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 New Campus

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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 New Campus" 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

30th 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
NPV: Net Present Value
IRR: Initial Return Rate
DCF: Discounted Cash Flow
PBP: Payback Period
BMS: Battery Management System
HVAC: Heating, Ventilation and Air Conditioning

List of Definitions

Asset: An asset is a resource with economic value, with the expectation that it will provide future benefit

Net Present Value: Is the difference between the current value of cash inflows and outflows. NPV is used in capital budgeting to analyse the profitability of an investment

Discount Rate: Measure of the depreciation of cash generated by an asset

Demand: Measure of instantaneous power (kW)

Usage: Measure of power consumption (kWh)

1 Project Introduction 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. This is key for the UK to achieve a low-carbon, sustainable and efficient energy system for the future [2]. The UK's vision is mirrored in the University of Bristol's new strategy, as it seeks to boost its world-class research capacity and promote innovation in policy, to increase sustainability [3]. The creation of a world-leading campus is an attractive means for the University to realise its vision. Consequently, the aim of this group project is to explore new digital technologies, to reduce both energy costs and energy usage to set a precedent in university campus sustainability.

Figure 1.1 describes the relationships between the individual project themes, where research in occupancy sensing, smart metering and building services will evaluate how energy usage can be optimised. Projects looking at smart thermal grids, energy system interactions and peak demand reduction, analyse methods to reduce the university's energy costs; providing financial incentives to increase the new campus's sustainability. The 5th year group project will unite this research, creating a smart ``brain'' [4], combining increased data collection with new technologies and strategies to provide a business case to develop sustainable energy services on the new campus, pushing the University to meet it is carbon neutral 2030 goal [3].

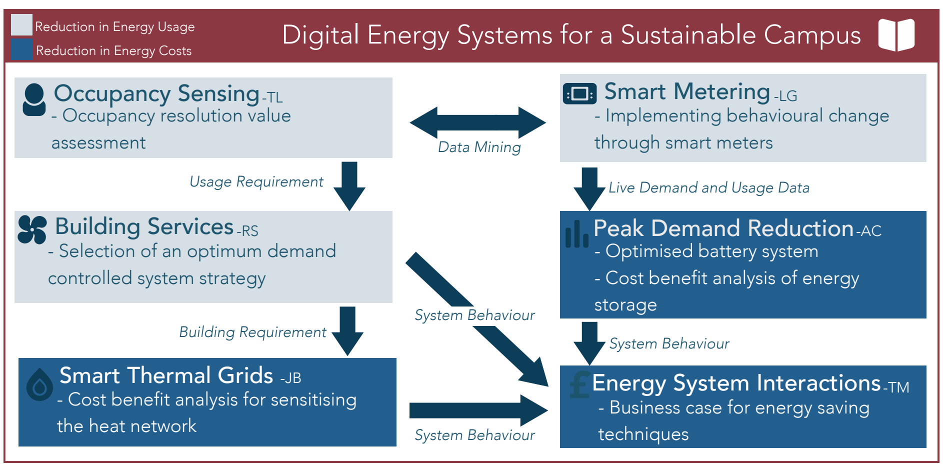


Figure 1.1: Group Design Project Diagram Showing Relationships Between Individual Projects

1.1 Individual Project Introduction

This project report investigates the feasibility of using energy storage systems (ESS) to reduce energy charges and increase sustainability for the University of Bristol. The technology will be implemented in the new Temple Quarter campus, where this project seeks to provide a a value incentive for investing in energy storage. Within the project, the university's energy profile and billing structure are analysed and simulated, used to define the bespoke energy requirements of the new campus. A comprehensive technology study of the different ESSs evaluates the feasibility of various systems, down-selecting the most appropriate battery for modelling. Through further evaluation of how the selected battery system would function, a model was designed to simulate battery system strategies analysing their impact. Finally, to find an optimum ESS solution, a large range of battery specifications are simulated, comparing results to find a battery which generates the most value.

The overall outputs of the project for use in the 5^{th} year group design project are:

- *Cost Based Analysis Business Case*: for investing in battery storage technology
- *Energy Profile Tool*: to build and understand the new university campus' Demand
- *Optimised Battery System Model*: producing best storage solutions based on energy profile tool

1.2 Objectives

To achieve the projects outputs, the following detailed objectives were defined:

Literature Review

1. Perform a detailed literature review and market analysis of energy storage technologies and research, evaluating using ESS to reduce peak energy demands, highlighting relevant techniques and limitations.
2. Investigate different energy storage solutions for the University's new campus, comparing parameters such as power-ratings, capacity, discharge times and costs to down selecting the best solution.

Definition of System Strategies

3. Define battery system strategies, establishing the key performance variables.

Modelling and Analysis

4. Analyse the university's current peak demand charges; understanding the current billing structure and collecting typical energy usage data.
5. Create a tool to generate demand profile (kW) from half-hourly usage (kWh) data provided defining energy profile of the new campus.
6. Create a model simulating the use of battery strategies to change the energy demand profile of the new campus, comprising of three stages:
   (a) A simulation of using the battery system against a current university building, analysing the effect of the system for use as a datum.
   (b) A simulation of using the battery system in the new university campus
   (c) An assessment on the optimum battery design to select based on the new campus's energy profile

Evaluation

7. Evaluate results of the simulation, concluding on the effectiveness of different battery systems. A cost-based analysis will be used to measure the feasibility of the different energy storage systems for the university comparing the value of the system against current challenges in using the new technology.

2 Background and Summary of Key Work and References

The following literature review provides an overview of using Energy Storage Systems (ESS) to lower energy costs. Using batteries in this manner is still novel, with a broad range of ESSs and use strategies available for evaluation; each producing dramatically different results when placed in different situations. By building a comprehensive understanding of the technology and new campus situation, an optimised energy storage system can be found, providing a full understanding of the value energy storage could bring to the new university campus.

2.1 Sustainability and Energy Storage Systems

The UK's energy grid uses many methods of providing the power required to meet the country's demand. This energy comes from both clean (hydro, wind solar etc.) and dirty (coal, gas etc.) sources. Due to the nature of most clean technologies, these sources are used to meet the UK's base load (power usage during off-peak periods) [5]. Periods of the day when energy usage is higher, (called peak demand) additional fast-acting dirty sources like combined cycle gas turbines are switched-on to meet this demand [6]. Peak demand periods are charged much more significantly, for this reason. An ESS proposes a new way to level out these peak periods, reducing the need for fast, responsive dirty technologies. By using energy storage technologies the University could reduce their emissions by up to 360gCO2 per kWh [7], while having the potential to save a significant amount of money.

2.2 University Energy 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 some granularity in the understanding energy charges originate from[8]. The University receives charges bundled together under four distinct themes [8], described below, where their applicability to energy storage technology is discussed.

1. **Unit Charge** - Base cost of energy consumption, making up 58% of the bill.
2. **Distribution Use of System (DUoS)** - Including capacity charge and DUoS rate.
   (a) **DUoS Rate** - there are three DUoS 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 [a]. Reducing DUoS rate charges is the main method of reducing peak demand charges; an ESS should be used during Red periods and charged during Green periods. These make up 20% of the bill [b].
   (b) **Capacity Charge** - this is where the customer sets their maximum demand (kW) level[10]. This is set above the actual maximum demand of a building, to reduce 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. Capacity charges make up a 4% of the monthly bill [b] where the risk surpassing the threshold exceeds any savings seen through implementing an ESS.
3. **Transmission Network Use of System (TNUoS)** - Three times of the year when the UK's energy demand is greatest, called TRIADs. These dates lie between November and February, separated by at least ten

[a]See page 27 of [9], 25.405 p/kWh in Red, against 0.147p/kWh in Green.

[b]See Figure 8.2 in Appendix

days in each financial year [11]. The average max peak demand (kW) across the three TRIADS [12], is multiplied by a tariff [13]; added to the customer's end of year bill. The University has become quite good at forecasting these periods [8], making it possible to schedule an ESS to reduce demand during these periods where power supply rate (kW) is crucial. These make up 7% of the monthly bill [b].

4. **Feed-In Tariff (FIT)** - Based on feeding back energy to the grid. Dependent on the battery system selected, there is potential to increases the value of the ESS by leveraging this charge. This charge is highly complex and frequently changing so will not be evaluated in this project.

2.3 Current Peak Demand Management Methods

Peak demand reduction is synonymous with peak shaving; the ability to control energy usage during intervals of high demand, to limit or reduce demand charges [14], [15]. Traditionally there are two methods for reducing peak demand for industrial complexes [14]. These are:

Load Shedding: This is reducing energy usage, by switching off certain systems during periods of peak demand [16]. An intelligent scheduling system or a simple forecasting tool can be used to execute load shedding [17], where systems are switched off autonomously or manually. Often load shedding is calculated daily using a schedule to set a fixed maximum energy limit [18].

- *Limitations*: Forecasting errors can significantly reduce the effectiveness of this system, where reactive methods are often better [18]. Getting university staff and students to shift their usage habits from peak times could be potentially costly [8], highlighted in experiments conducted by the University of Copenhagen [19].

On-site Generation: Adding off-the-grid capacity to the consumer [14]. The University currently uses diesel generators roughly ten times a year to reduce TRIAD charges; supported by [20]. Due to the environmental impact of using diesel generators, an ESS would act as an improved replacement for this method for reducing TRIAD charges.

- *Limitations*: The University currently has 0.5MW of PhotoVoltaic (PV) installed using nearly all available space [8]. 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. Pairing batteries with PV as a method of supply levelling appears unfeasible in the context of the University.

University Research: IODICUS, is a current University project, looking at reducing energy costs, by improving the amount of sensing data around the university's usage. This project produced middleware for an IoT deployment of energy sensors/actuators, and software to explore the resulting `big data' of the sensors [21]. Although the project did not evaluate using ESSs, the outcome of improving sensing data will help to improve the chosen ESS performance.

There are a limited number of commercially available solutions that use ESSs to reduce peak loads directly. ABB offers energy-storage, smart-grid, products which perform load levelling at grid level [22]. These systems are designed primarily for supply levelling, using forecasting methods and extensive ESSs to offset excess energy supply produced from renewable energies [23], rather than focusing on reducing its customer's 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 [24]. The technologies proved effective at reducing peak demand charges, but highlight the steep cost of the ESSs reduce the system's financial feasibility [25]. Based on there being no direct commercial solution this report sets to understand the components required to create an effective energy storage solution for reducing the university's new campus energy bills.

2.4 Peak Shaving Systems Literature Review

Acknowledging limitations in commercial peak-shaving ESSs, it is crucial to understand current research in using ESS technology to design an efficient system. Research is grouped, highlighting each section's significance and relevance to the development of the model.

2.4.1 Forecasting and the Use of ESS in Load Shifting

Using energy price forecasts, an ESS can be switched on to shift energy costs; purchasing energy at a cheaper rate, using this energy during peak times. [26] ran simulations to test NaS, Li-ion and Flow batteries, for an Italian commercial plant, failed to find viable return on investment (ROI)[26].[27] 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 business case for load shifting. These two conflicting results were due to the sensitivity in energy pricing. An independent investigation of this technique with the University, may prove feasible. [28] added a real-time operator to create an intelligent scheduling system for home prediction. 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. Modelling development will research:

- the implications of battery health on the lifetime value of the battery, for the battery selected
- increasing granularity in the University's usage data will to incorportate a real-time operator

2.4.2 Supply Levelling

Supply levelling is the most common use for ESS [29], using large batteries to reduce power fluctuations brought by the use of renewable technologies [30], [31]. Supply levelling works by storing excess supply, reducing peaks in the grid rather than in demand. [32] looked at improving supply for a residential home. Shiftable water heating was identified to account for 50% of household electricity use, so was used as the primary storage device. Excess load from wind turbines was used to heat water in excess supply periods bypassing an inverter improved energy losses [33]. Minimising conversion through inverters makes a large difference in the efficiency of the system. Supply levelling will not be addressed in this model due to the University's PV's contributing to only 0.5% of its supply [8].

2.4.3 Battery Sizing and Financial Modelling

There are numerous studies, analysing the business cases for ESSs. [26] and [34] 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 [35] and [36] evaluated financial models for particular case studies, showing that bespoke solutions achieved greater peak shaving reductions than returns promised by current generic products [22]. [26], [34], [35], [36] and [37] 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, [38] analysed both peak shaving and battery longevity for a large data centre. Through both experimentation and modelling, [38] 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 [39] and [25] also both support using a decentralised system.

[40], [41] and [42] show methods ways of optimising battery configurations. [42], 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 the required battery size and power for the new campus will be the primary focus of this project's model. [41] 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. The model will incorporate:

- An adaption of [40] modelling technique to find the optimal configuration of the ESS
- An assessment a decentralised battery system, focusing primarily on lab space

2.5 Comparison of Energy Storage Systems

The selected ESS will govern the cost and feasibility of a peak shaving system. An ESS converts electrical energy into a form stored for later use [43]. 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 [44], [45]. 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 technologies are too large and their frequency response is too slow for this application.
- **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 in

addition to large scale battery.

- **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 [46], fuel cells and Metal-Air Cells[43], [47]. These are the most appropriate ESS type for application.

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 [48] and efficiencies required to make the system justifiable, where only rechargeable batteries were compared.

2.6 Battery Selection - Tesla Powerpack 2

Due to the maturity of the technology, the fast frequency response in delivering power, Li-ion batteries were down-selected as the most viable option for achieving the project's aims. EOS and BYD and Tesla are currently the only companies that supply Li-ion batteries of an appropriate size. Due readiness in information around performance and price, the Tesla Powerpack 2 was chosen for this model, to improve the validity of results.

3 Battery Storage Technology Key Advantages and Challenges

Table 1 identifies the key values and challenges of using Li-ion technology. Overcoming challenges with high severity by developing a comprehensive understanding of their effects is the focus of the model developed in this project. This is necessary to create an effective cost based analysis of using a Li-ion energy storage system. To create strong arguments to how the system will overcome these challenges, assumptions used overcome these issues are discussed in this section.

Table 1: Showing the Advantages and Challenges of Using Energy Storage

Advantages	Challenges	*Severity*
Reducing Electricity Bills:	**Lifetime of Battery Too Short:**	4
• DUoS, TRIADS, Capacity Charges	• Cyclelife difficult to predict for application	
Supply Levelling:	**Cost of Battery High:**	5
• Maximising use of PV's and other Renewable Sources	• Purchase,Installation, maintenance	
• Providing predictable energy profile for new building	• Complexity in retrofitting	
Emergency Power:	**Change in Energy Regulation and Pricing**	5
• Supporting crucial systems, in power cuts	• Frequently changing costs structures	
Increasing Sustainability:	**Legal and Commercial Barriers to Entry:**	3
• Reducing usage during peak demand periods	• Energy companies may penalise battery use	
Support Regional Electricity Grid:	**Negative Environmental Effects:**	2
•Provides fast frequency supply and increases flexibility	• Effects of mass Li-ion mining not understood	
Security:	**Low Level of Technology Maturity:**	2
• Protection against cyber attacks	• Technology Still Maturing, Lacks Extensive Tests	
	Measure of Challenges - Severity Scale 1 (Low), 5 (High)	

3.1 Battery Economics

The primary objective of this project is to create a cost-based analysis business case for using a battery system giving a valid prediction of the value an ESS could generate. There are three ways the model will assess the

[c] See table 5, in the Appendices

value of the storage system; *net present value*, *pay-back period* and *total-savings*. Each of these results will be compared, crediting their merits and pitfalls, to give a full understanding of the battery's value.

3.1.1 Net Present Value

Net Present Value (NPV) describes the difference between the current value of cash inflows and outflows [49]. NPV is used in capital budgeting to analyse the profitability of an investment over the long-term. Batteries are a significant upfront investment, seeing little financial value for many years. As a consequence, purchasing the battery through finance is likely, adding an interest rate to the cost of the battery. Battery degradation and inflation are also factors, increase the discount rate required to correctly value financial performance over time.

The Internal Return Rate (IRR) is a method for finding the maximum discount rate before that an asset generates a negative NPV. This is found by setting the net present value to 0 and calculating the return rate. Equation 1, defines the secant numerical method used for calculating the IRR.

$$r_{n+1} = r_n - NPV_n \cdot \left(\frac{r_n - r_{n-1}}{NPV_n - NPV_{n-1}} \right) \tag{1}$$

Where r_n defines the n^{th} approximation of the IRR [50].

Using Equation 1 the maximum discount rate can be found using batteries at the extremities of the results (lowest and highest performers). If the IRR is found to be too low, the battery strategies will need revising otherwise it can be concluded that it is not feasible to invest in an ESS[d].

Total savings is the measure of NPV when the discount rate is set to zero; providing a clear understanding of the cash flow which the system generates.

3.1.2 Payback Period

The Payback Period (PBP) is the time for project savings to equal or exceed the cost of the investment [51]. This metric is used to measure risk. Minimising the payback period diminishes many high severity challenges of the battery, reducing the likelihood of energy billing change and the likelihood of the battery failing. The Tesla Power-pack 2 has 10 years warranty, reducing the risk of additional costs to replacement/repair the battery before it becomes profitable. As the battery will be viewed first as a financial investment by the University, having a short enough payback period will be essential to proving the battery systems viability.

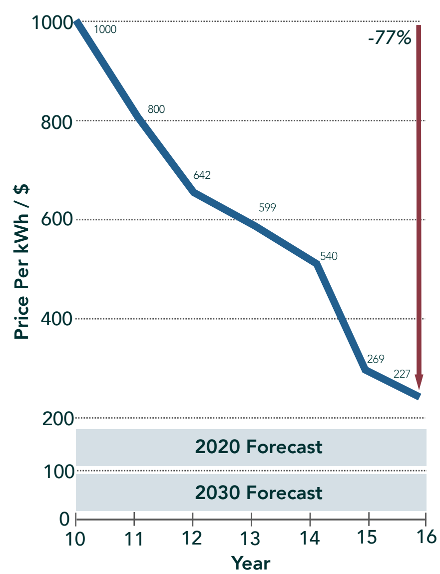


Figure 3.1: Plot of Li-ion Battery Prices 2010-2016 [52]

3.2 Li-ion Battery Costing

Over the last decade, Li-ion technology has advanced significantly, partly due to the rise in electric vehicles, slashing the price while improving efficiencies and energy densities. Figure 3.1 shows the trend in prices for the last six years and the predictions for the next 15. Between 2010 to 2016, battery pack prices fell ~77% from $1,000/kWh to $227/kWh. Current projections put the price of

[d] An IRR below 5% is considered unfeasible, although unquantified benefits may be present [51].

Li-ion battery pack prices below $190/kWh by the end of the decade, corresponding with the construction of the new campus, an further 16% reduction, consequently the feasibility of investing in the technology will continue to increase.

Data readily available on the Powerpacks's based on the battery's capacity (kWh) and maximum power (kW) **Powerpac95:online** This makes it possible to evaluate the optimum specification of battery for an energy profile. Unit costs start at £51,940 and scale infinitely. After purchasing the product, installation is the next largest cost to consider. The Powerpack comes almost as plug and play, including an inbuilt inverter simplifying the process extensively. The cost to install will be significantly greater when retrofitting to existing infrastructure as it is assumed a suitable foundations are necessary due for the battery fully operational in a university environment. In the case of the new campus, it is assumed that there are little additional costs in installing the battery system due to installation requirements, placed on the site's design.

Maintenance/operations costs are another factor to consider. The Powerpack uses a health checking system, requiring little training to monitor the battery. It seems likely that the University can use a member of the Estates team monitor the battery infrequently. Section 3.1.2, discussed the Powerpack ten-year warranty, eliminating any costs in the first 10 years. For these reasons maintenance/operations are assumed negligible.

By using today's battery prices, it is assumed the battery's cost will be under-estimated compared to when it will be installed in the new campus. This will reduce the uncertainty around the costing assumptions made.

3.3 Battery Lifetime Assessment - Understanding Battery Degradation

Sections 2.4.1 and 2.4.3, highlighted the importance of battery health in increasing the longterm value of an ESS. By operating the battery in a way that considers its longevity, further value can be generated. To correctly model how the Li-ion batteries degrade over time, the following section explains the different parameters which effect on battery health discussing how they should be regarded in the model.

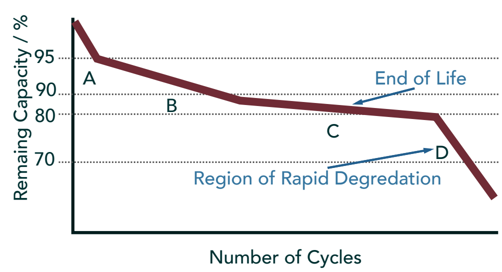


Figure 3.2: Plot of the General Relationship Between Battery Capacity and Cycle Number Extracted From [53]

Figure 3.2 shows the typical capacity degradation profile of a Li-ion battery. After the battery degrades below 80% (C) of it is original capacity, it is regarded to be in its end of life phase [54]. After this point, degradation becomes more rapid and unpredictable [53]. There is still potential for more energy to be delivered beyond this point [55], however, for the model to remain representative, after the battery's health reaches 80%, the battery should be regarded as dead.

The following list of parameters, gives a brief overview of these effect battery degradation, highlighting how they are regarded in the model

3.3.1 Temperature

By running the battery at a temperature too hot or too cold, increases a batteries rate of degradation significantly [56]. The Tesla Powerpack incorporates an internal liquid cooling and heating system which allows for pinpoint temperature control. A dual coolant and refrigerant loop system minimises the effects of temperature degradation, climates providing better efficiency than traditional HVAC systems. **Powerpac95:online** Due to safety reason, it is recommend that the battery is installed outside, making the battery susceptible to climate. England experiences a mild climate all year round, spending most of it is time between 3°C and 22°C [57]. These cooler temperatures favour the battery's performance. For both these reasons, the model will assume temperatures effect on degradation is negligible.

3.3.2 Depth of Discharge (DoD)

Depth of discharge is related to the number of active chemicals transformed with each charge/ discharge cycle [e]. Figure 3.3 shows experimental results of the effect of DOD on Lead-Acid batteries capacity, holds true for Li-ion [58]. At the rated cycle life of 5000, is was assumed a 70% DOD was used to test the battery lifespan [59]. This value was scaled accordingly. By restricting the possible DoD cycle life of the battery can be dramatically improved. It is common practice to select cells with more capacity than required. The battery's average depth of discharge over its lifetime should be recorded and used as a metric for the validity of the selected batteries expected lifetime.

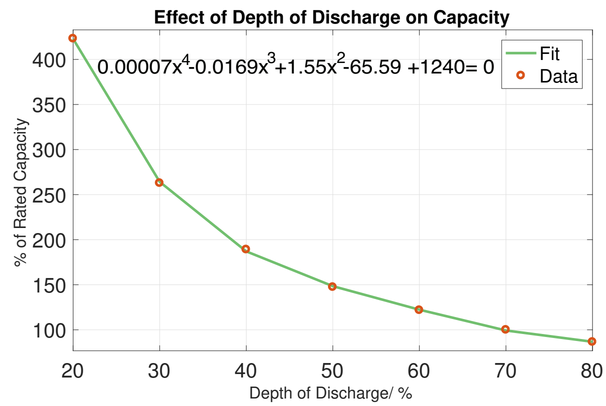


Figure 3.3: Plot of Depth of Discharge vs Rated Capacity, Interpolated From [58]

3.3.3 Usage

Over Depletion: Fully depleting a battery for extended periods can have detrimental effects on capacity. It is common for battery management systems (BMS), particularly in consumer electronics to power devices off above zero; negating some of the effects of depleted storage levels [61]. The model should prevent the battery from being depleted below 10% to offset this effect.

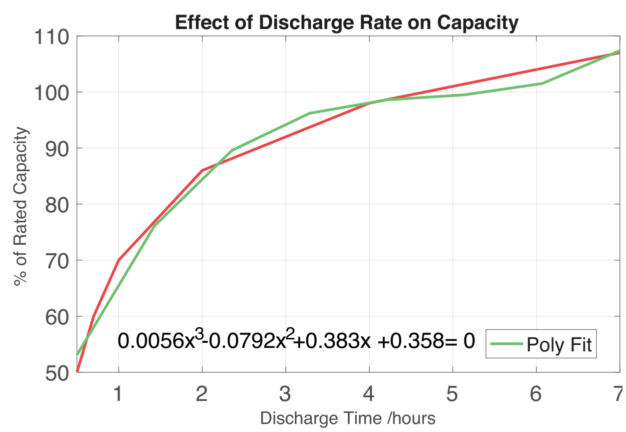


Figure 3.4: Plot of the Relationship Between Discharge Time and Rated Capacity, Interpolated from [60]

Discharge Time: When discharging batteries quickly, the effective capacity of the cell can be reduced [62]. The Peukert Equation is a method used to characterise cell behaviour with regards to capacity offset, when depleting the battery at high discharge rates. It is unclear what the Powerpack's Peurket number is, but it can be assumed to be between 1-1.02, where 1 is perceived as the battery performing well. [63], [64] [f]. The low Peurket number means discharge rate up to the rated power, has little effect on the battery's perceived capacity.

[e] See Figure 4.5, for a detailed description of battery cycling

[f] Li-ion's low Peurket number is another strong supporting factor why using Li-ion is well suited reducing peak demand where there may be instantaneous high levels in demand

Rate of discharge also effect the batteries lifetime[58],[60]. Using the experimental trend shown in Figure **??**, an equation for the effect of speed of depletion can be used to validate the effect of average discharge time. This parameter should be recorded by the model.

3.3.4 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, where current drawn into the battery will vary. Decreasing the battery's voltage will extend its life (partial charging) [66] [g]. By charging the battery too its' full capacity, or overcharging, the battery capacity will degrade quicker, becoming unstable. Cell chemistry causes pressure to rise, increasing temperature inside the cell, further reducing in the battery's capacity. The cell also has a lower thermal runaway temperature and will vent its temperature quicker than one that is partially charged. Consequently, Li-ion batteries are safer at a lower charge [67]. Due to these two issues, the battery should stop charging before reaching this threshold.

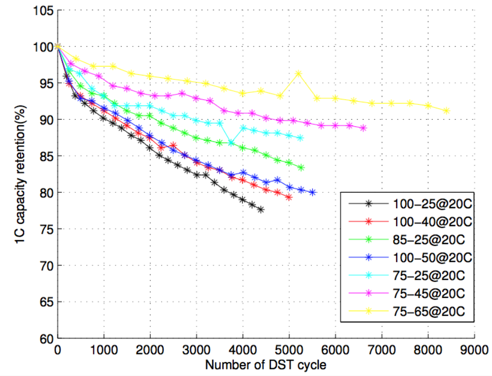


Figure 3.5: Relationship Between State of Charge and Cycle Life [65]

Charging Rate: Similar to discharge time, a reduction in battery capacity occurs at high discharge rates; due to the transformation of the active chemicals inside the cell being unable to keep pace with the current drawn, reducing cell capacity [58]. The model should maximise the charge time of the battery, to reduce this effect.

Figure 3.5 shows testing conducted on Li-ion cells combining the ideas found from battery charging and depth of discharge to increase the lifetime of the battery. Using this result, a charging range can be selected which optimises the payback period of the battery against the battery's lifetime.

4 Battery Model Definition

Through understanding the key design parameters for reducing the impact of challenges set in section 3, a viable model of the battery system was defined. Data was obtained for Senate House (a 7-storey University office/study building). This was used to create a characteristic demand and usage profile for Senate; then manipulated to create a representative energy profile for the New Campus. This section will define how the model was created, discussing the methodology and any assumptions made. Figure 4.1 describes an overview of the primary inputs, processes and outputs of the model.

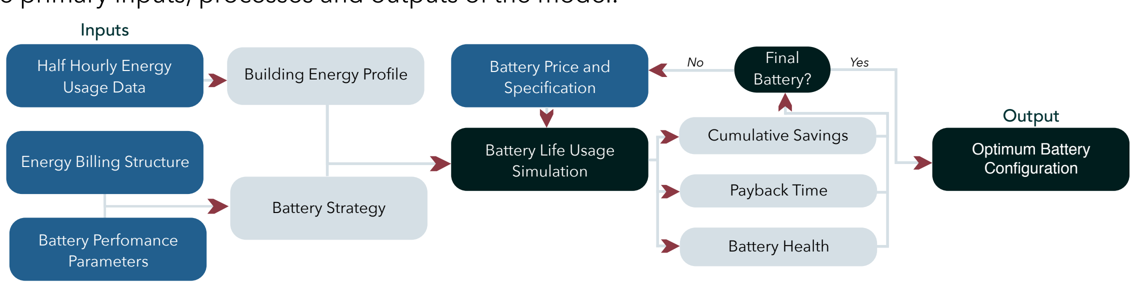


Figure 4.1: Diagram Showing Key Inputs, Processes and Outputs of Model

[g]See Figure 8.3 in the Appendix, showing the relationship of cell capacity and charge voltage, where a dramatic decrease in cell performance for cells charged to higher levels is visible

4.1 Model Development Requirements

A distinct set of modelling requirements were essential to ensure that a functional model was created which corresponded to the project's objectives. By building a flexible, simple model, any unnecessary complexity was removed; sparing both time and computational expense. A robust set of requirements also provided a basis for assessing the completeness of work. The following section defines these requirements.

4.1.1 Zero-Dimensional vs. Three-Dimensional Modelling

The zero-dimensional modelling approach is a technique used in the development cycle of a product, typically in the early stages. Zero-dimensional models are used to understand general performance of a system [68]. Instead three-dimensional models are implemented when detailed analysis is needed. The system dynamics of a zero-dimensional model are a function of the time while a three-dimensional model is a function of the time and space. For this reason, a zero-dimensional models are simpler and faster at generating solutions; enabling a much large number of simulations to be run. As multiple battery systems and strategies are being evaluated, zero-dimensional modelling method was used.

4.1.2 Code Optimisation and Ease of Development

A time-based iterative modelling method, based on a zero-dimensional approach, was selected to model a large variety of different battery specifications. Running the simulation through time requires performing calculations on large matrices. The model should be optimised for performance to minimise running times; helping improve the model performance and reduce data collection time, allowing for a greater amount of different battery specifications to be modelled [h]. It is essential that the model remains structured to allow for expansion as the project progresses. A function based approach must be taken throughout the development process to allow the model reach to its expected size and complexity. Without functions, structure will be poor increasing the difficulty in further develop and debugging.

4.1.3 User Interface

There is a strong likelihood of using this model for next year's group design project. The modelling functions outlined in the project's outputs, should operate independently from each other, working with a broad range of data. Being able to manipulate the model easily will mean others will be able to use the tools developed, making the model much more useful. The model, consequently, must allow for a range of inputs, which should be easily configurable. Design the model in this way, will also simplify data collection reduce the risk of introducing a systemic error, associated with the user entering incorrect inputs or false logic. Dates and times of the energy usage data inputted in the model will have a large effect on the results. It is important therefore that the model can read data files and use their dates, to create accurate runtime usage data. The data outputted by the model must be clear and easy to interpreted by any user, with minimal post-processing; this will improve the model's ability to be a design tool.

4.2 Creation of Senate House Billing Model

In order to validate the results of the model before testing on the new campus, the model was developed for use Senate House.

[h] See section 4.6 the methods used to create optimised code

Data for Senate House, was provided; describing half-hourly usage between 10/08/2014 and 10/08/2015. A bill was also provided for a months energy usage at the Victoria rooms [i] for the Bill provided}. A meeting with John Brenton [8] clarified that billing profiles for both buildings were identical. In order to gauge the size and power requirements of a battery system for Senate House, a minute by minute energy profile was required. Corresponding this energy profile with a bill identified how energy consumption correlated with the cost, allowing quick sensitivity calculations to select strategies likely to would have the greatest impact.

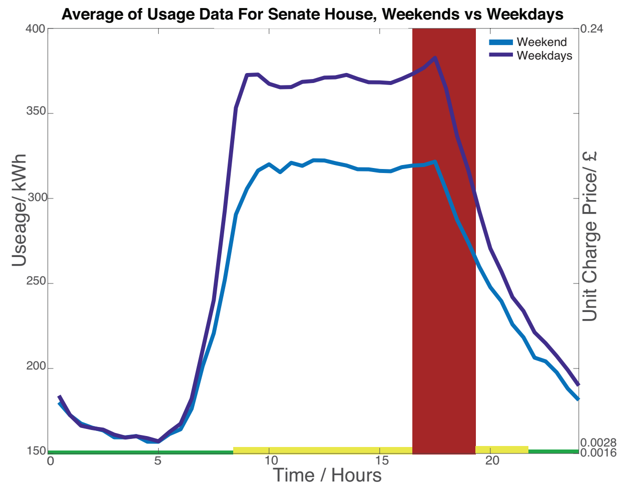


Figure 4.2: Plot of Mean Senate House Weekday and Weekend Usage, and Difference in Unit Charge Rates

Using this data, plots were used to visualise key trends in energy consumption, such as the variation of used based on time of day and period in the year. It was clear that the was a major difference between energy demand during the weekend and during the week, shown in 4.2, where total energy consumption was found to be three times greater over weekdays than the weekend. It was vital all these trends were replicated when the usage file was manipulated.

4.2.1 Representative Bill Creation

Section 2.2 described the components of the energy bill. It's clear that Red rate charges are a significant charge which an ESS can target, incorporating ~20% of the bill. To highlight the significance of the Red rate charge, Figure 4.2 shows the difference in DUoS rates. A preliminary model was designed to target Red rate charges only through load shifting. Using Senate's half-hourly data, each DUoS rate charges and unit charges was calculated. The energy profile was scanned to find which day the bill began, assigning each day as a weekends or weekday, crucial as Red rate charges aren't applicable on weekends. By creating a counter that looped through each half hour period, logic was be applied to categorise each half hour period into their respective unit rate. Total units consumed in Red, Amber and Green periods were found, where simple calculations revealed the the effect of load shifting could have. This crude model captured 79% of the monthly energy bill charges.

4.3 Representative Demand Profile

To simulate how a battery performs, power and capacity must be considered. Applying too much load on a battery can severely reduce the batteries cycle life, discussed in section 3.3. Due to the lack of available demand data for the University, assumptions were made to generate a valid demand profile based on the original half-hourly usage profile.

First, the usage data was broken down into a minute by minute representation. Through using linear interpolation, an identical looking graph of the original data was created, containing 1440 points representing each

[i] A Bristol University building used for lecturing, offices and teaching classes, see Figure {Development-38

minute, see Figure 4.3. This graph was then downscaled to give usage per minute (validated by summing all the points and comparing to the original data).

This crude profile, however, assumed that all usage varies linearly between time periods. In reality, this is not true. A more realistic demand profile was then created by finding the midpoint between values and assigning a random normally distributed number, in intervals of 10 minutes. Choosing an interval too small would deviate the total usage away from the original, while too big would subdue the shape of the graph. This method modelled how usage varied randomly minute by minute, similar to items being turned on and off frequently in a building, but held the original data's consumption trend. A standard deviation σ was then selected which would fairly represent the change in usage over time. For σ to be valid for a variety of different magnitudes in data, the value was trailed against a range of different data sizes. It was found that by assigning σ as a function of average usage and max usage, gave a fair, but conservative representation of how energy usage may look. Scaling by a factor of 2, converted usage from kWh to demand kW; producing a graph showing the peaky nature of energy demand for Senate House. By integrating the area under the demand curve, this graph was validated against the original data.

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 high-energy-consuming equipment that could cause a major spike in demand.

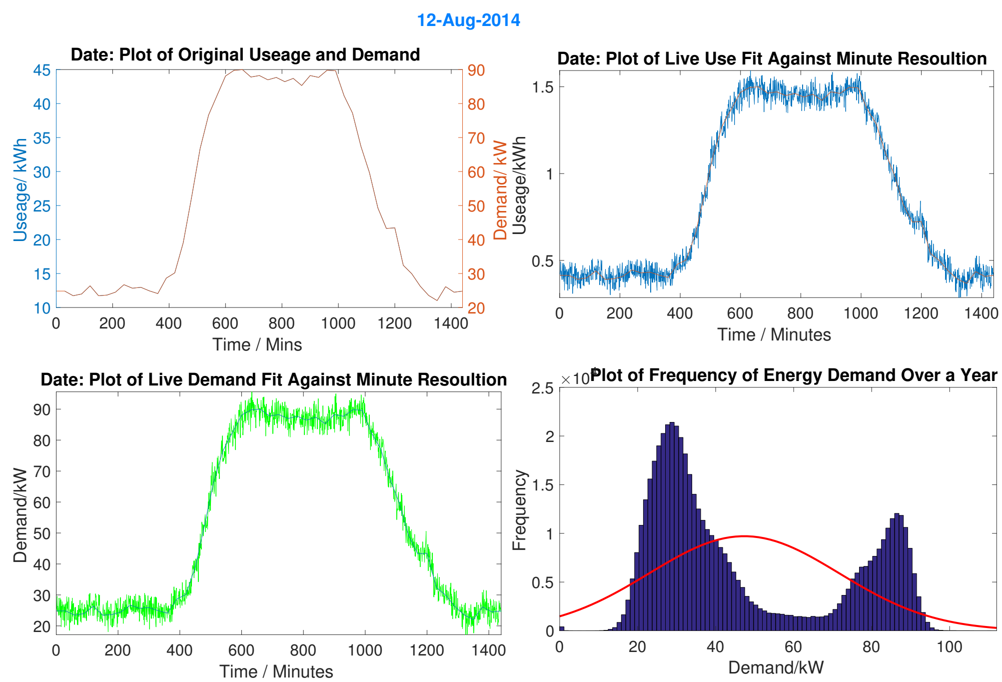


Figure 4.3: Plots of Usage and Demand Profile Generation and Histogram of Year Data

To fully understand the energy profile of the Senate house, histogram and as a cumulative distribution plots [j] were used to identify the typical demand of Senate House sees over the year, as well as the max demand the building experiences [69]. Figure 4.3 shows the demand profile of Senate House, providing insight into what requirements a battery system may need. It can be observed from in the histogram, that the demand of the

[j]See Figure 8.4 in the appendix to see Senate House's load profile

Senate House 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. Insights from the load profile also identified a battery rated to 40KW would cover, 5000 hours of the year roughly 55% of the year's usage.

4.4 Definition of the New Temple Quarter Campus

Understanding the outline of new campus was required to create a valid assumption of its energy profile. At the time of writing, no building plans were available. Instead many assumptions about the likely size and use of the campus were used to create a representative energy profile [k].

The campus will be designed for ~1500 resident students, having ~5000 staff and students on site during term. A range of facilities have been proposed for Temple Quarter Campus, however it is likely that the campus will constitute largely of tutorial rooms, a few lecture halls and offices. A meeting with John Brenton [8], made clear that creating an infrastructure to support postgraduate business studies made the most economical sense, and is likely to influence the Campus's design.

As tutorial rooms and office are similar to Senate House, It is assumed that the energy profile of Senate House will be transferrable to the new campus. It is unlikely the new campus will have any equipment that will distort the load profile greatly; where the campus is likely to have improved efficiency through employing the latest technologies in its construction and services (HVAC). Data on 125 rooms in halls of residence was also provided, with a higher degree of certainty of its applicability to the new campus. Footprints of both buildings were combined with laboratory data, testing the effects labs may have on any large spikes in energy usage. The final scaling factors used were:

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

4.4.1 Energy Profile Tool

Due to energy usage data files beginning on different dates and running for various periods of time, these records required adjustment to be correctly scaled and combined. To fully meet the project's outputs and modelling requirements, a program was created to manipulate various half-hour energy use files. An algorithm was set up to read the data dates and then convert this data into realistic demand profile. To simulate lifetime energy usage, copies of the energy profile were concatenated for the length of simulation, checking that each year began on the next day in the week from the end of the previous year. It was imperative that dates aligned, to make sure results were valid as the difference in energy usage between weekdays and weekends (see section 4.2), could cause the total savings to vary on a seven-year cycle pattern. Figure 4.4 outlines the logic of this program.

[k] See Table ? In the appendix for a breakdown of how the new campus was sized

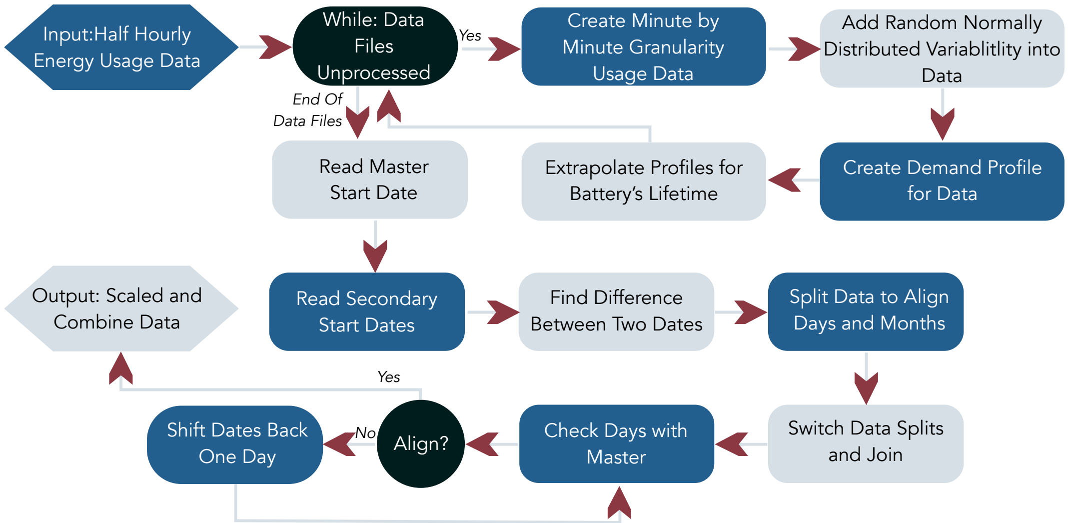


Figure 4.4: Logic of Energy Profile Tool Create New Campus Data

4.5 Definition of System Strategies

To fully understand the value of using battery storage, a representative simulations of how the battery would operate is required. This section defines the logic define the battery's operation. The model calculates both economical and technical battery performance based on the chosen battery strategies. The following section will discuss why the final strategies were selected, detailing their development.

4.5.1 Red Rate Charge Avoidance Strategy

As outlined in section 4.2.1, using energy consumed during Red rate periods was considerably more expensive than Amber and Green periods, making it a prime strategy. By switching the battery on during Red rate periods, then charging during Green periods, cost savings of up to 20% could be made. Currently, for the University, Red rates apply between 5 and 7 PM on weekdays making it simple to forecast, alleviating the need for complex prediction systems highlighted in section 2.4.1. During this period the battery would be drained at a rate up to its maximum output power; requiring demand and usage data to be checked simultaneously. If the load exceeded max power, energy supply was capped at this value. The battery would continue to be drained until either its minimum capacity was reached, or the Red rate period elapsed. The battery would then be fully charged during green ensuring all capacity was available for the next Red rate period is entered. This method was repeated for the run-length of the simulation.

4.5.2 Triad Avoidance Strategy

To correctly understand the effects of TRIAD avoidance in the model, TRIAD dates needed to be correctly identified. Using [70], the dates: 4/12/14, 19/01/15, 02/02/15 were used; aligning with the original Senate House data set as the as a master template for the new campus (discussed in section 4.4.1). These dates were used for the sequential years in the simulation as they were typical days in which TRIADS would fall. From observation, it was assumed that there was no increase in the University's usage during TRIAD periods, allowing for any day within that week to be used. To make sure these dates did not fall on fall weekends, days were checked and adjusted accordingly. It is assumed that daily variation in energy usage is negligible and instead energy trends are seen only on a monthly basis.

It was observed that TRIAD times all fell into Red rate periods, corresponding with the Red rate avoidance battery strategy. Using these dates and the time of 5:30, the TRIAD cost was calculated based on energy demand (kW). 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; due to the battery would only need to run for a few minutes to offset this charge.

At the end of each year in the simulation, usage on the three TRIAD dates 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 Control Strategy

The importance of optimising battery longevity was highlighted in 2.4.1 and 2.4.3. Section **??**, discussed the different variables which can affect a battery's longevity. An approximation of the battery degradation was taken, taking into account the effect of each of these variables as a battery control strategy.

The rated battery cycle life is taken to be the number of full cycles a battery can complete before it degrades to 80% of its original capacity [I]. This figure was used as a measure for how the battery should perform based on a normal use case. Using this assumption, the battery was degraded proportionally by the fraction of its current cycle.

For each charging iteration, the new max capacity became slightly smaller, reducing the size of the cycle. A counter was used to sum each charge, resetting when its value equalled the current cycle size; signifying one complete cycle. Using this method, battery's were degraded on their on their use, degrading quicker as they deterioted. This followed the battery cycle degradation trend shown in figure 3.2.

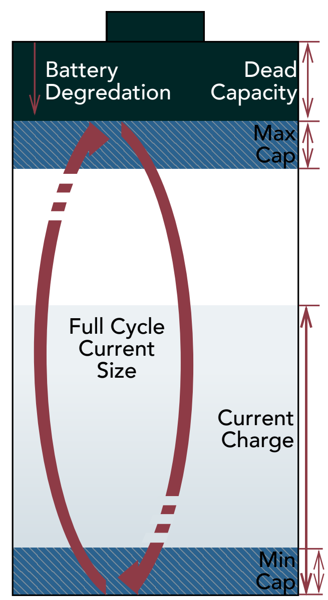


Figure 4.5: Showing Battery Degradation

By using the cycle-life metric, all battery degradation assumptions were based on the battery's operation and not the battery's chemistry. Assumptions on the batteries normal working parameters were made, limiting the battery to conform to these rules. This would prevent the battery running in a way that would majorly affect its longevity, making the prediction more accurate. These restrictions could be made greater or smaller at the expense of more or less chance of error on the battery health prediction. The following battery control measured were implemented:

- **Reduction in Depth of Discharge**: To reduce wear on the battery, the battery was confined to work within 10-90% of its current maximum capacity, allowing a maximum depth of discharge of 80%. Draining the

[I] This is quoted to be 5000 cycles for the Tesla Powerpack, see Figure 2 battery can cause detrimental effects on the while overcharging can also do the same. Working within these two parameters follows similar principles applied by Tesla in their electric cars [71].

- **Speed of Depletion**: A battery was never run above its max specified power. As the battery was rated at this value, it should be designed to cope with this level of use for no longer than 2 hours a day. The simulation will analyse the average discharge rate as a measure of the validity of the battery health
- **Temperature**: was assumed to remain within expected bounds, based on the assumptions made in section 3.3.1. Using the Red rate and TRIAD strategies would allow the battery to cool over weekends.
- **Charging**: The battery would only charge during Green periods, at a rate which would ensure the battery would be charged fully by the next Red period; this was based on the capacity required divided by the length of the Green rate period. Section **??** 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 such as trickling (seen on most modern smartphones), would be incorporated into the actual battery, but modelling these methods would not increase the accuracy of the model, so was been neglected.
- **Battery Efficiency**: This was regarded in the model by multiplying the energy drawn when charging by the additional losses caused inefficiencies. This assumption was made as it is likely that the battery once charged can supply what it has stored. The Powerpack 2 integrated inverter, supplies energy in AC, quoting its efficiency to this level (see figure 2). It is assumed that the quoted figure is very representative of the battery's efficiency in the system. Efficiency gains could also be achieved by designing the system, so it primarily sends power to DC first without transforming, this will not be evaluated in this project, see Figure 2.

The model was run until the either runtime elapsed or the battery reached its end of life value (80%), allowing results to be comparable. There are examples of batteries being used beyond their end of life cycle. Renault and connected energy have been investigating using the end of life Li-ion car batteries in home use applications [55], [72]. It is believed there is still plenty of life remaining, and the increased probability of failure is less of a problem when used for bill reduction purposes. In the case of the new campus, there are little-associated costs with batteries after they have been installed if the battery has paid itself back, the battery will continue to generate profit. If unpredictability is seen to be an issue, this may be the case if emergency power is seen as a key value of having the battery, then it may be possible Analysing this value is out of scope for this project so an end of life battery was be classed as having no value.

Table 2: Tesla Powerpack 2 Specification

Powerpack 2 Specifications	
Capacity (Per Pack):	210 kWh (AC)
Power (Per Pack):	50 kW (AC)
Net System Efficiency:	88% round-trip (2 hour system) 89% round-trip (4 hour system)
Operating Temperature:	-30°C to 50°C
Scalable Inverter Power:	from 50kVA to 625kVA (at 480V)
Depth of Discharge:	100%
Cycle Life:	5000 Cycles
Warranty:	10 Years
AC Voltage:	380 to 480V, 3 phases
Additional Features:	• Bi-Directional Inverter (Inbuilt) •Thermal Controller • Modular Scalable Design

4.6 Input Parameters and Multi-Battery Simulation

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 were modelled. Using actual data from Tesla [73], the real costs of the different battery specifications were modelled. To find trends in the different battery types, the modelled required iterating through numerous different battery specifications. To reduce computation time, parallel computing was implemented to iterate each discrete battery scenario in the 0D model.

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

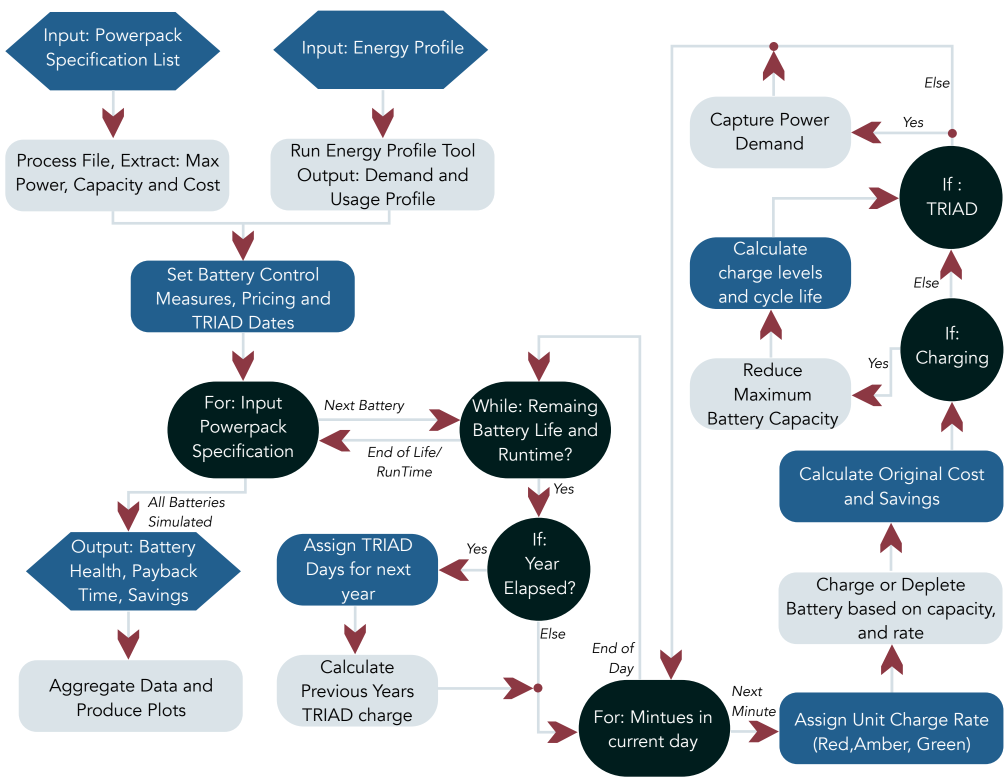


Figure 4.6: Logic Diagram For Multi-battery Simulation

To comply with the requirements set in section 4.1 The following methods were used to optimise the performance of MATLAB model.

- *Vectorisation*: storing data within multidimensional arrays and using vector operations
- *Variable Initialisation*: all matrices were initialised to reduce memory.
- *MATLAB Function Reduction*: functions such as linear interpolation are cumbersome. These were recreated and simplified, solving tasks more efficiently.
- *Parallel Processing*: Multiple cores on the processor were used to iterate through independent battery specifications in large multi-battery simulations. To achieve this successfully, code was rewritten to make all events discrete, substituted methods such as `while` and `break`. For large multi-parameter simulations,

this can increased the processing time significantly,.

- *Profiler Tool* : Within MATLAB, the performance of code can be measured in the amount of time it takes to run. This tool was used to identify bottlenecks within the model.
- *Single Integers*: Single integers are half the size of double integers, the default storage method for data within MATLAB. Double-precision floating point numbers allow the CPU to handle very large values. As this level of accuracy is unnecessary, use of 32bit single integers increased performance [74].
- *Do Not Repeat Yourself (DRY)*: Coding technique to improve readability and performance of code, through use of functions.

The result of this method reduced processing time per battery from ~110 seconds to under 10 seconds. This was crucial in allowing the 113 different battery simulation run quickly. The runtime of the multi-scenario program was reduced to 220 seconds. This allowed different sensitivities studies to be run, greatly improving the functionality of the tool.

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 [75]. Section 4 describes how the model was initially tested on Senate House to validate whether the model produced expected results. After being validated on Senate House the model was then run of the new campus energy profile.

5.2 Assumptions and Limitations

Table 3, summarises all the assumptions discussed in section 4. To create a valid model, all assumptions must be based on logical expectations on all parameters that may effect the system, thereby using the following assumptions, the model is validated.

Table 3: Showing All Assumptions Made for Simulation

	Assumptions	% Uncertainty
Energy Profile	• The new campus overall energy profile will have small peaks in demand only, due it being very unlikely for lots of equipment with high power consumptions to be switched on together	**50%**
	• Energy demand is assumed to be normally distributed between each half hour period	**20%**
	• Standard deviation of energy demand equals average between mean and max of data, following the assumption that peaks sizes are proportional to the total demand	**40%**
	• Daily variation negligible in energy usage is negligible, assume profile is unlikely to change over battery lifetime	**20%**
	• New campus profile is formed of Senate House, Hall data and Lab data only scaled according to their total footprint size	**30%**
Energy Billing	• Red rate periods remain the same for the duration of the simulation	**50%**
	• Energy prices and bills remain the same for the duration of the simulation	**90%**
	• TRIAD dates kept as close as possible to 4/12/14, 19/01/15, 02/02/15 (no weekends used)	**20%**
	• TRIAD Bills are divided equally over the next billing year	**10%**

Battery Health	• Battery degrades linearly from new to it's end of life value of 80%	20%
	• Battery parameters restrict battery to perform under normal use case, 5000 cycles for a max depth of discharge of 80%	40%
	• Battery does not overheat is temperature controlled and allowed to cool over weekends so does temperatures effect is assumed reliable	20%
	• Effect of depth of discharge and discharge rate on battery health is negligible based on normal constraints (effects discussed as secondary results)	80%
	• Normal working parameters prevent over depletion or over charging from occurring	10%
	• Battery cycle life instantaneously degrades when charging	10%
Battery Usage	• Battery efficiency losses occur only when charging	20%
	• Trickle charging and minimum charge rate employed	10%
	• Battery has health monitoring equipment, allowing it's health to be optimised	20%
Battery Costs	• Current Powerpack 2 costs are used to evaluate the cost of the investment. Assumed that the price will decrease and performance of battery's will improve at the time of the new campus build. Current costs are therefore used as a worst case scenario	5%
	•Installation costs have been assumed negligible due to new campus build absorbing this	30%
	• Maintenance cost assumed not applicable , as this cost will be very small	30%

The model is limited to working to these parameters only. Section ??, set an objective for the model to be developed so these parameters can be easily changed, allowing for the model to be easily customised to work with a different set of assumptions. Peaks in demand being higher than modelled, energy pricing changing and DOD and discharge rate effect on capacity all have high levels of uncertainty in the model. These were sensitivity checked to understand the effects of these assumptions being incorrect.

6 Results

The objective of this report was to evaluate whether there is the strong business case for investing in energy storage technology for the New University Campus. This section analyses the data gathered from the zero-dimensional model, discussing the value which optimum batteries specifications could bring to the new Temple Quarter campus. Figures 6.1 and 6.2, describes the energy profile for the new campus's usage during Red rate periods.

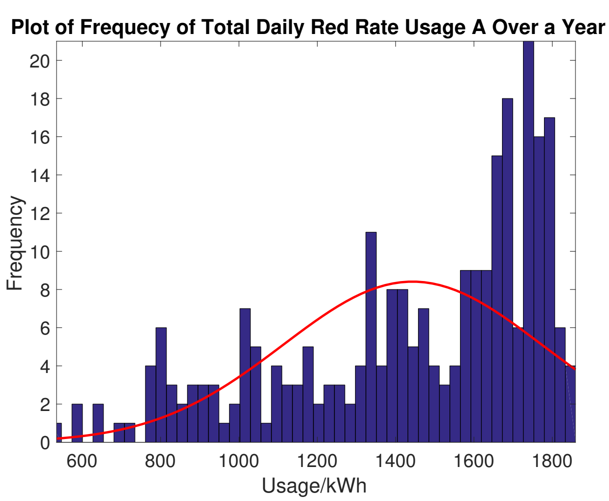


Figure 6.1: Histogram Showing Red Periods Total Daily Usage Frequency

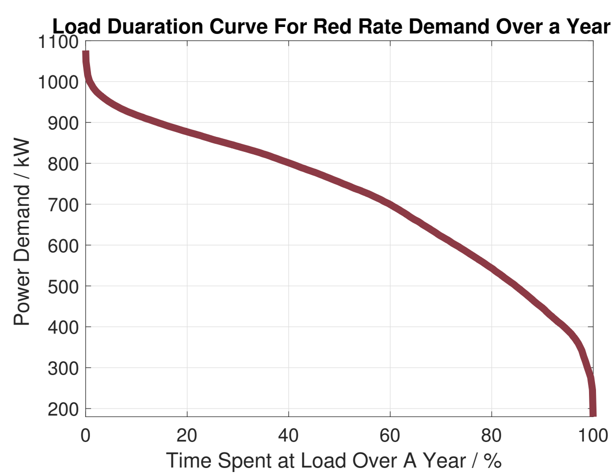


Figure 6.2: Time Spent at Power Demand Level

These energy profile plots, described the range of battery specifications which should be simulated. Figure 6.1, that how a battery with a usable capacity greater than ~1800kWh will have excess capacity to demand. By taking into account end of life degradation, battery's up to and end of life capacity of 2000kWh were modelled. Figure 6.2, describes the percentage of time the battery would spend at max load. A battery rated at 920kW would be only run at max load 10% of the time. As discharge rate effects capacity, battery's rated up to 1300kW were simulated. Based on this analysis 65 different Powerpack 2 battery specifications were identified as plausible solutions.

A 25 year runtime period was used to evaluate the battery performance over[m]; chosen on the assumption that most technology in the building will be replaced by this point, as the building begins to receive some refurbishment. Li-ion battery technology will have also significantly advanced, or at least drop significantly in price [n]. Using a set period will also reduce uncertainty in battery health and prevent favouritism for larger batteries. An investor is unlikely to look beyond 25 years, so savings made after these periods will not be considered. The following results will talk through the three key value measurements discussed in section 3.1.

6.1 Total Savings and Payback Period

Figure 6.3 shows the parabolic shape with a local maximum between the battery size and the total savings. For the new campus, a battery size of around ~2.2MWh generated the maximum total savings over the simulation run time. In contrast, Figure 6.4, highlights that a much larger range of batteries fell close shortest payback time of 6.3years, where power and capacity increased proportionally.

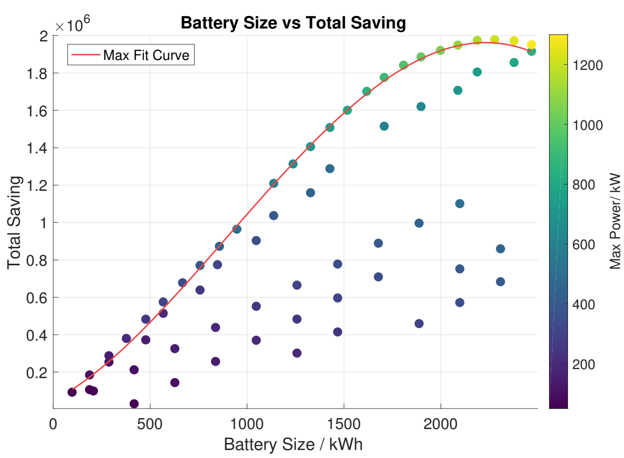


Figure 6.3: Battery Size Vs Total Savings

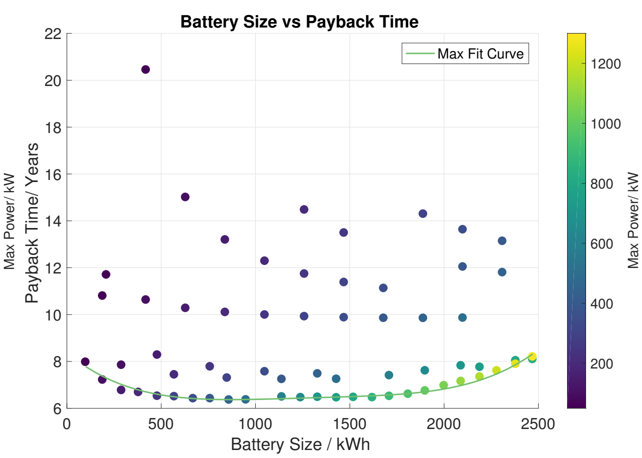


Figure 6.4: Graph of Battery Size vs PayBack Time

Figures 6.3 and 6.4, begin to give a good insight into the financial performance of the battery, however, presented in this form, it difficult for a designer to choose the optimum battery. To make the results more useful, an algorithm was made, which generated best-fit plots over the maximum battery specifications for the different total saving and payback time plots. Figures 6.5 shows how these curves plotted over the maximum values.

[m]See Page 27 of [76].

[n]See Figure 3.1 for a prediction in battery prices

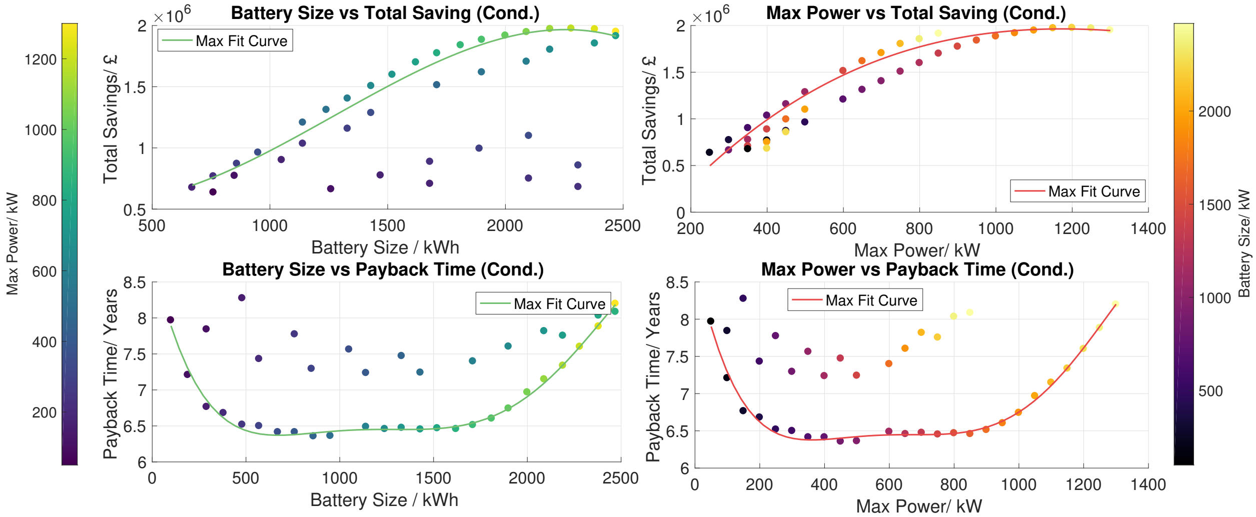


Figure 6.5: Graph Showing Top 40 Batteries with Fitted Curves for both Payback Time and Total Savings

By superimposing these max-fit curves, a graphical tool was created, allowing a designer to visualise the tradeoff between total savings and payback time, shown in Figure 6.6. A small region around the cross over point of the two plots shows the specifications of the optimum batteries. By creating a set of rules (e.g. the battery must have a payback period less than seven years), all the solutions become immediately apparent. A small shortlist of the batteries can be made, referring back to the original list of Powerpack specifications.

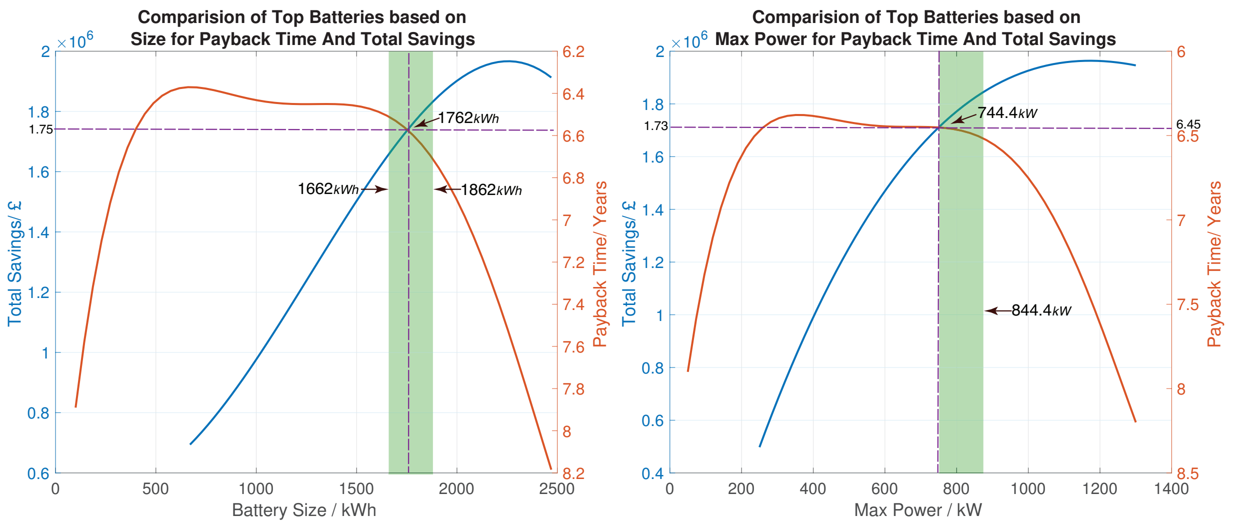


Figure 6.6: Comparison Between Fit Curves for Payback Period and Total Savings

Analysing Figure 6.6, the regions where the best trade-off between payback time and total savings (around where the two plots intersect) has been highlighted. The results show that a battery around 1762kWh and 744.4kW, produces a good compromise. Increasing capacity beyond increases total saving at the result of quickly decreasing the pay back period. Alternatively, when looking at max power, payback time is increases slightly for as power decreases. Up top 950kW, total savings dramatically increase, with very little decrease in payback time. The green region highlights the region after the intersection point, showing a battery larger than 745kW but less that 950kW, is optimum.

Measuring the payback period is necessary when evaluating the risk of investing in a battery. The longer the payback time, the greater the risk in either the battery failing or regulation changing diminishing the batteries value [o]. The Powerpack 2 specifications modelled, have a 10 year warranty; this eliminates any risk if the battery were to fail before this period. Changes in energy billing are therefore the biggest risk the technology faces. Energy contracts typically last no longer than four years [77], after which a change in pricing scheme could reduce the battery's value to zero. Knowing that $\frac{2}{3}$ of the investment has a very low risk of uncertainty rather than $\frac{1}{2}$, makes the investment much more attractive. These factors should be considered when choosing the design region of battery selection. For a structural investment, a payback period between 5 and 7 years is deemed good. The optimum battery payback time is 6.3 years falling within this range. From this analysis investing in Li-ion appear feasible.

6.2 NPV

Net present value was the second method used to assess the battery systems value. As long payback periods are inherently risky, NPV uses discount rates to devalue cash that is made further in the future. As discussed in section 3.1.1, the Internal Return Rate was found. This calculation found for the range of battery assessed that the average IRR was 11%,falling between 2 and 15%. Three discount rates of 3%, 7% and 12% were selected to understand the value of the different batteries based of the IRR calculation. Figure 6.7 shows the net present values of the various simulated batteries at these different rates.

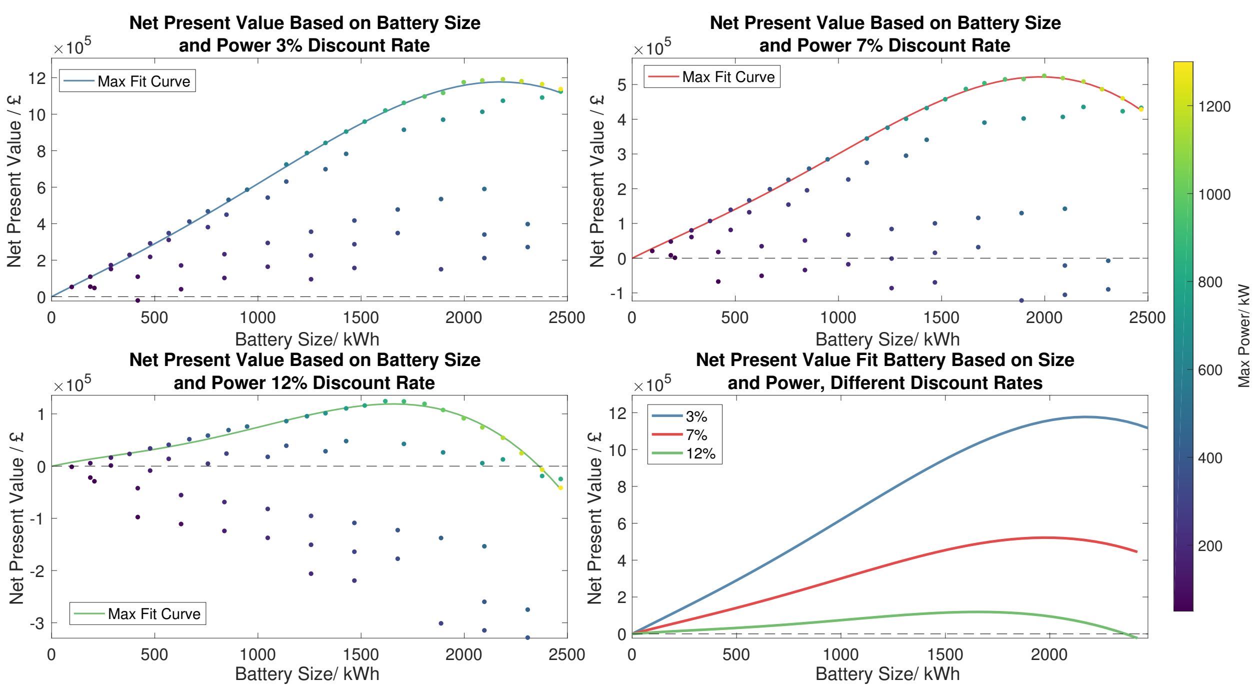


Figure 6.7: Net Present value at Different Discount Rates - Comparison

Using the different NPV rates, presented conflicting optimum batteries. Increasing discount rate favoured smaller. Looking across the result of it was decided that a batteries a 7% discount rate the following assumptions:

[o]See Table 1 for a more detailed description of the challenges that an ESS system faces

- **Battery Health**: As the battery will degrade each year until it reaches its end of life value, an assumption can be made that the value of the asset decreases proportionally to the battery's health. Looking at 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 its original value, equating to a discount rate of ~3.92% over the 25 year period. As each battery degrades differently, the discount rate due to battery healthy can be approximated to 4%.
- **Inflation**: Inflation is another factor of the discount rate. For the UK, this rate has varied between -0.1% and 3.5% for the last five years [78]. It is expected that the price of energy bills will increase with inflation, therefore this interest was neglected.
- **Interest Rates**: Discount rates can be used to incorporate interests on loans. As the battery would be purchased at the same time as the rest of the new campus it is assumed that the battery will be bought under the new campus's mortgage; keeping the interest rate low, approximated to 3%.

Using these approximations gives a discount rate of around 7% shown in figure 6.7.

6.3 Battery Health Analysis

In order to reduce computational time and simplify the model, assumptions were made to confine the battery to never work outside of normal working parameters. Section 3.3, discussed how discharge time and depth of discharge effect the battery lifetime. Based of experimental data, equations for how these factors effect were found. The way the model was created to measure average depth of discharge and discharge time, allowing the effect of these parameters to be analysed after completing the simulation. Understanding the effect of these parameters increases the validity of results. Figure 6.8 and 6.9 show the trend between depth of discharge and discharge for the different batteries.

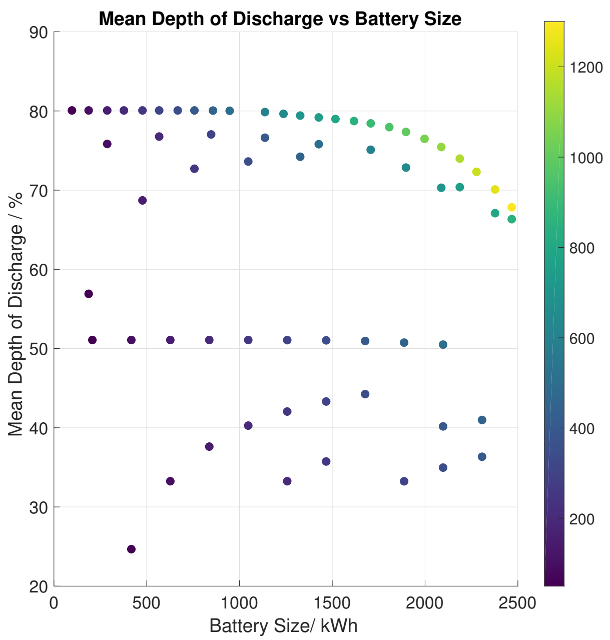


Figure 6.8: Depth of Discharge For Battery Lifetime

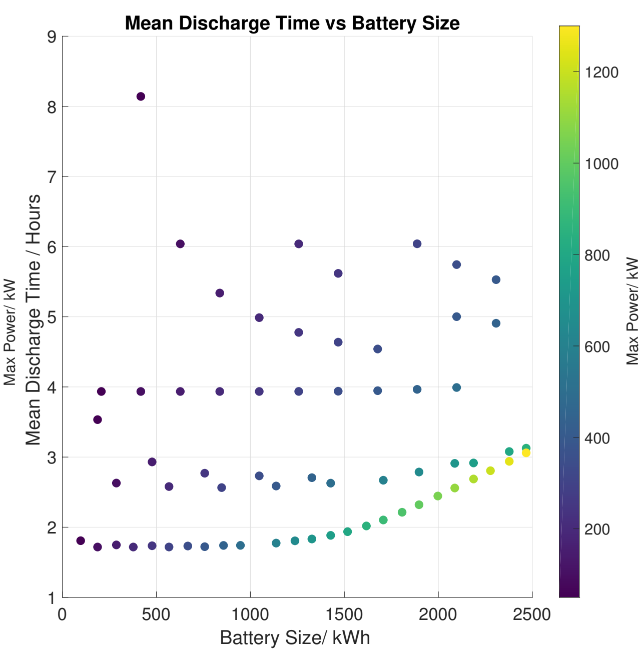


Figure 6.9: Expected Capacity Offset Due to Discharge Rate and Depth of Discharge

The patterns observed in Figures 6.8 and 6.9 occur due to the difference between maximum power and maximum capacity. Comparing this result to Figure 6.3, it can be seen that the batteries achieving the maximum total savings have DOD greater than 70%, but are not always fully discharged. Batteries appear to fall into two categories; one of high mean depth of discharge between 70-80% and one with a mean depth of discharge around 50%. This is a result of the relationship between capacity and max power, limiting the possible depth of discharge that the battery could reach in the two hour red rate period. With regards to the discharge rate in Figure 6.9, As capacity increases, discharge rate tends also increase, almost doubling against the high power lower capacity batteries.

Using the polynomial equations outlined in Figures **??**, 3.5 and an additional performance parameter describing a more realistic end cycle life size was found based on these two measurements. The results are shown in Figure 6.10.

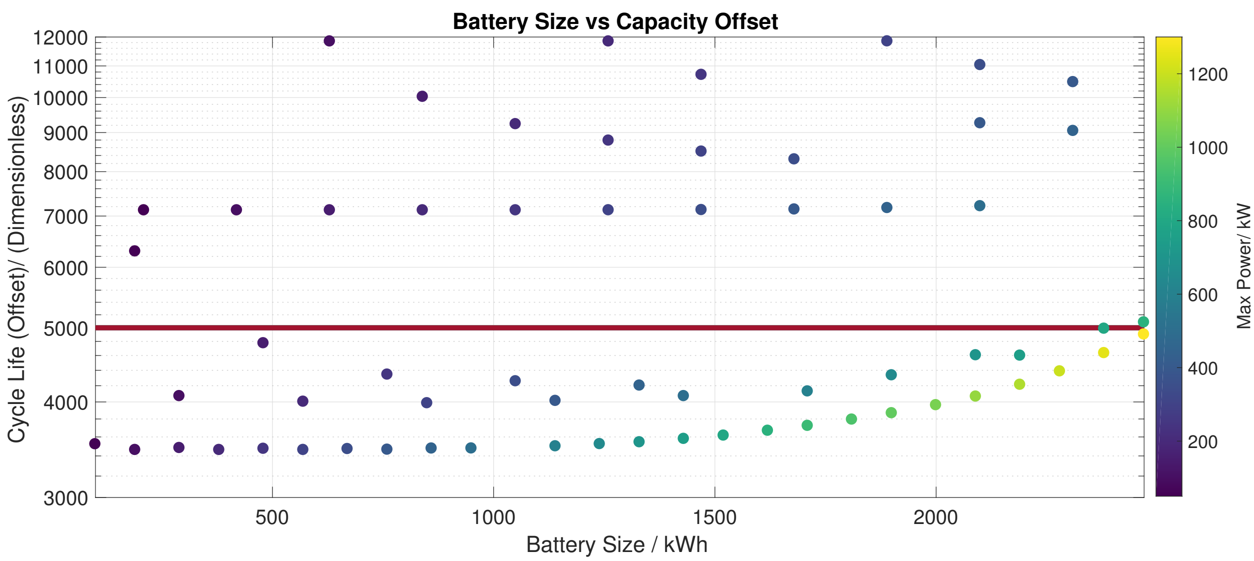


Figure 6.10: Showing the Expected Effect of Depth of Discharge and Discharge Time on Predicted Cycle Life

It is clear from Figure 6.10 that taking into account DOD and discharge time , the lifetime of the battery can either be reduced or increased significantly. As not all batteries will fully degrade by the end of the 25 year lifetime, slightly reduced capacity may not be a problem as the battery should still be functional beyond the end of life value. From research, it appears depth of discharge can have a more dramatic effect on the batteries lifetime. To make experimental effects of DOD comparable for the Powerpack, a conservative assumption of the battery being rated at 70% DOD was used. [59], however notes that it is possible higher DOD were used to achieve the 5000 cycle life. This would decrease the effect of DOD significantly, meaning many more batteries would increase in cycle life rather than decrease. For both these reasons it is unclear whether error in predicting battery will have a significant effect on the battery's value.

6.4 Discussion on Optimum Battery

Table 4, show the optimum battery configurations based on the metrics discussed perviously.

Table 4: Table Showing the Best Battery Results Comparing the different Economic Measurements

	Highest Performers			
Parameter	NPV	Total Savings	Payback	Max Plot
Battery Power (kW)	1050	1200	450	900
Battery Capacity (kWh)	2000	2280	860	1710
Purchase Cost (£)	803,630	915,980	343,100	683,420
Total Saved (£)	1,912,775	1,969,808	870,561	1,765,193
ROI (%)	238%	215%	254%	258%
Payback (Years)	6.95	7.59	6.36	6.53
NPV 7% (£)	522,613	483,657	256,381	498,150
IRR (%)	14%	12%	15%	15%
Mean DoD (%)	76.4%	72.2%	80.0%	78.4%
Mean Discharge (hrs)	2.40	2.80	1.73	2.10
Years Run	25.0	25.0	24.0	24.5
Annulised Savings (£)	76,511	78,792	36,302	72,117
Cycles Complete	4980	4709	5000	5000
Predicted Health	3960	4384	3476	3721

The following observations can be made on the results:

- The difference in NPV between the best NPV, total savings and max plot values is around £40,000, this is relatively marginal against the total cost of the investment
- A difference of only a years payback time can be observed by all the best performing batteries.
- All the batteries are run towards their maximum working threshold with high DOD and mean discharge times
- The maximum plot specification battery gives the highest Return on Investment (ROI), this measure helps understand how much money is made, compared to how much was invested.
- Annualised savings of all the battery excluding lowest payback ranges by £6,000 only. Between max plot and total savings, an increase in 35% in upfront cost creates only 9% more yield a year.
- Selecting a battery based on the lowest payback period has a significantly lower NPV and the likelihood of it failing before it reaches 5000 cycles is likely
- By selecting the battery with the largest total savings has the highest probability of not wearing out before it reaches the end of life

6.5 Sensitivity on Key Assumptions

- Graph of effect of peak demand rise by 25%
- Graph on the effect of change in pricing structure - decrease DUOS - increase Capacity ?

7 Conclusions and Future Work

7.1 Conclusions on Modelling Tool

- This project set out to create multiple tools that would be useful in both evaluating the value of a battery system whilst being flexible tools that can be used in the 5th year group project.
- *Energy Profile Tool:* to build and understand the New University Campus's Demand
- *Optimised Battery System Model:* producing best storage solutions based on energy profile tool
- *Business case:* for battery technology investment

7.2 Conclusions on Results

- Model confirms that it is financially feasible to purchase and use a battery to reduce energy bills
- Optimum battery can be selected using different values metrics based on the usage profile inputed.
- A 7 year payback period is lower than warranty on the battery, eliminating any risks in incorrectly modelling the batteries degradation
- After the battery has paid itself back there is nothing stopping it continuing to run until it ceases to function. Little maintenance is required after its is installed, so nearly all savings are instantly realised, this means the battery could theoretically continue to generate savings for the lifetime of the building (50 years)
- Due to the modular design of the Tesla Powerpack, after the system is initially installed it is feasible to swap the batteries out after they have worn out.
- The simulation is ran for a long period of time (25 years), there is a large amount of unpredictability particular in energy tariffs, that could dramatically alter the value of the battery system over it's life time. the sensitivity study showed......

Refer Back To Challenges and Compare how these challenges are either overcome or still barriers

- *Costs of Purchase too high*: the model proves that this barrier has been over come. As the battery will be purchased as an asset along with the buildings, land and other equipment that will be purchased for the new campus, it can be assumed that a very low interest rate will be taken on the battery.
- *Lifetime/ longevity of the battery too low*: Model of degradation shows that the lifetime of Li-ion is now feasible based on the battery being run in a controlled manner optimising it's longevity.
- *Frequent change of regulation and barriers to entry*: This is still the largest barrier to entry. Discussions with Western Power [77], noted that DUoS prices are very likely to change over this period. Due to the added flexibility that fast frequency response energy storage methods such as Li-ion batteries bring, it is in the energy suppliers interest to encourage customer to purchase this technology rather than penalise this. Much of further change in regulation may therefore support using Li-ion batteries, which could increase the batteries value further in the future.
- *Negative environmental effects:* expand further using references [79]
- *Technology still maturing*, Li-ion batteries have not been used in this manner before, for extended periods of time. However Tesla has been using batteries for over 10 years and has gathered some of the best

minds to understand how their batteries will function. A lot of research around Li-ion has been conducted showing that on a smaller scale the technology is mature enough. The nature of scaling should have no additional effects on the batteries performance. As the way in which the battery will be operated is well modelled, using strategies working in the batteries design parameters no undesired load scenarios should be place on the battery.

7.3 Future Work

- Can apply this model directly into 5th year, using the data tool to understand energy demand on a range of different sources including heat and gas. Transferrable to evaluating smart thermal grids with the use of CHP
- Further development of the degradation model and testing, to validate assumptions, work to be completed with Tesla
- Evaluate other methods such as frequency response to determine if additional value can be created
- Model the value of having a fixed demand profile for the new campus could have in reducing it's connection fee (there will be large upfront costs incurred on building the supply lines for the new campus, if this can be reduced by using batteries, how much could be saved ?)

8 Appendices

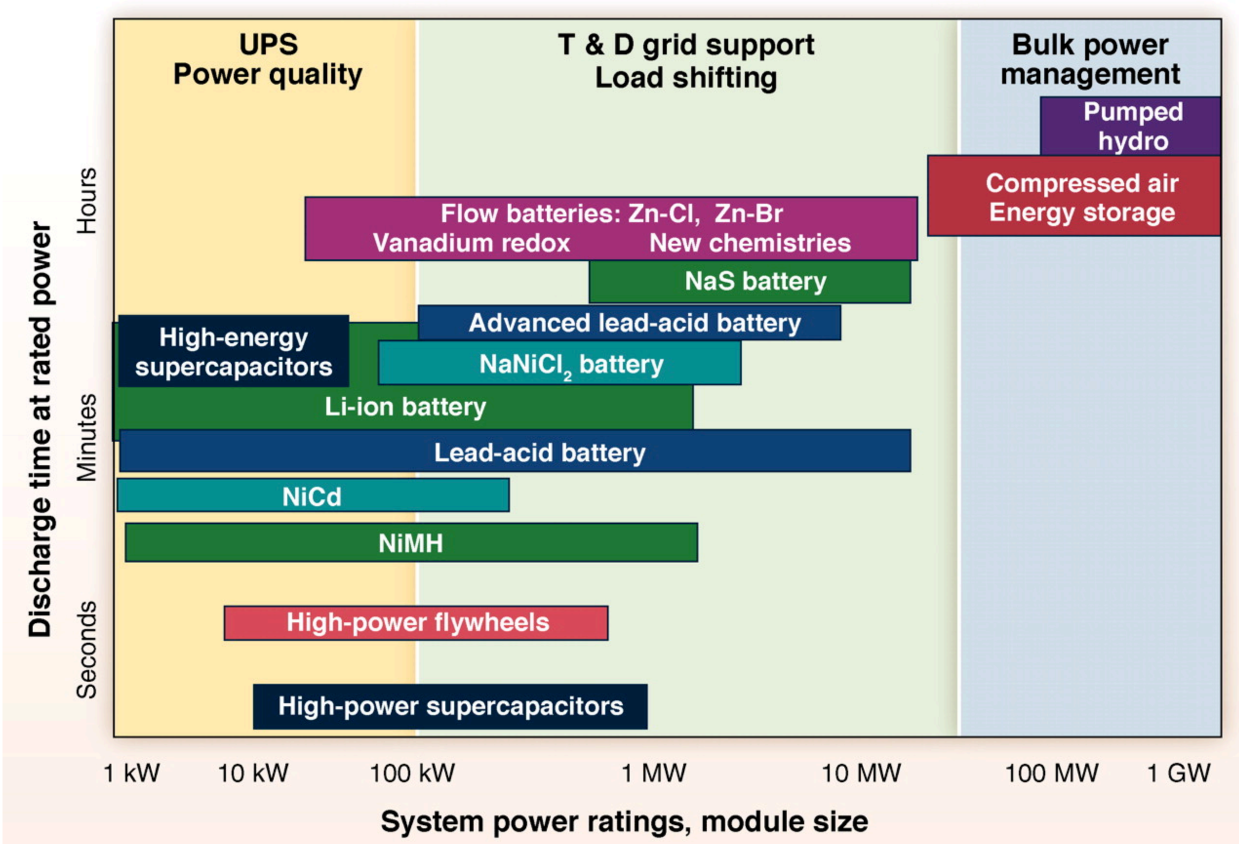
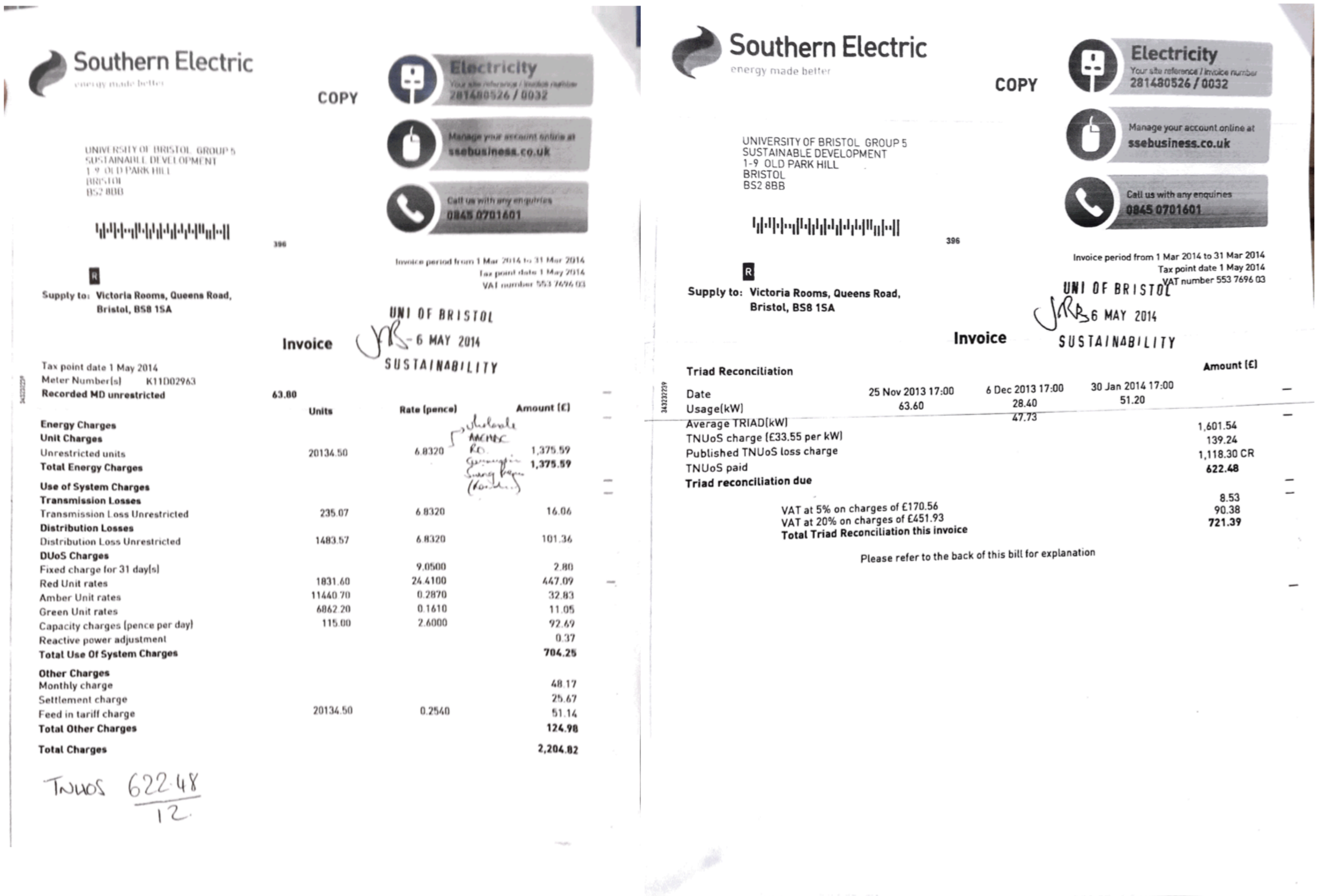


Figure 8.1: Diagram Showing Batteries Catorgised for Their Use Case [45]

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 5: Table Showing Battery Performance



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Tax point date 1 May 2014
VAT number 553 7696 03

Supply to: Victoria Rooms, Queens Road,
Bristol, BS8 1SA

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6 MAY 2014
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Invoice

Tax point date 1 May 2014
Meter Number(s) K11D02963
Recorded MD unrestricted 63.80

	Units	Rate (pence)	Amount (£)
Energy Charges			
Unit Charges			
Unrestricted units	20134.50	6.8320	1,375.59
Total Energy Charges			**1,375.59**
Use of System Charges			
Transmission Losses			
Transmission Loss Unrestricted	235.07	6.8320	16.06
Distribution Losses			
Distribution Loss Unrestricted	1483.57	6.8320	101.36
DUoS Charges			
Fixed charge for 31 day(s)		9.0500	2.80
Red Unit rates	1831.60	24.4100	447.09
Amber Unit rates	11440.70	0.2870	32.83
Green Unit rates	6862.20	0.1610	11.05
Capacity charges (pence per day)	115.00	2.6000	92.69
Reactive power adjustment			0.37
Total Use Of System Charges			**704.25**
Other Charges			
Monthly charge			48.17
Settlement charge			25.67
Feed in tariff charge		20134.50 → 0.2540	51.14
Total Other Charges			**124.98**
Total Charges			**2,204.82**

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6 MAY 2014
SUSTAINABILITY

Invoice

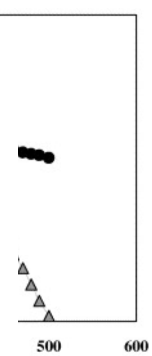
Triad Reconciliation				**Amount (£)**
Date	25 Nov 2013 17:00	6 Dec 2013 17:00	30 Jan 2014 17:00	
Usage(kW)	63.60	28.40	51.20	
Average TRIAD(kW)		47.73		
TNUoS charge (£33.55 per kW)				1,601.54
Published TNUoS loss charge				139.24
TNUoS paid				1,118.30 CR
Triad reconciliation due				**622.48**
VAT at 5% on charges of £170.56				8.53
VAT at 20% on charges of £451.93				90.38
Total Triad Reconciliation this invoice				**721.39**

Please refer to the back of this bill for explanation

Figure 8.2: Image of Energy Bill For Victoria Rooms

8.1 Battery Degredation

8.2 Senate Load Profile



ery Cycle Life

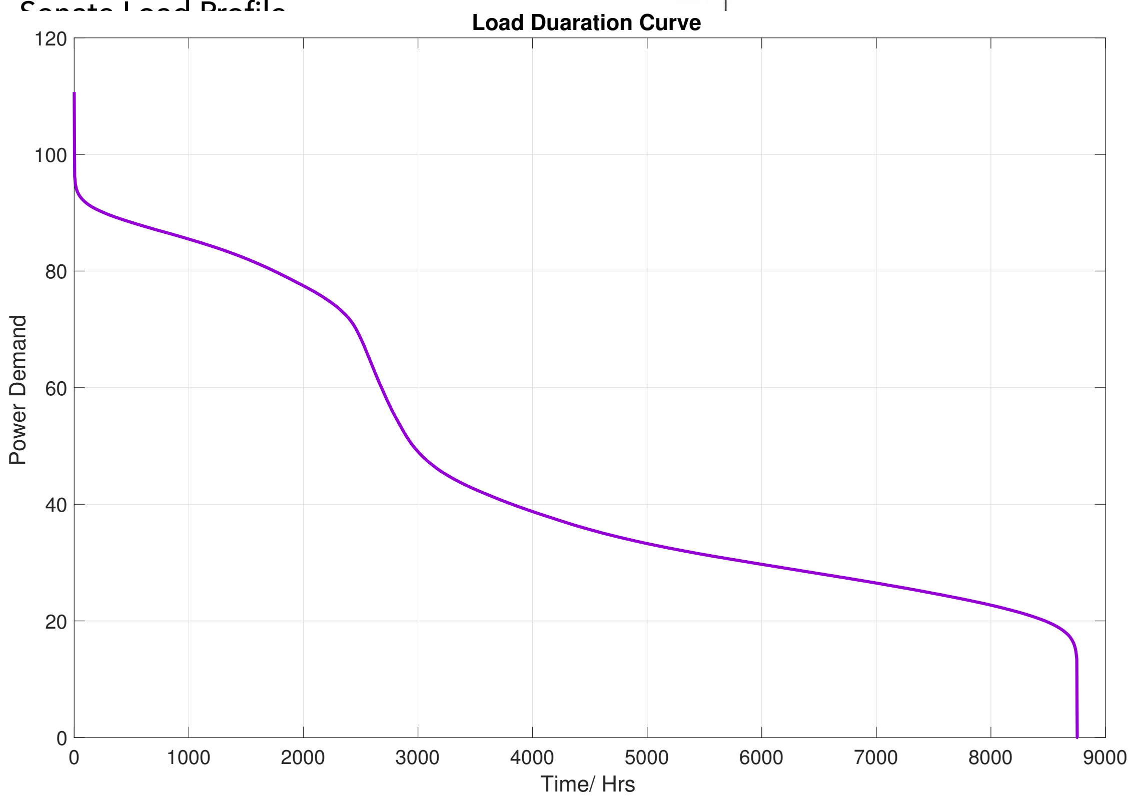


Figure 8.4: Load Duration Plot of Year Usage Data

8.3 Model Operation Parameters

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 6: Table Showing the Input Parameters of the Model

Above were 12143 words.

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