Load forecasting using fuzzy logic, artificial neural network, and adaptive neuro-fuzzy inference system approaches: application to South-Western Morocco

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ABSTRACT

The demand for energy on a global scale is continuously rising due to the expansion of energy infrastructure and the increasing number of new appliances. To address this growing need, an efficient energy management system (EMS) has become indispensable. By implementing EMS, both residential and commercial buildings can significantly improve their energy efficiency and consumption. One crucial aspect of enabling EMS to operate efficiently is load forecasting. The accuracy of load forecasting depends on numerous factors. A reliable load forecast model should consider the region's weather forecast, as it plays a crucial role in developing an accurate prediction. This study is about the medium-term load forecasting (MTLF) for the Province of Taroudant, Morocco, using historical monthly load and weather data for five years (2018 to 2022). To forecast consumed energy three methods are used namely artificial neural network (ANN), fuzzy logic (FL) and adaptive neuro-fuzzy inference system (ANFIS). This paper selects absolute percentage error (APE), mean absolute percentage error (MAPE), correlation coefficient (R) and root mean square error (RMSE) to compare and evaluate the prediction accuracy of models. It has been observed through results analysis that the ANFIS model produces very accurate forecasting prediction with MAPE of 4.75% while ANN and FL models give respectively MAPE of 7.36% and 8.42%.

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1. INTRODUCTION

To enhance the efficiency of operational management and strategic planning in both the procurement and generation of electric power, utilities are required to make crucial decisions. Load forecasting stands out as a pivotal task for utilities, serving as a potent tool for power system operators to elevate service quality and to improve grid security. Load forecasting can be categorized into four distinct types based on the time horizon and specific targets [1]–[3]: LTLF known as long term load forecasting: This method deals with forecasting loads for a period longer than one year. Its primary use is in strategic planning for the development of electric power systems, providing insights for future requirements and facilitating proactive decision-making. Medium-term load forecasting (MTLF) known as medium term load forecasting: focused on the forecasting of load over a period ranging from one week to one year. Its applications include the planning of fuel supplies and the effective management of units. STLF as short-term load forecasting: used to forecast load for duration ranging from one hour to one week, STLF assists in estimating load flow and making decisions to prevent overloading. VSTLF as very short-term load forecasting plays a critical role in reducing operating costs, maintaining efficiency in energy markets, and improving understanding of the dynamics within the monitored system when used to forecast load within a period of a few minutes to a few hours.

Multiple variables, including temporal factors and weather data, are considered by STLF. The medium and long-term forecasts take into account the categories and the number of customers, demographic and economic data, historical load profiles, weather data, as well as other relevant factors. It is noteworthy that weather conditions significantly influence the load forecast, particularly in short and medium-term predictions. Load forecasting considers multiple meteorological variables, with humidity, wind speed and temperature emerging as the main factors that are often used to predict the load demand [4]–[6]. Given the needs and goals, it is possible to choose any of the types previously mentioned.

This study specifically concentrates on MTLF for predicting future load in Taroudannt Province. A large number of forecasting methods have been the subject of literature studies, including the autoregressive integrated moving average (ARIMA) model [7], linear regression [8]–[10], artificial neural network (ANN) [11]–[13], fuzzy logic (FL) [14], [15], and adaptive neuro-fuzzy inference system (ANFIS) [16]–[19]. Based on this literature review, the ANFIS approach appears to offer more benefits due to its unique characteristics. The reason behind this can be elucidated by the fact that ANFIS represents a sophisticated hybrid system seamlessly integrating the learning approach of ANN with the logic reminiscent of human reasoning in the fuzzy logic (FL).

In this study, fuzzy logic, ANN, and ANFIS approaches are proposed for medium-term load forecasting based on a real case study. Using historical loads and meteorological data, three models are created to predict monthly loads for the Province of Taroudannt, located in the Souss-Massa Region of Morocco, for the five years 2018-2022. Inputs for all models are month index (MI), monthly mean temperature (T) and monthly wind speed (WS). The prediction values using FL are compared with the actual load and the results of both the ANN and ANFIS method. This paper is structured as follows; we start by briefly reviewing the load forecasting techniques. The second section is a description of the methodology and materials used in this work. Section 3 deals with the presentation and discussion of the results. While section 4 serves as the conclusion.

2. MATERIALS AND METHOD

2.1. Data collection description

In this study, the focus area is the Taroudannt Province, situated within the Souss-Massa Region of Morocco. Located in the southwestern part of the country. Taroudannt shares borders with specific provinces, as illustrated in Figure 1. To the west of Taroudannt lies the Agadir-Ida OuTanane Province, while moving northward brings us to the Chichaoua and El Haouz Province, both integral parts of the Souss-Massa Region. Heading southward, one comes across Tata and Tiznit Province, and towards the west are the Province of Chtouka Ait Baha and Inzegane Ait Mellol.

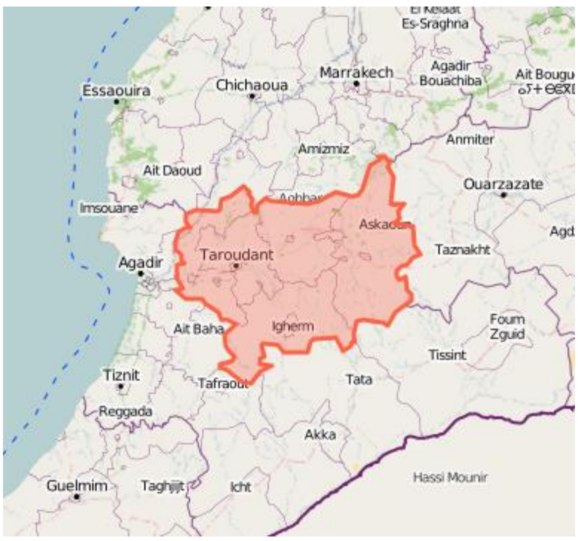
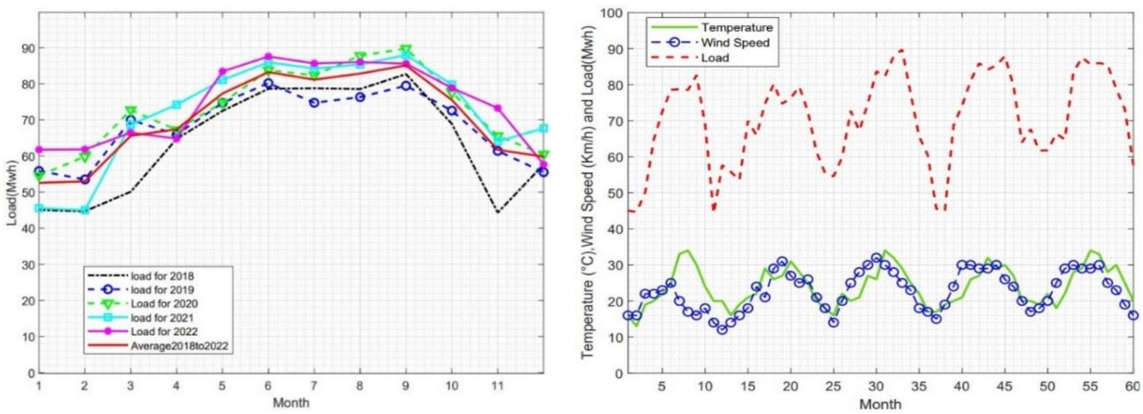


Figure 1. Location of Taroudannt Province

Electricity demand data for the Province of Taroudannt are used to build the prediction model. The 2022 data is selected to demonstrate the accuracy of the proposed forecasting models. The historical load database has been obtained from the National Office of Electricity, based in the city of Taroudant. The monthly load demand profiles for the Province of Taroudannt over the years 2018-2022 are shown in Figure 2(a). The plot has been generated based on the collected historic data. The weather data, including wind speed and temperature, as inputs were collected using the historical weather database of Morocco [20]. The variation of these inputs in correlation with the load as output is shown in Figure 2(b).

Due to weather characteristics in Taroudant Province, the consumed energy varies between the winter period and the summer period. It is possible to extract each of the following observations from Figure 2(a): the consumed energy increases to its peaks during summer and decreases significantly during non-summer. For each year, energy consumption is minimal in winter. The rise and fall of the load curves are noted in the autumn and spring seasons, respectively. Electricity consumption sees a gradual yearly increase, notably between the months of May and September. In 2020, a noteworthy surge in the province's energy consumption was detected, possibly linked to the period of lockdown imposed in Morocco due to the coronavirus disease 2019 (COVID-19) pandemic. Observations from Figure 2(b) lead to the following conclusions: during winter, load consumption decreases with decreasing temperatures. In summer, a direct relationship is evident between load consumption and temperature. Spring is characterized by a transition from cold to warm climates, with a corresponding relationship between load and temperature during the winter-summer transition. In autumn, the load consumption patterns resemble that of the spring months. Except for 2018, wind speed and temperature curves generally exhibit similarity.



(a) (b)

Figure 2. Variation of energy demand and weather variables in Taroudant (a) profile of load energy demand and (b) inputs variation in correlation with the load

2.2. MTLF using fuzzy logic

Fuzzy logic-based load forecasting models have been used for short, medium, and long-term forecasts, considering factors such as meteorological parameters and energy consumption patterns [15]. This approach has shown promising results in handling the inherent uncertainty in load forecasting, especially when dealing with real-world data that may not adhere to strict mathematical relationships [21]. The architecture of the fuzzy inference system (FIS) is shown in Figure 3.

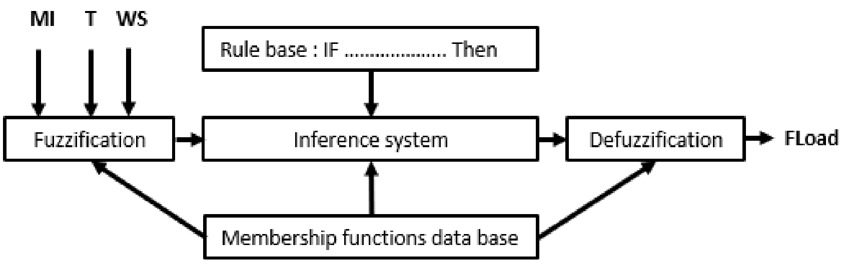


Figure 3. Fuzzy inference system structure

2.2.1. Implementation of fuzzy logic model using fuzzy logic designer tool

To implement the fuzzy logic model, the fuzzy logic designer tool is used in the MATLAB environment, as shown in Figure 4. This tool allows the design and testing of fuzzy inference systems for modelling the system behavior. The process of load forecasting using this tool can be summarized as follows: the first step is to design Mamdani fuzzy inference systems. Input and output variables are then added. Membership functions of all inputs and outputs are then specified. Define fuzzy if-then rules. Select fuzzy inference functions for: and operations, or operations, implication, aggregation and defuzzification. Next, adjust input values and view associated fuzzy inference graphs. The final step is to view output surface maps for fuzzy inference systems.

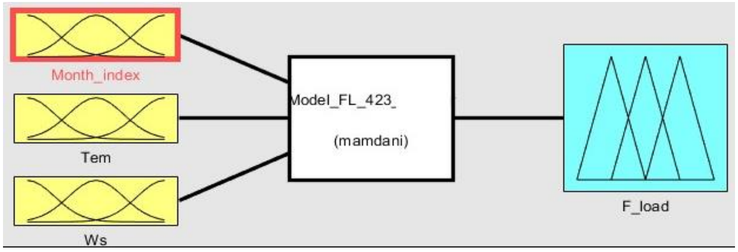


Figure 4. Fuzzy logic model using fuzzy logic designer tool

The FIS design is conducted through a sequential process [22], which involves identifying and fuzzifying inputs and outputs, establishing rule strength, deriving rule consequents, integrating rule consequents, and applying the defuzzification process. To select the best model, a series of tests are carried out using different defuzzification methods [14]. The model uses monthly average temperature (T), Month Index (MI) and wind speed (WS) as inputs and load as output. Inputs and output are sorted into low, medium, and high, and serve as classes of fuzzy sets. To determine the membership functions (MFs) for the different classes of the fuzzy sets, the examination of the data collected shows that inputs and outputs can be best classified according to the distribution shown in Table 1.

Table 1. Classes of fuzzy sets

Inputs and output	Discourse univ.	Classes
T in °C	13 to 35	**LT**: 13 to 24; **HT**: 22 to 35 and **LS**: 10 to 19
WS in Km/h	10 to 34	**MS**: 18 to 27 and **HS**: 24 to 34
Month index	{1,2,3, … ,12}	WINTER, SPRING, SUMMER, and FALL
Load in MWh	40 to 100	**LL**: 40 to 70; **ML**: 65 to 81 and **HL**: 78 to 100

In this work triangular MFs is selected. In fact, after a series of tests using three types of membership functions, it was found that the model using triangular MFs had the highest level of accuracy. Figure 5 shows the MFs of inputs and output. The input T has two MFs which are low temperature (LT) and high temperature (HT) in Figure 5(a). SPRING, WINTER, FALL, and SUMMER are the MFs of MI in Figure 5(b). High speed (HS), medium speed (MS) and low speed (LS) are the three MFs of the input WS in Figure 5(c). The forecasted load has three MFs in Figure 5(d). Where LL is low load, ML is medium load and HL is high load. A collection of fuzzy rules that establish connections between the input variables and the output variable is generated, as depicted by the rule editor displayed in Figure 6

2.3. ANN approach for MTLF

The process of conducting load forecasting using the ANN technique can be summarized as follows [23]–[26]: the first step is data collection and pre-processing. This includes retrieving historical load data with timestamps and normalizing to improve training performance. The dataset is then partitioned into training, validation, and test sets. The ANN architecture is then selected, input layers and hidden layers are defined, and an appropriate regression loss function is used. The model is trained using optimization algorithms, with continuous monitoring on the validation set to avoid overfitting. This is followed by evaluation on the test dataset to assess prediction accuracy. Once satisfactory performance is achieved, the model is deployed for load forecasting in a production environment. Continuous monitoring continues, allowing updates based on new data or changes in load patterns. Figure 7 shows the flowchart for the ANN model [27]. The primary objective of the learning algorithm (LA) is to modify the connection weights within the network to attain the intended outcome.

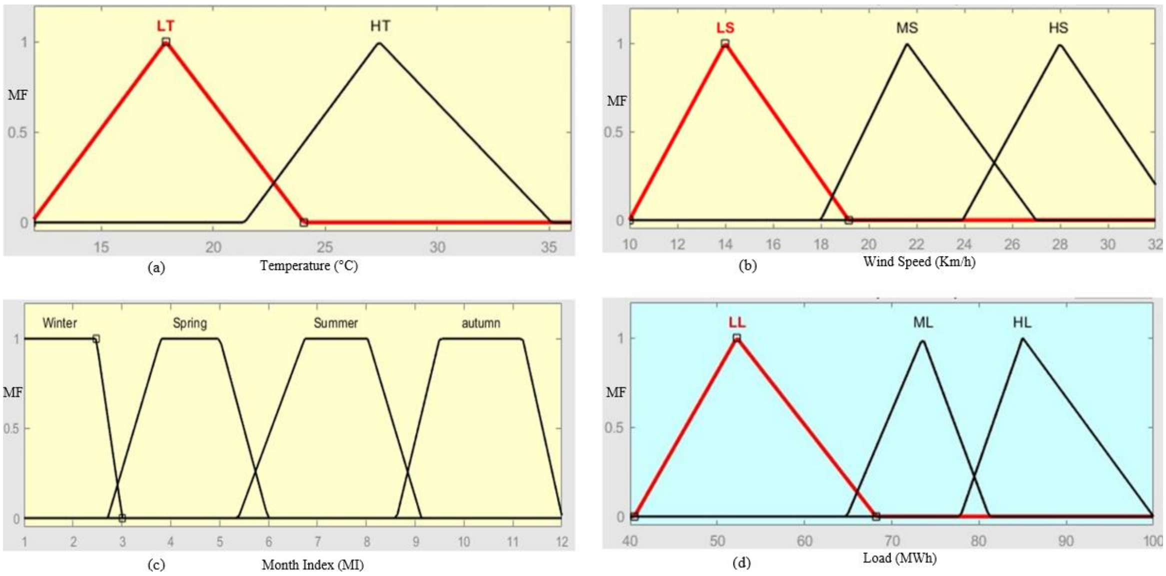


Figure 5. Membership functions used in FL model (a) MFs of input T (b) MFs of input WS (c) MFs of input MI and (d) MFs of output load

1. If (Month_index is Hiv) and (Tem is HT) and (Ws is HS) then (FLoad is LL) (1)
2. If (Month_index is Hiv) and (Tem is HT) and (Ws is MS) then (FLoad is LL) (1)
3. If (Month_index is Hiv) and (Tem is HT) and (Ws is LS) then (FLoad is LL) (1)
4. If (Month_index is Hiv) and (Tem is LT) and (Ws is HS) then (FLoad is LL) (1)
5. If (Month_index is Hiv) and (Tem is LT) and (Ws is MS) then (FLoad is LL) (1)
6. If (Month_index is Hiv) and (Tem is LT) and (Ws is LS) then (FLoad is LL) (1)
7. If (Month_index is Pr) and (Tem is HT) and (Ws is HS) then (FLoad is ML) (1)
8. If (Month_index is Pr) and (Tem is HT) and (Ws is MS) then (FLoad is ML) (1)
9. If (Month_index is Pr) and (Tem is HT) and (Ws is LS) then (FLoad is ML) (1)
10. If (Month_index is Pr) and (Tem is LT) and (Ws is HS) then (FLoad is ML) (1)
11. If (Month_index is Pr) and (Tem is LT) and (Ws is MS) then (FLoad is ML) (1)

Figure 6. Some fuzzy rules used to build FL model

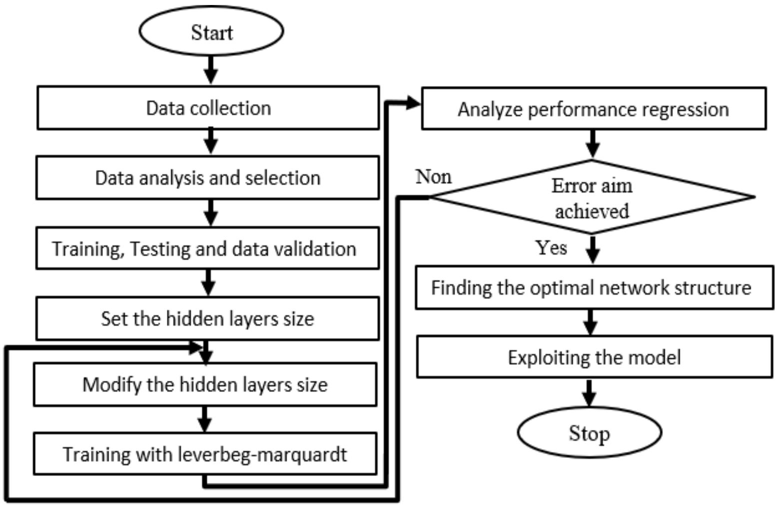


Figure 7. Flowchart of ANN

2.3.1. Implementation of ANN using MATLAB

To implement ANN model the collected data plotted in Figure 2 and saved in an Excel spreadsheet are used. Figure 8 shows the open tool used to generate ANN model. Different characteristics of parameters are used to achieve the best architecture with the fewest errors, such as hidden layer size, and training algorithm. has been examined. The architecture of ANN consists of three inputs and one output, organized in three distinct layers: the input layer, a hidden layer with 5 neurons, and the output layer. The training stage employed the Levenberg-Marquardt algorithm (LMA). The dataset was partitioned into three separate sets, with 70% assigned to training data, 15% to validation data, and another 15% to test data as also shown in Figure 8.

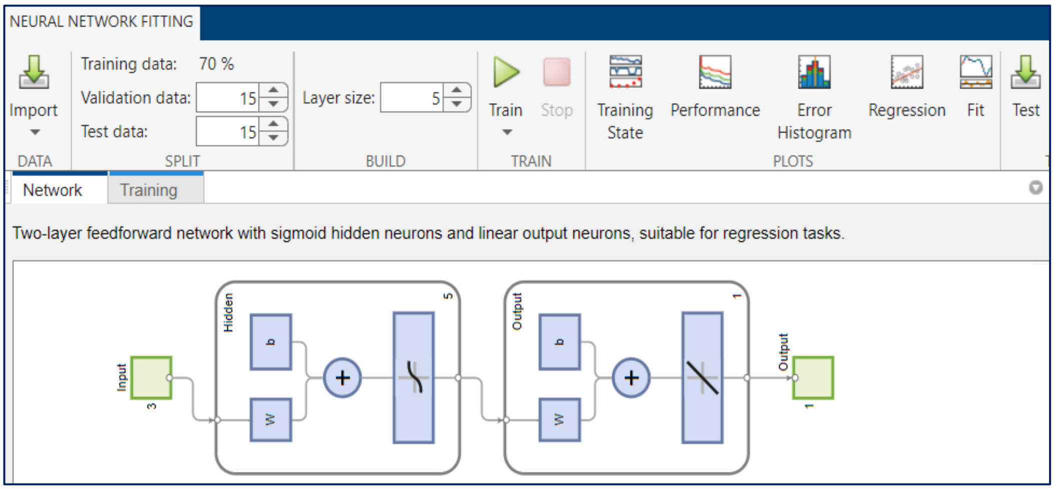


Figure 8. ANN open tool in MATLAB environment

2.4. ANFIS technique for MTLF

2.4.1. ANFIS architecture

The ANFIS was introduced in [28]. ANFIS is a hybrid intelligent model, it combines the strengths of ANNs, and fuzzy logic system. It is a powerful tool for modeling complex nonlinear systems, rainfall predicting [29]. Predicting the output power of a photovoltaic system [30]. The estimation of Li-Ion battery state of charge for hybrid vehicle [31], and load forecasting. Figure 9 shows the ANFIS architecture with two inputs, x_1 and x_2, and single output,$\hat{y}$. The fuzzy rules for the considered ANFIS model are expressed as:

- Rule I: if x_1 is A_1 and x_2 is B_1 then: $f_1 = p_1x_1 + q_1x_2 + r_1$
- Rule II: if x_1 is A_2 and x_2 is B_2 then: $f_2 = p_2x_1 + q_2x_2 + r_2$

where A_i and B_i represent the linguistic values defined by the fuzzy sets, and p_i, q_i, and r_i are known as consequent parameters. The layers in ANFIS can be broadly categorized into five main types, each serving a specific purpose in the overall system [32].

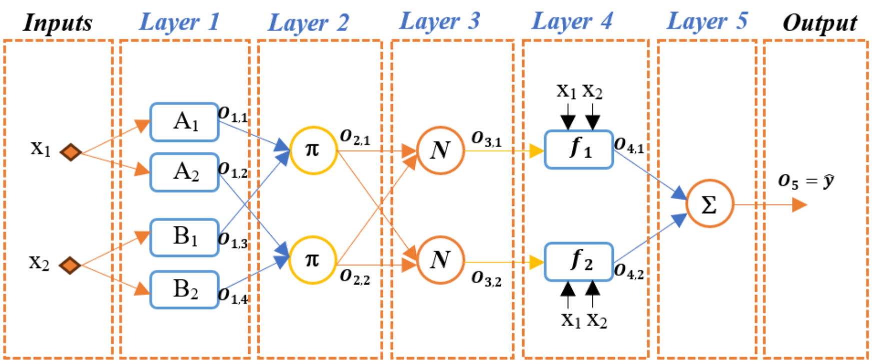


Figure 9. Simple ANFIS architecture with 2 inputs and one output

- Layer 1 (Fuzzification layer): Once the input data is received, it needs to be converted into linguistic terms to enable fuzzy inference. The fuzzification layer applies membership functions to the input data, transforming crisp numerical values into fuzzy linguistic terms.

$$O_{1,i} = \mu_{Ai}(x_1)\ for\ i = 1,2 \quad (1.a)$$

$$O_{1,i} = \mu_{Bi-2}(x_2)\ for\ i = 3,4 \quad (1.b)$$

where μ_{Ai} and μ_{Bi} are the membership grade of the inputs x_1 and x_2 in the A_i and B_i fuzzy sets, respectively. There are several suitable parameterized membership functions that can be used, such as the gaussian MF (*gaussmf*), generalized bell MF (*gbellmf*), triangular MF (*trimf*) [33].
- Layer 2 (Rule evaluation equations): This layer in a fuzzy logic system calculates the firing strength of the rules based on the combined effect of antecedent membership grades. This is calculated using the product operator:

$$O_{2,i} = \omega_i = \mu_{Ai}(x_1) * \mu_{Bi}(x_2) \quad for\ i = 1,2 \tag{2}$$

where ω_i is the firing strength of rule *i*.
- Layer 3 (Normalization equations): This layer normalizes the firing strengths of all rules to ensure that they sum up to 1. This is achieved by the given (3):

$$O_{3,i} = \overline{\omega}_i = \frac{\omega_i}{\omega_1+\omega_2} \tag{3}$$

where $\overline{\omega}_i$ is the normalized firing strength of rule *i*.
- Layer 4 (Defuzzification equations): The nodes of this layer are an adaptive node with node functions given by (4):

$$O_{4,i} = \overline{\omega}_i . f_i = \overline{\omega}_i . (p_i x_1 + q_i x_2 + r_i) \quad for\ i = 1,2 \tag{4}$$

where and p_i, q_i, and r_i are the consequent parameters.
- Layer 5 (Aggregation equation): This layer aggregates the outputs of all rules to obtain the final forecasted load value:

$$O_5 = \hat{y} = \sum_i \overline{\omega}_i . f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \quad for\ i = 1,2 \tag{5}$$

where $\hat{y}$ is the defuzzified output.

In addition to these five main layers, ANFIS also incorporates a learning algorithm, such as the backpropagation or the hybrid algorithm, to adapt its parameters in training phase. In the hybrid algorithm, the parameters are updated using two different methods [34], premise parameters and consequent parameters. The premise parameters a_i, b_i, and c_i, are optimized using a gradient descent algorithm. Where the consequent parameters p_i, q_i, and r_i which represent the model's output, are updated using a least-squares algorithm.

2.4.2. The proposed ANFIS model

To implement the ANFIS method, neuro-fuzzy designer of MATLAB environment is used as shown in Figure 10. Figure 11 presents the flowchart of ANFIS model [27]. The performances of the ANFIS model are also compared with the fuzzy logic and ANN model using the same dataset. ANFIS model takes the monthly average temperature (T), month index (MI), and wind speed (WS) as inputs, producing the monthly load as output. The data for 2018 to 2021 are selected for training, and the data for 2022 are used for testing.

To achieve the best architecture with the fewest errors, various parameters, such as MFs types, the number of MFs, and training methods, have been investigated. The best obtained feature of ANFIS after the tuning process is described as follows: the type of MFs is trapezoidal, number of MFs is 4, 2, and 3 for MI, T and WS respectively and number of epochs is 500. Figure 12 presents the structure of monthly model which consists of six layers, L1 to L6. L1 shows the model inputs. L2 represents the input MF which are Trapezoidal. L3 is rules and L4 is the output MFs. L5 represents the output as the result of a weighted sum and L6 is output of ANFIS model. The generated rules for ANFIS model are given in Figure 13.

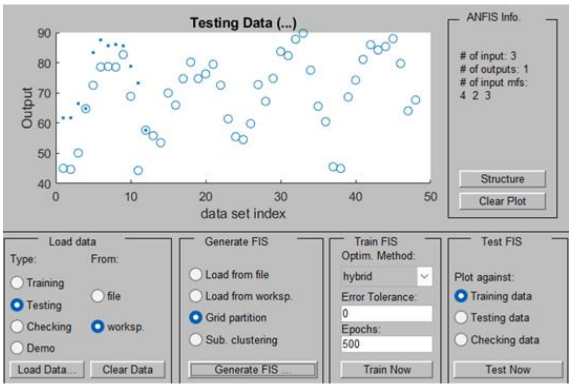


Figure 10. Data preparation and model parameterization in neuro fuzzy designer

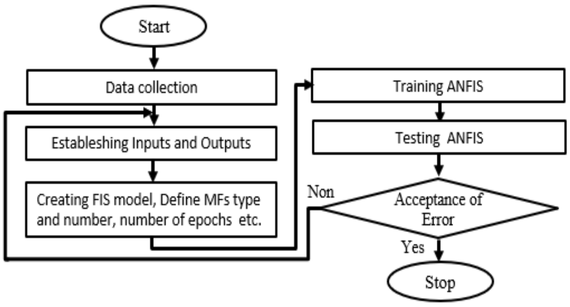


Figure 11. Flowchart of ANFIS

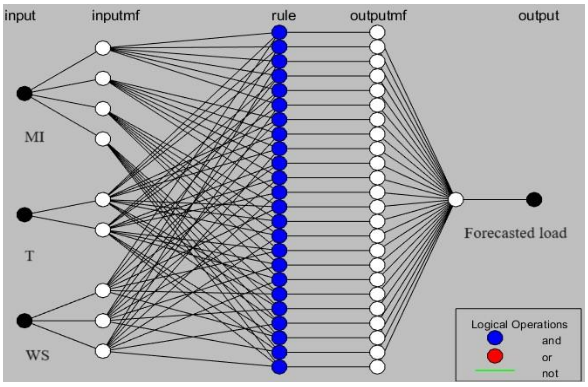


Figure 12. Framework of ANFIS

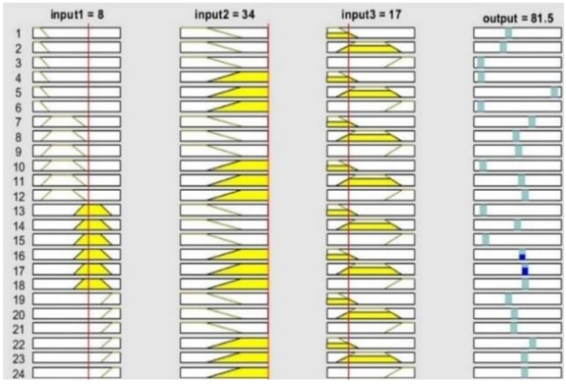


Figure 13. Rules viewer of the proposed ANFIS model

3. RESULTS AND DISCUSSION

3.1. Evaluation metrics

In the literature, various statistical methods are employed to calculate forecasting errors. In this work, absolute percentage error (APE), mean absolute percentage error (MAPE), root mean square error (RMSE) and correlation coefficient (R) criterion, are selected to evaluate the accuracy of the proposed models. APE, MAPE, RMSE and R formulas are given by (6)-(8).

$$APE(\%) = \frac{|ALoad(p)-FLoad(p)|}{ALoad(p)} \text{ and } MAPE(\%) = \frac{1}{n}\sum_{p=1}^{p=n} APE(p) \tag{6}$$

$$RMSE(\%) = \sqrt{\frac{\sum_{p=1}^{n}\left(ALoad(p)-FLoad(p)\right)^2}{n}} \tag{7}$$

$$R^2 = 1 - \frac{Sum\ of\ Squared\ Residuals\ (SSR)}{Total\ Sum\ of\ Squares\ (SST)} \tag{8}$$

where *ALoad* and *FLoad* are respectively the actual and forecast load, and n is the number of forecasts. *SSR* is the sum of squared differences between the observed values and the values predicted by the regression model. *SST* is the total sum of squared differences between the observed values and their mean.

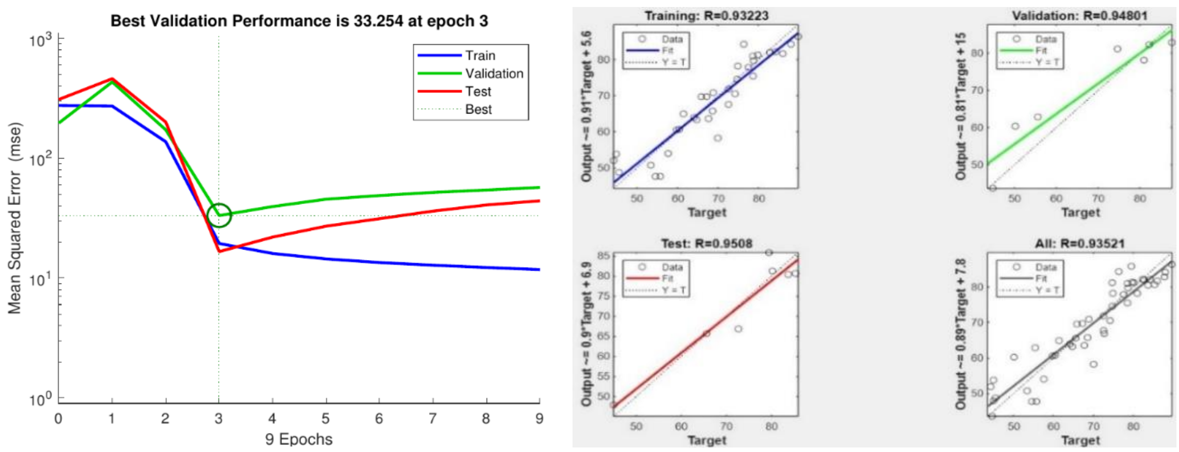
3.2. Obtained results

This section presents the obtained results. The first subsection examines the R, MSE, and RMSE metrics to evaluate and compare the accuracy of the three models. The second subsection analyzes APE and MAPE values, discussing the trade-offs between model complexity and forecasting accuracy for each approach, while also highlighting the challenges associated with each model. This analysis aims to assess how effectively each model captures the underlying patterns and variations within the data, enabling a comprehensive comparison of their predictive capabilities. The third subsection highlights the practical implications of these results for energy management in southwest Morocco.

3.2.1. R, MSE and RMSE values analysis

Figure 14(a) shows the evolution of the cost function (MSE) vs epochs. It can be seen that the best validation performance is 33.254 at epoch 3. While Figure 14(b) consists of four different graphs representing regression plots for testing, training, and validation. The training plot shows a good correlation between the output and the target with the R-value of 0.932. Additionally, it is observed that the testing regression plot yields an R-value of 0.951, and the validation plot exhibits a high relationship with an R-value of 0.948. The R-value across all analyses is 0.935.

From Table 2, the minimal and maximal R-value of the fuzzy logic and ANFIS models are, respectively, 0.8 and 0.92. In terms of root mean square error (RMSE), the ANFIS demonstrates a minimum of 4.32, while the FL model exhibits a maximum value of 6.86. All these analyses indicate a higher accuracy of the ANFIS in load prediction compared to the other two models.



(a) (b)

Figure 14. Performances of ANN model (a) ANN performance plot and (b) ANN regression plot

Table 2. R, RMSE and MAPE values of FL, ANN, and ANFIS for 2022

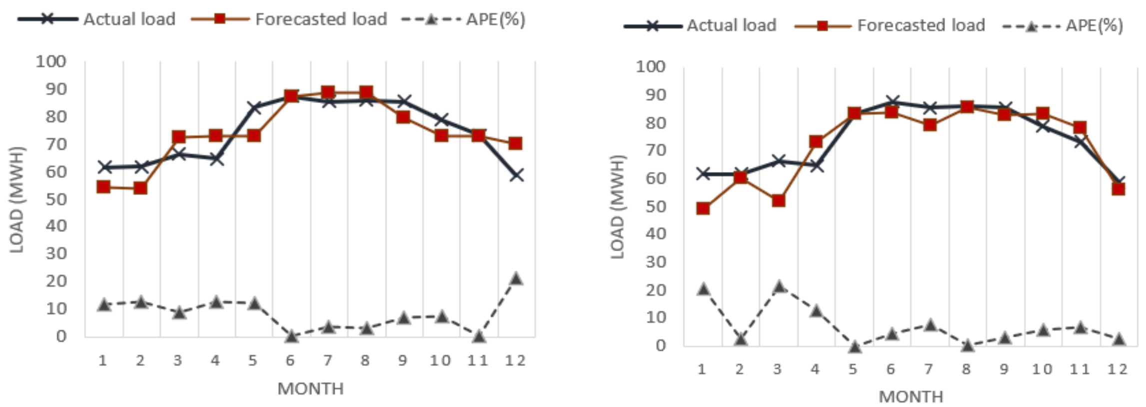
	Regression	RMSE	MAPE
Fuzzy logic	0.80	6.86	8.42
ANN	0.87	6.77	7.36
ANFIS	0.92	4.32	4.75

3.2.2. APE and MAPE values analysis

Figure 15(a) shows the monthly actual and estimated load pattern for year 2022 using FL model. Figure 15(b) presents the monthly actual and predicted load profile for year 2022 using ANN technique. Figure 16 illustrates the monthly actual and forecasted load pattern for year 2022 using ANFIS approach. As these figures show, the profiles of actual and predicted load curves are similar. In addition, compared to fuzzy logic and ANN models, the ANFIS model has very low error level and produces more accurate results.

The APE and MAPE are calculated using (6). From Figure 15 and 16 these observations can be extracted: the maximum value of the APE as 21.38% is recorded in December by the fuzzy logic model. The minimum deviation for the three models is observed during the summer. From the comparison of the 2022 results for FL, ANN and ANFIS presented in Table 2, the MAPE values for the ANFIS method are better than those for FL and ANN. These values for the FL and ANN models are approximately the same.

The choice between these approaches depends on the specific characteristics of the problem at hand, including the available data, the desired level of interpretability, and computational resources. Finding the right balance between model complexity and forecasting accuracy is crucial for developing effective and reliable predictive models. Table 3 discuss the trade-off between model complexity and forecasting accuracy for each approach, highlighting some challenges associated with the chosen model.



(a) (b)

Figure 15. Comparison of monthly actual and predicted load profiles for 2022 (a) monthly actual vs estimated load patterns using FL model and (b) monthly actual vs estimated load profiles using ANN model

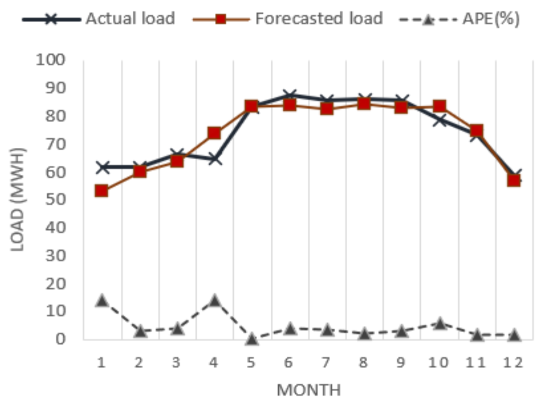


Figure 16. Monthly actual and estimated load pattern for 2022 using ANFIS model

Table 3. The trade-off between model complexity and forecasting accuracy with some limitations associated with the proposed model

Approach	Complexity	Accuracy	Challenges and limitations
Fuzzy logic	Tends to have relatively simple structures, consisting of fuzzy sets, membership functions, and a set of rules. It is intuitive to understand and interpret.	Can handle vague and imprecise input data well, making it suitable for problems where precise mathematical relationships are difficult to define. However, its forecasting accuracy may be limited in complex and highly nonlinear systems due to its simplicity.	Limited ability to capture complex nonlinear relationships, sensitivity to the choice of membership functions and rules, and difficulties in scaling to large datasets.
ANN	Can vary significantly in complexity, depending on the number of layers, neurons, and connections. Can capture highly complex relationships in data but may suffer from overfitting if not properly regularized.	ANN excels in capturing nonlinear relationships and can achieve high forecasting accuracy, especially in high-dimensional and complex datasets. However, they may require large amounts of data for training and can be challenging to interpret due to their black-box nature.	Susceptibility to overfitting, dependence on large amounts of data for training, black-box nature leading to reduced interpretability, and challenges in selecting optimal architectures and hyperparameters
ANFIS	ANFIS combines the simplicity of fuzzy logic with the learning capabilities of neural networks, resulting in a hybrid model with moderate complexity. It consists of fuzzy inference systems trained using neural network techniques.	It can handle nonlinearities and uncertainties in data while providing some level of interpretability compared to fully black-box neural networks. However, training ANFIS models can be computationally intensive, and selecting the appropriate structure and parameters can be challenging.	Computational complexity during training, potential overfitting if not properly regularized, difficulty in selecting appropriate fuzzy sets and rules, and limitations in handling extremely high-dimensional data

3.2.3. Forecasting models and actionable recommendations

The results of the study can hold important practical implications for energy management in southwest Morocco. By using the forecast results, stakeholders can make informed decisions and implement strategies to optimize energy management practices in the province. Based on the findings of the study, here are some actionable recommendations:

– Demand management initiatives: Operators can implement demand-side management initiatives to effectively manage energy consumption during periods of high demand, reducing overall energy costs and improving grid stability.
– Renewable energy investment: Stakeholders can use the forecast results to identify optimal locations for renewable energy projects and prioritize investments in sustainable energy infrastructure, thereby reducing reliance on fossil fuels and mitigating environmental impacts.
– Grid planning and expansion: Use forecasting models to inform grid planning and expansion efforts. By anticipating future energy demand trends, stakeholders can design a resilient and adaptable grid infrastructure capable of accommodating increased renewable energy integration and evolving consumer preferences.

3.3 Comparison with other works

This section presents and compares some load forecasting studies related to this work. Table 4 shows several works related to medium-term load forecasting in different countries. In general, the artificial intelligent techniques such as FL, ANN and ANFIS are the most popular methods used in load forecasting because of their simplicity and their high accuracy [35], [36]. The researchers employ diverse methodologies and time frames for MTLF. Stitou *et al.* [14] a one-year horizon has been considered for MTLF. The effect of weather on the forecast load in MTLF was extensively studied in the [14], [37]–[39]. Bunnoon *et al.* [40] focused on the study of load forecasting in Thailand using ANN for both modelling and forecasting, the relevant variables include industrial growth rate, consumer price rate, maximum and minimum temperature, rainfall rate, humidity rate and wind speed. Although the study areas vary in these investigations, the comparisons of performance indicators such as MAPE, RMSE, MSE, and R show a satisfactory range of error rates.

Table 4. Medium term load forecasting studies for comparison

Used techniques	Research work	Concerned country
FL	[14]	Morocco
ANFIS and FL	[37], [41]	Turkey, South African
MPL and PSO	[42]	-
ANN	[9], [38], [40]	Oman, Turkey, Thailand
ARIMA and ANN	[39]	Jeddah (A.S.)

4. CONCLUSION

In this paper a methodology for MTLF using ANN, FL, and ANFIS approaches is proposed. The correlation between load and weather variables, specifically temperature and wind speed, is established through a case study in Taroudannt Province of Morocco. This study is the first of its kind in this province of the country. The aim is to contribute to the improvement of the energy efficiency in the region of Souss Massa. This work has effectively conducted simulations for medium term load forecasting, employing three distinct approaches: ANN, FL, and ANFIS. When comparing the tested models, it is clear that each of them successfully captures the dynamic characteristics of the meteorological variables for load prediction. However, the model using the ANFIS and ANN methods stands out as it shows significantly more accurate results for the MTLF, with a MAPE of 4.78% and 7.36% respectively. Finally, it was observed that the deviation between the predicted load and the actual load using the FL model produces a MAPE of 8.42%. Other input parameters can be used to improve the accuracy of the results. However, these extra parameters increase the complexity of the system, making it hard to model.

Continuing the focus on energy management and efficiency, the next challenge is to create a microgrid (MG) for a rural area in southwest of Morocco. Simultaneously the task includes the development of an energy management system (EMS) for this MG by using other artificial intelligence approaches to enhance the reliability of the predictions, especially neural network-based uncertainty quantification methods. To improve the robustness of the model other task can be envisaged as part of this work, namely sensitivity analysis, for example load forecasting with analysis of temperature sensitivity, to assess the impact of the various input variables on the forecast results.

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