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Dynamic energy prices for residential users based on Deep Learning prediction models of consumption and renewable generation

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Abstract. New demand-side management models have emerged as a result of rising energy prices, the development of artificial intelligence, and the rise of prosumers. The purpose of this research is to use deep learning techniques to predict the energy production and demand of a prosumer network to determine dynamic prices for the local market. Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) were two methods that were taken into consideration for forecasting consumer demand and wind and solar energy generation. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were used to compare the various approaches. The results demonstrated that GRU, with 0.0273, 0.0158, and 49.8 in RMSE, MAE, and MAPE respectively, is the best method for predicting energy generation and consumption in our datasets. Demand management system dynamic prices were calculated on an hourly basis using input from energy generation and demand forecasts. Finally, an optimization method was developed for establishing the energy planning.

Key words. Dynamic price, Deep Learning, Optimisation, Residential sector, Prosumers.

1. Introduction

Energy demand growth is slowing due to high energy prices, heightened energy security concerns, and strengthened climate policies. Advanced economies still see declining demand for fossil fuels by 2030, but short-term actions are needed to reduce dependency [1]. Russia's invasion of Ukraine in 2022 has caused volatility and spikes in energy prices, leading to a recasting of the energy trade and investment landscape [2]. Renewables have held up well, but the crisis has shattered energy relationships and led to measures to strengthen energy security [3].
This war has not only exposed the EU's energy security, but has also shown the situation of energy poverty suffered by many of the EU's inhabitants as a result of soaring prices [4]. According to Eurostat, during the first quarter of 2022, household electricity prices in the European Union rose by 84% compared to the previous year [5]. In the meantime, the prices set for purchasing energy from prosumers have remained constant.
The emergence of collective self-consumption has enabled new energy solutions to emerge [6], such as the purchase and sale of energy in local markets that reduce the load on the grid itself and give the customer the possibility to valorize their energy [7]. Nowadays, marketers are the only agents responsible for buying and selling energy from prosumers at a set price, but what would it be like if the customers set their price? What would happen if these prices were dynamic depending on the availability of energy from the grid and the local network? This is what a local market for distributed energy resources refers to. In this context, a policy of self-supply models and energy empowerment of users is being implemented in Europe by developing energy local management models [8]. Data analysis techniques can be used to predict energy consumption and the generation of the prosumers of a local market [9]. The implementation of Machine Learning and Deep Learning allows real-time predictions with low precision errors of variables that were unthinkable until now, such as energy consumption and renewable energy generation.
The aim of this work is to present a methodology to estimate prices on an hourly basis according to the energy behavior of users. In this research, a network of five residential prosumers, average installed power 5.5 kW, with renewable generation based on photovoltaic and wind, without storage, with a data history of the last 3 years, has been considered. For the prediction, one Machine Learning model based on artificial neural networks (ANN) is used to estimate the next day's consumption of the five profiles, while the prediction of solar PV generation and wind generation uses two methods based on Deep Learning. In addition, an hourly optimisation model is used to present the dynamic prices offered in the local market, taking into account the availability of energy in the system.
This paper consists of five sections. Section 1 describes the current situation and introduces the gap this research aims to fill. Section 2 presents the methodology of the work and a description of the datasets used. Section 3 presents the results obtained in the work, from the comparison between the different Deep Learning methods such as dynamic power purchase and sale prices. Section 4 discusses the results obtained and compares them with those obtained in the literature. Finally, section 5 presents the conclusions and future scope of the research.

2. Methods

For this work, two different datasets were used for prediction and one dataset was used for energy planning that can be found in [10]:

A. Wind and solar generation data

A dataset from the Spanish System Operator was used to perform the solar and wind prediction. This dataset consists of hourly generation data from 01-01-2017 to 31-12-2021, approximately 4 years of data with 35146 non-zero values. It also contained climatological variables such as temperature, humidity, precipitations, irradiance, wind speed and wind direction.

B. Energy consumption data

A dataset of five residential customers obtained from the power company, Iberdrola Distribuidora i-DE website for the last four years, from 01-01-2017 to 31-12-2021, approximately 4 years of data with 35146 values was used for each residential profile.

C. Market price data

Data was obtained from the OMIE, the nominated electricity market operator in the Iberian Peninsula. An OMIE dataset with market prices of 2021 with 8760 values was used to establish the local market energy planning.

Two techniques were used to predict energy consumption and generation: Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). The Rectified Linear Unit (ReLU) was the neuron activation function. The error reduction method used is the Adaptive Moment estimation (Adam) and the mean square error (RMSE) is the loss function to be optimized. The best prediction method is the one that obtains the best score in the three error metrics: the root mean square error (RMSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE).

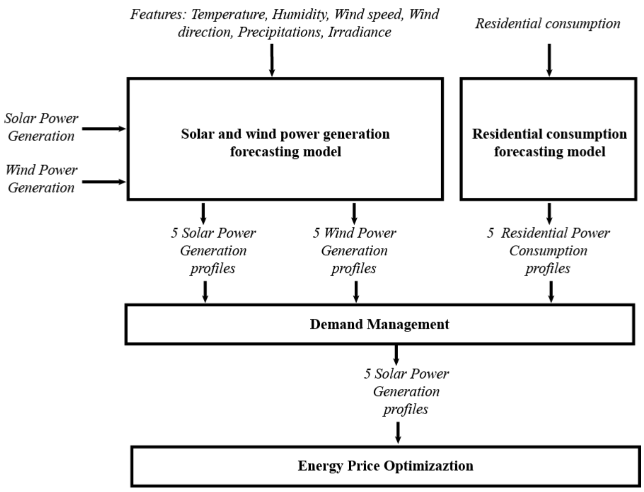

Fig. 1. Methodology of the work

The methodology (Fig. 1) carried out is presented below:

I. Preprocessing and data treatment.

First, the data processing was performed, since there were null or empty values in the data set. These values were replaced using the "ffill" method, which fills the empty values with the previous element. A descriptive analysis of the different sets of values was performed to find out their mean, standard deviation, quartiles Q1, Q2, Q3 and Q4, maximum and minimum. These values were then used to scale the variables between 0 and 1 using eq. (1).

$$y_{scaled,i} = \frac{y_i - min(Y)}{max(Y) - min(Y)} \quad (1)$$

II. Training the models.

Subsequently, the dataset is divided into two different training and test sets, composed of 80% of the values from the initial dataset to generate and train the model and the remaining 20% to test it**.** For this purpose, sequences of 24 values, one per day, were created for the training and test subsets.

Among the different models to be used, two were considered:

1. Long Short-Time Memory (LSTM)
2. Gated Recurrent Units (GRU)

Each of the LSTM-based models was composed of a perceptron consisting of three hidden layers with 50 units per layer over the output dense layer, while the GRU model was composed of two hidden layers of 50 units over the output dense layer. The output dense layer gives a single predictor variable, so the result vector has an output of type (none, 50). The details of the architecture of the different models are presented in Table I.

Table I. Architecture of the neural networks

Method	Recurrent layer	Output shape from input layer
Stacker LSTM	LSTM	(None, 50)
GRU	GRU	(None, 50)

III. Power demand and generation forecasting

Once the neural network model has been made, it is compiled using the mean absolute error as the loss function and Adam as the optimizer. Then, the model must be trained using the training data set. Therefore, the number of epochs and the sample size must be chosen correctly. In this work, one hundred epochs were used for the computation of each model with a batch size of 24. It was found that a larger number of epochs produced an overfitting of the system and it was necessary to introduce outliers to ensure that it generalized the model. The batch size was set to match that of the sequence size. Next, the model generates a sequence of values that serves as predictions for the next iteration, leading to the results of energy demand, solar and wind power generation. Finally, the error of the predicted values with respect to the true value is performed using the RMSE, MAE and MAPE metrics. (eq. (2), (3) and (4))

$$RMSE = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(y_i - \widehat{y_i} \right)^2} \quad (2)$$

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| y_i - \widehat{y_i} \right| \quad (3)$$

$$MAPE = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| \frac{y_i - \widehat{y_i}}{y_i} \right| \quad (4)$$

IV. Demand Management

Once the models are trained, they generate 5 different profiles of solar, wind and power demand generation to simulate the behavior of a local grid (Fig. 2). The profiles do not have storage, but the local grid does, allowing for greater combinations of trade-offs. As an application case, a storage of 12% of the maximum power, i.e., 3kW, was considered.

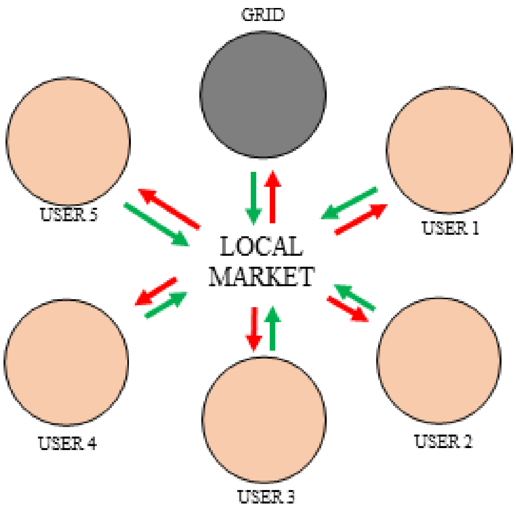

Fig. 2. Local market Management

The local market (Fig. 2) is composed of five residential customers that exchange energy within the local market. Three variables are involved in the model: storage, energy surplus and energy deficit. When there is not enough energy in the local market to supply the demand or when there is surplus energy, the grid is called upon. To manage the network, an energy balance is performed through eq. (5), where the sum of all energies entering the system is equal to the sum of all energies leaving the system.

$$\sum_{i=0}^{\infty} E = 0 \tag{5}$$

Eq. (6) is used to calculate the local market profit.

$$B = E_1 \cdot \pi_1 + E_2 \cdot \pi_2 + A_1 \cdot \pi_3 - D_1 \cdot \pi_4 - D_2 \cdot \pi_5 - A_2 \cdot \pi_6 \tag{6}$$

Where:

B	Benefit of the local market
E_1	Energy surplus of the local market
π_1	Selling price from the local market to the grid
E_2	Energy purchased from the grid
π_2	Purchase price from the grid
A_1	Energy from the available storage
π_3	Price of extracting energy from storage
D_1	Energy surplus of the local market
π_4	Selling price from the local market to the grid
D_2	Deficit energy of the local market
π_5	Purchase price from the grid
A_2	Energy that is stored
π_6	Price of extracting energy from storage

The mere exchange of energy does not maximize the energy management of the market. To this end, energy planning is then carried out. It has been considered that the price of extracting (π_3) or introducing (π_6) energy to storage is composed of a depreciation price of the equipment and the average price of the energy stored at that moment. However, in this study, no specific storage battery model was defined, so this depreciation term was dropped.

$$\pi_3 = \pi_6 = \pi_{Depreciation} + \frac{\sum E_1 \cdot \pi_1}{\sum E_1} \tag{7}$$

The conditions for using storage are presented:

Condition 1. To extract energy from storage, the storage price must be lower than the price at which the energy is purchased from the local market and the price at which it is sold to the grid.

$$\pi_3 < \pi_4,\ \pi_5 \tag{8}$$

Condition 2. To introduce energy from storage, the storage price must be higher than the price at which the energy is sold to the local market and the purchase price from the grid.

$$\pi_6 > \pi_1,\ \pi_2 \tag{9}$$

The following restrictions are also considered:

Restriction 1. The local market cannot buy and sell from the network at the same time.

$$E_2,\ D_2 \leftrightarrow (0,1) \Rightarrow E = \alpha \cdot E_2 + (1-\alpha) \cdot D_2 \tag{10}$$

Restriction 2. Energy cannot be output and input from storage at the same time.

$$A_1,\ A_2 \leftrightarrow (0,1) \Rightarrow A = \beta \cdot A_1 + (1-\beta) \cdot A_2 \tag{11}$$

V. Optimization for energy planning

Finally, an economic optimization of the network exchanges is performed based on IBM's CPLEX optimizer library, which is also in Python. An evolutionary optimization method with calculation processing parameter 30 minutes and objective variable *B* was used. Prices are intended to be obtained hourly, so this feature was crucial for the prediction.

3. Results

The results obtained for solar and wind power generation prediction (Fig. 3) with LSTM and GRU are presented in Table II. The LSTM model had a low root mean square error (RMSE) and mean absolute error (MAE) and high MAPE. The GRU model had RMSE, MAE and MAPE values of 2.73E-02, 1.58E-02 and 4.98E+01,respectively, suggesting that the GRU model is also capable of accurately predicting solar and wind energy. The local market was composed of 5 residential profiles with different profiles of wind and/or solar generation (Fig. 4).

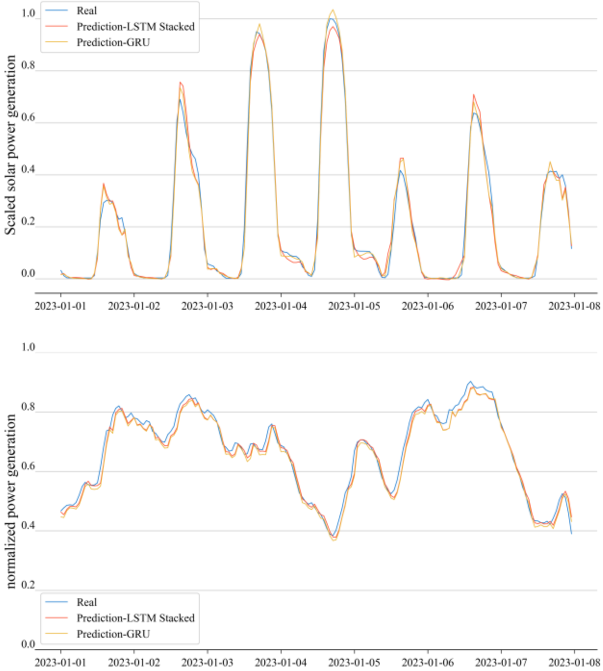

Fig. 3. Solar and wind power generation forecast

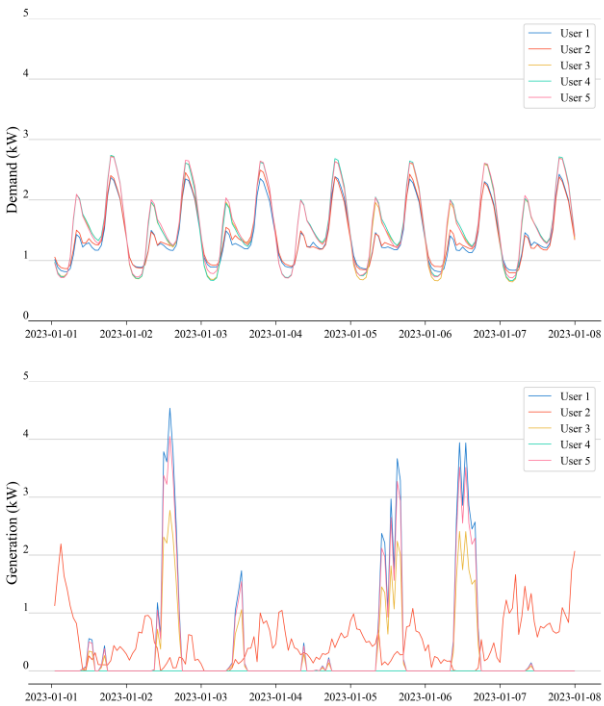

Fig. 4. Five residential profiles forecast

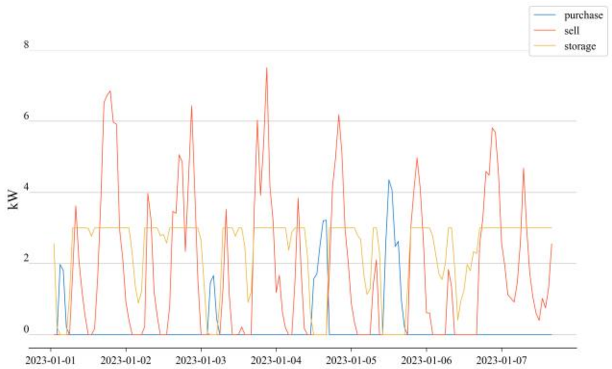

Fig. 5. Demand management

Table II. RMSE, MAE and MAPE results

Method	RMSE	MAE	MAPE
LSTM-1	2.84E-02	1.87E-02	3.01E+03
LSTM-2	3.47E-02	1.90E-02	1.07E+02
GRU-1	2.73E-02	1.58E-02	4.98E+01
GRU-2	3.29E-02	1.67E-02	8.96E+00

In implementing energy optimization, the energy purchase and sale strategy was defined (Fig. 5). The demand management is closely related to the storage capacity of the system because the depreciation term considered was zero. Finally, the following hour, the prediction is made again by entering the value of the previous hour and the optimization of the energy planning is repeated.

4. Discussion

The Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) forecasting methods are two deep learning techniques widely used in energy forecasting. LSTM is particularly useful for forecasting time series with complex and long-running patterns, while GRU is a simpler and more efficient technique. Both methods have advantages and disadvantages, and the choice between them will depend on the specific needs of each forecasting task and the dataset in question. In general, it has been observed that LSTM models tend to perform better when it comes to predicting extreme values or outliers in the time series. This is due to the ability of LSTMs to remember long-term information and handle complex data sequences. However, in terms of the best overall approximation of the time series, it has been found that GRU models tend to be more effective. This is due to the simplicity of the GRU design, which allows them to learn and generalize patterns in the data more efficiently than LSTM models. In [11], the author points out that based on accuracy metrics such as Mean Absolute Error (MAE) and Mean Squared Errors (MSE and RMSE), the best method for predicting demand and solar generation was the Stacked LSTM method, while for predicting wind generation the RNN method obtained the best results. However, in [12], the author points out that it is better to use different methods for each of the variables and makes a bibliographic review of the best methods. In summary, if good prediction of extreme values is sought, the LSTM model may be more suitable, while if the best overall approximation of the time series is sought, the GRU model may be more effective, which is consistent with our case. As for the activation function of the neural network, both the authors in the literature and I have used the rectified linear activation function (ReLU). Since we are dealing with non-negative variables (energy storage, surplus and deficit $\in [0, \infty]$), it is best to use this algorithm, which also speeds up the computation. It should be noted that these papers did not use the Adam optimiser to compile the model, but instead used Gradient Descent. Both methods are very similar. However, my methodology proposes an hourly prediction, which requires an efficient computation, but at the same time fast to process all the information. In that sense, the Adam optimiser is more efficient, since the learning rate of the neural network is variable for each of the features.

As for the CPLEX method used to optimize energy planning and obtain hourly prices, it is an optimization tool widely used in economic and energy planning problems due to its ability to solve optimization problems efficiently and accurately. In economic optimization, the CPLEX method is used to maximize a company's profits, minimize production costs, determine the optimal production quantity and set optimal prices. In the case of energy planning, CPLEX is used to maximize energy efficiency, minimize energy production costs and reduce greenhouse gas emissions. In addition, the CPLEX method can handle complex problems with constraints and multiple objectives, making it a tool for decision making in economic and energy environments. It is for this reason that its use has been chosen. In [5], the author carries out a literature review of the most widely used methods to establish a dynamic optimization of energy prices and proposes a non-linear exponential optimization method. However, in [6], the author presents an optimization based on Machine Learning with reinforcement learning that achieves better results. In our research, the CPLEX optimization was considered due the less computational expense, since the prediction of hourly consumption and generation has a high computational demand. Previous authors did not include the generation and consumption variables as proposed in this paper.

5. Conclusions

In conclusion, in this work neural network models, LSTM and GRU, and an economic optimization model with hourly prices have been implemented. They can be an effective tool for predicting solar PV and wind power and energy demand. Neural network models allow capturing complex and nonlinear patterns in the data, while the economic optimization model takes into account the cost of energy generation and distribution.

The accuracy of the predictions obtained with the proposed models was significantly higher than the predictions made with benchmark models, indicating that these models can be a useful tool for improving the management and planning of renewable energy generation and distribution. In addition, the accuracy of the predictions can be further improved by adding more data, such as weather and temperature.

In summary, this study highlights the importance of using deep learning and economic optimization models to predict renewable energy generation and energy demand. The ability to accurately predict renewable energy generation is critical to improving grid planning and management, which in turn can help reduce dependence on fossil fuels and mitigate the impacts of climate change. Ultimately, the models proposed in this study have the potential to improve the efficiency and sustainability of the global energy system and giving a new tool to fight the energy poverty empowering citizens.

6. Acknowledgment

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