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A New Hybrid Intelligent Method for Accurate Short Term Electric Power Production Forecasting from Uncertain Renewable Energy Resources

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ABSTRACT

In recent years, there has been a significant increase in the utilization of renewable resources for electricity generation. Consequently, accurate short-term forecasting of renewable power production has become crucial for power system operations. However, Renewable Power Production Forecasting (RPPF) presents unique challenges due to the intermittent and uncertain nature of renewable energy sources. This paper proposes a novel approach to short-term RPPF. The proposed model integrates various techniques, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Autoregressive Integrated Moving Average (ARIMA), Multi-Layer Perceptron (MLP), and Adaptive Neuro-Fuzzy Inference System (ANFIS). The aim is to enhance the accuracy and predictive performance of renewable power production forecasts. The suggested hybrid model employs the Modified Relief-Mutual Information (MRMI) feature selection technique to identify the most influential input data for prediction. Subsequently, the combined model generates a 24-hour ahead RPP prediction using a weighted output approach. By capitalizing on the strengths of each individual model, the combined method mitigates their weaknesses, thereby improving the overall efficiency of the forecasting process. The accuracy and performance of the proposed method are evaluated through two case studies involving solar farm power generation at the Mahan, Iran and Rafsanjan, Iran sites. The results demonstrate the effectiveness of the hybrid model in enhancing the accuracy of short-term RPPF. By combining multiple forecasting methods and utilizing the MRMI feature selection technique, the proposed method significantly improves prediction accuracy.

I. Introduction

Renewable energy sources, increasingly crucial for global electricity production due to their environmental benefits, reliability, and cost-effectiveness, are gaining prominence. [1]. Among them, solar photovoltaic (PV) is one of the most widely used. Solar energy, produced by photovoltaic panels, is a clean and inexpensive energy source that reduces reliance on harmful fossil fuels [2-4]. Despite these advantages, integrating significant PV energy into power systems poses operational challenges that affect electricity prices. Unlike traditional energy sources, PV systems exhibit heightened uncertainty in electricity generation, substantially impacting their profitability within the electricity market. Moreover, the variable and unpredictable nature of solar power presents challenges for grid operators and market participants in effectively managing and pricing electricity. Therefore, the uncertain nature of PV makes it difficult to predict accurately. Various methods have been proposed in recent years for PV power forecasting. These methods can be categorized into four groups: physical, statistical, artificial intelligence, and hybrid models. Physical models, which utilize meteorological and geographical data, are generally less effective for short-term RPPF. However, they often yield better results in long-term forecasting [5-7]. Statistical models used for short-term RPPF try to find the relationship between input and output [8-11]. Statistical models outperform physical models in RPPF. However, they cannot catch long-term dependencies within data. Artificial intelligence models such as artificial neural networks [12-16], support vector machine (SVM) [17], and fuzzy logic [18] are more accurate in short-term RPPF. They use historical data on meteorological conditions in order to forecast future solar radiation levels [19]. However, deep neural networks were shown to be much more efficient in short-term RPPF [20-26]. For instance, Liu et al. [27] integrated a deep network model with a feature selection technique in order to enhance the prediction accuracy. Sharadga et al. [28] studied different prediction methods for PV power output, including statistical and artificial intelligence-based approaches, to compare their performance. Alaraj et al. [29] introduced an ensemble approach using machine learning to forecast solar photovoltaic power, considering meteorological parameters. Authors in [30] combined a naïve Bayes algorithm, MLP, and LSTM to forecast solar power generation for the next hour and hourly for the following days. Zhu et al. [31] proposed a short-term wind power forecasting method based on a new hybrid model to enhance the accuracy of wind power prediction. Xiong et al. [32] developed a hybrid model combining complementary ensemble empirical mode decomposition (CEEMD), sample entropy (SE), random forest (RF), improved reptile search algorithm (IRSA), bidirectional long short-term memory (BiLSTM) network, and extreme learning machine (ELM) for wind power prediction. Chen et al. [33] presented a method for forecasting using multiple steps. They used ensemble empirical mode decomposition (EEMD) and improved K-harmonic mean clustering optimized by the Cuckoo search algorithm (CSA). Moreno et al. [34] developed a method called WSF that combines a decomposition model with LSTM for forecasting. Duan et al. [35] proposed a combined short-term wind speed forecasting model based on CNN-RNN and linear regression optimization to account for error. Kosana et al. [36] implemented a hybrid forecasting framework using improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN), BiLSTM, and autoencoder for wind speed forecasting.

Liu et al. [37] developed a system for wind speed forecasting that includes various techniques. They used ensemble empirical mode decomposition with adaptive noise (CEEMDAN) as a data preprocessing technique, the C-C method as a feature selection method, a multi-objective grey wolf optimizer (MOGWO) as a parameter optimization algorithm, and a multi-input multi-output least squares support vector machine (MIMOLSSVM) as a forecasting model. They also used evaluation metrics for interval WSF. Cai et al. [38] proposed a wind power mid-long-term forecasting method considering various wind energy characteristics to effectively predict future climate information. Scott et al. [39] explored machine learning techniques for forecasting PV generation systems. The method presented by Theocharides et al. [40] involved combining machine learning techniques with statistical post-processing to forecast solar power for the next day. In a similar vein, Heo et al. [41] proposed a multi-channel convolutional neural network approach to predict monthly photovoltaic power. Their method included utilizing raster image data to account for regional influences. Hu et al. [42] proposed a hybrid approach for short-term wind speed predictions. Their approach is based on a preprocessing algorithm and optimization theory. Aly [43] used recurrent Kalman filter (RKF), Fourier series (FS), wavelet transform (WT), and artificial neural network (ANN) for WSF and WPF. Juardo et al. [44] proposed an improved encoder-decoder-based CNN model for probabilistic short-term load and PV forecasting. Brester et al. [45] evaluated neural network models for site-specific solar PV forecasting using numerical weather prediction data and weather observations. The taxonomy of some of reviewed papers based on different aspects of their works has been listed in Table 1.

The proposed model combines several powerful forecasting techniques, including LSTM, GRU, ARIMA, MLP, and ANFIS. Furthermore, we employ the MRMI method for input selection to enhance the accuracy of our predictions. By leveraging the strengths of these diverse models, our hybrid approach aims to overcome the challenges posed by the intermittency and uncertainty inherent in renewable resources. Through the weighted combination of model outputs, we generate reliable and accurate predictions for the next 24 hours of renewable power production. The important contributions of proposed paper can be summarized as follows:

1- Hybrid forecasting models incorporating LSTM, GRU, ARIMA, MLP, and ANFIS are developed to accurately predict renewable power production for the next 24 hours. By combining the strengths of these individual models, the hybrid approach effectively compensates for their respective weaknesses, significantly enhancing overall forecasting performance.

2- In this study, the MRMI feature selection technique is introduced to identify input data with the highest predictive value for the LSTM, GRU, MLP, and ANFIS models.
content while minimizing redundancy. This approach ensures that the chosen input variables effectively capture essential aspects of renewable power production data, thereby improving the accuracy of forecasting models. By applying the MRMI feature selection technique, we enhance the performance and robustness of the LSTM, GRU, MLP, and

TABLE 1 CLASSIFICATION OF THE EVALUATED PAPERS

Ref.	Uncertain parameter	Prediction horizon	Feature selection	Model	Error
[30]	PV power	1 step ahead	×	naïve bayes algorithm- MLP-LSTM	MAPE index is between 8.76%
[31]	Wind power	1 step ahead	×	Temporal convolutional network	RMSE index is between 87.9475 to 100.0070 for three different data set
[32]	Wind power	1 step ahead	✓	ELM and BiLSTM models	MAPE index is between 5.34% to 35.07%
[33]	Wind speed	multi-step ahead	×	EEMD-Clustring-MLP	MAPE index is between 6.10% to 13.84%
[34]	Wind speed	multi-step ahead	×	Decomposition model-LSTM	MAPE index is between 5.62% for 12 hour ahead forecasting
[35]	Wind speed	1 step ahead	×	CNN-RNN	MAPE index is between 2.5481% to 6.0137%
[36]	Wind speed	multi-step ahead	×	CNN-BiLSTM	Performance is improved by 21% and 48%
[37]	Wind speed	1 step ahead interval forecasting	×	CEEMDAN-C-C feature selection-(MOGWO)-(MIMOLSSVM)	Coverage Probability (CP) is 6.73%
[38]	Wind power	1 step ahead	×	GWO-LSTM	MAPE index is 10.75% to to 18.24%
[39]	PV power	multi-step ahead	✓	Machine learning algorithms	RMSE index is 32 for random forest model
[42]	Wind speed	multi-step ahead	×	Hybrid model based on persistence model (PM)-AR-ARMA-ANN	MAPE is 34.28% for three step ahead forecasting
[43]	Wind speed and power	1 step ahead	×	Hybrid model based on RKF-FS-WT-ANN	MAPE is 3.6153%
[44]	Net load	multi-step ahead	×	CNN	RMSE index is 5.88
[45]	PV power	1 step ahead	×	ANN	RMSE index is 153.188

ANFIS models. The selected input data with the highest predictive value enable the models to focus on the most influential factors for RPPF. This contributes to more accurate and reliable predictions, facilitating better decision-making in areas such as energy planning, grid management, and renewable resource allocation. In summary, the MRMI feature selection technique makes a valuable contribution to the overall forecasting process, ensuring that the LSTM, GRU, MLP, and ANFIS models are equipped with the most relevant and non-redundant input data for accurate renewable power production prediction.

3- The paper presents a strong solution for predicting solar power generation in the next 24 hours. It introduces a reliable method that can be applied effectively to RPPF. This method is versatile and can be used for various renewable energy sources, such as wind and solar power. By forecasting power production for the next 24 hours, it provides valuable insights for energy grid operators, renewable energy developers, and policymakers. In summary, this paper offers a comprehensive and effective approach for RPPF, especially for predicting solar power generation. Using hybrid models, feature selection techniques, and a 24-hour prediction horizon, it serves as a valuable tool for improving energy planning, grid management, and the utilization of renewable energy.

The rest of the paper is organized in the following manner. In Section 2, we provide an overview of the framework used in the proposed method. The methodology of the proposed model is explained in detail in Section 3. Finally, in Section 4, we present the numerical results obtained from the study.

II. Methodology

Using the aforementioned hybrid model, the day-ahead prediction is obtained from the weighted sum of the outputs of each proposed prediction model. The presented hybrid model

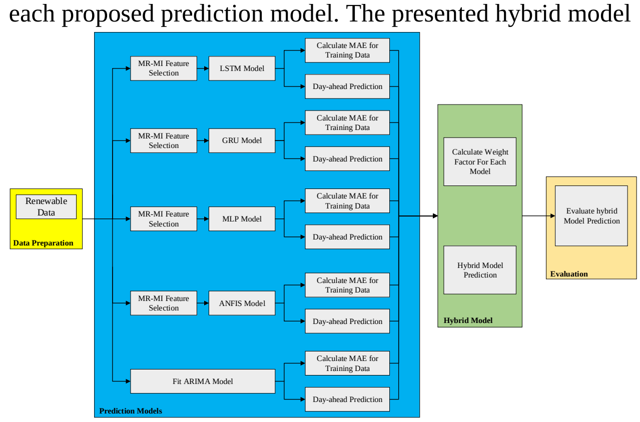

Fig. 1. Framework of the proposed hybrid model

significantly enhances the accuracy of RPPF. Combining multiple models allows each to compensate for the others' weaknesses, thereby improving forecasting efficiency. To implement the hybrid model, input data with the highest importance values are selected for LSTM, GRU, MLP, and ANFIS models using the MRMI feature selection method. These models then predict renewable power production for the next 24 hours. Unlike the other models, ARIMA does not undergo feature selection but establishes a relationship between input and output. Finally, the hybrid model's output is determined by applying appropriate weighting factors to the individual model outputs.

The framework of the proposed method is illustrated in Figure 1.

Here are the specific details of the proposed method.

Data preparation:

First, historical data is collected and standardized during the initial phase. Next, to forecast a particular day, the artificial intelligence models prepare training and target matrices. The training matrix has dimensions of 1200 by 400, while the target matrix is 1200 by 1. Specifically, training samples are selected up to the day preceding the last day of each month for which a prediction is needed. The ARIMA model, in contrast, operates as a statistical model for time series, representing the current series as a linear combination of past observations.

Prediction models:

The artificial intelligence models utilize the MRMI feature selection module to choose training samples with the highest predictive value. This MRMI method helps identify data with the potential to accurately predict outcomes. Conversely, the ARIMA model aims to establish a relationship between input and output variables. Specifically, the ARIMA model attempts to fit a model based on the historical time series data available before the prediction day. The Mean Absolute Error (MAE) value is calculated for each prediction model using the training data. This calculation determines the weight coefficient of each model in the hybrid model. Furthermore, each prediction model generates forecasts for the next 24 hours.

Hybrid model:

In this model, the weight coefficient for each prediction model within the hybrid model is determined using the method described in Section 3.7. The weight coefficient quantifies the importance or contribution of each model to generating accurate predictions. By multiplying each model's weight coefficient by its respective prediction output, the hybrid model produces forecasts for the next 24 hours. This combination of weighted predictions from multiple models enhances the overall forecasting accuracy of the hybrid model.

Evaluation

It is essential to evaluate the performance of the implemented method using key metrics. The efficiency of the hybrid model is validated by three error indices: Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). These established metrics provide objective measures to assess the precision of forecasting models. The error indices defined by Equations (1), (2), and (3) are used to measure the performance of the hybrid model. These metrics enable the evaluation of the hybrid model's accuracy in forecasting renewable power production over the next 24 hours. Analyzing these measures is crucial for assessing the reliability and efficiency of the proposed approach. Analyzing these measures is essential in assessing the reliability and efficiency of the proposed approach.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|S_i^{Real} - S_i^{For}\right|}{S_i^{Real}} \times 100\% \quad (1)$$

$$MAE = \frac{1}{N}\sum^{N}\left|S_i^{Real} - S_i^{For}\right| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i^{Real} - S_i^{For})^2} \quad (3)$$

Where N represents the total number of hours in each day, S_i^{Real} is the real value at the time i, S_i^{For} is the predicted value at the time i.

III. Problem description

A. MRMI feature selection approach

In this section, we propose the MR-MI approach to select the most suitable features. Feature selection is a widely employed method in machine learning, where a subset of the available data features is chosen for use in the learning algorithm. The forecasting process often requires a large amount of input data, including historical data. However, this data might contain unnecessary inputs that complicate the prediction of power system parameters, leading to decreased performance. Additionally, as the number of input features increases, more historical data is generally needed. However, the available historical data for forecasting is often limited. Therefore, it is essential to use a feature selection method to refine potential inputs, ensuring that only the most informative features are selected while filtering out less important ones. In this paper, we propose a feature selection method that begins by examining the similarity between input and output. Any candidate features showing only slight similarity to the target are discarded. Then, for each selected input from the previous step, if two inputs are closely related, one is chosen and the other is removed. In other words, the remaining features after these two steps are relevant and non-redundant candidates.

B. LSTM model

The study proposes using an LSTM network consisting of two layers, each with 100 hidden units. This design effectively captures complex behaviors and relationships within the data, leading to improved prediction performance. The LSTM has a unique advantage in its ability to preserve information across longer time sequences, making it particularly useful for forecasting time-series data, such as renewable power production. By retaining contextual information, the model can make accurate predictions for the following 24 hours. The chosen configuration strikes a balance between model complexity and computational efficiency, demonstrating the effectiveness of deep learning techniques in accurately forecasting renewable power production [46].

C. GRU model

The GRU offers an alternative to the more intricate LSTM model, providing a streamlined architecture with fewer trainable parameters [47]. The GRU incorporates two gates—the reset gate and the update gate—in contrast to the three gates in the LSTM, namely, the input gate, the forget gate, and the output gate. Unlike LSTM units, GRU gates do not have dedicated memory cells within each unit, resulting in a less complex architecture. Consequently, GRU models typically exhibit higher runtime efficiency compared to LSTM models. In this research, we propose using a GRU network with two layers, each containing 100 hidden units. By configuring the network with multiple layers and a sufficient number of hidden units, the GRU model can effectively capture complex patterns and relationships in the data. Although the GRU has a simpler structure than the LSTM, it still performs robustly in handling temporal dependencies and making precise predictions. The use of two layers with 100 hidden units ensures reliability without overburdening computational resources. The simplified architecture of the GRU network, combined with the chosen configuration, facilitates efficient training and prediction for RPPF. In summary, this study demonstrates the effectiveness of alternative recurrent neural network architectures, such as GRU, in capturing temporal dependencies and making accurate predictions. GRU's reduced complexity, computational benefits, and ability to handle sequential data make it a valuable tool for tasks like forecasting renewable power production.

D. MLP model

Artificial neural networks are computational models that mimic the operation of the human brain, consisting of interconnected neurons. In this study, we have utilized a MLP neural network, trained using the Levenberg-Marquardt (LM) learning algorithm. The LM algorithm is widely acknowledged as a highly efficient and effective learning mechanism for MLP models. The specific MLP neural network employed in this research adopts a feed-forward structure, where information flows unidirectionally from the input layer to the output layer. The model comprises two layers: the input layer, which receives the input data, and the output layer, which generates predictions. Additionally, hidden layers can be integrated between these two layers to capture intricate patterns and relationships within the data. Many applications opt for a two-layer MLP architecture because it strikes a balance between model complexity and learning capacity. However, it is important to note that the specific architecture and number of hidden units in each layer may vary depending on the complexity of the problem. In this study, the chosen architecture and configuration are determined based on the requirements and characteristics of the RPPF task. By utilizing MLP neural networks and the LM learning algorithm, this paper aims to harness the computational power of artificial neural networks to effectively learn and model the relationships between input variables and the desired output. The combination of MLP and LM provides a reliable and efficient approach for capturing complex patterns and making accurate predictions in RPPF.

E. ANFIS model

ANFIS is a hybrid artificial neural network model that integrates the principles of fuzzy logic and neural networks [48]. The ANFIS model combines the ability of fuzzy logic to handle linguistic rules with the powerful learning capabilities of neural networks. This fusion allows ANFIS to effectively capture and model complex relationships within the data. In this paper, the ANFIS network is utilized to enhance the performance of the forecasting model. The main parameters of the ANFIS network include the fuzzy inference system generation method, set to Fuzzy C-Means clustering (FCM), and the number of clusters, set to 10.

F. ARIMA model

The ARIMA function generates an ARIMA object that defines the functional form and stores the parameter values of an ARIMA*(p,D,q)* model for analyzing a univariate time series data, denoted as y_t [49]. The ARIMA model considered in this paper is represented by the following form:

$$\begin{aligned}(1-\varphi_1 L-\varphi_2 L^2-\cdots \\ -\varphi_{24}L^{24})(1-L)^2 y_t \\ = c \\ +(1+\theta_1 L+\theta_2 L^2 \\ +\cdots+\theta_{24}L^{24})\varepsilon_t\end{aligned} \tag{4}$$

Where, φ is parameter of non-seasonal autoregressive model, L is difference operator, c is model constant, θ is parameter of non-seasonal moving average model, and ε_t is the random variable.

G. Hybrid model

The paper presents a hybrid model that combines multiple prediction models to improve the accuracy of RPPF. This approach leverages the distinct strengths of each model while addressing their limitations, resulting in a forecasting technique that is both more effective and reliable. Traditionally, hybrid models assign equal weight coefficients to each prediction model, regardless of their performance, which can lead to suboptimal results. In this paper, we propose a new method where different weight coefficients are assigned to each model based on their MAE values. The MAE is calculated using the training results of each model, and the weight coefficients are determined through a specific equation.

$$\omega_i = \frac{\frac{1}{MAE_i}}{\sum_{i=1}^{n} \frac{1}{MAE_i}} \tag{5}$$

Where, ω_i is the weight coefficient of each prediction model, and n is the number of prediction models. Now that the weight coefficient of each prediction model is determined, the prediction of the hybrid model for the next 24 hours is calculated from the following equation:

$$Y_{Hybrid} = \sum_{i=1}^{n} \omega_i * y_i \tag{6}$$

Where, Y_{Hybrid} is the prediction of hybrid model for next 24 hours, and y_i is the result of *ith* prediction model for next 24 hours.

TABLE 2 RESULTS OF DIFFERENT PREDICTION MODELS FOR DAY-AHEAD PVPF FOR MAHAN PV POWER PLANT

Prediction model	Last day of March			Last day of June			Last day of September			Last day of December		
	MAE (MW)	RMSE (MW)	MAPE (%)	MAE (MW)	RMSE (MW)	MAPE (%)	MAE (MW)	RMSE (MW)	MAPE (%)	MAE (MW)	RMSE (MW)	MAPE (%)
ARIMA	0.5118	0.0910	24.5340	0.5343	0.6968	7.7187	0.0943	0.0619	7.5581	0.3935	0.1592	45.6098
MRMI-MLP	0.6582	0.5349	28.8859	0.7004	0.8772	7.2929	0.0454	0.1311	1.1040	0.4385	0.3412	54.9586
MRMI-ANFIS	0.7382	0.4848	30.5026	0.5116	0.6683	7.4918	0.1302	0.0722	2.6813	0.2185	0.1524	21.9730
MRMI-GRU	0.4280	0.0104	15.4680	1.1261	1.3156	12.8132	0.1240	0.0378	7.4690	0.2680	0.1297	25.4004
MRMI-LSTM	0.6975	0.5031	27.5882	0.9203	1.2134	10.2564	0.0537	0.0050	2.9719	0.1895	0.1355	19.1905
Hybrid model	**0.3376**	**0.0809**	**13.7206**	**0.1941**	**0.1291**	**7.3995**	**0.0811**	**0.0388**	**4.2464**	**0.1747**	**0.0468**	**29.4023**

IV. Simulation results

This section focuses on assessing the efficiency of the hybrid model in forecasting renewable energy generation, specifically for PV power production. To ensure the precision and effectiveness of the hybrid model, a variety of datasets are employed. Initially, historical solar production data from the Mahan and Rafsanjan photovoltaic power plants for 2020 are used to forecast future solar production. The study includes two case studies, each using distinct solar data to thoroughly evaluate the capabilities of the proposed hybrid model. To assess the proposed techniques, we utilized MATLAB R2020b, a widely used programming platform renowned for its applications in scientific research and data analysis. The goal of this study is to provide a comprehensive understanding of the hybrid model's efficiency and usability in forecasting renewable power production. To achieve this, we used real datasets and implemented the model on a well-established software platform.

A. PVPF of Mahan PV power plant

In the first case study, we performed day-ahead photovoltaic power forecasting (PVPF) using hourly data from the Mahan PV power plant. To evaluate the effectiveness of our method, we selected the last days of March, June, September, and December 2020 for analysis, consistent with the approach used in our previous case studies.

Table 2 presents the results of various prediction models for day-ahead photovoltaic power forecasting (PVPF). In this case study, six models are considered: ARIMA, MRMI-MLP, MRMI-ANFIS, MRMI-GRU, MRMI-LSTM, and the hybrid model. The results in Table 2 indicate that the hybrid model performs well in PVPF, demonstrating its capability to forecast PV power production with acceptable accuracy. The error indices further support this claim, as the hybrid model exhibits the best performance among the forecasting models on the last day of March. In contrast, the other methods do not outperform the hybrid model on that day. This underscores the limitations of relying solely on a single model for predicting different days with varying characteristics. Utilizing a hybrid model enhances the reliability and accuracy of the predictions, making it a preferable approach. The weights assigned to each model in the hybrid model are detailed in Table 3.

TABLE 3 WEIGHT COEFFICIENT OF EACH PREDICTION MODEL FOR MAHAN PV POWER PLANT

Month	ω_{ARIMA}	ω_{MLP}	ω_{ANFIS}	ω_{GRU}	ω_{LSTM}
Last day of March	0.208	0.113	0.296	0.098	0.285
Last day of June	0.241	0.106	0.311	0.087	0.255
Last day of September	0.2	0.1	0.3	0.1	0.3
Last day of December	0.261	0.102	0.275	0.107	0.254

The results of different seasons of the year have been compared. To use the results of the mentioned paper, the average MAPE error of different months for a season has been selected.

The graph in Figure 2 shows actual and predicted solar power generation at the end of each month using different models.

TABLE 4 MAPE ERROR OF DIFFERENT MONTHS

Prediction model	Spring	Summer	Autumn	Winter
MRIG-LSTM [50]	40.6012	18.5967	39.0396	35.5622
WT-MRIG-LSTM [50]	16.4554	7.6746	18.3332	17.8109
WT-MRIG-ELM [50]	14.3944	8.8431	25.4246	9.5635
ARIMA	24.5340	7.7187	7.5581	45.6098
MRMI-MLP	28.8859	7.2929	1.1040	54.9586
MRMI-ANFIS	30.5026	7.4918	2.6813	21.9730
MRMI-GRU	15.4680	12.8132	7.4690	25.4004
MRMI-LSTM	27.5882	10.2564	2.9719	19.1905
Hybrid model	13.7206	7.3995	4.2464	29.4023

. It is evident that the forecasts exhibit a higher margin of error, particularly during the final days of December and March, due to the highly variable weather conditions in these months compared to earlier days. It is important to note that all the models analyzed in the study focus solely on solar power production and do not account for other influencing factors. Despite this limitation, the hybrid model demonstrates reliability in predicting solar power generation for the following day. Its performance is commendable given the complex and fluctuating weather conditions during these months.

Figure 3 displays regression plots of different prediction models for the last day of December. In addition to the previously mentioned indexes, R2 has also been used to demonstrate the effectiveness of the proposed method for PVPF. The graph shows that the MRMI-LSTM prediction model has the highest R2 value. However, the hybrid model's R2 value is not significantly different from the MRMI-LSTM model. This suggests that the hybrid model performs well in accurately forecasting the PV power production, as the forecasted and real values are very close to each other. In conclusion, the previously mentioned methods are capable of effectively forecasting PV power production for the Mahan PV power plant.

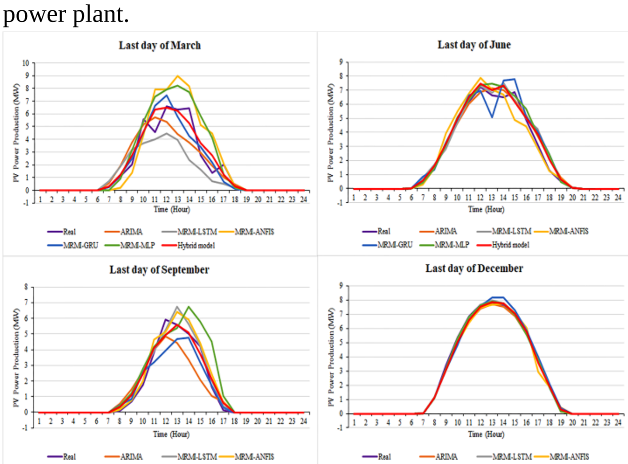

Fig. 2. Assessing various prediction models for Mahan PV power plant

B. *PVPF of Rafsanjan PV power plant*

In the second case study, hourly PV power production data from the Rafsanjan PV power plant in 2020 is used for day-ahead photovoltaic power forecasting (PVPF). The Rafsanjan PV power plant has a nominal capacity of 1.2 MW. As in the previous case studies, the last days of March, June, September, and December 2020 are selected for forecasting day-ahead PV power production using the proposed method.

Table 5 presents the results of different prediction models for day-ahead PVPF, similar to the previous case studies. The results clearly show that the hybrid model performs well in forecasting PV power production, demonstrating acceptable accuracy and outperforming other models based on the error indices. For example, on the last day of September, the MRMI-MLP model shows the best performance among the different forecasting models. However, the hybrid model performs comparably to the MRMI-MLP model and surpasses other methods. This underscores the limitations of relying solely on a single model for predicting days with varying characteristics. The use of a hybrid model improves the reliability and accuracy of the predictions. The weights assigned to each model in the hybrid model are detailed in Table 6.

Figure 4 illustrates the results for each month using different models. It is evident that the forecast error is relatively higher on the last days of December and March. These days are characterized by changing weather conditions, where factors such as temperature, radiation, and cloud cover significantly impact the forecasts. Despite these challenges, the hybrid model demonstrates its effectiveness in predicting day-ahead PV power production. The error values obtained from this method are within an acceptable range, indicating both accuracy and reliability.

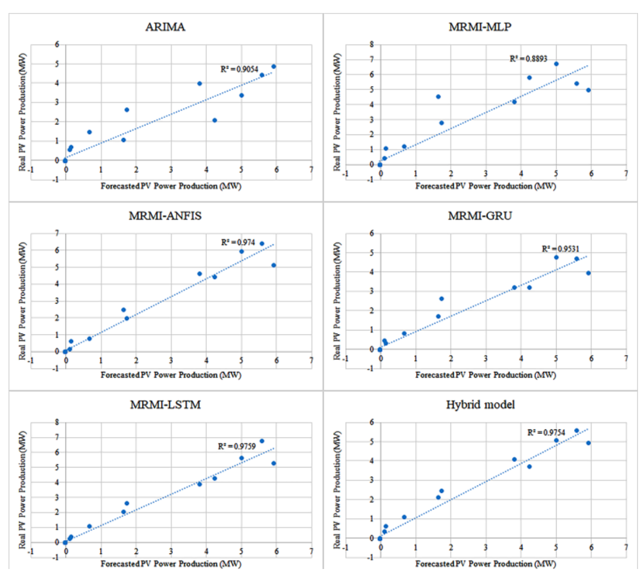

Fig. 3. Regression plot for the final day of December at the Mahan PV power plant

It is also worth noting that the day-ahead forecast relies heavily on the hybrid model, which greatly contributes to the precision of the predictions. This underscores the importance of using the hybrid model to achieve accurate day-ahead forecasts.

Figure 5 shows the R^2 index used to measure accuracy for the final day of December across different prediction models. Among the models considered, the MRMI-ANFIS prediction model achieves the highest R^2 value, indicating a strong correlation between the forecasted and actual values. This suggests that the MRMI-ANFIS model is highly accurate and reliable. Overall, the results confirm that the proposed method is effective in accurately predicting the PV power production for the Rafsanjan PV power plant.

I. Conclusion

In this paper, a hybrid model called RPPF is introduced, combining multiple forecasting models—ARIMA, MRMI-MLP, MRMI-ANFIS, MRMI-GRU, and MRMI-LSTM—to improve day-ahead predictions. By leveraging the strengths of these models and mitigating their weaknesses, the hybrid approach enhances forecasting accuracy and efficiency.

The MRMI technique is employed within the hybrid model to select the most predictive input data for the LSTM, GRU, MLP, and ANFIS models. To evaluate the model's performance, two case studies are conducted on PV power production in Mahan and Rafsanjan for the year 2020.

The results demonstrate that the hybrid model achieves satisfactory accuracy, as indicated by metrics like MAPE, MAE, and RMSE. These findings not only validate the effectiveness of the hybrid model but also highlight its potential for reliable and efficient forecasting of renewable power production. Future research could explore the applicability of this approach in other sectors of the energy system and consider additional factors that may impact the forecasting process. Additionally, prediction accuracy could be further improved by combining these methods within a closed-loop framework.

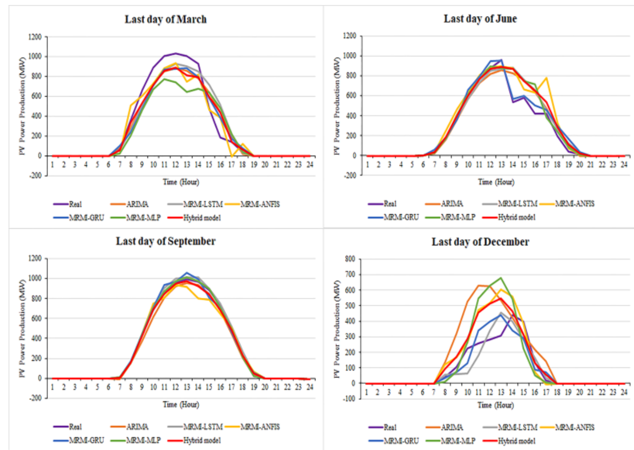

Fig. 4. Assessing various prediction models for Rafsanjan PV power plant

TABLE 5 RESULTS OF DIFFERENT PREDICTION MODELS FOR DAY-AHEAD PVPF FOR RAFSANJAN PV POWER PLANT

Prediction model	Last day of March			Last day of June			Last day of September			Last day of December		
	MAE (kW)	RMSE (kW)	MAPE (%)	MAE (kW)	RMSE (kW)	MAPE (%)	MAE (kW)	RMSE (kW)	MAPE (%)	MAE (kW)	RMSE (kW)	MAPE (%)
ARIMA	61.4656	20.6792	16.8260	48.5279	23.6963	22.5864	20.3033	19.7646	14.4021	77.5209	68.9528	67.3614
MRMI-MLP	95.3771	51.4258	22.0480	44.7761	33.7007	15.6763	5.4595	0.9276	4.7864	61.6852	34.4639	28.3559
MRMI-ANFIS	60.3823	23.8531	26.5322	61.3149	55.6033	19.2720	26.3523	15.3333	17.1840	48.3347	39.7238	32.1484
MRMI-GRU	60.2453	25.8259	18.6621	27.3876	24.4896	30.4020	16.0709	4.5092	15.7852	31.8057	0.0912	22.3722
MRMI-LSTM	63.3539	9.7691	17.8139	49.0751	32.8670	27.3831	13.7650	12.3796	15.2571	29.4512	7.0599	16.5769
Hybrid model	56.2347	23.5854	14.5869	46.7227	39.9648	19.3358	10.4980	7.4080	7.4487	41.4546	34.3694	27.6639

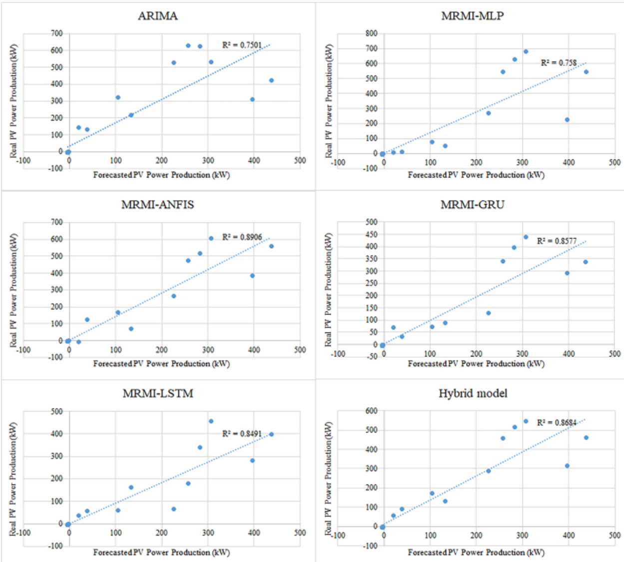

Fig. 5. Regression plot for last day of December for Rafsanjan PV power plant by different prediction models

TABLE 6 WEIGHT COEFFICIENT OF EACH PREDICTION MODEL FOR RAFSANJAN PV POWER PLANT

Month	ω_{ARIMA}	ω_{MLP}	ω_{ANFIS}	ω_{GRU}	ω_{LSTM}
Last day of March	0.260	0.132	0.249	0.111	0.248
Last day of June	0.218	0.101	0.302	0.106	0.273
Last day of September	0.194	0.120	0.283	0.099	0.304
Last day of December	0.205	0.115	0.311	0.101	0.268

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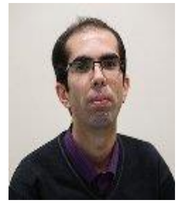

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