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Rainfall Prediction in Khorasan Razavi Stations Using a Hybrid Neural Network and Genetic Algorithm Approach

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Abstract

Accurate rainfall prediction is crucial for effective water resource management, especially in arid and semi-arid regions. This study proposes a novel hybrid approach, combining the Non-linear Auto Regressive with eXogenous inputs (NARX) neural network with a Genetic Algorithm (GA) for parameter optimization, aiming to improve daily rainfall prediction in Khorasan Razavi province, Iran. The performance of the proposed NARXGA model was compared with several benchmark models, including traditional time series models ARIMA, Holt-Winters Exponential Smoothing (HWES), and machine learning models, such as LSTM, CNN1D and the standalone NARX network. The models were trained and tested using five years of daily meteorological data from Mashhad. The results showed that the NARXGA model achieved the lowest Mean Squared Error (MSE) on both the training and test datasets, with values of 9.7453 and 11.5565, respectively, thus showing that the method can more effectively capture the non-linear patterns in rainfall data. A convergence analysis of the GA was also provided, as well as histograms of the error distributions, which further validated the superior performance of the proposed NARXGA model. This research highlights the potential of hybrid AI models for enhancing rainfall prediction accuracy and providing valuable insights for water management and drought mitigation in arid and semi-arid regions.

Keywords: Genetic Algorithm, Hybrid Model, Khorasan Razavi Province, NARX Neural Network, Rainfall Prediction.

1. Introduction

Accurate prediction of rainfall plays an important part in proper management of the water resources, particularly in arid and semi-arid regions. Rainfall plays a central part in the hydrologic cycle as an important factor, influencing agricultural production, drought mitigation, and flood control. With the ongoing climate change and increasing needs for water, accurate forecasting methods have never been of such prominence as they are today (Baig et al., 2024).

Traditional rain forecasting models are based on sophisticated mathematical formulations and physical mechanisms that require big sets of data and a great amount of computational resources (Barrera-Animas et al., 2022). However, with advances in artificial intelligence (AI) and machine learning (ML), there is the promise of using data-driven techniques for the building of more accurate and computationally less expensive models (Bochenek and Ustrnul, 2022). Among severaltechniquesof AI, artificial neural networks (ANNs) have gained prominence as an efficient tool for representing complex non-linear relationships between meteorological variables (Y.LeCun et al., 2015). Recurrent neural networks with their ability of sequential processing of the data have emerged as a common approach for time series forecasting (Hochreiter et al., 1997).

Aside from that, hybrid model strategies that merge optimization techniques with AI techniques have gained prominence in recent years. Genetic algorithms (GAs), inspired by the natural process of selection, are an extremely effective model for parameter optimization and model improvement (Goldberg, 1989). By the combination of the virtues of ANNs and GAs, more advanced hybrid models with more predictive strength than traditional methods may be developed (Kaveh and Mesgari, 2023).

This study investigates the potential of a hybrid Non-linear Auto Regressive with eXogenous inputs (NARX) network and genetic algorithm (NARXGA) for rainfall prediction in Khorasan Razavi province, Iran. This region faces severe water scarcity challenges, making accurate rainfall forecasting essential for supporting sustainable agricultural practices and mitigating drought and flood risks (Zabihi et al., 2022). Our approach aims to improve prediction accuracy by fine-tuning the parameters of the NARX neural network with the GA optimization. This study also examines the performance of the proposed NARXGA model against traditional ANN architectures, including NARX, Non-linear Auto-Regressive (NAR), and Non-linear Input Output (NIO) networks to evaluate its effectiveness.

The main objectives of this research are to:

- Develop a hybrid NARXGA model for daily rainfall prediction using meteorological data.
- Compare the performance of the proposed NARXGA model with that of traditional ANNs (NARX, NAR, and NIO) in a real-world setting.
- Evaluate the effectiveness of the genetic algorithm in fine-tuning the weights of the NARX model.
- Demonstrate how a hybrid approach can be utilized for more efficient and accurate rainfall forecasting.

Artificial Neural Networks (ANNs) have extensively been utilized in a variety of hydrologic environments owing to their ability to model complicated nonlinear relationships (Dotse et al., 2024). Different ANN architectures, such as Feedforward Neural Networks (FFNNs) and Recurrent Neural Networks (RNNs), have been utilized in explaining the spatiotemporal dynamics of precipitation (El Shafie et al., 2012; Akbari Asanjan et al., 2018). Specifically, RNNs—i.e., the Long Short-Term Memory (LSTM) networks and the Gated Recurrent Units (GRUs)—have proved superior in time series forecasting due to their ability to handle long-distance dependencies of the input data (Priatna and Djamal, 2020; Pujara and Paudel, 2024).

Despite their demonstrated effectiveness, artificial neural networks have some limitations. They require extensive amounts of training data and can be overfitting if not thoroughly trained. Moreover, the weights and biaswithin artificial neural networks are often initialized in an arbitrary way and thus may lead to inconsistent results (Sun et al., 2018). Choosing the best architecture for artificial neural networks may also be difficult when there is no prior experience. More recent studies have tackled the challenge of the need for hybrid models to address these limitations.

Hybrid models that bring together the best of different methodologies have gained much prominence in rainfall forecasting. Usually, these models harness artificial intelligence together with optimization methodologies for improvement. For instance, the combination of artificial neural networks (ANNs) with wavelet transform and decomposition methodologies has proved beneficial by accurately capturing a wide range of temporal scales in evidence with rainfall phenomenon (Wei and You, 2022).

Hybrid models have also been developed by fusing Support Vector Machines (SVMs) with ANNs. These have proved superior in comparison with models developed based on individual models (Xiang et al., 2018). These studies emphasize the importance of identifying a proper hybrid model for successful rainfall forecasting.

In recent years, combining artificial neural networks (ANNs) with evolutionary algorithms, including genetic algorithms (GAs), has produced promising results (Pham et al., 2024). Evolutionary algorithms provide an efficient method for the optimization of ANN architectures and parameters, thus enhancing predictive robustness and accuracy. The combination of evolutionary algorithms and ANNs addresses the limitations related to their respective methodologies alone, resulting in forecasting models that are both robust and adaptable. For example, in a study in 2023, it was shown that a recurrent neural network optimized using particle swarm optimization (PSO) performed better than traditional RNNs in the application of rainfall forecasting (Nemade et al., 2023). In this study, a hybrid model combining PSO with Long Short-Term Memory (LSTM) networks was used to forecast monthly rainfall, using PSO to optimize the model. Likewise, in another study, the authors hybridized genetic algorithms (GA) and particle swarm optimization (PSO) with a backpropagation algorithm in training a radial basis function network for the prediction of monthly precipitation (Wu et al., 2015).

Additionally, in an independent study, the researchers presented a methodology that utilizes deep reinforcement learning for the improvement of the structure of a hybrid model for rain forecasting, incorporating convolutional networks and genetic algorithms, thus making the hybrid model more robust for this particular task (Ngan et al., 2023). Another novel hybrid model was developed that combines Convolutional Neural Networks (CNNs) with the Gray Wolf Optimizer (GWO) for forecasting runoff for the year 2023 in a semiarid watershed (Aoulmi et al., 2023). Additionally, yet another study engaged a remote-sensing-derived data with meteorological inputs for conducting hourly rainfall forecasting using a hybrid model that combines the usage of an Auto-encoder and an LSTM network (Ponnoprat, 2021). Finally, a recent research effort employed a hybrid genetic algorithm-support vector machine (GA-SVM) model for forecasting rainfalls for 2024 that showed a higher prediction quality compared with the traditional support vector machine (SVM) (Lai et al., 2024).

Forecasting of rain in semi-arid and arid regions has specific challenges owing to limited records of available rainfalls, wide variability of rainfalls, and complexities in climatic conditions. There therefore arises an urgent need for specialized approaches in data-driven models for forecasting rainfalls. Recent studies have witnessed many researchers focus on the development of specialized models for specific geographical regions. For example, researchers have developed a hybrid model for predicting drought in an arid region using data collected by satellite remote sensing (Baig et al., 2024).

In particular, NARX networks combined with GAs present an effective approach for building robust and adaptive models for predicting rainfall in regions, such as Khorasan Razavi, where data is sparse and the rainfall pattern is very complex. These regions are typically characterized by high variability in space and time, which further justifies the use of a hybrid approach that can capture both spatial and temporal dependencies, such as the NARXGA proposed in this study.

2. Materials and Methods

2.1. NARX

NARX network is a recurrent neural network (RNN) with specific usage for time series forecasting. The topology of NARX network includes an input layer, a hidden layer, and an output layer with feedback from the output layer to the input layer. The feedback provides NARX network with the ability to model temporal dependences of the data. The NARX network can be expressed with the following equation:

$$y(t)=f(y(t-1), y(t-2), \ldots, y(t-d_y), x(t), x(t-1), \ldots, x(t-d_x)) \quad (1)$$

where:

- $y(t)$ is the output at time t.
- $x(t)$ is the external input at time t.
- dy and dx are the time lags for the feedback and external inputs, respectively.
- f is a non-linear activation function.

A typical NARX neural network comprises an input layer, hidden layer, output layer, and input delay function. Its basic structure is shown in Figure 1.

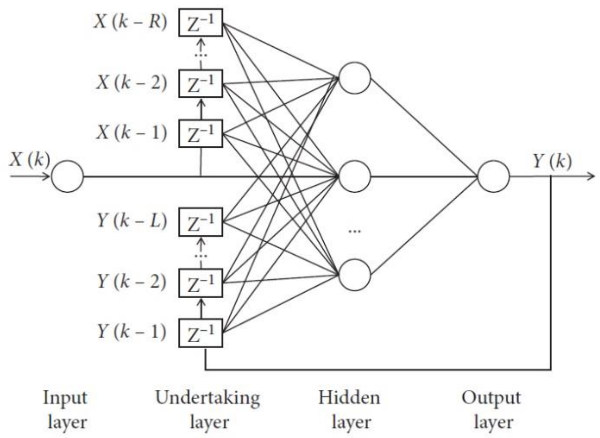


Fig. 1. Schematic diagram of NARX neural network structure.

The NARX network is trained using a backpropagation algorithm. The parameters of the network (weights and biases) are randomly initialized, and these parameters are updated iteratively to minimize the difference between the predicted and the actual rainfall values.

2.2. Genetic Algorithm

Genetic Algorithm (GA) is a stochastic optimization technique inspired by the process of natural selection. It starts with an initial population of candidate solutions (chromosomes) and iteratively evolves this population by applying genetic operators such as selection, crossover, and mutation to find the optimal solution. The steps of the GA are described as follows:

1. **Initialization:** A population of candidate solutions (chromosomes) is generated randomly.
2. **Fitness Evaluation:** Each candidate is evaluated using a fitness function.
3. **Selection:** Candidates with higher fitness are probabilistically chosen to serve as parents for the next generation.
4. **Crossover:** Selected parent chromosomes exchange segments of their genetic information (using a single-point or multi-point crossover) to produce new offspring that combine traits from both parents.
5. **Mutation:** With a low probability, random alterations (mutations) are applied to the offspring's genes. This step helps maintain genetic diversity and prevents premature convergence.
6. **Replacement:** The offspring are added to the existing population, thus creating the next generation. The worst individuals of the population are removed to maintain the population size.
7. **Termination:** The algorithm repeats the evaluation, selection, crossover, mutation, and replacement steps until a stopping criterion is met, such as reaching a predefined number of iterations or observing no significant improvement over several generations.

To evaluate the performance of the proposed model, several benchmark models, including traditional time series models and machine learning approaches, were implemented.

2.3. Autoregressive Integrated Moving Average (ARIMA)

ARIMA is a popular statistical time series forecasting model capturing autocorrelations of data. It has three components: Autoregression (AR), Integration (I), and Moving Average (MA)(Nelson, 1998). The AR part represents the dependence of an observation on some number of past observations, the I part represents non-stationarity through differencing, and the MA part represents the dependence of an observation on a residual error from applying a moving average model to past observations. ARIMA model is specified by three parameters: (p, d, q). Here, p is the number of lagged observations in the autoregressive or AR component, d is the number of times differencing is applied, and q is the order of moving average component.

2.4. Holt-Winters' Exponential Smoothing (HWES)

HWES extends simple exponential smoothing by adding components for trend and seasonality. It is widely used for forecasting seasonal data, making it an effective method for short-term water consumption forecasting in areas with distinct seasonal patterns (Lima et al., 2019). HWES consists of three main components:

- Level (l_t): The smoothed estimate of the series at time t.
- Trends (b_t): The estimated change in the series over time.
- Seasonality (s_t): The seasonal pattern in the data.

2.5. Long Short-Term Memory (LSTM)

LSTM is among the Recurrent Neural Networks (RNN) employed in recognizing long-term dependencies in sequence data through memory cells that retain information over long durations. LSTM has extensively been used for time series forecasting, including rainfall prediction, as it is capable of handling non-linear trends and detecting long-term patterns(Hochreiter et al., 1997). An LSTM cell contains three major gates(Salehinejad et al., 2017):

- Forget Gate (f_t): Decides how much of the past information should be discarded.
- Input Gate (i_t): Controls what new

information is stored in the cell state.

- Output Gate (o_t): Determines the next hidden state.

Each LSTM cell updates its internal cell state (c_t) and hidden state (h_t) using these gates.

2.6. Convolutional Neural Network (CNN)

Originally developed for image processing, CNNs have been adapted for time series forecasting by capturing local patterns in the data through convolutional filters. CNN models with 1D filters have been successfully applied to water consumption prediction, particularly for short-term forecasting (Wu, 2017). A 1D CNN consists of multiple layers:

a) Convolutional Layer: Extracts features from the input time series using 1D filters (kernels). Each filter slides over the input sequence to learn patterns. The output is a feature map that highlights important temporal dependencies.

b) Pooling Layer: Reduces dimensionality and extracts dominant features. Max pooling or average pooling is used to downsample the feature maps.

c) Fully Connected (Dense) Layer: Connects extracted features to the output prediction. The output can be a single value (regression) or a class label (classification).

2.7. Methodology

This section outlines the methodology adopted for rainfall prediction in Khorasan Razavi province, Iran. We propose a hybrid model that combines the Non-linear Auto Regressive with eXogenous inputs (NARX) neural network with a Genetic Algorithm (GA) for parameter optimization. The details of the model architecture, the GA optimization process, and the dataset used are described in this section.

The dataset for this study consists of daily meteorological data from six weather stations located in Khorasan Razavi province, Iran.Figure 2 illustrates a map showing the geographical locations of selected meteorological stations in Khorasan Razavi Province with green color. Table 1 provides a detailed description of these stations, including their station code, name, latitude, longitude, and elevation.

Fig. 2. The geographical locations of meteorological stations in Khorasan Razavi Province

The data spans from 2007 to 2011 and includes six key features that are highly influential on rainfall:

1. Total Cloud Cover
2. Maximum Wind Speed
3. Maximum Wind Direction
4. Relative Humidity
5. Minimum Absolute Temperature (in degrees Celsius)
6. Maximum Absolute Temperature (in degrees Celsius)

Table 1. Used meteorological stations in Razavi province

Station Code	Station Name	Latitude (°N)	Longitude (°E)	Elevation (m)
MSH	Mashhad	36.26	59.62	995
NYS	Nishapur	36.21	58.83	1250
SBZ	Sabzevar	36.21	57.67	978
THE	Torbat Heydariyeh	35.27	59.22	1329
TJM	Torbat Jam	35.18	60.83	950
GNP	Gonabad	34.36	58.75	1105

The dataset is divided into two subsets: 80% for training the model and 20% for testing its performance. This split ensures that the model's performance is evaluated on data it has not seen during training. Figure 3 shows this division in the rainfall data completely. The data is normalized using a min-max scaling method to ensure all features are within the same range, thus avoiding biased training. The scaling is given as follows:

$$v_i' = \frac{v_i - min_V}{max_V - min_V} \quad (2)$$

where:

- v_i is the original feature value.
- v_i' is the normalized feature value.
- min_V is the minimum value of feature v.
- max_V is the maximum value of feature v.

In this study, the NARX network is configured such that $y(t)$ represents the predicted rainfall and $x(t)$ denotes the meteorological features. A hyperbolic tangent activation function is used in the hidden layer because it effectively captures non-linear relationships while maintaining a smooth gradient, reducing the risk of vanishing gradients. While a linear transfer function is applied in the output layer ensures that the network can produce continuous rainfall predictions without restrictions on the output range.

The network consists of a single hidden layer with 10 neurons based on preliminary experiments, where increasing the number of neurons beyond this value resulted in marginal improvements while significantly increasing computational complexity. This configuration balances accuracy and computational efficiency. The time lags for both the output (dy) and external inputs (dx) were set to 10, determined through trial-and-error testing using different lag values. A lag of 10 provided the best trade-off between capturing long-term dependencies and avoiding excessive dimensionality, which could lead to overfitting.

To address the limitations of traditional training methods, a GA is employed to optimize the weights and biases of the NARX network. The steps of the GA in this research are described as follows:

1. **Initialization:** An initial population of chromosomes is created where each chromosome represents a set of weights and biases of the NARX network. Each weight and bias is represented by a gene with random values within a defined range (e.g., [-5, 5]). The chromosomes are randomly generated within this range.
2. **Evaluation:** The fitness of each chromosome is calculated using a fitness function which evaluates the performance of the NARX network with that specific set of weights and biases. In this study, the fitness function is based on the Mean Squared Error (MSE) between the predicted and observed rainfall values. The MSE is given by the following equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \quad (3)$$

where:

- n s the number of training samples.
- $\boldsymbol{y_i}$ is the actual rainfall value.
- $\boldsymbol{\tilde{y}_i}$ is the predicted rainfall value.

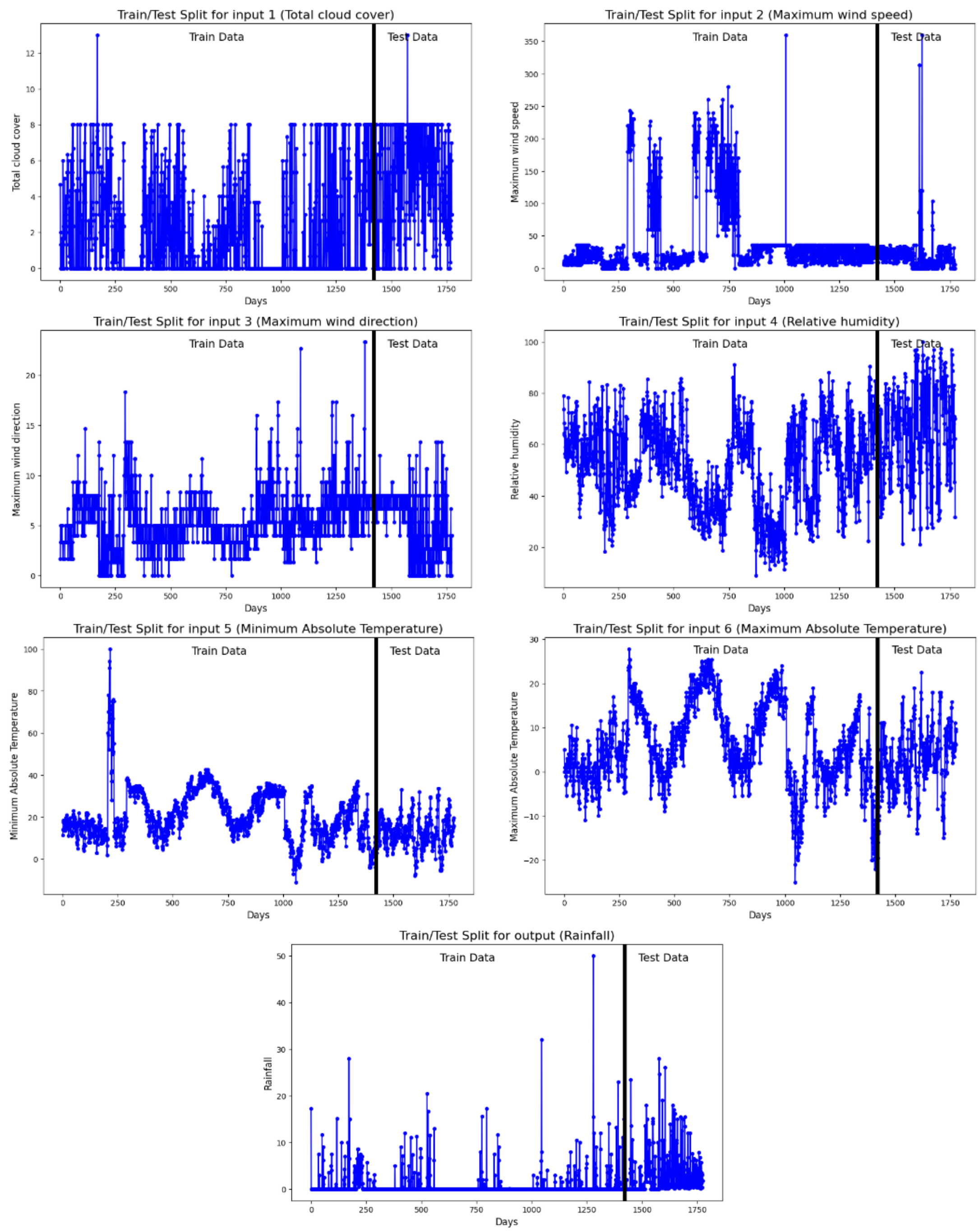


Fig. 3. The situation of the train and test data of rainfall

3. **Selection:** We used Roulette wheel selection for this step, with the higher fitness individuals being more likely to be selected.

4. **Crossover:** In this study, single-point crossover is used.

5. **Mutation:** A random value within a given range is added to a randomly selected gene.

6. **Replacement:** The offspring are added to the existing population, thus creating the next generation. The worst individuals of the population are removed to maintain the population size.

7. **Termination:** The algorithm is terminated when a pre-defined number of iterations is reached or when the fitness of the best performing chromosome has not improved in several generations, as specified in the parameters of the GA.

The proposed model, called NARXGA, integrates the NARX network with the GA optimization. This can be explained in the following steps:

1. Initialize the NARX model and population of chromosomes based on its architecture.

2. Use the training dataset to evaluate the fitness of each chromosome by calculating the MSE of the NARX network using the weights and biases specified by the chromosome.
3. Apply the genetic algorithm to find the best chromosomes based on their fitness.
4. Update the NARX network weights and biases using the best chromosome found by the GA.
5. Use the trained NARX network for prediction using the testing dataset.
6. Evaluate the performance of the trained NARX network by calculating its MSE and comparing with other approaches.

This framework enables the parameters of the NARX network to be optimized to achieve higher prediction accuracy, while taking into account the non-linearity of rainfall prediction. The details of the evaluation metrics and the comparison of the NARXGA model with other benchmark models are given in the next section.

3. Results and Discussion

This section presents the experimental results obtained from the implementation of the proposed NARXGA model for rainfall prediction in Khorasan Razavi province. We also compare the results of the NARXGA model with the results obtained from other benchmark models, including traditional time series models ARIMA, Holt-Winters Exponential Smoothing (HWES), and machine learning models, such as LSTM, CNN1D and the standalone NARX network.

Hyperparameter tuning is crucial for improving the predictive performance of time series forecasting models. In this study, grid search and cross-validation techniques were used to optimize the hyperparameters of each model. For machine learning models, training was conducted for 100 epochs with early stopping based on validation loss, using the Adam optimizer with learning rate decay. Statistical models were trained using maximum likelihood estimation. The optimized hyperparameters for each model are summarized in Table 2.

To assess the performance of the proposed NARXGA model and other benchmark models, we use the Mean Squared Error (MSE) as the evaluation metric. A lower MSE value indicates better prediction accuracy. We calculate the MSE for both the training and test datasets to evaluate the model's learning and generalization capability.

Figure 4 presents the Mean Squared Error (MSE) results of the proposed NARXGA model and other benchmark models for rainfall prediction in Khorasan Razavi province. Figure 1 shows the average values of MSE for different methods, along with the corresponding values for training and test datasets.

Table 2. Summary of the hyperparameters used in the experiments

Models	**hyperparameters**						
LSTM	#LSTM units	# layers	Dropout rate	Learning rate	Batch size	Optimizer	
	128	2	0.2	0.001	64	Adam	
CNN1D	#filters	Kernel size	Activation function	Pooling size	Learning rate	Batch size	Optimizer
	64	3	ReLU	2	0.001	64	Adam
ARIMA	p[1]	d[2]	q[3]				
	2	1	2				
HWES	α	β[4]	γ[5]	Seasonal period			
	optimized	optimized	optimized	optimized			
NARX	# Neurons of Hidden layer	dx	dy	f			
	10	10	10	hyperbolic tangent			

1- autoregressive order
2- degree of differencing
3- moving average order
4- Trend smoothing
5- Seasonal smoothing

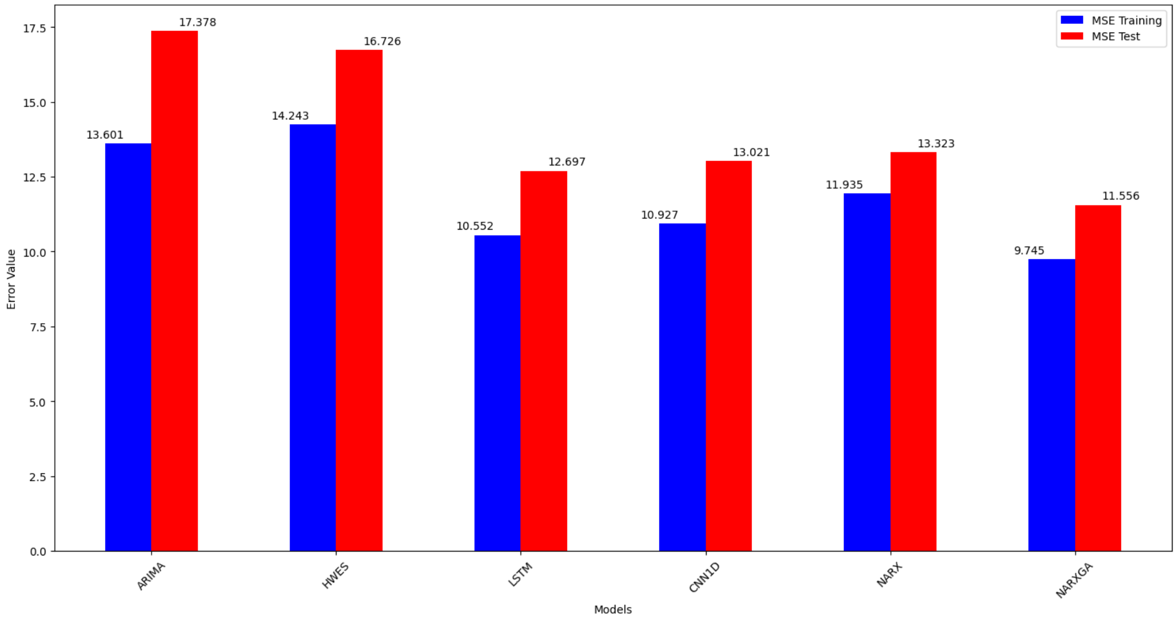


Fig. 4. Mean squared error (MSE) of different rainfall prediction models

In Figure 4, the y-axis shows the Mean Squared Error (MSE) of the predictions. This value, expressed in the square of the rainfall unit (e.g., mm²), indicates how far off the predicted values are from the actual measurements—a lower MSE means higher prediction accuracy.

As shown in Figure 4, the proposed NARXGA model achieved the lowest MSE on both the training and test datasets, with values of 9.7453 and 11.5565, respectively. This is a strong indication that the hybrid approach performs better than other benchmark models. The ARIMA model showed the worst performance with MSE values of 13.601 and 17.378 for the training and test sets, respectively. This indicates that this traditional time series model is not ideal for capturing the complex patterns and non-linearities in rainfall data. Similarly, the Holt-Winters Exponential Smoothing (HWES) model also performed relatively poorly with MSE values of 14.243 and 16.726 for the training and test data respectively, thus making it unsuitable for the given data. The LSTM model showed improved performance over ARIMA and HWES, yielding an MSE of 10.552 for training and 12.697 for the test data.

This shows that LSTMs are able to handle temporal dependencies better, due to their feedback loop mechanism. The CNN1D model also showed similar performance, with MSE of 10.927 for the training dataset and 13.021 for the test data. Although CNNs can effectively extract features, they do not always perform well on time series datasets. The standalone NARX model showed moderate results, with an MSE of 11.935 on training and 13.323 for the test data. This further highlights the importance of optimizing neural network architectures for the given task. The NARXGA model's improved performance is likely due to the GA's ability to fine-tune the parameters of the NARX network, thus helping to capture the complex non-linear relationships in the data and reduce overfitting. In addition to the Mean Squared Error (MSE) analysis presented in Figure 4, scatter plots in Figure 5were generated for both the training and testing phases to further evaluate the predictive performance of the models. These scatter plots illustrate the correlation between actual and predicted rainfall values, providing insights into the model’s ability to capture variability in the data.

Figure 6 illustrates the convergence of the genetic algorithm (GA) in optimizing the weights of the NARX network in the NARXGA model. The plot shows the best fitness value (lower is better) achieved by the GA over 100 iterations. Figure 7 illustrates the time series plots of observational rainfall values alongside predictions made by NARXGA model. In these plots, the black line represents the actual rainfall data, while the blue line represents the predicted values from NARXGA model.

We believe that NARXGA unifies the benefits of NARX model with parameter optimization using the genetic algorithm and thus delivers better predictions for rainfall than traditional models. The utilization of the genetic algorithm aids in the accurate adjustment of parameters, which subsequently contributes to improved generalization effectiveness while addressing the complexities that exist in rainfall data more effectively.

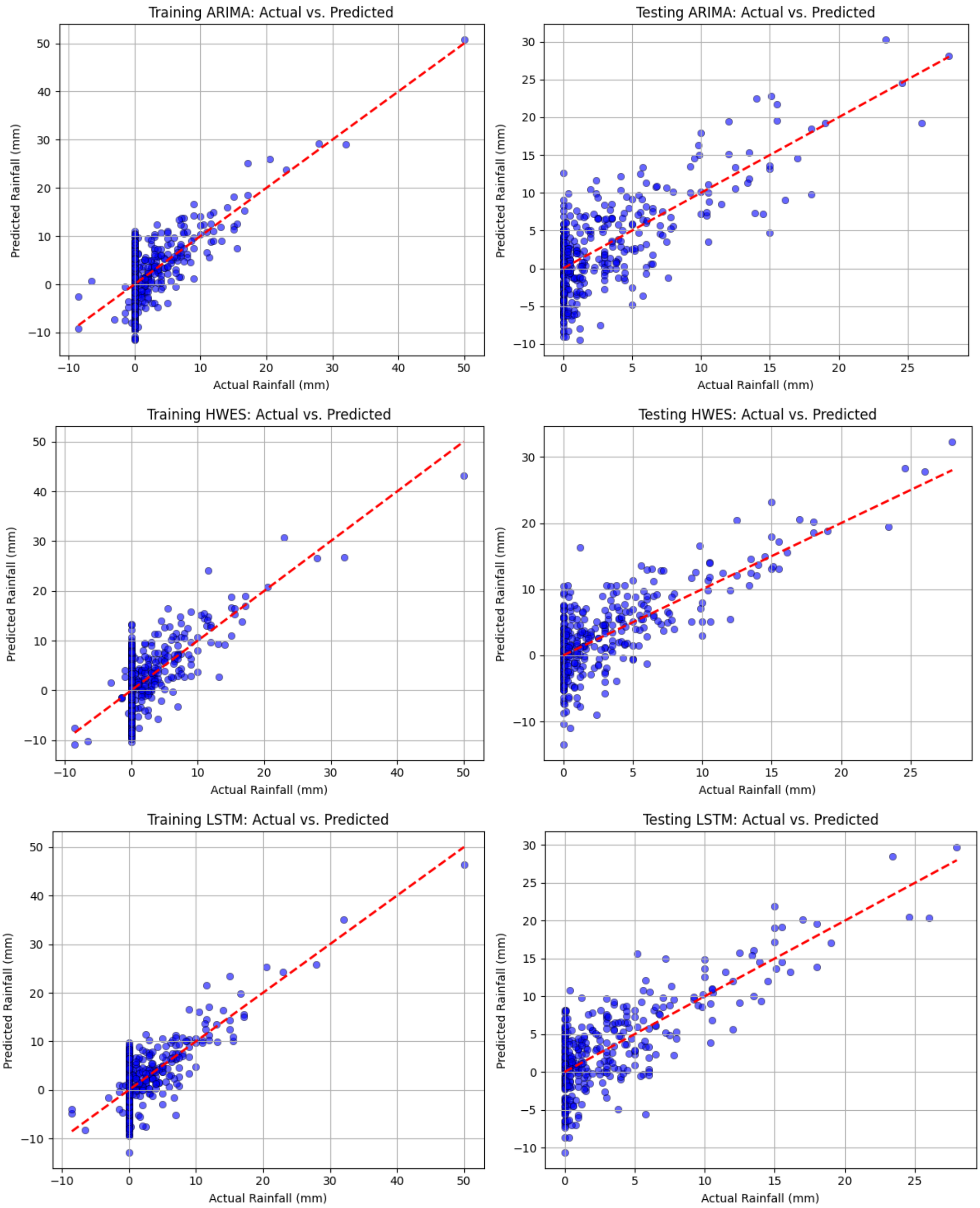
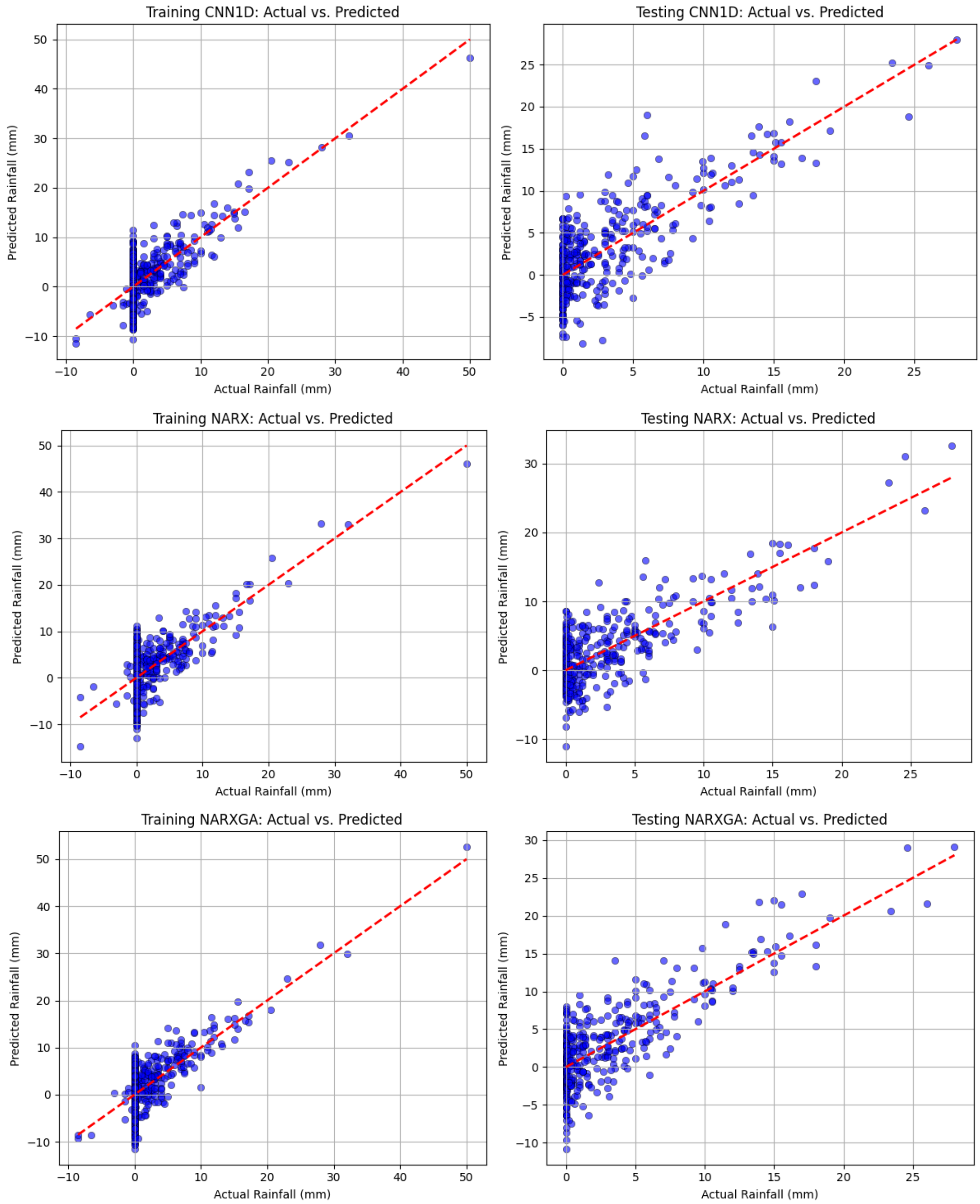


Fig. 5. Scatter plots for both the training and testing phases of different models



Continued Figure 5

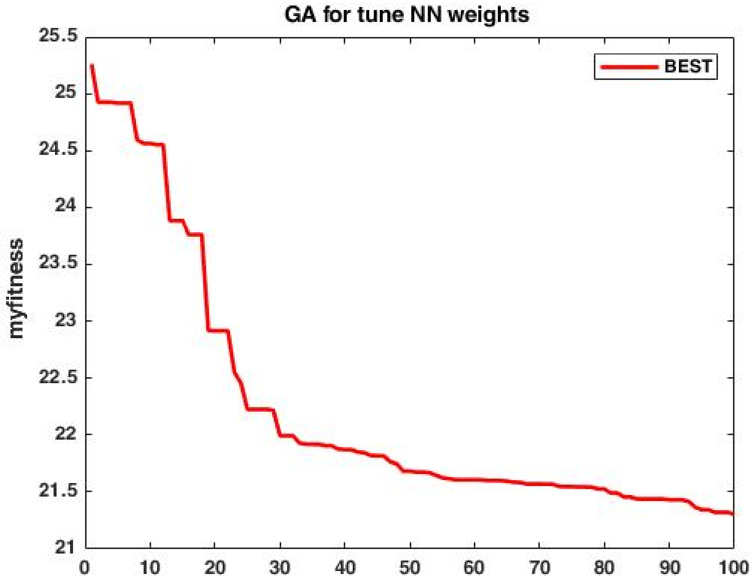


Fig. 6. The convergence of the genetic algorithm (GA) in optimizing the weights of the NARX network in the NARXGA model

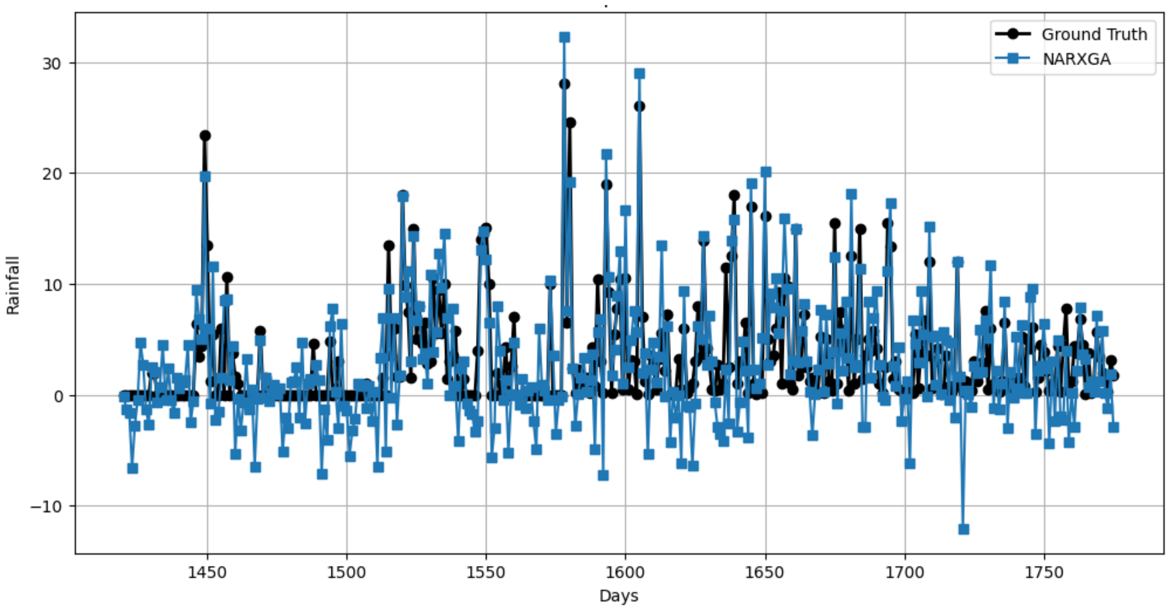


Fig. 7. Observational and prediction of rainfall by NARXGA model

Importantly, the research underlines the major relevance of proper parameter optimization for machine learning in obtaining desirable results.

The results of this study demonstrate that the proposed NARXGA model outperforms traditional time series models (ARIMA, HWES) and machine learning models (LSTM, CNN1D) in rainfall prediction. By leveraging the optimization capability of Genetic Algorithms (GA), our model achieved the lowest Mean Squared Error (MSE) among all tested approaches, highlighting its effectiveness in capturing non-linear dependencies in rainfall data.

Several previous studies have explored different approaches to rainfall prediction. For instance, Poornima and Pushpalatha (Poornima and Pushpalatha, 2019) implement an LSTM-based model for rainfall forecasting. This suggests that while LSTM networks are effective in time series forecasting, the additional parameter optimization provided by GA enhances the predictive performance.

A study by Ngan et. al (Ngan et al., 2023) employed a combination of CNN and GA for forecasting rain. Although convolutional neural networks (CNNs) are extremely potent feature extractors, they are not as suitable for sequential dependencies like recurrent-based NARX models. Our findings confirm the same as the individual model of our work based on CNN1D had higher errors than that of the NARXGA model.

Furthermore, earlier work by Le et al. (Le et al., 2020) demonstrated that conventional NARX models can identify non-linear time series patterns, but they tend to suffer from local minima issues when trained with standard backpropagation methods. The present study circumvents this restriction by including Genetic Algorithms for weight optimization, resulting in a more resilient model with enhanced generalization.

In contrast to the majority of traditional machine learning models with hand-tuned hyperparameters, our approach employs GA to automatically optimize the parameters of the NARX network. This reduces the risk of poor performance caused by incorrect hyperparameter selection and enhances the model's ability to capture complex rainfall patterns. The good performance of NARXGA in our study is a testament to the excellence of evolutionary optimization techniques in time series forecasting.

In spite of its strengths, the suggested model possesses shortcomings. A significant one is the small dataset (records of rainfall only for 5 years), and this will limit the model in identifying long-term climatic trends. Additional years of data included in the dataset, along with the inclusion of external meteorological factors like atmospheric pressure and wind patterns, can provide more precise forecasts.

4. Conclusion

This study has presented a novel hybrid approach, NARXGA, for daily rainfall prediction in Khorasan Razavi province, Iran. The proposed model combines the Non-linear Auto Regressive with eXogenous inputs (NARX) neural network with a Genetic Algorithm (GA) for parameter optimization, aiming to enhance the accuracy and reliability of rainfall predictions in a region that is highly susceptible to drought and water scarcity.

Through experimentation, the performance of the NARXGA model was compared with that of several benchmark models, including ARIMA, HWES, LSTM, CNN1D and NARX. The results clearly indicate that the NARXGA model outperforms all benchmark models, achieving the lowest Mean Squared Error (MSE) values on both training and test datasets. Specifically, the NARXGA model yielded an MSE of 9.7453 on the training dataset and 11.5565 on the test dataset, demonstrating superior predictive power. This can be attributed to the ability of the GA to effectively optimize the parameters of the NARX network.

The convergence analysis of the GA in Figure 1 shows that the GA is capable of iteratively improving the weights and biases of the NARX model, resulting in a final model that is well adapted to the given data and captures non-linear relationships. The histograms of error distribution for all the compared methods also corroborate this observation. As can be seen from Figures 2-5, the NARXGA model produces more consistent results that are more concentrated around the zero-error point compared to other benchmark models, thus signifying a lower error rate.

Despite these promising results, the model has certain limitations. NARXGA’s performance is sensitive to the choice of GA parameters (e.g., mutation rate, population size), and tuning these requires domain expertise or heuristic search. Moreover, the model’s reliance on historical data patterns may limit its adaptability under sudden climatic shifts or unseen weather anomalies. Future research could explore hybridization with adaptive learning mechanisms or ensemble strategies to improve generalizability across different climatic zones.

This study contributes to the advancement of rainfall prediction through multiple key innovations. First, it introduces a hybrid model—NARXGA—that integrates Nonlinear Autoregressive models with exogenous inputs (NARX) and Genetic Algorithms (GA) for parameter optimization. By leveraging the strengths of both recurrent neural networks and evolutionary algorithms, the proposed model addresses limitations of traditional time-series approach and enhances predictive reliability in complex environmental conditions. Second, the model's practical relevance has been demonstrated using real meteorological data from Khorasan Razavi province in Iran—an arid region where accurate rainfall forecasting is crucial for effective water resource management and agricultural planning. This empirical validation highlights the applicability and robustness of the model in a real-world context. Moreover, experimental results indicate that NARXGA outperforms several baseline artificial neural network architectures in terms of prediction accuracy. This improvement underscores the value of GA-based optimization in fine-tuning network parameters such as weights and biases. Finally, the proposed method maintains computational efficiency despite its enhanced performance. Its relatively simple structure offers a viable alternative to more complex deep learning models, making it especially suitable for operational deployment in data-scarce or resource-limited environments.

The results of this research have practical implications for water resource management and agricultural planning in arid and semi-arid regions. The findings from this research can be utilized for early drought warning systems, irrigation planning, and other applications that rely on accurate rainfall predictions.

Several avenues for future research have been identified. These include:

1. Expanding Dataset: Future studies can be performed using larger datasets with more features to further improve the accuracy of the model and to fully test the proposed method.
2. Spatial Analysis: Future research can focus on developing models that take spatial variability into account for more accurate regional rainfall prediction. Spatial information can be obtained from weather stations or remote sensing data.
3. Alternative Optimization Techniques: The performance of the proposed framework can be evaluated by integrating other evolutionary algorithms, including particle swarm optimization (PSO) or ant colony optimization (ACO) algorithms, which can potentially lead to even better results.
4. Deep Learning Integration: Exploring the use of deep learning methods within the proposed model, such as incorporating convolutional layers within the NARX model, can also further improve results.
5. Real-time Implementation: Testing the NARXGA on real-time data for practical applications will also be useful in fully evaluating the model.

5. Conflict of Interest

No potential conflict of interest was reported by the authors.

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