University of Bristol

Faculty of Engineering

Design Project 4 - Final Report

Investigation of the Use Energy Storage Technologies to Reduce Peak Demand Charges for the University of Bristol

Supervisors: *Email:*

Dr Theo Tryfonas Theo.Tryfonas@bristol.ac.uk

Author: *Candidate Number:*

Alexander Charles (67634)

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Acknowledgements

A paragraph should be written in place of this text, acknowledging all persons who have helped or contributed towards your project. All formally allocated supervisors should be acknowledged first followed by other university staff, representatives of external companies and people not falling in those categories such as peers and PhD students. The acknowledgement should indicate the nature of the assistance received, for example "I acknowledge Paul Rowe of OnAxis Ltd for providing the linear motors used in section 4 and Dr Simon Richards for help in writing the source code for the controller."

Declaration

> *The accompanying research project report entitled: "Investigation of the Use Energy Storage Technologies to Reduce Peak Demand Charges for the University of Bristol" is submitted in the fourth year of study towards an application for the degree of Bachelor of Engineering in Engineering Design at the University of Bristol. The report is based upon independent work by the candidate. All contributions from others have been acknowledged above. The views expressed within the report are those of the author and not of the University of Bristol.*

I hereby declare that the above statements are true.

Signed (author)

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Full Name

Alexander Charles

Date

22nd March 2017

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List of Acronyms

ESS: Energy Storage System

DUoS: Energy Storage SystemDistribution Use of System

TNUoS: Transmission Network Use of System

SQP: Sequential Quadratic Programming

ROI: Return On Investment

VRB: Vanadium Redox Batteries

PHS: Pumped Hydroelectric Storage

CAES: Compressed Air Energy Storage

CES: Cryogenic Energy Storage

TES: Thermal Energy Storage

SMES: Superconducting Magnetic Energy Storages

1 Aims and Objectives

The announcement of the new £300million University of Bristol Campus in Temple Quarter [1], presents an exciting new opportunity for digital innovations in sustainable energy. The government's 2020 smart meter rollout, is the first step for creating a smart energy grid, key to achieving a low-carbon, sustainable and efficient energy for the UK [2]. The UK's vision corresponds to the University of Bristol's new strategy, seeking to boost its world-class research capacity and promote innovation in policy to increase sustainability [3]. The creation of a world-leading sustainable digital campus is an attractive means for the University to achieve its vision. Consequently, the aim of this group project is to bring a explore of new digital technologies reducing both energy costs and energy usage, uniting these themes to set a new frontier in campus's sustainability.

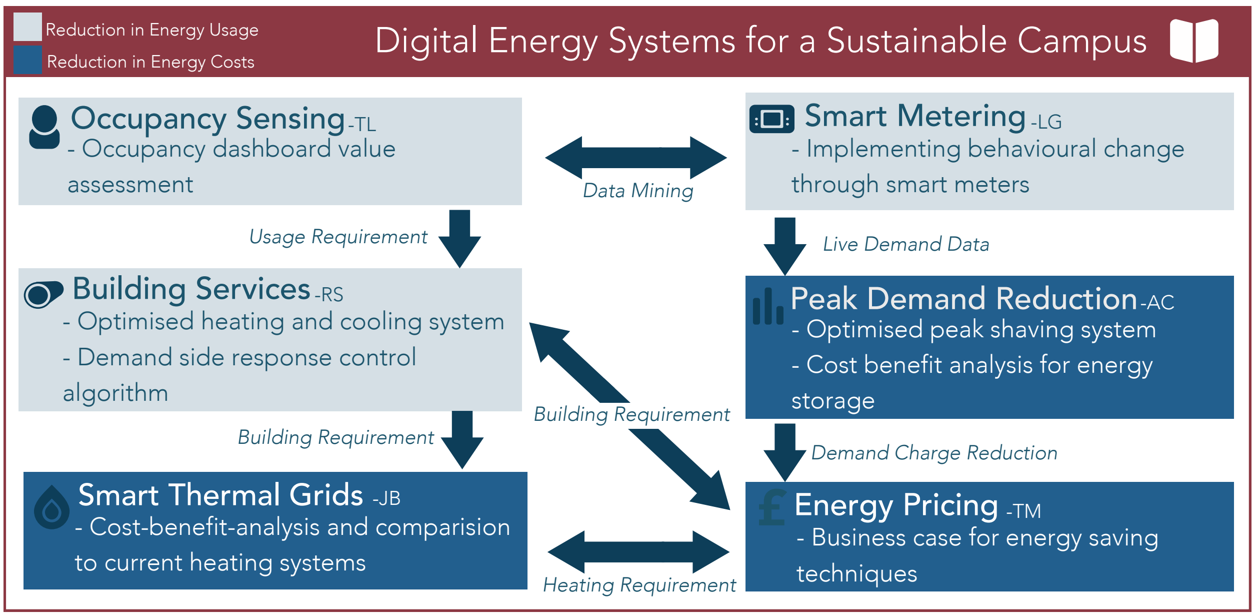

Figure 1.1: Group Design Project Diagram Showing Relationships Between Individual Projects

Figure 1.1 shows how the separate subjects of the project are split, where research in Occupancy Sensing, Smart Metering and Building Services will evaluate how energy usage in the new campus can be optimised. Smart Thermal Grid, Energy Pricing and Peak Demand Reduction, all analyse methods of reducing the University's energy costs. Where new energy pricing structures coupled with peak demand reduction technologies, can reduce the load on the grid, helping support sustainable energies. The 5th year group project will unite these themes, creating a smart ``brain'' through combining usage data with new technologies and strategies, providing a business case to develop sustainable energy services on the new campus, pushing the University to meet it's carbon neutral 2030 goal [3].

1.1 Individual Project Aim

The aim of this individual project is to investigate the feasibility of using an energy storage system (ESS) to reduce charges related to peak energy demand for the University of Bristol, implemented in the new Temple Quarter campus. Within the project, the University's peak demand charges will be analysed and simulated, modelling the bespoke energy requirements of the campus. Different peak-shaving system architectures will then be modelled against this usage and charge data, finding an optimum solution for the system's design concerning the system's capital cost against savings made from energy bills. This model will provide a comparison between using a decentralised system, for room by room use, or a centralised system, being applied to the whole building. The outputs of the project for 5th year will be a flexible model which produces an optimum peak-shaving system architecture for a given University scenario, providing a cost benefit analysis of using energy storage.

1.2 Objectives

Literature Review

1. Perform a detailed literature review, and market analysis of energy storage systems used to reduce peak energy demands, highlighting relevant modelling techniques and limitations.
2. Investigate different energy storage solutions, looking at their applicability to a University peak-shaving system, comparing parameters such as; power-ratings, discharge times, charge times and costs.

Definition of System Architectures

3. Define peak-shaving system architectures, establishing the key performance variables. This objective will include an investigation of peak demand sensing, smart metering usage, energy storage health monitoring, energy conversion, methods to split supply between an energy storage system and the mains and a comparison between decentralised and centralised energy storage models.

Modelling and Analysis

4. Analyse the University's current peak demand charges; understanding the University's current demand charge structure and collecting typical energy usage data. Parameters such as time of day and sources of energy peaks will be incorporated.
5. Produce a simulation to optimise the peak-shaving system, comparing metrics including; unit cost and reduction in peak kWh charges based on University billing structure. This model will provide a comparative analysis of the different system architectures. The model will detail savings against the University's current peak demand charges, being comprised of three stages:
   (a) A simulation of the University's a normal energy use case and peak demand charges, for use as a datum.
   (b) Inclusion of energy storage systems, simulating logic and detailing any prediction methods.
   (c) An assessment of the use of peak load shedding, supply levelling and forecasting to improve the performance of the model.

Evaluation

6. Evaluate results of the simulation, concluding on the effectiveness of different peak-shaving system architectures against particular scenarios. A cost-based analysis will be used to measure the feasibility of the different energy storage systems for the University.

2 Background and Summary of Key Work and References

The following literature review provides a comprehensive overview of current research towards using Energy Storage Systems (ESS) to reduce peaks in energy demand and lower utility costs for the consumer. Peak demand reduction is synonymous with peak shaving; the ability to control energy usage from a supplier during intervals of high demand, to limit or reduce demand charges [4], [5]. As this project is investigating reducing the peak demand charge for the University of Bristol, section 2.1, provides an overview of the University's energy bill, detailing which charges are effected by peak demand. Section 2.2 evaluates traditional methods of peak shaving, covering a brief look at ESSs current usage. Section 2.3 includes a broad range of research of ESSs in different case studies, optimising the system architecture and analysis on ESSs financial return on investment (ROI). This research will help in define system architectures for modelling. Finally section 2.4 analyses the applicability of different ESSs, down-selecting to leave a shortlist of ESSs to be modelled.

2.1 Peak Demand Charges

The University of Bristol's infrastructure, spans across three sites; the City Centre, Stoke Bishop and Langford. Across these locations, the majority of facilities receive separate energy bills, allowing a high degree of granularity in the understanding energy charges [6]. The University receives charges bundled together under four distinct themes [6], these have been ranked below based on the effect a peak-shaving system could have on the charge.

1. **Distribution Use of System (DUoS)** - This bill includes the capacity charge; where the customer pays for a maximum demand level in kW [7]. The capacity charge is set higher than the actual maximum demand, reducing the risk of breaching this threshold. If breached, the customer incurs substantial penalties, and the supplier increases the threshold for the next billing period. By levelling off peaks in energy demand, the capacity charge threshold can decrease. The capacity charge will be the key focus for the proposed peak-shaving system.
2. **Transmission Network Use of System (TNUoS)** - These come from three half-hour periods when the UK's National Grid demand is greatest, referred to as Triads. These dates lie between November and February and must be separated by at least ten days during the financial year [8]. The average max peak demand across the three Triads [9], is multiplied by a tariff for the respective zone in cost per kW [10]. Combined they become the TNUoS charge, added to the customer's end of year bill. The University has become quite good at forecasting these periods [6], making it possible to schedule ESSs to reduce peaks during these periods.
3. **Unit Charge** - Unit charges come at three different rates, green, amber and red[a], depending on the time of day. Energy costs during red periods are significantly higher (between 5pm-7pm). For Western Power (University's current supplier), there is a 17000% increase in price during these periods[b]. The unit charge

[a] See page 27 of [11].

[b] 25.405 p/kWh in red periods against 0.147p/kWh in green periods [11].

will decrease as a consequence of reducing peak demand, where an ESS should only charge in green periods.

4. **Feed-In Tariff (FIT)** - Based on feeding back energy to the grid. Peak-shaving will not be applicable.

2.2 Current Peak Demand Management Methods and Energy Storage Systems Usage

Traditionally there are two methods for reducing peak demand for industrial complexes [4]. These are:

- **Load Shedding**: This is reducing energy usage, by switching off certain systems during periods of peak demand [12]. An intelligent scheduling system or a simple forecasting tool can be used to execute load shedding [13], where systems can be switched off autonomously or manually. Often load shedding is calculated daily using a schedule to set a fixed maximum energy limit [14].
  - *Limitations*: Forecasting errors can significantly reduce the effectiveness of this system, where reactive methods are often better [14]. Due to the free flow of staff and students at the University's facilities, predicting peak demands accurately can become a greater challenge.
- **On-site Generation**: Adding off-the-grid capacity to the consumer [4]. The University currently uses some generators to reduce red zone unit charges, supported by [15] showing that fuel costs of running a diesel generators are lower than energy purchased in red zone rates. If a good return on investment is found from purchasing the asset, a diesel generator may be feasible to be used alongside an ESS during these periods.
  - *Limitations*: The University currently has 0.5MW of PhotoVoltaic (PV) installed using nearly all available space [6]. These PV's provide only 0.5% of the total energy demand, meaning the use of on-site generation to offset peak demand has a negligible effect in flattening the University's demand if used directly.

In addition to these limitations, statistics such as ``40% of energy use in the campus comes from 5% of the space, predominantly labs'' [16], make the University campus a unique case study for peak demand shaving, where energy storage systems appear more attractive than traditional techniques.

There are a limited number of peak shaving ESS solutions available commercially. ABB offers energy-storage, smart-grid products, which perform load levelling at grid level [17]. These systems are designed primarily for supply levelling, using forecasting methods and large ESSs to offset excess energy supply produced from renewable energies [18], rather than focusing on reducing its customers energy bills. One Cycle Control have created technologies to regulate peak-load and mitigate peak demand charges for commercial/industrial facilities using Li-ion batteries [19]. The technologies proved effective at reducing peak demand charges, but highlight that the steep cost of the ESSs reduces the system's financial feasibility [20]. Being able to sense peak loads and respond actively will maximise the performance of the system, while the ESS chosen will have the greatest effect on the systems cost. Section 2.4 evaluates these two different technologies.

2.3 Peak Shaving Systems Literature Review

Acknowledging limitations in commercial peak-shaving ESSs, understanding current research is crucial to designing efficient system architectures. Research is grouped, highlighting each section's significance, identifying areas for further research in work package 2.

2.3.1 Forecasting and the Use of ESS in Load Shifting

Using energy pricing forecasts, an ESS can be switched on to shift energy costs; purchasing energy at a cheaper rate, using this energy during peak times. Looking at the gap in energy prices, demand charges and investment costs for an ESS, NaS, Li-ion and Flow batteries, a basic on/off algorithm to shift energy purchasing from peak to off-peak times does not produce a viable return on investment (ROI) [21]. [22] highlights that billing peak periods were directly correlated with peak demand, requiring an even larger ESS to offset this demand. [23] used real hourly spot prices to decide the best times to turn on and off Vanadium Redox Batteries (VRB) and Polysulfide Bromide Batteries (PSB). Through sequential quadratic programming (SQP), battery sizes were optimised, finding PSB's had a better business case for load shifting. The fundamental differences between [21] and [23], were energy bills targeted and the granularity of the pricing data used. [14] evaluated different control strategies combining many forecasts to reduce errors in peak shaving over a monthly period. Weighted and lowest error forecasts were the best strategies for an energy management system and should be added to the system architecture if forecasting is used. [24] added a real-time operator to create an intelligent scheduling system based on a house to forecast. This system significantly improved the state of charge of the battery, freeing more energy for use in reducing peaks, highlighting that forecasts combined with real-time information can increase the performance of the system further. Work-package 2 will, therefore, look at using weighted and lowest error forecasts for an ESS, further understanding the implications of battery health, whilst work-package 3 will determine if the Universities energy usage data is responsive enough for a real time intelligent scheduling system.

2.3.2 Supply Levelling

Supply levelling is the most common use for ESS [25], using large batteries to reduce power fluctuations brought by the use of renewable technologies [26], [27]. Supply levelling works by storing excess supply, reducing peaks in the grid rather than in demand. The technology is, therefore, similar to peak shaving. [28] looked at improving supply for a residential home. Shiftable water heating was identified to account for 50% of household electricity use, being modelled as the primary storage device. Excess load from wind turbines was used to heat water in excess supply periods bypassing an inverter significantly improving energy losses. This research is supported by [29]. Minimising conversion through inverters makes a large difference in the efficiency of the system. An investigation into energy conversion and, using heat as a secondary storage method will be performed in work-package 2.

2.3.3 Battery Sizing and Financial Modelling

Numerous studies, analysing the business cases for ESSs have been conducted. [21] and [22] model the use ESSs broadly, to reduce the cost of all energy charges, revealing that the ROI is unlikely to be feasible beyond 2020. Papers including [30] and [31] evaluated financial models for particular case studies, showing that bespoke solutions achieved greater peak shaving reductions than returns promised by current generic products [17]. [21], [22], [30], [31] and [32] all present a strong arguments that a bespoke solution for the University will provide a better business case for ESS than generic commercial technology.

Investigating the benefits of a decentralised system, reducing peaks on a small scale rather than using one large central ESS, [33] analysed both peak shaving and battery longevity for a large data centre. Through both experimentation and modelling, [33] showed that when regarding the batteries lifespan, the ability to regulate load through a series of batteries can be more favourable than a centralised system. Research conducted by [34] and [20] also both support using a decentralised system. A simulation of the impact of lithium-ion batteries operated under a peak-shaving control algorithm identified cost-optimal battery configurations and their impact on grid demand, revealing that small short duration batteries were more favourable and cost effective for the customer, further supported by [32]. The model for this project will assess if this is also the case for a University facility understanding that a few rooms such as labs contribute to the majority of peak loads.

[35], [36] all [37] all show alternate ways of optimising the battery sizing configurations. [37], used a non-numeric modelling method, focusing on ultra-capacitors to find the optimal ESS. The results emphasised the constraint of storage capacity, showing an exponential decrease in value gained after a particular size of ESS. Finding this size for different University scenarios will be the primary focus of this project's model. [36] created an analytical model, using energy bands to regulate peak load, giving an optimum storage size for a given system; this was a straightforward and efficient method of modelling battery usage. [35] looked specifically at Vanadium Redox Flow Batteries (VRFB) arguing it benefits over other ESS methods, producing a MATLAB/Simulink for a residential use case, showing that VRFB can regulate its frequency efficiently, due to its fast response time, while still performing peak-shaving services. This project proposes using a similar modelling technique to [35], incorporating more ESSs.

2.4 Peak Shaving Technologies - Electrical Storage System (ESS)

The selected Electrical Storage System (ESS) will govern the cost and feasibility of a peak shaving system. An ESS converts electrical energy into a form stored for later use [38]. Electrochemical batteries characterise low maintenance, high round-trip efficiency, long cycle lives and high energy density's; arguably being the most appropriate technology for peak shaving [39], [40]. Batteries, therefore, have been chosen as the main focus for this study. The various storage methods can be characterised for different uses summaries below:

- **Energy Management:** for large scale storage, typically used by power plants for load levelling and ramping/load following.
  - Pumped Hydroelectric Storage (PHS), Compressed Air Energy Storage (CAES) and Cryogenic Energy Storage (CES) are the conventional technologies for high generation above 100MW. All these methods are on a scale too large to be considered for this project.
  - Large-scale batteries, flow batteries, fuel cells, solar fuels, CES and Thermal Energy Storage (TES) are suitable for medium-scale energy management with capacities of 10 -- 100 MW. These are appropriate for consideration for this project.
- **Power quality:** fast response times improve power quality allowing techniques such as the instantaneous voltage drop, flicker mitigation and short duration uninterrupted power supply

    - Flywheels, Batteries, Superconducting Magnetic Energy Storages (SMES), capacitors and ultra-capacitors have millisecond response time lower for storage sizes less than 1 MW - suitable perhaps in addition to large scale battery. Flywheel efficiency is too low for operational use, so has been removed from this study.
- **Bridging power:** Relatively fast response (< 1 s) but also have relatively long discharge time (hours). The typical power rating for these types of applications is about 100 kW -- 10 MW.
    - Batteries, flow batteries [41], fuel cells and Metal-Air Cells[38], [42].

By removing energy storage methods that would not be appropriate for the system a table was created [c] comparing ESSs. Batteries along with capacitors provide the response time [43] and efficiencies required to make the system justifiable, where only rechargeable batteries were compared. From section 2.3.3 a model of a University peak demand reduction system will need to compare different battery parameters along with their cost, to optimise the model.

2.5 Previous Bristol University Work IODICUS

2.6 Battery Capacity Modelling

2.7 Battery Selection - Tesla Power-pack 2

Selected Tesla due to lots of readily available information on pricing and sizes **Other Competitors** * Eos * BYD

Very limited information on their costs, technology still maturing (Eos) Can assume that competition will continue to drive the price down, unsure about UK distribution

[c] See table 3, in the Appendices

3 Battery Storage Technology Key Advantages and Challenges

This section discusses and defines how the model was created and the process used to generate results.

It is important to understand how a battery system can best be utilised to maximise it's effect. The following section will highlight the advantages and barriers of using a battery system. Understanding the advantages will highlight the best way to design a system architectures which leverages these points. It is this report objective to create strong arguments to how the system will overcome barriers to entry, laying out how all the assumptions in the model overcome these issues and address any qualitative issues in the following section

Advantages

- Reducing Electricity Bills:
  - Reducing the DUoS Charges
  - Reducing Triad Charges
  - Playing on the frequency response market (beyond project scope)
  - Reducing capacity charges
- Supply Levelling:
  - Leveraging maximum use of PV's and other renewable energy sources
  - Providing a fully predictable energy profile for new building. Useful in negotiating price when new power capacity has to be installed (very relevant to the new Bristol campus), saves paying for the new connection. [44]
- Emergency Power: Providing backup generation in the case of power cuts. Can support crucial systems alleviating risks associated with loss of power
- Sustainability:
  - Reducing peak load, reduces losses on the network. There is a green argument for running diesel generators in peak times. Batteries are a highly more sustainable.
  - Ensures self consumption of renewables

Challlenges

- Costs of Purchase too high:
  - Installation Costs too high, too complex - difficulty of retrofitting?
  - Unit Price of the battery is too high - (kWh)
  - Additional equipment cost, inverters
  - Maintenance cost
- Lifetime/ longevity of the battery too low, replacement costs/ dismantling cost make battery installation unfeasible
  - Unpredictability in cycle life of the battery may mean that lifetime is much lower than all good predictions
- Finance not feasible
  - Loan Interest > Savings

- Negative NPV
- Frequent change of regulation may mean that costs shift to reduce battery savings, use for reducing DUoS is still favoured by energy companies. May change if lots of people take up using batteries in this manner.
- Barriers to entry
  - Laws/ regulations
  - Penalisation from energy companies
- Negative environmental effects: Uses of large scale quantities may be hold undesired environmental risks
- Risk of injury/ explosion. Large batteries that overload, hold a very high risk of explosion. Battery system monitoring is key to ensuring the battery operates with in it's limits
- Technology still maturing, Li-ion batteries have not been used in this manner before, for extended periods of time

3.1 Battery Economics

The main objective of this project is to create a business case for using a battery system to reduce energy bills. Ultimately the model aims to produce the information required to justify whether investing in batteries is feasible and advise on the best battery to buy based on it's capacity and it's power rating. Due to the readily available commercial information of Tesla's Power-pack 2, this battery system was used to model financial feasibility and optimal product.

There are 3 ways the model will evaluate the value of the battery system, these are: *pay-back period*, *total-savings* (over a designated period of time) and *net present value* (calculated for different discount rates). Each of these methods results will be compared to crediting the merits and pitfalls of each to understand which battery system is the optimum for the system.

NPV Calculation: As the battery is a large up front cost, it is likely that the battery will be purchased on financing this means that interest on the loan has to be paid each year reducing the battery value. Additionally the battery will degrade in performance over time, this is key to understanding the value of the product over its life time. Using an Initial return rate Add return rate calc here the maximum discount rate can be found for a few batteries (using the extremes). This can then be used to set different discount rates, where 0 is used to illustrate the payback of the battery. Even with the battery degrading, it can be predicted that the battery will continue to degrade until failure. The net present value (NPV) is a way to examine costs and revenues while accounting for the time value of money. If the NPV of a system is positive, then the investment is predicted to provide a return on investment greater than the initial and ongoing cash expenditures associated with ownership of the system. A negative NPV indicates the returns are worth less than the cash outflows and the investment does not show a financial benefit, although unquantified benefits may be present. [45] Total-savings is the measure of net present value when the discount rate is 0.

Payback Period: The payback period (PBP) is the time in years it takes for project savings to equal or exceed the initial cost of the investment. This metric is included because of its ability to quickly communicate tangible value of a project. A system which yields a very short payback period is typically a profitable one because subsequent years of the project result in pure revenue for the system owner. A system which cannot be paid back over the lifetime of the system is a poor investment because money is still owed when the system is retired and no longer able to generate revenue. The payback period is reported as the first time where the project savings exceeds the debt, but care must be taken to also consider additional cash expenditures in later years. [45] The this model looks at the lifetime of investing in one battery system over a period of time so additional cash expenditure is ignored in this model.

3.2 Battery Costing

explanation of the Power-pack 2 costs, including warranty, maintenance, installation and any other additional costs. Discussion of the falling costs of lithium battery prices, refer to Diagram

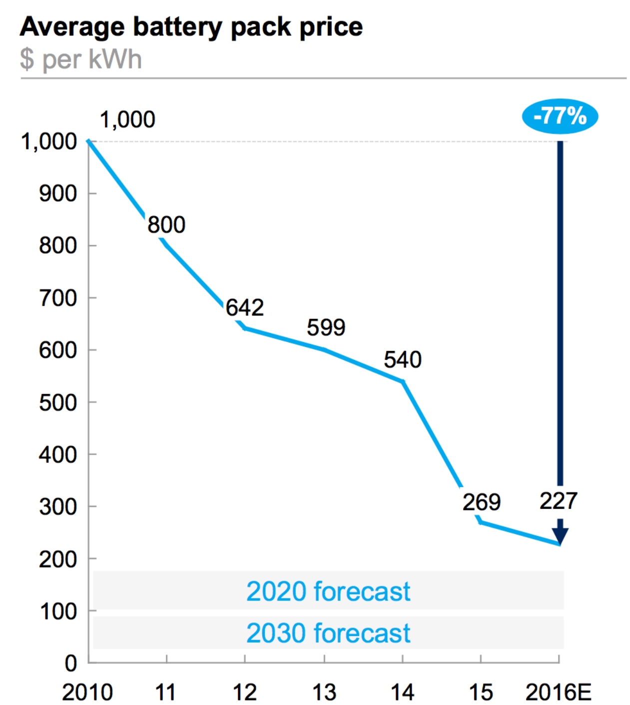

Figure 3.1: Plot of Battery Prices Reduction for 2010-2016 and Predictions for Future battery Prices [46]

Discussion of Li-ion Battery Falling costs, why now or the 5 year time period of the campus is a good time to buy, installation costs, probably large when retrofitting to an existing building, although the technology comes as almost plug and play, assume will need to be connected to where the mains supply enters the building in order to work in tandem with mains supply Other technology required such as inverters e.c.t.

3.3 Battery Lifetime Assessment - Understanding Battery Degradation

The below figure shows the typical profile a Li-ion battery follows as it degrades over time:

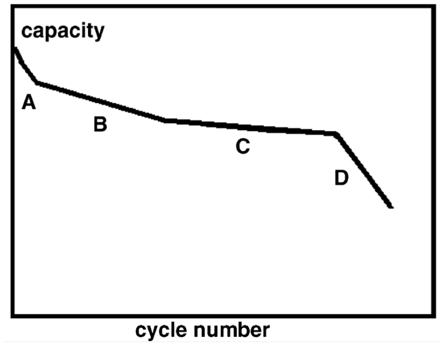

Figure 3.2: Plot of the General Relationship between battery capacity and cycle number [47]

After the battery degrades below 80% of it's new maximum capacity, the battery is regarded to be at its' end of life phase. It is important to note that there potential for a large amount of capacity to be delivered beyond this point, however as seen in figure 3.2, the battery tends to degrade a lot quicker. There are also issues with power degradation

The literature review revealed these factors to have the greatest effect on the rate in which the battery decays:

- Temperature: By running the battery at a temperature too hot or two cold, the battery will degrade much quicker Include numerical prediction here with reference [48]
- Charging:
  - Charging Level: The cycle life of a battery can be increased by reducing the cut off voltage of the battery. Battery voltage will be fixed at either high voltage three phase or at single phase 240V, instead current drawn by the battery will very. Decreasing the current drawn therefore will extend the battery cycle life, give the battery a partial charge instead of fully charing it. This has a similar effect to working at a lower DoD. [49]

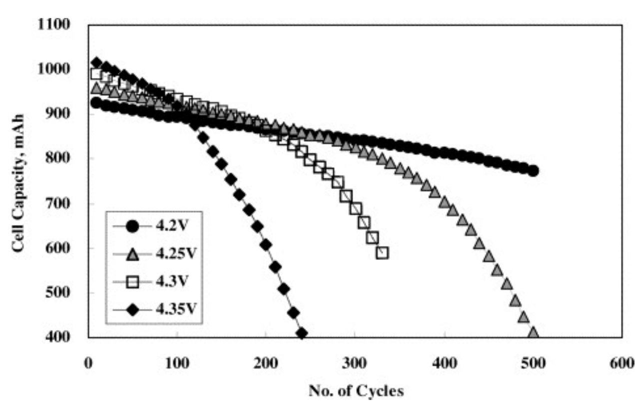

Figure 3.3: Plot of the Relationship Between Battery Cycle Life and Voltage of Charge [49]

  - Overcharging: By charging the battery too its' full capacity the battery or continuing to charge the battery beyond its designed voltage, the battery capacity can quickly degrade. The battery becomes unstable if inadvertently charged to a higher than specified voltage. Prolonged charging above 4.30V on a Li-ion designed for 4.20V/cell will plate metallic lithium on the anode. The cathode material becomes an oxidising agent, loses stability and produces carbon dioxide (CO2). The cell pressure rises and if the charge is allowed to continue, these can cause the temperature inside the cell to increase, furthering the reduction in the batteries capacity. A fully charged battery has a lower thermal runaway temperature and will vent sooner than one that is partially charged. All lithium-based batteries are safer at a lower charge. [50] Due to these two issues the battery should stop charging once it reaches a threshold below its maximum value.

  - Charging Rate: The capacity reduction at high discharge rates occurs because the transformation of the active chemicals cannot keep pace with the current drawn. The result is incomplete or unwanted chemical reactions and an associated reduction in capacity [51]

- Useage
  - Over Depletion: Leaving the battery fully empty for too long can have detrimental effects on capacity. It is common for battery management systems (BMS), particularly in consumer electronics to power the device off at a threshold above 0, to negate some of effects of low energy storage [52]. Add further evidence here
  - Speed of Depletion: The rate in which the battery is discharge can have a strong effect on the battery life time. The images below shows the effect on discharge rate on the rated capacity of a battery. [51],[53]

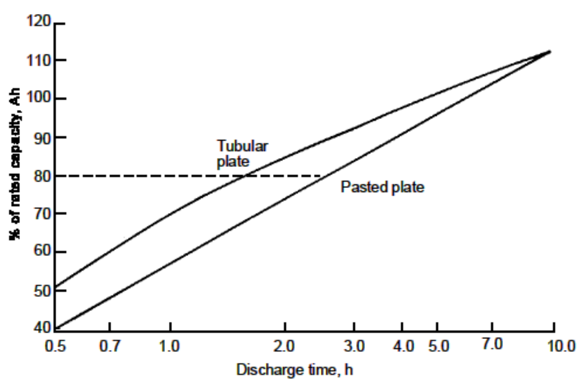

Figure 3.4: Plot of the Relationship Between Discharge Time and its' Effect on the Rated Capacity of a Battery [53]

- Depth of Discharge (DoD): Depth of discharge is related to the number of **active** chemicals transformed with each charge/ discharge cycle. One full cycle is seen as when the battery is charged to its full current capacity (noting that the capacity will degrade over time, making each cycle length smaller). It has been cited that there is a logarithmic relationship between depth of discharge and the cycle life of the battery [51].Note the graph above is for Lead-Acid batteries, but also holds true for Li-ion by restricting the possible DOD in the application, the designer can dramatically improve the cycle life of the product. Similarly the user can get a much longer life out of the battery by using cells with a capacity slightly more than required or by topping the battery up before it becomes completely discharged. [51]

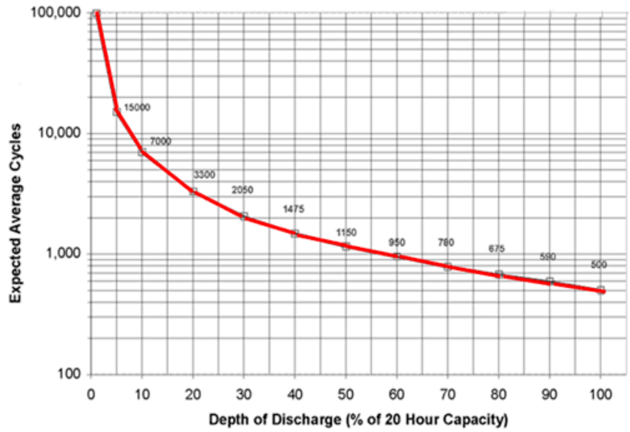

Figure 3.5: Plot of Depth of Discharge vs Cycle Life [51]

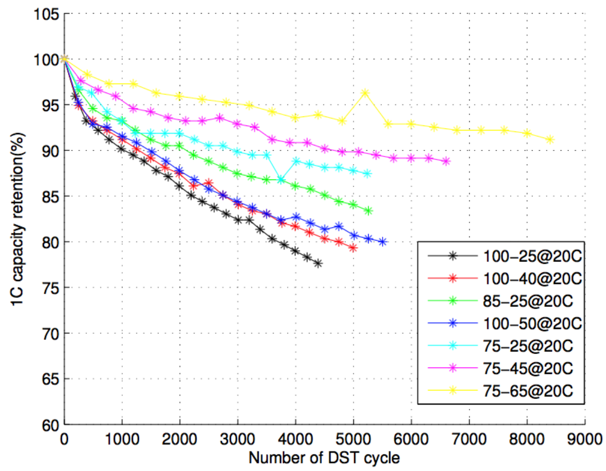

Figure 3.6: Plot of the Measured Relationship between battery State of Charge and it's Effect on the Cycle Number lifetime [54]

4 Battery Model Definition

Understanding the key design parameters highlighted in section ??. The model was created to capture as many of these drivers to maximise the models validity. Data was obtained for Senate house (a large University office/study space building). This data was manipulated to create a representative energy profile for the Senate and then the New Campus.

Overview of the final system Diagram

4.1 Model Development Requirements

4.1.1 0 vs 3D Modelling Approach

The 0D modelling approach is a technique widely used in the development cycle of a product, typically in the early steps of the cycle. The objective of the 0D model is to define the main characteristics and performance of the products. A 3D model is implemented later in the product development cycle to get a detailed analysis, to verify the accuracy of the 0D model and to predict risks and failures. In a 0D model, the system dynamics is a function of the time while in a 3D model, the system dynamics is a function of the time and the space. A 0D model is much simpler and faster to solve than a 3D model. This enables to run a large number of simulations and explore a large design space for our product. [55] Due to the level of accuracy required to achieve this reports objectives in the model and the timeframe that the model had to be constructed in a 0D model was created using the variables stated in section 4.5.5.

4.1.2 Code Optimisation

A time-based iterative approach, based around a zero dimensional approach, has been selected to model a large variety of different batteries. Running the simulation through time requires calculating large matrices which are number of days $\times$ 1440 (minutes in a day). The model should be optimised for performance to ensure that running times are minimised. This will help to improve model development and reduce data collection time. Possible methods to optimise the performance of MATLAB scripts are: Vectorisation data can be stored and manipulated within multidimensional arrays. Using vector operations, rather than manually moving and manipulating data inside the array, can greatly improve model speed. Avoiding heavy processing MATLAB functions such as the linear interpolation function. Instead, simplified versions can be developed to perform the same task. Initialising variables within the model. All arrays should be initialised within the memory. This prevents MATLAB from needing to create extra space within the memory each time a value is entered into an array. This is especially important when dealing with large datasets, as it can prevent running out of memory. Parallel processing for loops can be used for independent repeating tasks. This can be applied when multiple batteries as each loop is independent of the other.

4.1.3 User Interface

The model developed through this research project is likely to be used in the group project in the following year. Consequently, it is important that the model is easy to run and use. A range of inputs are required for each lagoon which should be easily configured and managed. This will also improve ease of data collection for this project and reduce the risk of introducing a systemic error, associated with the user entering incorrect inputs.

Model inputs should therefore be largely removed from the MATLAB script and kept within input files. A level of intelligence should also be built into the model to determine if the user inputs are valid. This would increase the robustness of the model and prevent errors from occurring within the model. It will also help to improve the stability of the model, as incorrect data will be less likely to be inputted. However, this requirement is likely to be more relevant in the following year, when multiple users are generating data from the energy model. It is important that the model is able to handle a range of variable input conditions

4.1.4 Ease of Development

Due to the nature of mathematical modelling, it is essential the model is structured to allow for development and expansion as the project progresses. This allows functionality to be added to the model without a large amount of upfront work. It also improves the speed at which changes can be implemented within the model. The use of functions within the script allows elements of the code to be re-used across the model. Nested functions (functions defined in the body of a parent function) can also be used when a large number of variables are required to pass back and forth between functions. This also provides modularity within the function and can reduce the amount of repeated code. It is important that a function based approach is taken through the development of the model in this research project due to the expected size and complexity of the model. Without this, the model is likely to have a poor structure and will be much harder to develop and debug.

4.2 Creation of Senate House Billing Model

Data was received for Senate house, giving usage in kWh for the previous half hour period. A bill was also provided for a months energy use at the Victoria rooms (another Bristol University building used for lecturing, offices and teaching classes). A meeting with John Brenton add reference clarified that billing profiles for both buildings were identical.

In order to gauge the size and power requirements needed for a building the size of Senate house, a minute by minute usage profile needed to be created and then cross checked against a representative bill to understand how the different charges are broken down and highlight charges to target the design of the battery system architecture too.

Using the half hourly usage data of senate house for a year, usage plots were created for different days in the year. It was clear that the was a major difference between energy demand during the weekend and during the week, shown in 4.1. Total energy consumption was 3 times greater over the weekdays than the weekend. When creating at usage data, it was imperative to make sure that weekday's and weekend matched completely in order to give an accurate representation about the energy usage.

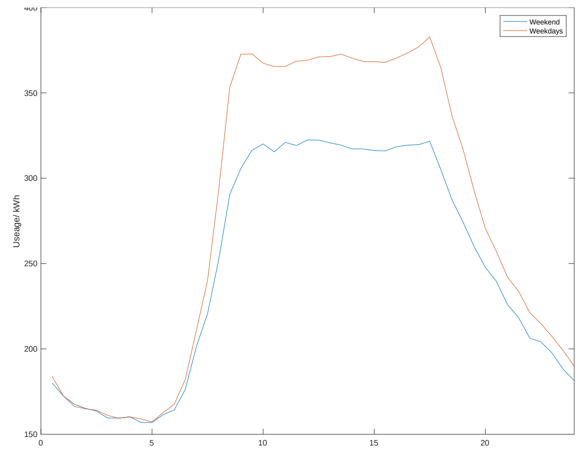

Figure 4.1: Plot of Mean Senate House Weekday and Weekend Usage

This data was good at giving a rough estimation of the battery size needed to produce some impact on the Universities energy bills.

4.2.1 Representative Bill Creation

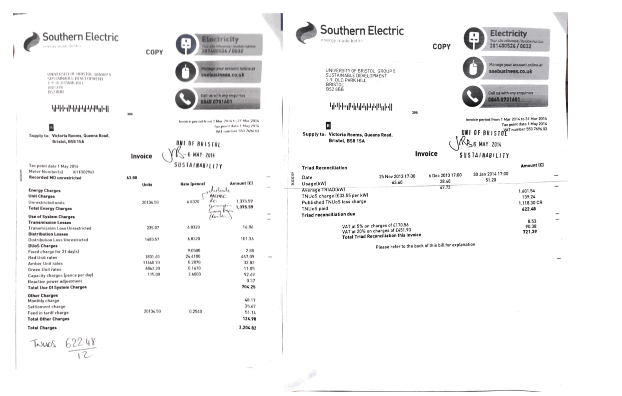

Figure 4.2: Image of Energy Bill For Victoria Rooms

Figure 4.2 shows a typical electricity bill for a University building. It is clear the red unit rates make up the largest part of the DUoS Charge and roughly 20% of that months total recorded charges. Instead capacity charges made up only 4% of the total bill. This realisation meant that the focus of the model would be to start by reducing the red rate charge through load shifting, and explore other charges if this proved to not be effective to offset investment costs. Figure 4.3 highlights the significance of the different unit costs.

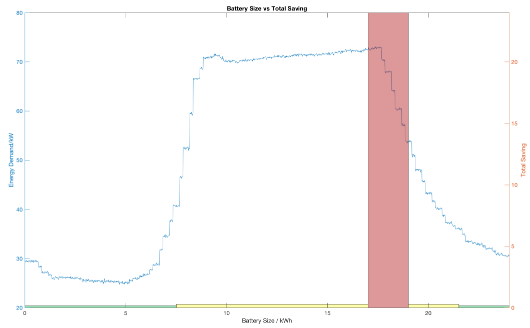

Figure 4.3: Difference in Unit Charge Rates

Using this data a model was created taking into account DUoS charges and multiplying them by their respective rate. This charge makes up and large % of the total bill showing roughly how much the unit rate costs.

To achieve this, the date of the usage data was scanned to find which day the bill began, then assigning the next 6 days, to be either weekdays or weekends. This was important as there are different DUoS rate at different times of day between weekdays and weekends. Creating a counter that loops through each half hour period, logic can be applied to categorise each half hour period into their respective unit rate. Total units consumed in red, amber and green periods were found allowing for some simple calculations to find the effect of load shifting. By shifting the load in red units to green rate charges, a significant saving could be made. By measuring the amount of units consumed in red periods gave a good estimation for the size range of the battery that would be required.

4.3 Representative Demand Profile

The second performance parameter of the battery is the maximum power it can supply, rated in kW. By applying to much load on a battery can ultimately cause it to fail, severely reducing the batteries cycle life. As there was no demand data available, a few assumption had to be made in order to generate an valid demand profile. First the half hourly usage data was split into a minute by minute representation, creating points at every minute by finding the gradient and constant between two points then splitting the distant into 30 equidistant points. This produced an identical graph to the fit, applied by Matlab. However as each point int he original graph represented usage for the previous 30 minutes, this was divided by 30 to give the usage per minute This can be validated by summing all the points and compare to the original graph.

This profile however assumes that all usage varies linearly between time periods. In reality this is not true. To generate a more realistic demand profile. The start, end and midpoint between two values were used as means in which a random number with a normal distribution was applied to give normally distributed values in intervals of 10 minutes, modelling how usage varies randomly minute by minute but holding the trend of the original data. Scaling by two, coverts usage from kWH into demand KW. This graph was then validated by integrating the area of the graph and comparing it against the summation of the original data. A standard deviation σ, was then selected which would fairly represent the change in usage. After trailing with a range of different scales of data, σ was set to the mean between the average usage and max usage. This gave a fair, but conservative representation of how energy usage may look.

Assumptions: Usage will have a peaky profile due to a large number of people in the buildings , switching numerous devices on and off frequently. For an office style building like Senate it is unlikely that there is any large equipment that could cause a major spike in demand.

The demand profile could then be plotted as both as histogram and as a cumulative distribution plot, identifying the typical demand of Senate house over the year, as well as the max demand the building experiences. Figures 4.4 and 4.5 show the demand profile of the building.

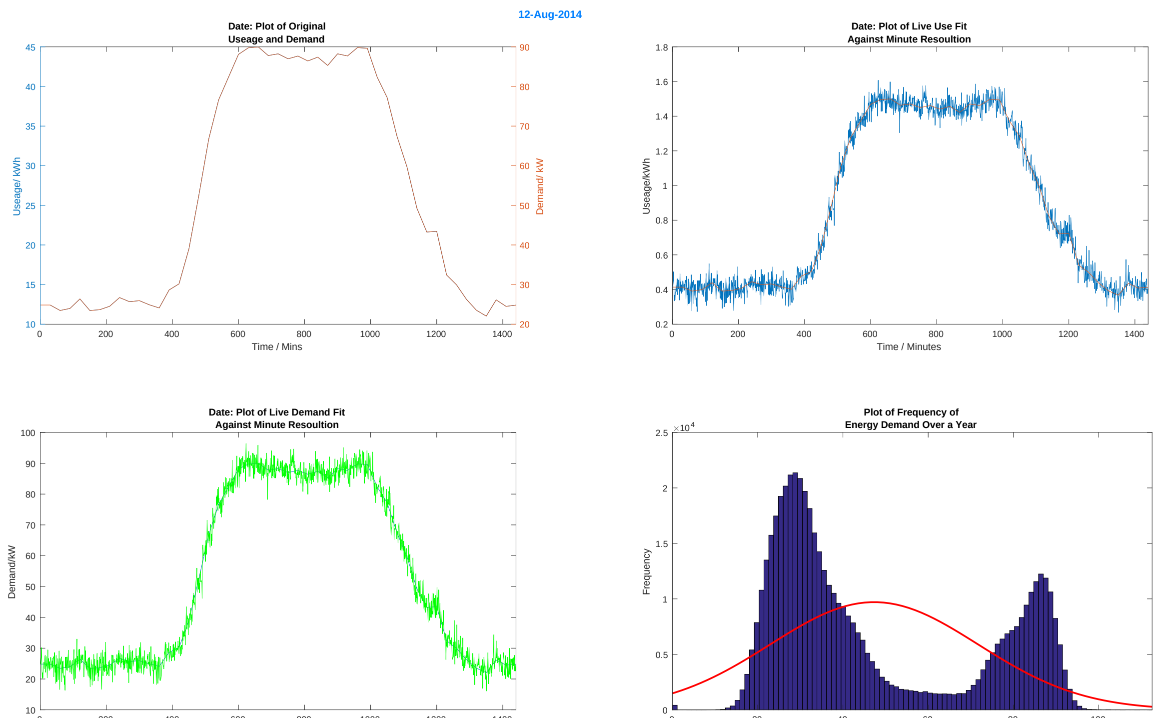

Figure 4.4: Plots of Usage and Demand Profile Generation and Histogram of Year Data

It can be observed from in the histogram in Figure 4.4, that the demand of the building typically falls between two points. One low peak representing morning and evening of 30KW and a second peak constituting the energy usage in the middle of the day, averaging around 80KW, but rarely ever exceeding 90KW.

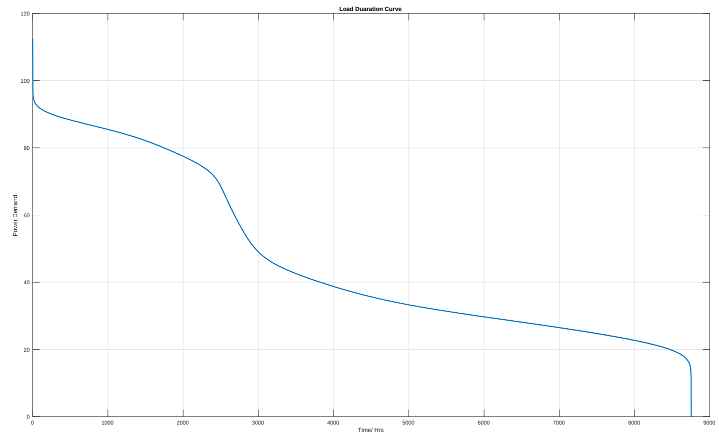

Figure 4.5: Load Duration Plot of Year Usage Data

The Load Duration Curve in Figure 4.5 takes demand for each hour and plots this in descending order, this shows the annual demand that can be met for a battery at a given power rating [56]. For Senate house, a battery rated to 40KW would cover, 5000 hours of the year roughly 55% of the years usage.

Taking both graphs together, selecting a battery which covers the mean power demand, may act be a good trade off.

4.4 Definition of New Campus Requirements

To fulfil the objectives of this project, an understanding of the design of the new campus needed to be assessed. As the building plans are still in their early stage, many assumptions about the likely size and use of the campus had to be understood in order to create a representative energy profile. Table *Insert Table of campus size/ rooms* in the Appendix shows the predicted new campus size and use stating relevant assumptions.

The campus will constitute around 1500 students in halls of residence and have around 5000 staff and students on site during term time. Although there have been a range of facilities proposed that the University campus will house, it is most likely that the building will constitute mainly of tutorial rooms, a few lecture halls and offices. A meeting with John Brenton [6], made clear that creating infrastucure to support postgraduate business studies made the most economical sense so is most likely to make up most of the final plans.

The energy profile of Senate house will be mostly transferrable to the new campus, as it is unlikely the new campus will have any devices that will distort the load profile greatly. In addition, the campus is likely to have improved efficiency through utilising the latest technologies in its construction and services (ventilation, heating e.c.t.). Data on 125 rooms in halls of residence was also provided, it is likely that this will almost be identical to a new build, due to student usage making it difficult to manage energy demand further. Using the foot prints of both building and adding some additional laboratory data to simulate if these creates any spike in energy usage.

The scaling factors were:

- Senate House (7840sqm) - **7.9x**
- Hall data (2761sqm) - **7.6x**
- Lab data (1 Lab Use) - **4x**

Due to these data files falling under different years and running between different dates, the data needed to be adjusted in order to be correctly scaled. An algorithm was therefore created to match the date shown in figure 4.6.

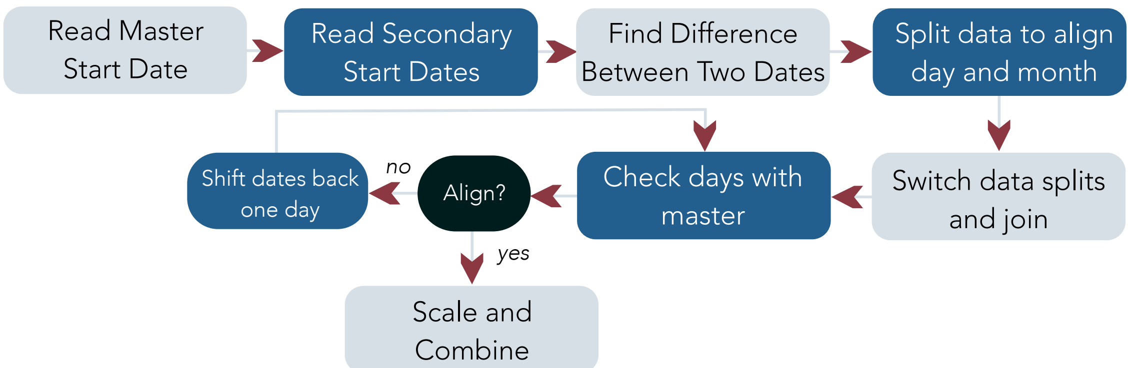

Figure 4.6: Logic of Data Aligning Tool To Create New Campus Data

Make assumptions very clear

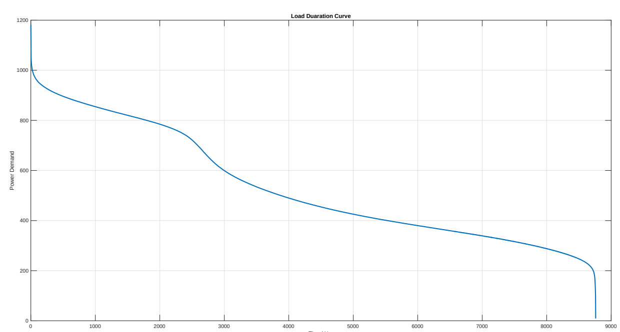

Figure 4.7: Load Duration Profile for the New Campus

4.5 Definition of System Architectures / Strategies

Defining how the batteries would run is imperative to understanding their economic feasibility. This section will define the logic used to define the operation of the battery and how the model was created to represent this.

Using the ``live demand data'', created in section **??**, a Matlab script was created simulate through a lifetime use case of the the battery for both Senate house and the new campus energy profiles. A script was created which duplicated these data input files for the length of simulation (in years), checking that each year began on the next day in the week from the end of the last year. Making sure dates aligned is imperative to making sure results were valid as the difference in energy usage between weekdays and weekends, shifts the total savings into a 7 year cycle pattern. Energy usage and demand data was then run through a second function which applied three strategies understanding battery performance from a technical and economical standpoint.

4.5.1 Red Rate Avoidance

As describe in earlier sections, the battery was limited to being switched on only during red rate periods. This period is always between 5 and 7 on weekdays and has assumed to remain the same for the entirety of the batteries lifetime. During this period the battery was allowed to drain itself at a rate up to it's maximum output power. This required demand and usage data to be checked simultaneously, to make sure the battery had remaining capacity and was not over loaded. If the load exceeded its maximum value the supply of energy was capped at this value. As the battery was used, capacity was decreased proportionally until live usage exceeded the remaining capacity and the battery was drained to its minimum capacity and switched off. Or the rate rate period elapsed.

The battery was then set to begin charging at a set rate when the red rate period was entered a green rate period. The charging rate was set based on the amount of charge required divided over the length of the green rate period. Early discussion of battery life cycle optimisation suggested that charging at a lower speed, particularly during the last 10% of charge, made a large impact on the battery lifetime. It is assumed here that smart charging techniques trickling (seen on most modern smartphones), would be incorporated into the battery. However the only value which will effect the outputs of this model is the capacity when the next red rate period is entered, therefore not necessary in this model.

This repeats for the run-length of the simulation, measuring the amount of money saved against the original costs of unit rate charges.

4.5.2 Triad Avoidance

To correctly understand the effects of TRIAD avoidance in the model, the dates correlating to each day needed to be correctly applied and matched against corresponding days. Using [57], the dates: 4/12/14, 19/01/15, 02/02/15 were used as aligning with the original Senate data used as a master for the new campus. These dates were used for the sequential years for days TRIADS would likely fall. Their corresponding days of the week were checked to make sure they did not fall weekends and adjusted accordingly if found to be the case. It is assumed here that daily variation in energy usage is negligible and instead energy trends are seen only on a monthly basis. This means that it does not matter if the TRIAD lands on a Monday or a Friday, and instead the date corresponds best with predicted weather pattern- the only variable likely to cause observable differences on a calendar data (any other variables have been ignored, particularly as these will cancel out over time).

These periods were all between 5 and 7 corresponding with the battery strategy already in place. Using these dates and the time of 5:30, the TRIAD cost was calculated based on energy demand at this time. Battery usage was then measured against the TRIAD cost to understand the reduction in energy demand delivered by the battery. The reduction in TRIAD rate was a factor of the batteries max power supply and not capacity. As the battery would only need to run for a few minutes to offset this charge.

At the end of each year in the simulation the three TRIAD costs were averaged to find the total cost. This was then spread evenly over the next year in the simulation, representing how TRIAD billing is split across each monthly energy bill.

4.5.3 Battery Degradation Modelling

As highlighted in section 3.3 discusses the different variables which can effect a batteries cycle life. An approximation of the batteries was taken, taking into account the effect of each of these variables and placing a battery usage strategy in place. The rated battery cycle life is taken to be the number of full cycles a battery can complete before it has degraded to 80% of it's original capacity. This figure was used as it is the best metric for how a battery should perform based on a normal use case. The model uses this assumption to degrade the battery by the fraction of it's cycle life that it has charged up by. For each charging iteration the new max capacity becomes slightly smaller, reducing the size of the cycle. A counter is then run summing up the amount the battery has charged. When this equals the current maximum, a complete cycle has been fulfilled. The effect of this method means that the battery will degrade faster the longer it has been applied. This follows the mean trend of battery cycle life shown in figure 3.2.

Any assumptions made about battery degradation were based on battery operation and not the batteries chemistry. Assumptions were made on what constitutes ``normal working parameters'', alleviating extremes in modes that have an exponential effect on how the battery degrades. To reduce wear on the battery, the battery was confined to work within 10-90% of it current maximum capacity, allowing a maximum depth of discharge of 80%. Draining the battery can cause detrimental effects on the whilst overcharging can also do the same. Working within these two parameters follows similar principles applied by Tesla in their electric cars add reference here. The battery was never run above it's demand maximum (max power KW), however no factor was used to degrade the battery quicker if it operated at this factor (a known cause of wear). As the battery was rated at this value, it should be designed to cope at this level of use for no longer than 2 hours a day.

Temperature was also assumed to remain within expected bounds. Britain only experiences hot days a few times a year and rarely drops below freezing, making it a better climate for battery operational temperatures than the states where average temperatures are a lot hotter. Using the two strategies defined above means the battery is only ever discharging or charging 5 days a week, with some charge on a Saturday mornings dependent on the battery selected. This allows the battery too cool down and perform any life enhancing cycling activities if relevant Consider how these two days could be used to improve the batteries lifetime.

The model was run until either the runtime reached it's end or the battery reached it's end of life value of 80%. This meant answer were comparable. It is worth noting that there are examples of batteries being used beyond their end of life cycle. This is being seen by Nissan/ Honda in recycling their car batteries to use in homes, as there are little associated costs with batteries after they have been installed if the battery has payed itself back, the battery will continue to generate profit. However as there is a lot of unpredictability about whether the battery will fail, this has not been regarded in the model and instead seen as the asset no-longer holding any more value.

Diagram of Battery Cycling Degradation

4.5.4 Battery Efficiencies

Battery efficiency was regarded in the model by multiplying the energy drawn when charging by the additional loses caused inefficiencies. This assumptions was made as it is likely that the battery once charged can supply what it has stored, although some losses will be incurred when transforming back to AC again. It is assumed that the efficiency figure regards both transformations. Efficiency gains could also be achieved by designing the system so it primarily sends power to DC first without transforming. Efficiency however does not play a huge part in improving costs savings due to the difference between charging in green periods and the red rate being so significant.

4.5.5 Input Parameters and Multi-Battery Simulation

In order to understand the optimum battery type for a given scenario, and then infer the total savings that the battery could generate; a large array of different batteries with different power ratings and capacities was modelled. This required iterating the model numerous times. To reduce computation time, parallel computing was implemented to iterate each discrete battery scenario in the 0D model.

The following Operational Parameters Were Used to Generate the Output Results Discussed in this report. Values stated as variables were varied per battery.

Upfront Costs:	Variable
Max Power:	Variable
Upfront Costs:	Variable
Depth Of Discharge *(DoD)*:	80%
Cycle Life:	5000 [@TeslaPow57:online]
Max Charge:	$\frac{1-\text{DoD}}{2+\text{DoD}} \times$ CurrentCapacity
Min Charge:	$\frac{1-\text{DoD}}{2} \times$ Current Capacity
End Life Value:	80%
Additional Costs:	£0
Charge Rate:	Max Power $\times$ 0.4 (In kWh per Half Hour)
TRIAD Days:	04-Dec-2014, 19-Jan-2015, 02-Feb-2015
TRIAD Rate:	£33.55 (price per KW)
Unit Rate:	6.832p
Red Rate:	24.41p
Amber Rate:	0.287p
Green Rate:	0.161p
Usage Variation σ:	$\frac{\text{Max Value + Mean Value}}{2}$ (For minute by minute granularity)

Table 1: Table Showing the Input Parameters of the Model

The following diagram depicts the model of the entire multi-battery system.

Large system Diagram of the Logic behind the model

It was important that the model was as clear and simple as possible. To improve clarity within the model, structures were used to group variables. The benefit of using structures is the ability to pass them into a function. Using structures throughout the Lagoon Energy Model function and Multiple Lagoon Model script allowed all the required variables to be passed between the function and script using one structure. This greatly improved the structure and clarity of the model script.

4.6 Performance Optimisation of Battery Storage Model

[58]

- Use Profiler Within MATLAB, the performance of a code can be measured in the amount of time it takes to run. The MATLAB profiler is a useful tool which records the amount of time spend in the different functions called within a script. The profiler can be used to identify bottlenecks within the model.
- Array Preallocation
- Vectorisation
- Reference Wildcards
- Delete Sub Matrices
- Convert to column vectors
- Parallel Computing For loops
- Minimised using MATLAB functions (linear interpolation etc.)
- Used single instead of double integers (half size of memory allocation). The default storage method for data within MATLAB is a double-precision floating point number (Mathworks, 2016). This method of representing a number within CPU memory is able handle very large values, however requires 64 bits per number. By storing numbers as a single-precision data type, only 32 bits are required, reducing the data size by a half. This helps to manage memory within the model.
- DRY coding technique

5 Validation of Model

5.1 Data File

By using the model with real data first taken from Senate house, the tool which creates live data could be validated through integration and direct comparison to the original usage data. As no data could be gathered on how the demand profile looks for Senate house, assumptions were made on the type of operations the building fulfils (see the table below); this was compared to demand data at Princeton [59].

5.2 Model

ADD Model validation thoughts, short as Assumptions hope to capture why the model is valid based on what has been used, validation table (excel) place simple calculation in body, additional thoughts on sensitivity analysis

5.3 Limitations / Assumptions

Create Full Table of Assumptions - ADD TOO HERE

- Office buildings are unlikely to have highly peaky demand profiles as there is no large devices that could cause spikes
- Red rate times remain the same for the entirety of the batteries lifetime
- Normal distribution of energy demand between each half hour period
  - Sigma = average between mean of data and max of data
- Trickle charging and minimum charge rate employed
- Daily Variation- negligible
  - Other variation in energy use ignored
  - Weather the only contributor worth noting
  - TRIAD dates kept as close as possible to the original (no weekends)

- Battery operation assumptions
- Does not overheat
- Run within normal working parameters
- Battery chemistry assumptions
  - Cycle life rating of battery indicates degradation in normal use case
- Battery efficiency losses lost on charging
  - Figure quotes both battery transformation

6 Results

This project aims to evaluate whether the value gained from purchasing batteries outweighs its large upfront costs and other challenges that battery technology faces. This section analyses the data gathered from zero-dimensional model and discusses the plausibility of using a battery and which battery is optimum based on a demand profile for both Senate House and the new University campus.

6.1 Senate House Battery Optimisation

* Graphs of NPV, Total Savings and Payback Time * Discussion on installation costs * Optimum battery to choose

6.2 New Campus Battery Optimisation

Using the input values defined in section 4.4, the model was used generated results for 113 different battery types. Due to the size demand profile of the battery requiring up to xkW in a during a red rate period, and requiring a capacity of up to ykWh, meant that many different solutions were plausible for providing the most value. By simulating for a range of batteries over a period of time, key trends between capacity and max power could be seen. A 25 year period was selected to evaluate the battery performance over. It is expected that after this period of time, technology will have significantly changed, refurbishments on the buildings will be under consideration and unpredictability on the long term use of the batteries will be reduced. The following results will talk through the three key value measurements discussed in section 3.1.

6.2.1 Total Savings and Payback Period

Due to the 25 year limit placed on the batteries, the largest batteries did not necessarily deliver the greatest savings due to their high purchase price not being converted into additional savings from the battery strategies having no further load to be shifted. Figure 6.1 shows the parabolic shape with a local maximum between the battery size and the total savings for a 25 year period. For the new campus, a battery size of around 2000 kWh appeared to be the best choice battery to select. The max power needs to be very high, with a 1.2-1.3 MW power response, to access these maximum total savings.

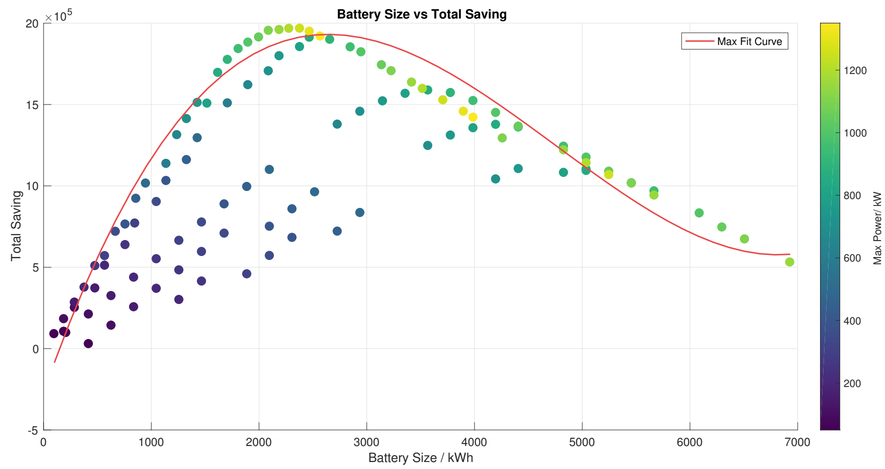

Figure 6.1: Battery Size Vs Total Savings

Looking at the payback period shown in Figure 6.2, a different story is told. The correct combination of max power and battery size is required to get a payback period between 6.3 and 8 years. Battery Sizes all remain below 2000kWh and provided that the battery size is paired with the correct maximum power, the shortest payback period can be accessed. After the 2000kWh mark, capacity rather than max power has the greatest effect in increasing the payback time.

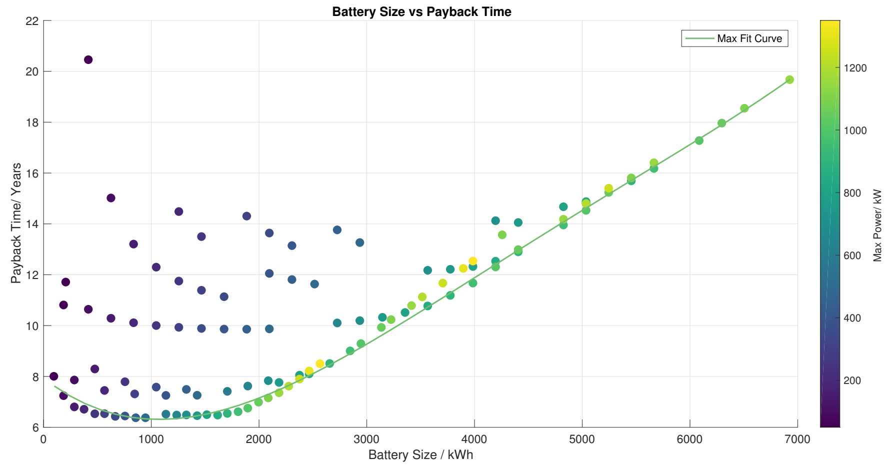

Figure 6.2: Graph of Battery Size vs PayBack Time

Figures 6.3 and 6.4 look to use a graphical approach, of choosing the optimum battery system based on both its capacity and power rating.

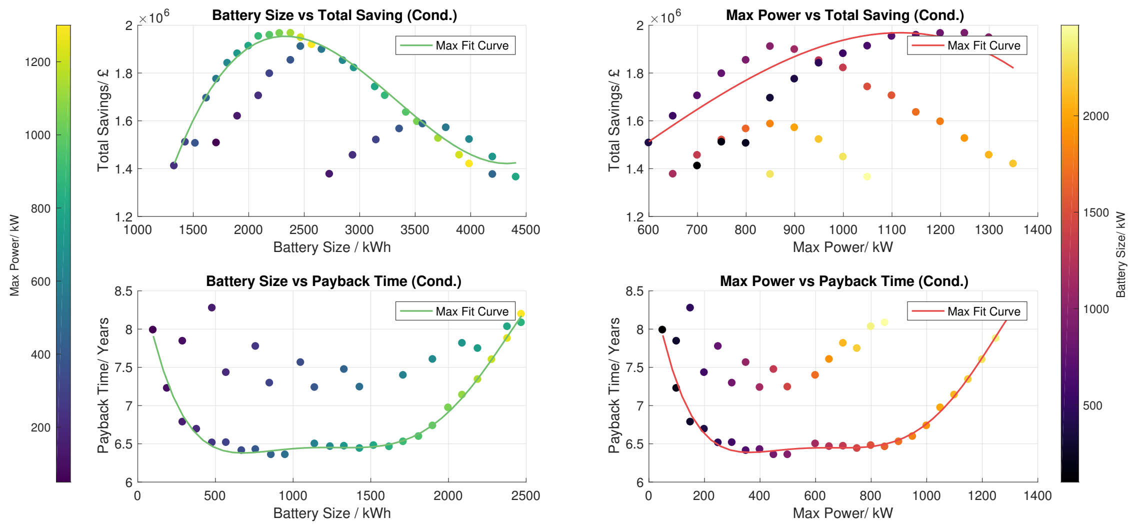

Figure 6.3: Graph Showing Top 30 Batteries with Fitted Curves for both Payback Time and Total Savings

A small region either-side of where the two plots cross in Figure 6.3, can be approximated to be the optimum battery battery parameters. A designer aiming to select a battery based on these two parameters would look here to make a selection then find the nearest corresponding battery on the market that fits these values. It is apparent that the is a very steep drop off in total savings for batteries that fall outside these bounds. For both max power and total capacity selecting a battery with a lower rating than this bound will minimise the payback time, whilst selecting above this region will increase the payback time exponentially.

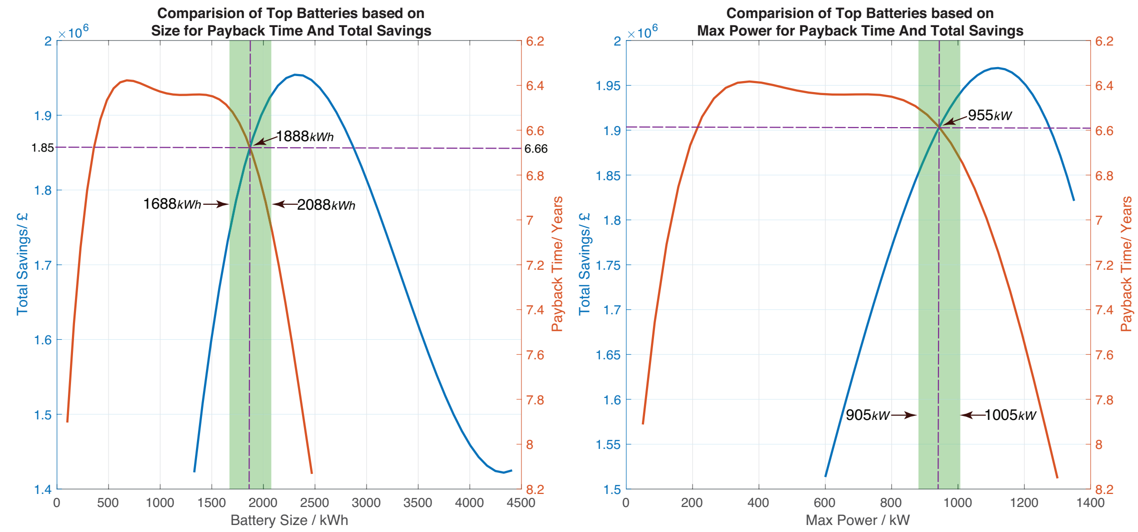

Figure 6.4: Comparison Between Fit Curves for Payback Period and Total Savings

Payback period is important measure when evaluating the investments risk. The longer the pay back period the more time there is for the battery to fail. For the Tesla Power-pack modelled, the batteries have a 10 year warranty. These reduces the risk significantly if the investment were to fail before this period. There are other risks associated with long payback periods are energy pricing changing significantly reducing the value that the battery creates. Energy contracts typically last no longer than 4 years,find reference in which billing structure could result in the batteries value dropping to zero - add sensitivity analysis. Knowing that $\frac{2}{3}$ of the investment has been paid back as opposed to only a $\frac{1}{2}$ or less can have dramatic effects on the risk of the investment. These factors should be considered when choosing the design region of battery selection.

6.2.2 NPV

An alternate way which tries to quantify risk, is by using net present value. Three rates of 3%, 7% and 12% were selected to understand the value of the different batteries. Figure 6.5, shows the NPV of the different batteries at these different rates.

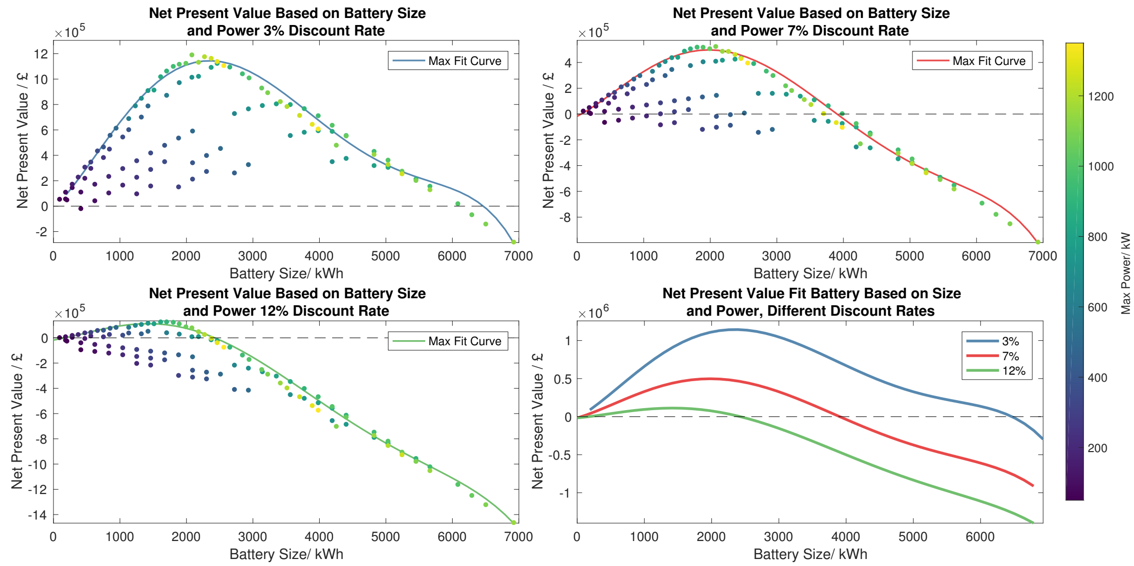

Figure 6.5: Net Present value at Different Discount Rates - Comparison

For discount rates of 3% and 7% the battery with the highest value was the same, having a power rating of 1100 kW and a capacity of 2090kWh. When the discount rate is increased much above 7%, it can be seen that the number of batteries that have a positive value is significantly reduced. The best value battery also becomes smaller rated to only 900kW and 1710kWh.

Selecting an appropriate discount rate is therefore key for deciding which is the best investment if using net present value. As the battery will degrade each year until it reaches its end of life value, it could be argued that the value of the asset decreases proportionally with this the remaining life of the battery. Looking at the the optimum battery at a discount rate of 7% (see Table **??** below), it can be seen that the specific battery ran for 4904 cycles. Based on this assumption the value of the battery would be 98% of it's original rate, this works out at a discount rate of roughly 3.92%. As this will be different for each batteries the discount rate based on remaining value alone must approximate all batteries a value of 3% therefore seems fair. Discount rate also takes into account inflation. For the UK this rate has varied between -0.1% and 3.5% for the last 5 years [60].An approximate value of 2% could be added to the discount rate to incorporate how money now is worth more than money later.

Finally discount rates can be used to incorporate interests on loans. As the battery would be a large one off payment that could be included in the mortgage on the new campus. This would keep the interest rate low, which can be approximated to 2%. Using these three approximations gives a discount rate of around 7% shown in figure 6.5.

6.2.3 Discussion on Optimum Battery

Below is a table showing the results of the battery which held the best NPV at a discount rate of 7%:

Parameter	*NPV Value*	*Best Value*
Battery Power Rating:	1100 kW	
Battery Capacity:	2090 kWh	
Total Saved:	£1,953,706	£1,966,697
Payback Period:	7.0959 Years	6.3562 Years
Mean DoD:	31.5759%	
Cycles:	4904	
Years:	25	

Table 2: Table Showing the Best Battery Results based on a Net Present Value of 7%

Comparing the results between Net Present Value and the Total Saving Vs Payback plots (see Figure 6.4),shows that the recommendation of NPV at 7% is larger than the recommendation from the total saving payback plot. This suggests that at this discount rate, total savings is worth more than a reduced payback time.

6.2.4 Battery Usage and Secondary Analysis

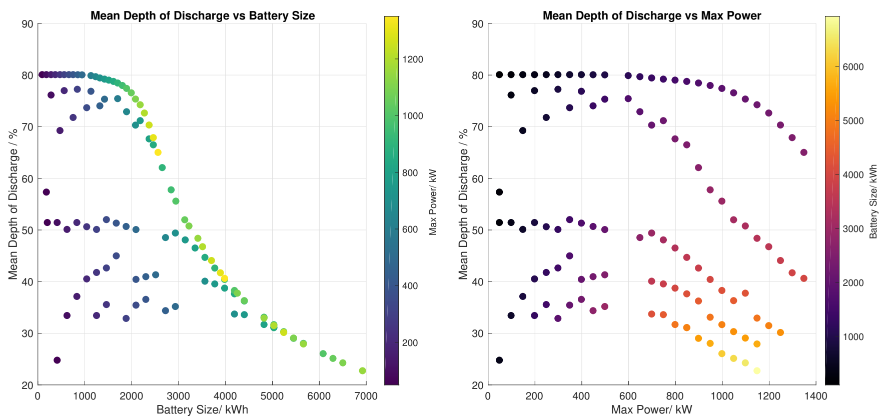

Figure 6.6: Depth of Discharge For Battery Lifetime

- Battery depth of discharge can vary greatly depending on the power rating and capacity, a trend can be seen as two separate

7 Conclusions and Future Work

7.1 Conclusions

7.2 Future Work

8 Appendices

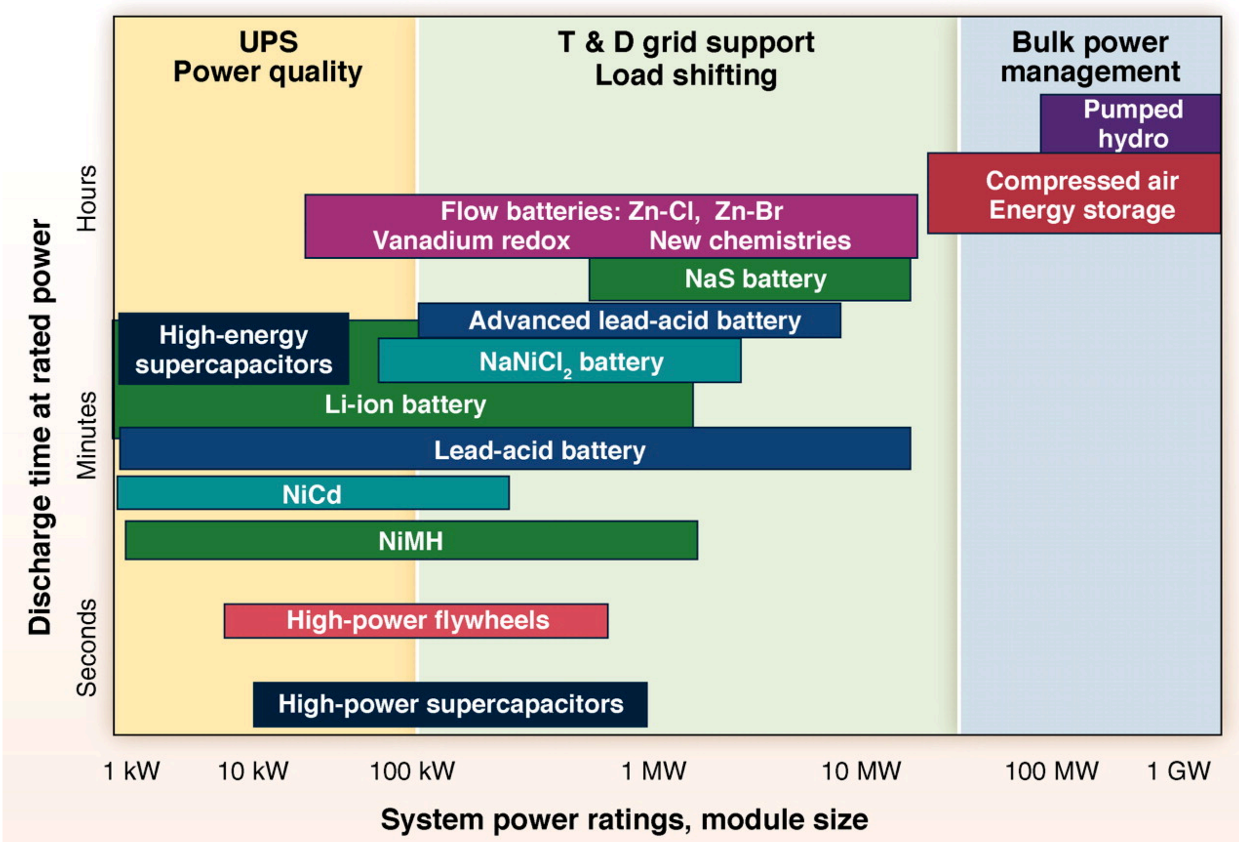

Figure 8.1: Diagram Showing Batteries Catorgised for Their Use Case [40]

Battery Characteristcs Comparison Table											
Battery Type	Lead Acid	Nikel		Lithium Ion			Sodium	Flow		Capacitor	
Battery Compostion		NiCd	NiMH	Colbalt	Magnanese	Phosphate	NaS	VRB	ZnBr	Standard	Ultra Capacitor
Degree of Maturity	High	Medium	Medium	Medium	Medium	Medium	Medium	Low	Low	High	Medium
Cost $/kW	300-600	500-1500	500-1500	1200-4000	1200-4000	1200-4000	1000-3000	600-1500	700-2500	200-400	100-300
Storage Cost $/kWh	2-50	800-1500	500-550	600-2500	600-2500	600-2500	300-500	150-1000	150-1000	500-1000	300-2000
Cycle Life	500-1000	2000-2500	300-500	500-1000	500-1000	1000-2000	2500	12000+	2000+	50000+	100000+
Charge Time hrs	8-16	1-2	2-4	2-4	1-2	1-2	1-2	1-2	1-2	0-0.5	0-0.5
Specific Energy Whkg^-1	30-50	45-80	60-120	150-250	100-150	90-120	150-240	10-30	30-50	0.05-5	0.05-5
Power Rating MW	0-20	0-40	0-40	0-0.1	0-0.1	0-0.1	0.05-8	0.03-3	0.05-2	0-0.05	0-0.3
Discharge Rate p Day %	0.1-0.3	0.2-0.6	1	0.1	0.1	0.1	20	0.01	0.01	0.4	20-40%
Discharge Time	Seconds - Hours	Seconds - Hours	Seconds - Hours	Seconds - Hours	Seconds - Hours	Seconds - Hours	Seconds - Hours	Seconds - 10hr	Seconds - 10hr	Milliseconds-1hr	Milliseconds-1hr

Table 3: Table Showing Battery Performance

Above were 42105 words.

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