Investigating Trading Strategies for a Battery with Electricity Markets

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1 Introduction

Electricity generated on the National Grid needs to be used immediately or stored. Batteries are a common electricity storage method , which have the advantage of a relatively short charge/discharge time, as well as high charging efficiency of up to 95% [19]. This 5% loss represents the percentage of electricity that will be dissipated during any exchange between the battery and the grid. Although the majority of global energy storage capacity is taken up by other forms of electrical storage, batteries are an increasingly popular choice, as they show the greatest potential for increased affordability. By 2030, battery technologies could see a decrease in price of over 70% [6]. In addition to this, batteries can be used more flexibly, as they can be used on a small or large scale.

Batteries can generate revenue through two different streams. Firstly, electrochemical storage helps to maintain the balance between the supply and demand of electricity. Any short-term imbalances between the supply and demand of the National Grid can be managed by batteries charging and discharging their stored electricity. Secondly, battery owners can trade electricity on the wholesale market. The volatility of energy prices is largely affected by the renewable market [2], so the continued adoption of renewable energy could allow for increasingly lucrative trading.

Given these different revenue streams, it follows that there is interest in trading electricity. This is a focus of Aurora Energy Research, a company which specialises in delivering investment advice on global energy markets using data driven intelligence. Developing this type of technology is crucial, considering the main position of electricity in the global energy transformation landscape. The main model that Aurora has developed is their Energy System Model, or AER-ES, which can predict future prices up to 2050 for major energy markets in Europe [3]. Another notable piece of intelligence that Aurora distributes is the AER-EN (Energy Network Model), which assesses the flows in an electrical grid, and then optimises its losses [3].

Reviewing the literature published in regards to optimising the trading strategies surrounding electricity markets shows that many different paths have been explored. The focus is mainly directed on the prediction of electricity prices, using Agent-based [12] or Long Short-Term Memory Recurrent Neural Network [20] approaches. Different methods can be applied to either intraday or day-ahead markets. While intraday markets correspond to the trading of electricity on the same day that it is delivered, day-ahead markets financially binds traders to electricity prices that will be delivered on the next day. Some literature extends the prediction of market prices in order to add the participation of a storage device to model the revenue generated from trading electricity, using Arbitrage spreads [9], or Deep Q-Learning methods [10].

The aim of this project is to maximise the profit gained by charging and discharging a battery to a choice of electricity markets, using a 3 year period of electricity market data from 2018 - 2020.

2 Market Data and Battery

The battery is assumed to be a price taker and to not influence any of the market prices. The battery initially costs £500,000 to purchase and install, and has an annual operational cost of £5,000. The lifespan of the battery is reached after 10 years or after a total of 5,000 cycles, with a cycle being equivalent to a complete charge and discharge of the battery. The maximum storage volume of the battery is 4MWh and the maximum charging or discharging rate is 2MW. The charging and discharging efficiency of the battery is 95%, and due to degradation the battery loses 0.001% of its total storage volume per cycle. These constraints are summarised in Table 3 in Appendix A.

The market data includes the prices of three wholesale electricity markets: Market 1, 2 and 3. The first two trade on a half hour time granularity, while the third trades on a daily time granularity. This means that the battery must charge/discharge at a constant rate for each full half hour period that it trades with Market 1 or 2. Similarly, the battery must charge/discharge at a constant rate for the full day when trading with Market 3.

Aside from the 3 market prices, the data contains Transmission System Electricity Demand, as well as different types of energy generation: Wind, Solar, Coal and Gas. All of this data is expressed in MW, at a half hour time granularity. This generation data is displayed in Figure 5 in Appendix A.

By investigating the profit that can be gained over the given 3 year period under different strategies, a set of trading strategies can be established which may be recommendable for future use in similar electricity markets.

3 Methods

As the lifespan of the battery is either 10 years or 5,000 cycles, the average number of cycles that should be used annually is 500, provided that each cycle remains profitable. Using less than this number would lead to the battery expiring due to its 10 year lifetime, meaning there is potential for trading, hence profit, which is unused. Since more frequent charging and discharging of the battery allows for short-time behavior of the markets to be exploited, a method has more opportunities to generate profit when trading on markets with a higher granularity and volatility. Market 1 and Market 2 are both traded at a finer granularity and are more volatile than Market 3. The volatility of the 3 markets can be compared by taking the standard deviation of the market prices. The standard deviations of Markets 1-3 are 18.26, 19.23 and 10.63 respectively. This shows that Market 3 is far less volatile, and this can also be confirmed visually in Figure 5 in Appendix A. Therefore, given these findings and the battery constraints, a method which trades only using Market 1 and 2 is recommended for maximising profit.

To investigate whether a profitable trading strategy is feasible over the 3 year period, the problem is initially framed as a static problem. It is assumed that the market prices are known for the future, and can therefore be optimised upon to maximise the balance, being the price of the electricity sold minus the price of the electricity bought, by the end of the period.

3.1 Solution to Static Problem

The amount of electricity in MWh that is charged to or discharged from the battery at each half hour time step, t, is represented by

$$\mathbf{x} = [x_0, x_1, \dots, x_{n-1}, x_n], \tag{1}$$

where n is the total number of time steps in the period. At a maximum charging rate of 2MW and with charging efficiency of 95%, the amount of electricity moved in any half hour time step, x_t, is bound by $-0.95 \leq x_t \leq 0.95$ MW. In this representation, a negative value for x_t indicates discharging, hence selling to a market. Aside from the choice of the amount of electricity, there is also a choice between Market 1 and Market 2 for which market to trade with at each half hour time step. Let z represent balance [£], then to increase z it is optimal to always buy from the cheapest market and sell to the most expensive market. The market prices at each step, $M1_t$, $M2_t$, are sorted into **B**, a list containing the lowest of the prices at which electricity should be bought, and **S**, a list containing the highest of the prices at which electricity should be sold. These are expressed as

$$\mathbf{B} = [\min(M1_0, M2_0), \min(M1_1, M2_1), \ldots, \min(M1_{n-1}, M2_{n-1}), \min(M1_n, M2_n)], \tag{2}$$

$$\mathbf{S} = [\max(M1_0, M2_0), \max(M1_1, M2_1), \ldots, \max(M1_{n-1}, M2_{n-1}), \max(M1_n, M2_n)]. \tag{3}$$

To ensure that electricity is only bought from the cheapest market and sold to the most expensive market, the change in balance at any step is given by

$$\Delta z = -\left[\frac{(x_t - |x_t|)}{2} S_t + \frac{(x_t + |x_t|)}{2} B_t\right], \tag{4}$$

where S_t and B_t are the corresponding elements of **S** and **B** at time step t. This works by setting the coefficient of B_t to 0 when the decision is to discharge, and setting the coefficient of S_t to 0 when the decision is to charge. Thus, the balance after a time period of n half hour steps is given by

$$z = -\sum_{t=0}^{n} \left[\frac{(x_t - |x_t|)}{2} S_t + \frac{(x_t + |x_t|)}{2} B_t\right]. \tag{5}$$

Since balance is to be optimised, Equation (5) becomes the objective function of a maximisation problem, where an optimal set **x** is to be found. Referring to the current amount of electricity stored in the battery as the capacity level, the charging and discharging of the battery must be constrained to avoid exceeding the capacity limits of 0 and 4MWh. This is encapsulated in a series of linear constraints, which ensure that the amounts of electricity moved into and out of the battery are limited by 0 and 4MWh by checking the sum of these amounts as each time step is reached in the period n. These constraints are shown in Equation (6).

$$\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix} \leq \begin{bmatrix} 1 & 0 & \ldots & 0 & 0 \\ 1 & 1 & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 1 & \ldots & 1 & 0 \\ 1 & 1 & \ldots & 1 & 1 \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{n-1} \\ x_n \end{bmatrix} \leq \begin{bmatrix} 4 \\ 4 \\ \vdots \\ 4 \\ 4 \end{bmatrix}. \tag{6}$$

Since the lifetime of the battery is limited to 5,000 cycles, It should use 1,500 cycles in the 3 year period in order to reach this total cycle limit at its expiration time of 10 years. Therefore, the optimisation is limited to $L = \frac{1500}{1096} \approx 1.369$ cycles per day, as there are 1,096 days in the 3 year period. Since a single cycle is completed after 4MWh have been charged and 4MWh have been discharged in some order, the daily cycle limit is enforced by the non-linear constraint

$$|x_0| + |x_1| + \cdots + |x_{n-1}| + |x_n| \leq 8L. \tag{7}$$

The storage degradation of 0.001% per cycle is taken into account by accordingly updating the upper limit of the linear constraints (6) each time a cycle is completed. The fixed operational cost of £5,000 per year is included by subtracting £15,000 from the final balance after the 3 year period.

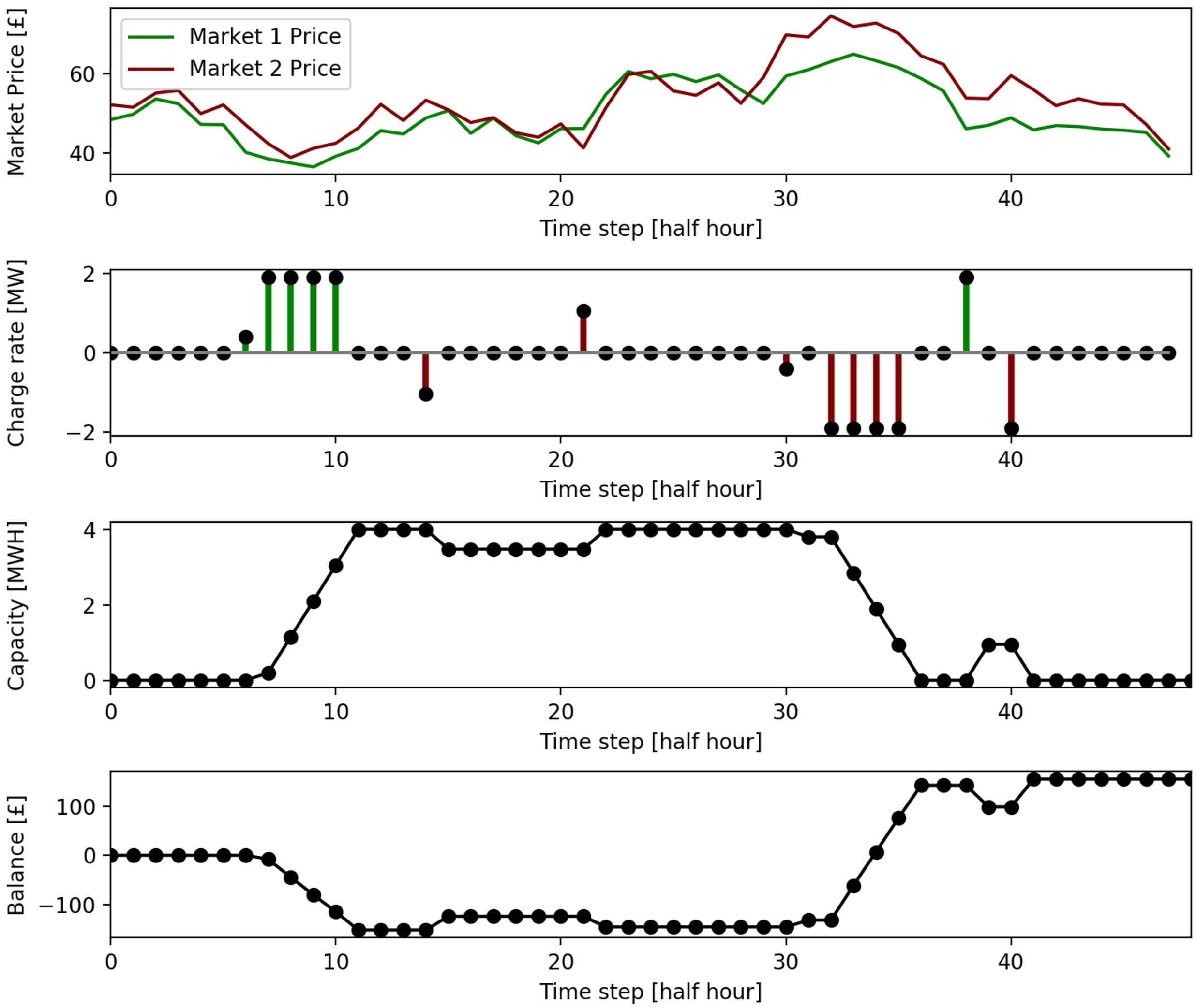

Figure 1: The charging rate, battery capacity level and balance at each half hour step of the first day in the data, as found by optimisation of the objective function (5) on the day's market prices. The colour of each stem in the Charge rate graph corresponds to the market with which the electricity is traded.

For a globally optimal solution across the 3 year period, the objective function (5) would be optimised with $n = 52,608$, taking into account the decision to buy or sell an amount of electricity at every time step. However, the search space for this problem is too large, even intractably so for some optimisation routines. Instead, the 3 year period is split into smaller time periods, over which local optimal solutions are found and then pieced together. To create a piecewise solution, the capacity level of the battery must be continuous between each period. This means that the starting capacity level for a given period must be attainable from the final capacity level of the previous period within the bounds of the max charging and discharging rates. However, the battery will always reach 0 capacity by the end of each period, otherwise it would still have electricity that can be sold, which would give a non-optimal balance. Therefore, continuity between the piecewise optimisations is met. In an investigation of a similar problem by Abramova and Bunn, an optimisation period of 1 day is suggested to be suitable for a battery with 0 initial capacity level for each period [9]. Taking $n = 48$, which corresponds to a time period of 1 day, a solution which is not globally optimal but is locally optimal for each day is found.

Figure 1 shows an example of the optimal set of charging and discharging decisions for the first day of the 3 year period, found by use of Scipy's optimize library in python on the objective function alongside the linear and nonlinear constraints. More specifically, optimize.minimize is used on the negation of the objective function with the Sequential Least Squares Programming (SLSQP) method [18].

Using this method, which will now be referred to as the Static Optimiser, the balance at the end of the 3 year period is £190,966, including the yearly maintenance costs. Assuming that the market trends behave similarly over the following seven years, the projected balance at end of 10 year period, and thus at the expiration date of the battery, is £636,553. Subtracting the initial purchase cost of the battery, a profit of £136,553 is expected to be made in total.

Since it is shown that profitable strategies exist, the next step is to investigate a profitable strategy which does not assume knowledge of the future market prices.

3.2 Random Trading Method

A control method, which is useful for comparison, is one with no trading strategy. This method operates by randomly buying, selling or holding at each half hour time step randomly utilising either Market 1 or 2, where holding is the action of neither buying or selling. The Random Trading Method (RTM) is, therefore, expected to be the least successful. The method is unable to vary its charging and discharging rates, which are set at the maximum rate of 2MW.

Although the method chooses the charging actions randomly, it is possible to have some influence on the actions taken. The probabilities for each buy, sell or hold choice can be altered, in order to influence the total number of cycles completed within the 3 year period. In order to maximise the number of cycles that the battery completes whilst maintaining its lifetime of 10 years, the battery should hold for $\simeq 70\%$ of the time as shown in Figure 6 within Appendix B. Therefore, the model must buy for $\simeq 15\%$ of the time sell $\simeq 15\%$ of the time.

Having defined the probability of each action, the method is run 10,000 times. Figure 7 in Appendix B shows the result, which resembles a Normal distribution. The average number of cycles used is 1,369 over the 3 year period, which translates to a projected average of 4,562 over the total 10 year time frame. Furthermore, the mean balance is calculated as a loss of £106 for the 3 year period. This value shows us that the RTM does not perform well, as expected, failing to turn a profit even before any of the battery costs are taken into account.

To prove that the results follow a Normal distribution, a Normal Q-Q plot is created, using the method described in Appendix B.1.

3.3 Near Mean Methods

These methods use a battery class created in python which incorporates the capacity and cycle limit constraints. The Near Mean Method calculates a mean over a range of the data. Initially the mean price of Market 1 and 2 over the 3 year period is used, which requires knowledge of the future. To be combine the markets it is assumed that the market with the maximum difference between the market price and the mean is the best market to trade with. The battery will charge by buying if the current price is lower than the mean price and discharge by selling if it is higher than the mean price. The maximum rate of charging and discharging occurs when the current price is a set distance away from the mean, which is defined by a parameter called linear scale length. The charging rate of the battery is proportional to the difference from the mean over the linear scale length. A grid search is performed for integers to find the optimal value of the linear scale length which results in a value of 20. This value gives £59,252 over the 3 year period, in 623 cycles, which gives a projected balance of £197,328 over the lifetime of the battery. Including the initial cost, this would lead to a loss of £352,672 over the lifetime of the battery.

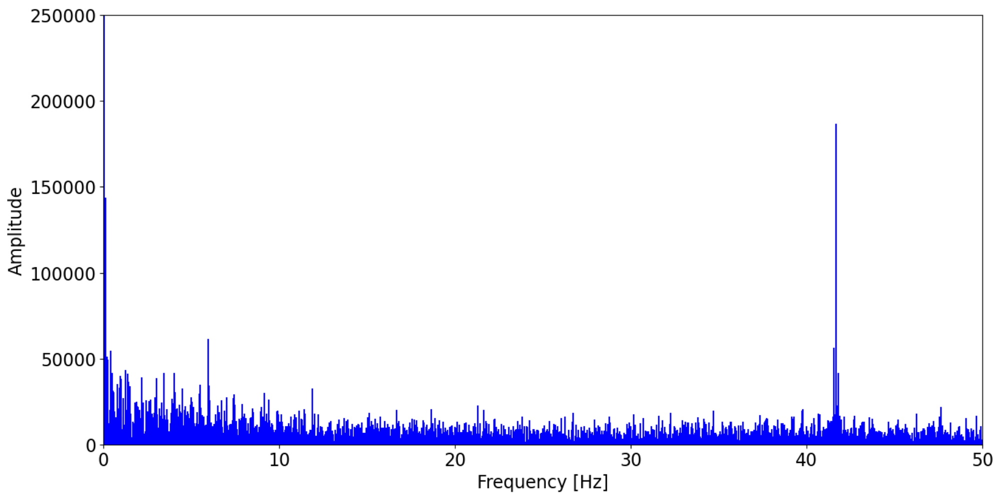

Figure 2: Fast Fourier transform on Market 1 data with a sampling rate of 2,000, where a peak in amplitude is indicated at 42Hz.

To turn this into a method which is usable without knowledge of future market prices, a mean from previous prices is used, called the Rolling Mean Method (RMM). To find the best length of mean window, a Fourier transform is used on the prices in order to determine the periodicity. The maximum non-zero amplitude occurs at 42 Hz as shown in Figure 2. The RMM calculated on the past 42 time steps with a linear scale length of 20 gives an expected balance of £330,481 over the lifetime of the battery. A weighted mean is then implemented using the amplitudes of the Fourier transform frequencies as weights over the past 42 time steps. The Weighted Rolling Mean Method gives an expected balance of £390,466.

3.4 Optimising Charging Rates on Predicted Prices

The Predicting Prices method estimates future prices of electricity markets and then predicted prices are used to optimise the charging rates. To predict the future market prices a recurrent neural network (RNN) is used. In order to find the optimal decisions for the next day the with the Static Optimiser from 3.1 it is necessary to predict the prices 48 time steps into the future.

To implement the RNN the data is split into a training set, which contains 40,000 market price points, and a test data set, which contains 12,608 market price points. The training data contains a validation set. The data is split in series as it is a time series data, and then normalised. The RNN is composed of a Gated Recurrent Unit (GRU) with 64 units then a dense layer with one unit to reduce the output to the predicted prices 48 time steps into the future. The performance of the GRU is measured by calculating the root mean squared error on the predictions for both the training and validation set. The GRU contains 3 epochs with a batch size of 10. The GRU is trained on both markets in order to predict the future price. This achieves a training loss of 0.1105 and validation loss of 0.1031. A plot of predictions from time point 40,000 to 40,096 is shown in Figure 3.

The Static Optimiser is then run over the predicted prices of the test data set giving a predicted balance of £109,595. The decisions from the predicted prices test set are then used with the market price 2 data achieving a predicted 10 year balance of £172,190.

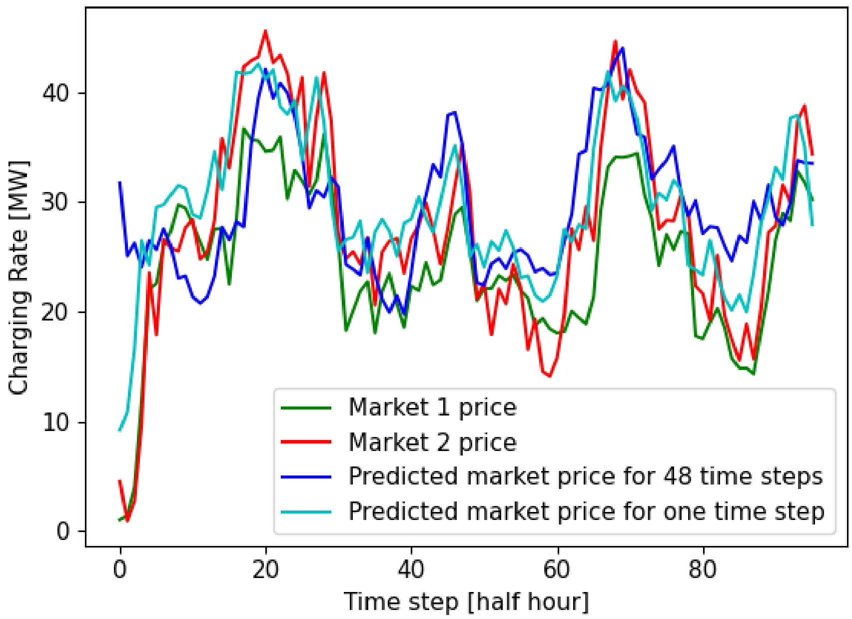

Figure 3: Predicted market price for 48 time steps ahead from time point 40,000 to 40,096 compared against market 1 and market 2 prices.

3.5 Predicting Decisions

The static optimiser uses the exact predicted prices and the uncertainty in the predicted prices is not be accounted for. Instead, it is possible to predict the charging rates by assuming that the static optimisation of the historic market data gives optimal values for the decisions, so they can be labels for the data. The decisions are predicted using a Long Short Term Memory Model composed of an LSTM layer with 64 units, LSTM with 64 units, a Dense layer with 64 units and a final dense layer, with three epochs and a batch size of 20. This method achieves a root mean squared loss of 0.8547 and a validation loss of 0.8733 . The predicted decisions are scaled back using the mean and variance then a hyperbolic tangent function is applied, followed by a min-max scalar Equation 8 with the minimum charging value $a = -2$ and the maximum charging value $b = 2$. Running the method with these decisions on Market 2 on the training data gives an expected 10 year balance of

£266,456, and an expected 10 year balance of £319,481 on the test data. The predicted decisions on the test data are compared to the static problem decisions in a confusion matrix in Table 1.

$$y = \frac{(y - \min(y))(b - a)}{\max(y) - \min(y)} \tag{8}$$

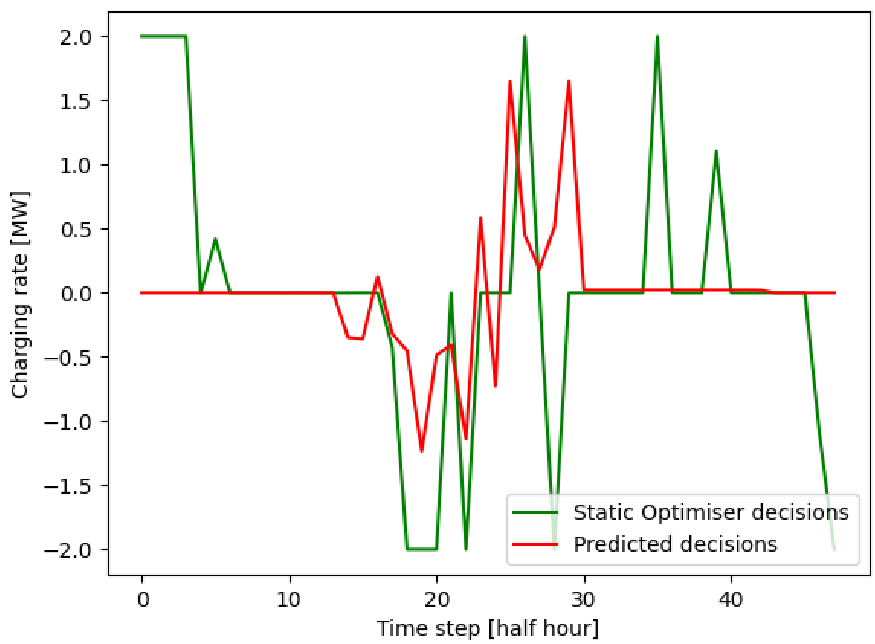

Figure 4: Predicted charging rate decisions and static problem decisions for the first 50 time steps of the test data set.

Static charging rates		Predicted charging rates			
		Buy	**Hold**	**Sell**	**Total**
	Buy	155	1,678	171	2,004
	Hold	1,868	6,545	1,752	10,185
	Sell	334	1,212	483	2,029
	Total	2,357	9,435	2,406	

Table 1: Confusion matrix of predicted charging rate decisions against the Static Optimiser charging rate decisions for the test data.

Method	Maximum Data Required	Expected Profit [£]
Static Optimiser	Next 24 hours	$+136,553$
Random Trading	None	$-550,353$
Near Mean	Entire data set	$-352,672$
Rolling Average Mean	Previous 24 hours	$-219,519$
Weighted Rolling Mean	Previous 24 hours	$-159,534$
Static Optimiser on Predicted Prices	Previous 24 hours	$-377,810$
Predicted Decisions	Previous 24 hours	$-230,519$

Table 2: Expected profits for all of the proposed trading methods where the second column represents the maximum market data required at any time step.

4 Discussion and Further Work

The assumption that the market trends remain similar for the following 7 years is a source of uncertainty for the projected 10 year balance of all methods.

The static problem optimisation gives the most profitable solution with full knowledge of the future market prices. Since this requires data which is unobtainable in the present, it is the least usable.

The piecewise nature of the optimisation gives rise to limitations on the profit. Since the battery is forced to fully discharge by the end of each day, some of the limited number of cycles are used in a way that is likely to be not optimal. Furthermore, there is no allowance to save cycles for time periods which are more volatile and hence more lucrative, should these periods exist in the available markets. The impact of these limitations tends to 0 as the size of the optimisation period tends to the entire 3 year span of the data. With more computing power available and a more efficient optimisation routine, solutions which are closer to the global optimum can be found, by using larger number of steps, n, per time period which is being optimised.

The Weighted Rolling Mean Method is simple but effective. The rolling mean discounts any data prior to the previous 48 time steps, which allows the decision process to be more reactive to local trends. This improves profit compared to the method using the mean of the whole three year data span. Using the the Fourier transform to weight the decisions further enhances this method by introducing varying importance across the time steps. This is the best method without using future data, but is only able to make 61.3% of the predicted balance of the static optimiser. This method did not make enough money to turn an expected profit over the lifespan of the battery, as seen in Table 2. The simplicity of the framework of this method limits the potential for extension. Using non-linear scaling functions for varying the charging rate could improve profitability by allowing higher rates for the larger fluctuations in market price. However, market prices greater than the linear scale length of 20 away from the rolling mean use maximum charging rate already so any increase in profit will not be substantial. Furthermore, this method could be extended to a proportional, integral differential (PID) controller with the charging rate calculated on the weighted rolling mean - the proportional component, the charge stored on the battery - the integral component and the gradient of the previous prices - the differential component. The PID controller would be able to recognise trends in the data in order to maximise the money made on the battery.

The Static Optimiser on Predicted Prices Method is limited by the charging decision routine being generated based on the results from the static problem. The future market prices can be predicted with a loss of 10.31%, and the graph Figure 3 shows the ability to capture the trend of the future prices. However, the Static Optimiser requires 48 time steps of predictions in the way it is currently implemented. The predictions further into the future have increasing error as errors are compounded, as shown by the difference in accuracy between 1 time step ahead predictions and 48 time steps ahead predictions in Figure 3. The Static Optimiser assumes the predicted prices to be exactly true and uses them to predict the future charging rates, therefore the error in the predicted prices creates the error in the overall method. The method makes more money on the true prices than the predicted prices as the predicted prices have less variance and capture less of the volatility in the market as seen in Figure 3. To improve this method, it would be necessary to take into account the error in predictions when implementing the trading strategy, as well as trying to minimise the number of time steps which are predicted.

Predicting decisions using an RNN requires the charging rates from the Static Optimiser in order to predict the future decisions. Predicting the charging rate based on past prices requires a prediction only 1 time step into the future. The requirement to predict 1 time step into the future is the reason that predicting decisions earns a higher final predicted balance than the Static Optimiser on Predicted Prices method which predicts 48 time steps into the future. Similarly to the Optimising Charging Rates for Predicted Prices, by using the static optimiser decisions as a ground truth this method is constrained by the short-comings of the Static Optimiser method 3.1. The results of Predicting Decisions can be compared to the results in "Trading electricity markets using neural networks" [11], which employs neural networks to predict market prices in order to make a decision whether to buy or sell. In comparison to trades that would have simultaneously been done on the real market, the algorithm correctly traded on 70.2% of sell decisions and 73.6% of buy decisions. These values can be compared to the ones found in Table 1, which made the correct decision on 73.9% of sell choices, and 31.7% of buys. This shows that while the sell accuracy achieved is comparable, the buy accuracy is far from it. This is due to the nature of the predicted decisions in our model. Their decisions are restricted to buying or selling, whereas in order to meet the cycle constraint on the battery in the model in the methods in this report the battery must hold for a large number of time steps. The decision to hold is taken approximately the same number of times in the static decisions and in the predicted decisions (10185 and 9435 respectively).

5 Conclusion

The battery can be charged and discharged on market prices using charging rates determined by the Static Optimiser subsection 3.1 to turn an expected profit over 10 years of £136,553. However, the profit is only 19.89% of the investment of £550,000 into the installation and operation of the battery. The existence of this solution demonstrates the feasibility of developing a strategy without knowledge of the future that is profitable. The most successful strategy found without knowledge of the future is the Weighted Rolling Mean Method, which makes a loss of £159,534. In this investigation there were no profitable trading strategies found which could be used without future market data. Therefore, a better method of predicting the future prices of the electricity market needs to be developed to produce a usable trading strategy that is profitable.

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A Battery Constraints and Data Visualisations

Battery Constraints	**Value**	**Unit**
Initial Cost	500,000	£
Maintenance Cost	5,000	£/year
Lifespan	10	years
Lifetime Cycle Limit	5,000	cycles
Maximum Storage Volume	4	MWh
Maximum Charge/Discharge Rate	2	MW
Charge/Discharge Efficiency	95	%
Storage Volume Lost	0.001	%/cycle

Table 3: Definition of the battery constraints.

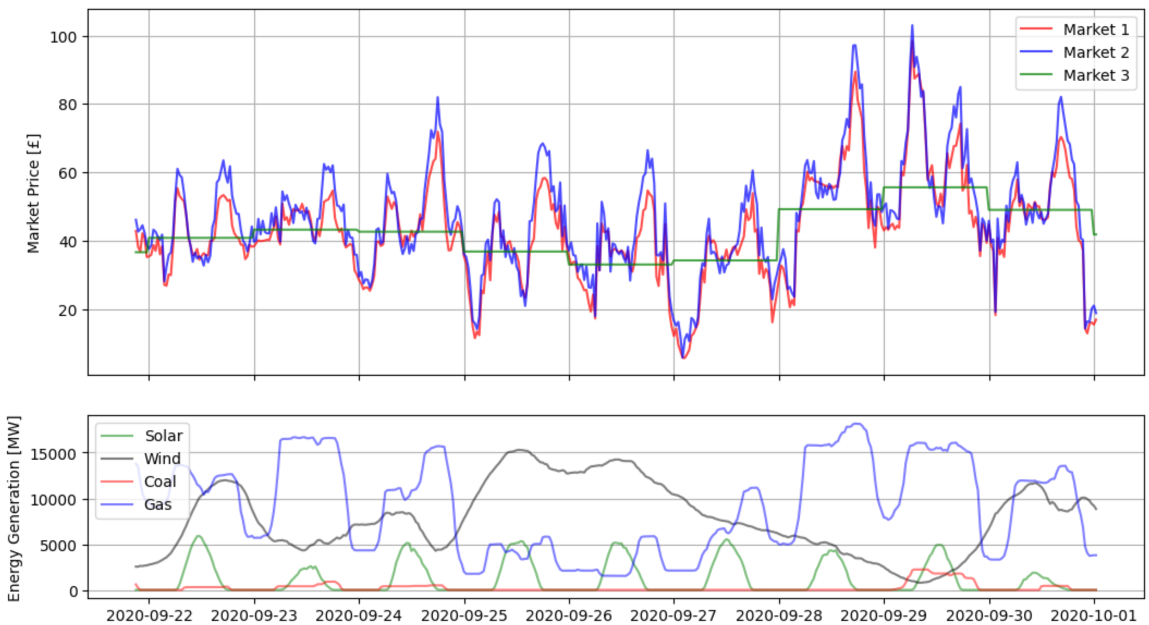

Figure 5: This graph displays the market price for Market 1 and Market 2 as well as the energy generation data breakdown for the same period.

B Additional RTM Information

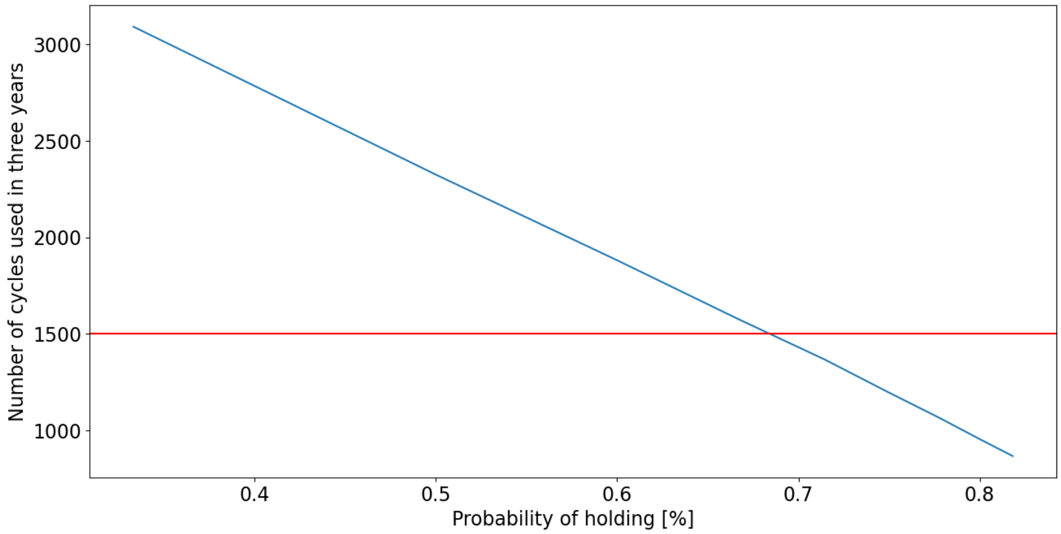

Figure 6: The number of cycles against the probability of the Random Trading Method holding, blue line, and the ideal number of cycles over the 3 year period, red line.

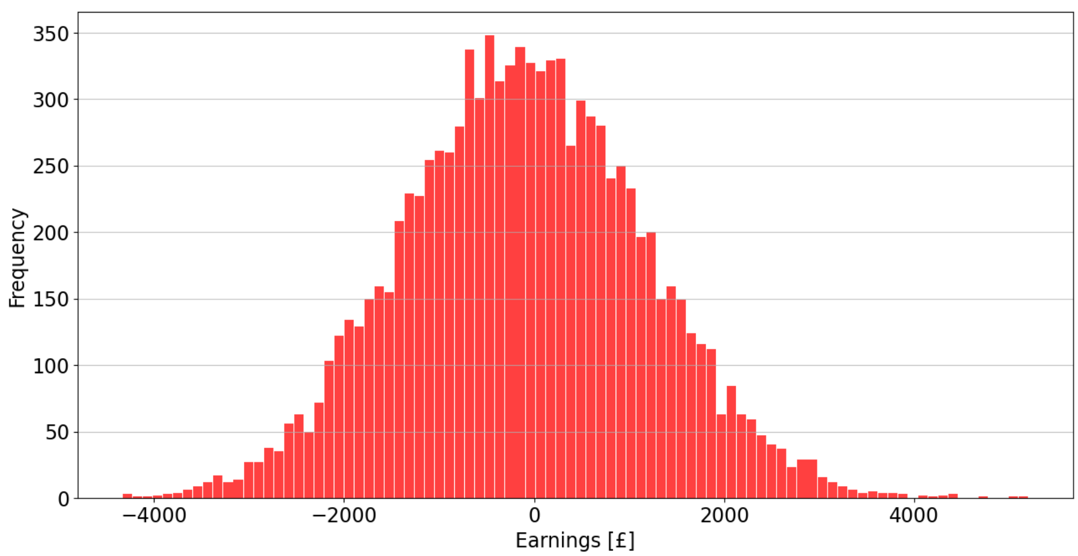

Figure 7: Histogram of the distribution of balances using the Random Trading Method over 10,000 runs.

In order for the battery to have an expected 10 year profit the final balance after 3 years must be $> 165,000$ if the battery lasts for its entire 10 year lifetime. This means that for the RTM to make a profit it must be $\frac{165,000-\mu}{\sigma} \approx 130$ standard deviations from the mean.

B.1 Proving a Normal Distribution Using a Q-Q Plot

A Normal Q-Q plot is a scatter plot of a sample quantile against a quantile of a Normal distribution which has the same mean and standard deviation as the sample quantile [14]. Here, the Normal distribution is defined by $\mu = -106.40$ and $\sigma = 1,268.79$. If the generated points follow an approximately straight line at an angle $\approx 45°$ then the sample quantile can be considered a Normal distribution. The Normal Q-Q plot for 100 randomly selected values from the balance of the Random Trading Method is shown in Figure 8. This graph displays the data as very closely following the trend of a straight line, this strongly suggests that the distribution of balances from the Random Trading Method form a Normal distribution.

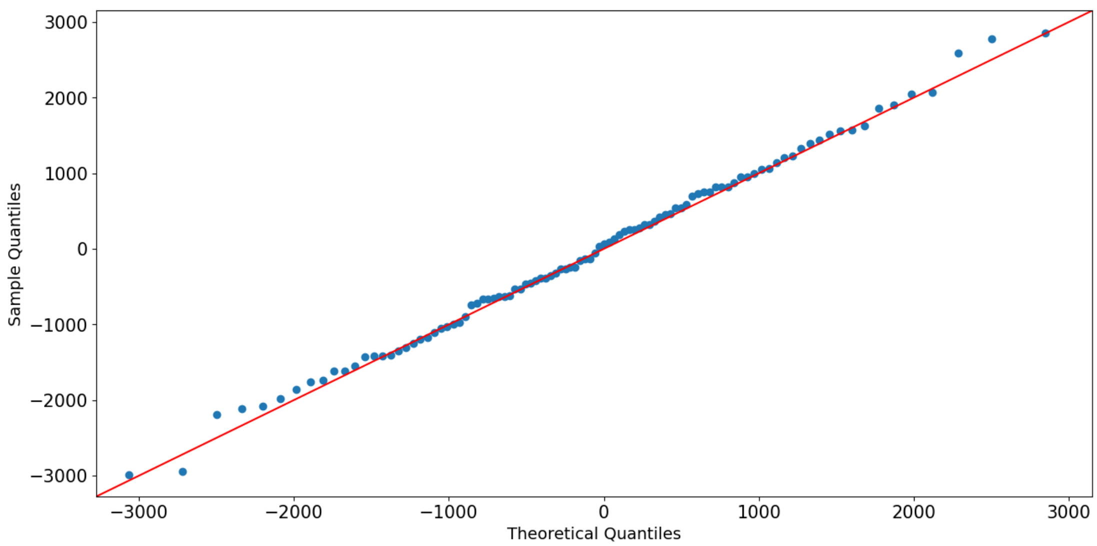

Figure 8: Normal Q-Q plot for 100 randomly selected values of the balance from the Random Trading Method over the 3 year period.

C Maximum Difference Method

In this case, future knowledge is limited to a chosen time period. At the beginning of each time period, the Maximum Difference Method (MDM) analyses the prices of Market 1 and 2, and calculates the largest difference in price between two points across either market. The strategy is to charge the battery whilst the price is at the lower of the two points and discharge whilst at the higher. Each time period is observed independently, so the battery is required to start and end each time period with 0 charge this limits the maximum value of the strategy. The other main constraint on this method is that the lower price must appear chronologically before the higher price, as the battery needs to charge before it is able to discharge.

The MDM is limited to one full charge and one full discharge per time period. A full (dis)charge of the battery completed in 2 hours when charging at the maximum charging rate 2. The exact charging strategy is then as follows: setting t as the time period of the lower price, the battery charges at time steps $t-1$, t, $t+1$ and $t+2$ in order to fully charge. Discharging the battery at the higher price follows the same strategy, however there can not be any overlap between the charge and discharge periods, due to the battery's incapability of charging and discharging simultaneously.

The time frame is optimised by calculating predicted balance per battery over it's lifetime against time frame in Figure 9 which shows the optimal time frame is 48 half-hourly time steps. A time frame of 48 leads to a predicted earning per battery of £399,092. The maximum peak at the 24 hour time period, as well as the smaller peaks at 12 and 48 hours, are suggestive of underlying seasonality of the data.

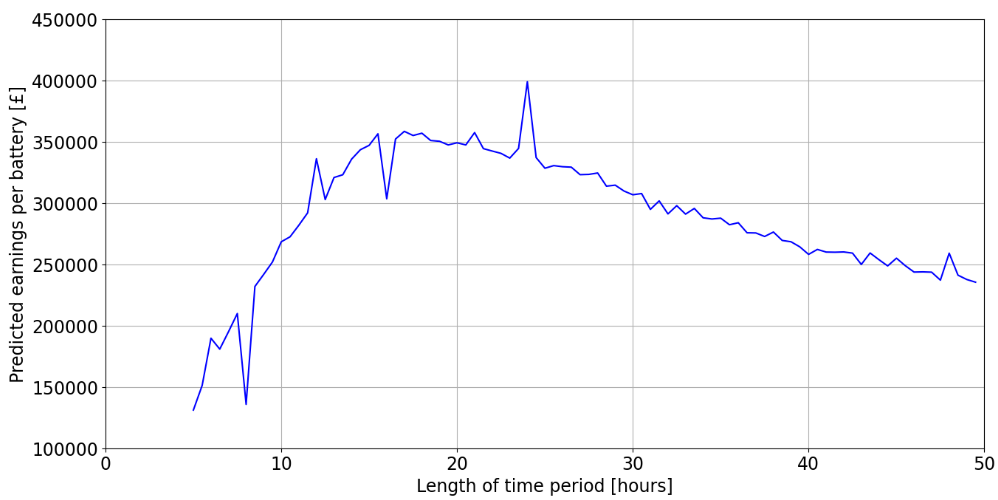

Figure 9: Predicted balance per battery with respect to the different time period lengths using the Maximum Difference Method.