while an alternative hypothesis \((H_a)\) states that the model coefficients are not equivalent to zero. The critical f-statistic \((f_{crit})\) is calculated using Equation 2.10:

\[
f_{crit} = F(1 - \alpha, n - 1, m - n)
\] (2.10)

where \(F\) represents the F-distribution, \(\alpha\) is the level of statistical significance (e.g. \(\alpha\) equals 0.05 or a confidence interval of 95%). The f-statistic of the regression \((f_{stat})\) is calculated by using Equations 2.11 - 2.13:

\[
f_{stat} = \frac{MSR}{MSE}
\] (2.11)

where

\[
MSR = \frac{\sum(\hat{y} - \bar{Y})^2}{n - 1}
\] (2.12)

and

\[
MSE = \frac{\sum(\hat{y} - y)^2}{m - n}
\] (2.13)

where \(MSR\) is the mean sum of squares for the model, \(\bar{Y}\) is the mean of the dependent variable observation vector \(Y\) and \(MSE\) is the variance of the model's error. If \(f_{stat} \) is greater than \(f_{crit}\) then the model's coefficient are likely not to be equivalent to zero.

The t-test for the regression coefficients established a \(H_0\) stating that a coefficient is equivalent to zero; the \(H_a\) states that a coefficient is not equivalent to zero. The critical t-statistic \((t_{crit})\) is calculated using Equation 2.14:

\[
t_{crit} = z(1 - \frac{\alpha}{2}, m - n)
\] (2.14)

where \(z\) is the Student t-distribution. The t-statistic \((t_{stat})\) is calculated for an individual coefficient by using Equation 2.15.
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\[ t_{stat} = \frac{\beta_i}{\sigma(\beta_i)} \]  

(2.15)

where \( \sigma(\beta) \) is the standard deviation of the regression coefficient \( \beta \). The variances of the regression coefficients are calculated by the diagonal elements of the variance-covariance matrix calculated by using Equation 2.16:

\[
\sigma^2(\hat{\beta}) = \text{MSE} \cdot (X^TX)^{-1} = \begin{bmatrix}
\sigma^2(\beta_0) & \ldots & \sigma^2(\beta_0, \beta_n) \\
\vdots & \ddots & \vdots \\
\sigma^2(\beta_n, \beta_0) & \ldots & \sigma^2(\beta_n)
\end{bmatrix}
\]  

(2.16)

where \( \sigma^2(\beta) \) is the variance of the regression coefficient \( \beta \). If \( t_{stat} \) is greater than \( t_{crit} \) then the regression coefficient is likely not to be equivalent to zero.

The autocorrelation and partial autocorrelation functions are used to identify significant lags in the time series for the ARIMA models. The algorithms operate by determining the similarity between the patterns of the current subsection and the lagged subsection. A lag’s inclusion is provided if the calculated correction is statistically significant. The autocorrelation function is presented in Equation 2.17:

\[
\rho_l(Y_t, Y_{t-l}) = \frac{1}{m-1} \cdot \frac{\sum(y - \bar{Y}_t)(y_{t-l} - \bar{Y}_{t-l})}{\sigma(Y_t)\sigma(Y_{t-l})}, \quad \text{for } 1 \leq l \leq M
\]  

(2.17)

where \( \rho(Y_t, Y_{t-l}) \) is the correlation between the observation vector \( Y_t \) and the lagged observation vector \( Y_{t-l} \); \( y \) is an observation within \( Y_t \), \( y_{t-l} \) is an observation within \( Y_{t-l} \), \( \bar{Y}_t \) is the mean of \( Y_t \), \( \bar{Y}_{t-l} \) is the mean of \( Y_{t-l} \), \( m \) is equal to the length of one period (e.g. second, minute, day, etc.) and is the length of \( Y_t \) and \( Y_{t-l} \) and \( M \) is the total number of periods in the observation set multiplied by \( m \).

The partial autocorrelation algorithm is given in Equations 2.18 and 2.19:

\[
r_l = \rho\left(\begin{bmatrix} Y_t - L(Y_t|Y_{t-1}, \ldots, Y_{t-(l-1)}) \end{bmatrix}, \begin{bmatrix} Y_{t-l} - L(Y_{t-l}|Y_{t-1}, \ldots, Y_{t-(l-1)}) \end{bmatrix}\right)
\]  

(2.18)

\[
L(Y|X) = \hat{\beta}X
\]  

(2.19)

where \( r_l \) is the partial autocorrelation statistic for lag \( l \), \( L(Y|X) \) is the model output of \( Y \) regressed onto \( X \), \( X \) is an matrix where each of its columns is a lagged observation vector and each row number corresponds to an element in the lagged observation vectors, and \( \hat{\beta} \) is a vector of estimated model coefficients (calculated using Equation 2.3) with each element corresponding to a lag in the observation.

Equation 2.20 is used to find the critical statistic to determine whether or not the lag is statistically significant:
If the absolute value of the calculated correlation or partial correlation statistic is greater than the critical statistic, the lag is said to have statistical significant. This provides the reason for the lag of the dependent variable being included in the model.

For time series models the Durbin-Watson test is used to identify whether or not the error of the model is autocorrelated. Autocorrelation in the error shows that the error of the model is not equivalent to white noise and has an underlying pattern. If the model error is autocorrelated, the model should be altered so that it accounts for the pattern. The Durbin Watson test is presented in Equation 2.21:

\[ d = \frac{\sum_{t=1}^{m} (e_t - e_{t-1})^2}{\sum_{t=1}^{m} e_t^2} \]  

(2.21)

where \( d \) is the Durbin-Watson statistic, \( e_t \) is the model’s error for forecast \( y \) for time \( t \), and \( m \) is the length of the forecast’s time series. The test for a positive autocorrelation is displayed in Equation 2.22 and the test for a negative autocorrelation is displayed in Equation 2.23:

\[ d < d_l \]  

(2.22)

\[ (4 - d) < d_l \]  

(2.23)

where \( d_l \) is a critical statistic. The model error is positively autocorrelated if \( d \) is less than \( d_l \), the model is negatively autocorrelated if \( (4-d) \) is less than \( d_l \). However, the tests are inconclusive if \( d \) is less than \( d_l \), or if \( (4-d) \) is less than \( d_u \) where \( d_u \) is a critical statistic. An alternative method for identifying autocorrelation in the error is to use the autocorrelation function or partial autocorrelation function.

If the time series being modelled is non-stationary or the influence of exogenous shocks does not dampen over time, the time series is said to have a unit root. Tests such as the Dickey-Fuller test can be used to identify whether or not there is a unit root. Discrete differencing (Equation 2.24) is required to account for the non-stationary properties. A time series model with a discrete difference is said to be integrated.

\[ \nabla y_t = y_t - y_{t-1} \]  

(2.24)

Exponential smoothing algorithms are analogous to time series models and can be used to account for change in the underlying trends and moving averages, while incorporating the influence of the past states of the time series. The double exponential smoothing algorithm is displayed as an example in Equation 2.24-2.27:
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\[ s_t = \gamma y_t + (1 - \gamma) (s_{t-1} + b_{t-1}) \]  \hspace{1cm} (2.25)

\[ b_t = \theta (s_t - s_{t-1}) + (1 - \theta) b_{t-1} \]  \hspace{1cm} (2.26)

\[ F_{t+1} = s_t + b_t \]  \hspace{1cm} (2.27)

where \( s_t \) is an estimate of the local mean, \( b_t \) is an estimate of the local gradient, \( F_t \) is the forecast of the local mean, and \( \gamma \) and \( \theta \) are smoothing coefficients which are estimated by an optimisation algorithm.

2.5.2.2 Neural networks

The machine learning modelling techniques rely on the use of self-learning algorithms. These algorithms map the linear and non-linear relationships between the dependent and independent variables. The most common techniques is the NN, which stores the relationships in a network of artificial synapses and neurons. NNs are organised into layers of neurons and synapses. The first layer of neurons is the input layer; each input neuron corresponds to a model variable. The synapses connect each neuron from the first layer to each neuron of the second layer. Each synapse has a corresponding weight which highlights the strength of the signal from the previous neuron. The neurons receive values that are multiplied by weights from the previous layer. Then the weighted values are summed and inputted into an activation function. The output of the activation function is sent to the next layer of neurons. This pattern is continued throughout the network. Each output neuron corresponds to the dependent variable being forecast, while the weights of the network are adjusted according to a training algorithm.

Figure 2—5 presents a simple NN, which has an input layer, a hidden layer and an output layer. The NN has two input neurons corresponding to the input variables (i.e. \( x_1 \) and \( x_2 \)), and two output neurons for the two output variables (i.e. \( y_1 \) and \( y_2 \)). The hidden layer has three neurons. Each neuron of the successive layer of neurons is connected by synapses from the neurons of the previous layer.

![Neural network diagram](image-url)

Figure 2—5 Neural network
The base equations (2.28-2.29) for a feed forward back propagation NN are as follows:

\[ v_j = \sum_{i=1}^{m} w_{ji} x_i \]  

(2.28)

where \( v_j \) is the output of the summation function for neuron \( j \), \( x_i \) is the output of the activation function for neuron \( i \) or an input, \( w_{ji} \) is the weight between neuron \( i \) of the previous layer and neuron \( j \) and there are \( m \) number of neurons in the previous layer.

\[ \hat{y}_j = \frac{1}{1 + \exp(-v_j \alpha)} \]  

(2.29)

where \( \hat{y}_j \) is the output of the sigmoid activation function for neuron \( j \) and \( \alpha \) is a constant which influences the slope of the function. The output of the function is a value ranging from zero to one.

The weights throughout the network are updated according to an iterative training algorithm. Equations 2.30 and 2.31 encompass the training algorithm for weights connecting to the output layer:

\[ \delta_j = \frac{d\hat{y}_j}{dv_j}(\hat{y}_j - y_j) \]  

(2.30)

\[ w_{ji}^{l+1} = w_{ji}^l + \omega \delta_j \hat{y}_i \]  

(2.31)

where \( \delta_j \) is the local gradient at neuron \( j \), \( y_j \) is the observation corresponding to neuron \( j \), \( l \) is an iteration number, \( \omega \) is the training rate and \( \hat{y}_i \) is the output of neuron \( i \) of the previous layer. Equations 2.32 and 2.33 are the training algorithm for weights connecting the hidden neurons with the network:

\[ \delta_i = \frac{d\hat{y}_i}{dv_i} \sum_{j=1}^{k} \delta_j w_{ji} \]  

(2.32)

\[ w_{ih}^{l+1} = w_{ih}^l + \omega \delta_i \hat{y}_h \]  

(2.33)

where \( k \) is the number of neurons in layer \( j \), \( w_{ih} \) is the weight connecting neuron \( h \) of the previous layer to neuron \( i \) of the current layer and \( \hat{y}_h \) is the output of neuron \( h \). The feed forward back propagation network is similar to regression due to the final training iteration denoting a model with the least error.

2.5.2.3 Accuracy statistics

To gauge a model’s performance accuracy statistics are required to be calculated. These statistics include the root mean squared error or standard error (RMSE), the mean
absolute error (\( MAE \)), the mean absolute percentage error (\( MAPE \)), correlation (\( \rho \)) and the coefficient of determination (\( R^2 \)). As different accuracy statistics capture different properties of the model they should be used in conjunction with each other. The \( RMSE \) is calculated by Equations 2.34:

\[
RMSE = \sqrt{\frac{\sum (\hat{y} - y)^2}{m-n}} \tag{2.34}
\]

\( MAE \) and \( MAPE \) are calculated by Equations 2.35 and 2.36:

\[
MAE = \frac{\sum \text{abs}(\hat{y} - y)}{m} \tag{2.35}
\]

\[
MAPE = \frac{\sum \text{abs}((\hat{y} - y)/y)}{m} \tag{2.36}
\]

The smaller the \( RMSE \), \( MAE \) and \( MAPE \) values are, the more accurate the model is. The correlation reflects how similar the two patterns are and is calculated by Equation 2.37:

\[
\rho(\hat{Y}, Y) = \frac{1}{m-1} \cdot \frac{\sum (\hat{y} - \hat{u})(y - u)}{\sigma(\hat{Y})\sigma(Y)} \tag{2.37}
\]

where \( \hat{u} \) is the mean of the forecast and \( u \) is the mean of the observation. The output of the correlation function is a value ranging from negative one to one. A zero means that there is no correlation between the forecast and the observation vectors. A value close to negative one (-1) or to positive one (+1) means that the two vectors are either negatively or positively correlated.

\( R^2 \) is the value between zero and one. The closer \( R^2 \) is to one, the more the model will be able to account for the observed variance in \( Y \) or the better fit the model has in accordance with observations. \( R^2 \) is calculated by Equation 2.38:

\[
R^2 = 1 - \frac{\sum (\hat{y} - y)^2}{\sum (y - \overline{Y})^2} \tag{2.38}
\]

2.5.3 Literature

2.5.3.1 Regression and time series models

Engle et al. (1992) developed a series of models ranging from pure autoregressive, univariate with day of the week dummy variables, bivariate and models with weather variables to forecast daily peak demand. The bivariate models involve a two stage forecasting process. The first stage involves forecasting the average daily load and uses the average load in the peak demand forecast model. The daily peak demand was found to be
influenced by previous peaks, day of the week, holidays, and weather. The most accurate model was an autoregressive model with day of the week dummy variables and weather variables denoting heating and cooling days.

Nogales et al. (2002) used time series models to forecast the next day’s electricity prices. The electricity price data is non-stationary, has multiple seasonalities, is responsive to the day of the week and holidays and is highly volatile. Dynamic regression and a transfer function approach were used to find the lags of the electricity price which produced models with the error being equivalent to white noise. These models were developed for the Spanish and Californian markets. Both the dynamic regression and transfer function approaches achieved similar levels of accuracy.

A weather ensemble model was compared with a traditional weather forecast model autoregressive moving average model to determine whether or not the technique would provide better electricity demand forecasts (Taylor & Buizza, 2003). The weather ensemble model involved averaging the results from 51 electricity load scenarios produced by the same number of weather forecasts. The traditional weather forecast model and component weather models of the ensemble were composed of day of the week dummy variables; the specific week dummy variables accounted for industrial activity, parabolic temperature response and a wind speed temperature interaction variable. The autoregressive moving average model (ARMA) consists of day of the week dummy variables, specific week dummy variables and moving average error terms. The ensemble model was observed to perform better than the traditional weather forecast and the ARMA models.

Mirasgedia et al. (2006) developed two sets of models for the daily electricity demand and the monthly electricity demand forecasts for Greece. Only the second set (the monthly forecast) included autoregressive terms to account for the autocorrelation in the models’ error. The first set (the daily model) was constructed from heating and cooling the day variables, the day of the week dummy variables, the month of the year dummy variables and holiday dummy variables. The monthly model consists of a long term trend, the monthly heating and cooling variables, the month of the year dummy variables and the holiday period variable. The second set of models expanded on the first set by adding four autoregressive terms for the daily model and one autoregressive term for the monthly model. The models with the autoregressive terms performed better than the models without those terms.

In their work, Soares and Medeiros (2008) used Brazilian electricity data to develop an hourly electricity load model. The model has 24 sub-models, one for each hour of the day. Each sub-model has a deterministic component and a stochastic component. The
deterministic component accounts for trends, seasonalities, day of the week dummy variables and holiday variables. The stochastic component accounts for deviations from the trends in the lags of the electricity load. Seasonalities provide a periodic function. A seasonal ARIMA model was used as the benchmark. It was integrated once, with the statistical significant lags included at day one and seven. The two component models performed better than the seasonal ARIMA model.

In another study, Taylor (2010) investigated the performance of the seasonal ARIMA models against seasonal exponential smoothing algorithms. Both sets of algorithms attempted to forecast the time series into the future, assuming that the past states of the system can provide inferences about the future state. The single seasonal models accounted for the intraweek seasonality. The double seasonal models emulated the intra-week and intra-year, or intra-day and intra-week data. Triple seasonal models encompassed the intra-day, intra-week and intra-year seasonalities. By combining the triple season models, the authors found the highest level of performance.

### 2.5.3.2 Machine learning models

In other work by Kassaei et al. (1999) and Cavallaro (2005), load forecast models were developed using NNs. Kassaei et al. (1999) used a hybrid fuzzy NN to forecast bus load. This load exhibited non-stationary behaviour due to its response to temperature, social events and industrial activities. For modelling purposes, the load was separated into a normal load and a weather sensitive load. A NN was used to model the normal load and a fuzzy system was used to model the weather sensitive load. The outputs of the two models were combined to make the forecast. The current temperature and average temperature were passed to a Gaussian membership function to classify the temperature. Cavallaro (2005) utilized a feed forward back propagation NN. The inputs in the NN included day of the week dummy variables, hour of the day, as well as load and average load for the same hour for the months of March, August and October. The model exhibited a low forecast error.

Szkuta et al. (1999) and Catalao et al. (2007) used NNs to forecast the electricity prices in the short-term. Szkuta et al. (1999) used lags of the system's power demand and lags of the system's marginal price as input variables. The NN was trained with back propagation; the NN models achieved satisfactory results. A three layered feed forward NN was used by Catalao et al. (2007) to forecast next week's electricity prices. The NN was trained by the Levenberg-Marquardt algorithm. The variable components of the model were day and week lags, and day of the week, weekend, and holiday dummy variables. The performance of the method when applied to the different regions was dependent on the variability of
the system being modelled. The method produced a higher level of error for the Spanish market than for the Californian market.

A number of other researchers (namely, Darbellay and Slama (2000), Abraham and Nath (2001) and Ringwood et al. (2001)) developed load forecast NNs and compared their performances against time series models. Darbellay and Slama (2000) used linear and non-linear autocorrelation functions to identify the significant lags for the NN and ARIMA models. The significant lags were identified as one hour, 24 hours and 168 hours. Four forecasting horizons were used to test the models. In each case the NN model performed better. When temperature variables were added the ARIMA model performed better. In their review of an evolving fuzzy NN, Abraham and Nath (2001) used the NN and ARIMA models. The evolving fuzzy NN was a combination of a fuzzy inference system and a NN. The variables (maximum daily temperature, minimum daily temperature, the load lagged one day, the hour of the day, the season and the day of the week) were entered into the input layer; then they were altered in the fuzzification layer. Next, the inferences were made in the rule node layer and the outputs were converted to the forecast. The evolving fuzzy NN model performed better than the NN and ARIMA models. In the Ringwood et al. (2001) study, the feed forward back propagation NN was compared to the ARIMA for the short, medium and long term models. For short-term models, the day of the week, the season, temperature and humidity influenced load were found to have the most influence on load. The NN models were observed to perform better than the ARIMA models.

2.6 Energy storage scheduling systems

2.6.1 Battery bank parameters
Batteries are made up of electrochemical cells which produce an electromotive force through redox reactions. The parameters of importance in the use of the battery banks and the design of the BES systems include a short circuit current (I_{sc}), an open circuit voltage (V_{oc}), capacity (C), total charge (TC), DoD, charge rating (CR), discharge rating (DR), efficiency (BE) and state of charge (SoC). I_{sc} is the current which passes through a wire from the battery’s terminals when no load is applied; V_{oc} is the voltage (potential difference) between the battery’s terminals when there is no current; the C of the battery bank is the amount of energy stored in kWh or the current that is able to be supplied in amp-hours (Ah); the TC (upper limit) and DoD (lower limit) are the operational limits on the battery bank’s charge. These variables are generally set as percentages of C. The CR and DR are the operational limits on the power and current that can be used to charge or discharge the battery bank. The batteries have internal resistance which leads to losses during the charge and discharge phases of the operation. BE is the efficiency of the battery
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or battery bank; it takes into account the losses from the internal resistance. The SoC is the amount of energy stored in the battery bank at a given point in time.

A number of battery properties define and affect the battery operation’s lifespan, which is denoted by its rated number of charge and discharge cycles. Typical lead-acid batteries are rated between 500 and 1500 cycles (Quaschning, 2005). As batteries undergo their charge and discharge cycles the efficiency and capacity of the batteries decrease. Overcharging, high cell temperatures and discharging below the DoD, degrade the batteries and reduce their lifespan (Garche & Jossen, 2000).

Battery management systems (BMS) are promoted to elongate battery lifespan and prevent damaging conditions from taking place (Garche & Jossen, 2000; Krein & Balog, 2002; Kaiser, 2007). The BMS developed by Garche and Jossen (2000), collects voltage and temperature information, controls charge and discharge processes, and prevents the occurrence of deep discharge, overcharge and high temperatures. To extend the life of batteries, a cell voltage balance system was proposed by Krein and Balog (2002). The main purpose of this system was the prevention of deep discharge and the overcharge of individual cells. Kaiser (2007) segregated batteries in the BES system so the BMS could engage in the targeted control. The target control is based on criteria, which includes the necessity for a battery to charge or discharge, the level of cycling of an individual battery and SoC.

2.6.2 Schematics

2.6.2.1 Customer side

A generic customer side BES with solar PV system is illustrated in Figure 2—6. The system has a battery bank with a BMS and a solar PV array connected to a direct current (DC) bus. The DC bus connects to a bidirectional inverter which, in turn, converts the DC to alternating current (AC). The AC bus connects to the rest of the household and the electricity network. The energy generated from the solar PV array can be used to charge the battery bank or be discharged to the AC bus. The energy stored within the battery bank can be discharged to the AC bus when the solar PV is not generating, during peak demand periods or during load levelling operations.
2.6.2.2 Network side

A network side BES system is displayed in Figure 2—7. The network services a number of distributed residential customers with some customers having installed solar PV arrays. The residential customers are connected to the three phase network. The transformer steps down the voltage from the higher voltage feeder to the lower voltage distribution network. In this network, the three phase battery bank is installed next to the transformer. The battery bank can be installed in other locations to achieve specific objectives such as voltage support. Further, the battery bank located on the network side and controlled by the distribution network operator can charge when the distributed solar PV arrays are generating as well as discharge during peak demand periods.
2.6.3 Scheduling systems

2.6.3.1 Overview

The main goal of the BES scheduling systems is to peak shave and valley fill to reduce the costs associated with supplying and consuming energy. Additional goals include maintaining power quality and improving the efficiency of renewable energy generators in supplying electricity, both of which can have the potential to abate further alterations to the electricity network. Figure 2—8 provides an example of a peak shave and valley fill operation for the winter load profile. For this particular day, the low demand periods occur during the early morning and early afternoon. The MP occurs between six and ten am and the EP occurs between six and ten pm. As denoted by the shaded area of the figure, the schedule of the BES is such that it is set to charge in the morning, discharge during the MP period, charge during the early afternoon and discharge during the EP period.

![Figure 2—8 Peaks shave and valley fill](image_url)

To calculate a schedule for the BES system information about future states (e.g. peaks and valleys) of the electricity network is required. The simplest form of this information is inferences about the time of occurrence and the duration of the peak demand periods based on historical load data. The information that is most commonly used includes load forecasts, time-of-use tariffs and energy market prices. Load forecasts are advantageous because they produce specific information about load states such as the occurrence, duration and the magnitude of peak demand periods, as well as similar properties for the low load periods. Time-of-use tariffs are designed to price electricity at different times of the day, according to the cost or value at those times. Under the time-of-use tariffs, the price of electricity is set to be high typically when the load is high. The energy market prices can be either a spot price or a future price. The higher the spot price, the higher the
demand in the network. The futures electricity price is formulated and based on the anticipation of the supply and demand by market participants. Similar to the spot price, as the futures price goes higher, the higher the anticipated load in the network.

The methods for calculating the schedule involve a single method or a combination of linear programming, heuristics, dynamic programming and optimisation routines. Linear programming involves structuring the model of the BES system and the schedule calculation in a linear sequence. When one operation has been completed the next operation is run until the end of the sequence. Heuristics are generalised rules that can be used to achieve an approximate solution to a complex problem in order to simplify a calculation or decrease computational requirements. The simplest heuristic in the scheduling case is a time based heuristics which dictates a time interval where the BES system should charge or discharge. The schedule calculation is divided into a series of sub-problems in a recursive manner. Each sub-problem is calculated once and the result is recorded. The best value, according to the criterion, is selected as the solution. An optimisation approach involves the creation of an objective function. The objective function is composed of a series of sub-functions representing different aspects of the system. Different states of each function have an associated cost or benefit according to a cost or benefit function. An optimisation routine is then used to either maximise the benefit or minimise the cost. In general, the optimisation approach involves modelling the BES system and assigning different cost functions to the load and BES states (e.g. a high load will have a high cost). All methods involving constraining the system is based on the input information and the BES system parameters.

2.6.3.2 Literature
Sanseverion et al. (2013) developed a scheduling system that uses a fuzzy logic controller, market energy prices and historical load data as input information. The price and SoC information are converted into categories of different levels by the fuzzy membership functions allowing for the establishment of a fuzzy rule set which dictates the charging and discharging of the BES system. Through the use of fuzzy rules, the fuzzy logic controller is similar to a heuristic based system. Electricity is being bought and sold, based on whether or not the system is charging or discharging. An example of the fuzzy rule set occurs when the price is low and the charge of the battery bank is low, then the system will charge. The scheduling error is determined by whether or not the system makes a profit or loss. If the system makes a loss, the membership functions are adjusted.

The scheduling systems developed by Lu and Shahidehpour (2005) and Hu et al. (2010) involved the use electricity prices and optimisation routines. Lu and Shahidehpour (2005) applied a combined solar PV and BES system with an initial scheduling system that is
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composed of two sub-problems. The first sub-problem involved scheduling the conventional generation in the grid to meet the load requirements. This is conducted using Lagrangian relaxation to find the least cost of supplying load through conventional generation. The price signal from the first sub-problem is sent to the second sub-problem. The BES with the solar PV objective function is also solved through the Lagrangian relaxation. The BES scheduling displaces the conventional generation requiring an iterative process that continues between the two sub-problems. The hourly dispatch of the schedule is optimised using power flow calculations through dynamic programming. Hu et al. (2010) relied on the day ahead spot price market to provide information about the demand in the electricity network for the next day. The goal of the optimisation routine is to maximise revenue for the owner of the BES systems; it is achieved through sequential quadratic programming.

A next day 24 hour load forecast based scheduling system for the LV distribution network was produced by Rowe et al. (2014). To mitigate the forecast error manifesting in the schedule dispatch, the forecasted load profile undergoes a filtering process. The peaks are increased and the widths of the peak periods are widened. The filtered forecast is passed to the scheduling algorithm that is constrained by the BES system parameters. The algorithm attempts to find the greatest peak demand reduction by iterating through a selection of parameters.

Jayasekara et al. (2014), Xu et al. (2010) and Riffonneau et al. (2011) developed schedule systems that relied on both the use of the electricity price and the load forecast information. Jayasekara et al. (2014) proposed the use of the energy storage to mitigate the power quality issues associated with high solar PV penetration in distribution networks. The system begins by forecasting the next day’s load profiles and the solar PV generation curve. This information is passed on to the optimisation routine which seeks to minimise the cost objective function. The objective function is composed of the total battery cost, time-of-use tariffs and the ratio of negative to positive sequence voltages. The day ahead electricity price market was used by Xu et al. (2010) to produce an initial schedule through the minimisation of the cost of the energy objective function. The real time control schedule adjustment and dispatch used the load forecasts and a receding horizon control strategy. Riffoneau et al. (2011) initialized a co-located solar PV and BES system by forecasting irradiance, temperature, load profile and price of energy. Using dynamic programming the scheduling system seeks to achieve optimal peak reduction.
2.7 Problem formulation

The three phase BES scheduling system is to be installed in the residential LV distribution network. In Australia, the LV residential distribution network delivers electricity to customers with a three phase network that supplies a 240 V (line to neutral). The LV distribution network is characterised by unbalanced phases and a high degree of variance and volatility. These characteristics can result in voltage fluctuations and phase angle and frequency distortions. The residential load profile is such that in summer the peak demand period occurs from six pm to nine pm. The winter load profile has an additional peak demand period in the morning, occurring between six am and ten am. Other periods of the day such as the early morning and the middle of the day have a low load. The solar PV generation curve is such that the generation starts during mid-morning, peaks during the middle of the day and declines until late in the afternoon. The lack of correlation between the residential load profiles and the solar PV generation curve occurs because the solar PV is generating when the demand during the day is low. This incongruity results in conventional generation not being replaced. In areas of high PV penetration this can lead to circumstances of power quality degradation, e.g. voltage rise (Alam et al., 2012).

The cost of supplying electricity in the distribution network is primarily governed by the provision of the infrastructure to meet the peak demand in the network. Additional infrastructure costs are born through the upgrading of components in the network to mitigate the power quality issues associated with the load characteristics and the high penetrations of solar PV. An avenue for reducing the costs of supplying electricity occurs through designing a BES scheduling system that will peak shave and valley fill, utilise pre-existing solar PV in the network and balance the load across the phases. To do this the BES scheduling system will require information about future load states, as well as a scheduling algorithm that will use the information to determine when the BES system should charge and discharge.

The NEM allows generators, network operators and retailers to make contracts to supply electricity to customers. The NEM only incorporates futures electricity prices and spot electricity markets for the generation level system and at this current point in time does not provide markets for LV distribution level electricity supply and consumption. Due to the absence of this market and electricity prices on the generation level not reflecting demand in different subsections of the electricity market, electricity price information cannot be used to optimally reduce peak demand. With the role out of smart-grid technologies, such as communication systems and smart metering, electricity load information can be collected continuously allowing for the development of load forecast models.
Similar to work conducted by Xu et al. (2010), two types of forecasts are required for the scheduling system to operate efficiently. The first type is a next day load profile forecast which is required as an input to provide an initial schedule. The load profile forecasts provide information about when peak demand periods will occur, their duration and magnitude, in addition to similar information pertaining to low load periods. The second type is a short-term load forecast model for the use in schedule adjustments to mitigate load profile forecast errors. A load forecast system for the residential LV distribution network must be able to provide reasonably accurate forecasts under circumstances of high variability and volatility. To mitigate these characteristics and with the knowledge that the general load profile patterns occur due to external influences (e.g. weather), a pattern recognition based load profile forecast system is proposed. Due to the ability of NN to find relationships between variables, a discrete classification NN can be trained using load profile patterns and associated external variables. In operation, the NN can select a load profile that is most likely to occur as the load profile forecast.

Scheduling systems based on optimisation routines are relatively complex to implement and can be more computationally taxing than alternative methods. The objective functions of these systems are composed of a series of cost functions which model components of the energy storage system and electricity network. The cost functions can be directly linked to components of the overall system if the price information exists (e.g. as local electricity prices). In the absence of price information, the cost functions need to be developed using a trial and error approach.

To reduce complexity and with knowledge of the results of optimally scheduled BES systems, a heuristics based scheduling system can be developed. The formulation of the heuristic is based on the result that a BES system which is not capacity constrained is the peak demand minus the $DR$. Given the load profile forecast, the scheduling algorithm can initialize by calculating a discharge portion from the given heuristic. Through a partial linear and dynamic programming process the scheduling algorithm can then constrain the output of the heuristic according to the BES $SoC$. Load balancing can only be conducted through the BES system's charging and discharging. To achieve load balancing the system is required to charge more from the phases that are least loaded and discharge more to the phases that are most loaded.
CHAPTER 3

Research method

3.1 Introduction

This chapter outlines the development of the three phase BES scheduling system for the residential LV distribution network. The BES is to be installed on the network side (see Figure 2—7) and managed by the distribution network operator enabling the BES to utilise pre-existing solar PV resources while operating independently. The scheduling system has a number of operational goals that are desired to be achieved, including peak shaving and valley filling, utilising solar PV generation in the network, load balancing and ensuring optimal usage of BES resources. Under peak shaving and valley filling, peak demand reduction is achieved through discharging the BES during peak demand periods. The valley filling component means that the BES will charge during low demand periods. The utilisation of solar PV involves charging the BES when solar PV is generating.

The enactment of these goals may not be mutually exclusive; they require an algorithmic hierarchy to be established which is based on importance. To yield the most benefit from the BES installations in the residential LV distribution network, peak demand reduction and the efficient use of BES resources are the highest ranked goals. Peak demand reduction allows for the deferral of network augmentation, while the efficient use of BES resources minimises the required capacity, thereby reducing capital costs. To ensure that these two goals are achieved, scheduling redundancy measures are required to mitigate errors. Further, the charging of the BES cannot rely solely on solar PV generation due to its intermittency. In turn, the utilisation of solar PV resources will be passively integrated. To maintain maximum peak demand reduction, the load balancing function will be designed to activate when the SoC of the BES is insufficient to meet the initial schedule.

The dispatch of schedules calculated from historical load data and forecasts of future load states of electricity prices can result in scheduling errors due to discrepancies between
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These types of information and the actual load experienced. This necessitates that the scheduling systems require two components. The first component is a scheduler that receives information which provides inferences about future load states and calculates an initial schedule. The second online component, the RTO, analyses the load in real time and adjusts the schedule (e.g. to mitigate the initial scheduling error).

The development of the scheduling system involves four objectives, as outlined in Figure 3—1. Each objective contains a number of stages (that must be completed) with a number of outcomes. The completion of each objective is necessary as the knowledge, models and algorithms are integrated into the next objective.

The pattern recognition based load profile forecast expert system is based on identifying relationships between load profile patterns and external variables (e.g. the weather). To better establish these relationships with external variables, properties of load profiles are to be forecast and used as input variables for the expert system. This places the first objective as the development of the load profile property forecast models. The outcome of the first objective includes knowledge of the relationships between the load profile properties, the external variables and the TEU, MP and EP forecast models for each phase.

The second objective involves creating the expert system that forecasts the next day load profiles for each phase. The third objective is the development of the initial scheduling system or scheduler. The scheduler receives the load profile forecasts from the expert system. Through a combination of heuristics and dynamic and linear programming, it aims to produce the initial schedule. The forth objective begins by integrating the outputs of the prior objectives. These integrated outcomes allow for the RTO to be established. The RTO receives the initial scheduling information from the scheduler and the historical load data; it also performs the analysis and adjusts the schedule (e.g. to mitigate any scheduling error). Finally, the integration of all prior outcomes with the completed RTO substantiates the scheduling system.

The completion of the first objective is presented in Chapter 4; the completion of the second objective is given in Chapter 5; while the completion of the third and fourth objectives are outlined in Chapter 6. Each chapter contains a detailed method section for the constituent subject sub-objectives.
Figure 3—2 displays the scheduling system's flow chart and how the outcomes of each objective are integrated into the system as a whole. The initialisation of the scheduling system begins at the start of the day and sets the time interval ($t$) as the value one. If $t$ equals one, the system acquires weather forecasts and historical load information. Then the system forecasts the load properties and passes the information to the expert system.
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The expert system, in turn, forecasts the load profiles for each phase. With the load profile forecasts the scheduler is then able to calculate the initial schedule for the day. The RTO receives the initial schedule. For each time interval the RTO analyses the historical load information and makes adjustments to the schedule if required.

![Diagram of BES scheduling system flow chart](image)

The electricity load data, used in the development of forecast models and testing of the scheduling system, was generously supplied by Energex from their smart-grid trial area. The electricity load data was from an LV distribution transformer located in an inner northern suburb of Brisbane, Queensland. The transformer supplies 128 residential customers. The average current, voltage and phase angle data for each phase is logged at 10 minute intervals. Overviews of the transformer’s load data are presented in proceeding chapters, according to the type of information required for the completion of objectives. The weather data was acquired from the Brisbane Aero weather station, located at Brisbane City, made publically available by the Australian Bureau of Meteorology.

3.2 Objective 1: Load profile property forecast models

3.2.1 Data pre-processing

The data pre-processing involves extracting the required information from the existing database. The TEU, MP and EP time series for each phase were formulated from the raw load data (see Equation 3.1). Each phase’s TEU time series was calculated from the time integral of each day’s load profile:

$$ TEU_d = \int_{t=1}^{t=m} LP_d \, dt, \quad \text{for } 1 \leq d \leq D $$  \hspace{1cm} (3.1)

where $TEU_d$ is the TEU for day $d$, $t$ is the time interval, there are $m$ number of time intervals in a day, $LP_d$ is the load profile for the same day and $D$ is the number of days in the load data’s time series. Once calculated, the TEU has $D$ number of elements.
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The EP time series for each phase was calculated (Equation 3.2) from the maximum value of the load time series over the evening period:

\[ EP_d = \max(LP_{d,m}, LP_{d,m+1}, \ldots, LP_{d,m}), \quad \text{for } 1 \leq d \leq D \]  

(3.2)

where \( EP_d \) is the EP for day \( d \).

The MP time series for each phase was calculated (Equation 3.3) from the maximum value of the load time series over the morning period:

\[ MP_d = \max(LP_{d,1}, LP_{d,2}, \ldots, LP_{d,m}), \quad \text{for } 1 \leq d \leq D \]  

(3.3)

where \( MP_d \) is the MP for day \( d \).

3.2.2 Data analysis

The analysis of the TEU, MP and EP time series include identifying the relationships between the time series and external variables. The identification of the relationships between the external variables allows for these relationships to be programmed into regression models. The relationships can be determined either graphically or empirically. External variables of interest include temperature, humidity and days of the week. Data analysis was conducted using the following process:

1. The time series were plotted against the individual external variables to graphically identify relationships.
2. A range of single variable models (e.g. linear, parabolic, polynomial, etc.) for each external variable were fitted to the time series and the accuracy of the statistics were calculated to determine the relationship and magnitude of the influence.
3. An identifiable relationship and a noticeable influence form the basis of the reasoning for an external variables inclusion in a model.

3.2.3 Development of load property forecast models

The TEU, MP and EP time series are split in half. The first halves of both time series were then used for the model development, coefficient estimation and hindcasting. The second halves of both time series (i.e. the validation time series) were used for forecasting and analysing model performance. The development of the load properties models was conducted according to a stepwise regression process:

1. A base model was first derived with the variable observed to have the most influence.
2. The model was then used to hindcast the model development time series and the accuracy statistics (e.g. \( R^2 \), \( RMSE \), \( MAPE \), etc.) were calculated.
3. The f-test for a lack of fit and a t-test for the regression coefficient were then calculated to indicate whether or not the model was able to explain the observations and whether or not the coefficient of the variable was not equivalent to zero.

4. If the fit was not statistically significant, or the coefficient of the variable was equivalent to zero, the base model was discarded and a new one was created. Otherwise, the next variable was added to the model.

5. The new model was used to hindcast the model development time series. In addition to the f-test and the t-test for the new regression coefficient, the new variable was omitted if its inclusion does not increase hindcast accuracy.

6. The process of calculating the accuracy statistics, the f-test and t-test was repeated until all the variables of interest were analysed.

As part of the process, autoregressive terms were identified by the use of autocorrelation and partial autocorrelation functions and the addition of further autoregressive terms was conducted according to the Durbin-Watson test to account for autocorrelation in the error time series.

**3.2.4 Analysis of model performance**

Model performance was determined by the ability of the model to forecast the observed load of the validation set. This was conducted graphically and the accuracy statistics were calculated. The graphical determination involved overlaying the forecast on top of the observations to identify whether or not the model was able to forecast the observed patterns and the circumstances when the model was unable to provide a reasonable forecast. The calculated accuracy statistics included $R^2$, RMSE and MAPE.

**3.3 Objective 2: Pattern recognition based expert system**

**3.3.1 Overview**

The pattern recognition based expert system is an algorithm that received input information (such as the forecasted load properties, and weather and seasonal variables) to select a load profile which is most likely going to occur. The expert system requires both an offline system to identify patterns and an online system to use the identified patterns for load profile selection. A pattern recognition method is required for the offline system. A discrete classification feed forward back propagation NN was used for this purpose due to its ability to map non-linear relationships. The NN required reliable input and output variables for training or mapping relationships. In order to do this a set of load profiles that repeat themselves according to reoccurrences of external variables is required. A correlation clustering algorithm was selected for finding clusters of similar load profiles,
categorising them and associating the groups with external variables. The mean of each cluster substantiates the set of repeating load profiles. Since each day’s load profile is different, the online component has post-processing routines which adapt the selected load profile to the forecasted load profile properties.

3.3.2 Data pre-processing

The load data time series were first separated into matrices in the form of Equation 3.4:

\[
LP = \begin{bmatrix}
LP_{1,1} & \cdots & LP_{1,m} \\
\vdots & \ddots & \vdots \\
LP_{D,1} & \cdots & LP_{D,m}
\end{bmatrix}
\] (3.4)

where \(LP\) is the load profile matrix. Each row of the matrix corresponds to a different day and each column of the matrix corresponds to a time interval of a load profile. There are \(D\) number of days and \(m\) number of time intervals in a day.

Matrices (one for each phase) containing external variables were then created in the form of Equation 3.5:

\[
X = \begin{bmatrix}
x_{1,1} & \cdots & x_{1,n} \\
\vdots & \ddots & \vdots \\
x_{D,1} & \cdots & x_{D,n}
\end{bmatrix}
\] (3.5)

where \(X\) is the matrix of variables. Each row of the matrix corresponds to a different day’s variable observations and each column is a separate variable. There is \(n\) number of variables. These matrices contain variables, such as TEU, EP, MP, weather variables and seasonal variables.

For the correlation clustering algorithm to assign load profiles to a cluster category categorisation matrices were required and were constructed according to Equation 3.6:

\[
Y = \begin{bmatrix}
c_{1,1} & \cdots & c_{1,C} \\
\vdots & \ddots & \vdots \\
c_{D,1} & \cdots & c_{D,C}
\end{bmatrix}
\] (3.6)

where \(Y\) is the matrix containing the cluster categorisations, \(c\) is a Boolean value, \(C\) is the total number of clusters and \(D\) is the number of days. \(c\) can equal either zero or one. A cluster categorisation is denoted if \(c\) is equal to one. All other columns in the same row are equal to zero.
3.3.3 Correlation clustering

There are many types of clustering and categorisation algorithms which rely on the use of different statistics. For the purpose of identifying similar load profiles, how well the load profiles match (e.g. peak at the same time and valley at the same time) each other is more important than how similar the means or medians are. $R^2$ and the correlation statistic indicate how similar vectors are by providing a value between zero and one. The statistics differ due to $R^2$ being more sensitive to differences in magnitudes than the correlation statistic. With this information in mind, the correlation statistic was chosen as the base for the clustering algorithm, which operates as follows:

1. A large number of clusters were created and the load profiles randomly assigned to each cluster.
2. The mean of each cluster was calculated, defined as the characteristic demand profile (CDP). The CDP established the underlying pattern of the cluster. The CDP was a vector with the length of $m$.
3. The correlations between each load profile and each CDP were calculated.
4. The load profiles were assigned to clusters having the highest correlation statistic.
5. Low numbered clusters were eliminated and the load profiles were reassigned.
6. The algorithm repeated itself from stage 3 until no more changes were made.
7. The final results were formulated in categorisation matrix $Y$.

Figure 3—3 provides an example result of the correlation clustering algorithm. There were a large number of load profiles categorised under this cluster. All load profiles exhibited a similar pattern. Within this cluster of the load profiles is the CDP that captures the underlying pattern.
3.3.4 Discrete classification neural network

A feed forward back propagation NN with sigmoid activation function neurons was selected to be the discrete classification NN. The training of the NN maps the non-linear relationships between each variable and each row vector of X with each cluster category of Y. Once training has completed and relationships have been recognized, the NN will be able to classify a set of inputs.

For a vector of input variables, the discrete classification NN outputs a vector of scores. Each element of the input vector corresponds to an input neuron. Each element of the output vector corresponds to an output neuron and a cluster category. The output neuron with the highest value indicates the cluster category that the input variables are most likely to coincide with. The CDP of the cluster category is selected to be the load profile pattern which is most likely going to occur for the next day.

To forecast the next day's load profile, input variables must be able to be used to infer future load states. The goal of objective one was to identify relationships between load and external variables and to develop load property forecast models. These relationships and forecast models form the input variables for the discrete classification NN.

Figure 3—4 presents a general representation of the discrete classification NN. Input variables are submitting to the input layer of neurons. Weights connect the input layer to the hidden layer and the hidden layer to the output layer. According to the inputted variables, the output layer yields a score for each cluster category. The graph on the right in the figure represents the selected CDP that is most likely to be the load profile pattern that will occur for the next day.

\[
y_i = (\sum_{j=1}^{k} \beta_i x_{i,j} + \sum_{j=0}^{k} \alpha_j \text{temp}_r \cdot j + \sum_{j=0}^{k} \gamma_j \text{humidity}_r \cdot j + w_0 \text{WE} + w_1 \text{PH} + w_2 \text{WD} + SF(i)
\]

Figure 3—4 Discrete classification neural network
3.3.5 Post-processing

Each of the load profile exhibits a similar pattern to the CDP. Within this cluster, the load profiles may differ from the CDP in terms of TEU, EP and MP. The selected CDP may also differ from the actual load profile in the same terms. For the most accurate load profile forecast the CDP must be adjusted according to the TEU, EP and MP forecasts. To achieve this outcome a MP forecast model was created using the same method as the TEU and EP forecast models. The TEU of the CDP was adjusted to the meet the TEU forecast according to Equation 3.7:

$$ CDP_l = CDP_{l-1} + \frac{(\hat{TEU}_d - \int_{t=1}^{t=m} CDP_{l-1})}{m} $$ (3.7)

where $CDP_l$ is the adjusted CDP, $l$ is the iteration number and $\hat{TEU}_d$ is the TEU forecast for day $d$. $CDP$ increases if the TEU forecast is greater and $CDP$ decreases if the TEU forecast is lesser.

The EP adjustment was commenced by establishing a weight vector (Equation 3.8):

$$ \bar{w} = [0.1,0.2,...,1,...,0.2,0.1] $$ (3.8)

where $\bar{w}$ is the weigh vector that has a length equal to the peak demand period. Each element of the vector corresponds to an element of the EP period with the middle element aligning with the EP value of the CDP. The process continues by establishing an adjustment vector (Equation 3.9):

$$ \bar{a} = \bar{w} \cdot (\hat{EP}_d - CDP_{EP}) $$ (3.9)

where $\bar{a}$ is the adjustment vector, $\hat{EP}_d$ is the EP forecast for day $d$ and $CDP_{EP}$ is the EP value of the CDP. The EP adjustment of the CDP concludes with the adjustment vectors addition to the EP period of the CDP (Equation 3.10):

$$ CDP_{L,EP} = CDP_{l-1,EP} + \bar{a} $$ (3.10)

where $CDP_{L,EP}$ is the EP adjusted CDP, $l$ is the iteration number and $EPP$ represents the EP period of the CDP.

The MP adjustment was conducted in a similar manner to the EP adjustment (Equation 3.11):

$$ \bar{a} = \bar{w} \cdot (\hat{MP}_d - CDP_{MP}) $$ (3.11)
where $CPD_{MP}$ is the MP value of the $CDP$ and $\overline{MP}_d$ is the MP forecast for day $d$. The middle element of $\bar{a}$ aligns with the MP value of the $CDP$. The MP adjustment of the $CDP$ concludes with the adjustment vector addition to the MP period of the $CDP$ (Equation 3.12):

$$CPD_{LMP} = CPD_{c-1,MPP} + \bar{a}$$

(3.12)

where $CPD_{LMP}$ is the MP adjusted $CDP$, and $MPP$ represents the MP period of the $CDP$.

### 3.4 Objective 3: Development of initial scheduling system

#### 3.4.1 Hierarchy of objectives

The scheduling system as a whole is designed according to a hierarchy of objectives derived from the primary goal of peak demand reduction and the ancillary goal of load balancing.

#### 3.4.2 Establish battery energy storage system model

For the subcomponents of the scheduling system to operate a model of the three phase BES system is required to be integrated. The three phase BES system comprises a battery bank and three inverters, in parallel on a DC circuit. Each inverter is synchronised to a separate phase of the electricity network. To allow for different charge and discharge magnitudes to occur on different phases each inverter is controlled independently. The battery banks charge and discharge operations are constrained by the battery bank's parameters (as outlined in Battery bank parameters Section 2.6.1). In addition to the battery bank parameters, the BES system is constrained by the inverter parameters, including the inverter discharge rating ($iDR$), the inverter charge rating ($iCR$) and the inverter efficiency rating ($IE$).

#### 3.4.3 Establish scheduling heuristic

The literature review revealed the existence of many types of scheduling systems that rely on a variety of algorithms, including optimisation routines and dynamic programming routines. The dispatched schedules are displayed in the form of the load being overlaid on the historical load without the dispatch. In circumstances where the capacities of the battery banks were not considerably constrained, the resultant peak demand reductions were equivalent to the $DR$ of the BES systems. Knowing this general optimisation routine and dynamic programming routine solution, with the capacity of the battery bank being unconstrained, a scheduling heuristic was established (see Figure 3—5).

The scheduling heuristic is expressed through the calculation of the discharge targets ($DT$). The $DT$ equals the MP or EP value minus the $DR$ of the BES system. The BES system can only discharge when the load is above the $DT$ and only charge when the load is below
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the DT. With the calculation of the DT each phase’s initial peak reduction portion of the schedule can be calculated. The initial schedule is the load above the DT minus the DT, multiplied by a negative sign. In the schedule vector, a negative value implies that the system is discharging, while the positive value implies that the system is charging. From here, the initialised peak reduction portions of each phase’s schedule are constrained according to the availability of the battery energy resources at the peak of the reduction periods.

3.4.4 Charging routines

Peak demand reduction is the primary goal of the scheduling system. To achieve maximum peak demand reduction, constrained by the BES system parameters, the SoC of the battery bank needs to be at or close to TC before the beginning of a MP or EP period. To achieve the primary goal, tiered charging routines were created. The primary routine (general charging) is to charge the battery bank until the SoC reaches TC. The second routine (load balance charging) activates if the SoC reaches TC before a MP or EP period. Each charging operation of the schedule is constrained by the iCR and CR.

The general charging routine ensures that the maximum SoC is achieved before a MP or EP period such that the maximum peak demand reduction can be achieved. The general charging routines involve charging the battery bank from each phase at the charge rating of the BES system. The charging continues until the load is greater than or equal to the DT.

The load balance charging routine activates if the SoC equals TC before a MP or EP period. Figure 3—6 illustrates the load balance charging routine. The first stage identifies the
period of the load profile forecasts where charging can take place. The charge period starts at the end of the last MP or EP period or starts with the load profile forecast and finishes at the start of the next MP or EP period or end of the load profile forecast. A charge vector (CV) is then created with the same length as the charge period. The elements of the CV equal the minimum value of the three load profile forecasts over the charge period. The CV is then continuously increased in magnitude; the area below the CV and above the load profile forecasts is the calculated charge schedule. The CV stops increasing in magnitude until the SoC at the end of the charge period equals TC. The result of this routine is that the battery bank is charged more from the phase with the least forecasted load and least from the phases with the higher forecasted loads.

![Diagram of load balance charging](image)

Figure 3—6 Load balance charging

### 3.4.5 Discharging routine and dispatch

At the start of the discharging routine the scheduler checks to see if the SoC is sufficient to reduce the peak according to the initial schedule. If there is an insufficient SoC, the routine engages in peak demand reduction through load balancing. This method prioritises phases by allocating more energy to higher loaded phases than lower loaded phases. The routine begins by setting each phase's DT to the minimum DT of all three phases. Similar to the load balance charging routine, the DT of all phases are continuously increased in magnitude and the discharge schedules are recalculated until the energy required to reduce the peaks equal the SoC of the battery bank at the start of the MP or EP period. The final result of the discharge routine is that the higher loaded phases are reduced more than the lower loaded phases.
Once the initial charge and discharge schedule has been calculated, the scheduler dispatches the schedule $DT$ for each phase and simulated the SoC to the RTO.

### 3.5 Objective 4: Real time operator

#### 3.5.1 Schedule error mitigation routines

There are two types of scheduling error that can occur. The first error is a result of the misalignment of the forecasted peak and the actual peak. The second error is the depletion of the battery’s energy resources before the end of the MP or EP period, such that the load shortfall must be compensated from the power grid. Both scheduling errors cause peak demand reductions to be inefficiently achieved and diminish the purpose of having a BES system for peak shaving and valley filling.

The first scheduling error is mitigated by reducing the reliance on the scheduler’s calculated $DT$ and short-term load forecasts. For each time interval the RTO forecasts the load. No discharging takes place if the load forecast is below the $DT$. When the load forecast is greater than the $DT$ and the scheduler for the current time interval is found to be in error, the schedule for the current time interval is recalculated. This is conducted by the difference between the load forecast and the $DT$, multiplied by a negative sign.

The second scheduling error is mitigated by raising the $DT$, which reduces the difference between the load or the load forecast and the $DT$, such that the calculated discharge is reduced. A decision making framework is required to decide whether or not raising the $DT$ is required and whether or not previous the $DT$ adjustments need amending. The decision making framework was developed from comparisons between the simulated SoC from the scheduler and the actual SoC from the operation of the BES system. If the actual rate of energy use is greater than the simulated rate of energy use, the $DT$ is raised. Alternatively, if the actual rate of energy use is lower than the simulated rate of energy use, the $DT$ is lowered. The $DT$ cannot be lowered below the original $DT$ calculated by the scheduler.

#### 3.5.2 Short-term load forecast model

A short-term load forecast model was developed for each phase. The change in the load over the short-term time scales (e.g. less than a couple of hours) does not correlate well with the external variables such as weather. In turn, the short-term load forecast models were developed according to the ARIMA method. The autocorrelation and partial correlation functions were used to identify seasonality in the load time series, while the Durbin-Watson test was used to enhance additional variables to account for the autocorrelation in the error term. For each time interval the RTO uses the short-term load forecast models to forecast load for the current time interval.
3.5.3 Charging routine
The RTO charging routine is activated when the BES system is set to charge according to the initial schedule provided by the scheduler. The amount of energy required to charge the battery bank for the current time interval can then be calculated. Similar to the scheduler's load balance charging routine, a CV is set according to the minimum load forecast. The CV is continuously increased in magnitude until the area below the CV and above the load forecasts is equal to the amount of energy required for the current time interval. The result of the RTO charging routine is to provide an additional load balancing operation. At the end of the routine the schedule for the current time interval is dispatched.

3.5.4 Discharging routine
The discharge routine is activated when the BES system is set to discharge according to the initial schedule provided by the scheduler. The discharge routine ensures that the schedule adjustment made by the scheduling error mitigation routines does not breach BES system parameters. If the schedule breaches BES system parameters, the schedule is adjusted. At the end of the routine the schedule for the current time interval is dispatched.

3.6 Conclusion
This chapter outlined the general research method for developing a three phase BES scheduling system such that it engages in peak shaving and valley filling and load balances. The development of the scheduling system mean it had to be tailored to the residential LV distribution network environment. The scheduling systems required information about the future to base the charge and discharge schedule calculations on. To have more precise inferences about the future, load profile forecasts were selected. A pattern recognition based expert system, that is not susceptible to the volatility of the LV distribution network, was chosen to forecast the load profiles. The load property forecast models were required as input variables for the discrete classification NN component of the expert system. The scheduling system comprises a scheduler that calculates an initial schedule and an RTO that analyses the historical load data against the initial schedule and adjusts the schedule if necessary. The scheduler, based on a heuristic that stated the optimal solution of an unconstrained capacity BES system, is the peak demand minus the rated output of the system. The load balancing occurs during the charging and discharging operations. The RTO was designed to have several routines that attempt to mitigate the scheduling error. The RTO dispatches the schedule when previous routines have ended.
CHAPTER 4
Forecasting load properties

Statement of contribution to co-authored published paper

This chapter includes a co-authored peer-reviewed paper.

The bibliographic details of the paper, including all authors, are:


My contribution to the paper included performing statistical analysis of the data, writing forecast model development and statistics algorithms, constructing the forecast models, reviewing the performance of the models and drafting the paper.

Signed: ___________________________ Date: ____________

Christopher Joseph Bennett

Countersigned: ___________________________ Date: ____________

Co-author: Assoc. Prof. Rodney Stewart (principal supervisor)

Countersigned: ___________________________ Date: ____________

Co-author: Prof. Junwei Lu (associate supervisor)
Chapter 4 – Forecasting load characteristics

**Autoregressive with exogenous variables and neural network short-term load forecast models for residential low voltage distribution networks**

Abstract: This paper set out to identify the significant variables which affect residential low voltage (LV) network demand and develop next day total energy use (NDTEU) and next day peak demand (NDPD) forecast models for each phase. The models were developed using both autoregressive integrated moving average with exogenous variables (ARIMAX) and neural network (NN) techniques. The data used for this research was collected from a LV transformer serving 128 residential customers. It was observed that temperature accounted for half of the residential LV network demand. The inclusion of the double exponential smoothing algorithm, autoregressive terms, relative humidity and day of the week dummy variables increased model accuracy. In terms of $R^2$ and for each modelling technique and phase, NDTEU hindcast accuracy ranged from 0.77 to 0.87 and forecast accuracy ranged from 0.74 to 0.84. NDPD hindcast accuracy ranged from 0.68 to 0.74 and forecast accuracy ranged from 0.56 to 0.67. The NDTEU models were more accurate than the NDPD models due to the peak demand time series being more variable in nature. The NN models had slight accuracy gains over the ARIMAX models. A hybrid model was developed which combined the best traits of the ARIMAX and NN techniques, resulting in improved hindcast and forecast fits across all three phases.

Keywords: forecast; electricity demand; residential; time series; autoregressive integrated moving average (ARIMA); ARIMA with exogenous variables (ARIMAX); neural network (NN)

**4.1 Introduction**

In recent years there has been substantial interest and speculation in the design and operation of smart grids, micro grids, and distributed energy resources (DER). The reason for this interest is that these emerging technologies may contribute to reducing peak demand and network congestion, minimizing disturbances and increasing network reliability (Ackermann & Knyazkin, 2002; Lu & Shahidehpour, 2005; Bayod-Rujula, 2009; Venu et al., 2009; Amjadi et al., 2010). As the technology matures, economic benefits may result from reducing capital and maintenance expenditures and deferring network augmentation (Lu & Shahidehpour, 2005; Oudalov et al., 2006; Hoff et al., 2007; Gil & Joos, 2008; Nottrott et al., 2012).
The sound operation of these emerging technologies will depend on ensuring that supply of power will meet the demand for power (Morais et al., 2010). Similar to the conventional electricity generation and supply system, these technologies will rely on accurate forecasting of future electricity demand (Hatzigryrion et al., 2005; Amjadi et al., 2010; Morais et al., 2010; Nottrott et al., 2012). The electricity demand forecasts will need to provide information on how much power is required to be generated at certain times, the scheduling of charging and discharging of energy storage systems, and be able to determine whether or not there are adequate resources to meet future demand with decision points to activate remedial measures such as load shedding, etc.

The current research is part of a larger project to develop an energy management control algorithm to schedule DER in residential low voltage (LV) distribution networks. The DER system incorporates solar photovoltaic (PV) generation and battery energy storage (BES). To adequately schedule DER, information such as the total amount of energy used in a day, magnitude of peak demand can be used to construct demand profiles for future days (Hernandez et al., 2013). Using concepts from Espinoza et al. (2005), a pattern recognition based expert system will incorporate forecasts of total energy use and peak demand in order to forecast future demand profiles.

This development total energy use and peak demand forecast models for the residential LV distribution network faces additional challenges due to greater variability and frequency of random “shocks” over modelling subsections of the electricity supply and distribution network which services a greater number of aggregated customers. The greater variability is due to the increase in the influence that individual customers have on the network as the number of customers serviced in a subsection decreases.

This paper sets out to identify the significant variables which influence demand in residential LV distribution networks and develop next day total energy use (NDTEU) and next day peak demand (NDPD) forecast models for each phase of a residential LV distribution transformer servicing 128 customers. Autoregressive integrated moving average with exogenous variables (ARIMAX) and neural network (NN) modelling techniques will be used to construct the NDTEU and NDPD models in order to draw model accuracy comparisons and determine whether or not combining the techniques will yield more accurate models.

4.2 Research background
Griffith University, Elevare, Ergon Energy and Energex, under the Queensland State Government 2012–2014 Research Partnership Grant, are participating in a large joint project to research and determine the feasibility of installing static synchronous
compensators (STATCOMs) with BESS in the LV distribution network in the South East Queensland (SEQ) region of Australia. STATCOMs are four quadrant pure sine wave synchronous inverters. STATCOMs are able to import and export real and reactive power, correct frequency distortions and dampen harmonics. Integrating STATCOMs with DER has the potential to mitigate DER power quality issues as noted by Ackermann and Knyazkin (2002) and Enslin and Heskes (2004). STATCOMs with BES have the ability to reduce peak demand through load shifting and also contribute to the enhanced management of power quality. Reducing peak demand and maintaining power quality have the potential to reduce network operational expenditures through the deferral of greater capital expenditures such replacing transformers and/or upgrading lines. The ultimate goal of the joint project is to design and quantify the effectiveness of STATCOMs with BES for reducing network infrastructure expenditures over their life cycle. The widespread implementation of STATCOMs with BES in the LV distribution network will be considered to be feasible if they have a life cycle cost that is lower than the business as usual scenario for providing power in the region.

4.3 Literature review

4.3.1 Short-term electricity demand forecasting

The length of the scheduling window for the energy management control algorithm is determined by the capacity of the BES and the level of the network in which the BES will be installed (e.g., customer, LV distribution network, and high voltage distribution network). Larger BES will be able to reliably achieve their objectives over time under conditions of charging and discharging. For the current research the capacity of the BES is limited by the cost of lithium-ion batteries. This financial constraint curtails the scheduling window of the energy management control algorithm. In conjunction with BES in the LV distribution network, the length of the scheduling window is limited to three days into the future. Regardless of battery costs, readers should note that there is a rapidly diminishing return from the long-term storage of power for the purpose of levelling spikes in demand in an LV network.

The length of the scheduling window bounds the daily peak demand and total electricity demand forecast models to the short-term forecasting horizon. Short-term forecast models focus on forecasting time intervals of minutes, hours, days to a week into the future. The most common techniques used to construct short-term forecast models include multivariable regression, time series analysis techniques and machine learning algorithms such as NNs (Engle et al., 1992; Darbellay & Slama, 2000; Ringwood et al., 2001; Taylor, 2003; Taylor & Buizza, 2003; Mirasgedis, et al., 2006; Taylor, 2010; Ko &
Lee, 2013). These techniques have been successfully applied to national grid level demand time series (Engle et al., 1992; Darbellay & Slama, 2000; Ringwood et al., 2001; Taylor, 2003; Taylor & Buizza, 2003; Mirasgedis, et al., 2006; Taylor, 2010; Ko & Lee, 2013). It has been observed that there is a limited amount of published literature on LV distribution network applications.

4.3.2 Summary of modelling techniques

Multivariable regression models are based on the use of the least mean square algorithm to estimate the coefficients of the model parameters. Model parameters are selected by the modeller with the aid of exploratory statistics to infer whether or not there are relationships between independent variables and the dependent variable the model is attempting to explain. Periodicities observed in the dependent variable can be identified by the use of the Discrete Fourier Transform and inserted into the model as a basis function. Diagnostic tests such as the f-test and t-test on regression coefficients reveal whether or not model parameters are statistically significant at a particular threshold level of significance (α). The calculation of the coefficient of determination (R²) and root mean square error (RMSE) describe the accuracy of the model in explaining the dependent variable.

Time series techniques, codified by Box and Jenkins (1970), are a set of modelling techniques which involve constructing forecast models with parameters based on permutations of the variable the model is to forecast. The autoregressive integrated moving average (ARIMA) p, d, q, is the general model of the time series techniques which encapsulates the autoregressive model, non-seasonal differencing and the moving average model. The “p” term represents the number of time lagged parameters; the “d” term represents the number of discrete differences the forecast variable’s data has undergone in order to remove seasonality; and the “q” term represents the number of time lagged forecast error parameters in the model to account for an observed moving average in the forecast variable’s data. The order of “p” and “q” terms can be identified by the use of the partial autocorrelation function. The level of difference can be determined by the use of an autocorrelation plot based on the nature of decay or the use of the Durbin-Watson (DW) statistic to identify autocorrelation in the forecast error (serial correlation). Coefficients of time series models can be estimated by regression or maximum likelihood estimators.

NNs are a set of modelling techniques which have a wide range of applications including statistical modelling, discrete classification, pattern recognition, control systems, etc. NNs mimic how biological NNs operate and learn. NNs are constructed from multiple layers of neurons connected by weights from each neuron to each neuron of the proceeding layer. Neurons are the base unit of the network. The weights between the neurons represent a
linear augmentation of the outputs from the previous layer's neurons. Individual neurons summate the previous layer's outputs multiplied by the weights and the result is processed in an activation function. Through a specified learning algorithm, the training process alters the weights throughout the network until the network has been identified to be an optimal model which explains the dependent variable. The main benefit of using the NN methodology over other techniques is that it is able to identify non-linear relationships between the independent and dependent variables.

### 4.3.3 Representative publications

Engle et al. (1992) set out to identify a next day peak electricity demand forecast model by testing univariate, bivariate and weather variable models. The coefficients of the models were estimated using regression. Engle et al. (1992) used Consumer Power's peak demand data for 1983 and 1984 for training and validation of the models. The highest performing univariate model was constructed with an autoregressive variable and holiday, holiday for the previous day, Saturday, Sunday and Monday dummy variables. The bivariate model consists of two stages. Stage one consists of a forecast of the next day's average electricity demand. Stage two uses the forecast of the average electricity demand as an input variable in the NDPD forecast model. Additional variables in the model were the same as the univariate model with an additional average electricity demand of the previous demand variable. The weather variable model was first constructed using the same variables as the univariate model with an additional lag of average demand variable. Weather variables included in the model were heating and cooling day variables which are determined by temperature thresholds. Engle et al. (1992) concluded by stating that the weather variable model was the best performing due to having the best validation statistics out of the set of models examined.

In an investigation of whether or not NNs are a better modelling technique than ARIMA, Darbellay and Slama (2000) constructed short-term (hourly) electricity demand models from the Czech Republic's 1994 and 1995 electricity demand data for comparison purposes. The Czech Republic's electricity demand data exhibited daily, weekly and yearly cycles. The first stage in the investigation was to determine whether or not there were non-linear autocorrelations by use of the mutual information criterion and to identify significant variables (representative seasons in the data). A univariate model and a model with an additional weather variable were constructed and compared using the two examined modelling techniques. The results suggested that the autocorrelations of the electricity demand data were predominantly linear which highlights that linear modelling techniques are suitable. The ARIMA and NN univariate models performed similarly while the ARIMA model with additional weather variables performed better than the NN.
Ringwood et al. (2001) used NN modelling techniques to develop short, medium and long-term electricity forecast models and compared the models against conventional techniques such as Box-Jenkins time series models. The structure of the models was determined by the use of the autocorrelation function. The comparison of the models displayed that the NN model performed better than the Box-Jenkins time series model.

In univariate models the seasonality as identified by the use of the autocorrelation and partial autocorrelation algorithms are the key determinants in forecasting future demand. If the time series is non-stationary, the change in mean must be accounted for. The Holt-Winters Seasonal Exponential Smoothing algorithm takes into account the local trend, moving average and the seasonality in the time series to produce a forecast model. Taylor (2003) set out to improve online univariate models by adapting the Holt-Winters Seasonal Exponential Smoothing algorithm to take into account an additional seasonal influence (Double Seasonal Exponential Smoothing). Taylor (2003) used half-hourly electricity demand data from England and Wales and compared the Holts-Winters Seasonal Exponential Smoothing and double exponential smoothing (DES) with daily and weekly seasonality. Once controlling for autocorrelation in the error term, Taylor (2003) noted that the DES model performed better. Taylor (2003) went on to adapt the algorithm to take into account three seasons and found that the method improved forecast accuracy.

Taylor and Buizza (2003) noted that weather variables are important determinants in short to medium electricity demand forecast models. To improve on current methods of forecasting electricity demand based on weather variables, Taylor and Buizza (2003) used forecasted weather ensembles to forecast multiple scenarios of future electricity demand. Ensemble forecasting is a method whereby a set of future states of a dynamic system is forecasted based on slightly different initial conditions. This technique is typically used in weather forecasting. Taylor and Buizza (2003) based the electricity demand forecast model off England's National Grid's weather dependent forecast model. The forecast model involves effective temperature, cooling power of wind and effective illumination. The weather ensembles were inputted into the model and the mean of the results were used as the forecast. The weather ensemble method was compared against a traditional weather model, actual weather for forecasting and an ARMA model with Friday, Saturday and Sunday dummy variables. Taylor and Buizza (2003) found that the weather ensemble method performed better than the traditional weather and ARMA models.

Mirasgedis et al. (2006) developed a daily and monthly electricity demand forecast models using weather variables. The non-linear response between temperature and electricity demand was decomposed into heating and cooling variables. The daily electricity demand forecast model was composed of heating and cooling variables and lags of the variables,
humidity variables, day of the week dummy variables, month of the year dummy variables, holiday dummy variable and autoregressive variables to correct for autocorrelation of the error term. The coefficients of the model were estimated by regression.

Support vector regression (SVR), dual extended Kalman filter (DEKF) and a radial basis function NN (RBFNN) were combined by Ko and Lee (2013) to create a short-term load forecast model with data from the Taipower Company (Taipei, Taiwan). The technique was then compared against a DEKF-RBFNN model and a RBFNN model. The SVR and the DEKF are used to determine the optimal inputs for the RBFNN from independent variables. Ko and Lee (2013) found that the combination of SVR, DEKF and RBFNN created a short-term forecast model which outperformed other models.

Hernandez et al. (2013) developed a next day demand profile forecast system for a microgrid by the use of a two stage system. The first stage is comprised by a series of NNs which forecasts demand profile properties such as peak loads and valley loads. The forecasts are fed into the second stage’s NN which produces a demand profile forecast with 24 values for each hour of the day. Demand data from Castilla y León (Spain) was used to train and validate the NNs. The system forecasted demand profiles with a high level of accuracy and boasted improvement in forecast accuracy over previous work.

**4.3.4 Model selection**

The significant variables which dictate the parameters of electricity demand forecast models are determined by the scope of the forecast models. Weather variables have little effect on short-term forecast models which forecast half-hourly or hourly ahead of time and are generally not used (Taylor & Buizza, 2003). The results of Darbellay and Slama (2000) displayed that the models without temperature variables performed insignificantly better.

As the forecast window is increased to forecasting a day ahead and greater, weather variables become more significant. In the next day load forecast models developed by Engle et al. (1992), Taylor and Buizza (2003), Mirasgedis et al. (2006), weather variables were significant components. Engle et al. (1992), Taylor and Buizza (2003) found that models with weather variables performed better than the comparison time series models.

Electricity demand time series data is non-stationary and contains many seasonal trends (Darbellay & Slama, 2000; Ringwood et al., 2001; Taylor, 2003; Taylor & Buizza, 2003; Taylor, 2010). The seasonalities in the data are identified by the use of the autocorrelation and partial autocorrelation algorithms. Darbellay and Slama (2000) and Taylor (2003) identified daily, weekly and annual trends which were used as variables in their models. The daily electricity demand forecast models developed by Mirasgedis et al. (2006)
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included day of the week and month of the year dummy variables. These dummy variables account for weekly and annual seasonality in the data set.

The proposed NDTEU and NDPD forecast models will require weather and seasonality variables to be effectively incorporated and the non-stationarity characteristics of electricity demand time series to be mitigated. The selected modelling techniques to develop the NDTEU and NDPD forecast models are ARIMAX and feed forward back propagation NN. ARIMAX is the general ARIMA model with the inclusion of exogenous variables such as weather variables. The NN models will have a similar input variable structure including both autoregressive terms and exogenous variables.

The results of the ARIMAX and NN models will be compared to determine which technique is most suitable.

4.4 Data

4.4.1 Source

Data for the LV transformer used in the construction of the load forecast models has been collected and provided by Energex (i.e., the power distribution company for the SEQ region). The transformer is located in an inner northern suburb of Brisbane, Queensland. The transformer distributes power to 128 residential customers. The metering resolution was such that the voltage, current and line to neutral power factor for each phase of the transformer was recorded at 10 min intervals. The data set covers the period from the middle of January 2012 to mid-February 2013. Weather data such as temperature and relative humidity (RH) were collected by the Brisbane City weather station, made publically available by the Australian Bureau of Meteorology and downloaded from their website. The first half of the data set was used for coefficient estimation or NN training and the second half of the data set was used for model validation.

The Brisbane resides in a subtropical climate region which is denoted by mild winters and hot humid summers. According to the Australian Bureau of Meteorology, January is the hottest month of the year with average maximum and minimum temperatures of 29.0 °C and 21.2 °C. July is the coldest month of the year with average maximum and minimum temperatures of 20.8 °C and 9.0 °C. The annual precipitation is 1028.2 mm where the greater majority of precipitation occurring during the months from November to March.

4.4.2 Overview

Figure 4–1 illustrates the daily total energy use and daily peak demand for each phase of the transformer. The period displayed by the graphs starts from the 12 January 2012 (Day 12) to the 6 February 2013 (Day 403). The daily peak demand data for each phase have
greater variability than the daily total electricity demand. The system is unbalanced with Phase 3 incurring the greatest load. The transformer experiences greater loads with higher variance during the summer and winter periods of the year. The yearly peak demand on the transformer occurs during summer. From these observations it can be stated that the daily total energy use and daily peak demand time series are non-stationary.

![Figure 4-1: Daily total electricity demand data and daily peak demand data](image)

The transformer incurred an abnormally high load on the 11 June 2013 (Day 12), which was the Queen’s Diamond Jubilee public holiday. Other public holidays did not coincide with loads abnormal for their respected times of the year. The suburb where the data was collected resides within an area with a high risk of flooding. As a result, the demand in the
system is significantly higher the day after a period of heavy rainfall in the greater catchment area when controlling for other variables. The most notable spike in demand occurred on the 29 January 2013 (Day 395) in response to heavy rainfall and flooding which occurred during the preceding days. These events are considered to be exogenous shocks to the system and can’t be forecasted ahead of time. To avoid biasing the models’ accuracy statistics, the exogenous shock data points were not removed.

Figure 4—2 displays the daily total energy use and daily peak demand temperature response for each phase of the transformer. What can be noted from each of the graphs is that the demand response to temperature is parabolic in nature. Greater loads are experienced during days with average temperatures below 18 °C and above 26 °C. This reinforces the observation from Figure 4—1 that during winter and summer months the transformer experiences greater loads. Daily average temperature explains daily total electricity demand with $R^2$ ranging from 0.57 to 0.71. In comparison, daily average temperature explains daily peak demand to a lesser degree with $R^2$ ranging from 0.48 to 0.60. Daily average temperature as a single determinant explains half or greater of the observed variance. This suggests that daily average temperature would be a key determinant in forecasting daily total energy use and daily peak demand. The temperature response observation is in line with weather variable observations made by Engle et al. (1992), Taylor and Buizza (2003) and Mirasgedis et al. (2006).

4.5 Research method

4.5.1 Overview

The following main steps outline the method for constructing the three clusters of forecast models (i.e., ARIMAX, NN and hybrid ARIMAX-NN):

1. Establish the modelling framework;
2. Forecast day-ahead local mean using the double exponential smoothing algorithm;
3. Selection of autoregressive terms;
4. Selection of exogenous variables;
5. Coefficient estimation; and
6. Validation of models.
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4.5.2 ARIMAX model

The selected modelling approach to construct the NDTEU and NDPD forecast models was the ARIMAX model. As previously noted, the ARIMAX model combines the ARIMA model with exogenous variables. To fulfill the ARIMA model component of the ARIMAX model, the Holt-Winters DES algorithm was employed as a model input variable. DES is analogous to an ARIMA (0, 2, 2) model which accounts for a changing mean throughout the time series and low frequency seasonality. The general ARIMAX model is described by Equation 4.1:

\[ y_t = \rho F_t + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{j=1}^{r} \omega_j w_j + e_t \]  

(4.1)

where \( y_t \) is the demand at time \( t \); \( F_t \) is the forecasted mean for time \( t \) calculated by the DES algorithm; \( \rho \) is the model coefficient for \( F_t \); \( y_{t-i} \) is the demand lagged by \( i \) time steps; \( \beta_i \) is the coefficient of \( y_{t-i} \); \( p \) is the maximum number of time lags; \( w_j \) represents the model's
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exogenous variables; \( \omega_j \) represents the coefficients of the exogenous variables; \( r \) is the maximum number of exogenous variables; and \( e_t \) is the error at time \( t \). The coefficients of the models are estimated by regression.

4.5.3 Neural network

The feed forward error back propagation NN was used. The output of each neuron throughout the network is calculated by Equations 4.2 and 4.3:

\[
 v_i = \sum_{h=1}^{m} w_{ih} x_h \tag{4.2}
\]

where \( v_i \) is the summation of the weights \( w \) connecting to the inputs \( x \) for neuron \( i \). There are \( m \) inputs with corresponding weights in the previous layer \( h \). If layer \( h \) is a hidden layer, each \( x_h \) is an output of a neuron from the previous layer.

\[
 \hat{Y}_i = \sigma(v_i) = \frac{1}{1 + \exp(-v_i a)} \tag{4.3}
\]

where \( \hat{Y}_i \) is the output of neuron \( i \); \( \sigma(v_i) \) is the sigmoid activation function and \( a \) is a constant which influences the gradient of the function.

The training of weights throughout the network is calculated using two algorithms. The first algorithm, equations 4.4 and 4.5, apply to the weights connecting to the last layer of neurons in the network. The second algorithm, Equations 4.6 and 4.7, apply to the weights connecting to neurons within hidden layers:

\[
 \delta_j = \sigma'(v_j) (\hat{Y}_j - Y_j) \tag{4.4}
\]

\[
 w_{ji}^{(t+1)} = w_{ji}^{(t)} + \tau \delta_j \hat{Y}_i \tag{4.5}
\]

where \( \delta_i \) is the local gradient at neuron \( j \); \( \hat{Y}_j \) is the forecast; \( Y_j \) is the observed value; \( Y_i \) is the output from neuron \( i \) of the previous layer; \( w_{ji} \) is the weight connecting neuron \( i \) to neuron \( j \); \( \tau \) is the training rate; and \( t \) is the training iteration:

\[
 \delta_i = \sigma'(v_i) \sum_{j=1}^{k} \delta_j w_{ji} \tag{4.6}
\]

\[
 w_{ih}^{(t+1)} = w_{ih}^{(t)} + \tau \delta_i Y_h \tag{4.7}
\]

where \( \delta_i \) is the local gradient at neuron \( i \); \( k \) is the number of neurons in the proceeding layer; \( w_{ih} \) is the weight connecting neuron \( i \) to neuron \( h \) of the previous layer; and \( Y_h \) is the output of neuron \( h \).
20% of the training data set is randomly separated to form a calibration set which is not used for updating the weights to ensure that the network does not over-fit the data. The training process is constrained by a maximum number of training iterations defined by the user. Accuracy statistics for the training and calibration sets are calculated for each iteration and if the accuracy statistics for both sets improve, the weights throughout the network are saved. The process continues until the maximum number of iterations is reached.

4.5.4 Double exponential smoothing

The DES algorithm is referenced from Gardner and Dannenbring (1980) and is outlined by Equations 4.8 to 4.10:

\[ s_t = \gamma y_t + (1 - \gamma)(s_{t-1} + b_{t-1}) \] (4.8)
\[ b_t = \theta (s_t - s_{t-1}) + (1 - \theta)b_{t-1} \] (4.9)
\[ F_{t+1} = s_t + b_t \] (4.10)

where \( s_t \) is an estimate of the mean at time \( t \); \( b_t \) is an estimate of the slope at time \( t \); \( y_t \) is the demand at time \( t \); \( F_t \) is the forecast of the mean at time \( t \); \( \gamma \) and \( \theta \) are smoothing constants estimated by an optimisation algorithm.

4.5.5 Autoregressive terms

The autoregressive terms of the models were selected from the use of the partial autocorrelation function and the DW statistic. Once the partial autocorrelation function has been calculated, lags with partial correlations above the threshold level (calculated by equation 4.11) are then identified as being significant. The DW statistic identifies whether or not the model's error term is autocorrelated. The addition or subtraction of autoregressive terms can mitigate positive or negative autocorrelation. If the addition or subtraction of autoregressive terms does not mitigate the autocorrelation in the error, a process of differencing is required to be undertaken. The DW statistic is calculated by Equation 4.12:

\[ \pm \frac{z_{1-(\alpha/2)}}{n^{1/2}} \] (4.11)

where \( z \) is a two-tailed score from Student's \( t \)-distribution with a level of significance \( \alpha/2 \); and \( n \) is the number of observations in the time steps within the time series. For the current research a confidence interval of 95% is assumed, therefore, \( \alpha \) equals 0.05:
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\[
DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=2}^{n}(e_t)^2}
\]  

(4.12)

where \( DW \) is the DW statistic, \( e_t \) is the model residual at time \( t \); and \( n \) is the number of observations in the time series. The DW statistic is compared against positive and negative autocorrelation thresholds at a level of significance \( \alpha \).

4.5.6 Exogenous variable selection and validation
The selection of exogenous variables was conducted based on a priori analysis to discern the response and a stepwise regression approach. Individual variables are added to each model and the accuracy statistics are calculated based on the coefficient estimation set or training and calibration sets. If the inclusion of a variable increases model accuracy, the variables is used. The accuracy of each model is estimated by forecasting over the validation time period and comparing the results against observations.

4.6 Results

4.6.1 ARIMAX models

4.6.1.1 Coefficient estimation and hindcast accuracy
Table 4—1 displays the results of the variable selection process and the value of each variable’s coefficient. The partial autocorrelation function displayed that there were either one or two significant autoregressive terms for each model. The DW test applied to initial model constructions displayed that the error term was positively autocorrelated for models which had one autoregressive term. An additional autoregressive term was added to these models to remove the autocorrelation in the error term. The observed parabolic temperature response, revealed in Figure 4—2, was added to the models in the form of \( \text{Temp}. \) and \( \text{Temp}^2 \) variables. RH and RH interacting with the parabolic demand response to temperature (i.e., \( \text{RH} \times \text{Temp}. \) and \( \text{RH} \times \text{Temp}^2 \) variables) was added to the models which increased hindcast accuracy statistics. The day of the week dummy variables were added to account for the effects that different days of the week have on demand. As previously discussed, the DES forecast accounts for the changing mean throughout the year. The NDPD models differed from the NDTEU models due to the inclusion of an intercept.

The DW test suggest that there is no autocorrelation in the models’ error terms. It can be inferred that the absence of autocorrelation in the error terms means that the \( RMSE \) and \( R^2 \) statistics are unlikely to be biased. The results of the t-test on regression coefficients are of higher magnitude than the level of significance suggesting that the set of coefficients are not statistically equivalent to zero. The t-test on regression coefficients displays that many coefficients are not statistically significant. During stepwise regression processes, when
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these variables were removed the RMSE increased and $R^2$ decreased. This coincided with the removal of the effects that different weekdays had on demand and the promotion of a temperature response which is not represented in the data. In order to achieve models with the best fits, these variables were not removed. This phenomenon can be attributed to the greater magnitudes of the $\text{Temp.}^2$, DES mean forecast and demand lag variables in comparison to temperature and day of the week dummy variables.

Table 4—1 ARIMAX coefficient estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>NDTEU (kWh) Coefficients</th>
<th>NDPD (W) Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Phase 1</td>
<td>Phase 2</td>
</tr>
<tr>
<td>Intercept</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Demand t-1</td>
<td>0.35</td>
<td>0.36</td>
</tr>
<tr>
<td>Demand t-2</td>
<td>-0.15</td>
<td>-0.09</td>
</tr>
<tr>
<td>Temp.</td>
<td>-129.82</td>
<td>-87.79</td>
</tr>
<tr>
<td>Temp.$^2$</td>
<td>3.47</td>
<td>2.41</td>
</tr>
<tr>
<td>RH</td>
<td>17.70</td>
<td>12.80</td>
</tr>
<tr>
<td>RH $\times$ Temp.</td>
<td>-1.38</td>
<td>-1.00</td>
</tr>
<tr>
<td>WD$_{Sun}$</td>
<td>1,577.84</td>
<td>1,201.33</td>
</tr>
<tr>
<td>WD$_{Sat}$</td>
<td>1,554.45</td>
<td>1,167.41</td>
</tr>
<tr>
<td>WD$_{Mon}$</td>
<td>1,509.32</td>
<td>1,139.58</td>
</tr>
<tr>
<td>WD$_{Tues}$</td>
<td>1,517.58</td>
<td>1,130.39</td>
</tr>
<tr>
<td>WD$_{Wed}$</td>
<td>1,508.34</td>
<td>1,139.25</td>
</tr>
<tr>
<td>WD$_{Thurs}$</td>
<td>1,515.09</td>
<td>1,120.43</td>
</tr>
<tr>
<td>WD$_{Fri}$</td>
<td>1,487.91</td>
<td>1,112.31</td>
</tr>
<tr>
<td>DES forecast</td>
<td>0.29</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Table 4—2 presents the ARIMAX hindcast accuracy statistics. The NDTEU models performed better than the NDPD models with $R^2$ statistics ranging from 0.77 to 0.87. The NDPD models had $R^2$ statistics ranging from 0.70 to 0.72. The lower accuracy of the NDPD models in comparison to the NDTEU models can be attributed to the peak demand time series having greater variance than the total energy use time series.

Figure 4—3 displays Phase 3's ARIMAX NDTEU and NDPD hindcasts which are representative of the other two phases. Both hindcasts align well with the observed data. Divergences between the NDTEU hindcasts and observed data were observed on Days 157 and 163. The divergence on Day 157 may be attributed to a spike in demand in response to a period of rainfall and a low daily temperature. Day 163 was a unique public holiday relating to the Queen's Diamond Jubilee, which had an abnormal spike in demand. In addition to Day 157, the NDPD hindcasts deviate from observations on Days 19, 32, 37, 51, 60, 81 and 106. The divergences on Days 19, 32, 37, 51, 60 and 81 coincide with high maximum daily temperatures above 30 °C.
### Table 4—2 ARIMAX hindcast statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>NDTEU (kWh)</th>
<th>NDPD (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Phase 1</td>
<td>2</td>
</tr>
<tr>
<td>RMSE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.84</td>
<td>0.77</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>4.51</td>
<td>4.21</td>
</tr>
<tr>
<td>DW</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stat.</td>
<td>1.80</td>
<td>1.85</td>
</tr>
<tr>
<td>t-test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sig.</td>
<td>71.03</td>
<td>45.09</td>
</tr>
<tr>
<td>t-test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sig.</td>
<td>1.96</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Demand t-1</td>
<td>101.74</td>
<td>90.56</td>
</tr>
<tr>
<td>Demand t-2</td>
<td>45.63</td>
<td>24.62</td>
</tr>
<tr>
<td>Temp.</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>Temp.2</td>
<td>3.84</td>
<td>3.89</td>
</tr>
<tr>
<td>RH</td>
<td>0.41</td>
<td>0.43</td>
</tr>
<tr>
<td>RH × Temp.</td>
<td>3.34</td>
<td>3.51</td>
</tr>
<tr>
<td>RH × Temp.2</td>
<td>115.57</td>
<td>119.92</td>
</tr>
<tr>
<td>WD_Sun</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>WD_Sat</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>WD_Mon</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>WD_Tues</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>WD_Wed</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>WD_Thurs</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>WD_Fri</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>DES forecast</td>
<td>82.69</td>
<td>25.38</td>
</tr>
</tbody>
</table>

**Figure 4—3 Phase 3’s NDTEU and NDPD hindcasts**

#### 4.6.1.2 Validation Accuracy

Figure 4—4 illustrates Phase 3’s ARIMAX NDTEU and NDPD forecasts against the validation set. From Day 203 to Day 393 the forecasts mostly followed the observed data. Following the trend of the hindcasts, the NDPD models exhibit a curtailed ability to forecast large demand spikes coinciding with daily maximum temperatures above 34 °C as seen on Days 339, 385 and 395. The NDTEU models were better able to forecast demand.
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on Days 339 and 385. On the 29 January 2013 (Day 395), the high spike in demand occurred on the day after a period of heavy rainfall and flooding. This exogenous shock resulted in a discrepancy between the forecast and observed data in this period.

Figure 4—4 Phase 3’s ARIMAX NDTEU and NDPD forecasts

Table 4—3 displays the accuracy statistics for the ARIMAX models’ forecasts. The NDTEU forecasts had a better fit to observed data than the NDPD forecasts. In comparison to the hindcasts, the forecasts had poorer fits with $R^2$ statistics ranging from 0.74 to 0.80 for the NDTEU models and from 0.56 to 0.65 for the NDPD models. NDTEU $R^2$ statistics decreased on the order of from 0.03 to 0.1 and MAPE increased by 2% to 2.9%. NDPD $R^2$ statistics decreased by 0.07 to 0.14 and MAPE increased by 0.36% to 0.75%.

<table>
<thead>
<tr>
<th></th>
<th>NDTEU (kWh)</th>
<th></th>
<th>NDPD (W)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Phase</td>
<td></td>
<td>Phase</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Day</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>RMSE</td>
<td>75.71</td>
<td>58.21</td>
<td>83.92</td>
<td>7,516.50</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.74</td>
<td>0.80</td>
<td>0.78</td>
<td>0.58</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>6.97</td>
<td>6.30</td>
<td>7.33</td>
<td>7.90</td>
</tr>
</tbody>
</table>

4.6.2 Neural network models

4.6.2.1 Training and hindcast accuracy

The NN models had similar variables to the ARIMAX models. The NDTEU NN models included one autoregressive term (i.e., Demand t-1), parabolic demand response to temperature, RH, RH-temperature interaction, day of the week dummy variables and DES forecast variables. The NDPD NN models included two autoregressive terms (i.e., Demand t-1 and Demand t-2), parabolic demand response to temperature, RH, RH-temperature interaction, day of the week dummy variables and DES forecast variables. The NDTEU models differed by the NN models including one autoregressive term rather than two. The NDPD models differed by the NN models not including an intercept variable.

NN have the ability to emulate non-linear relationships between the input variables and observations. During the process of constructing and training the NN models, it was
observed that denoting the parabolic response that demand had to temperature (i.e., Temp. and Temp.² variables), the training and calibration accuracy statistics improved and the models were better able to account for the response. This formed the argument for the inclusion of additional variables rather than a singular variable to account for the non-linear relationships.

Table 4—4 contains the NN hindcast accuracy statistics. Similar to the ARIMAX models, the NDTEU models performed better than the NDPD models with $R^2$ statistics ranging from 0.83 to 0.85. The NDPD models had $R^2$ statics which were 0.10 to 0.16 less than the NDTEU models. The DW statistics across the models indicate there is no positive or negative autocorrelation in the error terms. The NN models exhibited a similar level of hindcast accuracy as the ARIMAX models.

<table>
<thead>
<tr>
<th>NDTEU (kWh)</th>
<th>NDPD (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase 1</td>
<td>Phase 2</td>
</tr>
<tr>
<td>RMSE</td>
<td>57.74</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.83</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>4.82</td>
</tr>
<tr>
<td>DW</td>
<td>Dl</td>
</tr>
<tr>
<td></td>
<td>Du</td>
</tr>
<tr>
<td></td>
<td>Stat.</td>
</tr>
</tbody>
</table>

Figure 4—5 displays Phase 3’s NN NDTEU and NDPD hindcasts. The hindcasts fit the observations in the training set well for the majority of the time period. In comparison to the ARIMAX hindcasts, the models were less able to account for large spikes in demand such as the winter peak period. The NN yield benefits due to their ability to account for small changes in demand. The NN NDPD models exhibited the same discrepancies as the ARIMAX NDPD models on days where the maximum daily temperature was above 30 °C.

![Figure 4—5 Phase 3’s neural network NDTEU and NDPD hindcasts](image)
4.6.2.2 Validation accuracy

Table 4—5 contains the NN validation accuracy statistics. For both the NDTEU and NDPD models, the forecast accuracies were lower than the hindcasts. For the NDTEU models, $R^2$ statistics decrease on the order of 0.01 to 0.04 and $MAPE$ increased by 1% to 2%. To a greater degree, the NDPD models’ $R^2$ statistics decreased by 0.07 to 0.15 and $MAPE$ increased for Phases 1 and 3 by 0.04% to 0.87%. Phase 2’s NDPD forecast $MAPE$ decreased by 0.36%. The NN models had greater forecast accuracy than the ARIMAX models with higher $R^2$ statistics and lower $MAPE$.

Table 4—5 Neural network validation statistics

<table>
<thead>
<tr>
<th>NDTEU (kWh)</th>
<th>NDPD (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase</td>
<td></td>
</tr>
<tr>
<td>Phase 1</td>
<td>Phase 2</td>
</tr>
<tr>
<td>RMSE</td>
<td>67.31</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.80</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>5.81</td>
</tr>
</tbody>
</table>

Figure 4—6 contrasts Phase 3’s NN NDTEU and NDPD forecasts against observations over the validation set’s time period. Both NDTEU and NDPD forecasts replicate the general pattern of the observations. In addition to the not being able to forecast the exogenous shock on Day 395, the forecast continue the trend of the hindcasts not being able to account for large spikes in demand on Days 339, 353, 379, 385 and 395; each day having a maximum daily temperature greater than 33 °C. On the listed days it was observed that the ARIMAX models are better able to account for large spikes in demand than the NN models. For the duration of the time series, the NN models better account for small fluctuations in demand than the ARIMAX models.
4.6.3 Discussion

Both the ARIMAX and NN NDTEU and NDPD hindcasts and forecasts, for the majority of the time series, are in line with the training and validation sets’ observations. NDTEU models produced more accurate forecasts and hindcasts than the NDPD models. This is a result of the peak demand time series in comparison to the total energy use time series exhibiting a higher degree of variability and randomness. The distinguishing difference between the two sets of models is that the NDTEU models are better able to account for large spikes in demand than the NDPD models.

In line with the observations of Darbellay and Slama (2000), the accuracy statistics of both groups of models were similar with the NN models bearing marginally better results. The NN NDTEU forecasts had lower MAPE on the order of 0.38% to 1.79% than the ARIMAX. The MAPE of NN NDPD forecasts were lower by 0.18% to 0.68%.

Both modelling techniques were either constrained by randomness (noise) or lack of variables which influence the demand. Randomness in the data is attributed to the increase in influence that an individual customer has on the network as the electricity generation and supply system is subdivided into sections servicing smaller numbers customers (i.e., residential LV distribution network) and customer behaviour not being deterministic in nature. Temperature alone explains half of the demand experienced by the network and additional variables that incorporate seasonalities increase the models’ accuracy further. To better forecast demand, other variables which influence customer behaviour are required. Variables may include the broadcast times of popular sporting events or television programs.

Discrepancies between the ARIMAX and NN models’ hindcasts and forecasts were observed on days when there were unique events, such as the Queen’s Diamond Jubilee and minor flooding, or coincided with high daily maximum temperatures. To discern whether or not additional temperature variables should be added to the models or a post-processing algorithm should adjust the forecasts, analysis comparing model error and daily maximum temperatures was conducted. Figure 4—7 describes the relationship between model error and daily maximum temperatures for Phase 3’s ARIMAX NDTEU and NDPD models. For the NDTEU model, there is a statistically insignificant positive linear trend in error as daily maximum temperatures increases. The NDPD model bears a statistically insignificant negative trend in error as daily maximum temperature increases. The results of this analysis do not provide evidence to suggest that the inclusion of daily maximum temperature variables would improve model accuracy. Due to the error distributions being unbiased, a post-processing algorithm based on a daily maximum temperature threshold would not produce more accurate forecasts. This reinforces the
necessity for the inclusion of additional variables which may influence consumer behaviour.

Figure 4—7 Phase 3’s ARIMAX NDTEU and NDPD error vs. maximum daily temperature

4.7 Development of hybrid ARIMAX neural network hybrid

Both sets of models, ARIMAX and NN, had similar levels of hindcast and forecast accuracy. The ARIMAX models were better suited to forecasting the large spikes in demand and the NN models better handled small fluctuations in demand. To incorporate the beneficial traits of both of these approaches in order to improve hindcast and forecast accuracy, a hybrid model was developed.

The general principle behind the combination of the two models was to develop an optimization routine that utilized the NN model to forecast demand and when that forecast was above a certain threshold, the ARIMAX model’s forecast will be used. The optimization routine employed an iterative process to define the threshold boundary for using the ARIMAX forecasts. This hybrid ARIMAX-NN model was implemented for Phase 3’s NDTEU and NDPD models and thresholds were calculated using their respective hindcasts.

Table 4—6 contains threshold and accuracy statistics for the hybrid models when applied to Phase 3. The hybrid model showed better NDTEU and NDPD hindcast accuracies than the standalone ARIMAX and NN models. For the NDTEU models, the RMSE decreased by 4.88 kWh to 5.29 kWh. There was a 380 W to 640 W reduction in RMSE for the NDPD models. For the forecasts, comparing the hybrid models to the standalone technique models denoted a reduction in RMSE by 1.81 kWh to 13.49 kWh for the NDTEU models and 305.62 W to 537.56 W for the NDPD models. There was a slight increase in MAPE when comparing the hybrid with the standalone models.

Figure 4—8 exhibits Phase 3’s NDTEU and NDPD hindcasts and forecasts for the hybrid models developed. For each of the hindcasts and forecasts it can be seen that the NN models’ output accounts for the small fluctuations in demand. When the NN models’
output is equal to the identified thresholds or above, the ARIMAX models’ outputs are used instead such that the large spikes in demand are more accurately forecasted.

The use of both models as described above ensures that the better traits of the two techniques are utilized to provide an enhanced forecast of the residential LV network demand. The better hindcast and forecast fits are reflected in the reduction of RMSE. Forecasting demand in the LV network has received little research attention till recently, but power distribution companies now require bottom-up forecasting models that can handle the increasing penetrations of distributed renewable energy sources. LV network demand is notoriously volatile and requires hybrid techniques that can handle the large demand variance that occurs. This paper provides an attempt to create a suitable forecasting technique for this issue.

Table 4—6 Phase 3’s hybrid model statistics

<table>
<thead>
<tr>
<th>Threshold</th>
<th>NDTEU (kWh)</th>
<th>NDPD (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1,035</td>
<td>85,667</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hindcast</th>
<th>ARIMAX</th>
<th>NN</th>
<th>Conjunction</th>
<th>ARIMAX</th>
<th>NN</th>
<th>Conjunction</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>55.31</td>
<td>55.72</td>
<td>50.43</td>
<td>7,447.68</td>
<td>7,187.67</td>
<td>6,807.60</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.87</td>
<td>0.85</td>
<td>0.87</td>
<td>0.72</td>
<td>0.74</td>
<td>0.75</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>4.44</td>
<td>4.53</td>
<td>4.40</td>
<td>7.81</td>
<td>7.41</td>
<td>7.35</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Forecast</th>
<th>ARIMAX</th>
<th>NN</th>
<th>Conjunction</th>
<th>ARIMAX</th>
<th>NN</th>
<th>Conjunction</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>83.92</td>
<td>72.24</td>
<td>70.43</td>
<td>8,070.56</td>
<td>7,838.62</td>
<td>7,533.00</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.78</td>
<td>0.84</td>
<td>0.84</td>
<td>0.65</td>
<td>0.67</td>
<td>0.67</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>7.33</td>
<td>5.54</td>
<td>5.66</td>
<td>8.13</td>
<td>7.45</td>
<td>7.55</td>
</tr>
</tbody>
</table>

Figure 4—8 Hybrid model hindcasts and forecasts
4.8 Conclusion

The objectives of this chapter were to develop NDTEU and NDTD forecast models for the purpose of yielding information that a battery energy management system can use to schedule charging and discharging in a residential LV distribution network. Developing the models for a residential encounters additional challenges over larger subsections of the electricity supply and distribution due to increase in influence that individual customers have leading to greater variability and randomness. In turn, this chapter aimed to present the significant variables which influence demand and compare the performance of the ARIMAX and NN modelling techniques to determine which is most applicable.

The most significant variable which influences residential LV distribution network demand was temperature. The demand response to temperature was observed to be parabolic in nature and accounted for half of the demand experienced. Other variables included in the models which helped to explain demand were DES, autoregressive terms, RH, interaction between RH and temperature and dummy variables for each day of the week. DES accounted for the long term seasonalities in demand by estimating the local mean throughout the data set.

ARIMAX and NN NDTEU and NDPD models were developed for each phase of the network. For the majority of the time series the NDTEU and NDPD hindcasts and forecasts were in line with observations. The NDTEU models were more accurate than the NDPD models due to the peak demand time series being more variable in nature. The NN models were slight gains over the ARIMAX models. Each modelling technique yielded benefits such as the ARIMAX models being better able to account for large spikes in demand and the NN models accounted for small fluctuations better.

Hybrid ARIMAX-NN models were developed to capitalize on the beneficial traits of both the ARIMAX and NN sets of models. The system operated by relying on the NN models to forecast demand and if the forecast was above a defined threshold, the ARIMAX forecast was used. The hybrid model better catered for both the small fluctuations as well as the large spikes in demand when compared to the standalone technique models for both hindcasts and forecasts.

Discrepancies between the models' hindcasts and forecasts occurred on days where there were large spikes in demand coinciding with exogenous shocks such as an unusual public holiday, a prolonged rainfall event or days with high maximum temperatures. Days with high maximum temperatures were investigated against model error and it was found that there were no statistically significant relationships.
Chapter 4 – Forecasting load characteristics

To improve the accuracy of the models more research is required to investigate additional variables which influence customer behaviour. Future work will involve further investigations of customer behaviour, integrating the forecast models into an expert system which forecasts daily load profiles and developing a battery energy management control algorithm.

Acknowledgments

The authors are grateful to Energex for providing the data which made this research possible.

Author contributions

The author Christopher Bennett designed the research, conducted the programming, developed and validated the models and wrote the paper. Assoc. Prof. Rodney Stewart provided conceptual ideas behind the research, reviewed the results and edited the paper. Prof. Jun Wei Lu liaised with Energex such to provide access to the data, provided technical advice and reviewed the results and paper.
CHAPTER 5

Forecasting load profiles

Statement of contribution to co-authored published paper

This chapter includes a co-authored peer-reviewed paper.

The bibliographic details of the paper, including all authors, are:


My contribution to the paper included performing statistical analysis of the data, writing forecast model development and statistics algorithms, constructing the forecast models, reviewing the performance of the models and drafting the paper.

Signed: _______________________________ Date: ________________

Christopher Joseph Bennett

Countersigned: _____________________ Date: ________________

Co-author: Assoc. Prof. Rodney Stewart (principal supervisor)

Countersigned: _____________________ Date: ________________

Co-author: Prof. Junwei Lu (associate supervisor)
Chapter 5 – Load profile forecasting

Forecasting low voltage distribution network demand profiles using a pattern recognition based expert system

Abstract: The advent of distributed renewable energy supply sources and storage systems has placed a greater degree of focus on the operations of the Low Voltage (LV) electricity distribution network. However, LV networks are characterised by having much higher variability in time series demand meaning that modelling techniques solely relying on iterative forecasts to produce a next day demand profile forecast are insufficient. To cater for the complexity of LV network demand, a novel hybrid expert system comprised of three modules, namely, correlation clustering, discrete classification neural network, and a post-processing procedure was developed. The system operates by classifying a set of key variables associated with a future day and refining a recalled historical demand profile as the forecast. The expert system exhibited high hindcast accuracy when trained with a residential LV transformer’s demand data with $R^2$ values ranging from 0.86 to 0.87 and MAPE ranging from 11% to 12% across the three phases of the network. Under simulated real world conditions the $R^2$ statistic reduced slightly to 0.81-0.84 and the MAPE increased to 12.5-13.5%. Future work will involve integrating the developed expert system for forecasting next day demand in an LV network into a comprehensive distributed energy resource management algorithm.

Keywords: Expert system, energy, electricity, demand forecast, neural network, low voltage

5.1 Introduction

As the region-wide electricity generation and supply system steps down to the low voltage (LV) distribution network, the number of customers serviced by a transformer decreases, which in-turn, correlates with an increase in variability of time series electricity demand. Over short time periods (intraday to intraweek), demand is observed to have a greater degree of randomness, increased frequency of ‘shocks’ and less continuity between daily demand profiles of sequential days. The increase in variability can be attributed to the greater relative weighting of the behaviours of individual customers and influences of local phenomena e.g. weather, special events, etc.

The increase in demand variability poses a resource management problem for the operation of micro-grids and distributed energy resources (DER). As an example, a time based heuristic energy management control system for an energy storage system would not be able to adequately meet its objectives due the times at which the system should
optimally charge and discharge would be changing on a daily basis. Similar to the operation of the conventional electricity generation and supply system, to overcome this resource management problem, control systems will need to rely on demand forecasts. Demand forecasts will enable the derivation of information such as how much power is required, the scheduling of charging and discharging of energy storage systems, and whether or not remedial measures are required to be employed.

This current research focusses on the development of a forecasting component for an energy management control algorithm for the purposes of scheduling DER in residential LV distribution networks. For the energy management control algorithm to achieve the optimal scheduling of DER, it is necessary for the demand profile for the next and subsequent days to be forecast as well as its key features, such as the times of day when peak demand occurs and associated values.

Autoregressive Integrated Moving Average (ARIMA) modelling techniques have been shown to provide adequate forecasts when applied to systems with greater customer aggregation or longer forecast time intervals (Engle et al., 1992; Darbellay & Slama, 2000; Ringwood et al., 2001; Taylor & Buizza, 2003; Mirasgedis et al., 2006; Taylor, 2010). However, conventional modelling techniques such as ARIMA are sensitive to LV network prevalent uncharacteristic daily profiles and random shocks which will increase these models’ propensity to produce naïve predictions. Applying iterative forecasting alone, the residuals of the random shocks would bias subsequent forecasts. To overcome some of the deficiencies of traditional time series forecasting techniques, forecasting researchers have begun to explore the application of Artificial Neural Networks (NN) to forecast demand and demand profiles (Hippert et al., 2001; Beccali et al., 2004; Hippert et al., 2005; Sousa et al., 2012). The main benefits of the use of NNs include their ability to generalize, identify non-linear relationships and applicability to a wide range of applications (Hippert et al., 2001).

To achieve the research goal to forecast demand profiles for high variance LV residential distribution networks, an expert system based on pattern recognition which incorporates a clustering algorithm and NN was developed. This paper describes the development and validation process for the expert system when applied to three phases of an LV transformer supplying power to 128 residential customers located in Brisbane, Australia.

5.2 Research background

Griffith University, Elevare, Ergon Energy and Energex are working on a joint project to assess the feasibility of the installation of Static Synchronous Compensators (STATCOM) with battery energy storage systems (BESS) in the LV distribution network. Funding for
this project has been provided by the Queensland State Government 2012 – 2014 Research Partnership Grant. STATCOMs are four quadrant synchronous inverters with the ability to correct frequency distortions and dampen harmonics. The combination of STATCOMs and BESS will enable the reduction of peak demand on network infrastructure and the active maintenance of power quality. The installation of this technology has the potential to reduce network expenditures through the replacement or deferral of other expenditures such as replacing transformers and/or upgrading lines.

The assessment of the feasibility involves the design and quantification of the effectiveness of STATCOMs with BESS. A number of subprojects were initiated to achieve the project’s goals including determining the technical parameters, developing a STATCOM with BESS energy management control algorithm and performing economic analysis. The research reported in this paper denotes the completion of the demand forecasting component of the energy management control algorithm. Information generated from the determination of technical parameters, simulation of the STATCOM with BESS in the LV distribution network and physical trialling will be used as input variables in the economic analysis.

5.3 Literature review

5.3.1 Short-term electricity demand modelling

The most notable publications apply conventional modelling techniques including ARIMA, multivariate regression and machine learning techniques (e.g. support vector machines, fuzzy inference systems, NN, etc.). ARIMA($p,d,q$) is the general model of the Box Jenkins set of time series modelling techniques. The ‘$p$’ represents that number of lagged parameters (autoregressive parameters); the ‘$d$’ represents the number of discrete differences; and the ‘$q$’ represents the number of lagged forecast error parameters in the model to account for a moving average in the time series. Regression models in the electricity demand space involve the addition of deterministic parameters to the use of the lagged forecast parameters. Additional parameters may include weather, economic, behavioural and time dependent variables. Many regression models can be considered ARIMAX models due to the combination of the ARIMA model with exogenous variables. NNs mimic how biological neural networks model systems. NNs are composed of two or more layers of artificial neurons with synapse (weights) linking each neuron of the previous lay to the next. Signals (inputs) are multiplied by weights connected to the neuron, summated, inputted into the neuron’s activation function and the output is sent to the neurons of the next layer. A training algorithm adjusts the weights throughout the network in order to model the desired system.
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Engle et al. (1992), Taylor and Buizza (2003), Mirasgedis et al. (2006) and Taylor (2010) developed network demand time series models based on the ARIMA or regression modelling techniques. Taylor and Buizza (2003) and Taylor (2010) developed ARIMA models using the exponential smoothing, double seasonable exponential smoothing and triple seasonal algorithms. Taylor and Buizza (2003) used 30 minute demand data from England and Wales. Taylor (2010) used demand data from Britain and France. The research showed that the developed models were accurate and that accuracy increases as more seasonality variables are included in the models. Engle et al. (1992) and Mirasgedis et al. (2006) developed time series models with autoregressive parameters and additional variables including heating and cooling days, relative humidity (RH) and day of the week dummy variables. It was noted that models performed well and models with weather variables performed better than models without.

Kassaei et al. (1999), Darbellay and Slama (2000), Abraham and Nath (2001), Ringwood et al. (2001) and Cavallaro (2005) developed short-term electricity demand forecast models using NN. Darbellay and Slama (2000) used Czech Republic demand data and Ringwood et al. (2001) used Ireland’s Electricity Supply Board’s data to construct univariate NN models. The autocorrelation function was used to identify cyclical components in the demand time series and to structure the models accordingly. The models achieved a high level of accuracy and performed better than univariate ARIMA models. Cavallaro (2005) constructed a multivariate NN with variables such as day of the week and average temperature and noted a high accuracy. Kassaei et al. (1999) and Abraham and Nath (2001) combined NN with fuzzy logic. Kassaei et al. (1999) used a univariate NN to model normal loads and fuzzy logic model to model weather dependent loads. The forecast is generated by the output of the NN and fuzzy logic model. It was found that the NN and fuzzy logic model performed better than the singular NN model. Abraham and Nath (2001) applied an ARIMA, evolving fuzzy NN (EFuNN) and a NN to Victoria’s demand data. The EFuNN approach differs from a conventional NN since the neurons in the network are performing functions such as ‘fuzzification’ of inputs, rule based transformations and defuzzification. The weights in the network are altered by a training algorithm. The EFuNN performed the best out of the set of developed models.

The above mentioned models were all short-term electricity demand models applied to networks with a large number of consumers. All achieved high levels of accuracy and there were not any clear distinctions regarding which modelling method yields the best results. The work conducted by Taylor (2010) provided evidence that the greater number of seasonality variables included in the model accounted for increases in model accuracy. Engle et al. (1992), Darbellay and Slama (2000) and Mirasgedis et al. (2006) indicated that
the inclusion of deterministic variables such as weather variables improves model accuracy. An inference may be drawn from these studies that the inclusion of both ARIMA variables and deterministic variables would derive higher model accuracy. However, this inference becomes less applicable as the forecast period shortens due to the relationship between demand and deterministic variables not being apparent. Forecast windows such as a day ahead or greater are more responsive to deterministic variables.

5.3.2 Demand profile forecasting

For the case of short-term demand forecasting models (i.e. 30 minutes ahead, an hour ahead, etc.) iterative forecasting techniques are essential. Iterative forecasting is where the forecast at time $t$ is used as an input variable in the model to forecast at time $t+1$. This process repeats itself until the desired number of forecasts has been made. A shortcoming of this technique to forecast demand profiles is that the forecast errors in the initial forecast and each iterative forecast are compounded. Alternate modelling approaches have been developed including multivariate forecast NNs and ensembles of models and pattern recognition (Hippert et al., 2001). Multivariate forecast NN forecast the next day’s demand profile through the use of multiple output neurons for each time interval of the next day’s demand profile. The ensemble of models approach entails that there are independent models for each time interval of the next day’s demand profile.

Beccali et al. (2004), Hippert et al. (2005) and Sousa et al. (2012) used a multivariate forecast NN methodology in the development of short-term demand profile forecasting models. Beccali et al. (2004) used a self-organising map (SOM) algorithm to cluster similar demand profiles in order to provide demand profile indices and a NN with 24 output neurons for each hour of the day. Additional NN inputs to the indices included historical load data, historical weather data and day of the week dummy variables. Hippert et al. (2005) developed a multivariate forecast NN and compared it against alternative techniques such as naïve forecasts, ensembles of smoothing filters and ensembles of regression models. Hippert et al. (2005) found that the NN model performed better than the alternatives. Sousa et al. (2012) adapted a demand profiling technique to a NN with 24 output neurons.

The NN short-term load forecast (ANNSTLF) system described by Khotzanzad et al. (1997) utilizes both an ensemble of models and NNs capable of producing multiple forecasts. The ANNSTLF system is comprised of four NNs. Each NN forecasts distinct multiple hours and are sequentially combined to produce the next day’s demand profile. Input variables of the NNs include historical and forecasted temperature, historical and forecasted RH and historical demand data. The temperature is forecasted using an ensemble of NN models with multiple outputs and are combined using an adaptive scaling algorithm. RH is
forecasted by the use of a moving average algorithm. The system was applied to data from ten utilities and displayed a high level of accuracy. Fan and Chen (2006) developed a more advanced system which relied on a SOM to cluster demand profiles according to exogenous variables and multiple sets of 24 support vector regression models. When input variables are inputted into the trained SOM, it calls a specific set of 24 support vector regression models to forecast the demand profile.

Pattern recognition approaches involve an algorithm analysing a set of input variables and classifying according to a set of known or trained relationships. The SOMs employed by Beccali et al. (2004) and Fan and Chen (2006) are examples on the use of pattern recognition in the process of forecasting demand profiles. Beccali et al. (2004) used the output of the SOM as an input variable for the NN; whereas Fan and Chen (2006) used the output of the SOM to call a specific set of support vector regression models. Espinoza et al. (2005), Konjic et al. (2005) and Sousa et al. (2012) clustered demand profiles of customer demographics and applied the known demand profiles to other customers in order to produce short-term demand forecasts. As noted by Hippert et al. (2001), machine learning techniques such as NNs can be used specifically for pattern recognition. Dai and Wang (2007) furthered the use of NNs and pattern recognition to forecast the demand profiles of future days through load classification based on their associated input variables. The load sets are identified through clustering demand profiles against input variables. Each load set has a characteristic demand profile which in turn is used as the forecast.

5.3.3 Formulation of the expert system

An expert system is a program which has decision making capabilities based on reasoned knowledge. Many of the NN based demand forecast models discussed fulfil some properties of an expert system due to the way in which NNs model systems (i.e. self-learning features). Systems containing pattern recognition faculties such as Beccali et al. (2004), Fan and Chen (2006) and Dai and Wang (2007) best fulfil the criteria of being expert systems due to decision making vis a vis classification being central.

In order for the demand profile of residential LV transformers to be forecast, the modelling method employed must not be sensitive to high variance, low continuity of demand profile patterns of sequential days and presence of shocks. This biases the selection of a modelling method away from the iterative, ensemble modelling and some derivations of the multivariate NN forecast methods due to their reliance on historical demand data. Pattern recognition approaches are more versatile due to their ability to classify demand profiles based on their association with exogenous or deterministic variables.
To advance the approach, demand profile properties such as total load or total energy use (TEU), peak demand and morning peak can be used as input variables to better the classification of future demand profiles and post-processing. These properties can be forecast for future days using conventional techniques such as ARIMAX variables due to relatively lower variance in the TEU, peak demand and morning peak time series and greater response to exogenous variables. Their role in post-processing is to modify the characteristic demand profile such that the most accurate forecasts are produced.

5.4 Research objective
The core research objective was to develop an expert system to forecast the next day’s demand profile for the LV residential distribution network.

5.5 Data

5.5.1 Source
Energex (i.e. the power distribution company supplying South East Queensland, Australia) provided the data for the three phase LV transformer and the 128 residential customers the transformer supplied (i.e. case study area). The transformer is located in an inner northern suburb of Brisbane, Queensland, Australia. The metering of the transformer involved recording the voltage, current and power factor for each phase at 10 minute intervals. The phases of the transformer are unbalanced. The provided data set contains data for the period covering the middle of January 2012 to the middle of February 2013. Weather statistics used in this research, such as temperature and RH, were collected by the Brisbane City weather station and made available online from the Australian Bureau of Meteorology. The data from 2012 was used as input variables of the coefficient estimation of ARIMAX models and input variables for the training of the NN.

Brisbane has a subtropical climate and experiences mild winter and hot humid summers. Data sourced from the Australian Bureau of Meteorology (2013) displays that the hottest month of the year is January which has average maximum and minimum temperatures of 29.0° and 21.2°. The coldest month of the year is July which has average maximum and minimum temperatures of 20.8° and 9.0°. Brisbane has a mean annual precipitation of 1028.2 mm with the greater amount of precipitation occurring over the months of November to March.

5.5.2 Overview
Figure 5—1 displays 168 hour (7 day) subsections of phase 1’s smoothed demand time series denoting summer (a), autumn (b), winter (c) and spring (d) demand profiles. What
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is observed is that the shape of the demand profile changes throughout the year according to changes in customer behaviour in response to changes in temperature. Three types of demand profiles can be identified. The first which typically occurs during summer is characterised by a small or no peak during the morning and a large peak in the evenings. The second which occurs during autumn and spring periods has a small peak in the morning and a larger peak in the evenings. The third which occurs during winter has a large peak in the morning and a large peak in the evening.

Figure 5—1 Seasonal demand profiles

Figure 5—2 displays phase 1’s demand profile properties such as daily TEU (a), daily peak demand (b) and daily morning peak (c) for the 2012 component of the time series. The trend in the TEU time series is such that the greatest amount of energy is consumed during
the summer and winter periods of the year. Winter has a consistently greater level of consumption in comparison to summer which is more volatile. The yearly peak energy consumed of 1.3 MWh occurred in winter, on day 179. The peak demand time series follows a similar pattern with the greatest demands occurring in summer and winter. The yearly peak demand of 108 kW occurred in winter, on day 179. The morning peak time series exhibits a different pattern. The morning peak is constant for the first third and last third of the year. As daily temperature starts to decrease in the middle third of the year, the daily demand profile begins to exhibit the two large peak demand profile patterns. These time series reaffirm the observation that the shape of the demand profile changes due to customers’ responses to changes in temperature.

Figure 5—2 Seasonal demand profile properties
5.6 Method

5.6.1 Overview

5.6.1.1 Formulation

It was noted that the transformer’s demand profiles for consecutive days are inconsistent; differing in the profile’s shape and magnitude. What was observed throughout the year is that a finite group of patterns in the demand profiles repeat themselves according to repetitions in the set of external variables that affect demand such as temperature and day of the week. Periods where the demand profiles are more consistent are generally due to the set of exogenous variables on each day being similar. Due to the coincidence of the finite set of patterns and the respected sets of exogenous variables, a pattern recognition solution is feasible for forecasting future demand profiles. The general operation of the pattern recognition solution is such that a future day will have a set of exogenous variables. Based on this set of variables an algorithm will select a pattern from the group of patterns which will best represent the demand profile which will occur on that day. The development and the operation of the solution are distinct processes. To develop the solution the following steps are required:

1. Identify repeating patterns within the time series by clustering demand profiles by how well they correlate with one another. The cluster that a demand profile is a member of is that demand profile’s classification. The mean of each cluster and the characteristic demand profile (CDP) form the underlying repeating patterns.
2. The exogenous variables associated with each demand profile are to be associated with the group that the demand profiles are classified under.
3. A pattern recognition algorithm is to be trained to associate sets of exogenous variables to respected groups of demand profiles. The trained pattern recognition algorithm takes a set of exogenous variables as input variables and selects a cluster which the set most likely occurs under.

Following the listed steps, the expert system based on pattern recognition was developed using a correlation clustering algorithm and a feed forward back propagation NN.

5.6.1.2 Expert system development

Figure 5—3 displays the steps involved in the development and operation of the expert system. The development process begins with data pre-processing. The data is then passed into a correlation clustering algorithm that produces a set of identified clusters and variables associated with each cluster. This information is passed into a multivariate forecast NN. The NN is structured with an output vector with $k$ number of elements matching the number of clusters. The first element represents cluster 1 and the $k^{th}$
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element represents cluster \( k \). The NN is trained under the back propagation algorithm. From the identification of clusters, the demand profiles for each cluster are averaged to produce the set of CDPs. There’re \( k \) number of characteristic demand profiles. Characteristic demand profile 1 corresponds to cluster 1 and characteristic demand profile \( k \) corresponds to cluster \( k \).

The operation of the expert system to forecast the demand profile for a future day starts with the acquisition of the weather forecast for that day. This data is then supplied to three ARIMAX demand profile property forecast models. The weather forecast data and demand profile property forecast are supplied to the NN as input variables. These are combined with additional “known” variables such as day, week, month, public holiday, etc. The NN produces the output vector with \( n \) number of elements. Each element will have a value ranging from 0 to 1. This is analogous to estimations of the likelihood of a given set of input variables to be classified under a specific cluster. The set of input variables are classified under the corresponding cluster with the element which contains the highest
value or value closest to 1. If element \( x \) has the highest value then the set of input variables will be classified under cluster \( x \). The associated characteristic demand profile with cluster classification is then used as the demand profile forecast. The demand profile forecast is then improved by augmenting it according to the forecasted demand profile properties.

5.6.2 Pre-processing

Pre-processing of the data involved the following steps:

1. Removal of demand profiles from the set which contained 10 or more data points with missing data points.
2. Conversion of the 10 minute average power recordings to 30 minute average power recordings.

The removal of demand profiles with 10 or more missing points reduced the number of demand profiles from 366 to 349. The conversion from 10 minute average power recordings to 30 minute averages dampens the effect that random shocks have on the time series. This reduces the number of elements in the demand profile from 144 to 48. In turn, the demand profile forecast will be comprised of the average power value for 48 half hour intervals. Half hour intervals are sufficient to achieve the ultimate goal of this research.

5.6.3 Correlation clustering

The correlation clustering algorithm operates by clustering a set of vectors based on how well they correlate with different subsets of vectors. Correlation is calculated by the use of Pearson’s correlation equation (eq. 5.1). The output of the equation will range from 0 to 1. A value of 1 denotes a perfect correlation and a value of 0 denotes no correlation.

\[
\rho(X, Y) = \frac{1}{n-1} \sum \frac{(x-u_X)(y-u_Y)}{\sigma_X \sigma_Y} \tag{5.1}
\]

where \( \rho \) is the correlation statistic, \( X \) and \( Y \) are vectors, \( n \) is the number of elements in each vector, \( x \) is an element within vector \( X \), \( y \) is an element in vector \( Y \), \( u_X \) is the mean of \( X \), \( u_Y \) is the mean of \( Y \), \( \sigma_X \) is the standard deviation of \( X \) and \( \sigma_Y \) is the standard deviation of \( Y \).

Given \( k \) (user defined) set of clusters \( C=\{C_1,C_2,\ldots,C_k\} \), there will be \( k \) number of cluster means \( CDP=\{CDP_1,CDP_2,\ldots,CDP_k\} \). The calculation of the cluster means represent the underlying trends with the clusters that demand profiles DP can be correlated with. There’re \( n \) number of demand profiles. For each iteration of the clustering process, where \( t \) is the iteration number, the algorithm calculates the cluster means (eq. 5.2) and assigns demand profiles to each cluster (eq. 5.3 and eq. 5.4). The algorithm continues until user defined number of epochs has been reached.
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\[ CDP_i(t) = mean\left(C_i(t)\right) \] (5.2)
calculated for all clusters \( CDP_i \) for \( i = 1, 2, \ldots, k \).

\[ P_j = \{ \rho(DP_j, CDP_1), \rho(DP_j, CDP_2), \ldots, \rho(DP_j, CDP_k) \} \] (5.3)
where \( P \) is a set of correlation statistics between demand profile \( j \) and the set of cluster means. This is calculated for all demand profiles \( DP_j \) for \( j = 1, 2, \ldots, n \).

\[ C_i(t+1) = \{ DP_j: P_{i,j} = max(P_j) \ for \ 1 \leq j \leq n \} \] (5.4)
which states if correlation statistic \( P_{i,j} \) equals the maximum of the set then demand profile \( j \) will be classified under cluster \( i \). This is calculated for all clusters \( CDP_i \) for \( i = 1, 2, \ldots, k \).

After the correlation clustering algorithm has completed, the clusters are subdivided by magnitude. In order to derive the demand profiles within each cluster they are integrated, z-scored and separated by arbitrary intervals of deviations from the mean. The final number of clusters is \( k \) multiplied by the number of intervals of deviations from the mean.

5.6.4 Artificial neural network

5.6.4.1 Algorithm

The NN is constructed by layers of artificial neurons interconnected by synapse (weights) from one layer to the next. The NN chosen for discrete classification is a sigmoid activation back-propagation network. Each neuron receives input signals from a set of synapse and performs a function described by Equations 5.5 and 5.6. The NN is trained, with adjustments of the weights throughout the network to achieve the optimal forecast, according to Equations 5.7 to 5.10. Equation 5.7 is the training algorithm for weights connected to the output layer and Equation 5.8 is the training algorithm for weights of preceding layers. For the network to operate the input and output data was normalized. To prevent over fitting the algorithm randomly selects and separates 20% of the data in order to validate the model. The algorithm continues until user defined number of epochs has been reached.

\[ v_j = \sum_{h=1}^{m} w_{j,h} x_h \] (5.5)
where \( v_j \) is the summation of the weights multiplied by the outputs of each neuron (or inputs of the NN) respectively for neuron \( j \). There’re \( m \) number of neurons or inputs in the previous layer.
where $Y_j$ is the output of neuron $j$, $\sigma(v_j)$ is the sigmoid function and $\alpha$ is a constant which affects the gradient of the sigmoid function.

$$\delta_j = \sigma'(v_j)(\hat{Y}_j - Y_j)$$  \hspace{1cm} (5.7)

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \omega \delta_j Y_i$$  \hspace{1cm} (5.8)

where $w_{ij}$ is the weight connecting neuron $i$ to output neuron $j$, $\omega$ is the training rate, $v_j$ is the result of the summation function for neuron $j$, $\hat{Y}_j$ is the forecasted value, $Y_i$ is the observed value, $\delta_j$ is the local gradient at neuron $j$, $Y_i$ is the output of neuron $i$ of the previous layer and $t$ is the training epoch.

$$\delta_j = \sigma'(v_j)(\hat{Y}_j - Y_j)$$  \hspace{1cm} (5.9)

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \omega \delta_j Y_i$$  \hspace{1cm} (5.10)

where $w_{hi}$ is the weight connecting neuron $h$ to output neuron $i$, $v_i$ is the result of the summation function of neuron $i$, $\delta_i$ is the local gradient at neuron $i$ and $Y_h$ is the output of neuron $h$ of the previous layer.

### 5.6.4.2 Variable selection

The input variables of the NN are selected by a combination of prior statistical analysis and directed trial and error. Prior statistical analysis involves observing how demand changes for different external variables. It has been observed that variables such as temperature and humidity have effects on demand (Engle et al., 1992; Mirasgedis et al., 2006). Directed trial and error involves the addition and removal of variables according to whether or not they increase the accuracy of the model. When a variable is added or removed the network is retrained multiple times to establish accuracy baselines for the training and validation sets. Each time the network is retrained, a new validation set is selected randomly from the data set. The variable is added or removed depending on whether or not the baseline accuracies improve.

### 5.6.5 Forecasting

Each element $Y_i$ of the output vector of the NN $Y$ corresponds to a cluster $C_i$ within the set of clusters $C$. The future day's input variables are classified under the cluster $i$ where $Y_i$ equals the element with the maximum value within the vector $Y$. The forecasted demand profile $DP_f$ will equal the cluster mean $CDP_i$.
5.6.6 ARIMAX models

To improve forecast accuracy, forecasted demand profile properties such as next day peak demand (NDPD), next day morning peak (NDMP) and next day TEU (NDTEU) can be used to augment the forecasted demand profile. The three forecast models, NDPD, NDMP and NDTEU, are ARIMAX models that were developed for each phase of the network and validated. The ARIMAX models are populated with exogenous variables (e.g. temperature, RH, day of the week, etc.), autoregressive terms and the double exponential smoothing algorithm. The peak demand, morning peak and TEU time series contain data for 403 days. The first 190 days of the time series were used for model training (coefficient estimation via regression) and the remaining 201 days were used for model validation.

The morning peak and the peak demand forecasts can be used to adjust the amplitudes of the morning peak and peak demand of the demand profile forecast. The area under the forecasted demand profile curve can be adjusted to match the TEU forecast. The morning peak and peak demand adjustments of the demand profile forecast will alter its integral. To mitigate the likelihood of greater deviations from observations for the NDPD and NDMP adjustments, the morning peak and peak day demand values will be adjusted first then the TEU forecast.

5.6.7 Post-processing

5.6.7.1 Peak adjustment

The adjustment of the morning peak and peak demand follow the same algorithms. The first is the peak decrease algorithm set denoted by Equations 5.11 to 5.13. The second is the peak increase algorithm set denoted by Equations 5.14 to 5.16. Both algorithms initialize by halving the demand profile forecast into two vectors; one containing the morning peak and one containing the evening peak. The following discussion outlines the steps for calculating both vectors.

The peak decrease algorithm finds elements which have a higher value than the peak forecast described by Equation 5.11:

\[ EL = \{j: DP_{j,f} = DP_{j,f} > P_f \text{ for } 1 \leq j \leq n\} \] (5.11)

where \( EL \) is a set of element locations where the element has a greater value than peak forecast \( P_f \), where \( j \) is an element number and \( n \) is the length of the vector. The third step, Equation 5.12, in the algorithm set is to find the difference between the peak of the demand profile vector peak and the peak forecast:

\[ \Delta P = \max(DP_{j,f}) - P_f \] (5.12)
where $\Delta P$ is the difference between the element with the maximum value in $DP_j$ and the peak forecast $P_f$. The forth step of the peak decrease algorithm involves the adjustment of the values in the demand profile which are greater than the peak forecast:

$$DP_{EL,f} = DP_{EL,f} - \Delta P$$  \hfill (5.13)

which describes that the elements which have a value greater than the peak forecast $P_f$ that were adjusted downwards while maintaining the prior shape of the demand profile curve.

The peak increase algorithm calculates the difference between the peaks of the demand profile forecast and the peak forecasts using Equation 5.14:

$$\Delta P = P_f - \max(DP_{j,f})$$  \hfill (5.14)

where the variables are described above. The algorithm proceeds to create a vector with values ranging from 0 to 1 and 1 to 0 and multiplies it with $\Delta P$ as per Equation 5.15:

$$\Delta DP = [0,0.1,...,1,1,...,0.1,0] \times \Delta P$$  \hfill (5.15)

where $\Delta DP$ is the peak adjustment vector which has a scaled response to maintain the shape of the peak period of the original demand profile forecast. The peak adjustment vector is then added to the peak period (pp) according to Equation 5.16:

$$DP_{pp,f} = DP_{pp,f} + \Delta DP$$  \hfill (5.16)

which describes that the peak periods of the demand profile are adjusted according to the adjustment vectors. The adjustment vectors highest value overlaps with the peak demand element.

5.6.7.2 Total energy demand adjustment

The adjustment of the demand profile forecast according to the forecasted TEU follows a series of steps. These steps include: (1) calculate the integral of the forecasted demand profile; (2) calculate the difference between the integral and the TEU forecast; and (3) convert the difference value $\Delta TEU$ to an average power drawn over a 24 hour time period and add it to the demand profile forecast. These three calculation steps are described by Equations 5.17 to 5.19, respectively, as follows:

$$\Delta TEU = TEU_f - \int DP_f$$  \hfill (5.17)

where $\Delta TEU$ is the difference between the forecast $TEU_f$ obtained from the $NDTEU$ model and the integral of the demand profile forecast $DP_f$. 

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\[ \Delta Power = \frac{\Delta T EU}{r} \]  

(5.18)

where \( \Delta Power \) is the average difference in power drawn over a 24 hour time period and \( r \) is the number of discrete time intervals in the demand profile.

\[ DP_p = DP_f + \Delta Power \]  

(5.19)

where \( DP_p \) is the post-processed forecast.

### 5.7 Results

#### 5.7.1 ARIMAX models

The variables contained within the NDPD, NDMP and NDTEU models are outlined in Table 5—1. The variables which populate the models were selected on the basis that their inclusion improved accuracy statistics for both the training and validation sets. \( Demand t-1, Demand t-2, Temp., Temp.^2, RH \) and DES forecast variables are included in all models. The double exponential smoothing algorithm accounts for the changing local mean throughout the times series and is analogous to a ARIMA(0,2,2) model. The two autoregressive terms mitigate autocorrelation in the error terms and make the ARIMA components ARIMA(2,2,2) within the ARIMAX models. \( Temp. \) and \( Temp.^2 \) variables account for the parabolic response to temperature. NDPD and NDTEU models contain day of the week dummy variables and RH-temperature interaction terms. The morning peak time series was observed as not being responsive to different days of the week. NDPD has one additional variable which is the intercept.

<table>
<thead>
<tr>
<th>NDPD</th>
<th>NDMP</th>
<th>NDTEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>Intercept</td>
<td>-</td>
</tr>
<tr>
<td>Demand t-1</td>
<td>Demand t-1</td>
<td>Demand t-1</td>
</tr>
<tr>
<td>Demand t-2</td>
<td>Demand t-2</td>
<td>Demand t-2</td>
</tr>
<tr>
<td>Temp.^2</td>
<td>Temp.^2</td>
<td>Temp.^2</td>
</tr>
<tr>
<td>RH</td>
<td>RH</td>
<td>RH</td>
</tr>
<tr>
<td>RH*Temp.^2</td>
<td>-</td>
<td>RH*Temp.^2</td>
</tr>
<tr>
<td>Sunday</td>
<td>-</td>
<td>Sunday</td>
</tr>
<tr>
<td>Saturday</td>
<td>-</td>
<td>Saturday</td>
</tr>
<tr>
<td>Monday</td>
<td>-</td>
<td>Monday</td>
</tr>
<tr>
<td>Tuesday</td>
<td>-</td>
<td>Tuesday</td>
</tr>
<tr>
<td>Wednesday</td>
<td>-</td>
<td>Wednesday</td>
</tr>
<tr>
<td>Thursday</td>
<td>-</td>
<td>Thursday</td>
</tr>
<tr>
<td>Friday</td>
<td>-</td>
<td>Friday</td>
</tr>
<tr>
<td>DES Forecast</td>
<td>DES Forecast</td>
<td>DES Forecast</td>
</tr>
</tbody>
</table>

Table 5—1 ARIMAX model variables
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Figure 5—4 presents Phase 3’s ARIMAX models’ hindcasts and forecasts. For the majority of the training and validation time series, the hindcasts and forecasts follow the pattern of the observed data. In line with the accuracy statistics displayed in Table 2, the NDTEU hindcasts and forecasts exhibit a better fit to observed data than the NDPD and NDMP models. The NDPD and NDMP models display instances where the hindcasts and forecasts significantly deviate from observations. Divergences on days 29, 58, 59 and 155 were attributed to spikes in demand on the day after a period of heavy rainfall. The Queen’s Diamond Jubilee public holiday, day 163, had an abnormal spike in demand. The significant deviation on day 395 occurred the day after a period of heavy rainfall and minor flooding. The NDTEU models were observed to be less sensitive to the exogenous shocks.

Table 5—2 contains the models’ coefficient of determination ($R^2$) and mean absolute percentage error (MAPE) accuracy statistics for both the training and validation sets. The NDTEU models displayed the highest level of accuracy for the both the training and validation sets. The NDPD and NDMP models were less accurate than the NDTEU models. A possible explanation for this deviation in model accuracy could be that the peak demand and morning peak time series were more variable and had greater instances of random shocks than the TEU time series. The post-processing algorithm adjusts the demand profile forecast according to the TEU forecast after the morning peak and peak demand adjustments have been made. This enables a more accurate forecast to mitigate potential NDPD and NDMP forecast errors.

<table>
<thead>
<tr>
<th>Training</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Phase 1</td>
<td>Phase 2</td>
<td>Phase 3</td>
<td>MAPE 1</td>
</tr>
<tr>
<td>NDPD</td>
<td>0.72</td>
<td>0.70</td>
<td>0.72</td>
<td>7.05</td>
</tr>
<tr>
<td>NDMP</td>
<td>0.80</td>
<td>0.60</td>
<td>0.66</td>
<td>8.12</td>
</tr>
<tr>
<td>NDTEU</td>
<td>0.84</td>
<td>0.77</td>
<td>0.87</td>
<td>4.51</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Validation</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Phase 1</td>
<td>Phase 2</td>
<td>Phase 3</td>
<td>MAPE 1</td>
</tr>
<tr>
<td>NDPD</td>
<td>0.58</td>
<td>0.56</td>
<td>0.65</td>
<td>7.90</td>
</tr>
<tr>
<td>NDMP</td>
<td>0.75</td>
<td>0.44</td>
<td>0.66</td>
<td>10.12</td>
</tr>
<tr>
<td>NDTEU</td>
<td>0.74</td>
<td>0.80</td>
<td>0.78</td>
<td>6.97</td>
</tr>
</tbody>
</table>
5.7.2 Correlation clustering

Table 5—3 displays the number of demand profiles classified under each cluster. The correlation clustering algorithm was run until the most optimal clustering solution was found by minimising the number of low correlations within each cluster. This was achieved by an initial selection of 3 cluster nodes and further subdividing the clusters according to where z-scores of demand profiles are located (i.e. $z<-1$, $-1<z<1$ or $z>1$). This resulted in a total of 9 clusters per phase. The number of demand profiles per cluster ranged from 21 to 24.
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Table 5—3 Correlation clustering results

<table>
<thead>
<tr>
<th>Cluster</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase 1</td>
<td>33</td>
<td>38</td>
<td>33</td>
<td>37</td>
<td>34</td>
<td>30</td>
<td>57</td>
<td>54</td>
<td>33</td>
</tr>
<tr>
<td>Phase 2</td>
<td>21</td>
<td>23</td>
<td>36</td>
<td>36</td>
<td>43</td>
<td>32</td>
<td>51</td>
<td>64</td>
<td>33</td>
</tr>
<tr>
<td>Phase 3</td>
<td>58</td>
<td>67</td>
<td>36</td>
<td>34</td>
<td>46</td>
<td>29</td>
<td>27</td>
<td>25</td>
<td>27</td>
</tr>
</tbody>
</table>

5.7.3 Neural network

Table 5—4 contains the NN classification accuracy statistics. Each phase of the network has a separate NN with 9 output neurons corresponding to each cluster. 'Accuracy' is the percentage of correctly made classifications. 'Miss' represents the number of invalid or incorrect classifications. The higher the accuracy percentage and lower the miss percentage entails the better the NN is at correctly classifying a set of input variables. The accuracy percentage ranges from 0% to 100%. The miss percentage ranges from 2.15% to 11.11%. The overall accuracy and miss percentages for each NN range from 70.66% to 77.98% and 4.69% to 6.04% respectively. A possible explanation of the low classification accuracy of some clusters is that the cluster is too similar to another in terms of magnitude, shape and associated input variables. Post-hoc analysis of clusters having very similar characteristics resulted in some cluster mergers.

Table 5—4 Neural network classification accuracy

<table>
<thead>
<tr>
<th>Cluster</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase 1</td>
<td>42.85</td>
<td>77.41</td>
<td>89.28</td>
<td>77.41</td>
<td>68.00</td>
<td>100.00</td>
<td>86.36</td>
<td>87.50</td>
<td>73.07</td>
<td>77.98</td>
</tr>
<tr>
<td></td>
<td>6.45</td>
<td>3.58</td>
<td>2.15</td>
<td>5.01</td>
<td>3.22</td>
<td>2.86</td>
<td>5.73</td>
<td>9.31</td>
<td>3.94</td>
<td>4.69</td>
</tr>
<tr>
<td>Phase 2</td>
<td>0.00</td>
<td>61.90</td>
<td>93.75</td>
<td>74.19</td>
<td>89.47</td>
<td>74.07</td>
<td>100</td>
<td>85.41</td>
<td>95.65</td>
<td>74.93</td>
</tr>
<tr>
<td></td>
<td>9.31</td>
<td>5.01</td>
<td>2.15</td>
<td>4.30</td>
<td>2.50</td>
<td>2.50</td>
<td>7.88</td>
<td>7.16</td>
<td>4.30</td>
<td>5.01</td>
</tr>
<tr>
<td>Phase 3</td>
<td>81.63</td>
<td>81.13</td>
<td>66.66</td>
<td>50</td>
<td>82.85</td>
<td>62.96</td>
<td>31.57</td>
<td>100</td>
<td>79.16</td>
<td>70.66</td>
</tr>
<tr>
<td></td>
<td>5.37</td>
<td>11.11</td>
<td>7.16</td>
<td>6.45</td>
<td>9.67</td>
<td>4.65</td>
<td>4.65</td>
<td>3.22</td>
<td>2.15</td>
<td>6.04</td>
</tr>
</tbody>
</table>

5.7.4 Hindcast accuracy statistics

Table 5—5 highlights the accuracy statistics of the expert system applied when using the training data set. The accuracy statistics include root mean square error or standard error (RMSE), $R^2$, correlation and $MAPE$. The $RMSE$ displays the 1 σ confidence interval related to each phase. Each phase’s expert system had high levels of accuracy. Phase 1’s expert system had the least accuracy with an $R^2$ of 0.86, correlation of 0.93 and $MAPE$ of 12%. Phase 2’s expert system had the highest accuracy with an $R^2$ of 0.88, correlation of 0.94 and $MAPE$ of 11%. These reported high levels of accuracy indicate that the expert system’s sensitivity to miss-classifications is low.
Table 5—5 Expert system hindcast accuracy

<table>
<thead>
<tr>
<th>Phase</th>
<th>$R^2$</th>
<th>RMSE (W)</th>
<th>Correlation</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase 1</td>
<td>0.86</td>
<td>5210</td>
<td>0.93</td>
<td>12%</td>
</tr>
<tr>
<td>Phase 2</td>
<td>0.88</td>
<td>4346</td>
<td>0.94</td>
<td>11%</td>
</tr>
<tr>
<td>Phase 3</td>
<td>0.87</td>
<td>5231</td>
<td>0.94</td>
<td>12%</td>
</tr>
</tbody>
</table>

Figure 5—5 displays the $R^2$ statistic distribution for each phase’s expert system when the accuracy of each day’s hindcast is calculated independently. It is to be noted that after preprocessing of the data, the number of days used to train the systems were reduced to 349. Phase 2’s expert system had the greatest number of high accuracy forecasts with 143 days having $R^2$ statistics greater than 0.9. Phase 1’s and Phase 3’s expert systems had a similar number of high accuracy hindcasts with 97 and 91 days with $R^2$ statistics being greater than 0.9, respectively. As the aggregated $R^2$ statistics increases the performance of the models coincide. For each phase’s expert system there were between 6 and 14 days (approx. 2-4% of sample) where the accuracy of the forecasts deviated from observations such that the forecasts were considered to be of low accuracy ($R^2 < 0.5$).

Figure 5—6 displays a 7 day period comparing Phase 1’s observations verses hindcast. Each day, highlighted by vertical lines, is an independent hindcast. What can be observed is that the expert system is able to classify a set of input variables and use the characteristic demand profile of the corresponding cluster to produce a hindcast with a reasonable degree of accuracy. Differences between the expert systems’ hindcasts and observations can be attributed to randomness in the observation and the smooth curve of the characteristic demand profiles.
5.7.5 Validation accuracy statistics

To simulate real world performance, forecasted information was used as input variables over the training set period. Each of the forecasts incorporated as input variables contain error. This necessitates that the performance of the expert system will be hampered due to the compounding effect of the errors. Table 5—6 contains the accuracy statistics for simulated real world performance. In comparison to the expert systems’ hindcasts, its accuracy decreased slightly which is in line with expectations. The $R^2$ statistics decreased by 4 to 5 points; the RMSE increased by 500W to 900W; correlation decreased by 2 to 3 points; and, MAPE increased by 1.5%. Nonetheless, with $R^2$ statistics ranging from 0.81 to 0.84, correlations ranging from 0.90 to 0.92 and MAPE ranging from 12.5% to 13.5%, the expert systems exhibit a reasonable level of accuracy.

<table>
<thead>
<tr>
<th>Phase</th>
<th>$R^2$</th>
<th>RMSE (W)</th>
<th>Correlation</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase 1</td>
<td>0.81</td>
<td>6104</td>
<td>0.90</td>
<td>13.5%</td>
</tr>
<tr>
<td>Phase 2</td>
<td>0.84</td>
<td>4990</td>
<td>0.92</td>
<td>12.5%</td>
</tr>
<tr>
<td>Phase 3</td>
<td>0.82</td>
<td>6139</td>
<td>0.91</td>
<td>13.5%</td>
</tr>
</tbody>
</table>

Figure 5—7 displays the $R^2$ statistic distribution for each phase’s expert system when the accuracy of each day’s forecast is calculated independently. There were 349 forecasts per phase. As expected, the number of high accuracy forecasts ($R^2>0.9$) decrease by 46 to 60 in the simulated real world performance. The number of low accuracy forecasts increased by 23 to 34.

The ability of the expert system to correctly forecast a demand profile for a future day is dependent on the accuracy of the forecasted information. Figure 5—8 compares the
normalised error of Phase 2’s NDPD model against $R^2$ statistics of the demand profile forecasts for the last 50 days of 2012. As the error of the forecasted information increases (days 334 to 340) the ability for the system to select a characteristic demand profile and post-processes it such that it produces a reasonable forecast decreases. In turn, it can be stated that the forecast accuracy of the expert system can be improved if the error of the forecasted information decreases.

![Figure 5—7 Demand profile forecast accuracy distribution](image)

![Figure 5—8 Error analysis](image)

**5.8 Conclusion**

This chapter presented an expert system that was developed to forecast demand profiles in residential LV distribution networks in order to overcome potential issues created by high variance and frequent random shocks. The expert system was constructed by the
combination of demand profile property connection forecasts (i.e. TEU, peak demand and morning peak), correlation clustering, NN discrete classification and post-processing. The expert system operates by classifying input variables and calling a corresponding characteristic demand profile as the forecast. The post-processing component adjusts the forecast to better conform to demand profile property forecasts.

The expert system was trained using demand data from an LV residential transformer supplying 128 customers located in Brisbane, Australia. The expert system exhibited high hindcast accuracy with $R^2$ ranging from 0.86 to 0.87 and MAPE ranging from 11% to 12% across the network’s phases. An overlay of the hindcasted demand profiles and actual observations displayed that the expert system can correctly replicate the shape and magnitude of observed data. When analysing simulated real world performance by using forecasted input variable information, the $R^2$ statistic was reduced to a respectable 0.81 to 0.84 and MAPE increased to 12.5% to 13.5%. The accuracy of the expert system only slightly decreased in comparison to the hindcast, which is typical. When analysing the contributors to the accuracy decrease, it was noted that the system was susceptible to instances of poor demand profile property connection forecasts. This effects both the NN discrete classification and post-processing components of the system.

To improve the expert system’s future accuracy requires increases in accuracy of the demand profile property forecasts. This process would involve further detailed analysis of the existing data and further collected information to ascertain whether or not periods of poor property connection demand profile forecasts are due to exogenous shocks or anomalous behaviour. The authors intend to collect further data from the LV transformer and the 128 residential smart meters to provide a more comprehensive dataset for refining the expert system.

Future work will integrate the demand forecasting expert system into an energy management control algorithm to schedule the charging and discharging of BESS in LV residential distribution networks.
CHAPTER 6
Three phase battery energy storage system scheduling

Statement of contribution to co-authored published paper

This chapter includes a co-authored peer-reviewed paper.

The bibliographic details of the paper, including all authors, are:


My contribution to the paper included developing the scheduling system software including all subcomponents, repurposing a subcomponent for system sizing operations, extracting results data, analysing results and drafting the paper.

Signed: __________________________ Date: ____________
Christopher Joseph Bennett

Countersigned: _____________________ Date: ____________
Co-author: Assoc. Prof. Rodney Stewart (principal supervisor)

Countersigned: _____________________ Date: ____________
Co-author: Prof. Junwei Lu (associate supervisor)
Development of three-phase battery energy storage scheduling system for low voltage distribution networks

Abstract: Three phase battery energy storage (BES) installed in the residential low voltage (LV) distribution network can provide functions such as peak shaving and valley filling (i.e. charge when demand is low and discharge when demand is high), load balancing (i.e. charge more from phases with lower loads and discharge more to phases with higher loads) and management of distributed renewable energy generation (i.e. charge when rooftop solar photovoltaics are generating). To accrue and enable these functions an intelligent scheduling system was developed. The scheduling system can reliably schedule the charge and discharge cycles and operate the BES in real time. The scheduling system is composed of three integrated modules: (1) a load forecast system to generate next-day load profile forecasts; (2) a scheduler to derive an initial charge and discharge schedule based on load profile forecasts; and (3) an online control algorithm to mitigate forecast error through continuous schedule adjustments. The scheduling system was applied to an LV distribution network servicing 128 residential customers located in an urban region of South-east Queensland, Australia.

Keywords: battery energy storage, schedule, low voltage, three phase, forecast, real time operator, peak demand, load balancing

6.1 Introduction

There has been a substantial push by governments to promote the installation of residential solar photovoltaic (PV) array installations in the low voltage (LV) distribution network through subsidies and feed-in-tariffs. In Australia, residential solar PV installations have been promoted by the Renewable Energy Target and the feed-in tariff schemes (Australian Energy Regulator, 2013). As of the 2012–13 financial year, the Australian Energy Regulator (2013) reports that Australia’s combined rooftop solar PV capacity is 2,300 megawatts (MW). In South East Queensland (SEQ) the distribution network operator, Energex, noted that the number of customers with solar PV increased from 2,000 to 221,000 installations from 2009 to June 2013, with 74,000 installations taking place between June 2012 and June 2013 (Energex, 2013). The increase of customers with solar PV installations contributed to an increase price of energy, which led to a slight reduction in energy consumption from conventional sources and a shift in the
SEQ network peak to later in the day (Energex, 2013; Australian Energy Market Operator, 2014).

Daily peak demand in residential networks typically occurs in the evenings in summer and both late morning and evening in winter (Bennett et al., 2014a). Solar PV generation is dependent on the inclination of incoming solar radiation; hence, peak generation occurs during the middle of the day, typically when demand in the residential distribution network is low. Due to the behaviour of residential customers (i.e. concentrated energy demand activities in the evening) and the nature of solar PV generation, there is an incongruity between when energy is generated and when it is required. This can lead to power quality issues in the LV distribution network, such as overvoltage at points of common coupling and instances of reverse power flow to the distribution feeders (Alam et al., 2013). In some circumstances remedial measures such as tap changes or more costly network augmentations are required to manage the excess of power produced. Since solar PV generation rarely coincides with peak demand periods in the residential LV network, solar PV fails to contribute to supporting the network through reducing peak demand (Ausgrid, 2011).

The installation of distribution energy storage (DES) may be cost-effective in LV distribution networks with high penetrations of solar PV, load during peak demand period nearing the ratings limits of the LV transformer or unbalanced loads. The general concept is that the DES will charge from the grid during low demand periods or when solar PV is generating surplus energy and discharge during peak demand periods—known as ‘peak shaving and valley filling’ (Dunn et al., 2011). This concept will serve to level the demand profile, reduce peak demand and mitigate overvoltage and reverse power flow issues induced by high solar PV penetrations. A proven consistent reduction in peak demand derives value for the utility through electricity network augmentation capital expenditure deferrals. While historically DES has been viewed as a cost prohibitive for application in the LV network, advances in battery technology, feed-in-tariff schemes and the economy of scale effect from electrical vehicles, energy storage will become less cost prohibited in the future (Dunn at al., 2011; Weiss, et al., 2012; Higgins, et al., 2014).

To be effective, DES scheduling systems must optimally charge during periods of high solar PV generation or low demand and discharge during periods of peak demand. Many methods have been proposed in the literature to achieve this objective. The most common methods include the use of optimisation algorithms to minimise or maximise objective functions or through finding the optimal solution through dynamic programming (Marwali et al., 1998; Lu & Shahidehpour, 2005; Oudalov et al., 2007; Lee, 2007; Hu et al., 2010; Xu et al., 2010; Koutsopoulos et al., 2011; Grillo et al., 2012; Arghandeh et al., 2014;
Jayasekara et al., 2014). These systems achieve optimal solutions but their implementations are relatively complex. Alternatively, a less complex heuristics-based DES scheduling system that has been purpose-built to cater for the characteristics of the LV network and battery energy storage (BES), as proposed herein. The proposed scheduling system comprises three core components: (1) an expert system to forecast next day load profiles (section 6.3); (2) a scheduling algorithm that interprets the forecasts and provides a charge and discharge schedule (section 6.4); and (3) an online control algorithm to adjust the charging and discharging in real time to mitigate scheduling error (section 6.5).

6.2 Literature

6.2.1 Energy storage scheduling systems
The literature has proposed a number of different methods to construct DES scheduling systems to achieve one or more objectives such as engaging in valley fill and peak shaving operations, mitigating power quality issues and utilising distributed renewable energy generators, such as solar PV and wind turbines. For scheduling systems to calculate a schedule for BES, they must rely on information that allows for charging and discharging periods to be identified or inferred. Types of information that are relied on may include historical load data, load forecasts, time-of-use tariffs, energy market prices and costs of production. Methods used to calculate schedules include time-based heuristics, voltage or frequency set points, fuzzy logic controllers, objective function optimisation and dynamic programming.

6.2.2 Price signal based systems
Marwali et al. (1998), Lu and Shahidehpour (2005) and Koutsopoulos et al. (2011) developed scheduling systems that aimed to minimise the production cost of supplying electricity while attempting to peak shave and valley fill. The scheduling systems developed by Marwali et al. (1998) and Lu and Shahidehpour (2005) involve the coordination of thermal generators and co-located solar PV and BES. Marwali et al. (1998) separate the scheduling problem into three steps. The first step involves anticipating solar PV generation, thermal commitment and by how much the BES is required to be charged. The second step uses Lagrangian relaxation to minimise thermal commitment cost based on the thermal objective function. The final step minimises the total cost objective function. Lu and Shahidehpour (2005) follow similar steps as Marwali et al. (1998) to solve an initial schedule. From there, an hour ahead optimal schedule is calculated via network flow programming and linear programming. Koutsopoulos et al. (2011) assigns a convex cost function for instantaneous demand, which represents the increase cost as load
increases. Demand in the network is treated as a Poisson process of power requests. A BES cost objective function is solved through a process of dynamic programming.

Scheduling systems developed by Sanseverino et al. (2013), Hu et al. (2010) and Grillo et al. (2012) rely on price signals through the use of time-of-use tariffs, day-ahead energy market data, hour ahead market data and spot prices to optimise the charging and discharging of BES. The use of the day-ahead, hour-ahead and spot price markets gives the scheduling systems an accurate representation of what the load is going to be in the grid. A high price anticipates a high demand and a low price anticipates a low demand. The general principle behind these systems is to maximise profit or minimise cost of the operation of the BES. In turn, this is done through purchasing energy when the price is low (charging) and selling energy when the price is high (discharging). Sanseverino et al. (2013) solves the schedule by a fuzzy logic controller. The controller is tuned based on past demand history and an economic indicator. The Hu et al. (2010) and Grillo et al. (2012) scheduling systems set up a cost or profit objective function that reflects the capital and operations costs of the BES and takes into account the energy price market. Hu et al. (2010) solved the objective function through Lagrangian optimisation and Grillo et al. (2012) solved the objective function through dynamic programming.

Lee (2007) and Oudalov et al. (2007) sought to reduce the energy supply cost of industrial customers. Industrial customers are charged for energy supplied by both time-of-use tariffs and the maximum demand they consume. Lee (2007) and Oudalov et al. (2007) proposed that through BES and adequate scheduling, their load can be reduced and they will receive lower energy costs. Lee (2007) created an objective function representing the cost of energy to the industrial customer over a monthly period, which included the BES, and then used particle swarm optimisation to calculate the charge and discharge schedule. Oudalov et al. (2007) outlined two dynamic programming based systems where the first sizes the BES and the second schedules. The sizing of the BES is based on historical load data to achieve maximum benefit, which is defined as savings in electricity minus the capital, maintenance and operational costs. Scheduling relies on the customers' load profile, energy supply costs, BES parameters and the target value of maximum load.

6.2.3 Forecast based systems

Matallanas et al. (2012), Rowe et al. (2014a) and Rowe et al. (2014b) primarily rely on forecasting load to schedule the charging and discharging of BES. Matallanas et al. (2012) designed an active demand side management (ADSM) system for a smart, energy efficient home with appliances, solar PV arrays and BES connected to a centralised controller. The user selects deferrable appliances, such as washing machines, to be used during the day. Load and solar PV forecasts are supplied to the central controller. The controller then uses
a neural network (NN) to schedule deferrable appliances and the charging and discharging of BES so that the least load is exerted on the LV network. Castillo-Cagigal et al. (2011) integrated the ADSM system developed by Matallanas et al. (2012) with a BES control system for a residential premise with rooftop solar PV and BES. The goal of the BES control system is to maximise the consumption of energy produced by the solar PV. The ADSM ensures that deferrable loads are scheduled for when solar PV is generating. Energy produced by the solar PV not consumed by the deferrable loads is allocated to charging the battery bank. Energy is supplied by the battery bank when solar PV generation is insufficient.

Rowe et al. (2014) used a LV distribution network (household-level) forecasting technique developed by Haben et al. (2014) to provide load profile forecasts. The demand profile forecast undergoes a filter stage whereby peak demand is altered in magnitude and period. The scheduler receives the altered forecast and iteratively calculates a discharge set point where above the set point the system is set to discharge and below the system is able to charge. Rowe et al. (2014) further developed the scheduling system to include an online optimisation algorithm that operates by forecasting demand using a load scenario tree and optimises the schedule to maximise peak demand reduction.

6.2.4 Combined use of price signals and forecasts

Systems that use combined load and price forecasts provide advantages over pure price signal determined scheduling algorithms due to the ability for optimisation to take into account reducing peak demand and maximising value out of the systems. Jayasekara et al. (2014) set out to schedule customer side co-located solar PV and BES to achieve peak shaving and valley fill objectives. The systems operates by first forecasting load a day ahead and then filtering the forecast using a Fourier series to provide a 24-hour load profile forecast. Under the load profile forecast, the system minimises a daily operational cost objective function based on total battery cost, time-of-use tariffs and ratio of negative to positive sequence voltages. The system optimises the real time operation by use of the energy spot price. Xu et al. (2010) developed an initial schedule based on the day ahead energy market through minimisation of a cost of energy objective function. Real time control is conducted through forecasting price and loads and the scheduling is balanced through a receding horizon control strategy. Similar to Jayasekara et al. (2014), Riffonneau et al. (2011) formulated a scheduling system that applies to co-located solar PV and BES. The system initialises by forecasting irradiance, temperature, load profile and the price of energy. The optimisation of the system seeks to achieve optimal peak reduction at least cost through dynamic programming.
The scheduling system developed by Arghandeh et al. (2014) aimed at producing a charge discharge schedule through optimizing an objective function through a gradient based heuristic approach. The objective function includes the cost of purchasing energy when charging, saving costs when discharging, load profile forecasts, local marginal price forecasts, feeder losses and energy storage system constraints. For each time interval the local marginal price is forecast, the load is forecast and the optimization routine is run again to adjust the schedule before dispatch.

### 6.2.5 Set point voltage control

The integration of residential rooftop solar PV causes power quality issues, such as voltage rise in some areas. Alam et al. (2013) set out to use BES to mitigate power quality issues. The scheduling system responds in real time to voltage occurring at the point of common coupling. If the voltage is high (close to or above operational targets), the system sets the BES to charge. During the peak demand periods, voltage sag can occur. In response to voltage sag, the system sets the BES to discharge. In effect, the system follows the load occurring in the network to achieve elements of peak shaving and valley filling. Kabir et al. (2014) proposed a central control system which dictates the injection into the grid of real and reactive power for customer located distributed solar PV and energy storage. Kabir et al. (2014) first estimates the solar PV generation using a discrete time Markov chain process. If the probability of solar PV generation is greater than 50% and the resistance/reactance ratio is greater than a critical threshold the energy storage systems are set to charge such to prevent overvoltage. To prevent voltage sag, the energy storage systems are set to discharge. Results displayed that the control system was able to keep the voltage on the network within statutory limits.

### 6.2.6 Problem formulation

Using one or more types of information about the electricity network and the BES, the scheduling systems in the literature predominantly employ optimisation routines or genetic programming (Marwali et al., 1998; Lu & Shahidehpour, 2005; Oudalov et al., 2007; Lee, 2007; Hu et al., 2010; Xu et al., 2010; Koutsopoulos et al., 2011; Grillo et al., 2012; Arghandeh et al., 2014; Jayasekara et al., 2014). Optimisation algorithms depend on the creation of an objective function composed of functions that represent the system which is to be scheduled. These functions are in terms of costs or benefits for particular operations or components of the system. The optimisation of the objective function seeks to find a schedule that minimises a cost or maximises a benefit. Dynamic programming involves breaking the scheduling problem into a series of sub-problems, examines a range of scheduling solutions and chooses the highest performing (Marwali et al., 1998; Oudalov et al., 2007; Koutsopoulos et al., 2011; Grillo et al., 2012). The literature has conveyed that
optimisation algorithms, dynamic programming and other methods of calculating a schedule work well for finding the optimal solution given system constraints and objective functions.

These techniques are relatively complex to implement and depend on formulating objective functions and constituent functions that accurately represent how the scheduling system should operate given certain states. Unless direct relationships can be identified, such as economic costs or benefits based on the operation of the BES and time-of-use tariffs or energy markets prices, formulating and weighting functions is reliant on trial and error.

To avoid complexity and with knowledge of how a scheduling system should operate and what an optimal schedule should achieve, there is an avenue of calculating schedules based on a heuristics approach. Thus, a heuristics approach could be a viable alternative to approaches involving more complex optimisation algorithms. Many regions, including SEQ, do not have energy storage tariff arrangements or localised network pricing. In the absence of price signal based information, the proposed heuristics approach for BES scheduling will depend on load forecasts. Similar to Xu et al. (2010) and Arghandeh et al. (2014), the proposed scheduling system will have a component which provides an initial schedule based on forecasts and an online component which adjusts the schedule in real time.

6.3 Data

Data used in this research was sourced from a residential LV distribution network transformer that was supplied by Energex (the distribution network operator for SEQ). The distribution transformer supplied 128 residential customers located in an inner suburb of Brisbane, Queensland. The provided dataset contains current, voltage and phase angle recordings at 10-minute intervals and covers the period between the middle of January 2012 and the middle of February 2013. The phases of the network serviced by the transformer are unbalanced. Load experienced on one phase may not be indicative of load experienced on the other two phases. Weather data used were sourced from the Brisbane City weather station and made publically available by the Australian Bureau of Meteorology.

There are two distinct types of load profiles that occur in the network serviced by the transformer: the summer profile and the winter profile (see Figure 6—1). The summer load profile is characterised by low load in the early morning, an increased load between 7 am and 10 am and a peak demand period, which occurs in the evening between 6 pm and 10 pm. The winter profile has low load during the early morning, a morning peak (MP)
demand period between 6 am and 9 am, low demand during the middle of the day and an evening peak (EP) demand period between 6 pm and 10 pm. The magnitudes of the load in the MP demand period and EP demand period often differ. Days when load is high generally denote that the load during the EP demand period will be greater than the load during the morning period. Different permutations of the two distinct load profiles occur through the year based on external influences such as temperature, humidity, day of the week and exogenous events (Bennett et al., 2014a, Bennett et al., 2014b).

Figure 6—1 Summer and winter load profiles

The fluctuations in load throughout the year are predominately a product of customers’ uses of heating and cooling appliances in response to changes in temperature. Bennett et al. (2014b) observed that the load response to temperature is parabolic in nature and is able to account for half of the observed load. The relationship reflects consumers’ propensities to utilise heating and cooling appliances in the warmer and cooler periods. Figure 6—2 displays the magnitudes of the MP demand period and EP demand period throughout the year for phase 3. The MP remains relatively flat during periods of the year where temperature is average or warmer. The MP increases during colder periods of the year such as late autumn, winter and early spring. The EP demand is greatest during summer and winter and is relatively flat during autumn and spring.
6.4 Method

6.4.1 Overview
The operation of the proposed three-phase BES scheduling system for the LV distribution network is based on load forecasts. The system is designed to discharge during peak demand periods and charge the BES during periods when load is low and solar PV is generating. The BES is desired to be installed by the network operator and independent of co-located solar PV. Load forecasts provide the system information about the future to allow a schedule to be established. The LV distribution network typically has unbalanced phases; the load exhibits a high degree of variability and occurrences of random shocks.
Chapter 6 – Three phases battery energy storage system scheduling

(Bennett et al., 2014a; Bennett et al., 2014b; Rowe et al., 2014a; Rowe et al., 2014b). The conditions of the LV distribution network, combined with high penetrations of solar PV on the network, lead to hampered load forecast accuracy in comparison to sections of the electricity network that supply a greater number of customers. In turn, there are two conditions that the scheduling system is required to operate under: (1) variable and unbalanced load conditions synonymous with LV distribution networks; and (2) imperfect load forecasts (i.e. since LV networks are more variable than high voltage networks and thus more challenging to precisely forecast).

The scheduling system comprises three main components:

1. The first component is an expert system that forecasts each phase’s load profile for the day;
2. The second component is a scheduler that receives the load profile forecast and calculates a charge and discharge schedule;
3. And the third component is the real time operator (RTO): an online system that corrects the schedule dispatch in real time to mitigate forecast errors.

Figure 6—3 presents the scheduling system's flow chart. The scheduling system receives load data from the network at the start of each time ($t$) iteration. An iteration covers a period of 10 minutes in line with the transformer’s frequency of data logging. The load data are corrected by removing the effects of the previous iteration’s schedule dispatch and are then filtered to remove fluctuation from the load and yield the underlying moving average. If $t$ is the start of the day, the expert system is called and the scheduler is called. For all other times, the RTO subroutines are called and the schedule is dispatched.

![Figure 6—3 Scheduling system flow chart](image)

6.4.2 Battery energy storage system

Figure 6—4 contains a simplified schematic of the BES that the scheduling system emulates. The system contains a battery a bank and three programmable inverters on a
direct current circuit. Each inverter is connected to an individual phase of the network. This system allows for each inverter to be controlled independently. The individual control of each inverter facilitates the achievement of ancillary scheduling objectives such as load balancing.

The battery bank is defined by a number of variables including the capacity ($C$), state of charge ($SoC$), total charge ($TC$), depth of discharge ($DoD$), charge rating ($CR$), discharging rating ($DR$) and efficiency ($BE$). $C$ is the maximum amount of energy the battery bank can store. The $SoC$ is the amount of charge or energy stored in the battery bank. $TC$ is an upper limit on the amount of energy stored in the battery bank. $DoD$ is defined as the lower limit on the amount of energy stored in the battery bank. The $SoC$ should not breach the $TC$ and $DoD$ limits to preserve the operational lifespan of the battery bank. $DR$ and $CR$ denote the maximum amount of power that can be discharged to the network or used to charge the battery bank. The inverters have a specified discharge rating ($iDR$) and charge ($iCR$) and an efficiency ($IE$). The variables are set in accordance to the properties of the battery bank and inverters being used or by the user to achieve specific objectives.

The following set of equations (6.1 to 6.4) denotes the charging and discharging operations of the BES:

\[ SoC_t = SoC_{t-1} + \delta_t \] \hspace{1cm} (6.1)

where $t$ is the time iteration and $\delta$ is the change in charge.

\[
\delta_t = \begin{cases} 
\sum_{i=1}^{3} \delta_{i,t} \times IE \times BE, & \text{if } \sum_{i=1}^{3} \delta_{i,t} > 0 \land (SoC_{t-1} < TC) \\
\sum_{i=1}^{3} \delta_{i,t} \times \frac{1}{IE} \times \frac{1}{BE}, & \text{if } \sum_{i=1}^{3} \delta_{i,t} < 0 \land (SoC_{t-1} > DoD) 
\end{cases} \] \hspace{1cm} (6.2)

where

\[ DR \geq \delta_t \leq CR \] \hspace{1cm} (6.3)
and

\[ iDR \geq \delta_{i,t} \leq iCR \]  \hspace{1cm} (6.4)

\( \delta_i \) is the charge provided by inverter \( i \). The BES undergoes charging when the summation of \( \delta_i \) is positive. The value of the summation is reduced by multiplying it by \( IE \) and \( BE \) due to the inefficiencies of the inverters and battery bank. There is less power charging the battery bank than what is being drawn from the network. The BES is discharging when the summation of \( \delta_i \) is negative. To achieve a specific LV network peak reduction, battery and inverter efficiency factors mean that more power has to be drawn from the battery bank than the value of the peak demand reduction specified. The summation is divided by \( IE \) and \( BE \) to incorporate this efficiency reduction. The BES can only charge when the \( SoC \) is less than \( TC \) and can only discharge when \( SoC \) is greater than \( DoD \). Unit conversions have been omitted in this paper.

### 6.4.3 Expert system to forecast load profiles

The theory behind the expert system developed by Bennett et al. (2014a) is that certain shapes of load profiles repeat themselves based on external variables such as weather, day of the week, period of the year and corollaries such as total energy use (TEU, the integral of the load profile), MP and EP. A correlation-clustering algorithm was used to identify clusters of load profile patterns. The mean of each cluster was selected to represent the cluster. A discrete classification NN was trained (feed-forward back propagation) with each day’s external variables as inputs, and the cluster that the day was a member of was the output. This allows for the selection of a load profile that is most likely to occur. When the expert system is used to forecast, in terms of \( R^2 \), it has training accuracies ranging from 0.86 to 0.87 and validation accuracies ranging from 0.81 to 0.84 over the three phases of the network.

The incorporation of the expert system algorithm used in the scheduling system is presented in Figure 6—5. The algorithm acquires weather forecasts and uses the information to forecast TEU, MP and EP using time series models. The forecasted information is inputted into the NN and the network gives a score between 0 and 1 for each load profile output neuron. The output neuron with the highest score denotes the load profile that is most likely to occur. The selected load profile is adjusted according to the TEU, MP and EP forecast to improve forecast accuracy. The forecasted load profile, defined as \( LPf \), is then dispatched to the scheduler. The length of \( LPf \) is determined by the number of day being forecast. This process is conducted for each phase of the network.
6.4.4 Scheduler

6.4.4.1 Overview
The flow chart representing the scheduler is displayed in Figure 6—6. The scheduler receives the load forecast from the expert system, identifies significant peaks, initialises the schedule through calculations of $DT$ (discharge target), loops through the charging and discharging routines and dispatches the final schedule to the RTO.

The literature displays that the operation of a scheduling system through an objective function optimisation approach attempts to maximise peak demand reduction while minimising the use of BES resources. The optimisation process is constrained by the capacity of the BES and power ratings. If the system were not constrained by the BES capacity, maximum peak demand reduction would equate to the power output rating of the BES. This enables a heuristic to be established through Equations 6.5 and 6.6:

$$DT_i = \begin{cases} EP_i - iDR, & \text{for EP period} \\ MP_i - iDR, & \text{for MP period} \end{cases}$$  \hspace{1cm} (6.5)
where \( DT_i \) is the discharge target for inverter \( i \), which equals the magnitude of the peak minus the discharge rating of the BES. \( DT_i \) is a vector where the length of the vector is equal to the length of \( LPf \). The \( DT_i \) vector is composed of different threshold values that are allotted to the specific MP or EP periods they are calculated from. The scheduler uses the discharge target to create an initial schedule:

\[
\text{sched}_{i,t} = - (LP_{f,i,t} - DT_{i,t}), \quad \text{for } t \ni (LP_{f,i,t} > DT_{i,t})
\]

(6.6)

where \( \text{sched}_{i,t} \) is the schedule vector for inverter \( i \) at time \( t \) and it is calculated for the length of \( LPf \). As the scheduler operates, its \( \text{SoC} \) (which is defined as \( \text{SoC}_s \)) updates according to Equations 1 to 4. A negative \( \text{sched}_{i,t} \) value entails the system will discharge and a positive \( \text{sched}_{i,t} \) value entails the system will charge. Information that is dispatched to the RTO includes the \( \text{SoC}_s \), \( \text{sched}_{i,t} \) and \( DT_{i,t} \).

### 6.4.4.2 Identifying significant peaks

MP and EP of significance are required to be identified so that schedule initialisation can take place. Peaks are defined according to their amplitude (\( \alpha \)) and gradients (\( m \)) on either side. The amplitude threshold (\( t_\alpha \)) and gradient threshold (\( t_m \)) are determined by historical data or arbitrarily by the user. Significant peaks are identified according to the following algorithm:

1. \( LPf \) is subdivided into corresponding days.
2. The \( LPf \) for each day is split into morning and evening periods (MP and EP periods).
3. \( \alpha \) equals the greatest value of the period and the corresponding element is recorded.
4. If \( \alpha \geq t_\alpha \) and \( \text{abs}(m) \geq t_m \), then the peak is considered to be significant.

Schedule initialisation is conducted according to Equations 5 and 6.

### 6.4.4.3 Battery charging routines

The \( \text{SoC} \) is imported from the RTO in order to set the initial \( \text{SoC} \) for the schedule. The initial battery charging routine charges the battery bank according to Equation 6.7:

\[
\text{sched}_{i,t} = \begin{cases} 
  iCR, & \text{if } (\text{SoC}_{s,t} < (TC - 3 \times iCR)) \land (LP_{f,i,t} < DT_{i,t}) \\
  (TC - \text{SoC}_{s,t}) \div 3, & \text{if } (\text{SoC}_{s,t} < TC) \land (LP_{f,i,t} < DT_{i,t})
\end{cases}
\]

(6.7)

The Equation states that while the \( \text{SoC}_i \) is less than \( TC \), the battery bank will charge at the rate \( iCR \). When the \( \text{SoC}_i \) nears \( TC \) (i.e. \( TC - 3 \times iCR \)) the remaining charge is divided across the three phases so that \( \text{SoC}_i \) does not exceed \( TC \).
A valley fill charging routine commences if SoC equals TC before LPf,t ≥ DT,t. The purpose of the valley fill charging routine is to schedule charging specifically during low load periods and to balance phases by charging more from the least loaded phases. The valley filling routine operates by establishing a target vector CT as the minimum LPf,i value over the charging period and iteratively increasing the value of CT until the area between LPf,i and CT equals the amount of energy that is required to charge the battery bank. The charging period is defined between a start element (se) and a finish element (fe), which are calculated using Equations 6.8 to 6.10:

\[
se = \min(t), \quad \text{for } t \ni (LPf_{i,t} < DT_{i,t}) \land (1 \leq i \leq 3) \quad (6.8)
\]

\[
fe = \max(t), \quad \text{for } t \ni (LPf_{i,t} < DT_{i,t}) \land (1 \leq i \leq 3) \quad (6.9)
\]

where

\[
(1 \lor pp) > t < (np \lor length(LPf)) \quad (6.10)
\]

The calculation of se and fe is constrained either by the start of the scheduling period or the previous peak period (pp) and the next peak period (np) or by the end of the scheduling period with respect to the current t. This allows CT to be calculated by Equation 6.11. The iterative increase commences by adding an ‘adjust’ constant adj as represented by Equation 6.12. The iterative process ceases when SoC,i at the end of the charge period equals TC.

\[
CT_{l-1} = \min(LPf_{i,t}), \quad \text{for } (se \leq t \leq fe) \land (1 \leq i \leq 3) \quad (6.11)
\]

\[
CT_t = CT_{l-1} + adj, \quad \text{while } SoC_{se,fe} < TC \quad (6.12)
\]

where l is the iteration number. While the iterative process continues, the schedules for each phase are calculated:

\[
sched_{i,se \rightarrow fe} = \begin{cases} 
CT_t - LPf_{i,se \rightarrow fe}, & \text{if } (CT_t - LPf_{i,se \rightarrow fe}) \leq iCR \\
iCR, & \text{if } (CT_t - LPf_{i,se \rightarrow fe}) > iCR 
\end{cases} \quad (6.13)
\]

The valley fill charging routine enables the scheduling system to charge the BES more from the phase that is expected to have the least load and less from the phase expected to have the highest load.

Figure 6—7 graphically depicts the valley fill charge routine over a particular phase’s LPf. The shaded areas denote the operations of the BES system. The charge period starts at se and finished at fe (Equations 6.8 and 6.9). It is assumed that the LPf for the other two phases are greater in magnitude during the charge period. The initial CT is the minimum value of the LPf of the three phases (Equation 6.11) which was calculated to be 23 kW. The
CT increased from 23 kW in a loop (Equation 6.12) by adj each iteration until the amount of energy that is required to charge the battery bank from SoC_s to TC was available. The final CT was calculated to be 45 kW. The area between the LPf and the final CT is not completely allocated to charging due to the rate of charging is constrained by CR and iCR. The difference between CT and the other phases' LPf is less than the phase presented, therefore less energy is used to charge the battery bank from the other two phases.

![Load profile forecast (LPf)](image)

**Figure 6—7 Valley fill charge routine**

### 6.4.4.4 Peak reduction routine

When \( t \) is such that \( LP_{ft,t} > DT_{i,t} \), the peak reduction routine commences. This routine constrains the initial peak discharge schedule according to the available BES resources. The first step involves identifying how much energy is available for discharging:

\[
e_a = \begin{cases} 
  SoC_{s,t-1} - DoD, & \text{if } SoC_{s,t-1} > DoD \\
  0, & \text{if } SoC_{s,t-1} \leq DoD 
\end{cases}
\]  

(6.14)

where \( e_a \) is the available energy. The next step is to identify start and finish elements (i.e. \( se \) and \( fe \)) of the peak discharge schedule. \( se \) equals \( t \) when \( t \) is such that \( LP_{ft,t} > DT_{i,t} \). \( fe \) is calculated by Equations 6.15 and 6.16:

\[
fe = \max(t), \quad \text{for } t \ni (LP_{ft,t} > DT_{i,t}) \land (1 \leq i \leq 3)
\]  

(6.15)

where

\[
se > t \leq edp
\]  

(6.16)
where \( edp \) is the end of the discharge period. Identifying the peak discharge period allows for the calculation of how much energy is required to achieve the initial schedule:

\[
e_r = \sum_{t=se}^{fe} \sum_{i=1}^{3} sched_{i,t}
\]

where \( e_r \) is the energy required. If \( e_a \geq e_r \) no further actions are required, else an iterative \( DT_{i,se\rightarrow fe} \) adjustment process as described in Equations 6.18 and 6.19 should be applied to increase \( DT_{i,t} \):

\[
DT_{i,se\rightarrow fe,l-1} = \min(DT_{i,se\rightarrow fe}), \quad \text{for } 1 \leq i \leq 3
\]

\[
DT_{i,se\rightarrow fe,l} = DT_{i,se\rightarrow fe,l-1} + adj, \quad \text{while } e_r > e_a
\]

\( sched_{i,t} \) is updated according to Equation 6.20 and then \( e_r \) is updated according to Equation 6.17.

\[
sched_{i,se\rightarrow fe} = \begin{cases} 
-(LPf_{i,se\rightarrow fe} - DT_{i,se\rightarrow fe,l}), & \text{if } (LPf_{i,se\rightarrow fe} - DT_{i,se\rightarrow fe,l}) > 0 \\
0, & \text{if } (LPf_{i,se\rightarrow fe} - DT_{i,se\rightarrow fe,l}) < 0
\end{cases}
\]

Similar to the valley fill charging routine, by increasing \( DT_{i,t} \) the peak reduction routine also achieves load balancing by discharging more energy to the phase with the highest load and less to the phase with the least load.

Figure 6—8 depicts the peak reduction routine for an EP period over a particular phase's \( LPf \). It is assumed that the \( LPf \) for the other two phases are less than the presented \( LPf \). In this circumstance there is an insufficient SoC for the peak to be reduced according to the initial schedule. The discharge period starts at \( se \) and finished at \( fe \). The routine sets each \( DT_{i} \) to the minimum of the set (Equation 6.18). The \( DT_{i} \) for each phase increases in a loop (Equation 6.19) until the amount of energy required to reduce the peak to \( DT_{i} \) (Equation 6.17) equal the energy available in the battery bank (Equation 6.14). The difference between \( DT_{i} \) and the peaks of the other two phases are less than the presented phase. In turn, the energy allocated to reduce the peaks of the other two phases is less than the presented.
6.4.5 Real time operator

6.4.5.1 Overview

There are two types of scheduling system failure that are resultant from the inherent error associated with forecasting volatile LV networks. The first type relates to calculated schedules not aligning well with the load experienced in the network. The second type stems from the BES resources being prematurely depleted during the peak period, resulting in a sudden load spike. The primary function of the RTO is to analyse the network’s load in real time, compare it against the expert system forecast and engage in remedial measures to prevent these two failure types from occurring. The secondary function is to load balance the network under battery bank charging. The RTO has no prior knowledge of the future other than what forecasts provide.

The RTO first receives historical load \( L \), SoC, \( sched_i \), and \( DT_i \) information from previous stages in the scheduling system. In accordance with Figure 6—9, the RTO engages in \( DT \) adjustment, forecasts load for the current time interval, creates charging and discharging routines and dispatches the current time intervals schedule to the inverters and battery bank.
6.4.5.2 Discharge target adjustments

The increase or decrease of $DT_{i,t}$ directly controls how much the BES system discharges into the network. As $DT_{i,t}$ increases, the amount of discharge decreases. Conversely, as $DT_{i,t}$ increases, the amount of discharge decreases. Through adjustments of $DT_{i,t}$ and then $sched_{i,t}$, the resource depletion failure state can be avoided.

Information to base the adjustments is generated from the comparison between the rate of energy use anticipated by the scheduler recorded in $SoC_s$ and the real rate of energy use recorded in $SoC$. Figure 6—10 highlights the local gradients for $SoC_s$ and $SoC$ are calculated and defined as $m_s$ and $m_r$ respectively. If $abs(m_r) > abs(m_s)$ then the rate of energy use is not in accordance with the scheduler’s estimation. If the rate of energy use continues at $m_r$, there could potentially be a failure. The point when the scheduler estimates that the discharging period is over is defined as $min_s$.
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The point when SoC will equal DoD at current \( m_r \) is calculated by Equation 6.21:

\[
\min_r = \frac{\text{SoC}_{s,t-1} - \text{DoD}}{\text{abs}(m_r)}
\]  

(6.21)

Increases to \( DT_{t,i} \) are calculated according to Equations 6.22 to 6.25:

\[
a_1 = \begin{cases} 
\frac{\text{abs}(m_r) - \text{abs}(m_s)}{y - t + 1}, & \text{if abs}(m_r) > \text{abs}(m_s) \\
0, & \text{if abs}(m_r) \leq \text{abs}(m_s)
\end{cases}
\]

(6.22)

\[
a_2 = \left( \frac{\text{SoC}_{s,t-1} - \text{SoC}_{t-1}}{y - t + 1} \times \frac{1 - \text{SoC}_{t-1} - \text{DoD}}{TC} \right),
\]

if \( \text{SoC}_{t-1} < \text{SoC}_{s,t-1} \)

(6.23)

\[ DT_{t,i \rightarrow y} = a_1 + a_2 \]

(6.24)

where

\[ y = \begin{cases} 
\omega, & \text{if EP} \\
\frac{\omega}{2}, & \text{if MP}
\end{cases}
\]

(6.25)

where \( a_1 \) is the increase due to the real rate of energy use being greater than the estimated, \( a_2 \) is the increase due to there being less energy available at time \( t \) than what was estimated, \( y \) is the specific EP or MP time period and \( \omega \) is the number of time intervals in a day. In this case there are 144 10-minute intervals in a day. \( DT_{t,i} \) is adjusted from time \( t \) to the end of the period \( fe \).

Since load in the LV distribution network is highly variable, decreases to \( DT_{t,i} \) may be required to maximise peak reduction. Decreases to \( DT_{t,i} \) are conducted according to Equations 6.26 to 6.28:

\[
b_1 = \begin{cases} 
\frac{\text{abs}(m_r) - \text{abs}(m_s)}{y - t + 1}, & \text{if (abs}(m_r) < \text{abs}(m_s)) \land (\min_r > \min_s) \\
0, & \text{if abs}(m_r) \geq \text{abs}(m_s)
\end{cases}
\]

(6.26)

\[
b_2 = \left( \frac{\text{SoC}_{s,t-1} - \text{SoC}_{t-1}}{y - t + 1} \times \frac{\text{SoC}_{s,t-1} - \text{DoD}}{TC} \right),
\]

if \( \text{SoC}_{t-1} > \text{SoC}_{s,t-1} \) \land (\min_r > \min_s)

(6.27)

\[ DT_{t,i \rightarrow y} = b_1 + b_2 \]

(6.28)

where \( b_1 \) is the decrease due to the real rate of energy use being less than the estimated, \( b_2 \) is the decrease due to there being more energy available at time \( t \) and \( y \) is calculated by Equation 6.25. Both \( b_1 \) and \( b_2 \) are negative values or equal to zero. The recalculation of \( sched_{i,t} \) in response to \( DT_{t,i} \) adjustment is conducted using Equation 6.35.
6.4.5.3 Load forecast

The load on each phase is forecasted for the current time interval. This enables the best schedule for the current time interval to be calculated. Each phase has its own forecast model. The coefficients of the models are calculated using historical load data of the particular phase and regression. The general forecast model is described by Equation 29:

\[ L_f = \beta_1 L_{t-1} + \beta_2 L_{t-2} + \beta_3 L_{t-day} + \beta_4 L_{t-7\times day} + \beta_5 L_{t-14\times day} + \varepsilon \]  

(6.29)

where \( L_f \) is the load forecast for time \( t \), \( L \) is the historical load, \( \beta \) terms are model coefficients and \( \varepsilon \) is the model’s error term. Half of the historical load dataset was used for coefficient estimation and the other half was used for validation. Each phase’s validation \( R^2 \) equalled 0.99 and mean absolute percentage error equalled one per cent. The models had slight positive autocorrelation in the error terms entailing that if iterative forecasts were made, forecasts further from \( t \) will significantly deviate from the load that will occur.

6.4.5.4 Battery charging and discharging routines

To ensure that load balancing is maintained, the \( L_f \) for the current time interval \( t \) is used to evaluate the magnitude of the loads across the phases and a single time interval version to the scheduler’s valley fill charging routine is engaged. The initial schedule \( sched_{i,t} \) provided by the scheduler dictates the amount of energy that is required to charge the battery bank at the current \( t \) for each \( i \). Thus the first step in the process is calculating the required energy which is the aggregate of \( sched_{i,t} \) for the current \( t \):

\[ e_r = \sum_{i=1}^{3} sched_{i,t} \]  

(6.30)

The minimum value of the three load forecasts is set as the initial \( CT \). Through an iterative process (Equations 6.31 to 6.34), \( CT \) is increased according to an \( adj \) constant, and \( sched_{i,t} \) and \( e_a \) are calculated according to the new \( CT \):

\[ CT_i = \min(L_f_{1-3,t}) \]  

(6.31)

\[ CT_i = CT_{i-1} + adj, \quad \text{while } e_a < e_r \]  

(6.32)

\[ sched_{i,t} = \begin{cases} 
CT_i - Lf_{i,t}, & \text{if } ((CT_i - Lf_{i,t}) \leq iCR) \land ((CT_i - Lf_{i,t}) \geq 0) \\
iCR, & \text{if } (CT_i - Lf_{i,t}) > iCR \\
0, & \text{if } (CT_i - Lf_{i,t}) < 0 
\end{cases} \]  

(6.33)

and
\[ e_a = \sum_{i=1}^{3} sched_{i,t} \]  

(6.34)

The discharge schedule is updated in real time to mitigate misalignments between the \( LPf_i \) and actual load in the network and is must be updated in response to \( DT_{i,t} \) adjustments. The battery discharging routine commences for the current \( t \) when \( Lf_{i,t} > DT_{i,t} \) and calculates a new \( sched_{i,t} \) using a single time interval version of Equation 6.6. The new discharge schedule is calculated in Equation 6.35:

\[
sched_{i,t} = \begin{cases} 
-Lf_{i,t} - Dt_{i,t}, & \text{if } (Lf_{i,t} - Dt_{i,t}) \leq iDr \\
-iDr, & \text{if } (Lf_{i,t} - Dt_{i,t}) > iDr 
\end{cases} 
\]  

(6.35)

6.5 Results

6.5.1 Scheduler

A BES system with a \( C \) of 100 kilowatt hours (kWh), \( TC \) of 90 per cent (90 kWh), \( DoD \) of 20 per cent (20 kWh), \( DR \) of 40 kilowatt (kW), \( CR \) of 15 kW, \( iDR \) of 15 kW, \( iCR \) of 6 kW, \( BE \) of 97 per cent and \( IE \) of 97 per cent was applied in the SEQ LV network previously described. An initial SoC \( s \) was selected to be 50 kWh. The expert system provided three days (72 hours) of consecutive \( LPf \) for each phase. As previously noted, the training accuracy of the expert system is terms of \( R^2 \) ranged from 0.86 to 0.87 and the validation accuracy ranged from 0.81 to 0.84.

Figure 6—11 contains the results of the scheduler for each phase and the estimated SoC \( s \) for the duration of the three-day forecast period. The \( sched_i \) for each phase is displayed through the results of simulating the dispatch of the schedule for the BES system. When the system is charging, the schedule dispatch is greater than the forecast. When the system is discharging over the peak period, the schedule dispatch is less than the forecast. The magnitude of the load during the peak period of the forecast with the dispatched schedule applied is indicative of the \( DT \) for the period. Charging specifically occurs in the valleys and discharging specifically occurs during the peak period. The SoC \( s \) is maintained between the \( DoD \) and \( TC \) throughout the period. The SoC \( s \) decreases as the system is discharging and increases as the system is charging.

For the first period when charging commences, it can be seen that the scheduler sets the BES system to charge more from the phase that is estimated to have the least load (phase 3) and least from the phase estimated to have to the highest load (phase 1). Similar to the first charge period, the first discharge period indicates that more energy is allocated to the phase that is anticipated to have the highest load (phase 1) and least amount of energy is
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allocated to the phase that is anticipated to have the least load (phase 2). These results display that the scheduler attempts to achieve the secondary objective of load balancing.

Figure 6—11 Scheduler results

6.5.2 Real time operator

Using the same BES system properties and initial SoC of 20 kWh, Figure 6—12 illustrates the difference between the dispatch of the schedule with and without the utilisation of the RTO adjustments. Figure 6—12a highlights the BES resource depletion failure state. Without the RTO, the BES did not have enough capacity to continuously discharge throughout the entire peak period leading to a sharp increase in load on the network measured at the LV transformer. Figure 6—12b illustrates how the RTO module of the scheduling system overcomes the limitations of the scheduling forecasts. At the 20th hour mark, the RTO anticipates that there will not be a sufficient amount of energy available if it continues to follow the initial dispatch schedule. As a result, it increases the DT and the schedule is recalculated. At the 21st hour mark, the RTO temporarily decreases DT.

Figure 6—12 Scheduler results

6.5.2 Real time operator

Using the same BES system properties and initial SoC of 20 kWh, Figure 6—12 illustrates the difference between the dispatch of the schedule with and without the utilisation of the RTO adjustments. Figure 6—12a highlights the BES resource depletion failure state. Without the RTO, the BES did not have enough capacity to continuously discharge throughout the entire peak period leading to a sharp increase in load on the network measured at the LV transformer. Figure 6—12b illustrates how the RTO module of the scheduling system overcomes the limitations of the scheduling forecasts. At the 20th hour mark, the RTO anticipates that there will not be a sufficient amount of energy available if it continues to follow the initial dispatch schedule. As a result, it increases the DT and the schedule is recalculated. At the 21st hour mark, the RTO temporarily decreases DT.
To simulate the scheduling software analogous to real world conditions, the software was provided with unfiltered load data and imperfect forecasts. The results of the simulation for a 72-hour period are displayed in Figure 6—13. This figure shows a comparison between the original load and the results of the scheduling system dispatching charging and discharging schedules to the BES system for each phase. The SoC was recorded through the period and did not breach the TC and DoD limits. In comparison to the LPf, the load observed in the network exhibits a greater degree of variability as seen by the occurrence of double peaks within a peak demand period. From the results, the scheduling system was able to reduce peak demand across each phase and charge the battery bank during valleys. The scheduling system achieved its secondary objective of load balancing.
For the second day of the simulation period, more energy was allocated to phases 1 and 2, which had higher loads than phase 3. During the demand valleys, phases with lower loads were charged more than phases with higher loads.

6.5.3 BES capacity sizing method for LV networks

The developed scheduler module of the scheduling system also provides the architecture for a tool that can be used for optimally sizing BES in LV networks. This can be achieved by inputting a particular LV networks historical load data into the scheduling system as well as the simulated BES specifications (i.e. C, TC, DoD, CR, DR, etc.). The user can consider a range of commercially available BES and their particular specifications or alternatively use an optimisation routine (e.g. particle swarm, gradient-decent, Lagrangian, etc.) to identify a BES system to achieve specific valley fill and peak reduction objectives. The estimated goal performance (e.g. peak demand reduction, power quality improvement, load balancing, better solar PV utilisation, etc) for a simulated BES system can then also be used as empirical evidence for undertaking cost-benefit assessments. Such empirical evidence is important for electricity distribution utilities seeking to formulate sound business cases for installing BES in LV networks.

An example of the use of the scheduler for BES sizing is displayed in Figure 6—14. This example uses the same system parameters as the system used to demonstrate the results of the scheduler. C is altered to find the optimal size to achieve maximum peak reduction given the other system parameters and each simulation is run for a period of 200 days.
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The results for each phase of the simulations are presented in terms of mean daily peak reduction and the mean amount of energy allocated to reduce the peak.

![Graphs showing peak reduction and energy allocation](image)

Figure 6—14 Sizing battery energy storage system

When the capacity of the BES system is relatively low, the scheduler is less able to reduce the peaks. Phases 1 and 3 had the greater peak reductions than phase 2 by 6 to 7 kW. As a corollary, phases 1 and 3 were allocated a greater amount of energy to reduce the peaks. The reason for this is that phases 1 and 3 experiences higher loads than phase 2. The scheduler is better able to reduce the peaks as the capacity of the BES system increases. Phase 2 has the highest incremental gain in peak reduction. The incremental gains for phases 1 and 3 are curtailed after the BES system capacity reaches 100 kWh. After 100 kWh, the incremental gains continue for phase 2 until 175 kWh. At this point, additional investment in BES system capacity would not have a substantial effect on peak reduction. While a full life cycle cost-benefit assessment (outside scope of current paper) would precisely define the optimal BES sizing for this particular SEQ LV network examined, Figure 6—14 indicates that a 100 kWh capacity would likely be optimal.

6.6 Conclusion and future work

This research proposed a forecast and heuristic based three-phase BES scheduling system for the LV distribution network. The primary goal of the scheduling system was to charge the BES during periods of low demand and discharge during periods of high demand: peak shaving and valley filling. The secondary objective was to balance the load across the three phases. The scheduling system is composed of three main components: an expert system, a scheduler and a RTO. The expert system is used to produce load profile forecasts. The
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The scheduler receives the load profile forecast and creates an initial schedule. The RTO, which analyses recent historical load data against the scheduler’s output, engages in remedial measures if required. The RTO is primarily required to mitigate errors caused by the imperfect forecasted load profiles.

When implementing a BES system with particular specifications in the case study SEQ LV network, the developed scheduler was able to take the forecasted load profiles and produce a charging and discharging schedule. It was observed that the scheduler was able to set the schedule to charge during periods of low demand and discharge period peak demand periods while achieving its secondary objectives of balancing the load. Results display that more energy was charged from the phase with the least load and discharged to the phase with the highest load.

To achieve the primary and secondary goals in real time, for each time interval the RTO adjusts the schedule to mitigate initial scheduling error. The RTO does this by increasing or decreasing the amount of energy that is discharged based on discrepancies between the estimated SoC and the actual SoC. When the real rate of energy use is greater than the rate estimated by the scheduler, the RTO decreases rate of discharge. The RTO may correct the adjustment if the real rate of energy usage becomes less than the estimated rate. The RTO ensures load balancing during charging periods by redistributing the amount of energy that the battery bank is scheduled to be charged by to the least loaded phases. The results from operating the scheduling system in real time displayed, like the scheduler, the system was able to reduce peak demand, charge during low demand periods and balance phases. More energy was allocated to reduce the peaks of high loaded phases and the least loaded phases were charged from more.

The scheduler component was able to be repurposed and used to size BES systems in a particular LV network to achieve a set of desired goals (e.g. certain peak demand reduction) or gauge a particular system’s performance. To demonstrate this, simulations were run using the scheduler’s routines with different battery bank capacities. The peak demand reduction performance increased as the capacity of the battery bank increased. Performance gains started to decreased after 100 kWh and were hampered after 175 kWh. This indicated for the specific BES system, the capacity that was most likely to be optimal was 100 kWh.

In summary, the scheduling system was able to achieve its desired purpose and there are avenues for the development of BES system sizing applications. Future work on this research and development project involves three main stages. The first stage is to further improve the LV distribution network forecast accuracy. The second stage involves coding and installing scheduling firmware into an innovative three-phase LV network STATCOM
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(static synchronous compensator) with integrated BES that has recently been developed by one of the industry partners. The third stage is to implement and test the intelligent STATCOM with integrated BES in a trial LV network located in SEQ, Australia.

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CHAPTER 7

Conclusion

7.1 Research objectives and outcomes

7.1.1 Summary
A significant amount of resources have been allocated to the promotion of the installation of solar rooftop PV, particularly in residential LV distribution networks. The behaviour of residential load curves is such that the majority of electricity is usually consumed during the morning and evenings. In summer, peak demand occurs in the evenings and in winter there is an additional peak of similar magnitude which occurs in the morning. The solar PV generation curve is based on the inclination of solar irradiance. Solar PV generation increases during the morning, peaks during the middle of the day and decreases in the afternoon. The difference between the behaviour of residential loads and the solar PV generation curve entails that solar PV is generating during periods of low demand for electricity. This distributed PV generation and demand mismatch means that there is currently a poor utilization of solar PV resources. In some cases, excess solar PV generation can lead to power quality issues such as overvoltage which has the potential to damage electrical appliances and power electronics. Excessive solar PV capacity in a particular residential LV network can also exacerbate power quality issues related to unbalanced network phases. In some circumstances, the addition of distributed renewable generation sources has actually necessitated costly upgrades to the electricity network.

For the electricity generation and supply system to operate efficiently, the system’s infrastructure must be designed to meet the peak demand in the network. This characteristic of the electricity network means that a large proportion of the network’s infrastructure is underutilized for majority of the time. An increase in demand in the electricity network may trigger costly augmentations for the period that the additional capacity will be in use. The residential LV distribution network is characterised by high variability in load, occurrences of random shocks and unbalanced phases. Unbalanced phases in the electricity network contribute to power quality issues such as overvoltage.
Chapter 7 – Conclusion

and voltage spikes. Severely unbalanced networks may require an increase in the network's capacity or the manual rebalancing of the network at significant costs.

This research set out to provide a technological mitigation solution through the development of a three phase BES scheduling system for the residential LV distribution network. The scheduling system applies to a three phase BES system connected to the network operator’s side of the electricity network. The BES system comprises a battery bank and three inverters in parallel on a DC circuit, and each inverter synchronising with an independent phase of the electricity network. The operational goals of the scheduling system include:

1. Peak shave and valley fill: discharge the battery bank during peak demand periods and charge the battery bank during low demand periods;
2. Load balance through charging and discharging operations; and
3. Exploit pre-existing solar PV generation in the electricity network.

Benefits of the system may be derived from:

1. Reductions in peak demand and the associated deferrals in costly network infrastructure augmentations;
2. Load balancing which also enables load to be reduced from the phase contributing to peak demand and also mitigates power quality issues; and
3. Through better utilization of solar PV generation, overvoltage can be avoided and additional value can be yielded from rooftop solar PV installations.

The scheduling system comprises two main components. The first component is a scheduler that produces an initial schedule based on information that yields inferences about futures load states. The second component is an outline system (i.e. the RTO) that analyses load in real time in conjunction with the initial schedule, makes adjustments if necessary to mitigate scheduling error and dispatches the schedule. The development of the scheduling system was conducted according to four main objectives. The first two objectives pertained to creating the systems to forecast future load states. The third and fourth objectives involved developing the scheduler and the RTO. The objectives were as follows:

1. The creation of EP, TEU and MP load profile property forecast models. The EP, MP and TEU forecasts are used as input variables in the pattern recognition based expert system for identification of load profiles that are most likely going to occur.
2. The development of the pattern recognition based expert system. The purpose of the expert system is to forecast load profiles that are most likely going to occur in the future based on a set of input variables.
3. The writing of the scheduler algorithm. The schedule receives the load profile forecasts and calculates an initial charge and discharge schedule.

4. The writing of the RTO algorithm. The RTO analyses load in real time, makes adjustments to the schedule if required, and dispatches the schedule.

7.1.2 Load profile property forecast models

The purpose of constructing the EP, MP and TEU load profile forecast models was to provide information about future load profiles in a reduced form. Each property reflected a different aspect of the future load profile allowing for inferences to be made about what type of load profile that is most likely to occur. The forecast models were designed according to the ARIMAX (i.e. the combination of the ARIMA model and external variables) modelling method. The modelling method was selected due to the load profile properties being correlated with external variables such as temperature, humidity and the day of the week and lags of the property being forecast.

Chapter 4 contained the detailed method consisting of a number of stages for constructing the forecast models and presented the NDPD and NDTEU models for each phase. Chapter 5 presented the NDMP model for each phase. The first stage was identifying relationships between the load profile properties and external variables. Identified variables were used in the forecast models and formed a basis for further investigations for variable inclusion in the pattern recognition based expert system. The second stage involved using a stepwise regression approach to select the most significant variables to be used. The third stage involved analysing the performance of the forecast models. The forecast models were developed through the NN methodology to compare the performance of the ARIMAX method.

It was observed that the EP, MP and TEU variables had a parabolic response to temperature. The magnitudes of the variables increase during period of high temperature and increase during periods of low temperature. Temperature alone explained at least half of the observed trends in EP, MP and TEU. Variables that played minor roles included humidity, day of the week, autoregressive terms and the local mean forecast through DES. Out of the set of models the NDTEU models had the highest accuracy with $R^2$ ranging from 0.77 to 0.87 for the hindcasts and 0.74 to 0.80 for the forecasts. The NDPD models had the middle range accuracy with hindcast $R^2$ ranging from 0.70 to 0.72 and forecasts $R^2$ ranging from 0.56 to 0.65. The NDMP models had the highest degree accuracy variability with hindcast $R^2$ ranging from 0.60 to 0.80 and forecast $R^2$ ranging from 0.44 to 0.75. The difference between the accuracy statistics between the NDTEU models and the NDPD and NDMP models was due to the EP and MP time series being more variable and volatile in
nature than the TEU time series. The NN models performed similarly to the ARIMAX models.

Significant discrepancies between the forecasts and the time series were observed on days containing exogenous shocks. These days included the Queen’s Diamond Jubilee public holiday, a period of prolonged rainfall and high maximum daily temperatures. Model error was compared against maximum daily temperatures. It was observed that there was no trend in model error against maximum daily temperature. For the models’ accuracy statistics to be improved, more load data is required to capture potential yearly seasonality and identify additional variable to explain the variability in demand.

The NDPD and NDMP forecast models may be improved by pre-processing the EP and MP time series. Pre-processing may include filtering the time series to identify the underlying trends and remove the stochastic load movements. This will result in NDPD and NDMP forecast models that forecast the local mean of the EP and MP rather than the absolute value.

7.1.3 Pattern recognition based expert system
For the scheduler to produce an initial schedule, information about the future was required. Load profile forecasts were selected because the forecasts will provide more precise information about the magnitude, time of occurrence and duration of both peak demand periods and low load periods than what price based scheduling can provide. This enables the peaks to be more efficiently reduced and load balancing functions to be facilitated. The pattern recognition based expert system was selected to forecast load profiles. The reason for this was due the variable nature of load in the residential LV distribution network, which exhibits weak seasonalities due to the influence of external variables and random shocks (i.e. one-off events). Time series techniques based on iterative forecasting are susceptible to propagating forecast error due to the influences stochastic deviations from the underlying trend and the alteration of the underlying trend due to changes in external variables. The expert system identifies reoccurring load profile patterns, associates these patterns with external variables and forecasts load profiles based on input variables that are associated with one of the reoccurring patterns. Chapter 5 is substantiated by the development of the expert system.

The expert system is composed of a correlation clustering algorithm, a discrete classification NN and post-processing routines. The correlation clustering algorithm was selected for its ability to cluster similar load profiles (i.e. peak and valley at the same time). Each load profile has a day where it was recorded from and each day has a set of recorded variables such as weather, EP, MP, TEU and day of the week. These sets of variables are
then associated with a cluster according to where each associated day’s load profile was classified under. The means of the clusters formed the underlying repeating patterns. The discrete classification NN was trained using the back propagation algorithm. The input variables consisted of the set of recorded variables and the output variables consisted of the cluster numbers. The first output neuron corresponded to the first cluster and the \(n^{th}\) output neuron corresponded to the \(n^{th}\) cluster. The output neuron values ranged from zero to one entailing the likelihood that the set of input variables are associated with a cluster. The output neuron with the highest value denotes the cluster that the set of variables are associated with. The mean of the selected cluster is used as the load profile. Load profile forecasts are made by using NDPD, NDMP and NDTEU models’ forecasts as input variables instead of EP, MP and TEU load properties. The forecast load profile is then adjusted to match NDPD, NDMP and NDTEU forecasts to improve load profile forecast accuracy.

For each phase, three initial clusters were identified and then separated into nine clusters based on magnitude. Temperature, humidity, day of the week variables, and NDPD, NDMP and NDTEU forecasts were used as input variables in the NN. The ability for the NN to classify correctly was conveyed by two statistics: correct classifications in a cluster and incorrect classifications in a cluster. A correct classification means that a set of input variables related to a load profile has been correctly classified in the same cluster the load profile was classified. An incorrect classification means that sets of variables were incorrectly classified under a cluster. Across each phase the correct classification accuracy ranged from 70.66% to 77.98% and incorrect clustering accuracy ranged from 4.69% to 6.04%. It was observed that when an incorrect classification was made the set of input variables were classified under a cluster that is most similar to the correct classification. After post-processing mitigated incorrect classifications, the hindcast accuracy \(R^2\) ranged from 0.86 to 0.87 and the forecast accuracy \(R^2\) ranged from 0.81 to 0.84. The expert system’s ability to forecast was more accurate than the load profile property models. Treating each day as independent forecasts, \(R^2\) frequency distributions were constructed. Results indicated that for both hindcasts and forecasts the greater majority of days had an \(R^2\) statistic above 0.7.

Similar to the load profile property forecasts, the expert system’s load profile forecasts may be able to be improved by the use of filtered load time series data and the NDPD, NDMP and NDTEU models constructed using the filtered time series as input variables. This would result in forecasting the underlying trend in the data and would only useful in applications if the absolute value of the load is not required.
7.1.4 Scheduler

Chapter 6 contains the full development of the scheduler. The review of the literature displayed that the optimal scheduling of a BES system where the capacity of the battery bank was not a constraining was the peak of the peak demand period minus the output rating of the system. This allowed for a scheduling heuristic to be developed based on this principle as well as the goal to produce a scheduling algorithm that was not overly complex in design. The scheduling heuristic was used as a starting point for the scheduling algorithm. From there, the schedule was constrained according to the available battery energy resources.

The scheduler was designed to emulate the BES system; a battery bank and three inverters in parallel on a DC circuit. Each inverter is synchronised to a separate phase of the electricity network. The scheduler's algorithm is summarised as follows:

1. Receives load profile forecasts from the expert system.
2. Identifies significant peaks in the forecasts.
3. Runs scheduling heuristic to initialise the schedule and creates DT vectors.
4. If the load is less than the discharge and the battery bank's SoC is not equal to the TC, the system charges the battery bank.
5. If the battery bank's SoC equals the TC during the charging period, the scheduler runs the load balance charging routine. The battery bank is charged more from phases with lower loads and less from phases with higher loads.
6. If the load is above the DT, the system runs the peak reduction routine and checks if the SoC is sufficient to reduce the peaks according to the initialized schedule.
7. If the SoC is insufficient, load balancing through peak reduction is conducted. More energy is discharged to phases of higher loads and less to phases of lower loads.
8. The schedule, DT vectors and simulated SoC (SoCs) are dispatched to the RTO.

The schedule was observed to be able to fulfil its operational objectives such as peak shaving and valley filling and load balancing. The scheduler was able to be retooled to size BES systems based on historical load data. As an example, for a given set of BES system parameters, the capacity of the battery bank was increased and the performance of the peak reduction analysed. For this scenario it was observed that the benefit derived from increasing the capacity of the battery bank started to decrease at 100 kWh.

7.1.5 Real time operator

The main purpose of the RTO is to mitigate scheduling error caused by imperfect load profile forecasts. There were two types of errors that can occur. The first type of error is caused by a temporal mismatch between the load profile forecast and the actual load. The
second type of error is a depletion of the BES resources during the peak demand period leading to an increase in load measured at the transformer. The occurrence of either type of error negates the potential benefits of installing BES systems.

It was devised that short-term load profile forecasts and the adjustment of the $DT$ vectors can be used to prevent both type of error from occurring. The short-term load forecasts models (one for each phase) were developed according to the ARIMA method. In the near short-term timeframe, the change in electricity load is not correlated with external variables. The RTO algorithm is summarised as follows:

1. At the start of the day the RTO receives the initial schedule, $DT$ vectors and $SoC_s$.
2. At the beginning of each time interval the RTO receives historical load data and adjusts the $DT$ vectors according to the difference between the $SoC_s$ and the real $SoC$.
3. For each time interval the RTO forecasts the time interval’s load for each phase.
4. If the forecasted load is greater than the $DT$, the peak reduction routine is run.
5. If the forecasted load is less than the $DT$, the charging routine is run.
6. The RTO dispatches the schedule for the current time interval to the BES system.

The $DT$ is increased across the peak demand period if the real rate of energy use is greater than the simulated rate of energy use. The $DT$ is decreased across the peak demand period if the real rate of energy use is less than the simulated rate of energy use. The rates of energy use are calculated from the local $SoC_s$ and $SoC$.

The forecast of the load for the current time interval allows for the recalculation of the schedule in response to $DT$ adjustments. If the forecasted load is greater than the $DT$, the new schedule for the current time interval is the difference between the forecasted load and the $DT$. If the forecasted load is less than the $DT$ and the schedule is set to charge, the distribution of charging across the three phases is recalculated to ensure load balance charging.

The scheduling system was tested by simulating its operation in the electricity grid. For the simulation to be more representative of real world conditions, imperfect forecast models were used to forecast future load states. The results displayed that the system was able to achieve the desired objectives. The system was able to:

1. Peak shave and valley fill;
2. Load balance through charging and discharging operations; and
3. Charge during periods when solar PV is generating.

The performance of the scheduling system is limited by forecast accuracy and calibration. If the accuracy of the forecasts could be improved, system performance will also improve.
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This may be achieved by incorporating previous listed suggestions such as running a different type of filtering on the load time series. This will be permissible because the underlying trend of the load time series is more important than absolute values. There are a number of constants applied to equations in the DT adjustment phase of the RTO. More advanced calibration of these constants to achieve maximum performance will help to further mitigate scheduling error.

7.2 Study contributions

The literature covering the topic of LV distribution network forecast modelling is sparse. At present, the majority of research publications in this field of study are focused on forecasting models that are useful for sections of the electricity network that service greater numbers of customers (i.e. high voltage network). However, with the widespread advent of distributed small and medium scale grid-tied renewable generation sources, there is critical need to better understand the load characteristics of LV networks. This research highlights the variables that influence LV network demand and then develops EP, MP and TEU forecast models using the ARIMA and NN methods to compare model performance. The ARIMAX and NN models had a similar level of accuracy and the models weren't able to fully reproduce or forecast observations. This highlights the issue that that there are more external influences to be investigated to account for the high degree of variability and achieve better model performance. Events such as popular television shows and sports may have a significant influence and are still to be investigated; such events concentrate people in their home and when combined with certain seasonal conditions (i.e. reasonably hot/humid day) can lead to peak demand periods.

The use of traditional modelling techniques displayed that they were not able to fully capture the high degree of variability inherent in the load time series when used to iteratively forecast load profiles. In response to this issue, a pattern recognition based approach that is less influenced by such high variability was developed. The development of the expert system displays how different types of pattern recognition techniques can be combined and applied to the load forecasting space. The expert system was shown to achieve accurate load profile forecasts. The forecasting techniques applied in the herein described expert system have great potential for a range of smart-grid and micro-grid technology applications since they can handle highly variable load conditions.

Through this research a complete scheduling system was developed and presented. The scheduling system integrated a forecasting component, a scheduler that uses load profile forecasts to calculate an initial schedule and an RTO that adjusts and dispatches the schedule in real time. The scheduler’s use of heuristics enabled the system to be relatively
less complex than scheduling approaches that rely on the optimisation of objective functions. This research advanced the real time dispatch of schedules by taking into account that schedules calculated by using imperfect load profile forecasts have errors. These errors were mitigated through operations conducted by the RTO. Forecasts for periods greater than 30 minutes ahead were found to be too inaccurate to provide useful information. In turn, the DT adjustment algorithm relying on positive and negative feedbacks was formed. The DT adjustment algorithm was shown to be able to adjust the DT such that the BES system was able to continuously discharge over the peak demand period removing the need for developing a new forecast algorithm. Due to the relative simplicity of this scheduling system it can easily be integrated into other systems and iterated upon to achieve additional objectives.

The scheduling system laid the groundwork for a system sizing algorithm. As an example, the scheduler was repurposed to find an efficient size for a battery bank for the test network. Historical load data was used as an input and the repurposed scheduler outputted estimated performance results for different BES system parameters. The depiction of the results was in terms of the capacity of the battery bank. As the capacity of the battery bank was increased, the amount of peak reduction also increased until an upper limit was reached due to the output rating of other parameters. The repurposed scheduler can be further developed into a system sizing algorithm to provide network operators with precise estimates of what performance can be achieved for a certain set of system parameters. Alternatively, the system can be given performance requirements and an optimisation routine can find a parameter set that will yield the desired performance. With known system parameters, imperative life cycle monetary cost-benefit analysis can also be completed in order to determine whether or not the installation of a BES system would be feasible.

### 7.3 Research limitations

The limitations of the research include:

- The scheduling system was designed for residential LV distribution networks. Due to this scope restraint for the PhD project, other types of electricity network subsections were not included in this research. While the described overarching modelling framework would apply to a range of network scenarios, without adaptation to these scenarios (e.g. commercial or industrial network) the current models would likely cause scheduling error to occur due to the different shapes of load curves.
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- The load data used to construct and test the scheduling system was from one subsection of the electricity network (i.e. 128 residential customer connection LV network for a Brisbane suburb supplied by Energex). The scheduling system should operate in the same manner when applied to similar networks. However, testing of the scheduling system with load data from a number of other networks is advised, as it will improve the adaptability and validity of the system.

- The scheduling system has not yet been integrated into a BES system (i.e. prototype development). In turn, real world testing of the system has not been performed. For a full product to be developed and brought to market, pilot projects and testing is required.

7.4 Future research

Through three comprehensive journal articles, this research has laid the groundwork for future research. This research can be advanced in the following areas:

1. Development of a calibration algorithm;
2. Integration of herein developed theory into a BES system for real world testing and prototyping;
3. Development of full BES system sizing algorithm;
4. Repurposing software for commercial subsections of the electricity network;
5. Incorporating EV supporting the grid technology;
6. Virtual power station; and
7. Control and simulation of grid support agents.

For the scheduling system to be easily applied to other residential LV distribution networks, a calibration algorithm is required. The purpose of the calibration tool is to autonomously adjust coefficients within the RTO portion of the scheduling software. The calibration algorithm will simulate the operation of the scheduling system using historical load data and imperfect load forecast over the same period. The algorithm will sample through a series of different coefficient magnitudes and record the simulation performance. The algorithm will then model the sample set against the performance output. Using interpolation the set of coefficients that would yield the best performance would be selected.

Gauging the actual performance in the electricity network is vital for identifying ways in which the scheduling system can be improved and bring the system to market. For this to occur, the scheduling system is required to be integrated into a BES system. This will require writing firmware, building the communication systems and external information management systems. Writing firmware involves converting the system from its current
format to the format required by the BES system’s microcontroller. For testing to take place the BES system and electricity network is required to be monitored and recorded data to be sent to the information management system. Properties of interest include SoC of the battery bank, calculated schedules and voltage, current and phase angle for each phase of the electricity network. The information management system is to be a sever in a remote location that receives recorded data, weather and weather forecasts and engages in training forecast models, forecasting load and calibrating scheduling system coefficients.

To allow network operators to extract the most utility out of a BES system sizing decision support system (DSS), it should have two operational states. The first state would be that network operators are able to input a desired performance requirement, known system parameters and historical load data and the system sizing algorithm will find a set of BES system parameters (e.g. capacity, efficiency ratings and inverter ratings) that would achieve the desired performance. The second operation state would be that network operators are able input constant system parameters and historical load data and the system will present estimated performances for different sets of BES system parameters.

Life cycle monetary cost-benefit analysis would need to be a core feature of a BES system sizing DSS as it would allow network operators to select the most efficient approach for augmenting the electricity network.

Many of the concepts used to develop the scheduling system can be applied to creating a scheduling system for commercial electricity networks. This requires analysing commercial load data and identifying key aspects of the load curve, such as the number of and the time of occurrence of peak demand periods. This allows:

1. TEU and peak demand forecast models to be developed;
2. The pattern recognition expert system to be trained for commercial network purposes; and
3. The scheduler redesigned to focus on the key load profile characteristics rather than the morning and evening peak demand periods.

With the commercial scheduling system developed, the calibration algorithm can be used to achieve the most efficient performance. The most notable difference between a residential and commercial network is that the peak demand period will most likely occur during the day rather than in the evening. In the current SEQ electricity pricing context, medium to large sized commercial businesses may have the most to benefit from installing an intelligent BES system as proposed herein, as peak demand charges can be a considerable portion of their electricity bill and can be reduced considerably by a relatively modest reduction in peak demand through using stored energy.
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EV supporting the grid may become a real possibility if this type of vehicle represents a considerable share of total vehicles in any developed country. Supporting the grid can include using the energy storage with EV battery banks to reduce peak demand. The scheduling of EV charging and discharging is more complex problem than for a static battery bank. In addition to the uncertainty about future load states, there will also be uncertainty regarding the amount of energy available to be discharged into the electricity network throughout the entire peak demand period due to owners being able to connect and disconnect their EV at their discretion. Forecast models will have to be specifically designed to handle this extreme uncertainty. It is postulated that a stochastic model that will provide both the magnitude of available energy storage and the probability of its availability would be a reasonable method. This allows for a range of scheduling scenarios to be calculated and throughout the peak demand period scenarios can swapped based on new load and energy storage availability information. EV supporting the grid through peak demand reduction may have to be complimented by a small static battery bank to provide additional power if energy resource availability diminished due to actions of EV owners.

The virtual power station concept is a natural extension of all previously mentioned future research topics. The virtual power station concept entails that throughout the distribution network there are many agents with different DER arrangements. Each of the agents would operate their DER independently from one another in order to achieve their own objectives such as demand management, peak shaving and valley filling, power quality correction, generation source or load sink. To achieve their objectives they would have a tailored control system. Above the agent level there would be a control system operated by the distribution network operator. The network operator's control system (NOCS) would act in a similar fashion to AEMO. Each agent would be able to sell or bid on contracts and the NOCS will match the contracts in the market. In the event contracts can’t be matched or additional actions are required such as power quality management, the NOCS will step in and order agents in the system to engage in remedial measures. Remedial measures may include disconnecting agents from the grid, direct agents to generate power or direct agents to increase their loads. To develop the virtual power station concept the following steps are required to be fulfilled:

1. The development of individual agent control systems and objectives;
2. The development of the NOCS; and
3. The creation of a framework to engage in agent based modelling.

To increase the robustness of the virtual power grid concept it will be important to model and develop control systems for grid support agents. Grid support agents will be actively involved in maintaining power quality. The control systems (e.g. voltage set point control
and frequency set point control) for grid support agents will operate on second to sub-second intervals. These agents could be composed of different energy storage devices (e.g. batteries, capacitors, compressed air, etc.), renewable energy generators (e.g. solar PV and wind) and power electronics (e.g. STATCOM or inverters). To determine whether or not the grid support agents will achieve their objects requires modelling the agents and simulating their operations in an electricity network (e.g. IEEE test feeder).

7.5 Conclusion

This research set out to develop a three phase BES scheduling system for the residential LV distribution network; its core purpose would be to reduce peak demand and mitigate power quality issues prevalent in the LV distribution network (e.g. unbalanced loads and high concentrations of solar PV generation). The primary goal of the system was to peak shave and valley fill and ancillary goals were to balance loads and charge the battery bank during period when solar PV is generating. It is posited that network operators may be able to avoid or defer costly network augmentations through the installation of the herein proposed intelligent BES system. The scheduling system is composed of a pattern recognition based expert system that forecasts load profiles, a scheduler that uses the forecasted load profile to produce an initial schedule and an RTO that operates the system in real time to mitigate scheduling error and dispatch the schedule to the BES system. This scheduling system is distinguished from similar research due to being relatively less complex through the reliance of heuristics to calculate an optimal schedule. The heuristics were based on observations about optimally calculated schedules published in the literature. Simulations applying the developed scheduling system yielded results that demonstrated that it was able to peak shave and valley fill, balance load and charge during periods when solar PV is generating.

The scheduling system was developed according to four objectives: the construction of next day EP, MP and TEU forecast models, the creation of a pattern recognition based expert system, the coding of the scheduler and the coding of the RTO. The first objective is contained in Chapter 4, the second objective in Chapter 5 and the third and fourth objectives in Chapter 6. Chapters 4 to 6 have been disseminated as peer-reviewed journal papers.

The groundwork has been laid for many avenues of future research to take place, including the creation of network calibration algorithms, BES system sizing DSS, BES system prototyping and real world testing, repurposing of the scheduling system for commercial networks and for EV supporting the grid.
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