FORECASTING OF SOLAR RADIATION WITH ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Accurate estimation of solar radiation is of great importance for the effective use of solar energy and efficient management of energy grids. This study evaluated the effectiveness of Artificial Neural Networks (ANN), especially the NARX (Nonlinear Autoregressive with Exogenous Inputs) model in solar radiation estimation. The analyses conducted for nine different cities in Türkiye examined the estimation performances of the cities during the machine learning processes, including the learning, validation, and testing stages. According to the analysis results, Antalya and Mersin cities exhibited the best performance with the lowest Mean Square Error (MSE) values (0.2931 and 0.2897) and high correlation coefficients (R=0.9799 and R=0.9797). Trabzon had the highest MSE values (0.6203) and performed less than other cities. Despite relatively high error rates, Istanbul City strongly correlated. Evaluating the performance criteria during training revealed that İzmir and Istanbul demonstrated superior performance with low error values. According to the gradient values calculated during the training, Istanbul reflected the smoothest optimization process with the lowest value (33.3). Higher gradient values revealed the data complexity in cities such as Trabzon (84.4) and Van (57). These findings show that the NARX model is effective in solar radiation estimation and is a powerful method, especially in short-term forecasts. We evaluated the model's consistent performance in different cities by considering data complexity and computational efficiency. The study recommends applications of the NARX method on a larger scale and supported by different meteorological variables for future research.

Keywords: Solar Radiation Forecast, NARX method**Keywords:** Solar Radiation Forecast, NARX method

INTRODUCTION

The energy issue has always been a significant concern for governments. Due to the great consumption of the earth's fossil energy and its non-renewable nature, human beings are about to fall into the dilemma of energy shortage, and energy transformation and the search for renewable and clean energy are the problems people need to solve urgently (Bokde et al., 2019). Sivakumar et al. (2023) proposed nine novel ensemble models integrating VMD and DWT with machine and deep learning algorithms for accurate solar radiation forecasting in Indian cities. Their study demonstrated that these models significantly reduced prediction errors compared to traditional methods.

Ma and Chen (2023) introduced a hybrid deep learning model combining improved convolutional neural networks and recurrent neural networks to enhance short-term global solar radiation forecasting. This approach showed substantial improvements in forecast accuracy over existing methods. Zhang et al. (2023) presented a hybrid deep residual learning model for short-term solar radiation forecasting, showing improved performance through model optimization. This model effectively captured complex patterns in solar radiation data. Wang and Zhao (2022) introduced a novel image-processing technique for short-term solar radiation forecasting, leveraging machine learning algorithms for enhanced prediction accuracy. Their approach utilized high-resolution sky images to improve forecast precision. Manandhara, Temimi, and Aung (2023) proposed a short-term solar radiation forecasting approach using deep transfer learning techniques applied to images from a Total Sky Imager. The study highlighted the potential of transfer learning in reducing the modeling time and resource requirements for solar forecasting.

Liu, Wang, and Sun (2021) proposed a method for solar radiation forecasting using convolutional neural networks, demonstrating high accuracy and robustness in predictions. The model effectively handled various weather conditions and provided reliable forecasts. Chen and Lin (2024) explored using a gradient-boosting machine-learning model for predicting solar radiation, highlighting the model's high precision and efficiency. Their findings indicated that gradient boosting outperformed other machine learning techniques regarding forecast accuracy. Xu and Huang (2022) discussed various deep-learning models for forecasting solar radiation, demonstrating significant improvements in prediction accuracy. The study emphasized the importance of selecting appropriate features and model architectures for effective solar radiation forecasting. Li and Zhou (2021) proposed a variational mode decomposition-based random forest model for improving the accuracy of solar radiation forecasts. The model enhanced prediction capabilities by effectively capturing the inherent variability in solar radiation data. In conclusion, advancements in machine learning and deep learning have significantly improved the accuracy and efficiency of solar radiation forecasting. These innovative approaches offer promising solutions for better managing solar energy resources and optimizing the performance of photovoltaic systems.

METHOD

NARX Method

The Nonlinear Autoregressive model with Exogenous inputs (NARX) is a powerful tool for time series forecasting, particularly in the context of solar radiation prediction. The NARX model combines past values of the output series with current and past values of an exogenous series, allowing it to capture complex dynamic relationships. This method is particularly effective in handling nonlinearity and temporal dependencies in data, making it suitable for predicting solar radiation, which is inherently variable and influenced by numerous external factors.

1. Integration with Machine Learning and Deep Learning: The NARX model has been integrated with various machine learning and deep learning algorithms to enhance prediction accuracy. Techniques like Variational Mode Decomposition (VMD) and Discrete Wavelet Transform (DWT) are often used to preprocess data to improve model performance (Sivakumar et al., 2023).

For a simple neural network with one hidden layer, the forward propagation can be represented mathematically as:

Hidden Layer Output = $\sigma(W1 \cdot X + b1)$

Output Layer Output = $\sigma(W2 \cdot \text{Hidden Layer Output} + b2)$

Where X is the input vector, W1 and W2 are weight matrices for the hidden and output layers, respectively. b1 and b2 are bias vectors for the hidden and output layers.

2. Hybrid Approaches: Hybrid models combining NARX with other predictive models like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have significantly improved short-term solar radiation forecasting. These approaches leverage each model's strengths to effectively capture spatial and temporal features (Pothineni et al., 2022).

3. Transfer Learning: Researchers have explored transfer learning with pre-trained networks like AlexNet and ResNet-101 in conjunction with NARX models to reduce computational requirements and improve prediction accuracy. This approach benefits from leveraging features learned from large datasets, thus enhancing the model's ability to generalize to new data (Manandhar et al., 2023).

4. Ensemble Learning: Ensemble learning methods, which combine predictions from multiple models, have been employed further to improve the robustness and accuracy of NARX-based predictions. This method helps reduce the variance and bias in the predictions, leading to more reliable solar radiation forecasts (George et al., 2023).

5. Short-Term Forecasting: NARX models are particularly effective for short-term solar radiation forecasting, critical for operational efficiency in solar power plants. The ability to accurately predict solar radiation minute-by-minutely helps optimize energy production and grid management (Temimi et al., 2023). The Nonlinear Autoregressive model with Exogenous inputs (NARX) is a dynamic neural network model used for time series forecasting. It can be represented mathematically as::

$$Hidden\ Layer\ Output\ =\ \sigma(W1\ \cdot\ X\ +\ b1) Output\ Layer\ Output$$
$$=\ \sigma(W2\ \cdot\ Hidden\ Layer\ Output\ +\ b2)$$

Where X is the input vector, W1 and W2 are weight matrices for the hidden and output layers, respectively. B1 and b2 are bias vectors for the hidden and output layers.

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The Nonlinear Autoregressive model with Exogenous inputs (NARX) is a dynamic neural network model used for time series forecasting. It can be represented mathematically as:

$$y(t) = F\big(y(t-1),\ y(t-2), \dots, y(t-n),\ u(t-1),\ u(t-2), \dots, u(t-m)\big) + \varepsilon$$

where: $y(t)$ is the output at time t. $y(t-1), y(t-2), \dots, y(t-n)$ are the past values of the output.

$u(t-1)$, $u(t-2), \dots, u(t-m)$ are the past values of the exogenous input. F is a nonlinear function. $\varepsilon(t)$is the error term at time t.

ANALYSIS

Key Metrics: MSE (Mean Squared Error): Indicates the prediction error magnitude. Lower values represent better performance. R (Correlation Coefficient): Measures the strength and direction of the relationship between predicted and actual values. Higher values, nearing 1, indicate better predictive performance. In the learning and validation phases, the province with the smallest RMSE value and the most considerable r-square value was Antalya, while in the testing phase, it was Mersin. General Observations: Antalya and Mersin show the best overall performance with low MSE and high R values. Trabzon exhibits the weakest performance due to the highest MSE values, although the R values remain acceptable. İstanbul has higher MSE values than major cities like Ankara and İzmir, but the correlation remains strong.

NARX Method Outputs and Training Results Analysis for Nine Cities in Turkey

Table 1. Results of NARX model training MSE and R Analysis

City	Training MSE	Training R	Validation MSE	Validation R	Test MSE	Test R
Ankara	0.3397	0.9703	0.4521	0.9655	0.4067	0.971
Antalya	0.2931	0.9799	0.3055	0.9788	0.346	0.976
İstanbul	0.5038	0.9564	0.5212	0.9554	0.51	0.955
İzmir	0.3902	0.9731	0.3763	0.9743	0.3827	0.973
Malatya	0.3675	0.9758	0.3695	0.9761	0.4726	0.968
Mersin	0.3162	0.978	0.3127	0.9784	0.2897	0.98
Sivas	0.3675	0.9758	0.3695	0.9761	0.4726	0.968
Trabzon	0.6203	0.938	0.6398	0.9397	0.6021	0.938
Van	0.3416	0.9761	0.3625	0.9748	0.3416	0.978

Performance: Best Performance: İzmir (7.31), followed by İstanbul (7.83). Weakest Performance: Van (28.9), Trabzon (23.3), and Malatya (23). Gradient: Lowest Gradient: İstanbul (33.3) indicates a smoother optimization process. Highest Gradient: Trabzon (84.4) suggests a more complex learning process. Elapsed Time: Most cities have negligible elapsed time (00:00:00), except Ankara (00:00:05) and İzmir (00:00:04). Validation Checks: Consistent across all cities (6 validation checks), indicating a similar approach to determining convergence. Observations: Efficiency: Ankara and İzmir demonstrate a balance between good performance (low error) and acceptable computation time. İstanbul has excellent performance metrics but almost no elapsed time, showing high computational efficiency. Complexity: Cities like Trabzon and Van have high-performance values and gradients, suggesting that their data might have been more complex or more challenging to fit. Consistency: All cities completed training with the same number of validation checks (6), ensuring comparable convergence criteria.

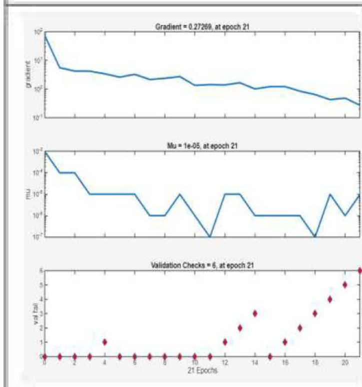
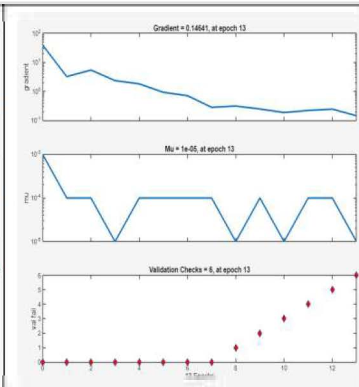
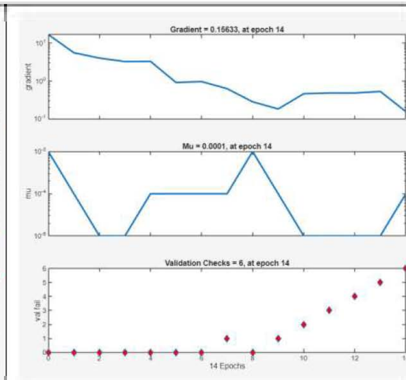
Table 2. Training Results Comparison

City	Initial Value	Stop Value	Target Value	Elapsed Time	Performance	Gradient	Mu	Validation Checks
Ankara	0	13	1000	00:00:05	18.9	81.9	0.001	6
Antalya	0	14	1000	00:00:04	17.9	82.1	0.001	6
İstanbul	0	13	1000	00:00:00	7.83	33.3	0.001	6
İzmir	0	13	1000	00:00:04	7.31	38.9	0.001	6

Malatya	0	16	1000	00:00:03	23	62	0.001	6
Mersin	0	9	1000	00:00:00	15.6	62.3	0.001	6
Sivas	0	15	1000	00:00:00	11.5	48.9	0.001	6
Trabzon	0	16	1000	00:00:00	23.3	84.4	0.001	6
Van	0	14	1000	00:00:00	28.9	57	0.001	6

Figure 1 illustrates that training the network improves its performance for the prediction model. We measure this kind of performance in terms of mean squared error and present it on a log scale. The network rapidly decreases the error during training. The final mean squared error is less than 10-1, and the test and validation set errors have similar low values indicating the sufficiently trained network. The researchers trained the network for nine epochs and completed the learning process upon achieving the target accuracy. Activating the Performance button generates a graph of the mean square error (MSE) versus the number of epochs (Fig. 1). Figure 2 illustrates the fluctuation in error functions to facilitate understanding of their behavior.

Figure 7 Training state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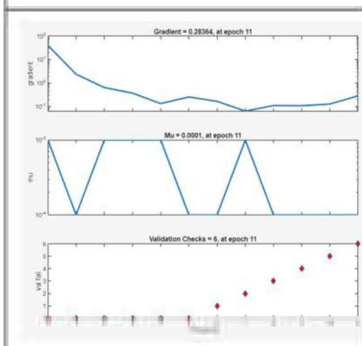	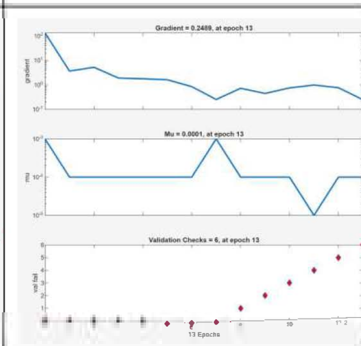	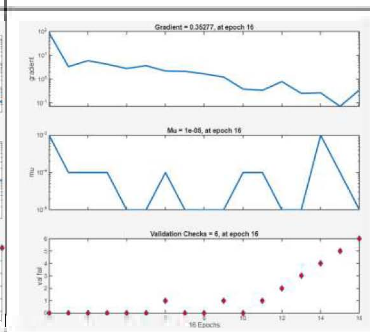
Izmir	*Malatya*	*Mersin*

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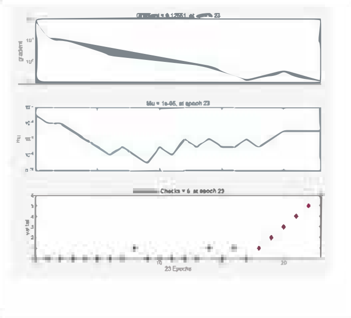
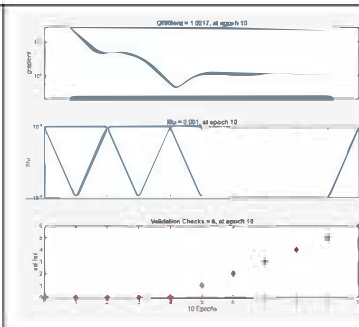
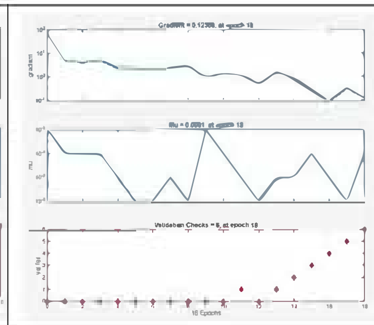
<tr><td></td><td></td><td></td></tr>
<tr><td>Sivas</td><td>Trabzon</td><td>Van</td></tr>
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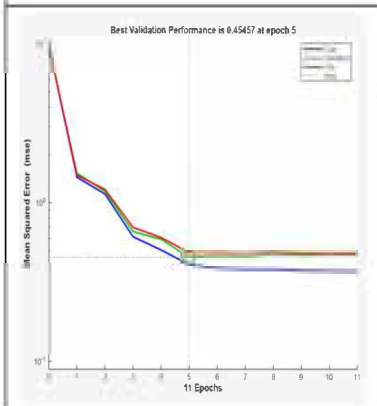
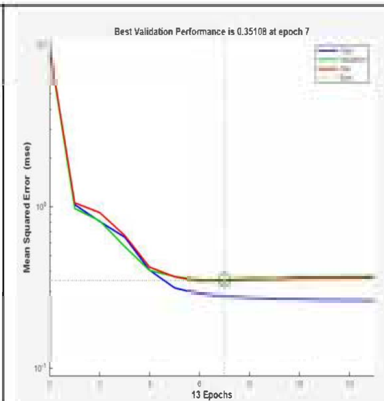
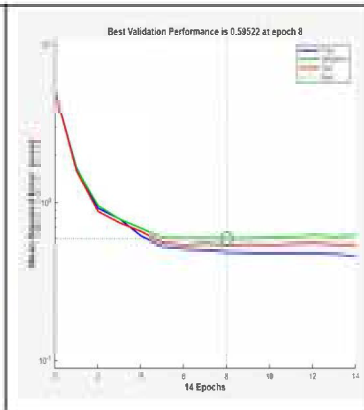
<tr><td></td><td></td><td></td></tr>
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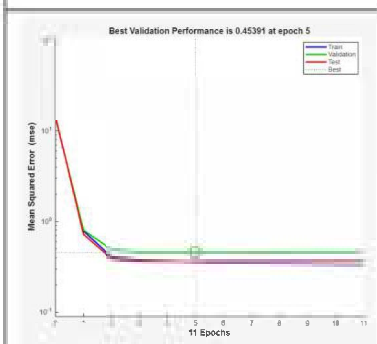
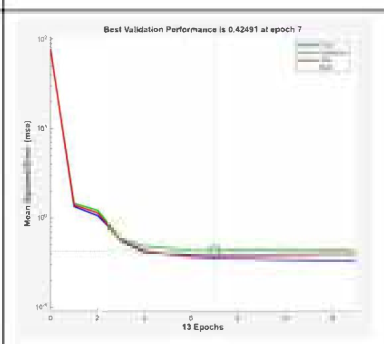
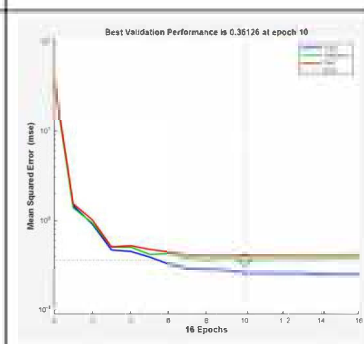
<tr><td></td><td></td><td></td></tr>
<tr><td>Izmir</td><td>Malatya</td><td>Mersin</td></tr>
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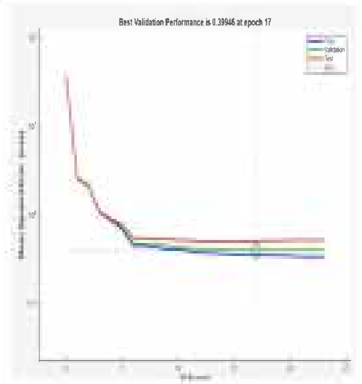
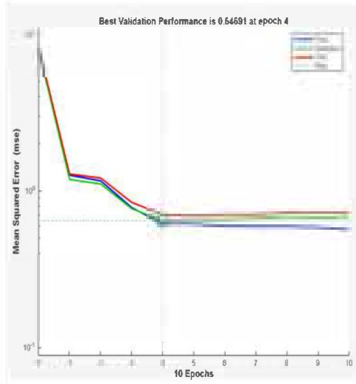
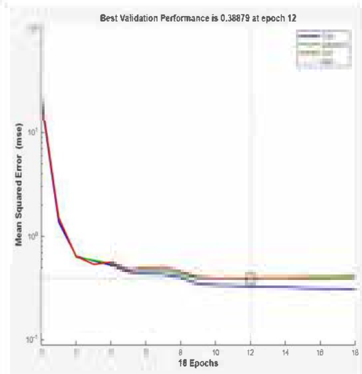
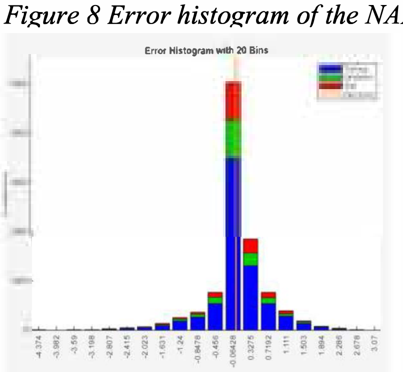
PROCEEDINGS BOOK

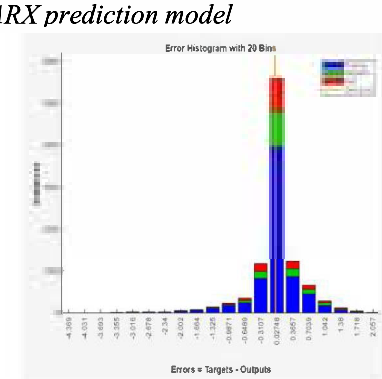
		
Sivas	*Trabzon*	*Van*

The above plot of the validation efficiency between the number of epochs and the root mean square error demonstrates that the green circle shows that training stopped when the validation error increased for nine iterations. The validation and test set errors have characteristics similar to those indicated by the green and red lines. It is clear that with an increase in the number of epochs, the MSE decreases for all trained, validation, and test data with an insignificant change in slope.

Figure 8 Error histogram of the NARX prediction model



Ankara



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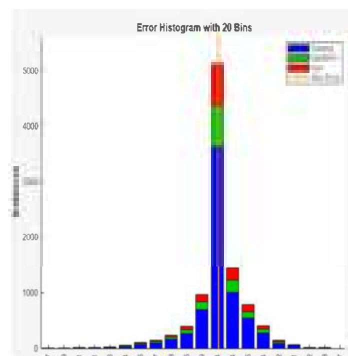
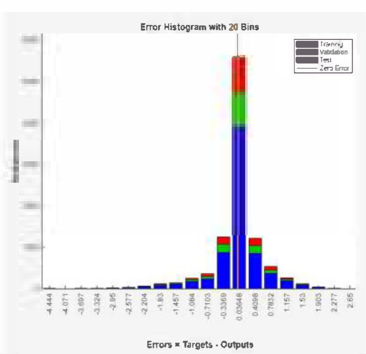
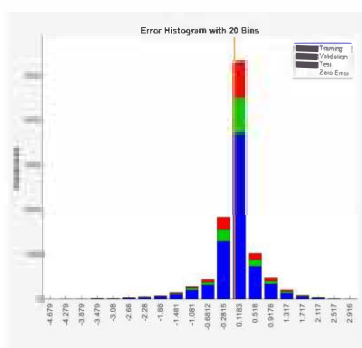


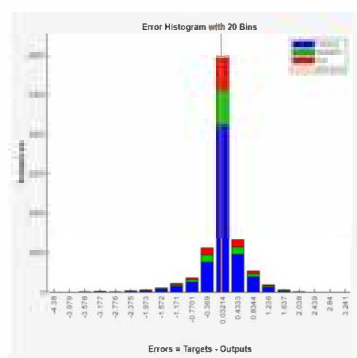
Istanbul



Izmir



Malatya



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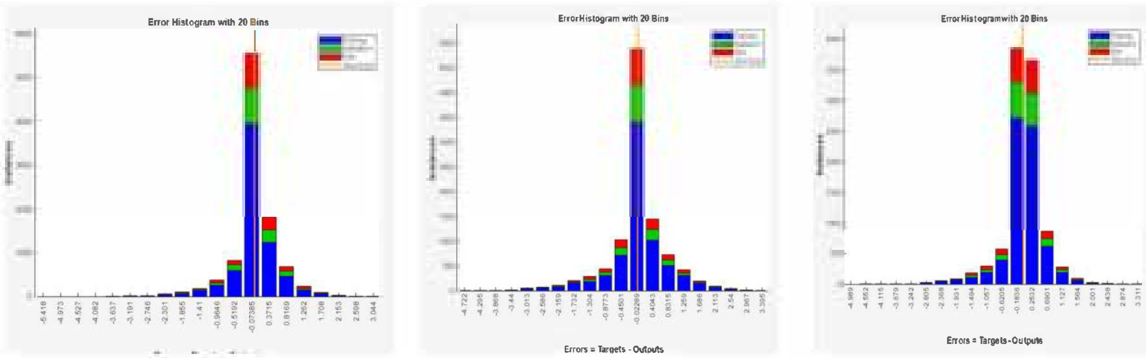
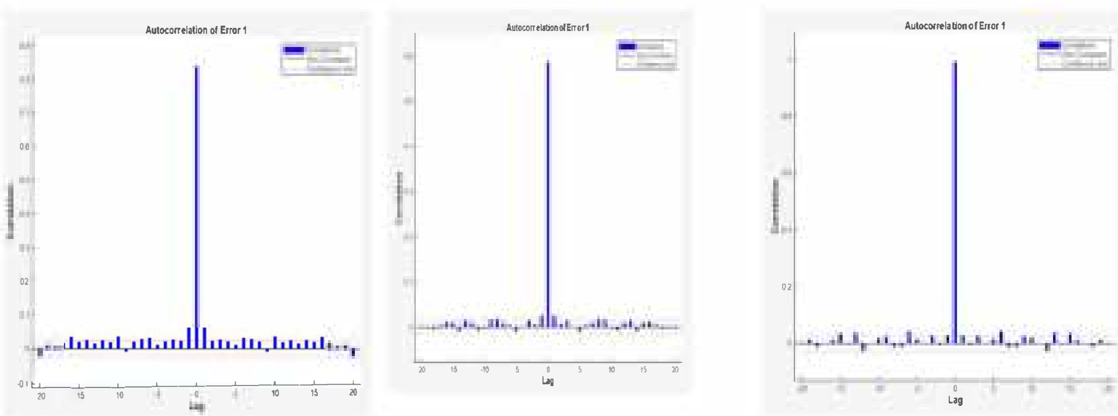


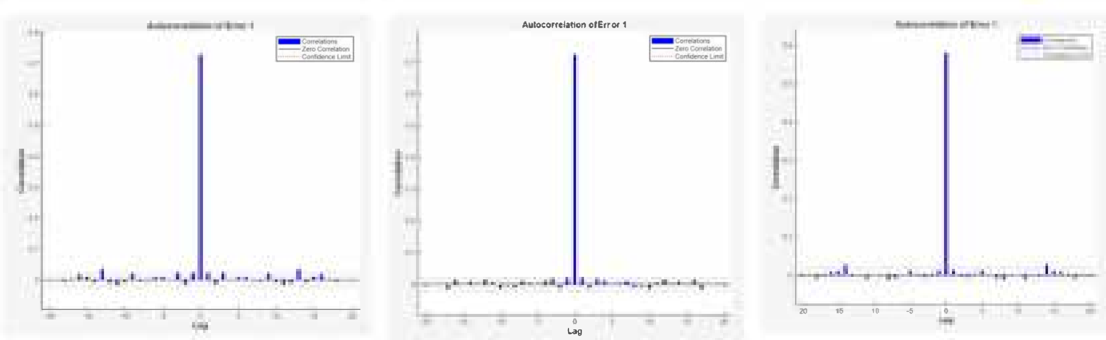
Sivas *Trabzon* *Van*

Figure 3 shows how the error sizes are distributed. Most errors are near zero, which illustrates a reasonably good fit. Figure 2 shows that the majority of the error histogram bins are around the middle of the histogram, where the maximum error is less than 4.857, the minimum error is more significant than −6.354, and many error values are around zero.

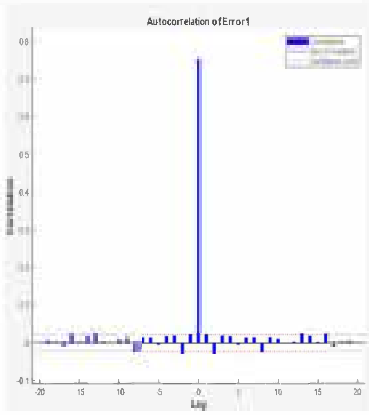
Figure 9 Autocorrelation of errors of NARX prediction model

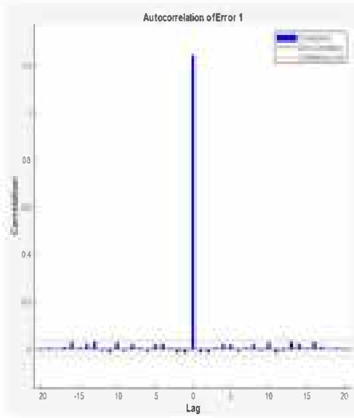


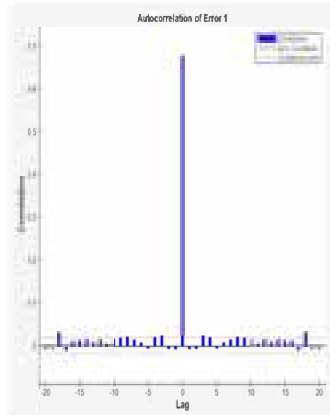
Ankara *Antalya* *Istanbul*



Izmir *Malatya* *Mersin*







Sivas *Trabzon* *Van*

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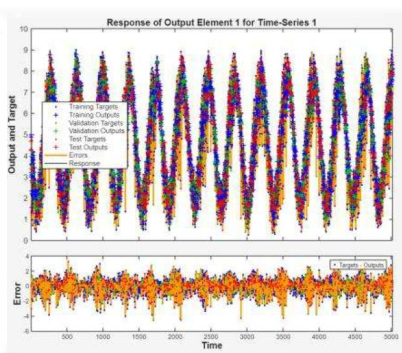
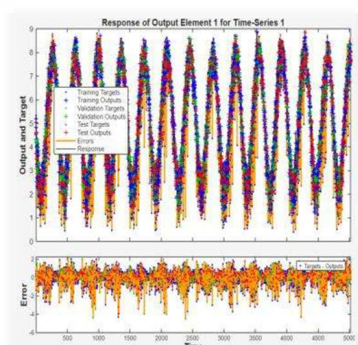
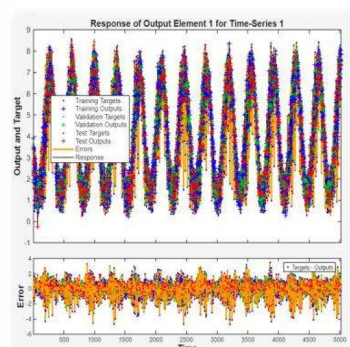
Figure 4 describes the function of autocorrelation of errors to validate the network performance. Autocorrelation measures how prediction errors relate to each other over time. For a perfect model, there should be only one non-zero autocorrelation value at zero lag (the mean squared error), which means there is no correlation between prediction errors and each other, and there is white noise. In our case, the autocorrelation of errors is within the 95% confidence interval around zero.

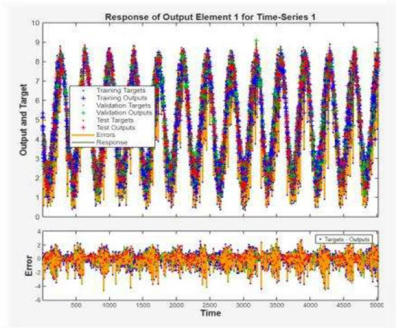
Figure 10 Response of NARX prediction model







Ankara *Antalya* *Istanbul*



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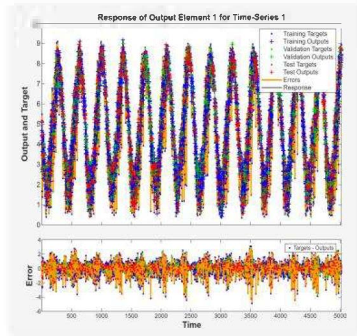

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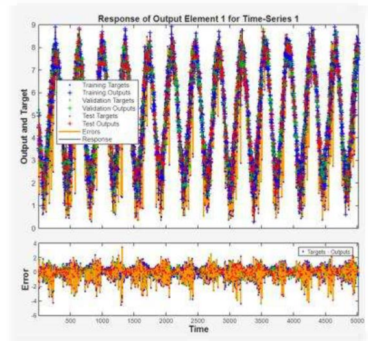
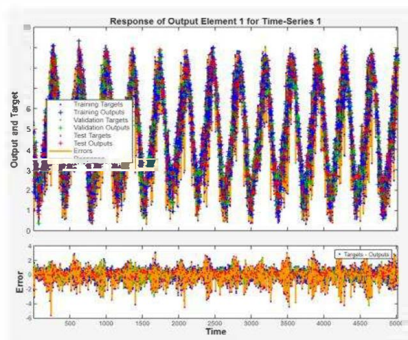


Mersin



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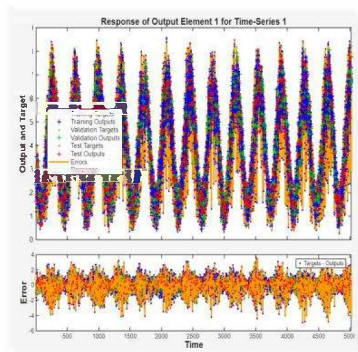

Trabzon

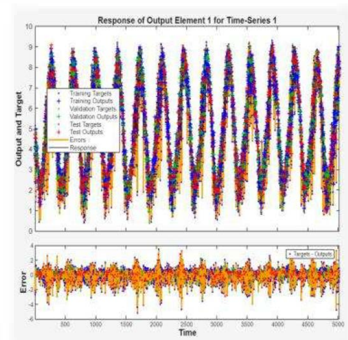

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Figure 5 below shows the results of the simulation. Based on it, we can assume that the NARX prediction model is adequate, as it shows a small number of errors with low magnitude. Figure 5 shows the relationship between target and predicted values for all datasets: training, validation, and testing. The results showed that the error values for the testing dataset are very low compared to validation and training datasets. Finally, the overall results of the training dataset showed a normal distribution of errors with excellent accuracy in predicting the training, validation, and testing data. The results indicated that the NARX model can predict the solar radiation of Nine cities. Figure 5 shows the relationship between target and predicted values for all datasets: training, validation, and testing. The results showed that the error values for the testing dataset are very low compared to validation and training datasets. Finally, the overall results of the training dataset showed a normal distribution of errors with excellent accuracy in predicting the training, validation, and testing data. The results indicated that the NARX model can predict the solar radiation of nine cities..

Table 3 Performance Evaluation of Machine Learning Models for Solar Radiation Prediction

Model	**RMSE**	**R²**	**MSE**	**MAE**	**MAPE**	**Prediction Speed**	**Training Time**	**Model Size (Compact)**	**Model Size (Coder)**
Neural Network	0.28267	0.98	0.28267	0.16844	4.50%	~220000 obs/sec	20.717 sec	~9 kB	~5 kB

Gaussian Process Regression	0.355	0.98	0.126	0.24	6.30%	~5600 obs/sec	338.86 sec	~445 kB	~436 kB
SVM	0.39979	0.97	0.39979	0.28624	8.50%	~73000 obs/sec	15.147 sec	~147 kB	~144 kB
Tree	0.42314	0.97	0.42314	0.20599	5.40%	~48000 obs/sec	7.1401 sec	~190 kB	~80 kB
Ensemble	0.45799	0.96	0.45799	0.34189	8.20%	~66000 obs/sec	240.91 sec	~173 kB	~34 kB
Kernel	0.47676	0.96	0.47676	0.34995	10.40%	~85000 obs/sec	309.37 sec	~12kB	~12 kB
Stepwise Linear Regression	0.54382	0.94	0.54382	0.42399	12.10%	~210000 obs/sec	87.438 sec	~40 kB	~17kB
Efficient Linear	0.99671	0.81	0.99671	0.75252	23.40%	~200000 obs/sec	2.5204 sec	~11 kB	~2kB

CONCLUSION

Table 3 presents a performance comparison of various machine-learning models used for solar radiation prediction. The evaluated methods include Neural Networks, Gaussian Process Regression, Support Vector Machines (SVM), Decision Trees, and Ensemble models. The lowest RMSE value of 0.28267 belongs to the Neural Network model, indicating high prediction accuracy. This model also exhibits a high R^2 value of 0.98, suggesting strong explanatory power. Gaussian Process Regression also shows a high R^2 value of 0.98, although with a relatively higher RMSE. The SVM and Tree models display similar performance with an R^2 value of 0.97 but lag behind the Neural Network regarding RMSE and MAE. The Ensemble method ranks last with an R^2 of 0.96 but still delivers acceptable performance. Regarding MAE, the Neural Network performs best with the lowest error.

All models' MAPE values are below 10%, indicating high accuracy. Regarding prediction speed, the Neural Network is the fastest model, while Gaussian Process Regression is the slowest. Its long training time (approximately 339 seconds) may make it less suitable for practical use. Regarding model size, the most compact is the Neural Network, with around nine kB. Gaussian Process Regression and SVM have significantly larger model sizes. Training time and model size are crucial factors for real-time applications. Overall, the Neural Network stands out as the best-performing method in terms of both accuracy and speed.

Our findings indicate that the nonlinear autoregressive with exogenous input(NARX)model with the Levenberg–Marquardt algorithm for network training can ensure a reasonable quality of the forecast of short time series. The NARX model performed the best according to MSE. Thus, we avoided overfitting along with reasonable predictive performance. These results demonstrate the potential for the NARX models compared to traditional statistical methods.

When we evaluated the metric results of the performance of this method, we calculated the RMSE, MAE, and MAPE performance values. These performance results are evidence of the superiority of the proposed method in solar radiation prediction. Researchers can use them to achieve more accurate and efficient predictions in future applications.

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