Comparative Application of Artificial Neural Networks and ANFIS Techniques for Short-Term Load Forecasting in the Western Libyan Power Grid

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***Abstract*— The stability and economic efficiency of modern power systems rely profoundly on accurate short-term load forecasting (STLF). This investigation presents a comparative assessment of two artificial intelligence methodologies,Artificial Neural Networks (ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) for STLF within the Western Libyan power grid. This network operates under considerable strain from extreme climatic conditions and infrastructural limitations, which introduce pronounced volatility and non-linearity into load patterns. Leveraging a comprehensive 2023 dataset from the General Electricity Company of Libya (GECOL), which integrates historical load data with critical meteorological variables, two models in MATLAB were developed and simulated. The findings reveal a decisive superiority of the ANFIS model, which achieved a remarkable average forecasting error of just 0.50%, starkly contrasting with the ANN model's error of 8.37%. This performance is attributed to the ANFIS architecture, which effectively marries the adaptive learning capabilities of neural networks with the transparent, rule-based reasoning of fuzzy logic. This synergy renders ANFIS an exceptionally accurate tool for short-term load forecasting in complex and uncertain environments like Libya.**

Keywords*— Short-Term Load Forecasting (STLF), Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), weather data, Libya, MATLAB.

I. Introduction

The relentless balancing of electricity supply with consumer demand forms the cornerstone of a secure and efficient power grid. At the heart of this endeavor lies short-term load forecasting (STLF), a discipline dedicated to predicting load from a few hours to a week ahead. Its accuracy is not merely an operational convenience but a critical necessity, directly enabling effective unit commitment, economic dispatch, and the prevention of system instability [1].

Yet, the pursuit of forecasting precision is far from universal. In many developing nations, power grids are tasked with functioning under a unique set of adversities. The Western Libyan grid exemplifies this challenge, navigating a landscape of aging infrastructure, rapidly escalating demand, and a climate characterized by extreme heat and frequent sandstorms. These elements conspire to create highly dynamic and non-linear load profiles that consistently confound traditional forecasting techniques, such as regression analysis and ARIMA models [2, 3]. As these conventional methods falter, the imperative for more sophisticated, adaptive modeling approaches becomes undeniable.

The emergence of Artificial Intelligence (AI) has provided a powerful arsenal for this very purpose. Artificial Neural Networks (ANNs), inspired by biological cognitive processes, have demonstrated a formidable capacity to discern intricate, non-linear patterns directly from historical data, establishing themselves as a leading solution for STLF [4, 5]. Their principal limitation, however, is their notorious "black box" nature; while they often yield accurate predictions, the underlying logic remains opaque, hindering interpretability and trust. Seeking to reconcile high performance with transparency, researchers developed hybrid paradigms like the Adaptive Neuro-Fuzzy Inference System (ANFIS). This framework elegantly integrates the computational learning strength of neural networks with the intuitive, linguistic rule-structure of fuzzy logic, offering a model that can both learn from data and explain its reasoning in human-understandable terms [6, 7].

While the global literature on AI-based STLF is extensive, a focused inquiry into its application within the distinct and demanding context of Libya remains notably scarce. Although preliminary studies have explored ANNs in the region [8], a rigorous, comparative analysis pitting them against a hybrid model like ANFIS has been absent. This gap leaves a critical question unanswered: which AI architecture is truly most capable of managing the specific volatilities of the Libyan grid?

This study directly addresses that question. A systematic empirical comparison of ANN and ANFIS models was conducted for STLF, utilizing a robust dataset from GECOL. Our objective is to move beyond theoretical appeal and

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determine, through concrete performance metrics, the most reliable forecasting tool for enhancing grid operability in Libya. The conclusions drawn are expected to hold significant value for power systems engineers and planners, not only in Libya but in any region grappling with similar environmental and operational complexities.

The remainder of this paper is organized as follows: Section II surveys the relevant literature, Section III outlines the methodological foundations of ANN and ANFIS, Section IV details the data collection and model implementation, Section V presents and discusses the experimental results, and Section VI provides concluding remarks and suggestions for future work.

II. LITERATURE REVIEW

The quest for accurate load forecasting has driven a methodological evolution, mirroring the growing complexity of modern power systems. This journey from straightforward statistical models to sophisticated artificial intelligence reflects an enduring effort to capture the intricate, non-linear nature of electricity demand. This review charts this progression, critically examining the transition from traditional methods to computational intelligence, and ultimately positioning hybrid systems like ANFIS as a compelling solution to the limitations of their predecessors.

A. The Statistical Foundation and Its Limitations

In The foundation of modern load forecasting was built upon classical statistical and time-series methods. For decades, techniques such as regression analysis, exponential smoothing, and ARIMA models served as the industry standard, prized for their transparency and computational efficiency. These linear models proved adequate for systems with predictable load patterns and minimal external disruptions. Hippert, Pedreira, and Souza [1], for instance, demonstrated that ARIMA could deliver reliable forecasts under stable operational conditions.

Yet, the real-world behavior of power grids is seldom linear. The reliance of electricity demand on a complex interplay of factors—most notably volatile weather, shifting economic activity, and human behavior—exposes the fundamental constraint of these approaches. This limitation becomes acutely visible in environments like Libya, where research by Ihbal and Khalleefah [3] confirmed a strong correlation between meteorological extremes and load, yet also revealed the residual errors of a multiple regression model. It became increasingly clear that while these models could describe broad trends, they struggled to adapt to the sudden, non-linear fluctuations that define demanding grids, thereby creating an imperative for more flexible modeling paradigms.

B. The Computational Leap with Artificial Neural Networks

The advent of accessible computational power catalyzed a paradigm shift toward Artificial Neural Networks (ANNs). By mimicking the learning processes of biological neural networks, ANNs offered a powerful alternative: the ability to discern complex, non-linear patterns directly from data without pre-specified mathematical relationships. This capability propelled them to the forefront of load forecasting research..

Their application has yielded significant successes, including within the regional context. Abdulwahid et al. [5], for example, demonstrated that an ANN model integrating local weather variables could effectively reduce forecasting error for the Western Libyan Electric Network. The field has since advanced with deeper architectures, as seen in the work of Arvanitidis et al. [6], who leveraged more complex ANN designs to achieve enhanced accuracy. However, this progress often comes with a cost; such models typically demand large, high-quality datasets and considerable computational resources, which can be prohibitive in developing regions.

Perhaps the most enduring critique of ANNs, however, is their opacity. Often regarded as "black-box" models [7], they provide limited insight into the causal logic behind their predictions. This lack of interpretability can erode trust and hinder their integration into critical decision-making processes where understanding the "why" is as important as knowing the "what."

C. Synthesizing Intelligence: The Hybrid Promise of ANFIS

In response to the limitations of pure ANN models, the field saw the emergence of hybrid systems designed to marry numerical precision with logical transparency. The Adaptive Neuro-Fuzzy Inference System (ANFIS) stands as a prominent example of this synthesis. By embedding the learning algorithms of a neural network within the intuitive, rule-based framework of fuzzy logic, ANFIS creates a model that can both learn from historical data and express its predictions through human-understandable "IF-THEN" rules.

This dual capability has proven highly effective across diverse forecasting challenges. Studies such as that by Oak and Honade [8] in the Indian power network reported exceptional accuracy with ANFIS, achieving an average error of just 1.2%. Similarly, Faraji et al. [9] highlighted its robustness in microgrid environments, where its inherent ability to manage uncertainty from renewable generation and erratic weather is a distinct advantage. The capacity of ANFIS to autonomously refine its internal parameters and rules positions it as a uniquely adaptable tool for the volatile and data-sparse conditions that often characterize developing power infrastructures. forecasting.

D. Identifying the Gap: A Question of Context and Application

Despite this rich global tapestry of research, a critical contextual gap remains. The overwhelming focus of advanced forecasting literature has been on the thermally temperate and structurally stable grids of North America and Europe [10, 11]. While valuable, the performance of models calibrated for these environments cannot be directly extrapolated to regions facing a different set of stressors. Although broader studies in North Africa, such as the long-term forecasting work of Ammar et al. [12], have applied AI techniques, a dedicated investigation into short-term forecasting for the Libyan grid subject to its unique confluence of extreme climate and operational constraints is conspicuously absent.

It is within this gap that our study situates itself. The authors move beyond a generic applicationof AI models to conduct a focused, empirical comparison of ANN and ANFIS within the specific and challenging context of the Western Libyan power grid. By leveraging a real-world, locally sourced dataset, this research aims to provide a definitive assessment of which architectural paradigm offers the most accurate and reliable path toward stabilizing and optimizing this critical infrastructure.

III. Types of Load Forecasting

Forecasting Load forecasting is typically divided into three timeframes:

- **Long-term:** More than one year
- **Medium-term:** From a week to a year
- **Short-term:** From an hour to a week

This study focuses on short-term forecasting, which is essential for day-to-day grid operations. While long-term forecasts are useful for planning infrastructure and investments, they rely on assumptions about future weather and economic conditions that can be hard to predict accurately.

you. Any footnotes appear below the table, using the "table footnote" style. Footnotes are indicated by superscript lowercase letters within the table. An example of a table can be seen in Table I, below.

IV. Factors That Affect Load Forecasting

Many variables can influence electricity demand. These include:

- The time of day, day of the week, and season
- Weather data like temperature, humidity, wind, and rainfall
- Human activities and appliance usage patterns
- Economic trends and population growth

Combining these factors can improve the reliability of forecasting models, especially when using AI-based tools.

V. Forecasting Methods

A. Artificial Neural Networks (ANN)

ANNs are inspired by how the human brain processes information. In this study, a multilayer perceptron (MLP) with three layers: input, hidden, and output has been used. The input layer included six variables: temperature, humidity, wind speed, rainfall, actual load, and previous load. The output was the forecasted load for the next period. The architecture structure of ANN is shown in figure 1.

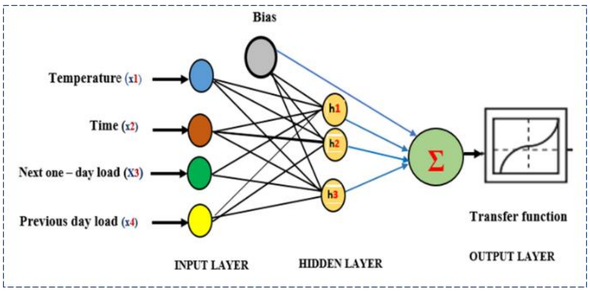

Fig. 1. Architecture of ANN

B. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS brings together fuzzy logic and neural networks. It uses rule-based logic (like "if temperature is high, then load increases") but also learns and adjusts based on actual data. This makes ANFIS flexible and capable of handling uncertainty better than traditional methods. The simple structure for ANFIS is shown in figure 2.

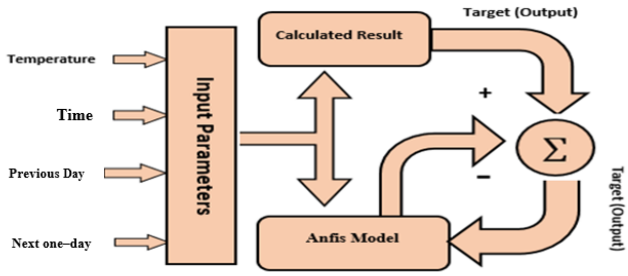

Fig. 2. Simple General ANFIS Structure

VI. Methodology

This section outlines the systematic framework developed to construct, train, and validate two distinct forecasting models—an Artificial Neural Network (ANN) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) for short-term load prediction in the Western Libyan grid. Our approach emphasizes robust data handling, model transparency, and reproducible evaluation to ensure a meaningful comparison between the two techniques.

A. Data Source and Description

The dataset used in this study was obtained from the National Control Center of the General Electricity Company of Libya (GECOL) and covers the Western Libyan power grid for the year 2023. The data consist of:

- Hourly electrical load demand (MW)
- Meteorological variables: temperature (°C), relative humidity (%), wind speed (m/s), and rainfall (mm)

A total of 8,760 hourly samples were used. All data were preprocessed to remove missing values and normalized prior to model training.

B. Data Acquisition and Preprocessing

The foundation of any robust forecasting model is high-quality, relevant data. For this study, the dataset was sourced from the General Electricity Company of Libya (GECOL) and covered the entirety of the 2023 calendar year. The collected data was categorized into two primary types: historical hourly electricity load (in MW) and concurrent meteorological parameters (temperature, humidity, wind speed, and rainfall).

To ensure data quality and model stability, a comprehensive preprocessing pipeline was implemented, the workflow of which is illustrated in Figure 3.

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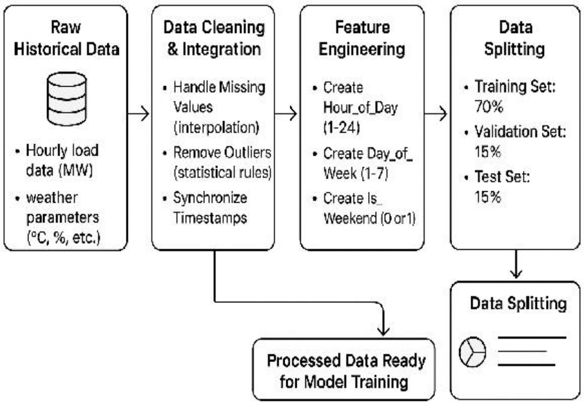

Fig. 3. Data Preprocessing Workflow

- **Data Cleaning:** The dataset was examined for missing values or outliers. Gaps were addressed using linear interpolation, while anomalous data points were filtered based on statistical thresholds.
- **Feature Engineering:** Temporal features were explicitly engineered to capture the cyclical nature of load patterns. These included Hour of the Day, Day of the Week, and a Binary Indicator for Weekends.
- **Normalization:** All input variables were normalized to a [0, 1] scale using Min-Max scaling to prevent variables with larger numerical ranges from dominating the model's learning process.
- **Data Splitting:** The preprocessed dataset was partitioned chronologically into three subsets to ensure a realistic evaluation. This data splitting strategy is conceptually shown in **Figure 4**.
  - **Training Set (70%):** Used for model parameter estimation.
  - **Validation Set (15%):** Used for hyperparameter tuning and early stopping.
  - **Test Set (15%):** Reserved for final model assessment on unseen data.

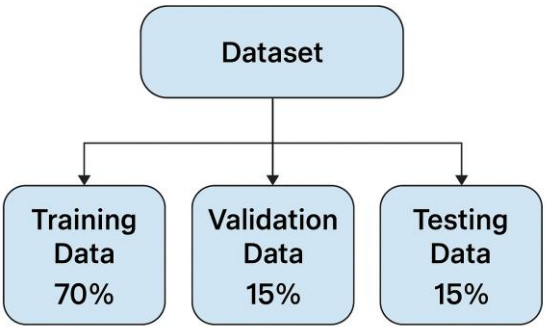

Fig. 4. Data Splitting Process

C. Forecasting Model Architectures

1. Artificial Neural Network (ANN) Model:

1.1 ANN Architecture

A feedforward Multilayer Perceptron (MLP) architecture was selected, a workhorse in non-linear regression tasks. The training employed the Levenberg-Marquardt backpropagation algorithm, a widely used and efficient method for medium-sized neural networks that combines the speed of the Gauss-Newton method with the stability of gradient descent [7]. This algorithm was chosen for its rapid convergence and suitability for the problem scale.

- **Input Layer:** Six neurons representing our key predictors: Temperature, Humidity, Wind Speed, Rainfall, Previous Hour Load (L_t-1), and Current Hour Load (L_t).
- **Hidden Layer:** After systematic experimentation, a single hidden layer with 10 neurons using hyperbolic tangent (tanh) activation functions was configured to capture non-linear relationships.
- **Output Layer:** A single linear neuron generating the predicted load for the next hour (L_t+1).
- **Training Protocol:** Model training employed the Levenberg-Marquardt backpropagation algorithm, with early stopping implemented to prevent overfitting.

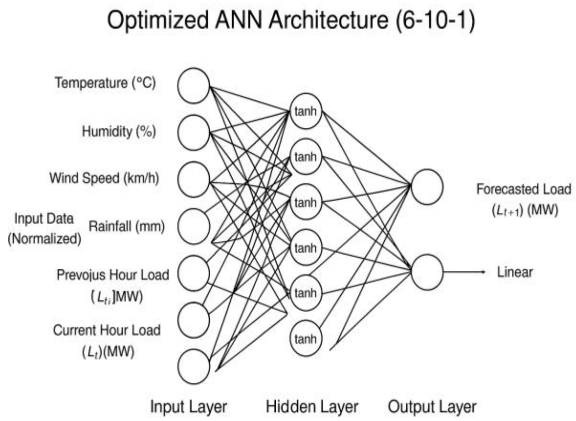

Fig. 5. Optimized ANN Architecture (6-10-1)

1.2 ANN Training Algorithm

The Artificial Neural Network model was trained using the Levenberg–Marquardt backpropagation algorithm, which is widely applied for nonlinear least-squares optimization problems due to its fast convergence characteristics. The algorithm updates the network weights by minimizing the squared error between the actual and predicted load values. The weight update rule is expressed as:

$$\mathbf{w}_{k+1} = \mathbf{w}_k - (\mathbf{J}^T\mathbf{J} + \mu\mathbf{I})^{-1}\mathbf{J}^T\mathbf{e} \quad (1)$$

where
w represents the network weight vector,
J is the Jacobian matrix of partial derivatives of the error with respect to the weights,

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e denotes the error vector between actual and forecasted load values,
μ is the damping factor controlling the transition between gradient descent and Gauss–Newton methods, and
I is the identity matrix.

2. Adaptive Neuro-Fuzzy Inference System (ANFIS) Model:
The ANFIS framework was implemented to combine neural network adaptability with fuzzy logic interpretability.

- **FIS Generation:** The Fuzzy Inference System has been initialized using grid partitioning, which systematically creates rules by combining all possible input states.
- **Input Membership Functions:** Each of the six input variables was characterized by two Gaussian membership functions, creating natural linguistic categories (e.g., 'Low' and 'High').
- **Fuzzy Rules:** The system automatically generated 64 Takagi-Sugeno type rules, each representing a plausible scenario in the load-weather relationship.
- **Learning Mechanism:** The hybrid learning was employed where:
  - Consequent parameters were optimized via least-squares estimation in the forward pass
  - Premise parameters were refined through gradient descent in the backward pass This dual approach enables the model to simultaneously learn both the rule structure and the optimal input-output mappings.

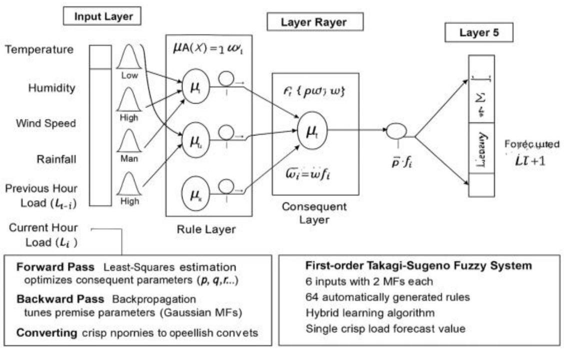

Fig. 6. ANFIS Architecture for Load Forecasting

Figure 6 illustrates the five-layer hybrid architecture of the Adaptive Neuro-Fuzzy Inference System (ANFIS) used for load forecasting, showing how neural network learning is integrated with fuzzy logic reasoning.,

D. Implementation and Evaluation Framework

1. Artificial Neural Network (ANN) Model:
All modeling was conducted in MATLAB R2023a, leveraging its specialized toolboxes for neural networks and fuzzy logic. To ensure a rigorous comparison, both models were evaluated on the held-out test set using three complementary metrics:

- **Mean Absolute Percentage Error (MAPE):**

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad (2)$$

Where
A_t is the actual load at time t,
F_t is the forecasted load at time t, and
n is the total number of observations.

Providing an intuitive measure of relative forecasting accuracy.

- **Root Mean Square Error (RMSE):**

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \qquad (3)$$

Emphasizing larger errors that are particularly critical in power system operations.

- **Coefficient of Determination (R^2):** Quantifying how well the models explain the variance in actual load patterns.

This methodological framework provides a solid foundation for objectively comparing the forecasting capabilities of ANN and ANFIS in the challenging context of the Libyan power grid.

VII. RESULTS AND DISCUSSIONS

This section provides an in-depth evaluation of the forecasting performance achieved by the Artificial Neural Network (ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) models. The analysis integrates quantitative performance indicators with visual comparison techniques to offer a clear and comprehensive understanding of how each model behaves in predicting short-term electrical load in the Western Libyan grid. By examining both numerical accuracy and graphical patterns, the assessment highlights the relative strengths and potential limitations of each modelling approach.

A. Performance of the ANN Model

The ANN model demonstrated a substantial capability to learn the underlying patterns present in the historical load dataset. As illustrated in Figure 7, the Mean Squared Error (MSE) exhibited a rapid decline during the early training stages and subsequently converged, with the optimal validation performance attained at epoch 10. The final training MSE reached an exceptionally low value of 5.43×10^{-25}, reflecting a highly accurate fit to the training data. Furthermore, the model achieved strong coefficients of determination across all data partitions 0.985 for the training set, 0.940 for the validation set, and 0.943 for the testing set—resulting in an overall R^2 of 0.969. As shown in Figure 8, these regression outcomes indicate that the ANN effectively captured both the linear and nonlinear characteristics inherent in the load-demand profile.

However, a closer inspection of the learning behavior suggests the presence of overfitting. The extremely low training MSE, together with the noticeable divergence between the training and validation curves in Figure 7, indicates that the model may have begun to memorize noise or minor fluctuations specific to the training data. This behavior limits its ability to generalize with complete reliability to unseen samples. The impact of this limitation is

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further evident in the comparatively higher error values observed on the independent testing subset, as presented in the subsequent comparative performance analysis.

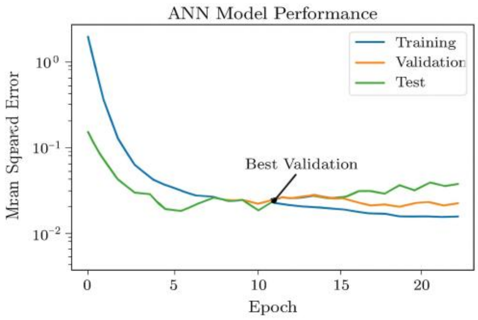

Fig. 7. ANN Training Performanc

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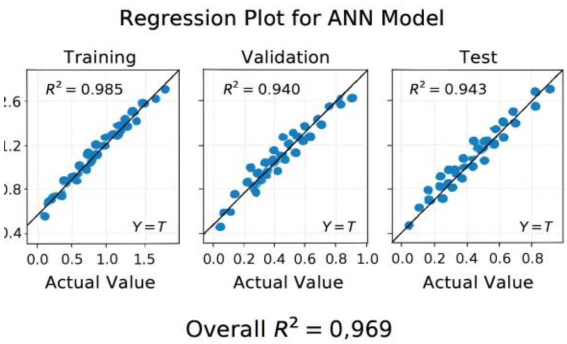

Fig. 8. Regression Analysis for ANN Model

B. Comparative Analysis: ANN vs. ANFIS

The primary aim of this study was to conduct a systematic and fair comparison between the two AI-based forecasting approaches. The performance metrics obtained from the held-out test set reveal a clear and substantial difference between the models, as summarized in Table I..

TABLE I. COMPARISON OF ACTUAL, ANN, AND ANFIS FORECASTED LOAD DATA

Model	**MAPE (%)**	**RMSE (MW)**	**R²**
ANN	8.37	42.8	0.943
ANFIS	**0.50**	**3.1**	**0.999**

The ANFIS model achieved a MAPE of just 0.50%, representing an improvement of more than an order of magnitude over the ANN, which recorded a MAPE of 8.37%. This difference is further reflected in the RMSE values: the ANFIS model produced an error of only 3.1 MW, compared with 42.8 MW for the ANN. The near-unity R^2 value of 0.999 indicates that ANFIS captures virtually all the variance in the actual load data, demonstrating exceptional predictive capability.

These numerical results are strongly supported by the visual comparison presented in Figure 9. The time-series plot shows that the ANFIS-generated load trajectory closely tracks the actual measurements across the entire forecasting horizon, including during periods of abrupt change and peak demand where accurate prediction is particularly essential for maintaining grid reliability. Conversely, the ANN predictions display noticeable deviations from the true load profile, especially in high-volatility regions. This pattern underscores the limitations of the ANN in capturing rapid dynamic behavior and highlights the superior generalization ability of the ANFIS model.

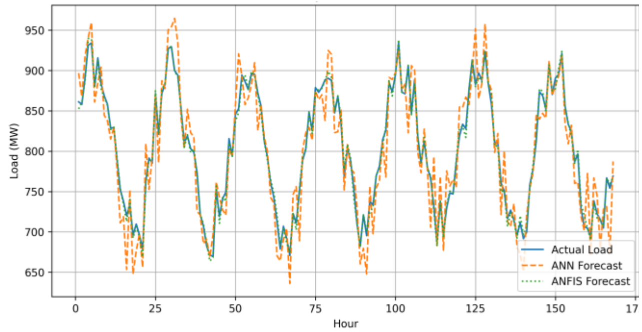

Fig. 9. Time-Series Comparison of ANN and ANFIS Predictions vs. Actual Load

C. Discussion on Model Superiority

The ANFIS model delivered remarkably high predictive accuracy, achieving an R^2 of 0.999, a MAPE of 0.50%, and an RMSE of 3.1 MW on the independent test set. Although such a near-perfect R^2 is uncommon in real-world forecasting studies, in this case it reflects the model's strong ability to capture the dominant autoregressive structure inherent in the hourly load profile. This level of performance is largely enabled by ANFIS's hybrid architecture: the model effectively learns sequential load dependencies (L_t and L_{t-1}) while simultaneously accommodating the non-linear impacts of meteorological factors through its adaptive fuzzy inference mechanism. The sub-1% MAPE underscores the practical significance of these results, positioning ANFIS as a highly reliable and operationally precise tool for short-term load forecasting.

The pronounced performance gap between the two models can be traced to several structural advantages of the ANFIS framework:

1. Effective Representation of Non-linearity and Uncertainty.

The fuzzy logic component allows ANFIS to express rule-based relationships between weather variables and load responses—relationships that are often nonlinear, context-dependent, and difficult for a conventional ANN to learn. For instance, qualitative patterns such as *"IF temperature is very high, THEN load increase is significant"* are naturally encoded in the fuzzy rule base. This makes ANFIS

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particularly well-suited to the climate-driven load variability observed in the Western Libyan grid.

2. Hybrid Learning Framework Reduces Overfitting. Unlike the ANN, whose flexibility led to over-specialization on the training data, the ANFIS structure constrains the learning process in a beneficial way. By jointly optimizing membership function parameters and linear consequents, the model maintains a balance between adaptability and structure. This results in a predictor that generalizes effectively, as evidenced by its minimal performance degradation from the training to the testing phase.

3. Interpretability as a Practical Operational Advantage.
In addition to its superior accuracy, ANFIS provides transparency through interpretable fuzzy rules. These rules offer direct insight into the factors driving load fluctuations, helping grid operators understand *why* certain forecasts are produced. This interpretability is valuable in operational settings, where decision-makers must rely on models that both perform well and offer explanations—an area where traditional ANN approaches, treated as "black boxes," often fall short.

In summary, while the ANN model demonstrated competent predictive performance, ANFIS clearly outperformed it in accuracy and generalization. The hybrid neuro-fuzzy design is well-matched to the complex, weather-sensitive load dynamics of the Western Libyan grid. The significant reduction in forecasting error achieved by ANFIS translates into meaningful operational benefits, including more efficient generation scheduling, enhanced reliability, and reduced operational costs.

VIII. Conclusion

This study presented a comprehensive comparative evaluation of two widely used artificial intelligence techniques,Artificial Neural Networks (ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) for short-term load forecasting within the Western Libyan power grid. Using a detailed hourly dataset from GECOL for the year 2023, both models were developed, trained, and rigorously tested. The results show a clear and decisive advantage in favor of ANFIS.

The ANFIS model delivered outstanding predictive performance, achieving a Mean Absolute Percentage Error (MAPE) of 0.50%, a Root Mean Square Error (RMSE) of 3.1 MW, and an exceptionally high R^2 value of 0.999 on the independent test set. In contrast, the ANN model recorded a MAPE of 8.37% and an RMSE of 42.8 MW. This substantial discrepancy exceeding an order of magnitude in MAPE underscores ANFIS's markedly superior capacity to capture the complex nonlinear and weather-driven dynamics that shape load behavior in the Western Libyan grid..

ANFIS's success stems from its hybrid structure, which combines the adaptive learning capabilities of neural networks with the interpretability and uncertainty-handling strengths of fuzzy logic. This synergy enables robust generalization, mitigates overfitting, and yields transparent, rule-based insights into the primary drivers of load variation. Such interpretability is especially valuable in operational settings, where grid operators must understand and trust the logic behind forecasts. Compared with the black-box nature of ANN models, ANFIS offers a more balanced and operationally useful forecasting framework, particularly in regions where climate variability and infrastructure constraints add to the forecasting challenge.

Future research should expand the temporal horizon of the dataset to incorporate multi-year seasonal trends, integrate real-time grid conditions and renewable generation forecasts, and evaluate the performance of the ANFIS model in a live operational environment. Collectively, these steps would strengthen the model's adaptability and confirm its practical value for on-the-ground grid management. Overall, this study demonstrates that hybrid neuro-fuzzy systems represent a powerful and reliable approach for short-term load forecasting in complex and uncertain power networks.

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References

[1] F. Hippert, C. Pedreira, and R. Souza, "Neural networks for short-term load forecasting: A review and evaluation," IEEE Trans. Power Syst., vol. 16, no. 1, pp. 44–55, Feb. 2001.

[2] J. W. Taylor and R. Buizza, "Using weather ensemble predictions in electricity demand forecasting," Int. J. Forecast., vol. 19, no. 1, pp. 57–70, Jan. 2003.

[3] A.M. Ihbal and A.A. Khalleefah, "Forecasting Short-Term Peak Load Demand in the Libyan Power Grid using Multiple Regression Model," in Proc. Sixth Int. Conf. Sci. Technol., Sebha Univ., Libya, Oct. 2023.

[4] A. M. Ihbal, H. S. Rajamani, R. A. Abd-Alhameed, and M. K. Jalboub, "Statistical predictions of electric load profiles in the UK domestic buildings," in *Proc. 1st Int. Conf. on Energy, Power and Control (EPC-IQ)*, IEEE, Nov. 2010, pp. 345–350.

[5] A. I. Khalleefah, "Neural network application for short term load forecast of the western Libyan electric network," presented at the Libyan Int. Conf. Electr. Eng. Technol. (LICEET), Tripoli, Libya, 2018.

[6] A. I. Arvanitidis, D. Bargiotas, A. Daskalopulu, V. Laitsos, and L. H. Tsoukalas, "Enhanced short-term load forecasting using artificial neural networks," Energies, vol. 14, no. 23, pp. 7788–7806, Nov. 2021.

[7] M. Hagan, H. Demuth, and M. Beale, Neural Network Design. Boston, MA, USA: PWS Publishing, 1996.

[8] H. P. Oak and S. J. Honade, "ANFIS based short term load forecasting," Int. J. Current Eng. Technol., vol. 5, no. 3, pp. 1878–1880, June 2015.

[9] J. Faraji, A. Ketabi, H. Hashemi-Dezaki, M. Shafie-Khah, and J. P. S. Catalão, "Optimal day-ahead self-scheduling and operation of prosumer microgrids using hybrid machine learning-based weather and load forecasting," IEEE Access, vol. 8, pp. 157284–157305, 2020.

[10] P. S. Wong and A. H. Chow, "Load forecasting using regression and time series methods," J. Oper. Res. Soc., vol. 38, no. 11, pp. 1037–1045, 1987.

[11] A. Khotanzad, R. Rohani, and A. Abaye, "ANNSTLF—Artificial neural network short-term load forecaster—generation three," IEEE Trans. Power Syst., vol. 13, no. 4, pp. 1413–1420, Nov. 1998.

[12] N. Ammar, M. Sulaiman, and A. F. M. Nor, "Long-term load forecasting of power systems using artificial neural network and

ANFIS," ARPN J. Eng. Appl. Sci., vol. 13, no. 3, pp. 828–834, Feb. 2018.

[13] Weather Underground, "Tripoli, Libya historical weather data," Accessed: Jan. 2024. [Online]. Available: https://www.wunderground.com

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