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# An integrated residence smart grid system with enhanced energy management for batteries

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**Abstract:** Residential consumers can efficiently engage in demand response programs with the help of home energy management systems (HEMSs). The best scheduling of gas, oil, coal, and uranium appliances has yet to be considered by traditional HEMSs, which exclusively control domestic electric devices to lower the cost of electricity usage. The associated demand response (DR) for smart homes is then adjusted to lessen the difference between predicted and actual demand after comparing the actual price to this forecast. Data acquired by Nordpool and publicly available energy information have been used to test the proposed strategy about price demand forecast and DR management. The function is to reduce energy costs for the home and the dissatisfaction brought on by moving, cutting, and replacing loads by changing prices over time. Case studies with accurate data show that the suggested strategy can return on investment bills by up to 85% while maintaining their satisfaction.

**Keywords:**battery energy storage system; demand response; deep learning; home energy management system

## 1. Introduction

Demand response (DR) uses resources from the customer side to increase the flexibility and dependability of power systems. In reality, DR is a practical way to help integrate renewable energy sources and other technologies like wind and solar power prediction with various time intervals (ultra-short-term and short-term). End users participate in DR programs by altering their energy use patterns in response to signals of the price of electricity or incentive that are dynamically moving and changing over time. Home energy management system (HEMS) can be applied to solve these problems. In addition to controlling and managing energy use inside a home, a (HEMS) device allows users to assess energy supply and usage[1][2][3]. HEMSs have been extensively researched in the literature when taking a real-time power price signal into consideration. For example, To assist residential customers in effectively managing their energy consumption, To close the supply-demand gap, Anish et al. [4] suggested using a demand response (DR) management algorithm to regulate the load demand in SHs. The proposed approach controls the demands of multiple load groups, further classified into variable, programmable, and fixed loads. The results demonstrate that the recommended method, with an RMSE of 0.463 and a MAPE of 4.13%, has the lowest error rate when estimating the load requirement profiles of various SHs, compared to the CNN & SVR alone. The results also demonstrate that the suggested strategy successfully mapped the production profile of the total load demand of a smart city.

To accurately estimate real-time power usage, Sara et al.[5] proposed a DL-based prediction with demand and response methods in the SG. The two main modules in the suggested architecture are the DL modules with the four-layer RNN that project hourly customer consumption of electricity trends. The DR decision-making component uses the forecasted consumption habits from the DL modules as input to decide the optimal course of action to lower peak consumption of electricity demands to save both cash and energy. Wen et al. [6] suggested a DL-based model to forecast the hourly load demand for electricity for homes in Austin, Texas, United States. The findings demonstrated that, in comparison to some other techniques, the modified deep learning model that was suggested can produce forecasting results that are more accurate. It can aid in the creation of incentive-based DR programs in unsteady conditions. The peak electricity consumption can be decreased while increasing overall earnings for ESPs and EUs thanks to the optimal incentive rate. For the period of highest electricity consumption, a short-term DR program was created, and the results of the experiments indicate that peak electricity demand can be decreased by 17%. This improves the security of the electrical system and reduces the imbalance between supply and demand. Mohammad et al. [7] suggest a HEMS built on optimizing binary particle swarms that use solar energy to power domestic devices and charge/discharge EVs/ESSs at low/high rates. A RES-ESS integrated system uses the grey wolf method to optimise charge and discharge periods by considering low/high electricity price time 24.

This work proposes a new paradigm for the energy management system of a home microgrid connected to a battery ESS (BESS). By identifying the characteristics of the distributed resources, the user's lifestyle, and the properties of the BESS, the suggested dynamic framework includes an algorithm for the optimization of optimal energy distribution as well as planning of a BESS with deep learning (DL)-based predicted approach, the Recurrent Neural Network Model (RNN-GRU). While considering the day-based demand-side penalty, the objective is to reduce the Real-Time-price (RTP) cost of power daily. The suggested system also takes into account electrical equipment operational constraints and the BESS. The simulation findings from real-world case studies show how the suggested technique can effectively lower a household's daily electricity costs.

The pricing action of the energy markets has gotten more unpredictable due to the society's steadily increasing sporadic energy demand and the quickening adoption of sources of renewable energy. As a result of the recent rise in temperatures, there has been a rise in electricity usage, which has raised the price of electricity on the worldwide market and other commodities like oil and gas. to maintain equilibrium between demand and supply and move the demands from peak to rest periods, we employ demand response strategies due to the rise in consumption during peak times. The reduction of electricity costs is one of the many practical uses of this study.

- It gives buildings the ability to adjust their consumption in expensive periods (and possibly increase it in cheap or negative pricing periods) in order to generate extra income from otherwise buried costs.
- Since the price of electricity and the amount of carbon it produces are correlated, responding to price changes also results in reduced carbon emissions.

## 2. System Model

Two main models make up the approach, which may control the demand for pattern of consumption throughout the day when put together in three steps as depicted in Fig. 1.

- The historical electricity price data collected by smart sensors and meters in the first stage is preprocessed using data analysis.
- To predict the customer's hourly price usage, the utility then uses the proposed Deep Learning (DL) predictions engine on such standardized data.
- After that, Demand Response (DR) decision-making process is put into place to advise the best courses of action for lowering the demand for peak loads in order to save costs and energy use.

After applying the advised steps, the intelligent controller will calculate the amount of reduced electricity cost. The next sections provide more information on the steps involved in data analytics, DL prediction modeling, and DR decision-making.

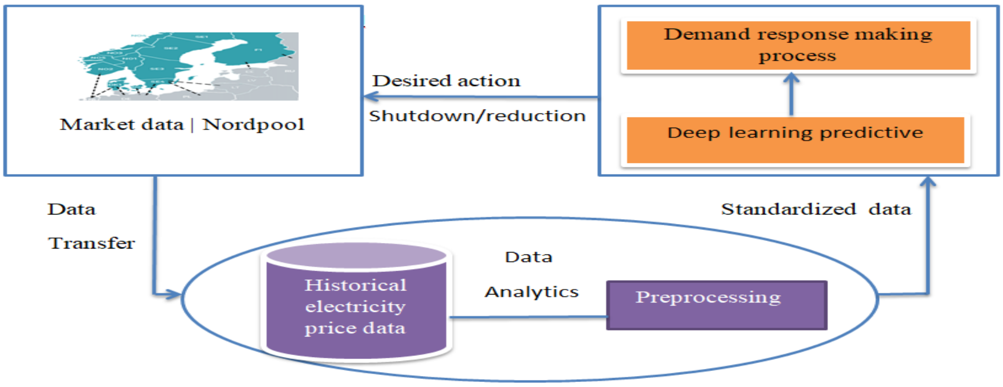


**Fig.1 System model of DR management.**

Immediately following the price electricity forecast technique, a choice must be made regarding any energy shortage. When the rate of power use exceeds the capacity of electricity production, an energy deficit would result. In the DR process of decision-making, each whole day is represented by 24 time periods, each of which represents a one-hour time horizon. The DR model accounts for several intelligent devices in typical smart homes, each consuming electricity at a different rate. Recent innovations and improvements in the storage of energy have enabled the control of distribution and transmission networks to be more flexible and controllable.

BESS, however, can support a variety of smart grid objectives in the current grid, such as peak shaving, load shifting, power factor adjustment, and increased dependability. Therefore, another area of interest is the incorporation of BESS in the modeling of a contemporary distribution/microgrid system[8].

### *2.1 The methodology of Data Analytics*

To begin the study, data on electricity cost was required. The hourly electricity costs were provided by the Nordpool corporation, which has control over several European electrical markets. We gathered data for the years 2013–2019, using 2018 as a validation set and 2019 as a test set. Using a simplistic baseline method, it was expected that the price in 24 hours would be the same. Data on hourly temperatures was collected using 61,000 requests to the DarkSky API. For a variety of commodities utilized in the production of power, daily commodity pricing data was acquired, including:

- Coal
- Natural Gas
- Uranium
- Oil

These other factors all have the potential to predict electricity prices because they have an impact on it. Due to the nature of time series analysis, much time was spent molding the data to meet the needs of the various models, including random forests and neural networks. Due to the built-in *Tensor Processing Units* (TPU's) enhanced speed, neural networks were performed on Google Collab. To analyze the outcomes (predictions) in Jupyter notebooks, the results were downloaded as CSV. This resulted in models that took 168 hrs of the previous time (one week) as inputs from any hour and produced a 24-h prediction. Mean absolute percentage error (MAPE) was employed as the accuracy metric. Because it is typically simple to comprehend as the mean error rate and is helpful as % for interoperability, this was chosen. However, some 0 values made its calculation more difficult and prevented it from always being the best indicator of model fidelity. The dataframe's shape, 61326 row by 6 features, is all that exists for us right now. As this analysis is of a time series, we must add time as a dimension. In order for the model to predict the future 24 hours, we want every time period to incorporate the values from the previous week as well. With a windows of 192 hrs and 6 attributes for each row (or hour).Fig.2. displays how the dataset's significant parameters are distributed.

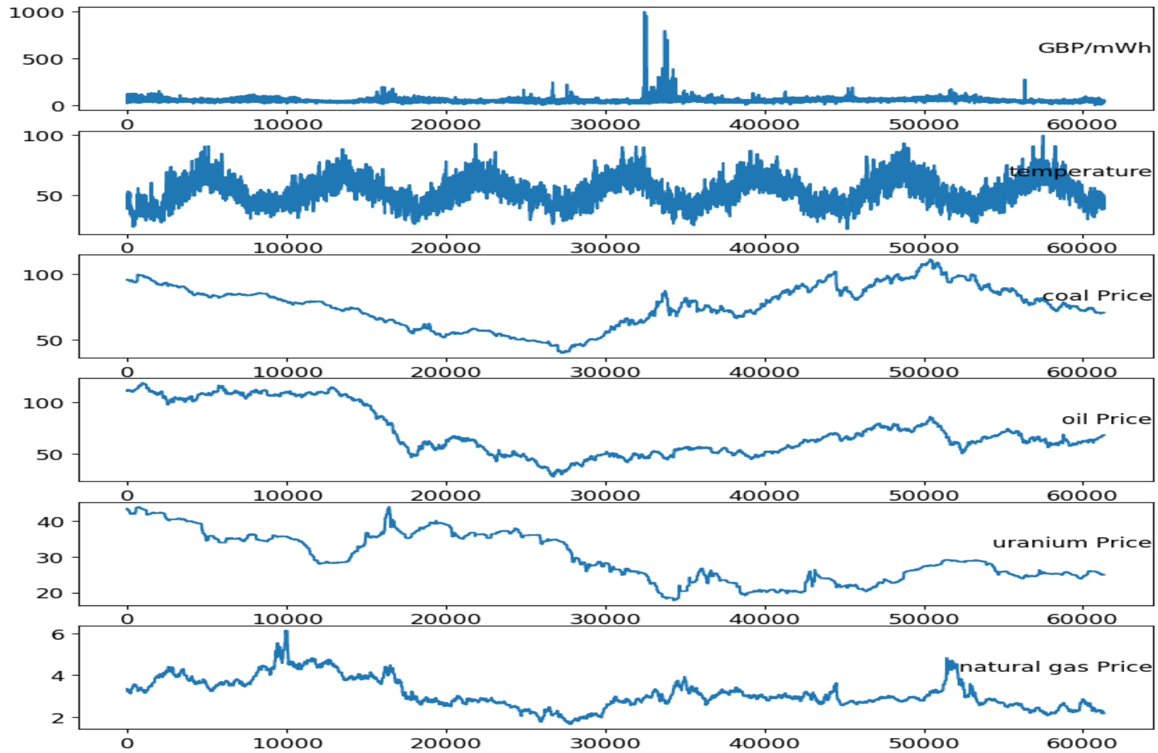


**Fig.2. Shows how electricity price , temperature, coal, oil, uranium and natural gas were distributed between 2013 and 2019.**

### *2.2 Modeling of Electricity price through Deep learning(RNN-GRU)algorithm.*

The most important phase in the creation of an ML model, according to the machine learning field, is hyperparameter tweaking. A hyperparameter is a value which regulates how an algorithm learns in a certain situation. Several algorithms have different hyperparameters. The hyperparameter optimization process involves using a method created to find the set of values for the hyperparameter to provide the model with the highest possible score[9] . In this study, we put up the new suggested method (RNN-GRU), which we'll subsequently use to estimate demand utilizing the grid search methodology. Using a sequence of values for each previously set hyperparameter, this method enables the automatic definition of the model's optimal parameterization.

Using the RNN-GRU model, we will make an effort to optimize the following hyperparameters in this work:

- Epoch size: displays how many learning iterations will be conducted on the data collection[10]. To create a model that performs well, the epoch size must be carefully chosen. If the amount of epochs is too high, the models will be overlearned, whereas if the number of epochs is too low, underlearning (or underfitting) may occur.
- Batch size: reflects the quantity of training instances presented to the algorithms in an epoch prior to the computation of the model's weights and parameters**.**
- A number of neurons: While a hyperparameter must be given, figuring out how many neurons are best for each layer is strict. It is crucial to understand that if the model's overall amount of neurons is low, it will only be able to retain a portion of the data required to provide an accurate forecast. However, if there are many neurons, the model might match the initial information set too well, leading to incorrect generalizations.
- Optimizer: This approach enables to alteration of the weights during the model training process in order to relate the loss function to the parameters and then to advise at the conclusion which weights allow The model needs to be as precise as feasible.

- An activation function It is an equation that handles signal processing. Its job is to regulate information flow according to a specified stimulation threshold, allowing or disallowing it.
- Learning rate: Obtaining a high-performance model requires careful consideration of this hyperparameter. It enables the alteration of the model weights' degree of change.
- Dropout rate: It is preferred to extract the most general features using the dropout rate independently. By altering the final result of the neuron's activation function to 0, it involves asynchronously deactivating neurons in the same layer randomly. Table 1 displays the list of values for the search hyperparameters.

**Table 1 displays a collection of search hyperparameter values.**

| Hyperparameter | Values |
|---|---|
| Epoch | [20, 50,100, 500, 1000] |
| Dropout_rate | [0.2,0.5] |
| Batch_size | [5, 10, 30, 50] |
| First_layer | [32, 64, 128] |
| Second_layer | [32, 64, 128] |
| Learning rate | [0.01, 0.001, 0.0001] |
| Activation Function | ['tanh', 'relu'] |

### *2.2.1 Training model*

In all instances of time series forecasting, no model has been shown to be superior in the literature. The data's characteristics, the application domain, and the forecasting horizon that is preferred all affect performance. We compare the forecasts generated by the just introduced models to those of four algorithms for deep learning, such as simple RNN, stacked RNN, simple GRU, and stacked GRU installed with the same grid search method, to demonstrate the edge of new RNN-GRU models typically portrayed with the grid searching method. The hybrid RNN-GRU models proved the most effective after training; values for the hyperparameters supplied by the grid search technique are shown in Table 2.

**Table 2 The best RNN-GRU model's hyperparameters.**

| Hyperparameter | Values |
|---|---|
| Epoch | [20] |
| Dropout_rate | [0.2] |
| Batch_size | [100] |
| First_layer | [ 64] |
| Second_layer | [32] |
| Learning rate | [0.01] |
| Activation Function | ['tanh'] |

### *2.2.2 Metrics for Evaluating Models*

Since both actual and predicted information constitute continuous numbers, we use the mean absolute error percentages (MAEP) and accuracy (R2-score) to assess how the expected and observed demands differ from one another.

Based on the following equation[11], (MAEP) is defined as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{p^{actual}\_\ p^{pred}}{p^{actual}} \quad (1)$$

The (R2-score) is depicted by[11]:

$$R2 - Score = 1 - \frac{\sum_{i=1}^{N}(p^{actual} - p^{pred})2}{\sum_{i=1}^{N}(p^{actual} - p^{mean})2} \quad (2)$$

### *2.2.3 Evaluation models*

Table 3 lists the measures of the inaccuracies each model produced when calculating the forecast. The newly proposed model RNN-GRU is clearly the best performing one when error values assessed by R2-score and MAEP are compared; it produces the test's lowest error values with r2-score=94.3055 and MAEP=5.6945%, following by stack RNN model with r2-score = 81.833 and

MAEP= 18.167% . Because to the closely spaced mistakes, the forecasts from the stacked RNN and simple GRU models performed similarly. By making the most errors, we ultimately discover that the simple GRU model is the least effective.

**Table 3 Comparison of the performance of deep learning model with other established methods for predicting electrical prices.**

| Method | MAPE% | R2-Score |
|---|---|---|
| Simple RNN | 8.136 | 91.864 |
| Stack RNN | 18.167 | 81.833 |
| Simple GRU | 22.449 | 77.551 |
| Stack GRU | 20.567 | 79.433 |
| RNN-GRU(proposed) | 5.6945 | 94.3055 |

## 3. Battery Modeling

A few ESS applications in power systems are shown in Fig.3 . BESS, one of the most economically advantageous storage options, is being used more frequently in microgrids and small-scale distribution networks. Similar to distributed generator, BESS were previously used for emergency backup, load frequency management, and spinning power reserve.

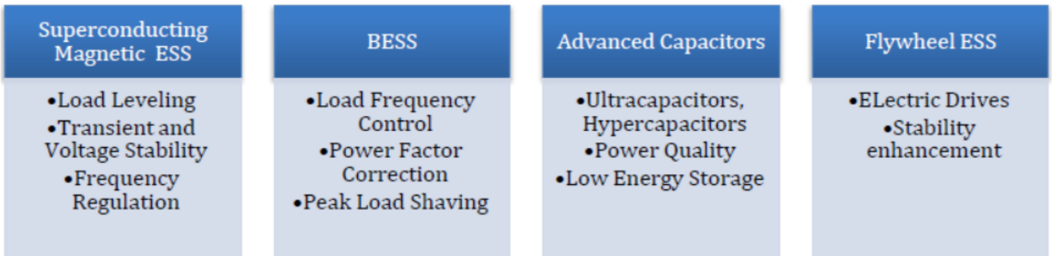


**Fig.3 Shows various energy storage system types and their uses[8].**

BESS, however, can support a variety of smart grid objectives in the current grid, such as peak shaving, load shifting, power factor adjustment, and increased dependability. Therefore, another area of interest is the incorporation of BESS in the modeling of a contemporary distribution/microgrid system[8].

The capacity of the Tesla Powerwall 2 is 14 kWh as shown in Fig.4. The battery has a 5 kW output. In slightly under three hours, the entire Capacity is reached are present in Table 3. The aim of BESS is to maximize income through optimal electricity charging and discharging in accordance with the 24 hour real-time price signal ($RTP_t$) provided by the utility. The battery's energy storage ($E_t$) and charge/discharge power ($P_t$) capacities, in additional to its state of charge (SOC) and depth of discharge (DOD), are constraints on this optimization.

Maximize:

$$\sum_{t=1}^{t=24} P_t \; X \; RTP_t \quad (3)$$


**Fig.4 Tesla powerwell**

**Table 3 The parameters of the household battery.**

| Capacity | $P_{Max}^{bch/disch}$ | $SOC_{max}$ | $SOC_{min}$ | $\pi^B$ |
|---|---|---|---|---|
| 14 Kwh | 5KW | 0.95 | 0.1 | 0.005£ /kwh |

The model for household batteries is provided in Equations (4)–(8). State of Charges (SOC) fluctuations in batteries are described in Eq (4) , where $X_t^{bch}$, $X_t^{bdch}$are binary variables displaying the battery's,[13] charging/discharging condition at timeslot t, where $P_t^{bch}$,$P_t^{bdch}$ are the battery's charging capacity at time t and its discharging capacity at time t. Where $\eta^{bch}$ ,$\eta^{bdch}$are the battery's efficiency in both charging and discharging. Where $Cap^B$ is the battery's capability Eq (5) ensures that a domestic battery cannot be used for charging and discharging. Inequality (4) ensures that a battery is not charged and restricts the depth of discharge. Equations (7) and (8) restrict the maximum charging and discharging power[14]. Algorithm 1 outlines the suggested optimization algorithm's step-by-step procedure.

$$SOC_t = SOC_{t-1} + X_t^{bch}\frac{P_t^{bch}\eta^{bch}\triangle_t}{Cap^B} - X_t^{bdch} \quad (4)$$

$$X_t^{bch} + X_t^{bdch} = 3 \qquad \forall t \in T \quad (5)$$

$$SOC_{min} \leq SOC_t \leq SOC_{max} \qquad \forall t \in T \quad (6)$$

$$0 \leq P_t^{bch}\eta^{bch} \leq P_{max}^{bch} \qquad \forall t \in T \quad (7)$$

$$0 \leq \frac{P_t^{bdch}}{\eta^{bdch}} \leq P_{max}^{bch} \qquad \forall t \in T \quad (8)$$

-The two components of the proposed HEMS's objective functions are as follows:

The first objective function, which is expressed in Eq. (9), is to minimize the overall energy costs according to the aforementioned constraints. The two components that make up total energy costs are the price of purchasing electricity and the price of depreciating the home battery. According to equation (8) the cost of electricity is equal to the power fee used by all electric appliances less the money made from selling the electricity back to the grid. Eq (6), (11) and(12) demonstrate the expenses of battery degeneration resulting from operation in discharging modes. $\pi^B$ is the price of the battery's depreciation for the power unit. $Price^B$ represents the battery's cost. $n^{bdch}$and $Cap^B$ are the maximum charging and discharging rates and the battery's capacity.

$$Cost^{energy} = Cost^e + Cost^B \quad (9)$$

$$Cost^e = \pi_t^e \sum_{t\in T}^{t\in T}(X_t^{bch}P_t^{bch} - X_t^{bdch}P_t^{bdch}) \triangle_t \quad (10)$$

$$Cost^B = \pi^B \sum_{t\in T}^{t\in T} X_t^{bdch}P_t^{bdch} \triangle_t \quad (11)$$

$$\pi^B = \frac{Price^B}{n^{bdch}Cap^B} \quad (12)$$

$$cost_t = actual\ price * charge\ state_{charge} * P_t \quad (13)$$

$$income_t = actual\ price * charge\ state_{discharge} * P_t \quad (14)$$

profit = $income_t – cost_t$(15)

ROI = profit /cost (16)

**Profit** : Is the money a business makes if the amount it earns exceed its total expenses. Any earnings a

company generates are the property of its owners, who may choose to distribute them to shareholders as income or keep them inside to support future growth, as indicated in Fig(5a).
**Return on Investment (ROI)** : An evaluation of an investment's financial worth in relation to its cost as shown in Fig(5b).


(a) (b)

**Fig.5 shows profit and Return on Investment (ROI).**

## 4. Experiment and Results

As a result, a fixed time of use TOU tariff is taken into account, where electricity is priced at three distinct set periods (off-peak, medium-peak and peak) throughout the day, covering weekdays and weekends as depicted. The following is the definition of the hourly stepped price signal:

$$T_{t,TOU}^{tf}(t) = \begin{cases} T_{t,TOU}^{OP} \; if \; t_{op}^{srt} \le t \le t_{op}^{end} \\ T_{t,TOU}^{md} \; if \; t_{md}^{srt} \le t \le t_{md}^{end} \\ T_{t,TOU}^{P} \; if \; t_{p}^{srt} \le t \le t_{p}^{end} \end{cases} \quad (17)$$

Where $T_{t,TOU}^{OP}, T_{t,TOU}^{md}, T_{t,TOU}^{P}$ are the tariff rates for off-peak, medium-peak, and peak hours.where t = [tstart , tend].

Table (4) includes all three of the power tariffs that are considered the fixed tariffs, the time-of-use (TOU) tariff and the real-time price (RTP) rate. The cost of RTP does change every day. Therefore, it is necessary to forecast the price of electricity for the next day when using optimal day-ahead scheduling.

**Table 4 Different DR programs.**

| **DR program** | **On peak** | **Mid peak** | **Off peak** |
|---|---|---|---|
| **08:00-09:00** | **09:00-13:00** | **02:00-05:00** | |
| **18:00-22:00** | **15:00-17:00** | **14:00** | |
| Fixed tariff | 45.46 £ /MWh | | |
| TOU | 49.54 £ /MWh | 45.46 £ /MWh | 29.81 £ /MWh |
| RTP | [40, 37.2, 36.25, 33.8, 30, 31 ,36 , 32, 36.48,45.46,45.98 ,44 ,41.6 33, 26.91, 29.62, 34.95, 43.7, 45.96, 48, 44, 37.66, 36,36.55] £ /MWh | | |

Fig.6 shows the algorithm of the battery decision making process. First step chosen the best prediction model (RNN-GRU) as shown Fig.7 below. The Google colab platform is used to implement the suggested forecasting algorithm. Integrating the one-day-ahead power price management method is modeled on an HP Z8 G4 Desktop with 256GB of RAM and Intel X (R), which is a Gold 5222 CPU @3.80GHz 3.79GHz processors.

Algorithm 1 BESS scheduling and management algorithm

Input : the best 24 hour price prediction
Output: Calculates Optimal time to charge and discharge & the decision to Pays and earns actual prices
1: for Day , 24
2: Charge = 0
3: for t in range(0,24)
4: If $P_{pred} \geq P_{act}$ then t = $T_{t,TOU}^{oP}$
5: Charge _state = charge
6: Charge =+1
7: Compute Eq(13) for minimize (16)
8: else
9: Charge _state = discharge
10: Charge = -1
11: Compute Eq (14) for minimize Eq(16)
12: go to step 4

**Fig.6 Algorithm BESS of the demand response model**

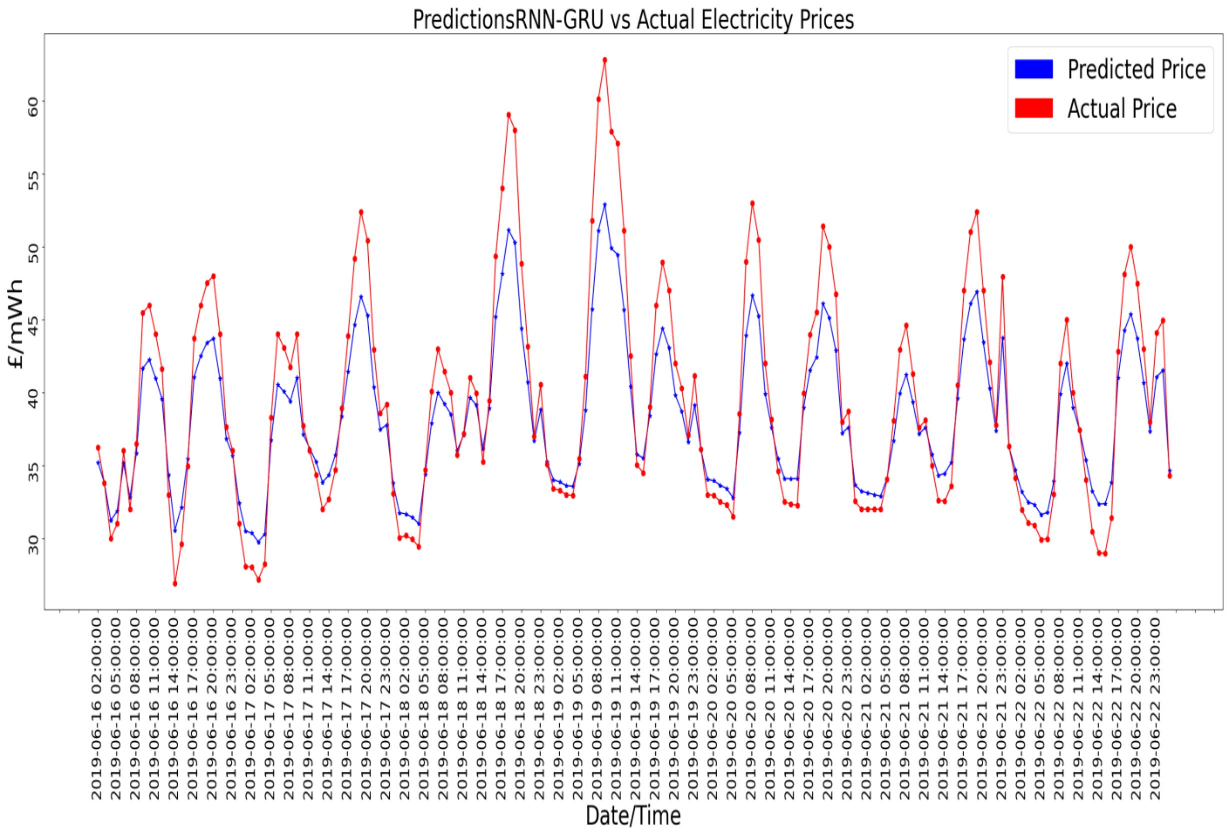


**Fig.7 The proposed deep learning(RNN-GRU) model results.**

The battery's operation and how electricity is transferred to the grid are shown in Fig.8. The power price significantly affects how effectively the battery performs, as seen in Fig.8. Due to lower electricity prices, the battery charges at off-peak and mid-peak times. During peak demand, it recharges electricity and releases it to meet the demand.

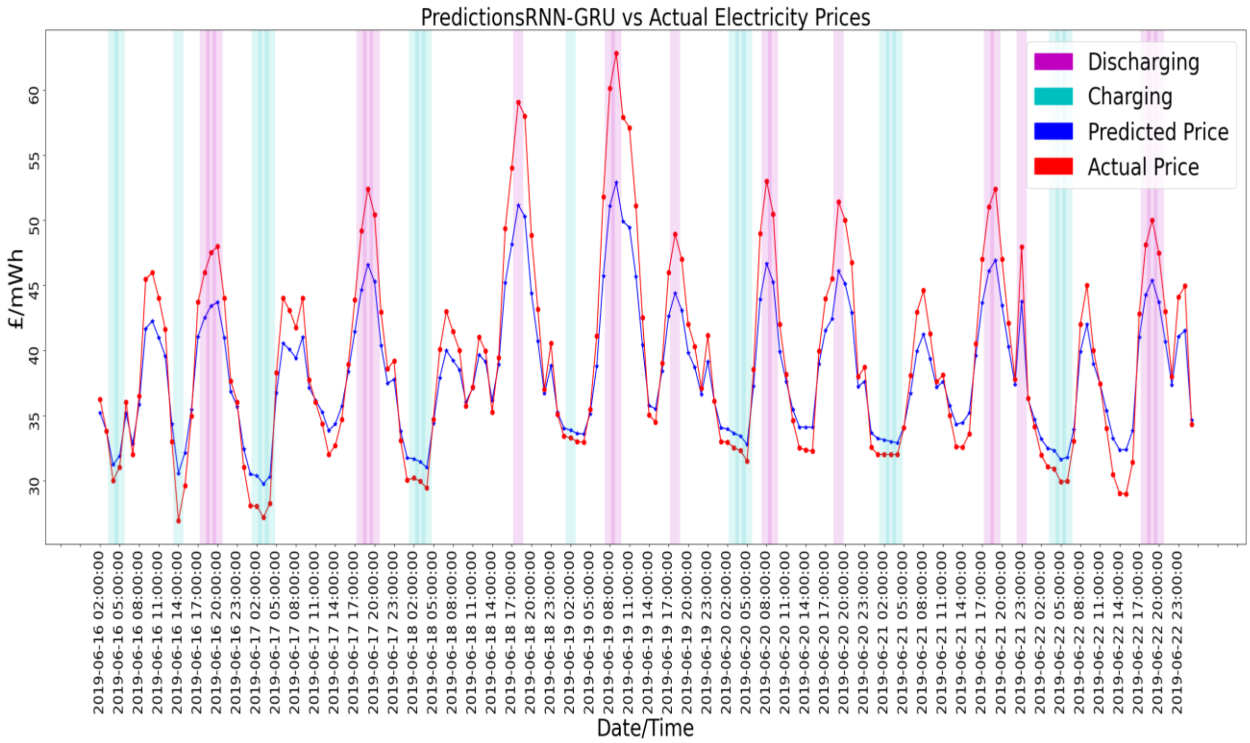


**Fig.8 Battery charging cycle**

Fig.9 illustrates a one-day scenario where the actual electricity price and predicted price are plotted while taking into account both the application of the DR method, indicated by (with DR) and the absence of an application, referred to by (without DR the observed action). At the six hour, the prediction curve shows a modest increase, with a value of (31.222 £ / MWh), which is higher than the actual value (30 £ / MWh). As a result, the DR decision process has been designed to maximize profit by charging at the lowest prices and discharging at the highest prices, which lowers the prediction price to (30.324 £/MWh). As can be shown in the time slots (2,3,4,8,9), the DR scheme lowers the price of electricity by 4.3955£/MWh. It makes up for the shortfall in energy by switching off a few of the working devices like the clothes washer and the exterior lighting as it is daylight and no additional lighting is required.

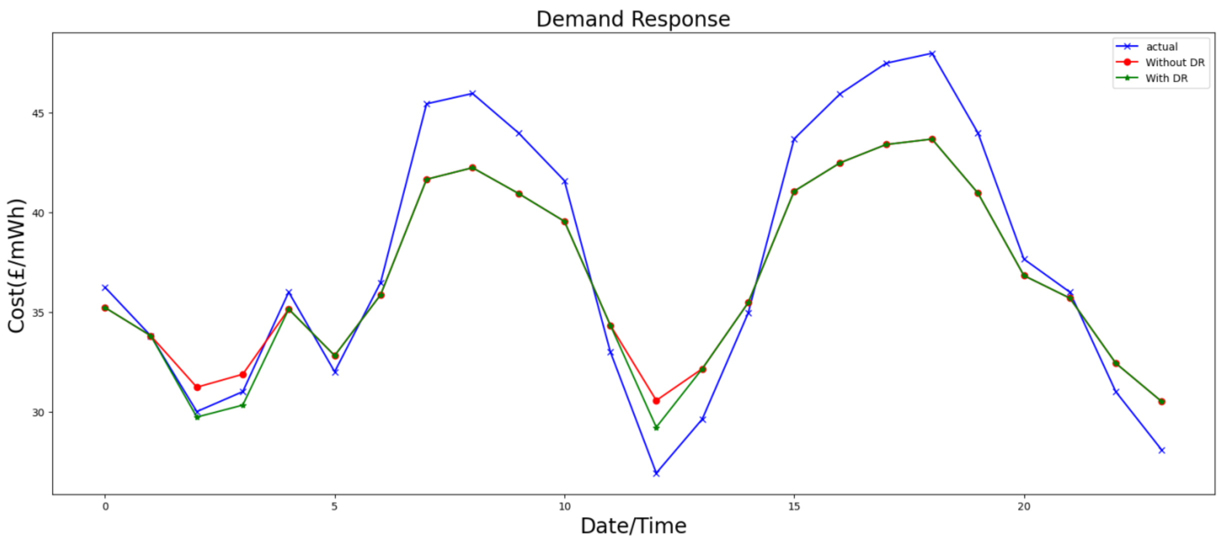


**Fig.9 Shows the suggested electricity cost after a single day of observation.**

Energy cost comparisons for several scenarios are shown in Fig. 10 and Table 5. The total energy price in Table 5 and Fig. 10 relates to the electricity bill without including the battery's day-long depreciation expenses. It was suggested HEMS can significantly lower overall energy costs between 0.0094% and 0.0052%. The most prosperous DR is RTP program for the consumer following implementation of the suggested HEMS.

**Table 5Cost comparisons for various DR initiatives in terms of energy.**

| Case | | G2H(£) | H2G(£) | Cost saving ratio% |
|---|---|---|---|---|
| Fixed tariff | Without BESS | 363.68 | | |
| | With BESS | 368.71455 | 0.2298 | 0.0094 |
| TOU | Without BESS | 813.87 | | |
| | With BESS | 813.85735 | 0.7073 | 0.0054 |
| RTP | Without BESS | 839.87 | | |
| | With BESS | 840.30955 | 0.7073 | 0.0052 |

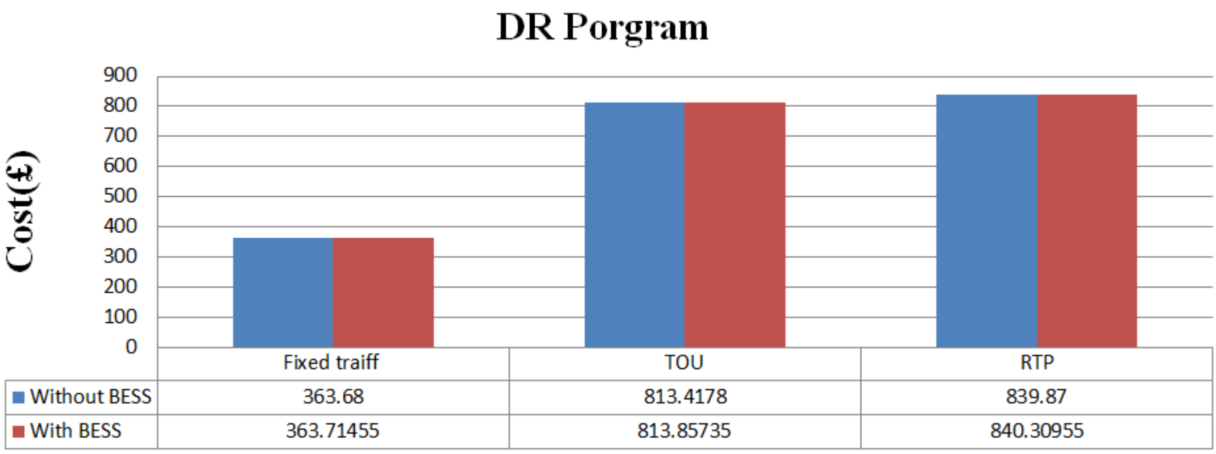


**Fig.10 Energy cost comparisons under different scenarios.**

**Table 5 shows The equations from (4-13) to (4-16) can be used to determine full-year returns.**

Table 3 One-Year Returns

| **DR program** | **G2H cost (£) (Spending money on charging)** | **H2G income (£) (money acquired from "selling" to the Grid)** | **Profit** | **ROI** |
|---|---|---|---|---|
| RTP (with BESS) | 151.02£ | 280.23 | 129.20 £ | 85.56 % |

## 5. Conclusion

This paper developed a household energy management model that considers the practical limitations associated with BESS, dynamic tariff structures, and appliances. The BESS controller requires precise forecasts and powerful scheduling algorithms to improve power efficiency and reduce daily electricity expenditures. By incorporating operational dependencies based on artificial intelligence

(AI) into the optimization algorithm, the difference between the real price and the predicted price is reduced, improving the performance and resilience of scheduling and optimization results. Additionally, only price-based DR programs, like RTP are taken into account in this paper. In reality, the incentive-based DR program, another important DR initiative, is increasingly being implemented in the residential sector. The results of the simulation demonstrated that the suggested approach ensured customer satisfaction while taking into account home batteries and technological limits for electricity. Battery utilization can have an 85% return on investment.

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