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Single electricity market forecasting and energy arbitrage maximization framework

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Abstract

The rapid deployment of renewable-based generation to meet the net-zero carbon targets has affected the wholesale energy paradigm. In the island of Ireland, the Single Electricity Market (SEM) aims to deliver high levels of supply security, reliability, and transparency through multiple markets with different trading time frames and clearing procedures. This paper proposes a powerful methodology to maximize the revenues from the participation in the SEM. A forecasting model of four successive stages based on neural networks is proposed to predict the demand and system marginal prices of the SEM ex-ante markets. An energy arbitrage optimization framework is proposed for battery energy storage systems (BESS) to maximize the arbitrage profits. The methodology efficacy is validated by achieving 91.1% selling accuracy, 97.9% buying accuracy, and 85.1% energy arbitrage net accuracy of the ideal case where the SEM data is perfectly-known for three consecutive months. Furthermore, the BESS degradation is evaluated and a cost-benefit analysis is introduced to evaluate the economic feasibility of BESS participating in the SEM ex-ante markets. The results reveal that the participation of BESS in the SEM solely is not profitable, however, under stacked revenues arrangement, the proposed methodology can be applied to boost the BESS revenues.

1 | INTRODUCTION

In order to meet the net-zero carbon targets, the integration of renewable energy generation is essential to decarbonize the electricity sector. In the island of Ireland, the deployment of low carbon generation is accelerating such that the wind penetration reached 35% in 2020 [1], with an ambition to reach 70% of the total electricity generation from renewable resources by 2030 [2]. The reliance on renewable generation requires careful planning and management due to the operational challenges associated with these resources [3]. BESS energy storage system (BESS) has been integrated recently to provide the system with different static and dynamic services in fast response which makes their integration beneficial in the energy evolution [3]. The installation of BESS is considered a promising option for the secure accommodation of more renewable energy.

Due to the integration of different distributed energy resources, the energy markets have to adapt by accommodating these resources efficiently and providing a high level of competition to assure supply security with reasonable energy prices. The electricity market of the island of Ireland was started in 2007 as a single wholesale market, combining two trading areas with different currencies: The Republic of Ireland (€) and Northern Ireland (£), named as single electricity market (SEM), and managed by the single electricity market operator (SEMO) [4]. The SEM allowed generators and suppliers to submit bids for a certain volume with a price during a specific period. In the SEM, the system marginal price (SMP) is used, which is determined based on the bids and demand using the Market Scheduling and Pricing algorithm. In order to cope with the energy evolution, the SEM has been evolved through the Integrated Single Electricity Market (I-SEM) project on the 1 October 2018. The new SEM provides more flexibility to market participants across the

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island of Ireland by introducing ex-ante markets (day-ahead and intraday) and balancing markets, which are cleared before the actual delivery.

Most energy market traders are interested in predicting the energy market on a period ahead basis to take the right actions that maximize the trading revenues. Hence, forecasting models for energy markets are needed. However, energy markets are location-dependent as each energy market has its own auctions and procedures. Thus, specific forecasting models should be introduced for each energy market. Yet, common techniques can be used such as machine learning models.

BESS has the opportunity to boost revenues in energy markets through maximizing energy arbitrage profits. However, optimization frameworks are essential that considers the BESS operational constraints as well as the energy market rules. In the literature, different studies have addressed forecasting models for energy markets and/or BESS energy arbitrage frameworks. In [5], a forecasting model is introduced based on an artificial neural network (ANN) to predict the SMP of the South Korean day-ahead market. Historical data of 15 years was used to train the ANN model in addition to a set of predictors represent similar days information. However, this study focused only on the day-ahead SMP. Another ANN model is introduced in [6] to provide short-term prediction up to 72 h for the SMP of the old Irish SEM using historical market data in addition to other predictors including weather factors and calendar indices. Though the SEM has been evolved in late 2018 and hence, the model presented in [6] might not be valid with the new SEM rules and auctions.

In [7], another short-term forecasting model is introduced to predict the market demand of the Irish SEM day-ahead market. Two methods were tested: ANN, and Holt-Winters's exponential smoothing method (HWETS). The ANN was trained using one-year demand historical data in addition to weather and calendar predictors. While the HWETS used only eight weeks of observations to train the model. Both methods show good results, however, the ANN outperformed the HWETS method. Yet, this study focused only on forecasting the day-ahead market demand and did not consider forecasting the market SMP. The Spanish energy market price was forecasted using regression-tree models in [8], the model was trained using 11 years of historical data in addition to calendric and other generation predictors. The study provided a comparison between regression tree models and the autoregressive integrated moving average method, and the results proved the outperformance of regression tree models.

The BESS participation in energy markets was addressed in [9], where an approach is proposed using ANN and long short term memory to forecast the day-ahead market demand and SMP in addition to determining the optimal BESS operation using a deep reinforcement learning technique to maximize the energy arbitrage revenue by considering the BESS degradation in determining the optimal BESS discharging/charging. In [10], a multistage approach is introduced to determine the optimal BESS schedule in the day-ahead, intraday, and reserve markets

of the Iberian energy market. However, market forecasting was not considered. The BESS energy arbitrage profits from the Irish SEM and enhanced services of the DS3 programme have been addressed in [11], where the expected profits were quantified from trading in the day-ahead market.

In [12–14], the sizing and operation of BESS to provide congestion management, reactive power support, and minimizing renewable curtailments in the distribution network of Northern Ireland were addressed. The application of BESS to provide frequency and inertia services in the Irish power system was investigated in [15, 16]. However, the previous studies did not consider the profitability nor the economic feasibility of deploying BESS under these services. In [17], the use of BESS to enhance the distribution network operation was introduced through a two-stage methodology to determine the look-ahead and real-time setpoints of multiple BESS to flatten the grid power curve. Additionally, study [17] explored the expected profits and the economic feasibility under the sole participation in the available services in the island of Ireland.

Trading in the energy markets require a robust forecasting model, several forecasting methods can be utilized as reported in the literature. Forecasting methods can be categorized into classical and machine learning. Classical methods such as exponential smoothing and autoregressive moving average models. While machine learning models include ANN and regression models. Both methods have proved to provide reasonable forecasting accuracy for different applications [18]. However, machine learning models can provide a long-term forecast with good accuracy compared to the classical methods which are crucial for planning applications such as energy markets. In addition, machine learning models have proved to outperform classical methods in predicting energy demand and prices as shown in [7, 8, 17]. Yet, machine learning methods require careful selection of the model predictors.

These predictors can include the market historical data, weather factors such as air temperature, wind speed, and wind direction in addition to calendar indices that include the trading interval/hour of the day, day of the month, day of the year, day of the week, and special days. More predictors can be used; however, the complexity of the model increases which also increases the training time. Furthermore, machine learning models such as ANN require careful selection for the model parameters (weights and biases), and the conventional training methods may fall into local optima [19]. Thus, to unlock the high performance of ANN, optimization-based approaches have been introduced such as [19–21]. However, the optimization should avoid overfitting the training data.

The weather predictors demonstrated to increase the forecasting model accuracy as shown in [6, 7]. However, these predictors can impose another challenge as they require another metrological forecasting model to be predicted. Hence, the resultant forecasting shall contain high errors as it accumulates forecasting errors of the weather predictors, especially for long-term forecasting. Additionally, the weather in geographical locations such as the island of Ireland is volatile and hence, robust weather forecasting methods should be used which adds

a burden to the energy market forecasting. Hence, it is advisable to avoid using weather predictors unless it is necessary. To summarize, the main challenges associated with the new SEM forecasting can be listed as follows:

1. It combines two different regions: The Republic of Ireland and Northern Ireland. This imposes a challenge in forecasting the demand and SMP, as for example, the holidays may differ between these two areas which can greatly affect the forecasting.
2. As the new SEM began in late 2018, historical data is only available for two years.
3. Contains high volatility due to the significant weather fluctuations in the island of Ireland in addition to the high generation from renewables, especially from the wind. Hence wind speed should be considered in the forecasting model, especially in forecasting the SMP as the market SMP is hugely affected by wind generation. While weather predictors are often avoided to mitigate the additional uncertainties, in the SEM, the wind speed cannot be discarded. Furthermore, the wind speed differs significantly across the island of Ireland, hence, it is difficult to select particular wind speed measurements to be used according to the available weather stations.
4. It consists of four ex-ante auctions; hence, specific forecasting models should be developed for each auction which increases the model complexity.
5. Most of the SEM auctions closes one day before the trading day, and hence, day-ahead forecasting cannot be used, and the forecasting should be conducted on a two-days ahead basis to be able to trade in the SEM, which will affect the forecasting accuracy.

This paper aims to propose a robust forecasting model for the SEM ex-ante auctions in addition to introducing an energy arbitrage maximization framework for the BESS participating in the SEM besides investigating the BESS economic feasibility. This work is motivated by the following gaps:

1. To the authors' knowledge, forecasting models of the Irish SEM have not been introduced in the literature. Study [7] considered only predicting the market day-ahead demand, however, the data used for training was for the old SEM and the study focused only on the day-ahead market demand.
2. Studies that optimize the ANN weights and biases utilize the same training set which may lead to overfitting the model on the training data [21].
3. For BESS registered in SEM but not active in energy arbitrage at present due to system limitations. Maximizing the BESS energy arbitrage profits from participating in the SEM ex-ante markets has not been investigated previously except in the authors' previous work [22], where a four layers optimization approach based on linear programming was introduced to maximize the energy arbitrage profits from participating in day-ahead and intraday markets. However, the forecasting was applied using a generic tool on a day-ahead basis. Additionally, the BESS charging optimization was not considered.

This paper extends and complements the authors' previous work [22] and aims to address the research problems identified from the previous studies through the following contributions:

1. Providing data analysis for the SEM using the available historical data that is believed to be beneficial to SEM participants.
2. Introducing a four-stage successive forecasting model to predict the SEM day-ahead market demand and SMP in addition to the intraday auctions SMP using ANN. Optimization algorithms are introduced to determine the optimal number of ANN hidden layers and neurons in addition to optimizing the weights and biases. A novel formulation is introduced to avoid overfitting the data and achieve a high level of generalization. On the other hand, the classical forecasting method using the HWETS method has been used to provide a comparative analysis. Furthermore, this paper demonstrates that in some cases, combining both classical and machine learning models can improve forecasting accuracy.
3. Proposing an energy arbitrage maximization framework for the BESS participating in the SEM that aims to determine the optimal BESS discharging/charging schedule across the SEM ex-ante markets that maximizes the revenues. The proposed framework is less complex compared to the one introduced in [22], which makes it easier to be applied for a different type of generation resources.
4. Providing three months of forecasting on a two-days ahead basis with reasonable accuracy and quantifying the expected BESS net arbitrage revenues with 85.1% accuracy of the perfect foresight case.
5. Quantifying the BESS degradation under the energy arbitrage using a well-established semi-empirical degradation model for the Li-ion BESS.
6. Evaluating the economic feasibility of BESS participating solely in the SEM energy arbitrage through cost-benefit analysis.

The rest of the paper is organized as follows: Section 2 introduces the SEM structure and data analysis, Section 3 explains the proposed methodology, Section 4 describes the proposed forecasting model, Section 5 presents the energy arbitrage maximization framework, Section 6 provides the simulation results, Section 7 quantifies the BESS degradation, Section 8 includes the cost-benefit analysis, the discussion is given in Section 9, and finally the conclusion is in Section 10.

2 | SINGLE ELECTRICITY MARKET (SEM)

In the current SEM, the SMP is determined using a cross-border hybrid electricity market integration algorithm (Euphemia) [23]. The simple orders in the day-ahead and intraday markets should consist of price-quantity pairs, with units in £/MWh and MWh respectively. Each price-quantity pair specifies a price and quantity of electricity in a specified trading period. During

TABLE 1 SEM ex-ante markets arrangements

Market	Order book opening time	Order book closure time	Trading periods	Auction duration
Day-ahead (DAM)	19 days before the trading day at 11:00 PM	One day before the trading day at 11:00 AM	11:00 PM–11:00 PM 1-hour period	24 hours 24 time-points
Intraday1 (IDA1)	19 days before the trading day at 11:00 PM	One day before the trading day at 5:30 PM	11:00 PM–11:00 PM 30 minutes period	24 hours 48 time-points
Intraday2 (IDA2)	19 days before the trading day at 11:00 PM	Trading day at 8:00 AM	11:00 AM–11:00 PM 30 minutes period	12 hours 24 time-points
Intraday3 (IDA3)	19 days before the trading day at 11:00 PM	Trading day at 2:00 PM	5:00 PM–11:00 PM 30 minutes period	6 hours 12 time-points

the day-ahead market (DAM), the trading period is 1 h, hence for selling, the exchange member should submit the MWh quantity at specific hours with a price. In the Intraday markets, the trading period is 30 min. So, the exchange member should submit the MWh quantity for a specific 30-min interval with a price. Additionally, the electricity suppliers enter the market to buy electricity by submitting their price-quantity pairs. After the auction gate closes, all orders are aggregated each delivery hour in the SEM and the Euphemia algorithm determines the SMP. The intraday market consists of three daily auctions. For the first intraday auction (IDA1) and second intraday auction (IDA2), the market is coupled with Great Britain (GB) bidding area via Moyle and EWIC interconnectors. The third intraday auction (IDA3) is a local auction and is not coupled with the GB bidding area. Usually, the available volume/demand for bidding in the IDA3 is very small, especially for Northern Ireland. Details on the SEM day-ahead and Intraday markets are given in Table 1 and are available in the SEMO rules [24].

2.1 | SEM ex-ante markets data analysis

As the SEM is new, the available historical data for DAM and IDAs are for the period between 1 October 2018 to the present. Two full years (2019/2020) of market data are available, however, one of these years (2020) is considered as an unusual year for the energy market as people's routines changed due to the Covid-19 and multiple lockdowns across the year. To analyse the differences between 2019 and 2020, the DAM data for these two years were obtained from [4, 25], the average market demand and SMP for the four seasons of the two years are illustrated in Figure 1.

As shown in Figure 1, the average winter/summer demand in 2020 is higher than in 2019. However, the average market prices in 2020 for the winter/summer is lower than in 2019. In 2019, the average SMP was £49/MWh, however, in 2020 this price dropped to £32/MWh. This can be related to the available generation as the market SMP is generally affected by the generation bidding which can be linked to several factors. Firstly, wind generation dominates energy production on the island of Ireland and the total wind generation in 2020 increased by 12.7% compared to 2019 [1]. Secondly, the pandemic has affected demand

in 2020 due to lockdowns and restrictions, especially in the industrial sector. Thirdly, the fuel prices have dropped significantly in 2020, for instance, the gas and oil prices in the UK were dropped by an average of 15.5% and 16.2% respectively compared to 2019 [26]. Finally, the SEM is maturing such that after one year of experience, the market experienced for the first time many days with negative average prices, started on the 5 April 2020 [4, 25]. Furthermore, it can be noticed from Figure 1 that despite the differences associated with the magnitude, the shape of demand or SMP is fairly typical for 2019 and 2020 throughout the seasons. In addition, the DAM SMP is dependent on the shape of DAM demand.

Another point of analysis is the periods of high and low SMP which are important for market bidders. For the SEM historical data 2019/2020, the four hours in each day with the highest SMP were obtained for the DAM, IDA1, and IDA2. Additionally, the four hours in each day with the lowest SMP were obtained for the DAM. The results were then combined as a form of occurrence percentage and illustrated in Figure 2.

As shown in Figure 2, the period with the lowest DAM SMP falls between 01:00 AM to 07:00 AM with a total percentage of occurrence of 78% and an average SMP of £22.4/MWh. While the period with the highest SMP for the DAM, IDA1, and IDA2 falls in the period between 6:00 PM to 10:00 PM with a total percentage of occurrence of 70% and an average SMP of £59.5/MWh. These periods are important as they can be used in a heuristic framework to maximize the total revenue obtained from the energy arbitrage. To compare the SMP shape of different markets across the year, Figure 3 illustrates the average SMP per market for each season determined using the SEM historical data of 2019/2020. As shown in Figure 3, the average SMP shape per season is kind of similar for the three markets with very minor differences which means that the SMP of IDA1 is dependent on DAM SMP and similarly the IDA2 SMP is dependent on IDA1 SMP.

3 | PROPOSED METHODOLOGY

The aim of this paper is to introduce a reliable forecasting model for the SEM ex-ante markets using ANN with the aid of SEM historical data and other predictors. Different predictors

FIGURE 1 Average DAM volume and SMP for each season in 2019 and 2020

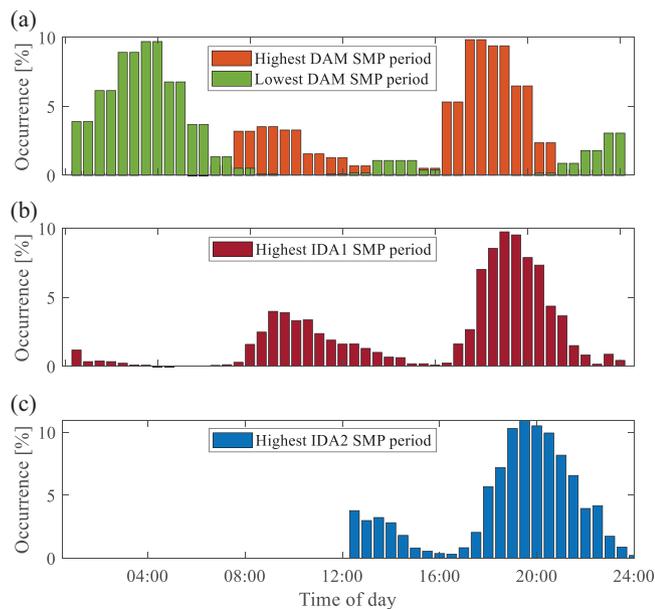
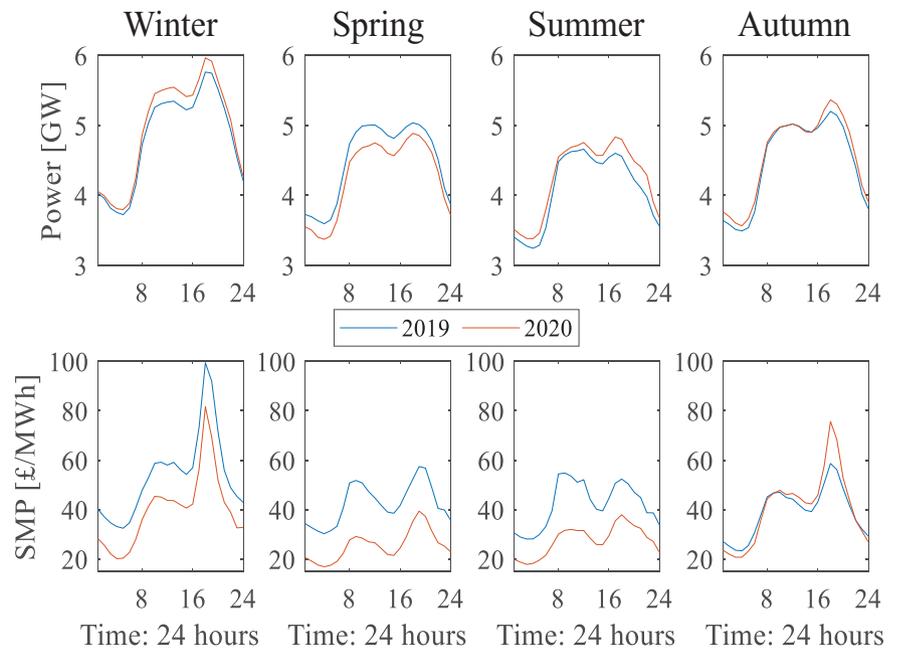


FIGURE 2 Occurrence of highest/lowest SMP periods throughout 2019/2020: (a) Highest/lowest SMP period for the DAM, (b) highest SMP period for the IDA1, and (c) highest SMP period for the IDA2

were tested to obtain the simplest yet most effective combination of predictors. The outputs of this forecasting model are then being used to maximize the total revenue using a developed energy arbitrage maximization framework. This framework aims to determine the optimal BESS schedule to maximize the revenues from trading in the SEM ex-ante markets. Afterwards, the expected revenues are quantified, and a cost-benefit analysis is provided. The proposed methodology is illustrated in Figure 4.

4 | SEM FORECASTING MODEL

In order to optimize the bidding in the SEM, a forecasting model should be available. In [22], a generic forecasting tool was used and showed that the revenues can be boosted with a high accuracy forecasting model. However, the forecasting tool used in [22] cannot be used efficiently in practice for long period ahead. Hence, a customizable forecasting algorithm should be introduced that considers a different set of predictors to provide more accurate results. Forecasting models of energy markets relies mainly on the available historical data in addition to a set of other predictors (e.g, weather and calendar) used to train a machine learning model. The problem with using weather data is that these data also require forecasting which accumulates the uncertainties. In addition, the market historical data is very important as it is the core of the training process and greatly affects the resultant forecasting model, hence, long historical market data is crucial in building a reliable forecasting model. The new SEM started on 1 October 2018, hence, only two full years (2019/2020) of market data are available which is very challenging in achieving a reliable forecasting model.

In this paper, a four-stage successive forecasting model is proposed using ANN, illustrated in Figure 5. The first stage aims to determine the DAM demand/volume, the second stage is introduced to predict the DAM SMP, the third stage predicts the IDA1 SMP, and the fourth stage aims to predict the IDA2 SMP. As illustrated in Figure 5, the proposed model is successive such that each stage is dependent on the results obtained from the previous stage. This is because the SEM ex-ante markets are dependent on each other as shown in Figure 3, hence, the result obtained from each stage is used as a predictor for the next stage. The predictors used for each stage of the forecasting model are detailed in Table 2.

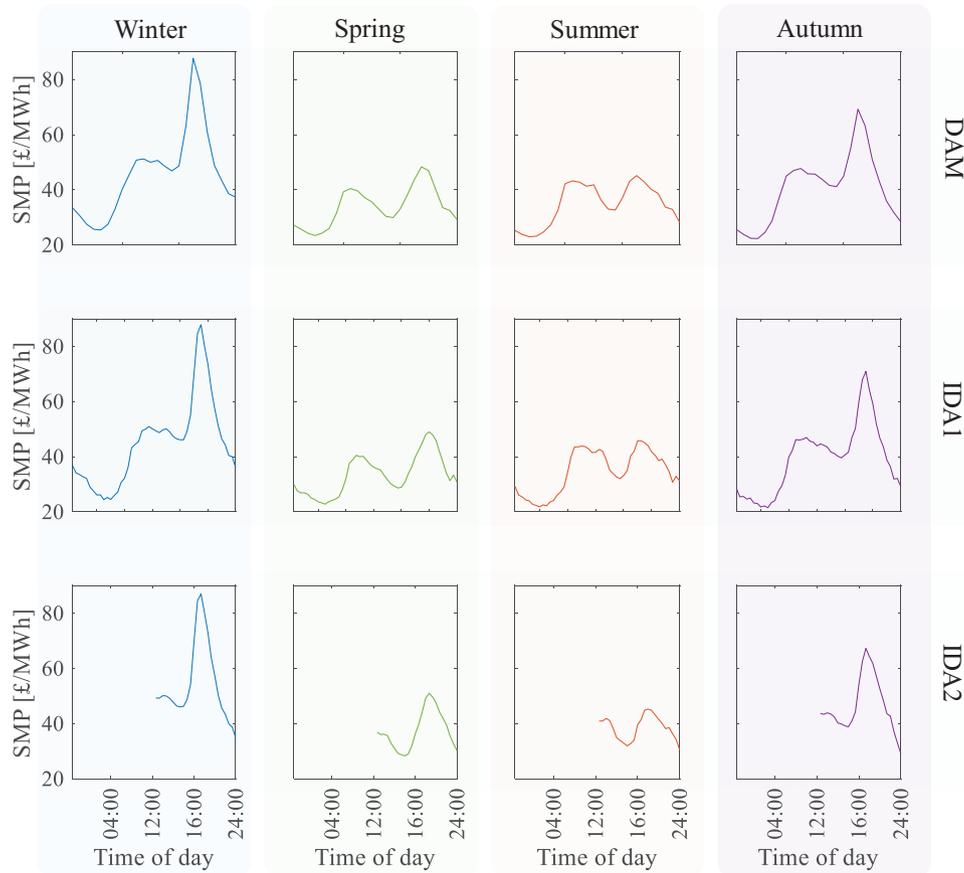


FIGURE 3 Average SMP obtained from 2019/2020 SEM data for the DAM, IDA1, and IDA2 for different seasons

As given in Table 2, only three predictors are used to represent the calendar: the hour of the day is used to capture the change of market with respect to each hour of the day, the day of the year is used to capture the market variation due to change in season, and the day of the week is used to capture the change in market demand and SMP throughout the week. Other predictors were tested such as the week of the year, day of the month, the month of the year, and special days (i.e., holidays). However, the results were not improved and hence, they were discarded. The calendar predictor of special days might be useful in some models to capture the change in demand/SMP during holidays, however, long historical data should be available as the holidays represent only 2.5% of the year. In addition, as the SEM combines two different areas, the public holidays may differ between Northern Ireland and the Republic of Ireland, hence, this predictor was not considered. The other predictors are related to the SEM historical data or obtained from the previous stages. The wind speed is used as a predictor for the DAM SMP only as it cannot be discarded (comparison between adding/removing wind speed predictor is given in Section 6.1 to show the impact of wind speed on the DAM SMP). However, for the other stages including the DAM demand, weather predictors were not included to mitigate the error accumulation. Note that, other predictors were tested for each stage, and the predictors given in Table 2 are the best combinations with less complexity.

4.1 | Data pre-processing

The available SEM historical data is from October 2018 to the present and can be obtained from [4, 25]. The adopted data used to develop and evaluate the proposed forecasting model is specified as follows:

- A dataset of two complete years (1 January 2019 to 31 December 2020) is used to train and optimize the model, which will be named as the prime dataset.
- A dataset of three months (1 January 2021 to 31 March 2021) is used to assess and evaluate the model, which will be named as the independent dataset.

The prime dataset is divided into two parts: (1) Training set (70% of the prime dataset) used for the training, validation, and testing, and (2) Optimization set (30% of the prime dataset) used for optimizing the ANN hidden layers and neurons in addition to the controlling parameters (weights and biases). The training set is divided randomly as 60% training, 20% validation, and 20% testing.

For the second stage of the proposed forecasting model, wind speed is required. However, as the SEM covers all the island of Ireland, hence, it is difficult to adopt wind speed measurements from a single weather station as the speed varies significantly across the island. Therefore, wind speed measurements were

FIGURE 4 Proposed methodology structure

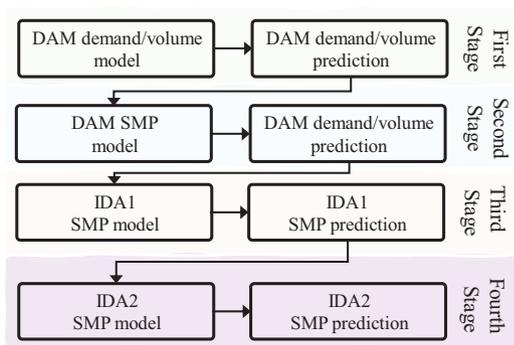
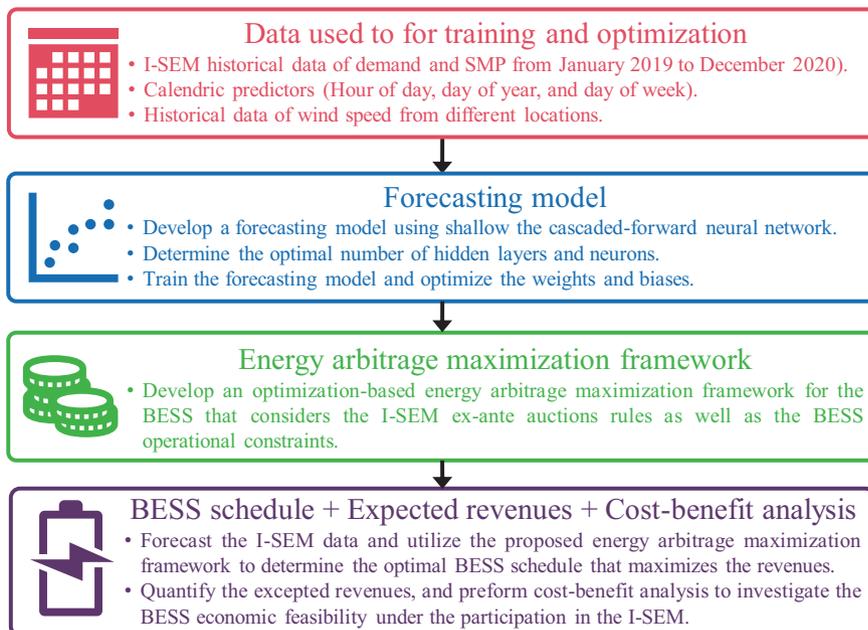


FIGURE 5 Proposed SEM four-stage successive forecasting model

obtained for six different weather stations located across the island of Ireland (Mullingar – Sherkin Island – Malin Head – Mace Head – Johnstown – Roches Point) from [27]. The selection of these stations is correlated with the existence of wind farms in these areas and to cover all the island [28]. A map of the locations of these weather stations and wind farms on the island of Ireland is shown in Figure 6.

The measurements obtained from these weather stations were tested as separate predictors and as a single predictor represents the average wind speed. The measurements of the following weather stations (Johnstown – Roches Point) negatively affected the results, and hence they were discarded. The measurements of the other four weather stations improved the results, and the results between using these measurements as separate predictors or as a single predictor of the average speed were comparable. Hence, for the sake of simplicity, the adopted wind speed measurement was calculated by taking the average wind speed measurements of the following four weather stations (Mullingar – Sherkin Island – Malin Head – Mace Head).

TABLE 2 Predictors used for each stage of the forecasting model

Stage	Number of predictors	Description
First stage	5	<ol style="list-style-type: none"> 1. Hour of day 2. Day of year 3. Day of week 4. DAM demand of same hour two days ago 5. DAM demand of same hour week ago
Second stage	8	<ol style="list-style-type: none"> 1. Hour of day 2. Day of year 3. Day of week 4. DAM SMP of same hour two days ago 5. DAM SMP of same hour week ago 6. Wind speed of same hour 7. DAM demand of same hour two days ago 8. DAM demand forecasting obtained from the first stage
Third stage	6	<ol style="list-style-type: none"> 1. Hour of day 2. Day of year 3. Day of week 4. IDA1 SMP of same hour two days ago 5. IDA1 SMP of same hour week ago 6. DAM SMP forecasting obtained from the second stage
Fourth stage	8	<ol style="list-style-type: none"> 1. Hour of day 2. Day of year 3. Day of week 4. IDA2 SMP of same hour two days ago 5. IDA2 SMP of same hour week ago 6. IDA1 SMP of same hour two days ago 7. IDA1 SMP of same hour week ago 8. IDA1 SMP forecasting obtained from the third stage

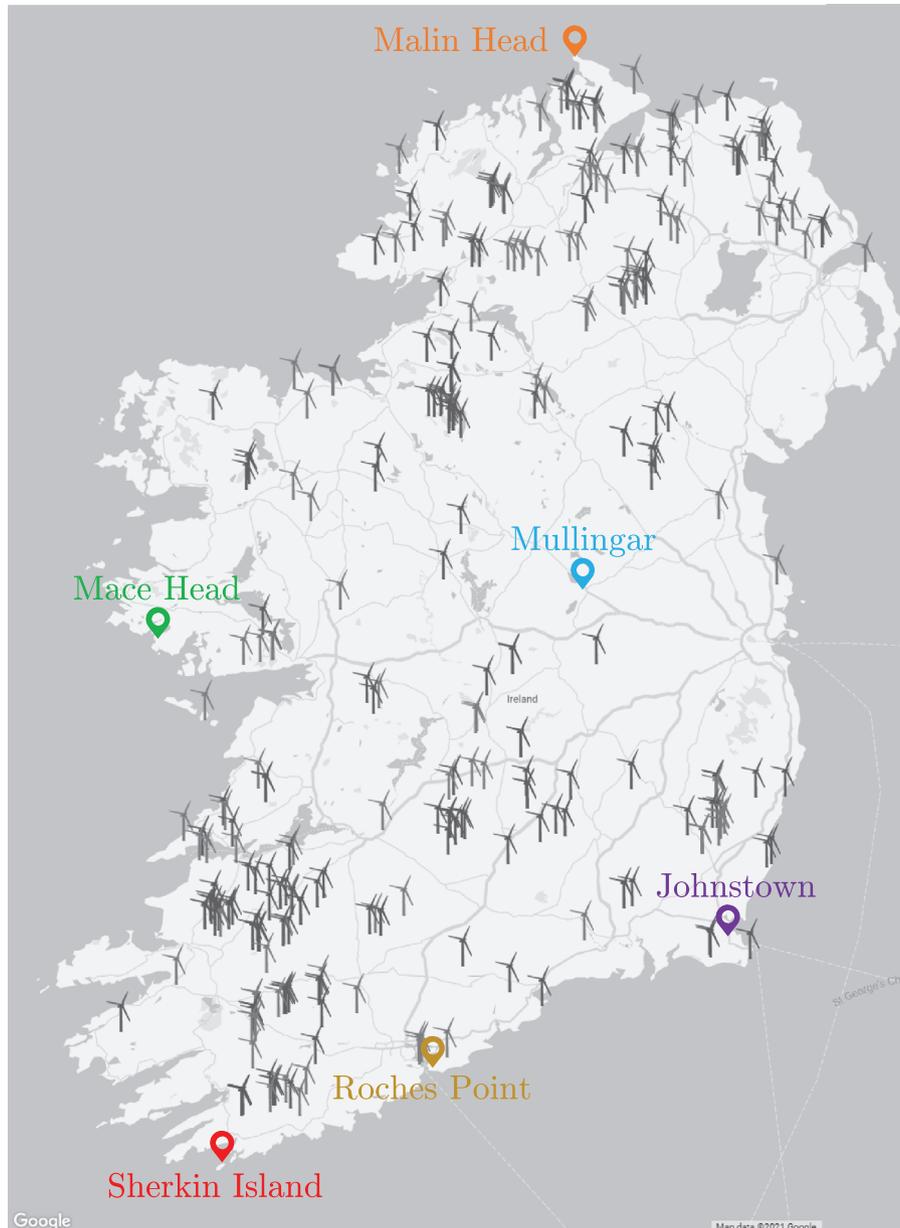


FIGURE 6 Map showing the locations of weather stations and wind farms on the island of Ireland (reproduced with the aid of the interactive map of Wind Energy Ireland [28])

The measurements recorded by these weather stations were obtained from [27].

4.2 | ANN setup

The ANN is well known in demand and market forecasting and has been used widely in this area [29]. ANN consists of an input layer, hidden layers, and output layer. The hidden layers consist of a number of neurons to connect and map the inputs with the outputs. ANN with a single hidden layer is called shallow, while ANN with more than one hidden layer is called deep [30]. The connections strength between the inputs and outputs through the neurons of the hidden layers are represented by

weights. An activation function is used to trigger the output of the neurons based on the weighted sum of the inputs. Biases are existed to shift and adjust the activation function by adding a constant. The values of the weights and biases are determined and updated by the training function. Additionally, the data processed by ANN need to be normalized to speed up the learning process and to improve the output accuracy [31]. The following specifications define the adopted ANN setup for the proposed forecasting model:

1. ANN type: The adopted ANN type is the cascaded-forward neural network (CFNN). CFNN is a type of ANN similar to the traditional feed-forward neural networks, however, the CFNN has a direct connection from the input layer and

every previous layer to the following layer which allows the network to capture the nonlinearity between the inputs and outputs [32].

2. Data normalization: The data is normalized by scaling the data to have a mean of 0 and a standard deviation of 1.
3. Activation functions: The tan-sigmoid function is used as a hidden layer activation function as it has been widely used in this application [33], and a linear transfer function is used for the output layer activation function [34].
4. Training function: The Bayesian regularization backpropagation is used to train the ANN and determine the initial optimal values of weights and biases for better generalization [35].

The number of hidden layers and hidden neurons is determined using an optimization algorithm detailed in the next section.

4.3 | ANN optimization

The number of hidden layers and neurons are usually determined empirically. There is currently no proven theoretical rule in determining the optimal hidden layers and neurons for a specific application. For the hidden layers, usually, one single layer is sufficient in representing any type of problem [36]. However, some applications require two hidden layers. More than two hidden layers increase the complexity of the model as well as the training time and might be not necessary. For the neurons in each hidden layer, there are many empirical rules that can be used such as the geometric pyramid rule presented in [37] which states that the number of neurons for a single hidden layer equals to $\sqrt{p \times r}$ where p is the number of predictors/inputs and r is the outputs. It is important to carefully determine the number of neurons to avoid overfitting the model as with many neurons, the model will memorize the training dataset well but will suffer from a lack of generalization and this may reduce the prediction accuracy of the independent dataset [36, 37].

In this paper, an optimization algorithm is introduced to determine the optimal number of hidden layers and neurons using black-box optimization. The decision variables of this optimization algorithm represent the number of hidden layers and the number of neurons in each hidden layer which are treated as integer variables with lower bounds of 1 and limitless upper bounds. The objective of this optimization algorithm is to minimize the root mean squared error ($RMSE$) between the forecasted and the actual data as well as maximizing the Pearson correlation coefficient (R), expressed in Equation (1) as:

$$\min \left(\frac{RMSE}{R} \right) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i^p - y_i^a)^2} \quad (2)$$

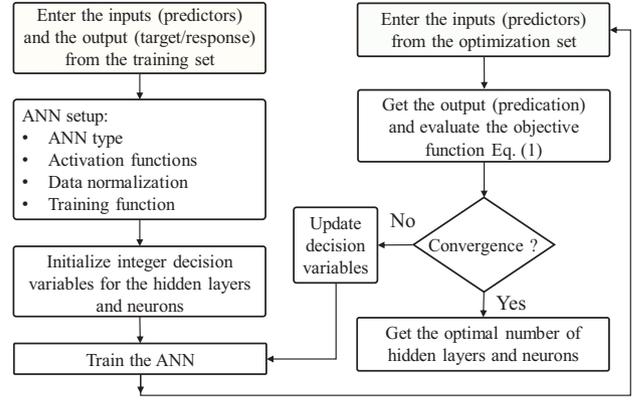


FIGURE 7 Proposed optimization algorithm for the ANN hidden layers and neurons

$$R = \frac{1}{N-1} \sum_{i=1}^N \left(\frac{y_i^a - \mu^a}{\sigma^a} \right) \left(\frac{y_i^p - \mu^p}{\sigma^p} \right) \quad (3)$$

where N is the number of points in the dataset, y_i^p is the predicted value, y_i^a is the actual value, μ^a and σ^a are the mean and standard deviation of the actual values, and similarly μ^p and σ^p are for the predicted values. This optimization is solved using the Surrogate optimization solver due to its capability in solving black-box optimization with integer variables.

In order to prevent overfitting the training set, a separate dataset (optimization set) is used to evaluate the objective function to obtain the optimal number of hidden layers and neurons that maximize the model generalization. The proposed optimization algorithm flowchart is illustrated in Figure 7.

After determining the optimal hidden layers and neurons (n) using the previous optimization algorithm, the weights and biases are also optimized. Generally, the Bayesian regularization backpropagation is used to determine the optimal combinations of weights and biases that minimizes the error based on the training set, however, sometimes it falls into local optima. Therefore, to increase the model generalization, another optimization algorithm is introduced to optimize the weights and biases with the aid of training and optimization sets. After the model has been trained, the vector that contains the weights and biases can be obtained with a length of l . For ANN with a single hidden layer, this length can be given as:

$$l = n(p+2) + p + 1 \quad (4)$$

The proposed optimization algorithm aims to find the optimal values of weights and biases using decision variables with a length of l that minimizes the following bi-objective function that is formulated using the weighted sum method ($w_1 = w_2$):

$$\min \left(w_1 \frac{RMSE_1}{R_1} + w_2 \frac{RMSE_2}{R_2} \right) \quad (5)$$

$$\text{subject to } R_1, R_2 > 0 \quad (6)$$

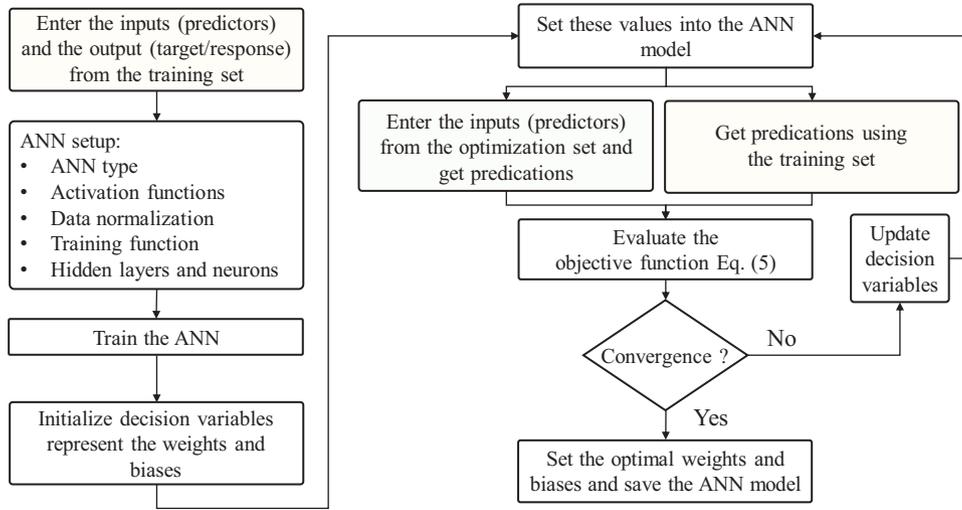


FIGURE 8 Proposed optimization algorithm for the ANN weights and biases

$RMSE_1$ and R_1 are calculated from the predictions against the training set, while $RMSE_2$ and R_2 are calculated from the predictions against the optimization set. Constraint in Equation (6) is treated as a soft constraint using static penalty function to avoid the optimization algorithm from going into negative correlation such that correlation coefficients must be maintained positive. The proposed optimization algorithm aims to adjust the weights and biases by minimizing the RMSE and maximizing the correlation coefficients between the predictions and actual values for the training and optimization sets to achieve high generalization. Some studies optimize the weights or biases for the training set only such as in [21] which may lead to overfitting. Hence, a separate set such as the optimization set used in this paper is beneficial to prevent overfitting the training data. The proposed optimization algorithm is a boundless black-box optimization problem and solved using the NLOpt solver [38]. The process of optimizing the weights and biases is illustrated in Figure 8.

4.4 | Holt-Winter's exponential smoothing method (HWETS)

HWETS method is one of the popular classical methods for time-series forecasting [39]. In this paper, this method has been used to provide a comparison against the proposed ANN forecasting model and to evaluate the effectiveness of a hybrid model that combines both methods. The HWETS smoothing parameters are optimized using the training set to achieve high performance.

It is worth mentioning that other machine learning models were tested for the proposed four-stage successive forecasting model including Gaussian process regression, ensemble tree regression, and support vector machines. The results were comparable; however, the training time of ANN is very convenient compared to the other machine learning models, which allows for testing different sets of predictors to select the most effi-

cient model with less complexity. All the previous work was developed on MATLAB environment, the surrogate optimization solver was utilized using the global optimization toolbox, the NLOpt was used via the OPTI toolbox [40], and the ANN was developed using the deep learning toolbox.

5 | ENERGY ARBITRAGE MAXIMIZATION FRAMEWORK

In this paper, a framework is proposed that aim to maximize the BESS revenues obtained from the energy arbitrage participation in the SEM ex-ante markets. In [22], a similar approach was introduced for the SEM, where the ex-ante markets were treated as separate optimization layers, in each of these layers a linear programming problem was solved that aims to maximize the profits from BESS discharging, while the optimal participation factor for each market was settled by an outer layer using global optimization. This work extends [22], by dealing with the ex-ante markets into a single problem which reduces the computation time in addition to considering reducing the BESS charging costs to maximize the energy arbitrage gains. The proposed framework aims to determine the optimal BESS discharging schedule through the SEM ex-ante markets that maximize selling profits as well as determining the optimal BESS charging schedule through the DAM that minimizes the buying costs. The required inputs associated with the BESS/inverter specification and the market data are tabulated in Table 3.

The market data (SMP and volume) are unknown until the market closes and the SEMO announce them; hence, their values are obtained from the forecasting model introduced in Section 4. The objective function of this framework aims to maximize the trading profits formulated in Equation (7) as:

$$\max \left(\sum_{m \in M} \left(\sum_{t \in T_d} \rho_t (P_t^{di} \tau) \right) - \left(\sum_{t \in T_c} \rho_t (P_t^{cb} \tau) \right) \right)_{m=1} \quad (7)$$

TABLE 3 BESS energy arbitrage maximization framework inputs

Input	Symbol	Description
BESS capacity	E^{cap}	BESS nameplate capacity [MWh]
Rated power	P^{max}	BESS maximum output/input [MW]
BESS system efficiency	η_b	The output/input efficiency of the BESS system [%]
Depth of discharge	DoD	Maximum discharging capacity percentage [%]
State of charge limits	SoC	Maximum and minimum SoC limits [%]
Trading period duration	τ	Duration of a single period (1 for DAM, 0.5 for IDA)
SMP	ρ	SMP [£/MWh]
Volume	Vol	Market available volume [MW]

where m represents the market (1 for DAM, 2 for IDA1, 3 for IDA2 and 4 for IDA3), M is the number of markets, P_t^{di} is the discharge power (MW) at time t , T_d is the discharging period, P_t^{cb} is the charging power (MW) at time t , and T_c is the charging period. The previous optimization problem in Equation (7) is subject to the following constraints.

BESS system efficiency: Ratio of output-to-input power for the BESS throughout the charge and discharge.

$$P_t^{di} = \eta_b P_t^{dis} \quad (8)$$

$$P_t^{cb} = \frac{P_t^{chr}}{\eta_b} \quad (9)$$

$$\eta_b = \sqrt{\eta_{rte} \eta_{pcs}} \quad (10)$$

where P_t^{dis} is the BESS power output and P_t^{di} is the inverter power output which used to calculate the bidding capacity and selling price, P_t^{chr} is the required BESS charging power and P_t^{cb} is the input power to the charger which is used to calculate the buying costs. η_{rte} is the BESS round-trip efficiency and η_{pcs} is the power conversion system (PCS) efficiency.

- a. **BESS rating:** The output/input power of the BESS must not exceed its predefined limit at any time.

$$0 \leq P_t \leq P^{max}; \quad \forall t \in T; P_t \in \{P_t^{dis}, P_t^{chr}\} \quad (11)$$

- b. **Depth of discharge (DoD):** The maximum discharged capacity should not exceed the specified value determined by the DoD percentage value to protect the BESS from excessive discharge and to increase its lifespan, the BESS usable capacity (E^{us}) can be calculated considering the DoD in Equation (12) as:

$$E^{us} = DoD \times E^{cap} \quad (12)$$

- c. **State of charge (SoC):** SoC is the percentage measurement that indicates the available capacity of the nameplate capacity still in the BESS. The SoC must be maintained within the pre-

defined limits.

$$SoC^{min} \leq SoC_t \leq SoC^{max}; \quad \forall t \in T \quad (13)$$

$$SoC_t = SoC_{t-1} + \frac{P_t^{cb} \eta_b \tau}{E^{cap}} - \frac{P_t^{di} \tau}{E^{cap} \eta_b}; \quad \forall t \in T \quad (14)$$

$$DoD = SoC^{max} - SoC^{min} \quad (15)$$

- d. **Market volume:** At any time-point, the bidding capacity must not exceed the available market volume for bidding.

$$P_{m,t}^{di} \leq Vol_t^m \quad (16)$$

- e. **Market power:** At any time-point, the discharged power in all markets must not exceed the BESS power rating.

$$\sum_{m \in M} P_{m,t}^{di} \leq P^{max}; \quad \forall t \in T \quad (17)$$

The optimization solver initializes a set of variables x represents the discharging/charging according to the dispatch horizon (T) of each market such that $x \in \{P_t^{dis}, P_t^{chr}\}$. In order to avoid initializing discharging/charging variables at the same time-point without adding a hard constraint, the dispatch horizons are specified ahead such that from 01:00 AM to 08:00 AM are set for charging and the rest of the day is specified for discharging. These periods were determined with the aid of SEM data analysis in Section 2.1. To unify the trading periods, all the markets are modified with a half-hourly trading period ($\tau = 0.5$). For the full-day dispatch horizon, the number of variables is 104 for the discharging (34 for the DAM, 34 for the IDA1, 24 for the IDA2, and 12 for the IDA3) and 14 for the charging. These variables are constrained by the upper bound of the BESS rating Equation (11). While Equations (8), (9) are satisfied within the objective function Equation (7), and Equations (13)–(17) are formulated as hard constraints.

The previous settings are the default settings for the proposed BESS energy arbitrage maximization framework. Moreover, few modifications are introduced to accommodate the

market participation factors that were introduced in [22]. The concept of the market participation factors is to divide the BESS discharging capacity among the ex-ante markets according to a pre-defined factor for each market. The modified framework adopts these factors by considering the following constraints:

$$\sum_{t \in T_d} (P_t^d \tau)_m = \alpha_m E^{us}; \quad \forall m \in M \quad (18)$$

where α_m represent the market participation factors such that:

$$0 \leq \alpha_m \leq 100\% \quad (19)$$

$$\sum_{m \in M} \alpha_m = 100\% \quad (20)$$

The proposed BESS energy arbitrage maximization framework formulation can be easily solved using different off-the-shelf solvers. In this paper, the WORHP solver [41] has been adopted due to its effectiveness in providing optimal solutions in a short execution time. The WORHP adopts sequential quadratic programming and interior point method to solve convex and nonconvex problems efficiently.

6 | SIMULATION RESULTS

6.1 | Forecasting model results

The proposed forecasting model is evaluated using the prime and independent datasets explained in Section 4.1. The results from the ANN optimization algorithm indicates that a single hidden layer is sufficient for all the proposed stages, and the number of neurons is specified as 5 neurons for the first stage and 4 neurons for each of the other three stages. The forecasting results are evaluated using the RMSE, R-value, and mean absolute error (MAE). The results are given in Table 4.

As shown in Table 4, for the first stage, the proposed ANN model achieved a very high positive correlation for both datasets. Additionally, the HWETS achieved good results, however, the ANN outperformed the HWETS by 20% on average. By combining both models into a hybrid model (ANN+HWETS) by taking the results obtained from the HWETS as an additional predictor for the ANN, the results were improved by 5% on average compared to the results obtained from the ANN solely. For the second stage, the ANN achieved a high positive correlation and outperformed the HWETS by 30% and the results from the hybrid model were improved slightly for the independent dataset, however, the predictions against the prime dataset were not improved. For the third stage, the ANN achieved a high positive correlation with 28% improvements compared to the HWETS. However, the results obtained from the hybrid model were only improved for the prime dataset. Similarly, the ANN outperformed the HWETS by 26% for the fourth stage and the hybrid model results were slightly improved for only the prime dataset.

It can be concluded that the classical method such as HWETS can be used to predict the time-series data with a low level of volatility such as demand prediction. However, it fails to achieve reasonable results for the data that contains a high level of volatility such as the SMP. Hence, for a hybrid model, the HWETS can be used to enhance the ANN results for demand prediction (i.e., with the first stage). Furthermore, it can be noticed from the results that the proposed ANN optimization algorithms prevented overfitting the training set and managed to achieve a high level of generalization for the ANN model as the differences between the results of the prime dataset (that include the training set) and the independent dataset are not significant, hence the proposed ANN model has a high level of reliability.

Moreover, the accuracy of the proposed forecasting model decreases with stages such that the fourth stage has the worst error metrics. This is because the proposed model is successive and hence, each stage accumulates errors from the previous stage. The motivation behind using this successive structure is that in practice, the SEM ex-ante markets are dependent on each other and the relation between them cannot be neglected. It should be noted that the available SEM data consisted of only two years of historical data and long historical data is needed to produce a more accurate model. Additionally, the proposed model aims to forecast the SEM on a two-days ahead basis which adds another challenge as the day-ahead results are unknown. Furthermore, the proposed ANN model relies mainly on the historical predictors which are easily accessible, the only predictor that may require another forecasting model is the wind speed which can be obtained using a meteorological model with high accuracy, especially for short-term forecasting [42]. Nevertheless, these models are out of the scope of this paper and the wind speed measurements are assumed to be known.

The wind speed is important as it affects the DAM SMP due to the high participation of wind energy in the island of Ireland and consequently affects the other model stages. Without the wind speed, the predictions of DAM SMP are worsened by 20% as shown in Table 5, which will also worsen the results of the third and the fourth stages.

To visualize the results obtained from the proposed forecasting model, one week of the independent dataset (from 23 January 2021 to 29 January 2021) was simulated and the forecasted results against the real data are shown in Figure 9. As shown in Figure 9a, the demand was forecasted with very good accuracy with a mean absolute percentage error (MAPE) of 3.3% and MAE of 0.156 GW. Additionally, the SMP of different markets was forecasted with reasonable accuracy as shown in Figure 9b–d with MAE of £9.5/MWh for the DAM SMP, £10.5/MWh for the IDA1 SMP, and £15/MWh for the IDA2 SMP. Despite the errors in SMP predictions, the SMP profile shapes are predicted with very good accuracy. This is important as with the aid of the SMP profile shape, the most lucrative periods for trading in the day can be determined and hence can be used in maximizing the revenues for generation bidders through participation in the SEM. On the other hand, the periods with low SMP can be also identified which can assist the

TABLE 4 Results summary for the forecasting models

First stage (DAM demand/volume)			Second stage (DAM SMP)			Third stage (IDA1 SMP)			Fourth stage (IDA2 SMP)		
ANN (1 hidden layer, 5 neurons)			ANN (1 hidden layer, 4 neurons)			ANN (1 hidden layer, 4 neurons)			ANN (1 hidden layer, 4 neurons)		
Error metric	Prime dataset	Independent dataset	Error metric	Prime dataset	Independent dataset	Error metric	Prime dataset	Independent dataset	Error metric	Prime dataset	Independent dataset
R-Value	0.9	0.91	R-Value	0.84	0.81	R-Value	0.82	0.79	R-Value	0.8	0.75
RMSE [GW]	0.351	0.322	RMSE [£/MWh]	11.79	22.29	RMSE [£/MWh]	13.8	25	RMSE [£/MWh]	14.8	31.6
MAE [GW]	0.277	0.248	MAE [£/MWh]	7.83	12.1	MAE [£/MWh]	9.6	12.4	MAE [£/MWh]	8.8	16
HWETS			HWETS			HWETS			HWETS		
R-Value	0.82	0.85	R-Value	0.62	0.57	R-Value	0.64	0.55	R-Value	0.6	0.47
RMSE [GW]	0.454	0.406	RMSE [£/MWh]	16.93	31.08	RMSE [£/MWh]	18	36	RMSE [£/MWh]	20	43
MAE [GW]	0.349	0.320	MAE [£/MWh]	11.04	18.72	MAE [£/MWh]	12	19	MAE [£/MWh]	13	23
ANN + HWETS			ANN + HWETS			ANN + HWETS			ANN + HWETS		
R-Value	0.91	0.92	R-Value	0.84	0.84	R-Value	0.83	0.76	R-Value	0.82	0.63
RMSE [GW]	0.334	0.301	RMSE [£/MWh]	12.3	19.32	RMSE [£/MWh]	10	28	RMSE [£/MWh]	14.5	46.7
MAE [GW]	0.266	0.230	MAE [£/MWh]	8.11	11.02	MAE [£/MWh]	7	15	MAE [£/MWh]	8.5	24

TABLE 5 Results for the second stage without the wind speed

Second stage (DAM SMP)		
Error metric	Prime dataset	Independent dataset
R-value	0.7	0.69
RMSE [€/MWh]	15.93	26.72
MAE [€/MWh]	10.33	16.25

suppliers in buying electricity with low SMP as well as assisting BESS owners in charging with low SMP. It should be mentioned that the IDA3 can be added to the proposed forecasting model by adding a fifth stage similar to the fourth stage of the IDA2. However, it has not been considered in this paper as the bidding in this auction is not guaranteed as the available volume for bidding is too small.

6.2 | BESS energy arbitrage

In this paper, the energy arbitrage revenues are calculated for a BESS of 4 MWh / 1 MW, DoD of 80% (SoC_{min} of 20% and SoC_{max} of 100) so that the BESS usable capacity (E^{us}) is 3.2 MWh, PCS efficiency of 95% and BESS roundtrip-efficiency of 95%. As showed in [22], the participation in IDA3 is not guaranteed as the volume/demand available for bidding in this

market is very small, hence in this paper, the IDA3 is not considered and the proposed methodology is only implemented for the DAM, IDA1, and IDA2. In addition, it is assumed that the BESS completes one cycle per day for the SEM participation only.

6.3 | SEM 2019/2020 data results

The first part of the results is to use the energy arbitrage maximization framework to calculate the total revenues that can be obtained using the SEM historical data of two years 2019/2020. The results summary is shown in Figure 10. The BESS achieved a total gain of £138,800 from discharging/selling in the SEM ex-ante markets, with an average value of £69,400/year. The discharging gains in 2019 are higher than the gains in 2020 by 12.5%. The charging costs are averaged as £32,178/year. Note that in 2019, the charging costs were higher than the costs in 2020 by 36.4%. This is because in 2020, in many days the BESS was getting paid to charge due to negative SMP. This can be correlated with increasing the renewable generation in the Island of Ireland, especially from the wind such that the events with system non-synchronous penetration (SNSP) at 50% or higher in 2020 increased by 40% compared to 2019 [1] as well as the other factors explained in Section 2.1. The energy arbitrage net is averaged as £37,222/year. Note that the previous results were obtained assuming perfect knowledge of the SEM data,

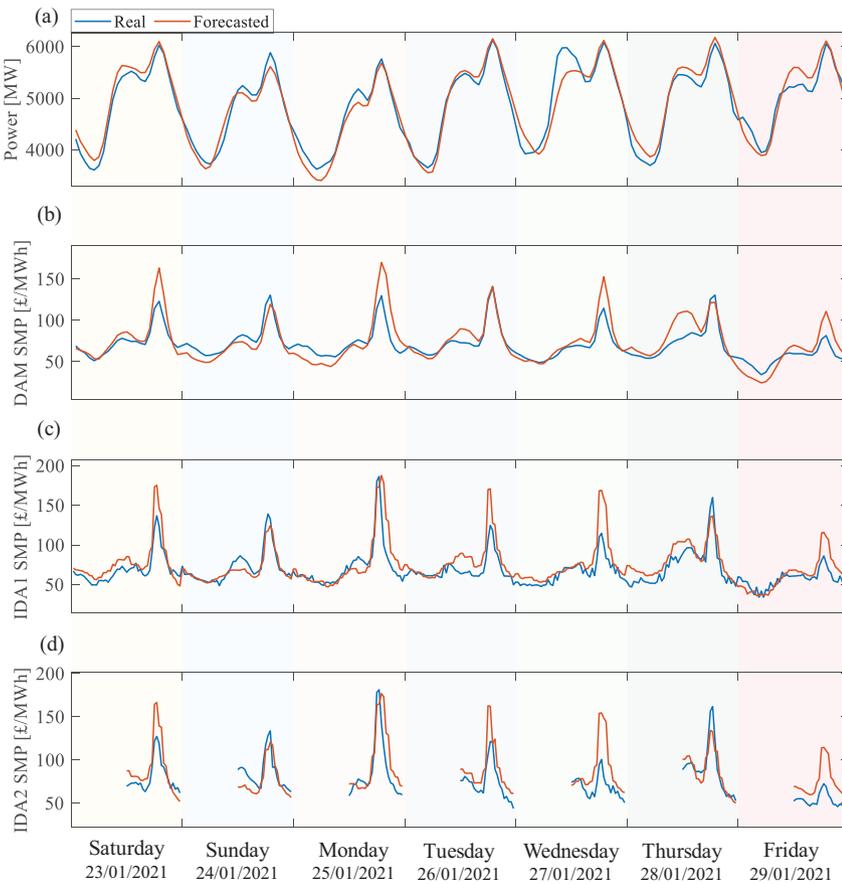


FIGURE 9 Results obtained for six different days in 2021 using the proposed four stages successive forecasting methodology: (a) DAM demand, (b) DAM SMP, (c) IDA1 SMP, and (d) IDA2 SMP

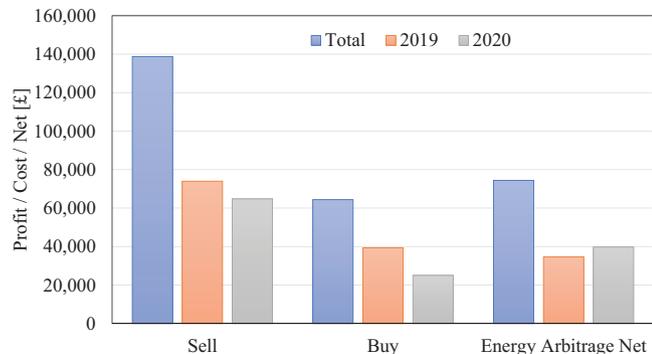


FIGURE 10 BESS energy arbitrage results obtained from trading in the SEM through 2019/2020

TABLE 6 Average of 2019/2020 market participation factors

	DAM [%]	IDA1 [%]	IDA2 [%]
Annual	29.4	37.2	33.4
Winter	34	30.2	35.8
Spring	23.1	40.2	36.7
Summer	32.3	40.6	27.1
Autumn	27.5	38.7	33.8

however, in practice, these amounts might change which will be addressed later in the paper.

Furthermore, the daily market participation factors were calculated as percentages of the usable capacity by determining the BESS capacity used in each market. The daily results were obtained from the simulations of 2019/2020 and were used to determine the annual average factors as well as the average factors per season as shown in Figure 11 and given in Table 6.

As shown in Figure 11, the highest participation factor was for the DAM in 2019. While in 2020, the highest participation factor was for the IDA1. This means that the IDA1 SMP in 2020 was higher than in 2019 and hence, it is more profitable to sell electricity in the IDA1 compared to the DAM, but it was more profitable to trade in the DAM compared to the IDA1 in 2019. In addition, the participation factor of IDA2 is also higher compared to the participation factor of DAM in 2020. This means that the trading in the intraday markets is more profitable than the trading in the day-ahead market in 2020 as the real-time uncertainties are higher and the generation positions were subject to more changes compared to 2019. Additionally, the year 2020 had unusual events due to the lockdowns and government restrictions which may affect also the uncertainties associated with real-time demand. Thus, more historical data of the SEM is required to form a complete picture of the optimal participation factors for different years. The market participation factors are important for BESS bidders as they can be used to reduce the errors associated with a forecasting model with low accuracy or with naïve forecasting as well as being used individually as a form of heuristic BESS scheduling.

6.4 | SEM 2021 data results

In this part, the SEM data of 2021 for three months (from 1 January 2021 to 31 March 2021) is being used to evaluate the effectiveness of the proposed forecasting model as well as the energy arbitrage maximization framework. Five cases are simulated described as follows:

1. Case A: With perfect knowledge of SEM data. This case simulates the maximum revenue that can be obtained assuming a perfect forecast.
2. Case B: Forecasted data using the proposed forecasting model. This case simulates the revenue that can be obtained using the proposed forecasting model.
3. Case C: Forecasted data using the proposed forecasting model and participation in the DAM only. This case quantifies the revenues from the participation in the DAM only.
4. Case D: Using previous year market data (i.e., naïve forecasting). This case simulates the revenues that can be obtained without using a forecasting model by using the same SEM data of the previous year.
5. Case E: Using previous year market data in addition to the annual average market participation factors given in Table 6, and heuristic scheduling periods from Figure 2. This case simulates the impact of market participation factors and predefined scheduling periods on enhancing the results of naïve forecasting.

The results summary for the previous five cases is illustrated in Figure 12. As shown in Figure 12, the proposed methodology achieved good values in terms of selling/buying compared to the ideal case (Case A). Compared to Case A, the MAPE of Case B is 8.9% for selling, 2.1% for buying, and 14.9% for energy arbitrage net. By trading only in the DAM (Case C), the MAPE was increased to 10.7% for selling and 18.5% for the energy arbitrage net. By using previous year data (i.e., naïve forecasting) in Case D, the MAPE is 22% for selling, 4% for buying, and 37.3% for the energy arbitrage net. While by applying predefined scheduling periods (From 02:00 AM to 07:00 AM for charging/buying and from 04:00 PM to 10:00 PM for discharging/selling) in addition to using the average annual market participation factor (from Table 6) in Case E, the error metrics were improved compared to Case D to 14% for selling, and 25% for the energy arbitrage net.

The results show that for these three months, participation in DAM only will reduce the total energy arbitrage revenues by 3.6%. Additionally, the forecasting model proved to provide good accuracy as shown from the results of Case B. Note that, the ideal case (Case A) is unrealistic as the SEM data cannot be fully predicted. Hence, the obtained results are very reasonable with respect to the available historical data used to train the forecasting model. These results will improve as the amount of available historical SEM data increases. Furthermore, the results show that without using a forecasting model (i.e., naïve forecasting using previous year data) in Case D, 62.7% energy arbitrage net of the ideal case has been achieved. This is considered a poor result compared to the results of Case B (85.1%).

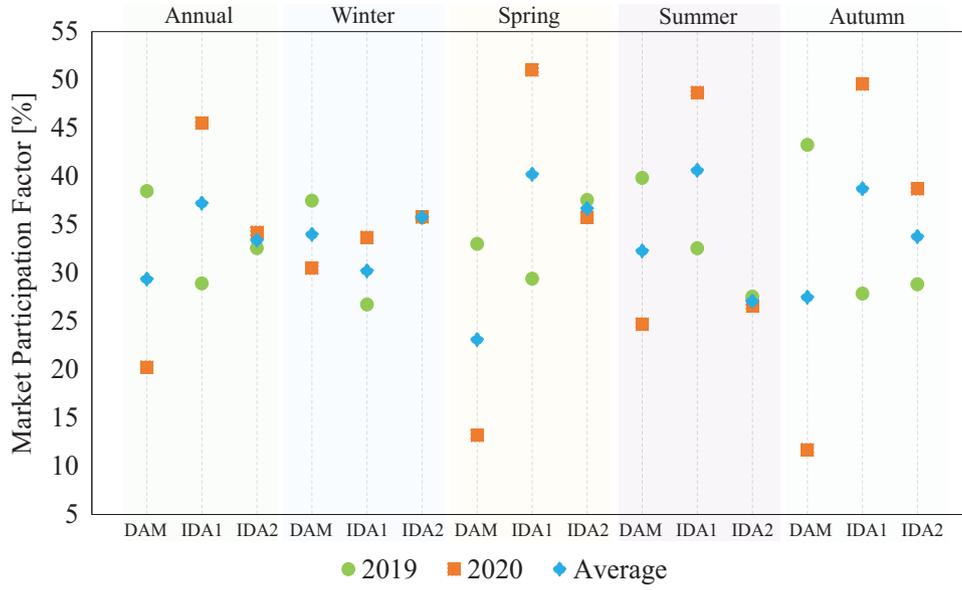


FIGURE 11 Optimal average market participation factors for 2019 and 2020

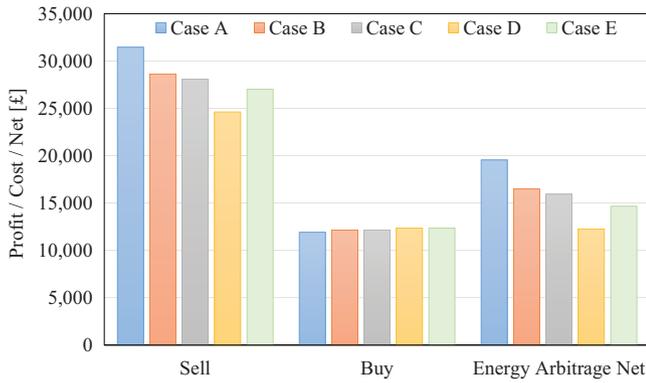


FIGURE 12 BESS energy arbitrage for three months in 2021 under five different cases

However, as this result was obtained without the complexity of using a forecasting model, it could conversely be considered a satisfactory result. The problem with using naïve forecasting is that the trading may not be profitable in some days and so should be avoided. For instance, the energy arbitrage was negative for six days in the three months for Case D. Hence, a robust forecasting model is essential to maximize the revenues and provide a good planning horizon. Furthermore, by specifying particular capacity for each market using the annual market participation factors obtained in Table 6 in addition to setting scheduling periods obtained from analysing the SEM historical data in Figure 2, the energy arbitrage results of the naïve forecasting have been improved by 33% in Case E.

7 | BESS DEGRADATION

The BESS degradation is an important factor that should be considered in scheduling the BESS. In order to quantify the loss

in BESS capacity due to the energy arbitrage participation in the SEM ex-ante markets, the semi-empirical Li-ion cycling ageing model in [43] has been adopted. In this paper, it is assumed that the BESS technology is Li-ion. The ageing model has been used to quantify the BESS ageing life indicator (L) to be used in determining the BESS state of health (SoH) at the end of lifetime using Equations (21) and (22):

$$L = 1 - (p_{SEI} e^{-r_{SEI} f_{cyc}} + (1 - p_{SEI}) e^{-f_{cyc}}) \quad (21)$$

$$SoH = 1 - L \quad (22)$$

where f_{cyc} is the linearized cycling degradation function, p_{SEI} and r_{SEI} are coefficients related to the solid-electrolyte Interphase, more details related to the calculation of f_{cyc} and the SEI coefficients are available in [43].

The BESS SoC profile was obtained from simulating the BESS operation in the SEM through two years from Section 6.2 (a). The rainflow counting algorithm [44] has been used to analyse the SoC profile and extract the data required for the degradation model. The BESS ageing life indicator (L) is calculated at the end of two-year operation and scaled for 10 years of operation which is the warranted lifespan of Li-Ion BESS [45]. The cycling ageing throughout the two years is illustrated in Figure 13.

The results from the ageing model show that the BESS capacity degrades by 3.14%/year with 365 full cycles through participation in the SEM. This loss in capacity factor represents the BESS ageing life indicator (L). By scaling for 10 years of operation, the BESS is assumed to reach an SoH value of 68.6%. This value represents the SoH (residual capacity) at the end of 10 years of operation which is adequate as the BESS is considered to reach the end of life when the residual capacity reaches 60–80% [43].

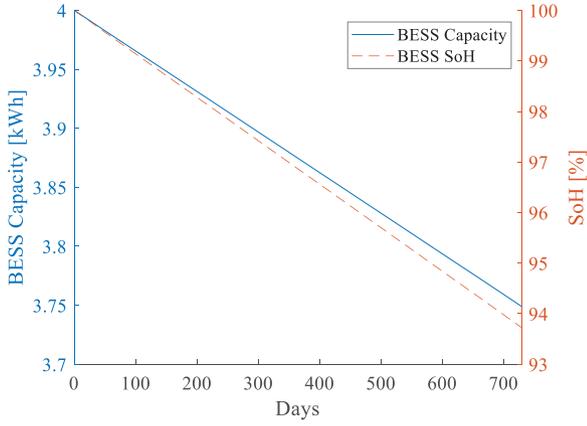


FIGURE 13 BESS cycling degradation throughout two years of operation in the SEM

TABLE 7 CBA parameters

BESS CEX [£]	1,008,000 (£250/kWh)
BESS OEX [£/year]	13,500
Interest rate [%]	5
Annual loss in capacity [%]	3.14
Energy arbitrage [£/year]	31,639

8 | COST-BENEFIT ANALYSIS

In this paper, cost-benefit analysis (CBA) is conducted to evaluate the economic feasibility of BESS participation in the SEM ex-ante markets. The CBA is performed by calculating the total savings (TS), net present value (NPV), annual return on investment (ARO) and the discounted payback period based on the annual energy arbitrage net ($Earb^t$) for BESS lifetime (LT) as:

$$NPV = TS - CEX \quad (23)$$

$$ARO = \frac{NPV}{LT \times CEX} \quad (24)$$

$$TS = \sum_{n=1}^{LT} \frac{Earb^n (1 - L_n) - OEX}{(1 + ir)^{n-1}} \quad (25)$$

where CEX represents the capital expenditures, OEX is the annual operation expenditures, ir is the interest rate, and L_n represents the annual loss in BESS capacity due to degradation. The discounted payback period is calculated at zero NPV.

The CBA parameters are tabulated in Table 7. The BESS CEX was obtained from a recent report by the National Renewable Energy Laboratory [46] for the 2022 mid scenario which represents the Li-ion BESS total system including the PCS and other component costs. The OEX was determined based on the network charges (4500 £/MW/year) [22] in addition to the operation and maintenance costs (£9000/year) obtained from

the IRENA report [47]. An interest rate of 5% is considered to reflect the mid-point value of the department for Business, Energy and Industrial Strategy interest rates [48]. The BESS annual loss in capacity (L_n) was obtained from the ageing model in Section 7. In Section 6.2 (a), the annual energy arbitrage net was determined as £37,222. However, these values were obtained assuming a perfect forecast. By considering an error of 14.9% obtained in Section 6.2 (b), the realistic annual energy arbitrage net can be then determined as £31,639/year, approximately £87/day.

The CBA results show that the BESS sole participation in the SEM ex-ante markets is not profitable as the BESS cannot pay back the investment costs as the total savings at the end of 10 years is £114,051 with an NPV of -£893,950 and ARO of -8.9%. Even with low projections of BESS costs, the BESS trading in the SEM solely is not advised. With current CBA parameters, the annual payments required for BESS to break even in a lifetime of 10 years is £158,200/year, approximately £434/day, which is fivefold the current SEM energy arbitrage net. Currently, the main purpose of BESS integration is to provide different ancillary services to the transmission and distribution systems, and the existence of BESS is rationalized mainly based on these services. However, under a stacked revenue arrangement, the BESS can simultaneously participate in the SEM energy arbitrage in which the proposed framework can be used to boost revenues.

9 | DISCUSSION

The ongoing energy evolution accelerates the deployment of low carbon technologies and generation which impose technical challenges to the network operators. The existence of SEM is motivated by this energy evolution and to provide detailed real-time monitoring to the energy paradigm as well as assist in reducing the market prices by increasing the levels of competition to deliver high levels of supply security and transparency. Forecasting SEM demand and SMP is crucial for traders to maximize profits by selecting the optimal trading periods and capacity. The proposed four-stage successive forecasting model provided reasonable accuracy in predicting the SEM demand and the SMP shape. However, more historical data is required to provide a more reliable model.

It is noteworthy that the SEM DAM has decoupled from interconnection with GB and the wider EU market since 1 January 2021 due to Brexit and became local as the IDA3. This should affect the DAM SMP, which increases the forecasting uncertainties as the proposed forecasting model was trained and optimized using market data before the Brexit (from 1 January 2019 to 31 December 2020). However, the results achieved in Section 6.1 for the independent dataset (from 1 January 2021 to 31 March 2021) show very reasonable forecasting accuracy which proves the efficacy of the proposed forecasting model in capturing the uncertainties. Furthermore, in practice, the proposed forecasting model should be trained and optimized regularly by updating the historical data on a rolling basis to increase its accuracy by capturing the change in demand and SMP, thus

the variations caused from the decoupling, or any other uncertainties should be captured sequentially.

The results show that generation bidders should distribute their orders across the ex-ante markets as the SMP values for some days are more attractive in intraday markets than the day-ahead market. The proposed energy arbitrage maximization framework has the capability to determine the optimal trading periods with capacity across the ex-ante markets with the aid of a forecasting model. The results show that despite the uncertainties associated with the forecasting, the proposed energy arbitrage maximization framework with the proposed forecasting model have shown the capability to achieve 91.1% selling accuracy, 97.9% buying accuracy, and 85.1% energy arbitrage net accuracy of the ideal case where the SEM data is perfectly known. Furthermore, the proposed energy arbitrage maximization framework can be easily adjusted to consider other types of distributed energy resources, thus widening its application.

It is anticipated that the SEM analyses provided in this paper are beneficial for the SEM traders. For instance, the periods with the highest/lowest SMP identified from 2019/2020 in Figure 2 can assist the decision-maker in selecting heuristically the best scheduling periods. On the other hand, the optimal market participation factors can assist BESS owners in determining the bidding capacity for each market which can be used to mitigate the forecasting uncertainties of poor forecasting as shown in the results section (Section 6).

The paper was extended to consider the BESS degradation through the participation in the SEM using the proposed energy arbitrage maximization framework and the results show that the annual loss in BESS capacity is adequate for 10 years operation. Furthermore, the BESS profitability was considered by conducting a cost-benefit analysis and the results show that the sole participation of BESS in the SEM is not profitable. However, under a stacked arrangement or as a part of aggregation, the proposed methodology can be used to maximize the profits from the SEM.

From the participation in the SEM only, annual selling profits and buying costs of £20,278/MWh and £9232/MWh, respectively can be achieved for a BESS with 100% system efficiency. BESS owners should stack revenues to maximize profitability and rationalize BESS existence through participation in multiple services. For instance, in the island of Ireland, besides the SEM, the BESS can participate in the enhanced services provided by the Irish transmission system operator (TSO) through the DS3 programme [49], as well as providing flexibility and other services to the distribution system operator (DSO) through the FLEX or FESS projects [50, 51]. Under these schemes, the expected BESS revenues were quantified previously in [11, 17].

The main challenge of stacking BESS revenues is the overlapping in services as a contracted BESS with TSO/DSO services may not be available to participate in other services unless the BESS is oversized, or there are some pre-defined contracted scheduling periods that may change according to the month and the need of TSO/DSO. In this case, the BESS might be available to distribute its available capacity whenever it is not contracted with the TSO/DSO. However, more research is required to investigate the validity of this assumption as well as exploring

the conflicts and synergies of the simultaneous participation in the island of Ireland which is considered as future work.

10 | CONCLUSION

This paper proposed a powerful methodology to maximize the revenues from participating in the SEM ex-ante markets. A forecasting model of four successive stages has been proposed to predict the day-ahead and intraday auctions of the SEM. The proposed forecasting model was developed using CFNN, while optimization algorithms were introduced to optimize the CFNN performance by determining the optimal number of hidden layers and neurons as well as the optimal values of weights and biases that minimizes the forecasting errors through a novel formulation that prevents overfitting the training data and achieves a high level of generalization. For this type of application, the paper demonstrated that machine learning models such as ANN outperformed the classical method of HWETS method. In addition, a hybrid model of both methods has proven to increase the model accuracy for low volatile variables such as demand forecasting.

Furthermore, an energy arbitrage framework was introduced for BESS owners to maximize the energy arbitrage gains from participating in the SEM ex-ante markets. To mitigate the forecasting uncertainties in the case of using naïve forecasting or a forecasting model with poor accuracy, the SEM historical data was analysed and the periods with highest/lowest SMP values were identified as well as the optimal market participation factors. Finally, for BESS operating in the SEM, the BESS degradation was quantified, and a cost-benefit analysis was conducted.

The results proved the effectiveness of the proposed methodology in achieving 91.1% selling accuracy, 97.9% buying accuracy, and 85.1% energy arbitrage net accuracy of the perfect forecast case. Compared to using naïve forecasting, the proposed methodology achieved an improvement of 26% for the energy arbitrage net. It is important to highlight that although the proposed forecasting model is specified for the SEM, the forecasting model structure can be insightful for other energy markets. Additionally, the proposed energy arbitrage maximization framework was formulated for the BESS. However, the proposed framework could be applied using the same objective function for other types of distributed energy resources with simple modifications to consider their operational constraints.

The limitation of this work concentrates mainly on enhancing the SMP forecasting accuracy of SEM ex-ante markets. Future work should focus on enhancing the accuracy of SMP predictions. However, as there is currently limited available SEM historical data for training a robust forecasting model, other techniques can be tested such as data augmentation to extend the training data.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

NOMENCLATURE

$\eta_{rte}, \eta_{pcs}, \eta_b$	The efficiency of BESS, PCS, and all system [%]
E^{cap}	BESS nameplate capacity [MWh]
E^{us}	BESS usable capacity [MWh]
P^{max}	BESS rated power [MW]
P_t^{ch}	BESS charging power at time t [MW]
P_t^{di}	BESS discharging power at time t [MW]
T_d, T_c	Discharging/charging periods
Vol_t^m	Market m volume at time t [MW]
f_{cyc}	Linearized cycling degradation function
p_{SEI}, r_{SEI}	Solid-electrolyte interphase formation portion and rate ratio coefficients
w	Multi-objective function weights
α_m	Market m participation factor [%]
ρ_t	SMP at time t [£/MWh]
Acronyms	Parameters, indices, and variables
ANN	Artificial neural network
ARO	Annual return on investment
BESS	Battery energy storage system
CBA	Cost-benefit analysis
CEX	Capital expenditures
CFNN	Cascaded-forward neural network
DAM	Day-ahead market
HWETS	Holt-Winters's exponential smoothing method
IDA1	First intraday auction
IDA2	Second intraday auction
IDA3	Third intraday auction
I-SEM	Integrated single electricity market
MAE	Mean absolute error
NPV	Net present value
OEX	Operational expenditures
PCS	Power conversion system
RMSE	Root mean squared error
SEM	Single electricity market
SEMO	Single electricity market operator
SMP	System marginal price
TS	Total savings
DoD	Depth of discharge [%]
$Earb^a$	Annual energy arbitrage net [£]
L	BESS ageing life indicator
LT	BESS lifetime [Years]
SoC	State of charge [%]
SoH	State of health [%]

T	Dispatch horizon
ir	Interest rate
l	Length of the vector of ANN weights and biases
m, M	Index of the market, set of markets
p	Number of ANN predictors/inputs
t	Index of time
n	Number of neurons in the ANN
τ	Trading period duration

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REFERENCES

- Eirgrid: System and renewable data summary report. <https://www.eirgridgroup.com/site-files/library/EirGrid/System-and-Renewable-Data-Summary-Report.xlsx> (2020). Accessed 01 Mar 2021
- Eirgrid: Renewable Electricity Support Scheme. <https://www.eirgridgroup.com/customer-and-industry/renewable-electricity-support-scheme/> (2021). Accessed 09 Mar 2021
- Mohamed, A.A.R., Morrow, D.J. & Best, R.: The deployment of low carbon technologies in modern distribution networks. In: 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), pp. 1–5 (2019). <https://doi.org/10.1109/ISGTEurope.2019.8905643>
- SEMO: Integrated Single Electricity Market. SEMOpX. <http://www.semopx.com/> (2020). Accessed 01 Jan 2021
- Jufri, F.H., Oh, S., Jung, J.: Day-ahead system marginal price forecasting using artificial neural network and similar-days information. *J. Electr. Eng. Technol.* 14(2), 561–568 (2019). <https://doi.org/10.1007/s42835-018-00058-w>
- Li, P., Arci, F., Reilly, J., Curran, K., Belatreche, A., Shynkevich, Y.: Predicting short-term wholesale prices on the Irish single electricity market with artificial neural networks. In: 2017 28th Irish Signals and Systems Conference (ISSC). Killarney, Co Kerry, Ireland, pp. 1–8 (2017)
- Kavanagh, K., Barrett, M., Conlon, M.: Short-term electricity load forecasting for the integrated single electricity market (I-SEM). In: 2017 52nd International Universities Power Engineering Conference (UPEC). Heraklion, pp. 1–7 (2017)
- González, C., Mira-McWilliams, J., Juárez, I.: Important variable assessment and electricity price forecasting based on regression tree models: Classification and regression trees, Bagging and Random Forests. *IET Gener. Transm. Distrib.* 9(11), 1120–1128 (2015)
- Cao, J., Harrold, D., Fan, Z., Morstyn, T., Healey, D., Li, K.: Deep reinforcement learning-based energy storage arbitrage with accurate lithium-ion battery degradation model. *IEEE Trans. Smart Grid* 11(5), 4513–4521 (2020). <https://doi.org/10.1109/TSG.2020.2986333>
- Heredia, F.-J., Cuadrado, M.D., Corchero, C.: On optimal participation in the electricity markets of wind power plants with battery energy storage systems. *Comput. Oper. Res.* 96, 316–329 (2018). <https://doi.org/10.1016/j.cor.2018.03.004>
- Brogan, P.V., Best, R., Morrow, J., Duncan, R., Kubik, M.: Stacking battery energy storage revenues with enhanced service provision. *IET Smart Grid* 3(4), 520–529 (2019)
- Mohamed, A.A.R., Morrow, D.J., Best, R.J., Bailie, I., Cupples, A. & Pollock, J.: Battery energy storage systems allocation considering distribution network congestion. In: 020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), pp. 1015–1019 (2020). <https://doi.org/10.1109/ISGT-Europe47291.2020.9248982>
- Mohamed, A.A.R., Morrow, D.J. & Best, R.J.: Real-time model predictive control of battery energy storage active and reactive power to support the distribution network operation. In: The 9th Renewable Power Generation

- Conference (RPG Dublin Online 2021), p. 6 (2021). <https://doi.org/10.1049/icp.2021.1356>
14. Bagchi, A., Best, R., Morrow, D.J., Pollock, J., Bailie, I., Cupples, A.: System service provision capabilities of storage devices connected to a MV distribution network: A Northern Ireland case study. In: The 2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT). Washington, DC, pp. 1–5 (2020)
 15. Al Kez, D., Foley, A.M., Morrow, D.J.: A comparative assessment of battery energy storage locations in power systems with high wind power penetrations. In: 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe). Madrid, Spain, pp. 1–6 (2020)
 16. Brogan, P.V., Best, R.J., Morrow, D.J., McKinley, K., Kubik, M.L.: Effect of BESS response on frequency and RoCoF during underfrequency transients. IEEE Trans. Power Syst. 34(1), 575–583 (2018)
 17. Raouf Mohamed A.A., Morrow D.J., Best R.J., Cupples A., Bailie I., Pollock J.: Distributed battery energy storage systems operation framework for grid power levelling in the distribution networks. IET Smart Grid. 4(6), 582–598 (2021). <https://doi.org/10.1049/stg2.12040>
 18. Brockwell, P.J., Brockwell, P.J., Davis, R.A., Davis, R.A.: Introduction to Time Series and Forecasting, Springer, New York (2016)
 19. Aljarah, I., Faris, H., Mirjalili, S.: Optimizing connection weights in neural networks using the whale optimization algorithm. Soft Comput. 22(1), 1–15 (2018). <https://doi.org/10.1007/s00500-016-2442-1>
 20. Naz, A., Javed, M., Javaid, N., Saba, T., Alhussain, M., Aurangzeb, K.: Short-term electric load and price forecasting using enhanced extreme learning machine optimization in smart grids. Energies 12(5), 866 (2019). <https://doi.org/10.3390/en12050866>
 21. Muralitharan, K., Sakthivel, R., Vishnuvarthan, R.: Neural network based optimization approach for energy demand prediction in smart grid. Neurocomputing 273, 199–208 (2018). <https://doi.org/10.1016/j.neucom.2017.08.017>
 22. Mohamed, A.A.R., Morrow, D.J. & Best, R.J.: Maximizing the profits of battery energy storage systems in the integrated single electricity market. In: The 9th Renewable Power Generation Conference (RPG Dublin Online 2021), p. 6 (2021). <https://doi.org/10.1049/icp.2021.1344>
 23. PXs, P.J.T.R.: Euphemia public description. pcr market coupling algorithm. Tech. Rep. (2016)
 24. SEMO: I-SEM Rules. *SEMOpx*. <http://www.semopx.com/rules-and-monitoring/market-rules/> (2016). Accessed: 28 April 2021
 25. SEMO: SEMOpx Historical Market Data. <https://www.semopx.com/market-data/static-reports/semopx-historical-market-data-final-v2.pdf>. (2021). Accessed: 09 Sep 2021
 26. ‘Prices of fuels purchased by major power producers. *GOV.UK*. <https://www.gov.uk/government/statistical-data-sets/prices-of-fuels-purchased-by-major-power-producers>. Accessed: 04 June 2021
 27. ‘Historical Data - Met Éireann - The Irish Meteorological Service. <https://www.met.ie/climate/available-data/historical-data>. Accessed: 16 April 2021
 28. Wind Energy Ireland: Wind Farm Interactive Map. <https://windenergyireland.com/about-wind/interactive-map>. Accessed: 09 June 2021
 29. Kalogirou, S.A.: Applications of artificial neural-networks for energy systems. Appl. Energy 67(1–2), 17–35 (2000)
 30. Bianchini, M., Scarselli, F.: On the complexity of neural network classifiers: A comparison between shallow and deep architectures. IEEE Trans. Neural Networks Learn. Syst. 25(8), 1553–1565 (2014)
 31. Sola, J., Sevilla, J.: Importance of input data normalization for the application of neural networks to complex industrial problems. IEEE Trans. Nucl. Sci. 44(3), 1464–1468 (1997)
 32. Warsito, B., Santoso, R., Yasin, H.: Cascade forward neural network for time series prediction. J. Phys.: Conf. Ser. 1025(1), 012097 (2018)
 33. Cecati, C., Kolbusz, J., Różycki, P., Siano, P., Wilamowski, B.M.: A novel RBF training algorithm for short-term electric load forecasting and comparative studies. IEEE Trans. Ind. Electron. 62(10), 6519–6529 (2015)
 34. Hayati, M., Shirvany, Y.: Artificial neural network approach for short term load forecasting for Illam region. World Acad. Sci. Eng. Technol. 28, 280–284 (2007)
 35. Burden, F., Winkler, D.: Bayesian regularization of neural networks. In: Artificial Neural Networks. Vol. 458, pp. 23–42. Humana Press, Totowa, NJ (2008)
 36. Heaton, J.: Introduction to Neural Networks with Java. Heaton Research, Inc. (US 2008)
 37. Masters, T.: Practical Neural Network Recipes in C++. Morgan Kaufmann (US 1993)
 38. Steven, G.J.: The NLOpt nonlinear-optimization package, (2014). <http://github.com/stevengi/nlopt>
 39. Hyndman, R.J., Athanasopoulos, G.: Forecasting: Principles and Practice. OTexts (Australia 2018)
 40. Currie, J., Wilson, D.I., Sahinidis, N., Pinto, J.: OPTI: Lowering the barrier between open source optimizers and the industrial MATLAB user. Foundations of computer-aided process operations 24, 32 (2012)
 41. Büskens, C., Wassel, D.: The esa nlp solver worhp. In: Modeling and Optimization in Space Engineering. pp. 85–110, Springer, New York (2012)
 42. Ferreira, M., Santos, A., Lucio, P.: Short-term forecast of wind speed through mathematical models. Energy Rep. 5, 1172–1184 (2019)
 43. Xu, B., Oudalov, A., Ulbig, A., Andersson, G., Kirschen, D.S.: Modeling of lithium-ion battery degradation for cell life assessment. IEEE Trans. Smart Grid 9(2), 1131–1140 (2016)
 44. E08 Committee: Practices for Cycle Counting in Fatigue Analysis. ASTM International. <http://www.astm.org/cgi-bin/resolver.cgi?E1049-85R17> (2020). Accessed: 11 Dec 2020
 45. Mongird, K., et al.: Energy Storage Technology and Cost Characterization Report. Pacific Northwest National Lab.(PNNL), Richland, WA (2019)
 46. Cole, W., Frazier, A.: Cost Projections for Utility-Scale Battery Storage: 2020 Update. National Renewable Energy Lab.(NREL), Golden, CO (2020)
 47. IRENA: Electricity Storage and Renewables: Costs and Markets to 2030. <https://bit.ly/36Pk5T5> (2020) Accessed 01 Mar 2021
 48. BEIS: Electricity Generation Costs. <https://rb.gy/zkpk36> (2016). Accessed 09 Feb 2021
 49. EirGrid: DS3 System Services. <https://www.eirgridgroup.com/site-files/library/EirGrid/DS3-System-Services-Qualification-Trials-Process-Outcomes-and-Learnings-2017.pdf> (2021). Accessed: 16 March 2021
 50. ‘FLEX | Northern Ireland Electricity Networks. <https://www.nienetworks.co.uk/flexibility> (2021). Accessed: 16 March 2021
 51. Northern Ireland Electricity Network.: FESS. <https://bit.ly/3bELisY> (2020). Accessed 10 Jan 2021

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