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Hybrid Estimation Model (CNN-GRU) Based on Deep Learning for Wind Speed Estimation

Cem Emeksiz[1*] and Muhammed Musa Fındık[2]

[1*]*Department of Electrical and Electronics Engineering, Tokat Gaziosmanpasa University, Tokat, Turkey (cem.emeksiz@gop.edu.tr)* *(ORCID: 0000-0002-4817-9607)*

[2]*Department of Electrical and Electronics Engineering, Tokat Gaziosmanpasa University, Tokat, Turkey (fmuhammedmusa@gmail.com)* *(ORCID: 0000-0003-3786-6089)*

Abstract – Nowadays, the need for energy is increasing day by day. In order to meet this demand, renewable energy sources that have a more environmentally friendly structure than fossil-based sources come to the fore. In recent years, researchers have been paying great attention to wind energy. Because it has the many economic and environmental advantages. In particular, wind speed is very important parameter for electric energy production form wind energy. Therefore, estimation of wind speed is very important for both investors and manufacturers. A hybrid model for wind speed estimation with deep learning methods is proposed in this study. The proposed model consists two main deep learning methods (Convolutional Neural Networks (CNN) and Gated Recurrent Unit (GRU)). The proposed model was applied in two case studies (weekly and monthly wind speed estimation). The reliability and accuracy of the proposed model were tested by performance criteria (MAPE, R^2, RMSE). In order to measure the success of the model, a comparison was made with 5 different deep learning methods (CNN-LSTM, CNN-RNN, LSTM-GRU, LSTM, GRU). It has been observed that the CNN-GRU hybrid model, which was used for the first time in the field of wind speed forecasting, achieved a high percentage of success as a result of comparisons made.

Keywords *– Renewable energy, Wind energy, Wind speed estimation, Deep learning methods, Hybrid estimation model*

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I. INTRODUCTION

Energy resources have an extremely important place in the lives of societies in terms of social and economic sustainability. Energy demands are increasing rapidly with the increasing population in the world. However, one of the most important indicators of the social and economic development of countries is energy production and usage [1]. The interest and demand of developed and developing societies for energy has increased with the industrial revolution. This increase continues rapidly in the current century. Meeting the energy needs is important for the survival of societies and individuals [2].

Many of the developing countries still prefer fossil-derived traditional energy sources such as oil, coal and natural gas in order to meet their energy needs and increase their industrialization and production capacities [3]. Despite this, the fact that fossil fuels cannot be supplied in terms of raw materials in the coming centuries, their harmful effects on the environment and their economic disadvantages are very important issues to be considered.

In recent years, renewable energy sources have started to play an active role in meeting the energy needs and demands of societies. Renewable energy sources have low investment costs and are environmentally friendly sources. For this reason, renewable energy sources are of vital importance in order to follow a more sustainable energy policy both environmentally and economically. Renewable energy sources are classified as biomass, solar, wind, geothermal, tidal, hydrogen and hydraulic energy. Among the renewable energy sources, wind energy stands out more than other sources in terms of its advantages [4]. In last decade, the installed capacity of wind energy has been growing increasingly around the world. In 2020, the installed power in the world was reached from 650 GW to 743 GW [5].

Environmental and meteorological conditions should be taken into account in determining the regions planned for the establishment of wind farms. These conditions are wind speed, wind direction, pressure, temperature, etc. consists of parameters. The most important of these parameters is wind speed, because the chaotic behavior of the wind and its discontinuity both increase the production cost and reduce the reliability of the power system [6], [7]. In addition, fluctuations in the wind make it difficult to balance the input and output power in the grid.

Therefore, an accurate wind speed estimation is vital for wind power generation systems. Thus, both the stability of the power systems are ensured and the concerns about the investments to be made in the wind energy industry are eliminated [8], [9]. In recent years, many researchers Many researchers used different estimation models. According to properties of models, these models are divided into basic groups as statistical, physical artificial intelligence and hybrid models, respectively. [10].

Cadenas and Rivera compared autoregressive integrated moving average (ARIMA) and artificial neural networks (ANN) methods. 7 years of wind speed data were used for their study. Data used in the study collected from La Venta, Oaxaca, Mexico [11]. A fractional f-ARIMA model was studied in another study. Researchers of study aimed to estimate wind power generation and wind speed 24 and 48 hours in advance with this model. They compared their results with the persistence model (PM). It was emphasized that the proposed method was more successful [12]. Erdem and Shi estimated wind speed. They used autoregressive moving average (ARMA) models and the accuracy and consistency of these approaches were compared [13]. Ding et al. applied the secondary decomposition method to the wind speed time series in the preprocessing process. They adapted the ARIMA model to the overall structure to make predictions with the decomposed series [14]. Torres et al. estimated the hourly average wind speed by comparing the ARMA and PM model. It was observed that the performance of the ARMA model was better. In particular, it was emphasized that the error rates in the ARMA model were lower [15].

Kalogirou made a feasibility study. He used the ANN in different renewable energy systems. In particular, he focused on solar steam facilities, wind speed estimation, solar radiation photovoltaic systems and solar water heating systems [16]. A new ANN model was proposed in study of Yayla and Harmancı. In the model, two stations were used and estimation process was made by using hourly wind speed data [17]. Wavelet recurrent neural networks (WRNN) were used in another study. Results obtained show that performance of the proposed model is within a defined and acceptable error range [18]. Li estimated wind power generation in his study. Recurrent multilayer perceptron neural networks (RMLP) were used in the study. The Kalman-based back propagation algorithm was tried while the network was being trained. When the estimation results were compared, it was determined that the proposed method for long-term estimation was more beneficial [19].

Nowadays, popular deep learning methods have been commanly prefered in many literature studies for wind speed estimation [20]. Convolutional neural networks (CNN) [21], long-short term memory (LSTM) [22], neural network structural learning [23], recurrent neural network (RNN) [24] Transfer learning [25], etc. These deep learning methods are the most popular ones and used widespread.

LSTM was used to estimate electrical energy demand in other study. Authors created a multi-input and multi-output structure by using the seasonal data in long-term forecasting [26]. A 2D CNN structure was prefered for estimating short- and long-term wind energy in another study. Also data used in study were preprocessed bu using wavelet transform. A particle swarm optimization algorithm was preferred to determine the CNN weights [27]. An attention-based gated repetitive unit (AGRU) method was used for estimating short-term wind energy in the study of Niu et al. [28]. In another study, time series data were decomposed. Classification and complexity were calculated using decomposed data. LSTM and fuzzy entropy were used to perform these operations [29].

In presented study, a hybrid model based on deep learning was proposed as an alternative to the classical methods used in wind speed estimation. The proposed hybrid model consists of Gated Recurrent Unit (GRU) neural network and Convolutional Neural Network (CNN). Similarly, although there are literature studies using independent deep learning methods, the hybrid structure created was tried for the first time in the field of wind speed estimation. This situation constitutes the original and innovative aspect of the study. In addition, the hybrid estimation model obtained by using deep learning methods showed better performance in wind speed estimation. The proposed model has been compared with 5 different deep learning methods. It has been observed that the proposed model gives more accurate and reliable results in all comparisons. Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), Root Mean Square Error (RMSE), which are widely used in the literature, as performance metrics, were preferred.

II. Materials and Method

The combination of Convolutional Neural Network and Gated Repetitive Unit (CNN-GRU) was preferred in the creation of the proposed hybrid model for wind speed estimation. As mentioned earlier, this combination is used for the first time in wind speed estimation. Similarly, it was tested with combinations in other literature studies in which deep learning methods were used together. The structures commonly used in the literature and tested in comparison with the proposed model are CNN-LSTM, CNN-RNN and LSTM-GRU was selected. Moreover, these methods were also used independently in estimation, and the estimation performance was compared. The structures that make up the proposed hybrid model, the acquisition of data and the preprocessing steps applied to the data are explained in detail in the following sections. In addition, experimental studies were carried out using MATLAB software on a computer with an Intel i7 processor, a 1650ti graphics card, and a 16 gigabyte RAM capacity.

A. Data collection and preprocessing

The measurement station established in Tokat Gaziosmanpasa University Taslıciftlik Campus. All wind speed data used in study were collected this station. The measurement mast of the measurement station from which the wind speeds are obtained is given in Figure 1. The measuring mast is 12m and has 1 wind direction measurement sensor and 2 wind speed measurement sensors on it. Pressure and temperature sensors are located inside the power box located at the bottom of the measuring mast. The energy needed for the sensors is met by a solar panel with a power of 10 W. In addition, a marina type AIRX-400W wind turbine was placed on the wind turbine measurement mast to be used in the wind power analysis studies planned later.

The wind speed data used in the study were collected at 1-hour intervals, and a 3-year data (2018-2020) set was used. The collected data were divided into groups on average weekly, and monthly. Normalization process was applied between 0-1 in order to eliminate noise-containing values from the separated data and to obtain a clearer result. The normalization process is extremely important in order to determine the data ranges for more accurate analysis and also to increase the success of the regression process. Normalization process is applied in order to transform the data into a more regular format. The operations given in Equation 1 are applied to linearly normalize the data [30].

$$x' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

x' represents the normalized data. x_i represents the data to be normalized. x_{min} and x_{max} represent the lowest value and the highest value in the data, respectively.

Fig. 1. Measurement station

Average weekly and monthly histogram graphs of wind speed data obtained by grouping and normalization process were created. Figure 2 and 3 show the histogram distribution graph and the variation of the average weekly wind speeds.

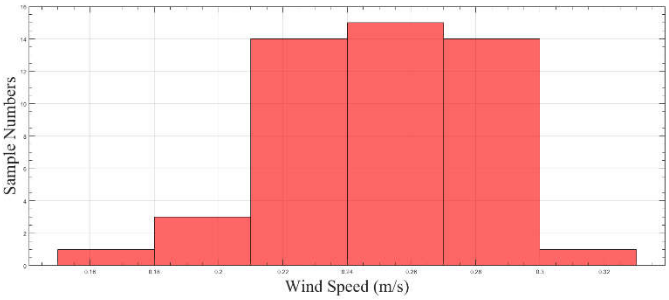

Fig. 2. Histogram distribution of average weekly wind speeds

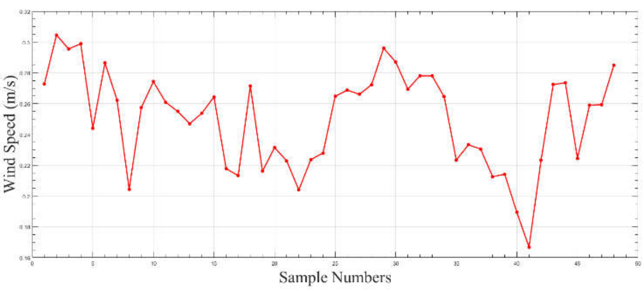

Fig. 3. Average weekly wind speeds

While creating the weekly data, grouping was made in the first 4 weeks of each month in order to provide a standard in the analyzes and to be compatible with the literature studies. Thus, an average of 48 weekly data sets were created. The main purpose of estimating on average weekly data is to observe the effect of low number of data sets on network performance. In this data set, 36 (75%) wind speed data were used for training and 12 (25%) wind speed data were used for testing.

Figures 4 and 5 show the histogram distribution graph and variation of monthly average wind speeds. While creating this data set, a total of 8760 wind speed data were used by taking the averages of each month of the 3 years. Of these data, 6570 (75%) data belonging to the first 9 months were separated as training data, and the average monthly data for the last 3 months of 2190 (25%) as test data.

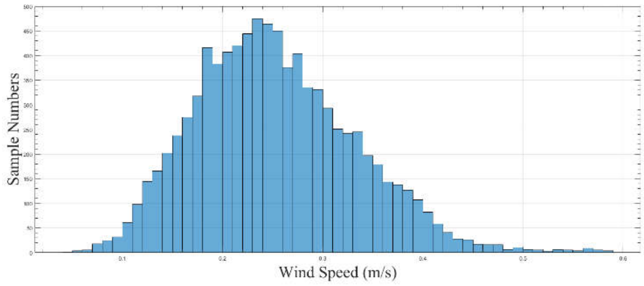

Fig. 4. Histogram distribution of average monthly wind speeds

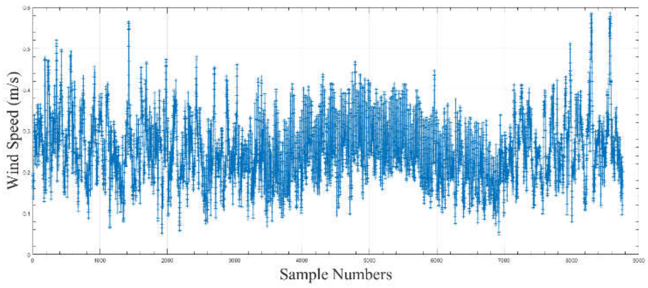

Fig. 5. Average monthly wind speeds

B. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) is a deep neural network structure that can operate in many areas such as classification, identification, prediction [31] and many other deep learning methods [32]. These used methods draw attention with their high classification accuracy [33], [34]. CNN is an architecture inspired by artificial neural networks and can learn end-to-end information collected. CNN can also handle large-scale data thanks to its sufficient capacity and smart model structure. The advantages of convolutional neural networks can be listed as separating objects from the background without applying preprocessing, providing higher performance compared to image identification processes with traditional methods, and predicting with high accuracy in time-series-based operations. The disadvantages of CNN are the long training period, the need for powerful Graphics Processing Unit (GPU) cards and high memory capacities.

Convolutional neural networks consist of more than one parameter and layer. Its layered structure enables it to achieve very successful results in attribute determination [35]. Convolutional neural network architecture is given in Figure 6. There are two basic layers in CNN. One is the convolution layer and the other is the pooling layer. CNNs aim to extract the important features of the image with some basic operations in these two layers [34].

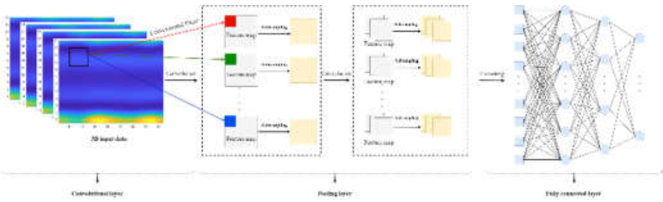

Fig. 6. CNN architectural structure [36]

The convolution operation is the process of convoluting the image filter with initially random values with the input image. The convolution layer is the basic building block of CNN, which is not found in traditional ANN. Instead of connecting the cells in all layers and renewing the connection weights, the convolution process is used in small regions. The output is a powerful algorithm presented to solve the over-learning problem, which reduces the overall error of the large neural network. In a dropout algorithm, a single neuron does not rely on the formation of other neurons, thus reducing the neuron's adaptation complexity. Thus, CNN was developed to learn more robust features and stable structure [37-41]. The term of dropout means that not including some of the units in a neural network in the next layer. The proposed hybrid model was obtained by combining two-dimensional CNN and GRU networks and the parameters of the hybrid model were summarized in Table 1.

Table 1. Model parameters

Convulation Layer 1	Filter size: 32 Mini Batch size: 64
Convulation Layer 2	Filter size: 32 Mini Batch size: 64
Convulation Layer 3	Filter size: 32 Mini Batch size: 64
Convulation Layer 4	Filter size: 32 Mini Batch size: 64
Convulation Layer 5+ Pooling	Filter size: 32 Mini Batch size: 64 Pooling method: Average pooling
GRU Layer	Filter size: 128 Mini Batch size: 64 Dropout: 0.25

C. *Gated Repeating Unit (GRU)*

Nowadays, there are many different variations of the LSTM architecture. One of these variations, and generally the most preferred, is the Gated Repetitive Unit (GRU). It aims to solve the disappearing gradient problem that comes with the classical recurrent neural network. GRU and LSTM are designed similarly, so they can produce very successful results [42].

In the structure of the GRU architecture, the forget gate and the entrance gate are combined. Basically, these are two vectors that decide what information should be passed to the output. What's special about gates is that they can be trained to hide information long before it washes out information over time or deletes non-predictive information.

The gated repetitive unit, for example in speech recognition, is part of a particular recurrent neural network model that aims to use connections through a series of nodes to perform machine learning tasks associated with memory and clustering. The gated recurrent unit helps to adjust the neural network input weights to solve the vanishing gradient problem, which is frequently encountered in recurrent neural networks [43]. The GRU architecture is presented in Figure 7.

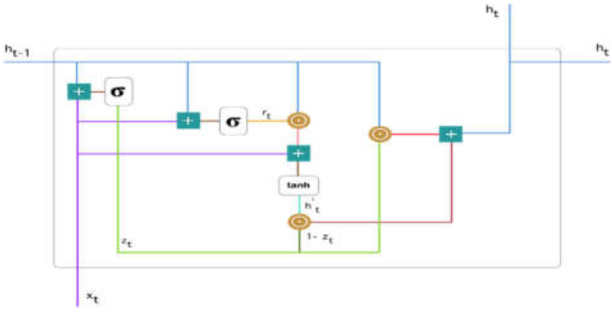

Fig. 7. Gated repetitive unit architecture [44]

The port update process takes first place in GRUs. The z_t update gate is calculated with the formula given below.

$$z_t = \sigma(W^{(z)}x_t + U^{(z)}h_{t-1}) \tag{1}$$

When x_t is added to the mesh unit, its own weight is multiplied by $W^{(z)}$. The update gate helps the model determine how much of the historical information from previous time steps should be forwarded [45]. The model provides great advantages such as copying all the information from the past and eliminating the lost gradient problem [44]. In Figure 8, the gate update process in the GRU architecture is modeled.

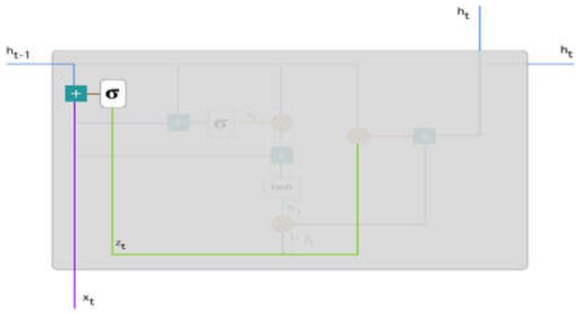

Fig. 8. GRU gate update [44]

The reset gate is used to decide how much of the past information on the model will be forgotten. This process is performed with Equation 2 [42].

$$r_t = \sigma(W^{(r)}x_t + U^{(r)}h_{t-1}) \tag{2}$$

The formula used is the same as the update gate. The difference between the formulas is in the weight and usage of the stage. Figure 9 shows where the reset gate is located.

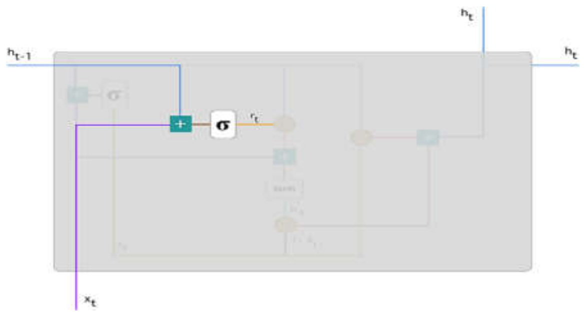

Fig. 9. Reset gate [44]

As in the previous operations, the weights corresponding to h_{t-1} and x_t values are multiplied and the results are summed, and then the sigmoid function is applied. If it is taken a look at exactly how the gates will affect the final output in the current memory context; firstly, it is started with the usage of the reset gate. A new memory context is introduced that will use the reset port to store relevant information from the past.

The operations given in Equation 3 are applied sequentially. The current memory operation is shown in Figure 10.

$$h'_t = \tanh(Wx_t + r_t \cdot Uh_{t-1}) \quad (3)$$

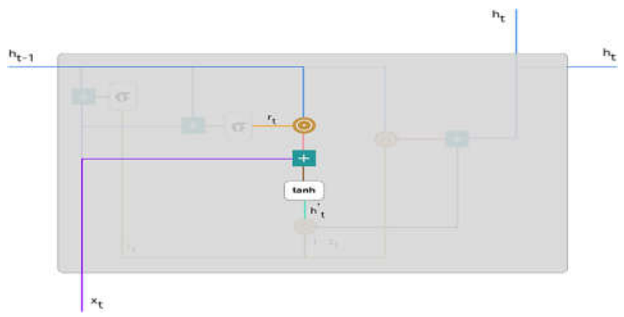

Fig. 10. Current memory operation [44]

r_t and h_{t-1} are multiplied. After that the result obtained is summed with input x_t. h'_t is produced by using tanh function.

As a final step, the network has to calculate the h_t vector, which holds the information for its current unit and transmits it to the network by using Equation 4. In order to do this, the update port is needed. Determines what to collect from the current memory content.

$$h_t = z_t \cdot h_{t-1} + (1 - z_t) \cdot h'_t \quad (4)$$

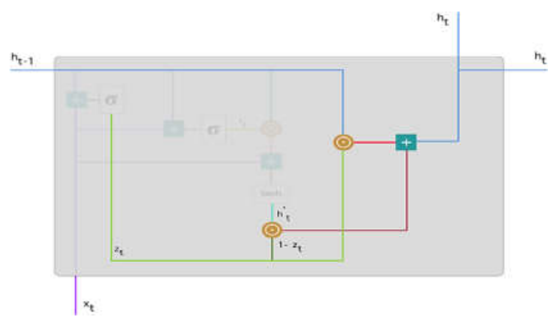

Fig. 11. Calculation of the function that holds and transmits information for the current unit [44]

$1 - z_t$ is calculated by using z_t according to Figure 11. It produces a result in the dark red line combined with h'_t. z_t is also multiplied with h_{t-1} blue line in item-by-item multiplication. Finally, the h_t blue line is obtained as a result of the sum of the outputs corresponding to the red lines in Figure 11.

III. RESULTS

The hybrid CNN-GRU model proposed in the study was used independently for weekly and monthly wind speed estimations. The results obtained were interpreted and evaluated according to performance metrics. In addition, the performance of the hybrid model used in 2 separate case studies was compared with GRU, LSTM, LSTM-GRU, CNN-LSTM and CNN-RNN network structures. The results of the case studies are presented in detail in the following sections.

A. First Case Study

The hybrid estimation model proposed for weekly estimation, which constitutes the first stage of the study, performed the estimation process with a higher accuracy rate than the other models as a result of the analyzes made. The performance of both the proposed hybrid model and other models is presented in Table 2. The RMSE value in the proposed hybrid model is 0.0306, and the closest value to this error value was obtained with the LSTM model. The highest error rate occurred in the standalone GRU model. The variation of the error metrics of the models and the regression rates are clearly seen in Figure 12.

Table 2. Performance comparison of weekly estimation

Metrics	**CNN-GRU**	**LSTM**	**LSTM-GRU**
RMSE	**0.0306**	0.0309	0.0397
R^2	**0.9841**	0.983	0.9732
MAPE	**0.1106**	0.1165	0.1395
Metrics	**GRU**	**CNN-LSTM**	**CNN-RNN**
RMSE	0.0695	0.0387	0.0483
R^2	0.9142	0.9769	0.9681
MAPE	0.227	0.1254	0.1746

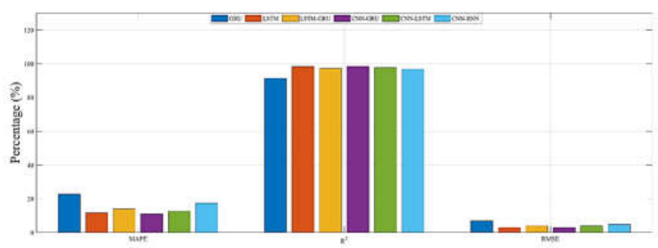

Fig. 11. Performance graph of weekly estimation

It is showed that the comparison of the estimated wind speed changes and the actual wind speed changes in Figure 12 – 17 for all models. When the estimation graphics of the models are examined; The change in the 12-week data group, which was estimated from the 48-week data set, is seen.

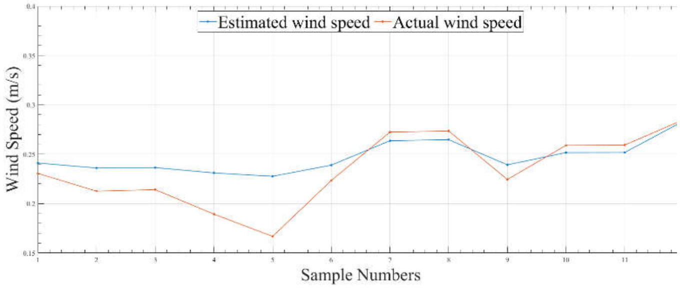

Fig. 12. Estimation graph of CNN-GRU

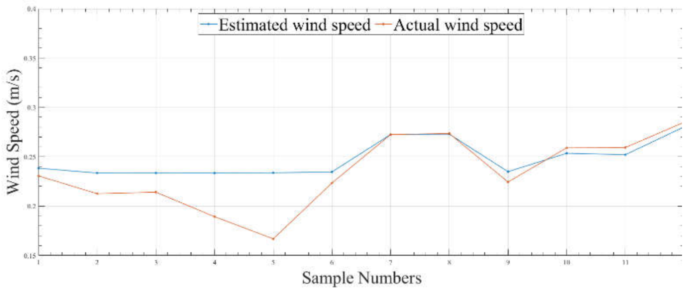

Fig. 13. Estimation graph of CNN-LSTM

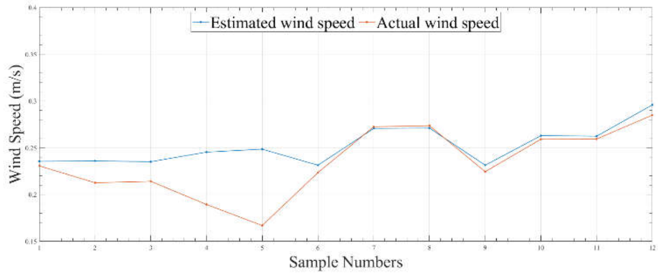

Fig. 14. Estimation graph of CNN-RNN

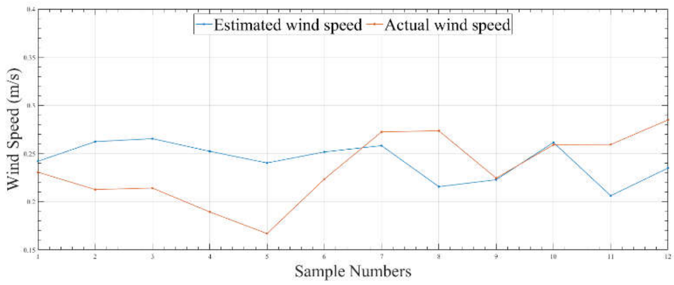

Fig. 15. Estimation graph of LSTM-GRU

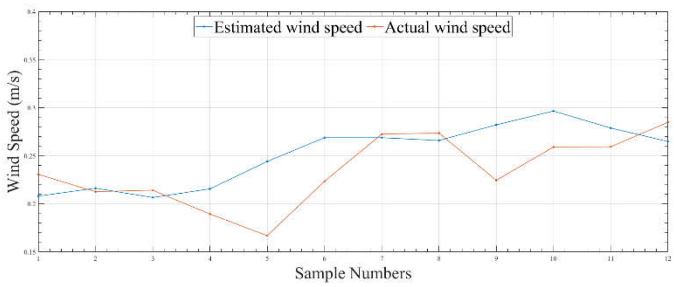

Fig. 16. Estimation graph of GRU

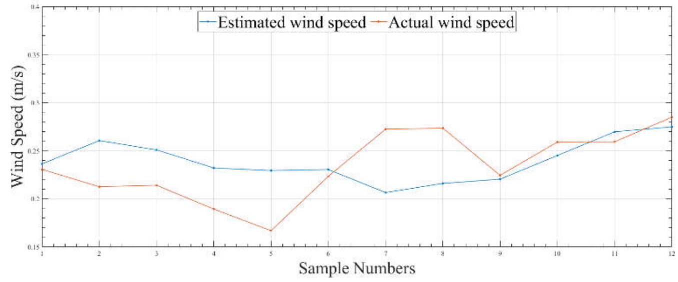

Fig. 17. Estimation graph of LSTM

Also, the aggregate variation of both the actual and the estimated wind speed data is shown in Figure 18. When Figure 18 is examined, it is seen that the proposed model exhibits a trend closer to the actual wind speed data change.

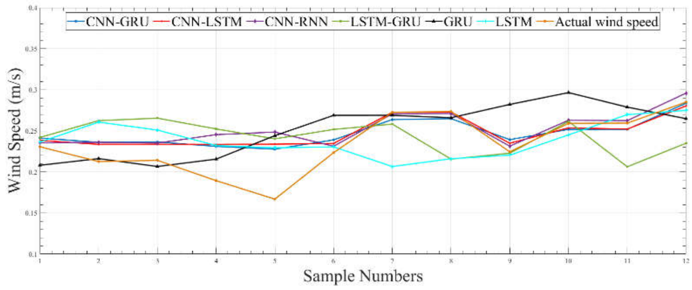

Fig. 18. Variation of actual wind speed and predicted wind speed for all models

B. Second Case Study

The performance of both the proposed hybrid model and other models is presented in Table 3. The RMSE value obtained with the proposed hybrid model is 0.0127, and the closest value to this error value was obtained with the CNN-LSTM model. The highest error rate occurred in the LSTM-GRU model. The variation of the error metrics of the models and the regression rates are clearly seen in Figure 19.

Table 3. Performance comparison of monthly estimation

Metrics	CNN-GRU	LSTM	LSTM-GRU
RMSE	**0.0127**	0.097	0.1194
R^2	**0.9977**	0.8658	0.7966
MAPE	**0.0409**	0.3492	0.3544
Metrics	**GRU**	**CNN-LSTM**	**CNN-RNN**
RMSE	0.1087	0.0189	0.0206
R^2	0.8316	0.9923	0.9893
MAPE	0.3797	0.0498	0.0526

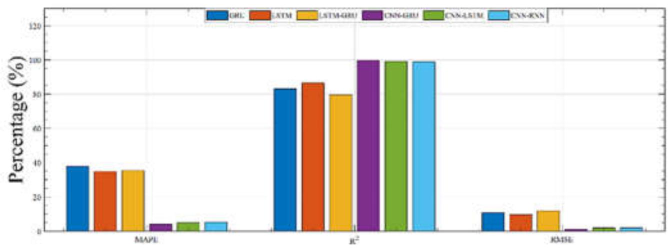

Fig. 19. Performance graph of weekly estimation

It is showed that the comparison of the estimated wind speed changes and the actual wind speed changes in Figure 20 – 25 for all models. In addition, the estimation results in the proposed hybrid model show a behavior closer to the change of actual wind speed data. It was determined that the model memorizes and oscillates continuously in a certain range in the estimations made in these models as a result of the examination of the LSTM-GRU, GRU and LSTM (Figure 23-25) graphs.

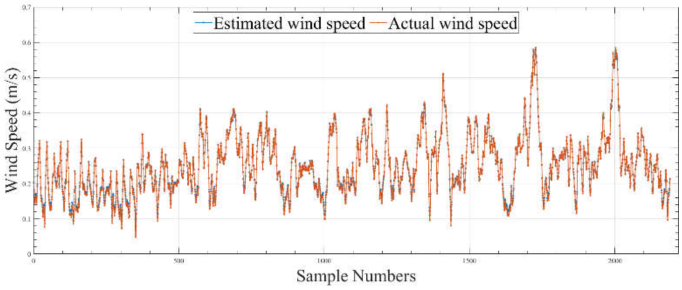

Fig. 20. Estimation graph of CNN-GRU

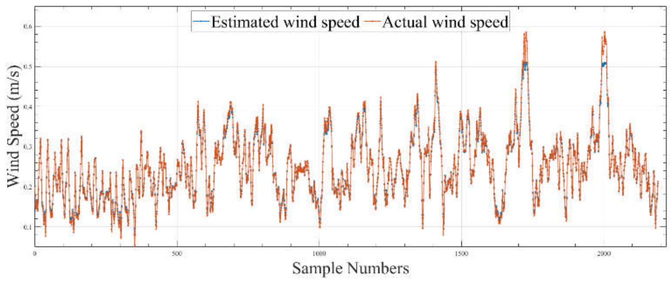

Fig. 21. Estimation graph of CNN-LSTM

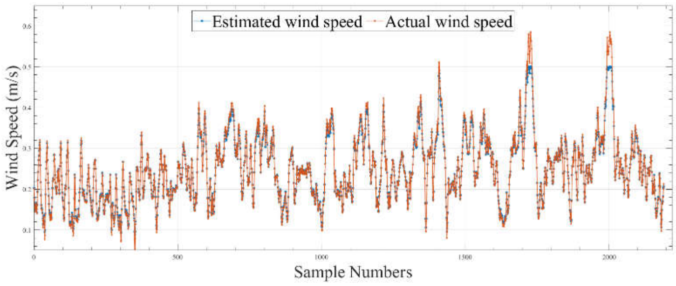

Fig. 22. Estimation graph of CNN-RNN

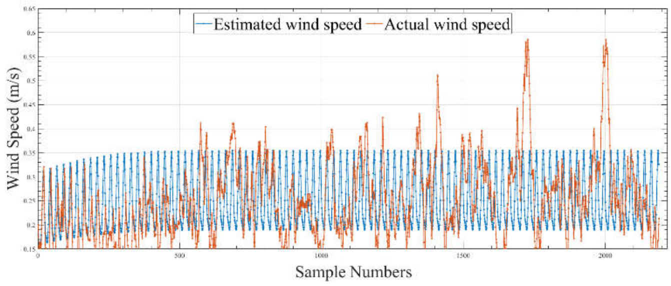

Fig. 23. Estimation graph of LSTM-GRU

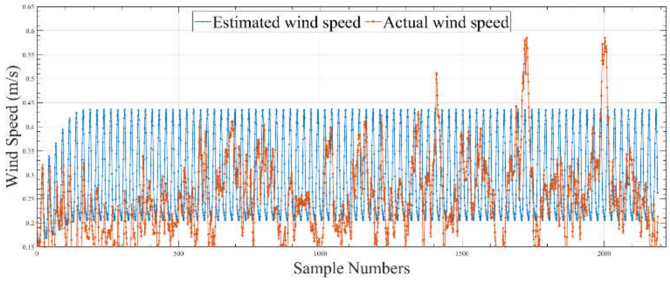

Fig. 24. Estimation graph of GRU

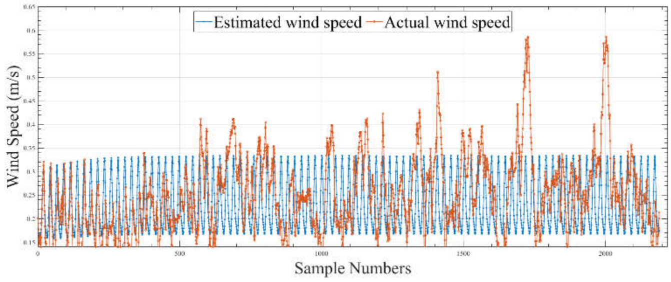

Fig. 25. Estimation graph of LSTM

IV. DISCUSSION

Nowadays, energy has an extremely important place in consumer societies. Energy is needed for the development of societies and a sustainable life. Many successful models in which economic and environmentally friendly approaches are used to meet the increasing energy demands have come to a very important point today. Especially in the field of renewable energy, very important studies and progress have been made in recent years. Considering the advantages of wind energy, which is among these sources, it is seen that it is preferred more than other sources. Wind speed is very important parameter for electric energy production form wind energy. This allows researchers to develop different and useful models in the field of wind speed estimation so that wind energy can be used more efficiently. Therefore, in this study, a hybrid estimation model, which is used for the first time for wind speed estimation, is proposed by using deep learning methods. The proposed hybrid model was used in the estimation process separately in 2 case studies and its performance in these case studies was evaluated according to the determined performance criteria (MAPE, R^2, RMSE). In addition, the performance of the proposed model was compared with 5 different deep learning models in the literature (CNN-LSTM, CNN-RNN, LSTM-GRU, GRU, LSTM) in order to make the interpretation of the performance more meaningful.

In the results obtained in the weekly wind speed estimation process, which constitutes the first case study, it was observed that the hybrid model showed more accurate and reliable results (MAPE: 0.1106, RMSE: 0.0306, R2: 0.9841).

In the monthly wind speed estimation that constitutes the second case study, it is clearly seen that the proposed hybrid model outperforms the other models according to the obtained performance criteria (MAPE: 0.0409, RMSE: 0.0127, R^2: 0.9977). It was observed that in some models (LSTM-GRU, LSTM, GRU) used for comparison purposes in monthly wind speed estimation, the structure goes to memorization rather than estimation.

In this study, it was seen that the hybrid model proposed for the first time for wind speed estimation showed more successful results. In particular, the obtained results were compared with other models used in the literature and validation was performed. One of the important inferences obtained in the study is that the independent use of the models to be preferred especially in the field of wind speed estimation results in higher error results. The other is emphasized that hybrid forecasting models should be preferred more. Another inference is that the more preferred deep learning methods, especially used in the field of image processing, also show successful results in numerical estimation processes. For this reason, it is planned to evaluate the performance with different data pre-processing methods to be applied to the data in addition to the estimation model proposed in the planned studies for the future.

Authors' Contributions

The authors' contributions to the paper are equal.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics

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