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Prediction of renewable energy consumption in homes: Comparison of artificial neural network models

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Abstract. This study analyses the prediction of renewable energy consumption in a single-family house located in Extremadura, Spain, using three neural network models: MLP, LSTM and GRU. The house has a 4.08 kWp photovoltaic installation and data recorded every five minutes during the year 2024, which allowed daily and seasonal patterns to be identified. The MLP stood out for its accuracy and computational efficiency, achieving an R^2 greater than 0.99. Both the LSTM and its simplified version GRU, originally designed to capture temporal dependencies, had limited performance because the current data do not depend on the previous data. The results obtained are extrapolated to other contexts, such as commercial buildings or industrial facilities, thanks to the ability of the models to integrate universal contextual and temporal variables. The results suggest that future integrations with digital twin technology could further optimize real-time energy management. This work establishes a solid foundation for advancing the application of artificial intelligence in sustainable and adaptive energy planning for different scenarios.

Key words. Neural networks, energy consumption, renewable energies, energy efficiency.

1. Introduction

Efficient energy management in photovoltaic (PV) installations has evolved significantly with the integration of advanced technologies such as Digital Twin and energy consumption forecasting, which together enable informed renewable energy management decisions. Applying Digital Twin technology to a PV installation means having a virtual representation of an energy installation that in real time allows the detection and classification of faults (improving the maintenance of PV installations) and the prediction of renewable energy generation [1].

The management of energy consumption has become a fundamental strategic tool for the efficient management of energy consumption in homes [2] as well as for the operational planning of companies [3]. This process involves predicting the energy requirements of households [4] and organizations [5] through time series analysis, using methods that can be classified into time horizons: short, medium and long term. In addition, the integration of battery storage systems, both physical and virtual, plays a crucial role in optimizing this energy forecasting and management. Each horizon has specific objectives adapted to different contexts [6].

In the domestic sphere, it ranges from anticipating the consumption of minutes or hours to optimize the use of household appliances to planning short- and long-term energy efficiency improvements in the home [7], including the implementation of storage system [8]. In [9] ANNs (artificial neural networks) are indicated as pillars in modern energy management in residential microgrids, with MLP and LSTM as the most versatile architectures.

For enterprises, this includes managing the renewable energy produced on a daily basis and developing both physical and virtual energy storage systems. This allows better adaptation to demand fluctuations in both sectors, improving grid stability and renewable energy integration [10].

To study the energy management of PV installations, it is necessary to analyze what the generation and consumption of these installations is and will be like [11]. For this purpose, in this work we are going to predict the renewable energy consumption of a single-family house, using artificial intelligence techniques. The house under study is located in Castañar de Ibor, a municipality in the province of Cáceres, in the Autonomous Community of Extremadura, Spain. This location is important to understand the climatic and social context that may influence energy consumption patterns.

The house has a 4.08 kWp photovoltaic installation, whose Digital Twin has already been validated in a previous work [12]. This aspect is important to highlight, as it provides a solid basis for the current study, enabling a deeper understanding of energy generation at the site.

The study presents an innovative approach to predicting energy consumption using artificial neural networks. Three neural network architectures are compared for predicting renewable energy consumption: the Multi-Layer Perceptron (MLP), recognized for its ability to capture complex non-linear relationships through interconnected hidden layers; Long-Short-Term Memory

Networks (LSTM), designed to manage temporal dependencies through regulatory gates (input, forgetting and output) that control the flow of information over time; and Closed Recurrent Units (GRU), a simplified variant of LSTMs that optimizes computational efficiency. The data analyzed covers the renewable energy consumption of a home in Extremadura throughout 2024, with records every 5 minutes, allowing the identification of daily patterns (such as hourly variations in the use of household appliances) and seasonal patterns (such as changes in photovoltaic production between winter and summer), providing a solid basis for training models capable of adapting to energy fluctuations.

The three models that have been compared in this work have been saved in "pth" format for later implementation together with Digital Twin technology in real-time energy management systems.

2. Neural network models energy consumption

In the context of the increasing integration of renewable sources and the need to optimize energy use, machine learning models have emerged as key tools for efficient energy management, enabling accurate predictions and dynamic decisions in various sectors.

In the study [13] The MLP model was used to predict energy consumption in seawater greenhouses due to its ability to handle non-linear relationships between structural variables, such as dimensions and roof transparency. The effectiveness of the MLP as a predictive tool for optimizing energy consumption in factories is highlighted in [14], offering a practical solution to improve the sustainability of the industrial sector through advanced technologies.

In [5] an energy consumption prediction model based on neural networks of long and short-term memory (LSTM) was developed for a steel production plant. It was concluded that LSTM networks are effective tools for predicting energy consumption in complex industrial facilities.

The use of advanced deep learning models to predict energy consumption in three countries, Brazil, Canada and France is evaluated with four recurrent neural network architectures: LSTM, stacked LSTM, bidirectional LSTM and GRU in [15]. This paper shows that deep learning-based models can outperform traditional statistical approaches in predicting energy consumption. It also highlights the importance of tailoring models to the specific characteristics of the national energy system, such as dependence on renewable or fossil fuel sources.

In [4] The use of recurrent neural networks for the prediction of energy consumption in residential microgrids is proposed, using real data from a community in Norway. Five deep learning models were compared: RNN, LSTM, GRU, Bi-LSTM and Bi-GRU. The results of the study demonstrate that deep learning-based models can be effectively integrated into smart systems to manage residential microgrids, optimizing energy use and facilitating prosumer participation in electricity markets.

In [16] various recurrent neural network (RNN) architectures for predicting energy consumption in smart grids are analyzed and compared. The authors evaluate three main models: simple RNN, LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), with the aim of identifying the most efficient model for handling multivariate temporal data. The results highlight the usefulness of the GRU model for predicting energy consumption in smart grids, facilitating a better integration of renewable sources and a more efficient management of the electricity system.

2.1. Multi-Layer Perceptron (MLP)

It is a widely used neural network model for time series prediction due to its simple and easy-to-program structure, which makes it easy to understand and apply. In addition, the MLP can approximate any continuous function with a single hidden layer, provided it contains enough neurons, making it a universal approximator [17]. This makes the MLP a model adaptable to complex, multidimensional prediction problems. Its balance between modelling capability and computational efficiency makes it an ideal tool for real-time applications and large data sets [6].

The MLP has a multilayered structure consisting of:

- *Input layer.* This is the data received by the model (e.g. time variables such as month, time or day of the year, etc.)
- *Hidden layers.* They process information through linear combinations of the inputs they receive and non-linear activation functions (such as logistic or hyperbolic tangent).
- *Output layer*. Generates the prediction (energy consumption in this study).

Each neuron in the hidden layers calculates its output as represented in equation 1.:

$$y_j = \sigma \left(\sum w_{ji} \, x_i + b_j \right) \tag{1}$$

Where σ (neural activation function) is a non-linear activation function, w_{ji} are synaptic weights and b_j is a bias. This non-linearity allows complex relationships to be modelled in the data. In contrast, neurons in the output layer usually have a linear one as output function.

MLPs excel in time series prediction, as they can learn historical patterns to predict future values. To use them for this purpose, it is necessary to group the available data into two sets: one to train the neural network and another to validate the model.

It is in the learning process that the MLP acquires the ability to approximate the behavior of the data set it processes. To do this, it will process the data it receives, generating an output response that will be compared to a desired one, thus generating an error. This error will be backpropagated to the input by adjusting the weights of each neuron to minimize its value. The algorithm that performs this process is known as Backpropagation, that has become one of the hallmarks of this type of neural network.

2.2. The Long-Short-Term Memory Networks (LSTM)

These are recurrent neural architectures designed to model complex temporal dependencies using a system of control gates and internal memory [18]. The term recurrent refers to the fact that the neurons of one layer are not only connected to the neurons of the previous layer, but also to the neurons of the same layer, thus feeding each other. Its structure is defined by a series of functional blocks within the "neuron", each of which consists of three key mechanisms:

1. *Entrance gate* (i_j). Decide what new information will be stored in memory.
2. *Forgetting gate* (f_j). Determines which previous "stored" data (internal status) will be discarded.
3. *Exit gate* (o_j). Controls what information will be transmitted to the next layer and to other neurons in the same layer.

The internal state c_j^t of the neuron shall be updated by the expression of equation 2:

$$c_j^t = i_j \cdot z_j + f_j \cdot c_j^{t-1} \tag{2}$$

while the output of the neuron will be given by the expression in equation 3:

$$y_j = o_j \cdot \sigma(c_j^t) \tag{3}$$

Thus, the internal state (long-term memory) of a neuron at a given point in time, represented by c_j^t, is regulated by three main mechanisms. Firstly, the entrance gate, i_j, which has the function of deciding whether new information arriving at the neuron should be added to its long-term memory. On the other hand, the forgetting gate, f_j, determines whether some of the existing memory should be discarded or retained. Finally, the exit gate, o_j, decides whether the current internal state of the neuron, once processed by an activation function such as the hyperbolic tangent, will be used as output.
The training of the LSTM is done with a version of the algorithm from *Backpropagation* used by the MLP that considers the feedback between neurons.

2.3. Recurrent Unit with Gates (GRU)

It is a simplified version of LSTM networks that was developed for speech recognition applications. It reduces complexity through two key changes. First, it eliminates the output activation function: the external signal from the neuron (y_j) directly coincides with its internal state (c_j^t) modulated by a gate (o_j) (equation 4). Second, it replaces the forgetting gate with an integrated mechanism: the updating of the neural state combines the new information (z_j) and the previous memory (c_j^{t-1}), regulated by a single gate (i_j). Thus, the state is redefined as reflected in equation 5.:

$$y_j = o_j \cdot c_j^t \tag{4}$$

$$c_j^t = i_j \cdot z_j + (1 - i_j) \cdot c_j^{t-1} \tag{5}$$

This allows both components (new and old) to coexist proportionally thanks to the values of i_j between 0 and 1. This gate fusion optimizes sequential processing with fewer parameters.

3. Methodology

This study focuses on the comparison of three neural network models (MLP, LSTM and GRU) for predicting energy consumption in a single-family house with a photovoltaic installation. A methodical process was designed that included data preparation, model design, training and validation.
Data preparation was a crucial step to ensure that temporal characteristics were adequately represented. The original date (YYYYY-MM-DD) was transformed into variables such as day of the year (1-366), week of the year (1-52) and month (1-12). These features allowed capturing long-term seasonal patterns, such as annual and weekly variations. In addition, the time of day, originally expressed as HH:MM, was converted to minutes from midnight (0 to 1440), which provided a more suitable continuous numerical representation for the models. To further enrich the temporal information, derived variables such as the sine and cosine functions of the day of the year were included, which allow representing annual seasonality's in a continuous way, avoiding discontinuities between the last day of the year and the first one.
Contextual variables were also considered. For example, a binary variable was included to identify whether a day was a public holiday (1) or not (0), as well as another to indicate whether it was a weekend. This approach allowed the model to capture changes in consumption habits associated with non-working days. Nine variables were thus defined which shape the input vector to each of the three neural models analyzed.
Data normalization is a critical step to ensure that all features enter the model on a comparable scale, preventing variables with larger numerical ranges from dominating the learning. In this case, the StandardScaler method was applied [19] using the formula in equation 6:

$$z = \frac{(x - \mu)}{\sigma} \tag{6}$$

Where μ is the mean value of the training data and σ is the standard deviation. This process ensures that the data has a mean of 0 and a standard deviation of 1, preventing variables with larger scales from dominating the model.
The dataset was divided into two parts: 80% for training and 20% for validation. All three models shared the same input and output characteristics. The inputs consisted of nine processed time variables: month of the year, day of the week, weekday, weekend indicator, holiday, hour in minutes from midnight, day of the year, sine and cosine coding's of the day of the year, and week number. The output was the renewable energy consumption in 5-minute intervals, expressed in kWh.
Four widely recognized error metrics such as MSE (Mean Square Error), RMSE (Root Mean Square Error), MAE (Mean Absolute Error) and R^2 (Coefficient of Determination) are used to assess the accuracy and efficiency of each prediction model. In addition, Scatter Plots have been also used. They allow us to show the relationship between the actual values and the predictions generated by the models. This provides a clear and direct assessment of the accuracy of the model fit and detects possible patterns or deviations in the data.

The simulations were carried out in the Python programming environment with the PyTorch machine learning package, using a computer.
The MLP architecture consisted of two hidden layers (50 and 25 neurons respectively) with ReLU activation functions and an output layer consisting of neurons with linear activation functions. The Levenberg-Marquart algorithm was used for training, with L2 regularization (α=0.001) to avoid overfitting, and an early stopping mechanism that stops training if the error function of the training algorithm does not improve in 10 consecutive iterations. The PyTorch implementation included fixed seeds (42) to guarantee reproducibility.
In the case of the LSTM model, a single hidden layer structure with 32 computational cells (neurons) followed by a fully connected MLP-like layer with linear neuronal activation functions was defined. Training was performed over 30 epochs, with a batch size of 64, an Adam optimizer (learning rate 0.001) and L2 regularization (λ=0.0001). The PyTorch implementation also included fixed seeds (42) to ensure reproducibility.
For the GRU model, an architecture with a single inner layer with 32 computational cells was also defined, followed by a linear output layer that generates the energy consumption prediction. The training was set up as for the LSTM model with 30 epochs, batch size 64, Adam optimizer (learning rate 0.001) and L2 regularization (λ=0.0001). The PyTorch implementation also included fixed seeds (42) to ensure reproducibility.
Simulations were carried out using the Python programming environment, with the PyTorch package. A computer with a 64-bit operating system was used, equipped with a 2.6 GHz Intel Core i7-10750H processor, with 6 cores and 12 logical threads. In addition, an NVIDIA GeForce RTX 2060 graphics card was used.

4. Results

The performance of the three neural network models (MLP, LSTM and GRU) was evaluated using the metrics Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2) which can be seen in table 1. The results obtained in the training and validation sets allow us to identify key differences in terms of predictive accuracy and computational efficiency between the analyzed architectures.
The MLP model showed outstanding performance, with an MSE of 0.4565 in the training set and 0.4677 in the validation set. Its RMSE values were 0.6756 and 0.6839, respectively, while the MAE was 0.4637 in training and 0.4692 in validation. The R^2 reached significantly high values in both training (0.9934) and validation (0.9933), indicating that the model explains almost all of the variability in energy consumption.
Figure 1 shows the accuracy of the MLP model, comparing actual values and predictions in the training and validation sets. The graph clearly visualizes how the predictions align with the actual values, highlighting the model's ability to capture complex non-linear relationships with high accuracy.

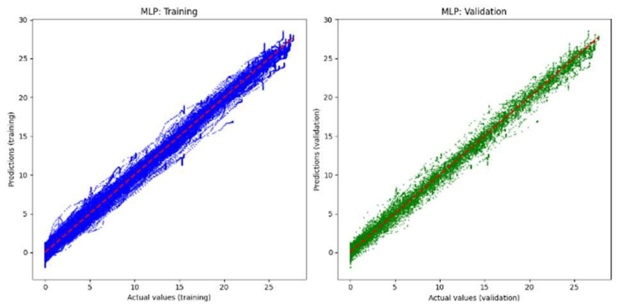

Fig. 1. Accuracy of the MLP model in the training set: Predictions versus actual values (left). And accuracy of the MLP model in the validation set: Predictions versus actual values (right).

These results highlight the ability of the MLP to capture complex non-linear relationships between the temporal variables processed, achieving high predictive accuracy with a relatively simple architecture.
On other hand, the LSTM model presented similar metrics to the MLP, with an MSE of 5.2735 in training and 5.1640 in validation, an RMSE of 2.2964 and 2.2724, an MAE of 1.3698 and 1.3590, and an R^2 of 0.9236 and 0.9264 respectively. Although its design is aimed at modelling long-term time dependencies, its performance did not significantly outperform the MLP due to the stationary nature of the dataset used.
Figure 2 presents the accuracy of the LSTM model, comparing the actual values and the predictions generated in the training (left) and validation (right) sets. The data in Figure 2 is sparser compared to Figure 1. This is evidenced by the lower alignment of the points with the reference line, indicating that the LSTM predictions have more variability with respect to the actual values. This scatter reflects a lower predictive fit of the LSTM model.

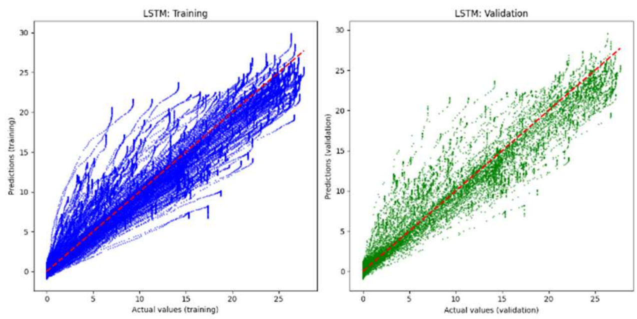

Fig. 2. Accuracy of the LSTM model in the training set: Predictions versus actual values (left). And accuracy of the LSTM model in the validation set: Predictions versus actual values (right).

The GRU model, however, stood out for its balance between accuracy and computational efficiency. In the training set, it obtained an MSE of 4.7827, an RMSE of 2.1869, an MAE of 1.3379 and an R^2 of 0.9307. In the validation set, it achieved an MSE of 4.6718, an RMSE of 2.1614, an MAE of 1.3260 and an R^2 of 0.9334, outperforming both LSTM and MLP in all metrics evaluated, except in R^2 against MLP.
In Figure 3, a better alignment of the points with the reference line is observed compared to Figure 2, especially in the validation set. This indicates that the GRU model

has a better predictive fit and less scatter in the data than the LSTM.

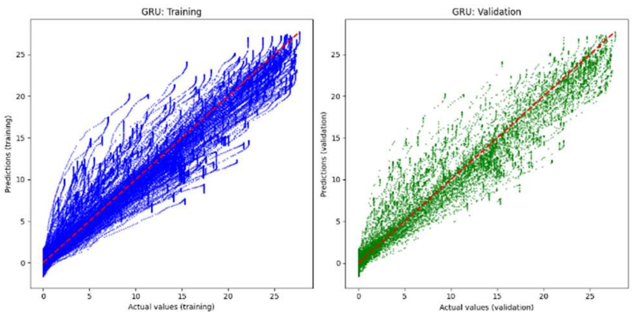

Fig. 3. Accuracy of the GRU model in the training set: Predicted versus actual values (left). And accuracy of the GRU model in the validation set: Predictions versus actual values (right).

The results obtained by the three models (MLP, LSTM and GRU) in the validation stage can be seen in table 1. The table shows significant differences in terms of predictive accuracy. The MLP stood out for its high accuracy, achieving an R^2 of 0.9933 in the validation set, indicating that almost all of the variability in energy consumption was explained by the model. This was achieved with simple and efficient architecture, ideal for static problems. On the other hand, the LSTM, designed to capture long-term temporal dependencies, obtained an R^2 of 0.9264, but had a higher mean absolute error (MAE: 1.3590) compared to the MLP. Finally, the GRU, a simplified variant of the LSTM, slightly outperformed the LSTM with an R^2 of 0.9334 and lower errors (MAE: 1.3260).

Table 1. Comparison of error metrics and predictive accuracy between MLP, LSTM and GRU models at the validation stage.

Model	MSE (Validation)	RMSE (Validation)	MAE (Validation)	R (Validation)
MLP	0.4677	0.6839	0.4692	0.9933
LSTM	5.1640	2.2724	1.3590	0.9264
GRU	4.6718	2.1614	1.3260	0.9334

5. Discussion

The model with the best metrics in this study, based on neural networks, was the MLP. This model has great potential to be adapted to different types of dwellings and regions. Although the analysis focused on a single-family house located in Extremadura, Spain, with a specific PV installation, the results obtained suggest that the approach is scalable and flexible. This scalability is based on the model's ability to integrate contextual and temporal variables that are universal and can be adjusted according to the particularities of other environments. The model could be adapted for multi-family dwellings or commercial buildings by including specific architectural and thermal characteristics, such as overall building size, thermal insulation materials and ventilation systems [20]. For example, in regions with extreme climates or different energy consumption patterns, it would be possible to incorporate additional variables related to the local climatic conditions [21]. These adaptations would allow extending its applicability to different contexts, optimizing energy management and facilitating the integration of renewable sources in different scenarios. In addition, this approach opens the possibility of developing customized strategies to improve energy efficiency and adapt the model to the specific needs of each region or type of dwelling [22].

6. Conclusion

This study has evaluated three neural network models (MLP, LSTM and GRU) for the prediction of renewable energy consumption in a single-family house with a photovoltaic installation. The results highlight the MLP as the most accurate and efficient model, with an R^2 very close to 1 in the validation set, which positions it as an ideal tool for static and real-time applications. The GRU showed an optimal balance between accuracy and computational efficiency, while the LSTM, designed to capture long-term temporal dependencies, had limited performance due to the stationary nature of the data used.
Although the analysis focused on a specific dwelling located in Extremadura, the findings are extrapolable to other contexts, such as commercial buildings, companies or regions with different climatic characteristics and consumption patterns. The ability of the MLP to integrate universal contextual and temporal variables allows its adaptation to diverse environments, opening up possibilities for optimizing energy management in multiple scenarios. This includes multi-family dwellings to industrial facilities, where architectural and climatic characteristics could be incorporated to improve predictive accuracy.
In addition, this work establishes a solid foundation for exploring future integrations with digital twin technologies. Virtual representation of energy facilities could benefit from the predictive models analyzed here, facilitating real-time monitoring, fault detection and autonomous decision-making on energy generation and consumption. The results suggest that such integration could further enhance energy efficiency and smart management of renewable resources in various environments.

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