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A hybrid adaptive neuro-fuzzy inference system and reptile search algorithm model for wind power forecasting

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ABSTRACT

Estimating the number of wind ranches generated in the upcoming minutes, hours, or days is the focus of wind power forecasting. Deep learning has garnered a lot of interest in wind control estimation because of how well they perform classification, grouping, and recurrence. The adaptive neuro-fuzzy inference system was successfully applied in wind power forecasting. However, its performance relies on optimal selection of hyperparameters. This study introduces a novel predictive model by incorporating the reptile search algorithm with adaptive neuro-fuzzy inference system (ANFIS) for short-term wind power forecasting. It employs reptile search algorithm (RSA), known for adjustable parameters, disentangled search, and consistent outcomes, to optimize ANFIS's hyperparameters. Additionally, via exploitation during training, RSA performs a selection of best features in the dataset that contributes to the classification accuracy of ANFIS. This aims to enhance precision of the anticipated yield. Employing authentic wind power data from Jordan is undertaken to evaluate efficiency. The performance is compared with alternative techniques, including artificial neural networks, random forests, and support vector machines. Findings showed that ANFIS-RSA performs competitively for the well-known Chinese benchmark dataset (99.9% accuracy; 0.99 R^2; 10.54 MAE; 11.62 RMSE) and is more robustly accurate than others over the Jordanian dataset (0.84.6% accuracy; 0.96 R^2; 0.098 MAE; 0.203 RMSE).

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1. INTRODUCTION

In recent times, researchers have increasingly focused on wind energy sources, attracted by their advantages in comparison to other forms of energy, such as fossil fuels. However, a drawback of wind energy is its reliance on weather conditions for the effective operation of wind farms. Therefore, accurate prediction of wind power becomes highly significant for optimizing the utilization of potential renewable energy sources. Many works have invested a great deal of time and energy into improving wind power forecasting methods by combining statistical and physical methods. Physical methods, like the numerical weather prediction model, employ rules regulating atmospheric behavior to anticipate local wind speed and direction based on weather data [1]. On the other hand, statistical methods minimize the difference between predicted and observed values by utilizing large amounts of historical data and optimizing model parameters. Statistical-based models are the best choice for short-term wind power forecasting because they are less expensive to acquire and process than mathematical weather prediction data [2], [3]. Several statistical methods have been suggested for projecting wind power in the near future. Time series techniques were the focus of early methodologies, as [4], [5] have shown. However, these approaches face several significant drawbacks, one of which is their lack of accuracy [6].

Lately, conventional deep learning-based methods like artificial neural network (ANN) [7], decision tree (DT) [8], arbitrary timber [9], and utilization of adaptive neuro-fuzzy inference system (ANFIS) in wind power forecasting have been extensive [10]. Although conventional deep learning methods are typically computationally straightforward, their capacity to extract complex features and attain high prediction accuracy is typically constrained [11]. Many improvements have been made in the literature [12] but it was limited to some performance measures/evaluation metrics (*e.g.*, prediction accuracy and/or root-mean-square error (RMSE)). Therefore, this study aims to utilize the simplicity of implementing the ANFIS model while improving the forecasting accuracy using a powerful optimizer, namely, the reptile search algorithm (RSA). The RSA can efficiently exploit the hyper-parameters of the ANFIS for an effective feature selection process, which eventually may lead to a robust and accurate performance of the forecasting model.

The motivation behind introducing ANFIS-RSA in this study lies in the desire to enhance the performance of the ANFIS model and rectify the issue of low accuracy arising from the unstable selection of its hyperactive parameters. This need was addressed by numerous optimization methods proposed in the literature. According to Amroune [3], traditional approaches such as grid search and gradient descent were employed to optimize the hyperparameters of a forecasting model, such as support vector machine (SVM). Still, they proved unfit to perform large-scale computations with high precision. Many studies including [3] recommended dealing with this problem by considering metaheuristics (*e.g.*, nature-inspired algorithms including particle swarm optimization) which are more stable and robust the wind power forecasting. The use of a metaheuristic leads to the optimization of a model's hyper-parameters to increase the forecast accuracy.

However, it is worth noting that the performance of such metaheuristics with multiple parameters can influence the efficiency of the forecasting model. Hence, it is important to select a metaheuristic carefully considering the number of parameters (*e.g.*, involved in the space exploration mechanism) as well as the structure of internal mechanisms (*e.g.*, local search method). This may affect the optimization of the hyper-parameters of the model (*e.g.*, ANN). Moreover, Liu *et al.* [12] highlighted three main drawbacks associated with swarm optimization algorithms, which include concerns related to parameter tuning, initialization process, and boundary issues.

Abualigah *et al.* [13] suggested a model that employs RSA for fine-tuning the hyperparameters of the ANFIS model, aiming to enhance its prediction accuracy. The performance assessment of the developed wind power forecaster involves the utilization of real-life wind farms in Jordan and standardized Chinese benchmark datasets, such as Hexi Corridor. This is then compared to results obtained with other existing models of forecasting: decision tree (DT), random forest (RF) or linear regression (LR) and/or hybrid approaches.

The primary goal and contributions of this study are summed up as follows: i) Present an enhanced ANFIS model incorporating the use of RSA for optimizing ANFIS hyper-parameters, thereby enhancing prediction efficiency; ii) Apply the developed ANFIS-RSA model for short-term wind power forecasting using historical datasets obtained from wind farms in Jordan and China; iii) Evaluate and analyze the predictive performance of the suggested ANFIS-RSA model using metrics such as correlation coefficient (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), and root-mean-square error (RMSE); and iv) Compare the accuracy of the proposed model with alternative techniques. This paper is structured as follows. Section 2 provides the background for the approaches. The general framework of the proposed forecasting model is presented in section 3. Section 4 includes comparisons and simulation results. Finally, section 5 concludes with key findings.

2. LIERATURE REVIEW

This section will highlight the recent developments of several forecasting models with their weaknesses and limitations, which are used by various researchers. Then, the development of a novel forecasting model will consider those weaknesses and limitations in terms of wind characteristics, accuracy, and stability. The main point of starting this project is to refer to the literature to find the most recent works and how we can support our arguments regarding the forecasting model in this research. As we found, there are many models in the literature. The models have not reached the best accuracy value in the forecasting process, particularly for the wind power problem.

2.1. ANFIS prediction models for wind power forecasting

Several recent and interesting publications have implemented the prediction of wind power forecasting and other related concepts. This subsection tackles only the implementation of the traditional ANFIS prediction model as well as the enhanced versions of the model by incorporating the optimization process for data dimensionality reduction (*aka* feature selection). Which has a great impact on high-accuracy predictions; that is our research has been inspired by the sufficient concept of incorporating ANFIS and an optimization algorithm. Some examples from the literature are the following.

In the studies of [14], [15], the authors concentrated on forecasting wind turbine output power by incorporating wind speed and operational features. They employed an ANFIS model with multi-source data fusion on a dynamic window, conducting computational analyses on time series window datasets derived from a wind farm in Mauritania with a 30-moving window. Their model gained superior predictions compared to nonparametric models and other similar machine and deep learning techniques from the literature. In summary, their findings suggested that the prediction model shows promise in accurately estimating output, contributing to enhanced sustainability through improved control of wind turbine operations.

With encouraging outcomes, Kaysal *et al.* [16] used the conventional, stand-alone version of ANFIS to forecast Turkey's electrical load. Laouafi *et al.* [17] discussed neuro-fuzzy systems, wavelet packet decomposition principles, the advantages of data preprocessing, and forecast combination frameworks for wind power forecasting. The suggested approach is utilized to guarantee forecasts for a time horizon of one hour ahead of time, using quarter-hourly measurements of wind power generation in France as the source of data. The results show that the suggested model is more accurate than others with an average MAPE of 3.408%.

2.2. Other prediction models for wind power forecasting

Several recent and interesting publications have implemented the prediction of wind power forecasting and other related concepts. This subsection discusses only the implementation of the other prediction models than ANFIS as well as the enhanced versions using well-known optimizers. Some examples from the literature are the following.

Xiong *et al.* [18] proposed a hybrid prediction model consisting of a shuffled frog leaping algorithm with a backpropagation neural network for short-term prediction of wind power forecasting. Their model is based on a gradient descent algorithm for search space exploration to improve the accuracy score of the neural network. They tested their prediction model on a Chinese wind power forecasting dataset. Their model showed a better performance than other models including backpropagation, gated recurrent unit (GRU), and long short-term memory (LSTM) in terms of accuracy, stability, and efficiency. Similar work with more optimization efforts based on aquila optimizer with LSTM was proposed by Zheng *et al.* [10].

Amroune [3] proposed two hybrid models, a hybrid support vector regression gray wolf optimization algorithm, and a hybrid support vector regression (SVR) and manta ray foraging optimizer. The two hybrid models outperformed several traditional models and other hybrid models including the particle swarm optimization. In study [19], a hybrid improved cuckoo search algorithm (HICS) is proposed to optimize the hyperparameters of the support vector regression machine, employed for short-term wind power output prediction (HICS-SVR). The suggested HICS-SVR showed greater capacity to forecast short-term wind power output in comparison to previous SVR variations. The HICS-SVR does, however, have several drawbacks, such as its intricate structure. Other worthy approaches with the same advantages (*e.g.*, speed) and limitations (*e.g.*, model’s overfitting) are proposed by Shahid *et al.* [20] and Xia and Wang [21]. All of these have been applied to the Hexi Corridor Chinese dataset.

For more information and recent advances in prediction for wind power, please refer to [22]–[27]. They provided comprehensive systematic reviews of statistical and machine learning and deep learning methods for wind power forecasting. Other useful readings of wind farm and resource datasets are found in [28], [29].

3. METHOD

3.1. Data collection

In this research, the proposed forecasting model will be tested on a benchmark dataset for the wind power forecasting problem to prove its ability. Moreover, the proposed model will be further applied to a real dataset from different sources to illustrate its effectiveness in real power generation. To ensure better generalization, a cross-validation approach is applied. The input data is randomly divided into two portions for the cross-validation process: training and validation (testing). The data's training portion is used to train the network. The validation data collection authenticates the network and controls network design settings.

3.2. Adaptive neuro-fuzzy inference system

The ANFIS model is a combination of neural networks and fuzzy systems, which includes time series prediction and forecasting. This model is considered the best and most efficient forecasting model in the literature [10]. The "IF-THEN" rules are used in the fundamental framework of ANFIS to generate mapping inputs and outputs. Fuzzy variables at the model's input and output are necessary for creating an ANFIS model for a dynamic process, as Figure 1 illustrates. Through the fuzzification process, the fuzzy variables take advantage of past knowledge about the physical behaviors of the system. Where $L1_i$ is the node, *I* output and *x* and *y* are the layer 1 inputs.

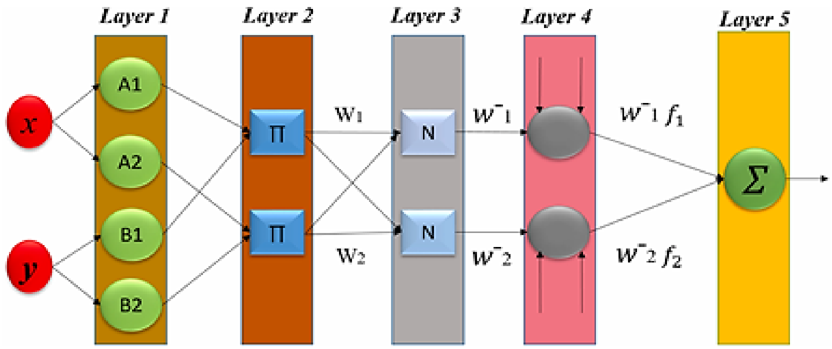

Figure 1. The original ANFIS structure [10]

The main model of ANFIS is described as (1)-(4):

$$L1i = \mu A_i(x) \quad (1)$$

$$i = 1, 2, \ldots., L1_i = \mu B_i - 2 \quad (2)$$

$$i = 3, 4 \quad (3)$$

$$\mu(x) = e^{((x-p_i)/a_i)2} \quad (4)$$

Here, A_i and B_i are the membership values of μ, and refers to the generalized Gaussian membership function. Furthermore, the premise parameter set is denoted by a_i and p_i. The result of layer 2 is calculated as (5).

$$L2i = \mu A_i(x) * \mu B_i - 2(y) \quad (5)$$

The result of layer 3 is calculated as (6).

$$L3i = w_i = (w_i / sum\ (w_i)\ ) \quad (6)$$

After choosing the input and output variables, as well as the collection of related data, the initial step in developing the model is to create a set of primary members by ANFIS. For more information on ANFIS structure and formulations please refer to [30].

As was previously mentioned, ANFIS is composed of multiple layers, with nodes in each layer carrying forward fuzzy parameters. Fuzzy inference systems (FIS) with distributed parameters are comparable to this. It employs a backpropagation technique to adjust fuzzy parameters and splits previous information into subcategories to minimize search space. An adaptive neural network with a linear input-output relationship is the final predictive model. The ANFIS structure typically consists of five distinct layers:

a. Layer 1 involves fuzzification, wherein inputs are classified using adjustable fuzzy membership functions (MFs) such as Gaussian-shaped ones. To build the ANFIS model, the input and output data are partitioned into rule patches using fuzzy c-mean (FCM). FCM, a widely used fuzzy logic clustering method, partitions input data into clusters essential for fuzzy logic. It determines the center of each cluster, facilitating subsequent operations on the data.

b. Layer 2 involves rules, where the rule operator (AND/OR) is employed to obtain a single output representing the antecedent results for a fuzzy rule by multiplying the incoming signals. In essence, this layer determines the weights of the MFs.
c. Layer 3 known as normalization, serves as the interpolation layer, indicating the firing strength of a rule relative to the total firing strength of all rules.
d. Layer 4 defuzzification, carries out the execution of the output generated from rule inference, multiplying them with the Sugeno fuzzy rule's function.
e. Layer 5 cumulative, involves the application of the weighted average summation method for determining the network output.

3.3. Reptile search algorithm

Abualigah *et al.* [13] introduced the RSA, a revolutionary nature-inspired meta-heuristic optimizer inspired by crocodile hunting behavior as shown in Figure 2. Using well-known benchmark datasets that included classical functions and actual engineering challenges, the RSA was assessed. The assessment shows a better performance than various optimization algorithms in the literature. As all meta-heuristics are known to be vulnerable to early convergence towards local optima, the RSA has undergone a variety of improvements across different optimization problems by hybridization, modification, or parameter-turning approaches. Some examples of recent improvements are:
a. Hybrid RSA and slap swarm algorithm [31], [32] for medical image segmentation.
b. Enhanced RSA utilizing a multi-hunting coordination strategy for addressing global optimization problems [33].
c. Improved RSA for regression and classification problems [34], [35].
d. Boosted RSA for engineering problems [36].
e. Chaotic binary RSA and a feature selection method for classification problems [37].
f. Improved RSA for industrial engineering problems [38].
g. Enhanced RSA with simulated annealing for feature selection in the medical field [39].
h. RSA and remora optimization algorithm with quantum mutation for solving data clustering problems [40].
i. Modified RSA for numerical optimization problems [41].
j. Levy flight-based RSA with local search for power systems engineering design [42].

Chauhan *et al.* [43], [44] have conducted other applications of the traditional RSA such as optimization and prediction. The RSA is utilized as an enhancement strategy for other metaheuristics such as the hybridization of ant colony optimization with RSA for Churn prediction conducted by Al-Shourbaji *et al.* [45]. Most importantly, the RSA has been used to enhance the adaptive neuro-fuzzy inference system for relating swelling potentiality conducted by El Shinawi *et al.* [30] which also triggered our motivation to adopt their approach for the wind power forecasting problem.

As mentioned earlier, the RSA is a metaheuristic inspired by the movement patterns of reptiles in search of food. Generally, the RSA begins by randomly initializing a population of solutions, representing the individuals or parameters of a problem. Each solution is then evaluated based on the problem’s objective function. The RSA then applies a series of iterative updates to the solutions, which are based on the movement patterns of reptiles. The RSA has several advantages, making it a promising optimization algorithm for solving various optimization problems and machine learning applications. Some of these are:
a. Efficiency: it is simple and computationally efficient, which requires only basic mathematical operations. This makes it suitable for solving large-scale optimization problems with many decision variables (*e.g.*, feature selection in classification tasks).
b. Diversification: it incorporates a mechanism for diversifying the search process by introducing random perturbations to a subset of solutions. This helps avoid stagnation in local optima and enhances its global search capabilities.
c. Convergence: it has shown to converge to high-quality solutions converge quickly and effectively, even for complex and multimodal optimization problems. This is due to its ability to balance exploiting the best-performing solutions and exploring the search space.
d. Robustness: it is robust to noisy and uncertain objective functions and non-differentiable functions. This makes it suitable for solving real-world applications that often involve uncertainties and noise.
e. Flexibility: it can be easily adapted to different optimization problems by adjusting its parameter settings. This allows it to be applied to various optimization problems in various domains (*e.g.*, machine learning prediction models).

However, some drawbacks of the RSA are also concerned with improvements that may affect its performance. The main concern is premature convergence. The RSA reliance on the leader’s movement may cause the algorithm to converge prematurely to a local optimum, especially if the leader’s movement becomes stagnant. This may affect the algorithm's ability to explore the search space effectively and find the global optimum.

In technical terms, the RSA is elucidated concerning its exploration of the search space (referred to as global search) and exploitation of the solution space (referred to as local search) phases. These phases take inspiration from the social behavior, surrounding mechanics, and hunting techniques observed in real crocodiles [13]. The two primary stages of crocodile activity involve encircling (exploration), achieved through high walking or belly walking, and hunting (exploitation), accomplished through hunting cooperation or coordination.

According to Abualigah *et al.* [13], during the encircling phase, which is part of the RSA's exploratory behavior, crocodiles walk in two different ways while encircling and updating their position: high walking and belly walking. The RSA alternates between exploration and exploitation search stages based on different scenarios, such as dividing the total number of iterations into four parts or splitting the number of iterations into four segments. The exploration mechanisms, guided by two main search approaches, focus on the search space and methodology to identify improved candidate solutions. Throughout this search phase, a specific requirement must be met. On the other hand, the hunting phase involves searching around the solution's space where crocodiles use two hunting techniques while updating the position of crocodiles: hunting coordination and hunting collaboration, according to their hunting behavior. For a comprehensive discussion and detailed information on RSA structure and formulations including equations of the exploration and exploitation phases, please refer to [13].

3.4. The ANFIS-RSA prediction model

This study presents the ANFIS-RSA prediction model, where the ANFIS is assisted by the RSA to obtain a high accuracy of predictions for wind power forecasting. The RSA's exploration and exploitation abilities are utilized in the prediction model to diversify and/or intensify the learning process of the ANFIS. Figure 2 illustrates the complete procedure of the ANFIS-RSA prediction model for wind power forecasting.

In essence, the constructed prediction model aims to enhance ANFIS performance by incorporating RSA operators to determine the suitable ANFIS parameters. The complete procedure of the prediction model is outlined as follows:

a. Initialization phase:
   - Define parameters of RSA, mainly the β and α. In which, β is the exploration controller set to 0.005 only in the initialization phase, while α is the exploration controller (controls search accuracy) set to 0.1 only in the hunting phase to determine the difference between the best solution (*e.g.*, near-optimal at each iteration) found so far and the current solution.
   - The dataset undergoes preprocessing, involving its division into two sets: a training set (70%) and a testing set (30%), determined through experimental evaluation.
   - RSA begins with randomly generating an initial population of candidate solutions based on the dataset.

b. Training phase:
   - Initial configurations are generated to represent the RSA's population, with each configuration derived from the ANFIS settings. The training set undergoes training using the ANFIS model tailored specifically for that set.
   - Then, the quality (the predicted output of ANFIS model with the smallest fitness value) of each configuration (for each solution in the population) is evaluated by computing the fitness value defined as the RMSE.
   - RSA examines the stopping condition (*e.g.*, reaching maximum iterations). If the stopping condition is met, the training phase is terminated and the testing phase is executed. Otherwise, the RSA selects the best solution found so far, and then the RSA updates the population and repeats the training phase.

c. Testing phase: once the stopping condition is met, the testing phase is executed by considering the best configuration for the built ANFIS model to apply it to the testing set for the prediction process that will be evaluated based on the RMSE. The predictive model then terminates the whole process with the final prediction output.

The developed ANFIS-RSA predictive model seeks to enhance ANFIS performance by harnessing the search and iterative capabilities of the RSA. This involves tuning the MFs to achieve lower error rates and improve prediction quality in the ANFIS configuration. The RSA is employed in the learning stage (training phase) to identify suitable configurations (hyper-parameters) for the weights between layer 4 and layer 5 of ANFIS.

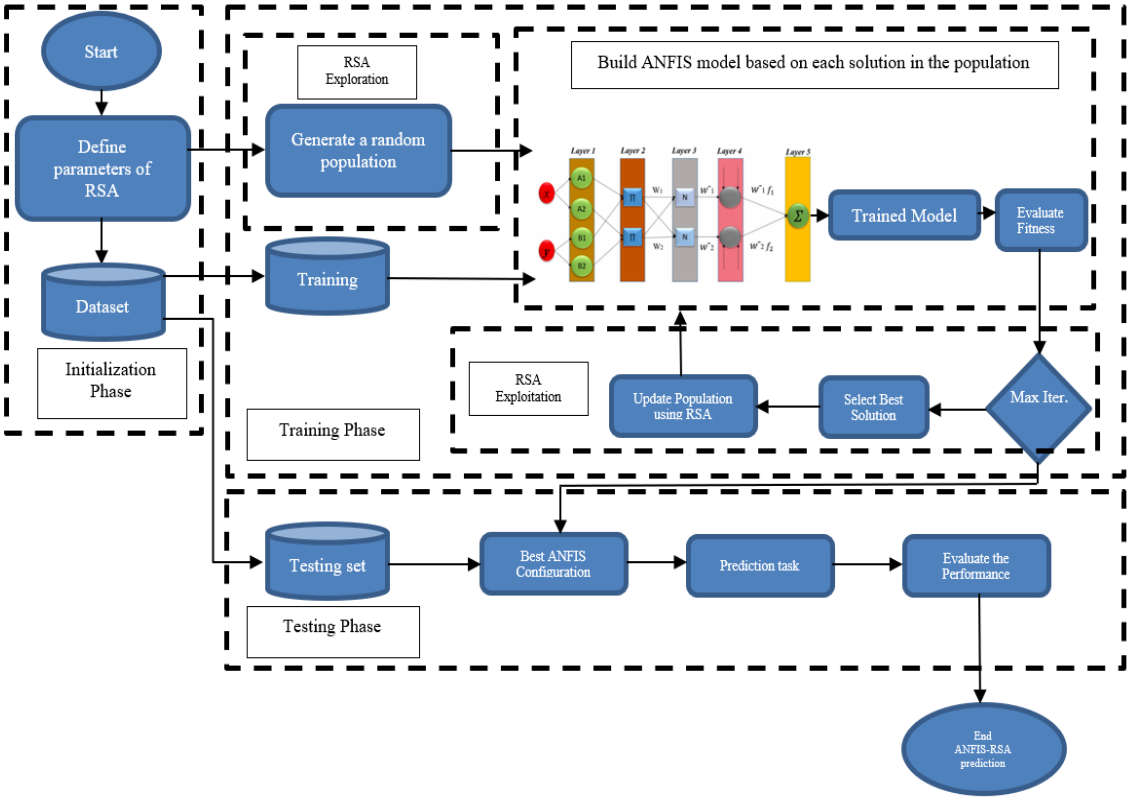

Figure 2. The proposed ANFIS-RSA prediction model

4. RESULTS AND DISCUSSION

It is expected to develop an efficient forecasting model using the proposed artificial intelligence optimization technique to efficiently deal with wind power forecasting. The targeted (unknown) results can benefit when using real data from Jordan and/or other countries. Also, improve the prediction performance of the benchmark data and models.

4.1. Description of datasets

The effectiveness of the hybrid ANFIS-RSA model was assessed using actual power generation data from wind farms in Jordan and an additional benchmark dataset, the Chinese (Hexi Corridor) dataset. The Jordanian dataset has limitations that make it partially unreliable for testing the proposed forecasting method. These limitations are due to the lack of information and details of the Jordanian wind farms and their observations, including hub temperature, active power rate, bearing shaft and gearbox oil temperature, blade pitch angle, and other attributes that might play a significant role in improving the accuracy of the forecasting task. It only consists of the information and readings of 13 turbines such as longitudes and latitudes, mast height, installation and termination dates, and wind speed monthly as well as yearly basis for 4 years in a row. Hence, the well-known Chinese dataset is considered for further experimentation toward robust and reliable testing and evaluation of the proposed forecasting model. The Jordanian dataset has few attributes that provide little information that may be exploited by the forecasting prediction model to obtain a high score of accuracy.

On the other hand, although it has 28.5% missing values, the Hexi corridor dataset has 19 out of 21 numerical attributes of high impact information that may lead towards high accuracy scores. Therefore, the idea behind a highly accurate and stable model is the ability to effectively employ a feature selection mechanism that eliminates fewer interesting attributes while exploiting few attributes yet potentially have an impact on improving the prediction accuracy. It typically has a variety of rotor, turbine, and weather characteristics. Data was collected between January 2018 and March 2020. Ten-minute intervals have been used to record readings.

4.2. Evaluation procedure and comparative methods

The commercial MATLAB R2020b software is used for the ANFIS-RSA model analysis on MS Windows 10 with an Intel Core-i7 CPU and 16 GB of RAM. The search methods employed in the proposed

RSA are distinctive and will be contrasted with those of other existing algorithms. There are several models published in the literature, and only highly successful models will be selected for the purposes of the comparisons. In this investigation, commonly associated standard statistical error metrics found in the literature, such as MAE, MAPE, RMSE, and R^2, are utilized to assess the predictive accuracy of the proposed model.

This study has conducted several traditional machine learning techniques to build a baseline accuracy score for the Jordanian benchmark that enables an efficient evaluation of the ANFIS-RSA model. Table 1 shows a comparison of the proposed model against machine learning models. Accuracy, precision, and recall are associated with evaluating the performance of classification tasks. They are used to measure the quality of predictions obtained by the models, especially when dealing with imbalanced datasets (*e.g.*, Jordanian dataset) where one class may be more prevalent than the other. However, in the context of forecasting, precision and recall are known to be indirectly applicable to forecasting tasks in many scenarios. Forecasting typically involves predicting continuous values (*e.g.*, temperature and sales) rather than discrete class labels. Hence, precision and recall are used in this study as side views of the results with little indication.

Therefore, in forecasting, different metrics that are appropriate for evaluating accuracy and performance are used depending on specific goals and characteristics of the dataset. Some common metrics for forecasting tasks include:

– MAE: calculates the mean absolute difference between predicted and actual values.
– MAPE: quantifies the percentage difference between predicted and actual values.
– RMSE: is the square root of the MSE and gives a sense of the typical size of errors.
– Accuracy: measures the proportion of correct predictions.
– R^2: aids in evaluating the degree to which the model's predictions align with the variability in the actual data.

The formulas of the error measurements are expressed as (7), (8):

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} |x_i - m_i| \tag{7}$$

$$RSME = \frac{1}{N} \cdot \sum_{i=1}^{N} (x_i - m_i)^2 \tag{8}$$

where N is the number of predictions, Σ is the sum of absolute errors, and x_i represents the i-th actual value of a time series and mi is the value that was forecasted, for the same position in the series, by the model. Note that the lower the value (towards 0), the better the forecasting model is. In addition, precision, recall, and F1-score for measuring the performance are calculated as:

$$Precision = \frac{T+}{m+} = \frac{T+}{(T+)+(F+)} \tag{9}$$

$$Recall = \frac{T+}{x+} = \frac{T+}{(T+)+(F-)} \tag{10}$$

$$F1 = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} \tag{11}$$

where $T+$ is a true positive direction, an actual positive, predicted positive, on the other hand, $F+$ is a false positive direction, an actual negative, predicted positive. Whilst $F-$ is a false negative direction, an actual positive, predicted negative. $x+$ is the actual value of the time series, and $m+$ is the predicted (forecasted) value of the same time series. Note that the higher the value, the better the model's performance is.

4.3. Experimental results

According to Table 1, it is shown that the proposed ANFIS-RSA model has less accuracy score than *e.g.*, LSTM, naïve Bayes (NB), LR, and RF. However, it has competitive scores and stability indications such as recall, F1-score, MAPE, and specifically RMSE, and R^2. All presented models in the table have not reached a greater accuracy score than 90%, because the Jordanian dataset is limited to a small size and low distribution around target forecasting labels, which can be seen in R^2. For a more thorough comprehension of the outcomes of the proposed model, the graphical representations in Figures 3 to 7 elucidate the performance of the ANFIS-RSA model on the Jordanian dataset. Figure 3 displays errors during the training and evaluation phases, enabling tracking of the model's efficiency over time. Specifically, it identifies patterns that helps understanding temporal dependencies in the dataset.

Figure 4 illustrates the comparison between actual wind speed values and the model’s estimates over time. It aids in understanding the model's capacity to capture temporal trends. However, the predictions line up differently than in previous models (actual vs predicted). Hence, the predictions are many times one-time step behind the actual values, which is uncommon. Figure 5 showcases errors over the time span. Monitoring errors over time helps identify periods of accurate and inaccurate predictions.

Table 1. Performance evaluation of the proposed ANFIS-RSA *vs*. other classifiers for the Jordanian dataset

Model	MAE	MAPE	RMSE	R^2	Precision	Recall	F1-Score	Accuracy
NB	1.529	7.187	1.118	0.85	0.913	0.84	0.88	0.8983
LR	2.971	8.363	2.111	0.87	0.7727	0.8947	0.83	0.8814
K-nearest neighbor (K-NN)	1.136	3.965	1.112	0.7333	0.7333	0.7333	0.73	0.8667
RF	1.655	4.333	1.342	0.83	**0.913**	0.8077	0.86	0.8814
SVM	3.811	9.363	3.218	0.82	0.7692	0.8333	0.80	0.8333
LSTM	1.122	4.012	1.080	0.89	0.8333	0.9091	0.87	**0.90**
Multi-layer perceptron	3.871	8.471	2.980	0.68	0.75	0.6667	0.71	0.8333
ANFIS	1.001	**0.8514**	5.5141	0.76	0.7826	0.75	0.77	0.8136
The proposed ANFIS-RSA	**0.0989**	7.0815	**0.2038**	**0.967**	0.7777	**1.0**	**0.875**	0.8461

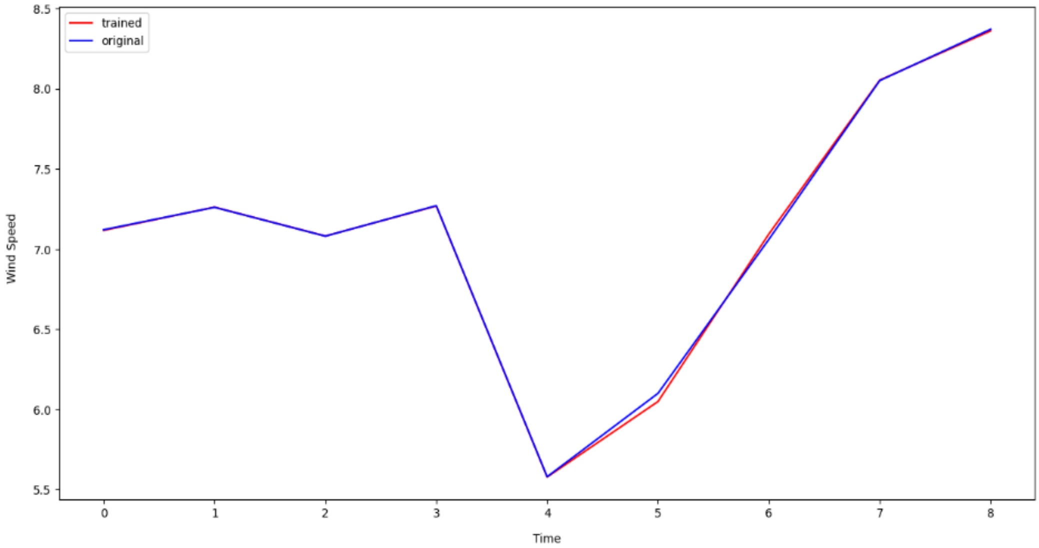

Figure 3. Actual vs. predicted wind speed of the model for the Jordanian dataset

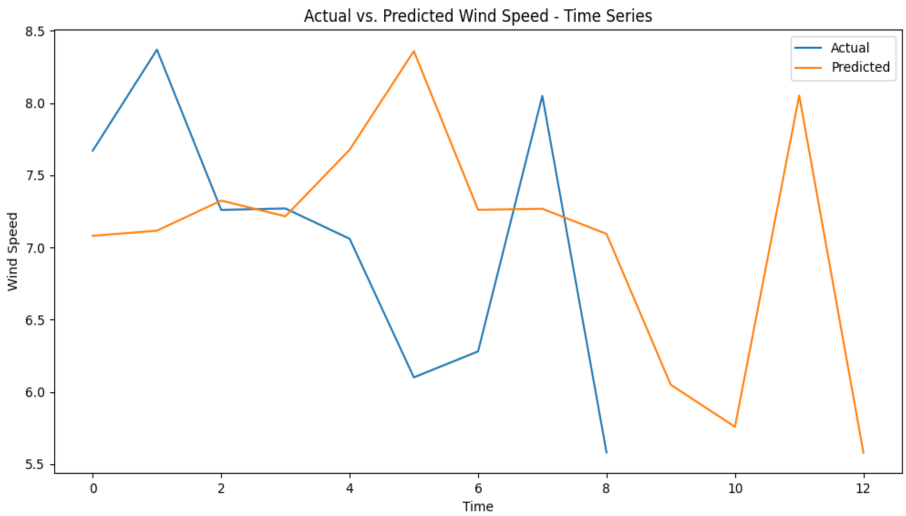

Figure 4. Actual vs. predicted wind speed of the model for the Jordanian dataset (Monthly wise)

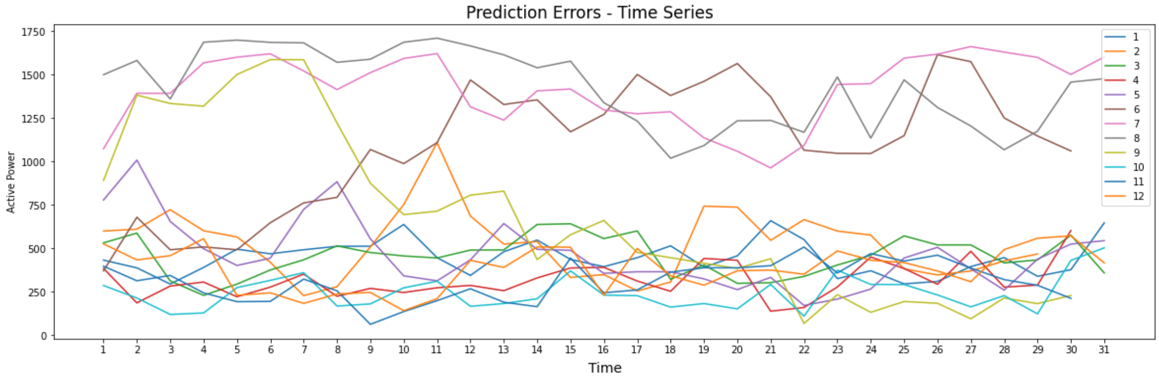

Figure 5. Model’s MAE for turbines T1–T12 as a function of wind direction by time for the Jordanian dataset

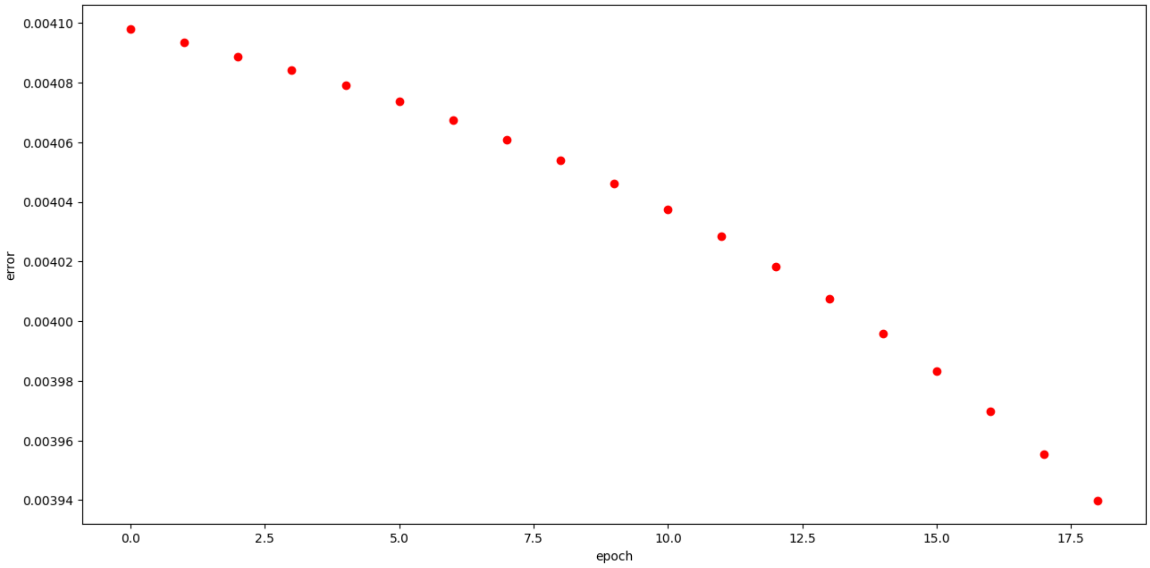

Figure 6. RMSE by epochs of the model for the Jordanian dataset

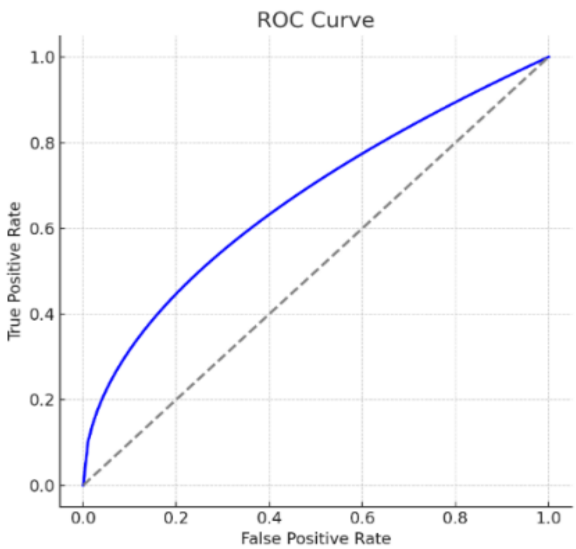

Figure 7. ROC curve for testing the model

Figure 6 is used to visualize the distribution of errors in the model's predictions. It assists in identifying and analyzing error patterns to enhance the model's performance. It is indicated that the MAE and loss decrease incrementally with each epoch. Figure 7 demonstrates the receiver operating characteristic (ROC) of the model’s performance evaluated on the testing dataset, thus concluding the model’s test error.

4.4. Discussion

It can be concluded that great efforts have been made to improve and develop the forecasting model adjusted for wind speed by using the ANFIS-RSA, which is an important and powerful tool in data analysis supported by an accurate schema (exploration and exploitation mechanisms in the RSA). The proposed model succeeded in achieving effective predictions, refer to Tables 1 and 2. The RSA is manipulated according to the forecasting concept by changing the values of Alpha and Beta instead of different weights for the fitness values. Hence, the performance of the forecasting model is improved, and accurate wind speed adjustments are made. Due to the limitations of the Jordanian dataset, this study conducted further implementation to sufficiently validate the performance of the proposed ANFIS-RSA model over the Chinese dataset. Elaziz *et al.* [36] provided a comprehensive description and investigation of the Chinese dataset.

Numerous traditional machine-learning techniques have been applied specifically to Hexi Corridor dataset. On the other hand, a few numbers of hybrid models are applied to the same dataset including neural networks with optimization algorithms. One recent example is the Seagull optimization algorithm and Aquila optimizer (SOAAO) by Abd Elaziz *et al.* [36] to optimize the dendritic neural model. In addition, most hybrid models did not report their detailed results and observations, only they concerned MAE and RMSE.

The proposed ANFIS-RSA seems to forecast the monthly trend accurately and precisely, which is explained by the 0.99 correlation coefficient (R^2) better than all other models except the RF. The MAE and RMSE metrics show reduced error for this sequence compared to other models using the same forecasting window. The MAPE metric has produced meaningful results for the proposed model while most models have failed to describe the results precisely. The proposed model thoroughly indorsed training, turning, and testing, to capture the relationship of wind speed and active power. For the month ahead forecasting request, a resampling technique can be used to turn the dataset into weekly or daily steps but these risks losing high-quality data points. Table 2 also shows the training and validation accuracy scores of the proposed ANFIS-RSA model on the Jordanian dataset. The proposed model obtained a high score of test accuracy, 99.988% better than most of the predictive models and competitive to RF and LSTM in terms of accuracy.

Table 2. Performance evaluation of the proposed ANFIS-RSA vs. other classifiers for the Chinese dataset

Model	MAE	MAPE	RMSE	R^2	Precision	Recall	F1-Score	Accuracy
NB	168.948	7.426	281.173	0.925	0.7009	0.8957	0.7864	76.666
LR	0.0777	1.0746	0.1231	0.955	0.91	0.79	0.83	91.151
K-NN	119.905	5.559	259.636	0.895	0.8468	0.7683	0.8056	93.454
RF	56.5428	3.325	281.173	**0.999**	0.94	**0.97**	**0.95**	99.995
SVM	20.2187	4.684	50.268	0.996	0.848	0.8185	0.833	84.259
LSTM	196.084	8.1666	234.503	0.906	0.9556	0.915	0.9349	**99.996**
MLP	206.038	0.4574	399.271	0.757	0.8658	0.7722	0.8163	83.333
ANFIS	1.288	0.7967	5.2983	0.975	0.8244	0.7799	0.8015	94.696
BP-ANN [18]	0.7536	0.3263	-	0.9106	-	-	-	-
BP-SFLA-ANN [18]	0.5079	0.2213	-	0.9374	-	-	-	-
LSTM [46]	0.7854	03886	-	0.8834	-	-	-	-
GRU [47]	0.9216	0.4675	-	0.8547	-	-	-	-
BP-SFLA-RMSprop-ANN [18]	0.4083	0.1841	-	0.9539	-	-	-	-
SOAAO [36]	**0.03080**	6.500	**0.04317**	0.952	-	-	-	-
The proposed ANFIS-RSA	10.543	**0.0261**	11.626	**0.999**	**0.971**	0.907	0.9381	99.988

Overall, based on all metrics presented in Tables 1 and 2, the proposed is among the best three forecasting models for both Chinese and Jordanian datasets. Other models are clearly inferior in terms of accuracy scores, precision and recall, or MAE and R^2. Models such as SVM and NB did not fit the curve well, while multi-layer perceptron was overfitting and resulting in wrong predictions. The MLP with its many parameters is not learning properly, maybe due to the dimensionality of the input data is too low for it, especially in the Jordanian dataset, making learning difficult for such many parameters. This issue is handled properly by the ANFIS with its handful of parameters, where the intermediate layer learns all patterns properly, especially for the Chinese dataset. However, ANFIS, LR, and K-NN models capture the data effectively, but cannot reduce the error. Although the LSTM obtained the highest accuracy score (99.996), it has more hyperparameters than any other model, thus making it hard and time-consuming to tune efficiently.

The forecasted wind power value is quite near to the target value, according to all of the measures shown in Tables 1 and 2. Furthermore, for both datasets, the suggested ANFIS-RSA model had the highest R^2 of any model. This refers to the high correlation between the target value and the predicted wind power as determined by the ANFIS-RSA model. As a result, for all datasets, the ANFIS-RSA combination produced better results than the standard ANFIS. Simultaneously, ANFIS-RSA application produced competitive results to RF, LSTM, and SOAAO. On the other hand, it demonstrated a high performance with superior results than classical and hybrid models such as BP-ANN, GRU, BP-SFLA-ANN, and BP-SFLA-RMSprop-ANN. Figures 8 to 11 also demonstrates the performance of the ANFIS-RSA forecasting model.

Figure 11 demonstrates the ROC of the model's performance evaluated on the testing dataset, thus concluding the model's test error. It is concluded that ANFIS's prediction accuracy is improved significantly by the RSA optimizer. Furthermore, one may contend that the exploration and exploitation stages of RSA are capable of identifying locations that are practical and have ANFIS parameters that are ideal. This improves wind power forecast performance. Even yet, the ANFIS-RSA still takes a lot of time, particularly when there are more parameters.

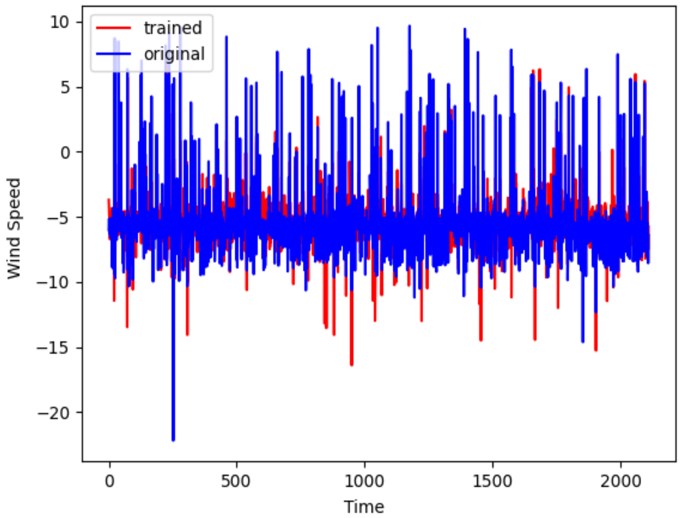

Figure 8. Model performance-actual vs. predicted for Hexi corridor dataset (forecast horizon of 20h)

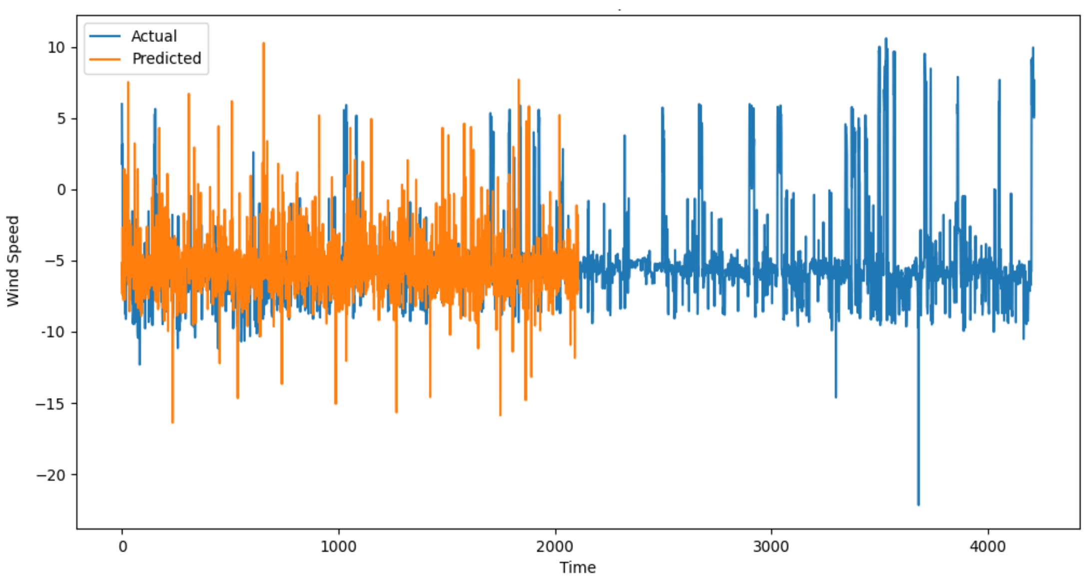

Figure 9. Model performance-actual vs. predicted for Hexi corridor dataset (daily bases)

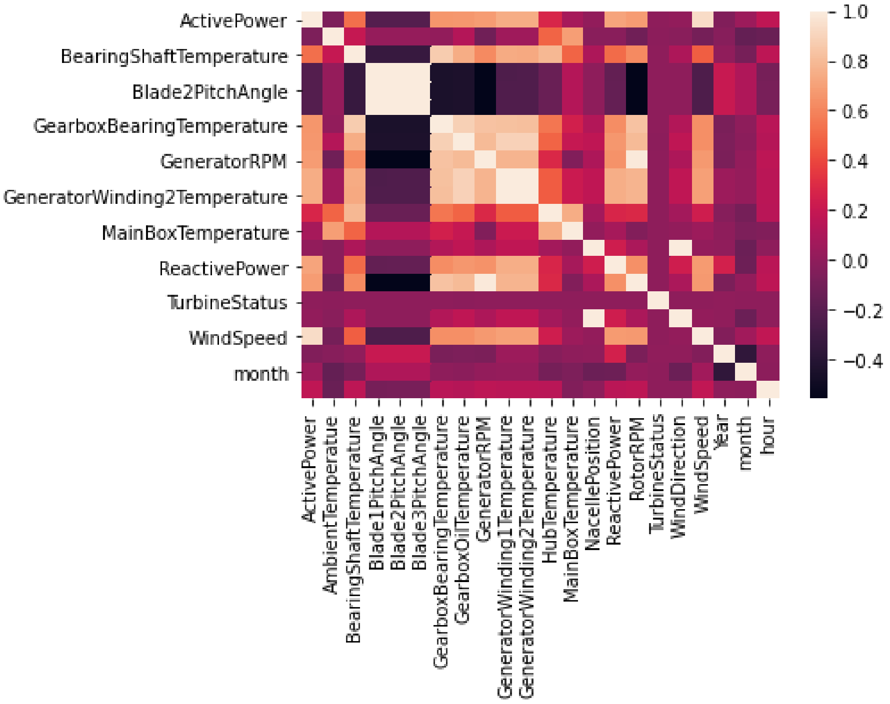

Figure 10. Heat map of features (best selected) correlation for Hexi corridor dataset

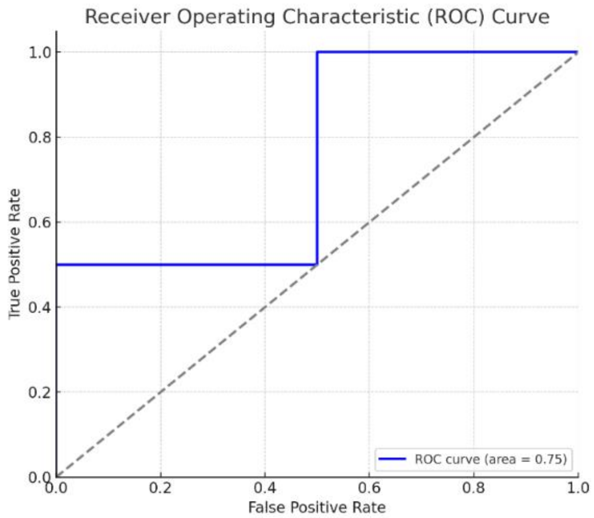

Figure 11. ROC curve for testing the model

5. CONCLUSION

This paper presented a competitive wind power forecasting approach based on the ANFIS-RSA model. The ANFIS was enhanced using RSA optimization method to improve the forecasting accuracy via iteratively tuning its hyper-parameters. The RSA mainly contributed in boosting the search diversity of ANFIS to overcome its search limitations. Hence, the combination between ANFIS and RSA stabilizes the learning process in the training phase, which leads to fast and effective forecasting. The proposed ANFIS-RSA model achieved promising results including highly accurate predictions. The model has obtained 99.988% accuracy closely following LSTM and RF, 0.9381 F1-score closely following RF, 0.907 recall following RF and LSTM, and relatively fair RMSE (11.626) compared to other models. The low RMSE value suggests a close correspondence between the model's predictions and the observed values. On the other hand, the proposed model has outperformed all models in terms of precision (0.971), R^2 (0.999), and MAPE (0.0261) which concludes its balanced performance across the dataset as well as the validation of the learning process. These results proved the effectiveness and accuracy of the proposed model in forecasting the wind power specifically for the Chinese dataset, while showing an outstanding performance regarding the Jordanian dataset.

The superiority of the ANFIS-RSA model was further assisted by visual comparisons like residual plots. Its capacity to precisely mapping the underlying patterns and relationships in the data was shown by these visuals. The study of the results offered more proof of the model's importance and dependability. The robustness of the outcomes was guaranteed by statistical comparisons involving several RSA iterations.

Because of its versatility, the ANFIS-RSA model can be evaluated and adapted for a wide range of datasets in future work. Furthermore, further validation will be carried out to identify the ANFIS-RSA model's shortcomings, generalizability, and robustness. This would guarantee the model's dependability under varied circumstances and aid in determining the model's efficacy in various scenarios. However, although ANFIS-RSA converges quickly, it has one concerning limitation such as selection of appropriate features or utterly optimize its parameters. This causes inaccurate predictions with small datasets or fewer provided features. This can be solved in future studies by employing another local search within the RSA.

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AUTHOR CONTRIBUTIONS STATEMENT

The first author conceived of the presented idea (conceptualization). The second author developed the theoretical formalism (methodology). The third (corresponding) author performed the computations and experiments, including performed the analytic calculations and the numerical simulations (formal analysis). The fourth author discussed the results and contributed to the final manuscript (including original draft preparation and writing reviews and editing). All authors verified the analytical methods and the findings of this work.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest.

INFORMED CONSENT

Informed consent was obtained from all individual participants included in the study.

ETHICAL APPROVAL

This article does not contain any studies with human participants or animals performed by any of the authors.

DATA AVAILABILITY

Data are available from the authors upon reasonable request.

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