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Recurrent Neural Network Based Model Development for Energy Consumption Forecasting

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Abstract
The world population is increasing day by day. As a result, limited resources are decreasing day by day. On the other hand, the amount of energy needed is constantly increasing. In this sense, decision makers must accurately estimate the amount of energy that society will require in the coming years and make plans accordingly. These plans are of critical importance for the peace and welfare of society. Based on the energy consumption values of Germany, it is aimed at estimating the energy consumption values with the GRU, LSTM, and proposed hybrid LSTM-GRU methods, which are among the popular RNN algorithms in the literature. The estimation performances of LSTM and GRU algorithms were obtained for MSE, RMSE, MAPE, MAE, and R^2 values as 0.0014, 0.0369, 6.35, 0.0292, 0.9703 and 0.0017, 0.0375, 6.60, 0.0298, 0.9650, respectively. The performance of the proposed hybrid LSTM-GRU method, which is another RNN-based algorithm used in the study, was obtained as 0.0013, 0.0358, 5.89, 0.0275, and 0.9720 for MSE, RMSE, MAPE, MAE and R^2 values, respectively. Although all three methods gave similar results, the training times of the proposed hybrid LSTM-GRU and LSTM algorithms took 7.50 and 6.58 minutes, respectively, but it took 4.87 minutes for the GRU algorithm. As can be understood from this value, it has been determined that it is possible to obtain similar values by sacrificing a very small amount of prediction performance in cases with time limitations.

1. Introduction

The operation of electrical networks has been costly and difficult to maintain for years. The main purpose of those who operate electricity networks is to maintain the balance between production and consumption in any emergency or weather condition. There is a trend towards renewable energy sources to reduce the damage to the environment while providing sustainable energy needs. One of the main reasons for this trend is that, depending on the energy consumption in the building sector, CO2 emissions occur at rates of 38% and 36% in the USA [1] and Europe [2], respectively. It is reported that the energy obtained by using fossil fuels causes an increase in the CO2 emission rate. Harmful emissions, such as CO2 from fossil fuels used to obtain energy, also cause global warming [3]. For the stated reasons, there is a tendency towards renewable energy sources both to provide energy efficiency and to not cause global warming.

The production of scientifically based structures instead of classical structures will enable the creation of structures that consume less energy. It is seen that new plans and projects are put into action by using high investments around the world in order to create structures that consume less energy. [4] conducted studies on the extent to which renewable energy sources reduce the harmful emissions of fossil fuels to the environment in the Latin American region for sixteen years. There are studies trying to find the points to which building

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designers should pay attention in the construction of new types of buildings with low energy consumption [5]. While they talk about the importance of parameters that building designers should implement for energy savings, they report that human life is affected by energy consumption.

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With the development and spread of renewable energy sources, production has become more intermittent. In order to maintain distribution in case of interruption, it is necessary to estimate how much the consumption of the generated energy will be during the year. Furthermore, there is a serious increase in consumption as a result of the rapidly increasing population growth in the world. As a result of increasing population growth, there is an increase in the energy demand consumed. There are studies that state that energy demand is not only a population-dependent situation [6]. With the growth of the population and economy, a significant increase in energy consumption is observed [3], [7], [8]. It is estimated that a large part of the world's population will migrate from rural areas to urban areas in the coming years [9]. To support this information, an increase in the population of one quarter of the city with the largest population of a country like China is observed in the world. Energy consumption in the country of China is reported to grow at an annual rate of 5.6%, approximately three times the world average [10]. In this situation, it is stated that it is necessary to save energy by reducing harmful emissions in all countries with an increasing urbanization rate, especially China [7]. When this information is evaluated, it is an undeniable fact that there is a great increase in the world population.

Plans are proposed every year by different countries in order to control energy consumption around the world [11]. The main purpose of these plans is to prevent energy waste by controlling unnecessary energy consumption. Energy should be consumed, managed, and planned in an efficient and waste-free manner in all areas, especially in the building. Accurate consumption management and planning require effective energy consumption forecasting models. For this purpose, deep learning-based energy consumption estimation models are proposed using data from the ENTSO-E Transparency Platform, which distributes electricity to the European market.

The main contributions of this study to the literature for estimating energy consumption are listed below.

- Data normalization has been applied so that energy consumption data consisting of large data collections can be evaluated accurately and quickly.
- Two different models based on LSTM and GRU have been developed to accurately analyze the energy consumption estimation on the normalized data.
- To measure the performance of three different deep learning models based on the proposed LSTM, GRU, and LSTM-GRU, the traditional measurement metrics R^2 score, MAPE, RMSE, MSE, and MAE values are presented comparatively.
- When the results obtained from the R^2 score, MAPE, RMSE, MSE, and MAE values are examined, it is seen that a 0.98 accuracy rate is obtained from the proposed LSTM-GRU based model.

The next sections of the article are planned as follows. In the second part, the energy consumption dataset and the deep learning models run on this dataset are introduced. In the third section, the results of the R^2 score, MAPE, RMSE, MSE, and MAE performance obtained from the proposed deep learning models are presented comparatively. In the last section, the results of the study are evaluated. At the same time, suggestions for further work are presented.

2. Material and Methods

This part of the study is given under two subtitles: Material and Method. First of all, the information about the data set used in the study is discussed in detail in the material section.

2.1. Material

The data set used in this article was shared by the ENTSO-E Transparency Platform, which distributes electricity to the European market [12]. The dataset contains energy consumption data in megawatts (MW) for European countries from January 2015 to August 2020 at 15, 30 minute, and 1-hour time intervals. The dataset used in the study is a publicly available dataset that contains energy consumption data of fifteen countries, from Austria to Spain, and from France to Germany. In this dataset, Germany dataset was used for performance measurements.

The data was initially normalized in the 0-1 range. The quarter, hour, month, year, day of the year, day of the week, day of the month, week of year values presented in Table 1 are used as input features in the study. The energy in MW produced was used as the output value. The detailed information about the used features is presented in Table 1. In the study, 44,565 of the 44,568 energy consumption data, the details of which are presented in Table 1, were used. As seen in studies in the literature [13], dividing the data into two as training and testing according to the K-fold 5 value positively affected the performance of the study. For this reason, the energy consumption data in the study are divided into two separate parts as training and testing according to the K-fold 5 value, as it is in the studies [13]. The methods presented here in Section 2.2 Methods section performed training and testing operations on the K-fold 5 value on the data in Table 1.

Table 1. Features used in energy consumption estimation

Raw inputs date	Inputs								Outputs
Datetime	Quarter	Hour	Month	Year	Day of year	Day of week	Day of month	Week of year	MW
2015-01-01 00:00:00	1	0	1	2015	1	3	1	1	41342.5
2015-01-01 01:00:00	1	1	1	2015	1	3	1	1	40135
….	….	…	…	…	….	…	….	…	…
2017-05-15 15:00:00	2	15	5	2017	135	0	15	20	60972.5
….	….	…	…	…	….	…	….	…	…
2019-07-11 08:00:00	3	11	7	2019	192	3	11	28	66236
….	….	…	…	…	….	…	….	…	…
2020-01-31 23:00:00	1	23	1	2020	31	4	31	5	49399.5

2.2. Methods

In the study, algorithms in the RNN structure were used, which are frequently used in time series data in the literature. Firstly, the GRU structure was used for this purpose. After this structure, the LSTM structure, which is an RNN algorithm and was suggested later in the literature, was used.

2.2.1. GRU

The GRU algorithm does not use a memory unit to control the information flow in the RNN structure. If desired, it can be used directly in all confidential situations without any information control. GRU-based models have fewer parameters than advanced RNN models. For this reason, there is less processing load, and as a result, it can be trained quickly. At the same time, less data is needed to generalize. The biggest disadvantage of the GRU method is that its success may be low when processing too much backward data in the backlink algorithm [14]. On the other hand, it is preferred because the training period mentioned above is short and there are situations where it can still give good results.

The GRU structure generally has two gates [15]. These gates are reset and updated gates. The reset gate determines how the new entry into the GRU unit is combined with the memory one step ahead. Another gate in the GRU, the update gate, determines how much of the previous state is retained. The equations used for these gates are detailed below.

$$Update\ gate\ \ (u_t) = \sigma\left(W^u x_t + U^{(u)} h_{t-1}\right) \tag{1}$$

$$Reset\ gate\ (s_t) = \sigma\left(W^s x_t + U^{(s)} h_{t-1}\right) \tag{2}$$

$\boldsymbol{W}$ used in Eqs. (1) and (2) represents at time t. $\boldsymbol{h_{t-1}}$ shows hidden layer values at time t-1 in Eqs. (1) and (2). $\boldsymbol{U}$ represents the GRU cell units in Eqs. (1) and (2). $\boldsymbol{\sigma}$ represents the sigmoid activation function.

2.2.2. LSTM

In general, there are problems with vanishing and exploding gradients in RNN structures [16], [17]. The main reason for this problem is that the weight matrices (W(k)) in the structure of the network are updated by multiplying one after the other. As a result, the gradient is encountered as being lost in the backpropagation stage of the RNN algorithms or exploding unstable to large values. As mentioned above, the main cause of this instability is sequential collisions. Despite all these disadvantages, RNN structures naturally give good results in short-term backpropagation between the previous step and the current step [18]. However, it gives lower results in long-term backpropagation processes. This problem is aimed at being solved using the LSTM method with the use of long-term memory [19]. Since the data is evaluated in short sequences in the LSTM method, the problems of back propagation operations in RNN algorithms are solved [20]. At the base of the LSTM algorithm, there are three gates and one layer shown in Figure 1 [17].

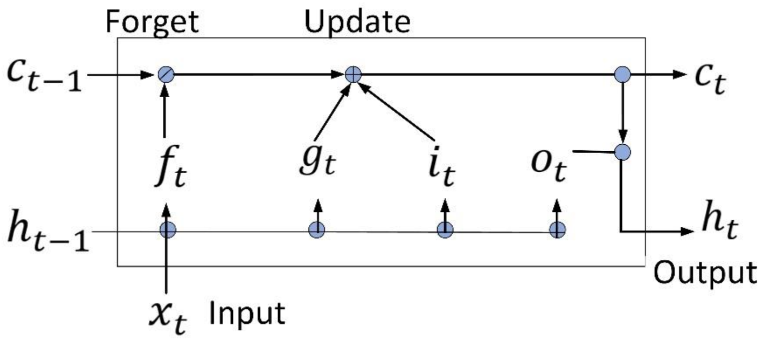

Figure 1. LSTM cell structure

The terms f_t, i_t, and o_t respectively presented in Figure 1 refer to forgetting entry and exit gates at time t. g_t represents the state layer. The contents of these variables are presented in Eqs. (3)-(6).

$$f_t = \sigma\left(W_f X_t + U_f h_{t-1} + b_f\right) \tag{3}$$

$$i_t = \sigma(W_i X_t + U_i h_{t-1} + b_t) \tag{4}$$

$$o_t = \sigma(W_o X_t + U_o h_{t-1} + b_o) \tag{5}$$

$$g_t = tanh\left(W_g x_t + R_g h_{t-1} + b_g\right) \tag{6}$$

W, R, and b are used in Eqs. (3)-(6) represent the weights, repetition weights, and biases between gates, respectively.

3. Results and Discussion

As stated in Section 2.1, in the experimental study, the data were first subjected to the normalization process. -The training and test data for K-fold 5 value are then divided into two groups. Finally, the system is trained with the training data according to the GRU algorithm described in Section 2.2.1. The parameters used in the GRU algorithm during the training phase are presented in Table 2 in detail.

Table 2. GRU setting parameters

Parameter	Value
Layers	7
Loss	Mean absolute error
Optimizer	Adam
Epochs	50
Batch size	32
Activation	tanh

The layers in Table 2 represent the layers in the GRU algorithm, and the function in Eq. (7) is used in the optimizer GRU algorithm. Although SGD and RMSprop optimization methods were used other than Adam, the best results were obtained with the Adam optimization method. The parameters used in Table 2 and the normalized state of the training and test data of the energy consumption obtained as a result of the GRU algorithm are presented in Figure 2.

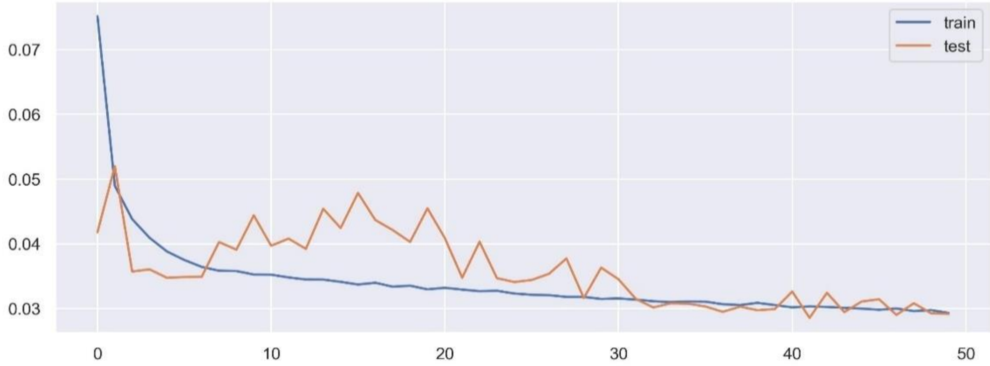

Figure 2. GRU model training and test loss graph

Figure 3 depicts the data converted to real values. As can be seen in Figure 3, the difference between the actual values and the predicted values is very close. At this stage, R^2 score, MSE, RMSE, and MAPE values were used in error evaluation processes. The values obtained by the GRU algorithm are presented in detail in Section 4.

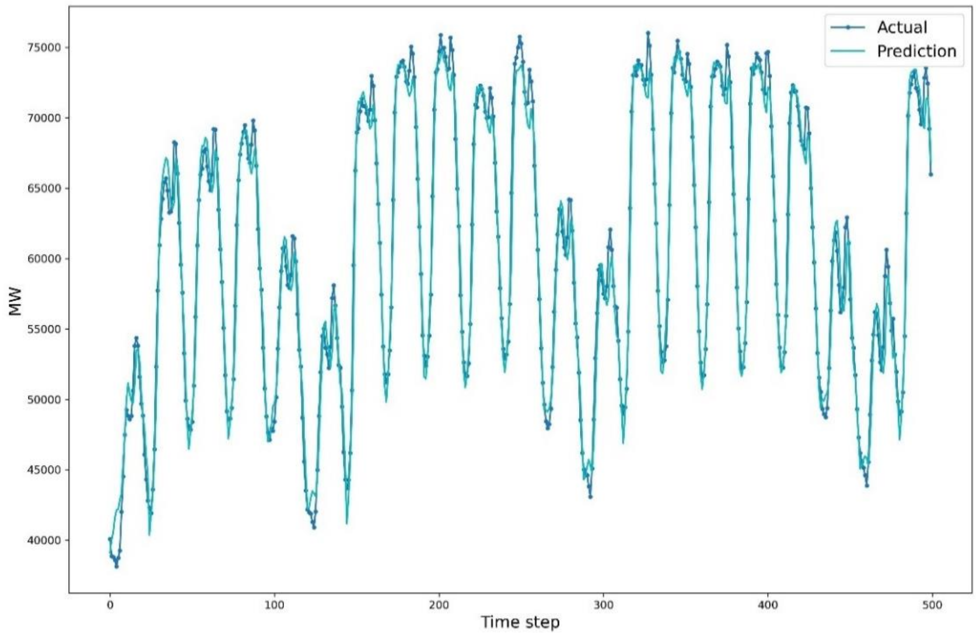

Figure 3. Predictions made by GRU model

In the second stage of the study, training and testing of the system were carried out using the LSTM algorithm described in Section 2.2.2 and the parameters presented in Table 3. At this stage, unlike in Table 2, the number of layers was increased by using ReLU for the activation function.

Table 3. LSTM setting parameters

Parameter	Value
Layers	10
Loss	Mean absolute error
Optimizer	Adam
Epochs	50
Batch size	32
Activation	ReLU

The results of the training and test values obtained with the LSTM algorithm are presented in Figures 4 and 5. While the normalized version of the obtained values is presented in Figure 4, the actual values are shown in Figure 5.

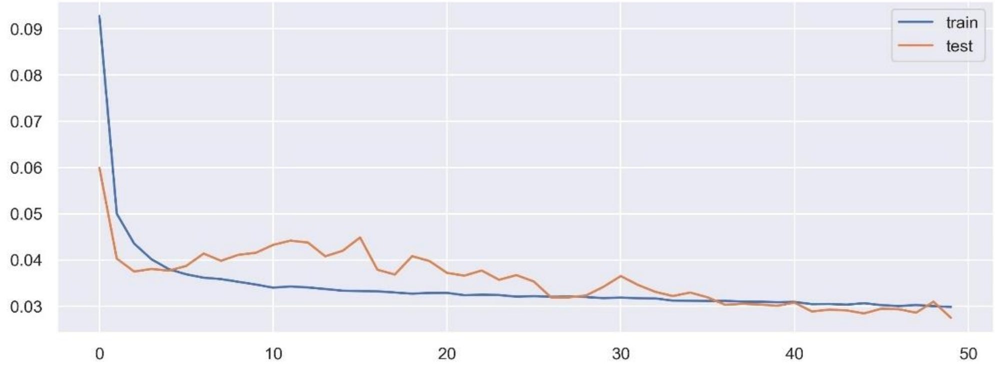

Figure 4. LSTM model training and test loss graph

When Figures 4 and 5 are examined, the difference between the actual values and the predicted values is very close. At this stage, as in the GRU algorithm, R^2 score, MSE, RMSE, and MAPE functions were used to measure the error values.

The results of the training and test values obtained with the LSTM algorithm are presented in Figures 4 and 5. While the normalized version of the obtained values is presented in Figure 4, the actual values are shown in Figure 5.

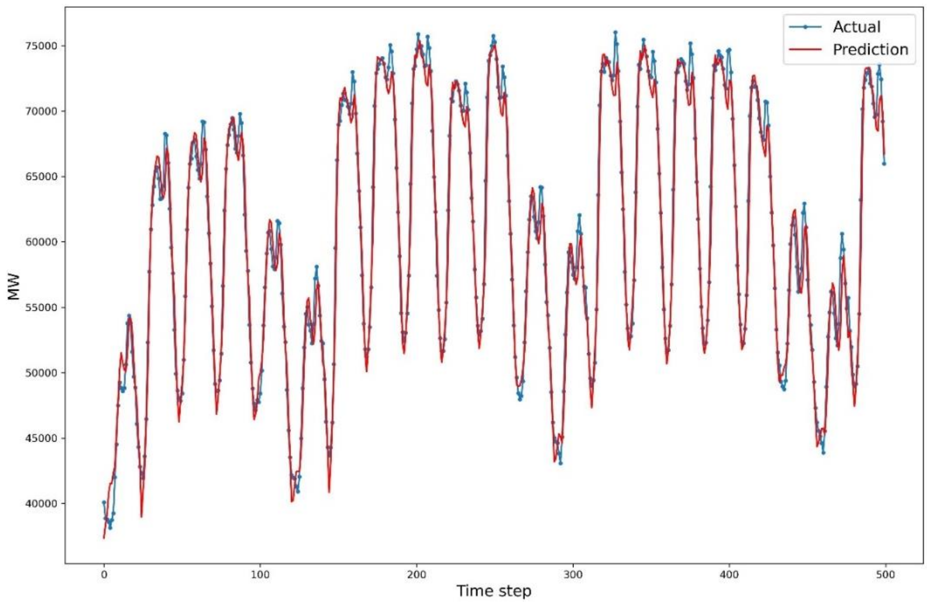

Figure 5. Predictions made by LSTM model

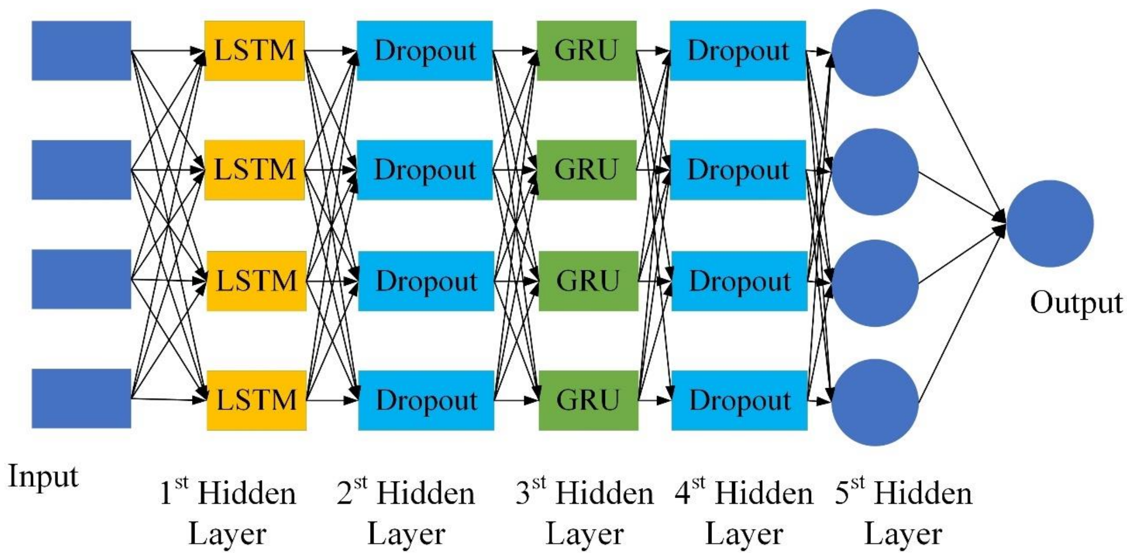

Figure 6. Proposed LSTM-GRU hybrid model

LSTM and GRU based LSTM-GRU hybrid model, the first layer is LSTM with 100 hidden neurons tanh activation function, the second layer is a forgetting layer with a rate of 20 percent. The third layer consists of a GRU layer with 20 hidden neurons. In the fourth layer, the forgetting layer, with a rate of 20 percent, has been added. In the fifth and sixth layers, there are 64 and 1 hidden neuron fully connected layers.

All features are first given to the model as input to the LSTM layer. Each LSTM neuron creates weights by performing operations on the data. The output obtained from the LSTM layer is left at 20% to prevent overfitting and is transmitted to the third layer, the GRU layer. In this layer, the weighing process continues. The resulting weighted values were transferred to the fully connected layer, leaving it for the second time for overfitting. The fully connected layer acts as a normal neural network layer. The weight values obtained from this layer are transmitted to the output neuron and the weight is produced. Error values were obtained by comparing the obtained output value with the real energy data. The update process continued until the minimum error value was obtained, as much as the number of iterations in other models. In the specified update processes, the loss, optimizer, epochs, and batch size values specified in Table 2 and Table 3 were treated as the same as the values used in other GRU and LSTM models.

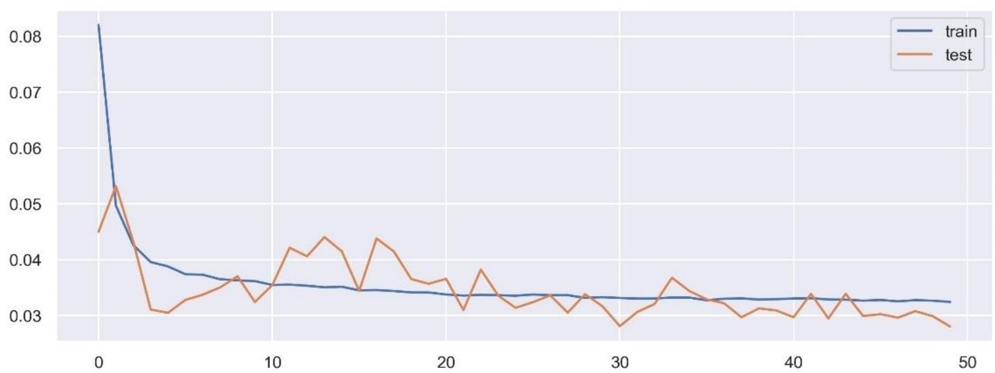

Figure 7. Proposed LSTM-GRU model training and test loss graph

When Figures 7 and 8 are examined, the difference between the actual values and the predicted values is very close. At this stage, as in the LSTM and GRU algorithms, R^2 score, MSE, RMSE, and MAPE functions were used to measure the error values.

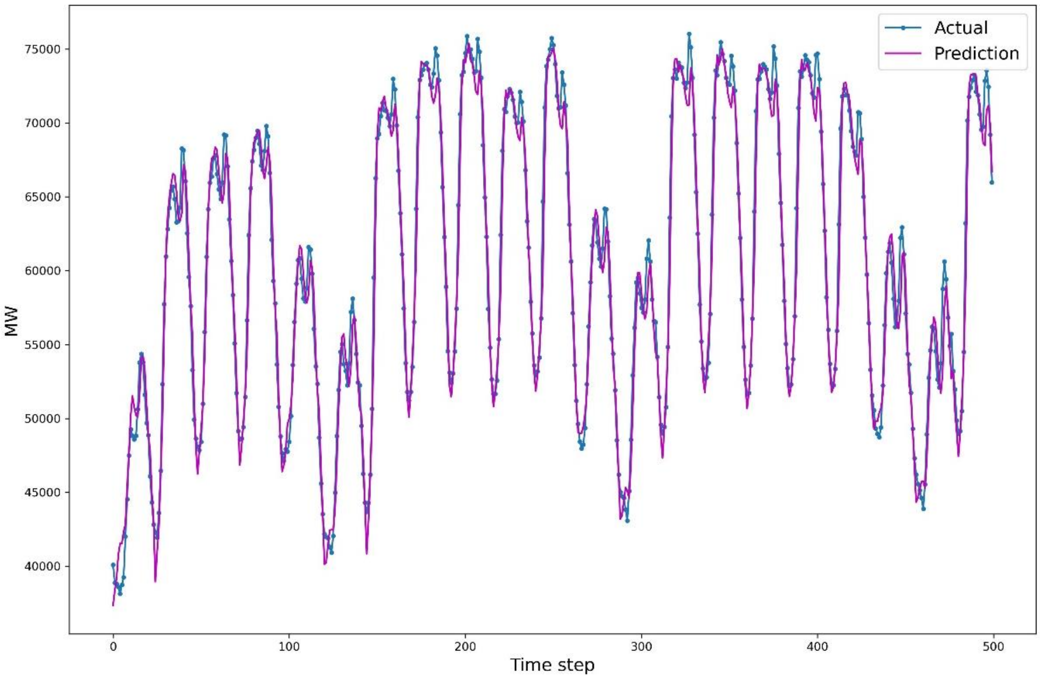

Figure 8. Predictions made by the LSTM-GRU model

Recent studies in the field of energy consumption [21]–[23] show that the problem of estimating energy consumption is still a unsolved area. In the first of these studies [21], it is stated that energy costs increase as industrialization and population increase. For this reason, it is reported that it is important to model energy use effectively with different models. When Table 4 and Table 5 are examined, it is seen that the fine-tuned structure of the proposed hybrid model gives more successful results than the GRU and LSTM models with the same settings. This success rate has been measured based on the best performance criteria in the literature. In addition, LSTM, and GRU [24] give better results in time series predictions than classical machine learning methods. At the same time, unlike [21]–[23] studies, the GRU method has been shown to consume less memory and be faster.

None of the LSTM, GRU, and hybrid models proposed in the article have been published in any study in the literature. For the first time in this study, the characteristics were run according to the details given in Table 2, Table 3, and Figure 6. In terms of the specified features, it differs from the studies published in recent years [21]–[23]. With the technical progress and development of machine learning algorithms such as ANN, the deep integration of LSTM and ANN structures instead of fully connected ANN gave a better result than the ANN method alone [25].

With the support of the mentioned international article, in this study, the ensemble hybrid model and the GRU model, which is a faster architecture close to LSTM and LSTM, are combined. In the results obtained by combining, the results of the proposed models in terms of MAPE, MAE, MSE, RMSE, and R^2 performance criteria are given, while in the study [21], only R^2 and MSE results are given in detail. At the same time, while this study was evaluated only in terms of ANN, LSTM was evaluated in terms of GRU and hybrid models. The difference between the LSTM model, which has different hidden layers, and the classical ANFIS-based models is compared in the estimation of energy consumption [22]. The model we propose is different from the study [22], both in terms of the GRU model and the hybrid model. The models used in the study of Bilgili et al [22] were evaluated according to the MAPE measurement metric. In our proposed study, MSE, RMSE, MAE and R^2 measurement metrics were used in addition to the MAPE measurement metric. Finally, the effect of short-term and long-term variables on energy consumption estimation was examined with a machine learning algorithm called Random Forest [23]. In this study, deep learning models with better results have been developed by making connections between layers in the proposed models, instead of connecting layers with all their attributes to each other with a small structure.

4. Conclusion and Suggestions

It is stated that there is a tendency towards renewable energy sources instead of fossil fuels, which can cause high CO2 emissions. Renewable energy sources, on the other hand, are interrupted from time to time as there is no continuous access. In this case, energy consumption should be managed by providing accurate estimates. Data normalization was performed on the recommendations of [26] in the study on the fuel consumption imperative. In order to perform an accurate consumption analysis in line with the recommendations of [27], time series data consisting of 15, 30 minute, and 1-hour time intervals were used in this article. With the study we carried out, it was aimed to estimate the energy consumption values in Germany. For this purpose, 44,565 data were used in the [12] data set. The data used were separated as training and test data according to the K-fold 5 value but were normalized.

In the next step, training and testing processes were carried out according to the parameters determined in both models using the GRU, LSTM, and LSTM-GRU models, which are popular RNN [28]–[31] models in the literature. The MSE, RMSE, MAPE, MAE, and R^2 score values are presented in Eqs. (7)-(11) were used to measure the prediction success of both designed systems, respectively [32].

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(Y_i - \hat{Y}_i\right)^2 \tag{7}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(Y_i - \hat{Y}_i\right)^2} \tag{8}$$

$$MAPE = \frac{100}{m}\sum_{i=1}^{m}\left[\frac{Y_i - \hat{Y}_i}{Y_i}\right] \tag{9}$$

$$MAE = \frac{100}{m}\sum_{i=1}^{m}\left[\frac{Y_i - \hat{Y}_i}{Y_i}\right] \tag{10}$$

$$R^2 = 1 - \frac{\sum(Y_i - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2} \tag{11}$$

The results of the performance measurement used for both methods are presented in Table 4. As can be seen from the results presented in Table 4, the performance results obtained from the LSTM, GRU, and proposed hybrid LSTM-GRU algorithms are close to each other. The proposed hybrid LSTM-GRU algorithm performed one level better than the other proposed models. It can be used to create energy consumption forecasting models in a similar way in both models.

Table 4. Results obtained on the normalized Germany energy consumption data set

Algorithm	R^2 Score	MSE	RMSE	MAE	MAPE
Hybrid Model	0.9720	0.0013	0.0358	0.0275	5.89
LSTM Model	0.9703	0.0014	0.0369	0.0292	6.35
GRU Model	0.9650	0.0017	0.0375	0.0298	6.60

On the other hand, when the training time of both methods is compared, it has been determined that the system is trained in a shorter time with the GRU method. The training times obtained for both models proposed in the article are presented in Table 5. At this stage, which algorithm should be chosen for similar topics may be preferred depending on the hardware and time of the users.

Table 5. Training times

Training Algorithm	Time (Min)
LSTM Model	6.58
GRU Model	4.87
Hybrid Model	7.50

Contributions of the authors

The contributions of each author to the article should be indicated.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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