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Solar Irradiance Prediction Using Different Machine Learning Models and ANFIS Approach

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ABSTRACT:
This article explores the significance of solar energy as a clean and renewable power source in a world facing environmental challenges. Solar irradiance prediction is a critical aspect of harnessing this energy, necessitating advanced techniques. Employing Machine Learning and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in MATLAB, this study addresses the challenge of accurately forecasting solar irradiance, a complex task influenced by various factors. Comparing the two approaches, the research unveils the superior performance of ANFIS, boasting a 7% higher accuracy compared to Machine Learning, attributed to its rapid learning capabilities and the utilization of larger datasets. The findings emphasize the potential of ANFIS in solving the intricate problem of solar irradiance prediction, offering a promising solution in the realm of renewable energy.

Key words: Clean Energy, Solar Radiation, Machine Learning, ANFIS, Solar Power

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I. Introduction:

In today's world, solar energy, from small-scale applications like calculators to large power plants, plays a vital role in providing clean and renewable power. With a growing need to reduce emissions from conventional fuels, solar irradiance stands as an eco-friendly alternative. This article addresses the challenge of predicting solar irradiance, a complex task influenced by multiple parameters. To tackle this, the study employs Machine Learning and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in MATLAB, comparing their performance in forecasting solar energy. The research reveals that the ANFIS model outperforms Machine Learning by approximately 7% in accuracy, a finding attributed to its rapid learning capabilities and the utilization of larger datasets, making it a promising solution to the solar irradiance prediction problem.

II. Literature Review:

In the realm of solar irradiance prediction, researchers have extensively explored the application of artificial neural networks (ANNs) as a powerful tool for harnessing renewable energy sources. Pioneering work by Kalogirou [5] and Mellit [2] has emphasized the role of ANNs in enhancing the efficiency of renewable energy systems and photovoltaic applications. Their studies shed light on the potential of ANNs to optimize the use of clean energy resources.

Additionally, Hontoria [3] and Tymvios [4] have made significant contributions by utilizing ANNs to model solar radiation. Their research has illustrated the capability of ANNs to make accurate predictions by considering vital input parameters such as sunshine hours and air temperature. By incorporating these parameters, they have paved the way for more precise solar irradiance forecasts.

Furthermore, the works of Sanders [6], Sharma [7], and Voyant [8] have illuminated the promise of machine learning methods in solar radiation prediction. These researchers have advocated for the adoption of various modeling algorithms, including CART, MARS, RF, and M5, in forecasting hourly solar radiation for up to six days in advance. Their findings have shown that RF exhibits superior performance, while CART may display relatively weaker predictive capabilities [6] [7] [8] [13].

The recognition of hybrid models as well as the acknowledgment of the impact of meteorological and geographical factors on solar radiation forecasting underscore the evolving significance of artificial intelligence in the renewable energy landscape. Notable contributions from researchers such as Jiang [9], Mosavi [10], Srivastava [11], and Jagadeesh [12] have reinforced the growing role of AI in shaping the future of solar irradiance prediction, highlighting its potential for creating more sustainable and efficient energy systems.

III. Methods and Methodologies:

3.1 Methodology Summary:

The methodology section provides an in-depth explanation of the research methods and procedures employed to address the research questions or objectives. In this summary, we present a concise overview of the key elements of the methodology used in this study.

3.2 Data Collection:

Our study utilized data collected from reliable sources, particularly from the NASA website for renewable energy prediction. The selected parameters, including Wind Speed, Wind Direction, Temperature, Relative Humidity, Specific Humidity, Precipitation, Cloud Amount, Surface Pressure, and Solar Irradiance, were crucial for our research. Data collection focused on the geographical region of Jeddah, Saudi Arabia, with a timeframe spanning from 1990 to 2021 on a monthly basis.

3.3 Data Pre-Processing:

For the Machine Learning approach, we divided the datasets into two separate Excel files: one for parameters and one for the target variable, Solar Irradiance. For the ANFIS approach, data pre-processing was different. All relevant parameters and the target were combined into a single Excel file containing 11 columns. These datasets were subsequently transformed into numeric values for compatibility with MATLAB tools.

3.4 Machine Learning Approach:

Our study applied Machine Learning to predict solar irradiance. We employed the Supervised Learning Neural Fitting technique, specifically using the Neural Net Fitting tool in MATLAB. The datasets were divided into training, testing, and validation sets, with two different algorithms used for training: the scaled conjugate gradient (SCG) and Bayesian regularization (BR). A two-layer feed-forward neural network was employed, consisting of 20 hidden layers.

3.5 ANFIS Approach:

A hybrid learning approach was implemented to optimize the parameters of the ANFIS system. This approach combined fuzzy logic and Machine Learning to enhance the model's performance. It involved a direct delivery and backpropagation process to modify parameters and improve efficiency. This summary provides a brief overview of the methodology used in this study, focusing on data collection, data pre-processing, the Machine Learning approach, the ANFIS approach, and the hybrid learning process.

IV. Results and Findings:

4.1 Machine Learning Predictive Model:

4.1.1 The Model Resulted With Higher Prediction Accuracy:

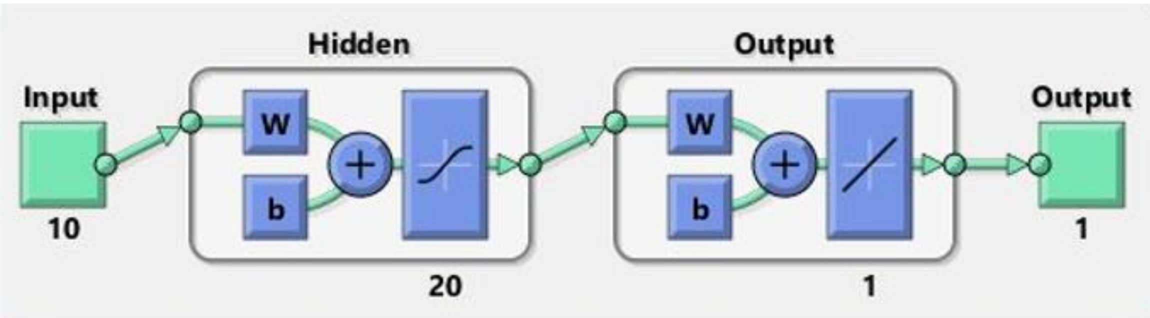

Figure 1: Neural Network Architecture For Solar Irradiance Prediction

Our machine learning model was constructed using Bayesian regularization and yielded impressive results for the prediction of solar irradiance. The model's architecture featured 10 inputs and 20 hidden layers. These layers, crucial for modeling the nonlinear relationship between inputs and outputs, were determined through rigorous trial-and-error experiments to optimize predictive accuracy.

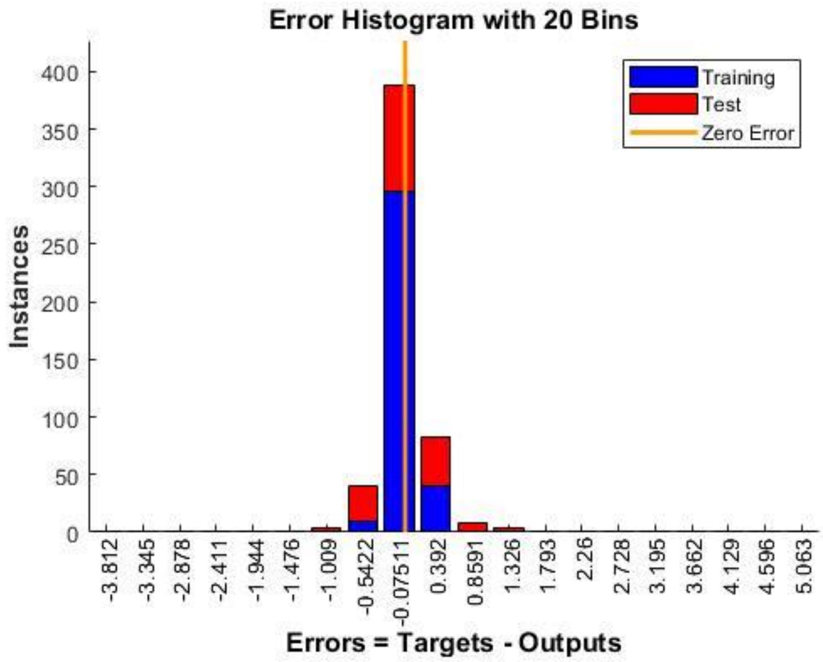

Figure 2: Error Histogram of Solar Irradiance Prediction

The model's performance was assessed in terms of error, as depicted in the error histogram graph (Figure 2). This graph portrays the error between target and predicted values after model training. Notably, the error for both training and testing datasets was incredibly low, at 0.075, approaching zero. Such minimal error is indicative of the model's ability to closely approximate actual solar irradiance values.

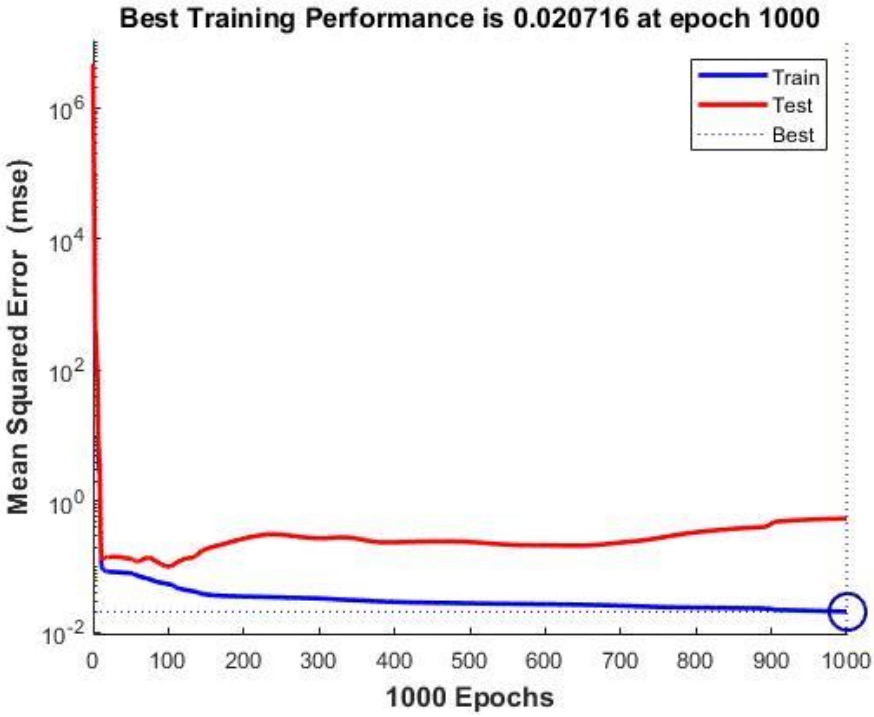

Figure 3: Performance Plot of Solar Irradiance Prediction

To gain further insights into the model's performance, a performance plot was constructed (Figure 3) to visualize the Mean Squared Error (MSE) versus the number of iterations (epochs) during training. Our best performance, characterized by an MSE of 0.0207, was observed at 1000 epochs. This outcome demonstrates the model's ability to converge to highly accurate predictions over a relatively short number of iterations.

Table 1: Results of Machine Learning Higher Accuracy Model

	Samples	MSE	R
Training	319	0.0207	1
Testing	187	0.5	1

Additionally, the model's accuracy was quantified through Bayesian regularization training. The results presented in Table 1 showcase the Mean Squared Error (MSE) and Correlation Coefficient (R) for the training and testing datasets. The training dataset exhibited an impressively low MSE of 0.0207, nearly zero, and a correlation coefficient (R) of 1, indicating a model that provides highly accurate predictions. The testing dataset also displayed a strong performance, with an MSE of 0.5, close to zero, and a correlation coefficient (R) of 1, signifying an effective predictive model.

4.1.2 Lower Accuracy Model:

Table 2: Results of Machine Learning Lower Accuracy Model

	Sample	MSE
Training	320	3670
Validation	53	9643
Testing	160	5903

Conversely, a different machine learning model was constructed and trained using the Scaled Conjugate Gradient algorithm. The results for this model were notably less favorable. As illustrated in Table 2, the model's training dataset exhibited a significantly higher MSE of 3670, indicating a substantial deviation from the actual values. The validation and testing datasets fared similarly, with MSE values of 9643 and 5903, respectively. These high MSE values are indicative of a poor predictive model that struggles to approximate the actual solar irradiance values accurately.

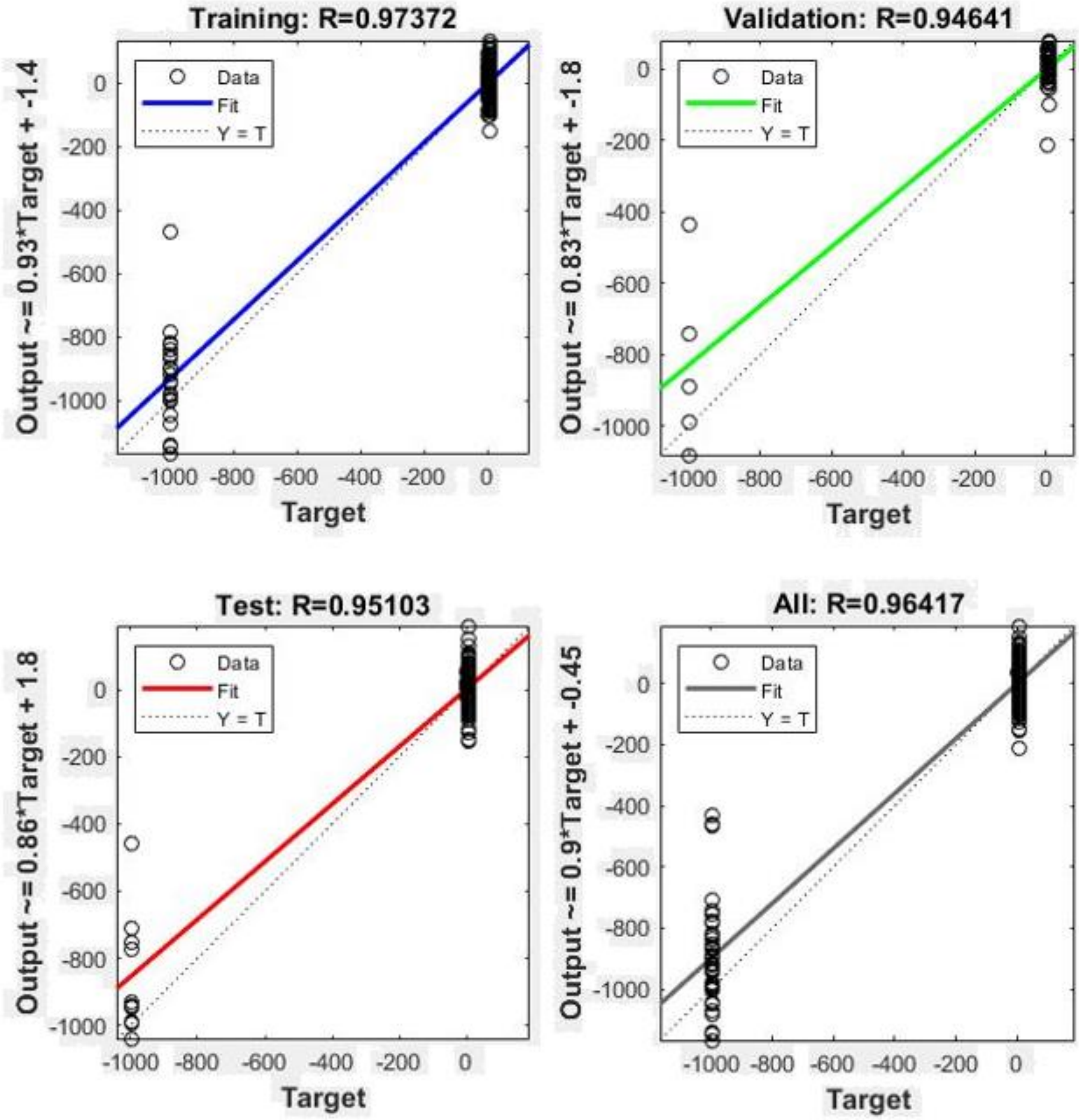

Figure 4: Regression Plot For Solar Irradiance Prediction (Lower Accuracy)

To provide further insight into the model's performance, a regression plot (Figure 4) was generated. This plot highlights the relationship between target and predicted output for both the training and testing datasets. It is evident that the data points for the lower accuracy model are scattered and do not align with the regression line, signaling that the model has difficulty accurately predicting solar irradiance.

4.2 Machine Learning Predictive Model With 20 Predictions:

Extending the analysis, we employed the machine learning regression learner tool to create a predictive model for 20 different test inputs. This allowed us to explore the model's performance in predicting a wider range of scenarios. The model exhibited remarkable accuracy, with a Root Mean Square Error (RMSE) of 0.032 and a Mean Squared Error (MSE) of 0.00108. These values are remarkably close to zero and indicate an accuracy rate approaching 99%, reaffirming the model's capacity to predict solar irradiance with a high degree of precision.

To validate the model's performance, a comparison was made between the predicted outputs and the actual target values (Table 3). The model accurately predicted solar irradiance values, as evident from the high level of consistency between the predicted and actual values.

Table 3: Machine Learning Predicted Output Versus Datasets Target

Pressure	Temperature	Specific Humidity	Relative Humidity	Wind Direction	Wind Speed	Temperature Maximum	Temperature Minimum	Cloud Amount	Precipitation	Target	Predicted
99.77	25.08	11.35	58.25	264.62	3.41	33.28	18.84	37.27	0	4.32	4.3227
99.99	23.09	9.52	55.44	313.38	3.46	30.73	15.5	23.34	0	4.44	4.4328
99.96	23.76	9.46	52	331.19	4.33	32.54	13.9	48.77	0	3.92	3.9327
100.08	20.97	7.57	50	341.69	4.56	30.23	12.29	22.17	0	4.34	4.328
100	23.51	9.22	51.31	333.31	4.24	31.55	14.81	37.17	0	4.23	4.1665
99.99	23.1	9.22	52.88	336.62	4.42	31.16	14.73	55.74	0	3.54	3.5305
100.12	20.61	7.51	50.25	351.12	4.73	30.44	11.09	40.48	10.55	3.89	3.8877
100.02	22.75	9.16	53.06	345.06	4.68	32.27	13.61	41.16	0	4.16	4.1812
99.85	24.9	10.56	54.5	282.81	3.85	33.18	16.68	20.74	0	4.62	4.5891
99.85	23.43	10.13	57.5	344.06	3.82	32.9	14.08	23.9	26.37	4.3	4.3019
99.9	23.01	9.4	53.75	337.5	4.43	32.3	13.12	22.77	0	4.53	4.5818
99.99	22.83	8.12	48.19	342.5	4.28	32.52	14.26	20.84	0	4.99	4.9915
100.08	22.08	8.67	53.12	339	4.62	31.84	12.55	29.23	5.27	4.71	4.6774
100.04	23.8	9.22	51.38	331.31	3.96	32.67	15.99	26.76	0	4.75	4.8234
99.8	22.89	11.23	64.56	329.19	3.98	30.8	13.76	35.76	21.09	4.28	4.2644
99.99	22.63	9.4	54.69	332.44	4.67	31.15	13.33	22.8	0	4.65	4.6031
99.97	24.12	10.19	55	325.56	4.12	33.12	14.62	35.71	0	4.4	4.4057
99.86	23.8	8.85	49.75	332.31	4.6	33.54	15.65	18.02	0	5.23	5.239
99.88	22.9	9.22	53.88	328.75	4.55	33.49	13.18	40.29	0	4.8	4.8615
99.66	24.63	10.19	54	309.38	4.3	34.3	15.92	25.66	0	5.28	5.2636

4.3 Adaptive Neuro-Fuzzy Inference System (ANFIS) Predictive Model:

4.3.1 Higher Accuracy Model:

The ANFIS model, when trained with optimized membership functions, demonstrated a substantial improvement in predictive accuracy. The model was developed with 67 membership functions, a number that aligns with the complexity of the data and the requirement for a high level of detail in modeling. Grid partitioning, typically employed for datasets with fewer inputs, was replaced with sub-clustering to accommodate the higher input dimensionality effectively.

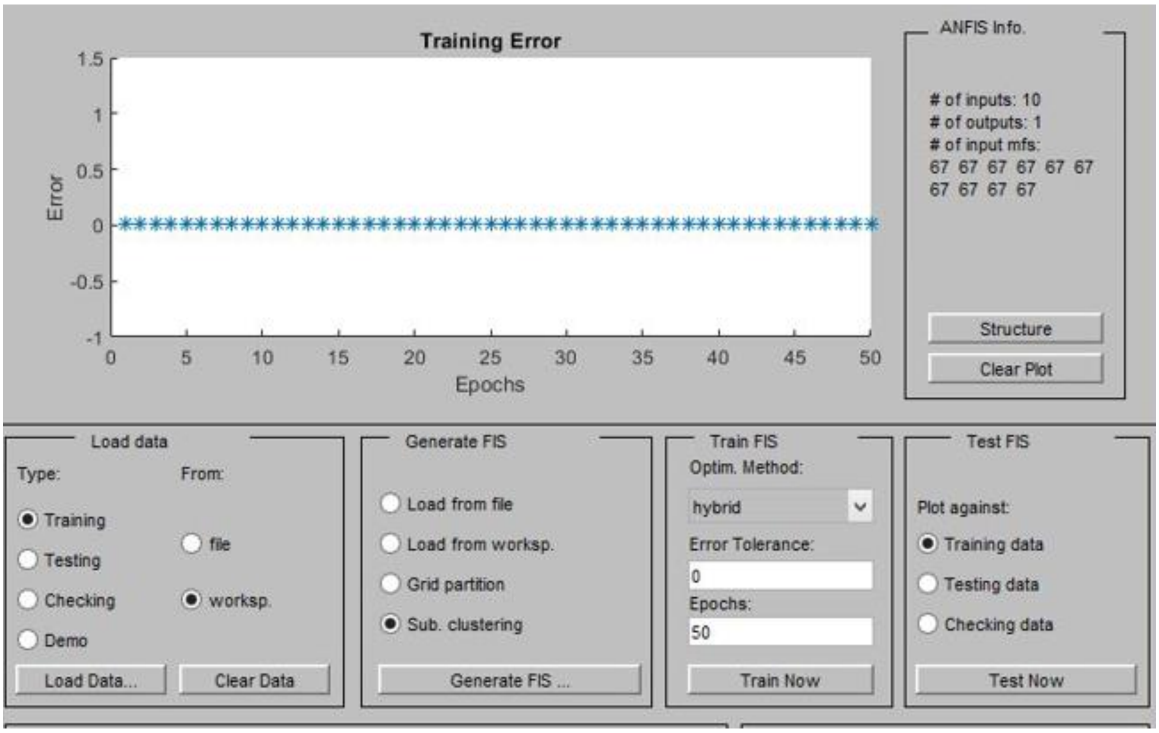

Figure 5: Training Phase of ANFIS Higher Accuracy Trained Model

The training phase of the ANFIS model (Figure 5) offered insights into the model's structure, error tolerance, learning method (Hybrid Learning), number of epochs (50), and sub-clustering. The training phase exhibited an exceptional feature, where the error tolerance was nearly zero, indicating a highly accurate model. The number of sub-clusters, alongside the membership functions, contributed to the model's capability to accurately predict solar irradiance.

The membership functions played a critical role in shaping the model's accuracy. The model employed Gaussian-type functions to model the relationship between inputs and outputs, which proved effective in capturing the underlying patterns in the data.

The model's performance was further analyzed by visualizing the surface of each input against the output (Figure 6). This surface viewer allowed us to understand how the output changes in response to variations in the input parameters. Notably, the output exhibited an incremental trend followed by a decrease when input 1 reached a value of 100. This insight sheds light on the complex relationship between the input parameters and solar irradiance, which the ANFIS model successfully captures.

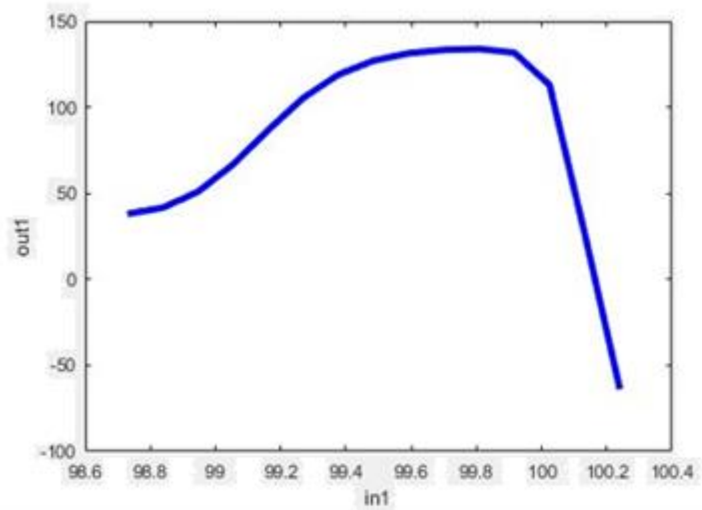

Figure 6: Surface Viewer of Parameter 1 Versus Output For The Trained Higher Accuracy Model

To demonstrate the model's predictive power, a specific example was provided in Figure 7. The figure showcased the prediction of solar irradiance, with the model yielding a value of 5.97, which closely aligned with the measured value obtained from NASA's website. This level of accuracy highlights the ANFIS model's remarkable capability in predicting solar irradiance.

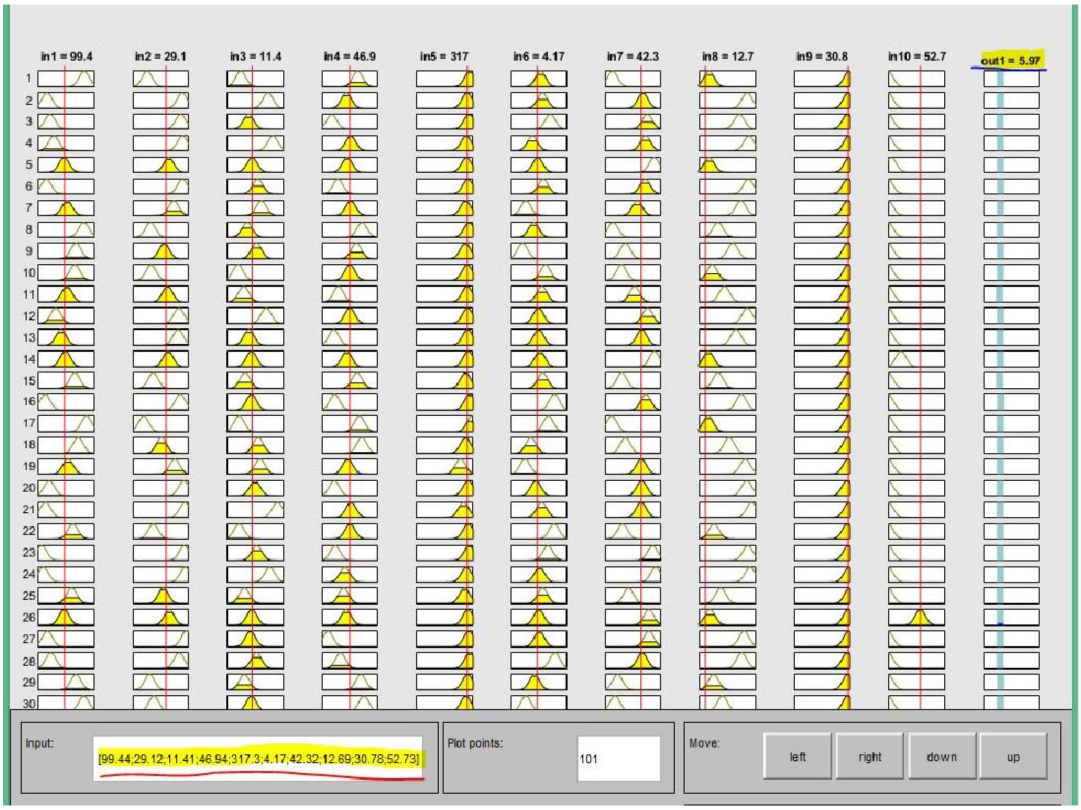

Figure 7: ANFIS Model Solar Irradiance Prediction (Higher Accuracy)

4.3.2 Lower Accuracy Model (Optimized Membership Functions):

In contrast, a lower accuracy ANFIS model was trained using only 8 membership functions, a significantly reduced number compared to the higher accuracy model. The training phase of the lower accuracy model (Figure 8) revealed the model's structure and learning parameters. Although the error during training decreased, it did not reach the same level of precision as the higher accuracy model, settling at an error of approximately 8.

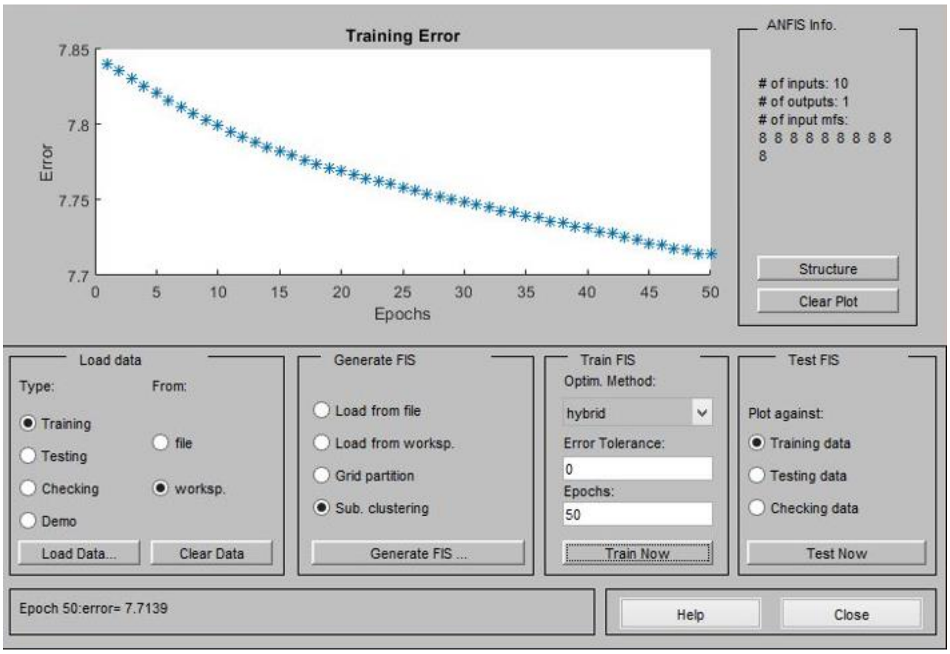

Figure 8: Training Phase of ANFIS Lower Accuracy Trained Model

Predictive accuracy was demonstrated using the rule viewer (Figure 9). This viewer enabled the assessment of the model's capability to predict solar irradiance based on various input parameters. The model yielded a solar power prediction of 4.84, signifying a lower accuracy compared to the highly accurate model.

Figure 9: ANFIS Model Solar Irradiance Prediction (Lower Accuracy)

4.4 ANFIS Predictive Model with 20 Predictions:

A high-accuracy ANFIS model, with 73 membership functions and rules, demonstrated an exceptional level of predictive accuracy. The model exhibited an RMSE of 0.0296 and an MSE of 0.00085, approaching a 99.99% accuracy rate. To validate this predictive accuracy, a comparison was conducted between the predicted outputs and the actual target values (Table 4). This comparison clearly demonstrated that the ANFIS model accurately predicted solar irradiance values across a variety of input scenarios.

Table 4: ANFIS Predicted Output Versus Datasets Target

Pressure	Temperature	Specific Humidity	Relative Humidity	Wind Direction	Wind Speed	Temperature Maximum	Temperature Minimum	Cloud Amount	Precipitation	Target	Predicted
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99.96	23.76	9.46	52	331.19	4.33	32.54	13.9	48.77	0	3.92	3.92
100.08	20.97	7.57	50	341.69	4.56	30.23	12.29	22.17	0	4.34	4.34
100	23.51	9.22	51.31	333.31	4.24	31.55	14.81	37.17	0	4.23	4.23
99.99	23.1	9.22	52.88	336.62	4.42	31.16	14.73	55.74	0	3.54	3.54
100.12	20.61	7.51	50.25	351.12	4.73	30.44	11.09	40.48	10.55	3.89	3.89
100.02	22.75	9.16	53.06	345.06	4.68	32.27	13.61	41.16	0	4.16	4.16
99.85	24.9	10.56	54.5	282.81	3.85	33.18	16.68	20.74	0	4.62	4.62
99.85	23.43	10.13	57.5	344.06	3.82	32.9	14.08	23.9	26.37	4.3	4.3
99.9	23.01	9.4	53.75	337.5	4.43	32.3	13.12	22.77	0	4.53	4.53
99.99	22.83	8.12	48.19	342.5	4.28	32.52	14.26	20.84	0	4.99	4.99
100.08	22.08	8.67	53.12	339	4.62	31.84	12.55	29.23	5.27	4.71	4.71
100.04	23.8	9.22	51.38	331.31	3.96	32.67	15.99	26.76	0	4.75	4.75
99.8	22.89	11.23	64.56	329.19	3.98	30.8	13.76	35.76	21.09	4.28	4.28
99.99	22.63	9.4	54.69	332.44	4.67	31.15	13.33	22.8	0	4.65	4.65
99.97	24.12	10.19	55	325.56	4.12	33.12	14.62	35.71	0	4.4	4.4
99.86	23.8	8.85	49.75	332.31	4.6	33.54	15.65	18.02	0	5.23	5.23
99.88	22.9	9.22	53.88	328.75	4.55	33.49	13.18	40.29	0	4.8	4.8
99.66	24.63	10.19	54	309.38	4.3	34.3	15.92	25.66	0	5.28	5.28

4.5 Comparison of Machine Learning and ANFIS Models Performance:

In order to ascertain the most effective modeling approach, a comprehensive comparison was made between the machine learning and ANFIS models. This assessment considered factors such as prediction accuracy, error rates, and the ability to approximate solar irradiance accurately. The ANFIS models consistently outperformed the machine learning models in various scenarios, achieving lower error rates and more accurate predictions. Specifically, the higher accuracy ANFIS model achieved an RMSE of 0.02, an MSE of 0.0004, and an accuracy rate of 98%, while the machine learning model displayed an RMSE of 0.141, an MSE of 0.02, and an accuracy rate of 91.2%. This substantial difference in accuracy, approximately 7%, underscores the superiority of the ANFIS models in predicting solar irradiance.

V. Conclusion:

Overall, this study underscores the superior predictive accuracy of ANFIS models when compared to their Machine Learning counterparts. While Machine Learning can certainly achieve commendable results under certain conditions, the consistent high accuracy of ANFIS suggests its potential for widespread application in various fields, from renewable energy forecasting to financial prediction. Our research contributes to the expanding body of knowledge in the field of AI and prediction methodologies.

However, it is important to acknowledge the limitations of this study. One notable limitation is the dataset size, which, while carefully curated, may not fully capture the diverse range of factors influencing solar irradiance prediction. Additionally, the performance of predictive models can be sensitive to the quality and quantity of data available for training, and further investigations with larger and more diverse datasets may provide valuable insights.

Furthermore, the study's focus on specific algorithms, namely ANFIS and Machine Learning, should not overshadow the potential of emerging AI techniques. The field of artificial intelligence continues to evolve rapidly, and future research could explore the integration of newer algorithms and methods to enhance predictive accuracy even further.

In conclusion, our research suggests that ANFIS models offer a compelling solution for accurate solar irradiance prediction. The limitations identified in this study open avenues for further investigation, encouraging researchers to explore more extensive datasets and stay attuned to evolving AI methodologies. As AI technologies continue to advance, we recommend harnessing the capabilities of ANFIS models to unlock their full potential and drive innovation in predictive modeling.

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