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# Multicriteria Decision Making for Selecting Forecasting Electricity Demand Models

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**Abstract:** Sustainable electricity consumption is considered a pivotal element in the effective governance and growth of any institution. Accurate electricity demand forecasting is essential for strategic planning and decision making. However, due to the numerous existing forecasting approaches, many forecasters find it challenging to select the best model. Currently, there is no robust approach for selecting the best forecasting model when considering conflicting error measures. This paper proposes a novel methodology using a multicriteria decision making (MCDM) approach to determine the most appropriate forecasting model for electricity demand, considering various interdependent error measures. The Analytical Network Process (ANP) was applied to determine the weights of evaluation criteria, while the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was employed to select the best forecasting model. The proposed methodology was tested and validated with a real case study in Tunisia using the opinions of experts and stakeholders. The results show that multiple regression and exponential smoothing are the best alternatives and outperformed the other models. Additionally, a sensitivity analysis is presented to test the robustness of the final ranking. This serves to assist decision makers to select the best forecasting model.

**Keywords:** decision making; multicriteria; electricity demand forecasting; error measures; model selection

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## 1. Introduction

Energy has been the major driver of economic and human development around the world. It is of great significance for achieving the goals of sustainable development. The security of energy supply is an inherent element of strategic energy decision making [1]. This issue is even more crucial when it comes to electrical energy because, unlike to other energy sources, it cannot be stocked for long-term consumption. Therefore, electricity demand forecasting is a critical process in power system operation and planning, having a significant influence on the decisions of energy policymakers.

In recent years, forecasting electricity consumption has been the focus of extensive research [2]. Numerous forecasting methods have been developed to precisely predict future electricity demand [3]. Hamzaçebi et al. [4] developed four different artificial neural networks to predict the monthly electricity consumption in Turkey. They used four performance measures to select the best one: mean absolute error (MAE), root-mean-square error (RMSE), post-error ratio (C), and mean absolute percentage error (MAPE). Furthermore, Son and Kim [5] suggested five forecasting models: long short-term memory (LSTM), support vector regression (SVR), artificial neural networks (ANN), auto regressive integrated moving average (ARIMA), and multiple linear regression (MLR), to study the forecasting of monthly demand for residential–sector electricity. The resulting forecasting performance was evaluated based on six performance measures including RMSE, MAE, MAPE, post-error ratio C, and unpaired peak accuracy (UPA). In other research by Angelopoulos et al. [6], the disaggregation model and MLR method were used to forecast the annual net electricity demand in the Greek interconnected power system. They found that the ordinal regression models performed considerably better than the MLR model in terms of the statistical accuracy, resulting into a minimum MAPE equal to 0.74%. Yörük et al. [7] studied a variety of forecasting models, including MLR, exponential smoothing (ES), Winter's method, and ARIMA methods, selecting the best model using various error measures (RMSE, MAPE, MAE, and $R^2$). In Korea, Shin and Woo [8] compared three different machine learning algorithms, namely random forest (RF), XGBoost (XGB), and LSTM models, using RMSE and MAPE as performance measures to select the most suitable model. In [9], the authors used ANN, support vector machine (SVM), Gaussian process regression (GPR), MLR, decision tree (DT), and gradient boosting decision trees (GBDTs) to forecast electricity consumption in Hong Kong. They compared the performance of these different algorithms using statistical criteria including R-square, average deviation, RMSE, MAPE, and normalized mean bias error (NMBE).

There are many more similar studies that have been proposed in the field of electricity demand forecasting. According to the abundant literature, electricity demand forecasting can be classified into two main categories: conventional models (linear regression models, econometrics, time series, etc.) and artificial intelligence (AI) models (such as ANN, SVM, DT, and RF).

A consensus has developed around the forecasting of electricity demand, particularly regarding the selection of forecasting models that use several error measures to support the selection of the best forecasting model. Although it is recommended to use different error measures to evaluate forecast models, these measures can often yield contradictory results. For example, a forecasting model might perform well according to one error measure but poorly according to another, leading to conflicting outcomes in model evaluation. As a result, many researchers have introduced additional methods for model selection, such as Akaike Information Criterion (AIC) [10,11] and Schwartz's Bayesian Criterion (SBC) [2,12], as the most popular methods for selecting the best model among a finite set of models. Nevertheless, these approaches are limited to evaluating models within the same class and cannot effectively choose a forecasting model from different classes.

The state-of-the-art literature highlights significant advancements in electricity demand forecasting models in recent years [13]. Although numerous models are available, policymakers frequently encounter challenges in selecting the most appropriate one for their specific demand projections. Current methodologies offer various approaches to model selection, often relying on error measures and information criteria, such as AIC and SBC, for evaluation. However, a gap remains in the literature, as no existing study has proposed a comprehensive approach to evaluating multiclass electricity demand forecasting models using multiple interdependent error measures. This gap emphasizes the need for a robust framework that aids the selection of electricity forecasting methods, which is precisely what this paper seeks to address.

When faced with the challenge of making a decision after considering numerous opposing evaluation criteria, a MCDM is employed [14]. From this perspective, MCDM appears to be the most appropriate tool to support those involved in the decision-making process. In the literature, many research studies have applied the MCDM approach to various fields, including energy [15,16], manufacturing systems [17,18], supply chain issues [19,20], and business management [21,22], with this trend steadily increasing over the past several years. However, up to the present moment, no study has delved into the application of MCDM for selecting electricity forecasting models. Therefore, this paper aims to develop a MCDM methodology for selecting the best forecasting model, taking into account various criteria (error measures). Based on two stages of MCDM, ANP is employed to determine the weight of the measures. Thereafter, TOPSIS method is applied to conduct the ranking of six alternatives: autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average (SARIMA), exponential smoothing (ES), multiple linear regression (MLR), decision tree (DT), and random forest (RF). To test the robustness of final ranking, a sensitivity analysis is carried out.

In summary, the main contributions of this study are twofold. First, it aims to examine the relationship between annual electricity demand and influential factors. Second, this paper proposes a novel procedure of MCDM to select the best-performing model for robust long-term electricity demand forecasting, considering multiple evaluation criteria. This research serves to assist Tunisian electricity policymakers and decision makers in planning and managing energy.

The rest of this paper is organized as follows: Section 2 describes the proposed research methodology and verifies the effectiveness of the proposed framework with a Tunisian case study. Section 3 outlines the results obtained from the application, along with a related discussion. The final section (Section 4) provides our conclusions and future research directions.

## 2. Materials and Methods

This section proposes a framework consisting of three main parts: electricity demand forecasting, MCDM, and robustness analysis to evaluate and select the best available alternatives from the set of forecasting models. The principal structure and the main stages of the proposed methodology for forecasting robust long-term electricity demand are described below (Figure 1).

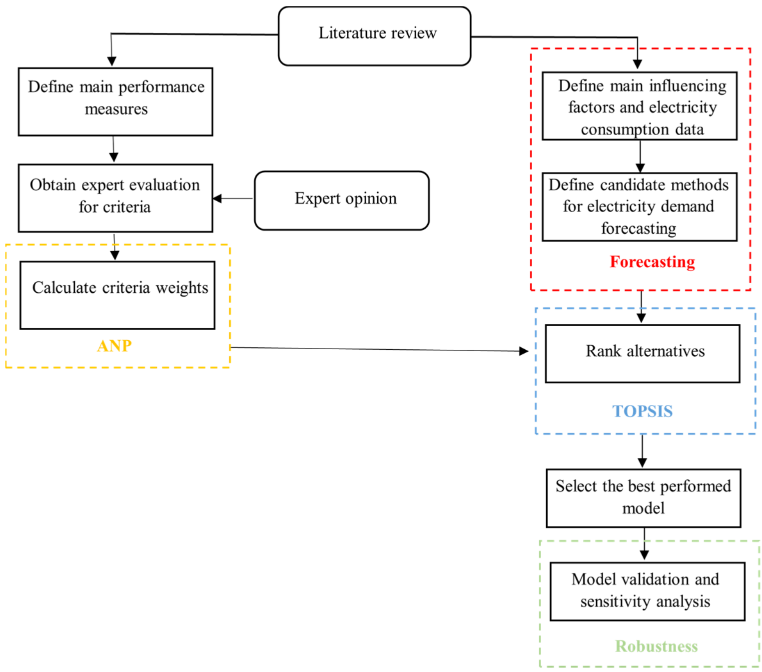


**Figure 1.** Framework of the proposed methodology.

The forecasting part of the study starts with obtaining electricity consumption data and defining the main influencing factors. These variables are used as inputs to the forecasting models. In the second step, the hybrid MCDM procedure (ANP–TOPSIS) is applied to select the best forecasting model from a set of alternatives. Finally, a robustness analysis is conducted via validation of ranking and sensitivity analysis. Each of the aforementioned methodological steps is detailed in the following subsections.

### *2.1. Data Collection*

The first step is to collect the annual electricity demand and the factors that could affect electricity consumption by reviewing the scientific literature.

- Electricity demand evolution in Tunisia

In recent years, Tunisia has faced an electricity supply issue. The electricity demand in Tunisia is rapidly increasing. Therefore, it is eager to provide the best procedures, plans, and resources for balancing electricity supply and demand. As a result, implementing an electricity demand forecasting model becomes crucial for sustainable energy planning in Tunisia. In this study, annual electricity consumption data and relevant variables that could influence electricity demand from 1995 to 2021 were collected from published statistics by the World Bank Group, the National Institute of Meteorology, and the UN Arab Region Data and Policy Support Hub (Appendix A). The evolution of the annual total net electricity demand in Tunisia for the period 1995–2021, is plotted in Figure 2. According to the data, consumption has been considerably increasing and exhibits linear growth. This is due to several influencing factors that affect electricity consumption.

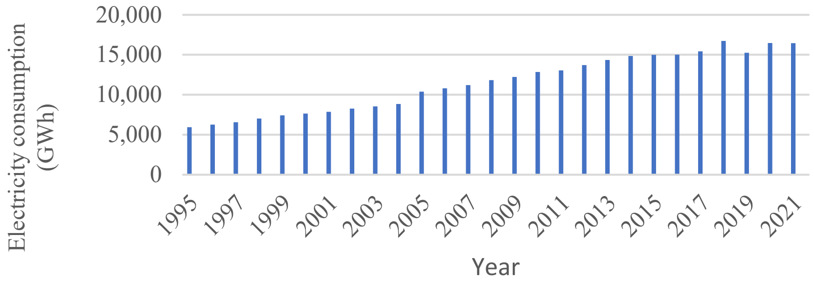


**Figure 2.** Annual electricity consumption from 1995 to 2021.

- Feature extraction

Selecting the appropriate input variables for demand forecasting is a crucial aspect of the forecasting process [18]. Nevertheless, most of previous studies have focused on a limited set of climatic and social variables as influencing factors. In some cases, the selected variables may lead to forecasting errors. These factors were often selected based on human intuition, without a method to identify the most suitable influencing factors for reliable electricity demand forecasting. Therefore, in this study, we identified influencing factors for our forecasting models through an extensive literature review. To refine our selection process, we conducted interviews with national energy experts. These interviews provided valuable industry insights, helping us confirm and refine the selected factors to ensure they are practical and relevant to real-world situations. Following this, we analyzed the correlation matrix between these variables and electricity demand, which further highlighted the interconnections between key factors and their impact on energy consumption. The correlation matrix shows the relationship between independent and dependent variables, with values ranging from −1 to 1. Values close to 1 indicate a strong positive linear relationship, values close to −1 indicate a strong inverse relationship, and values close to 0 indicate no linear relationship [23].

In this study, long-term electricity demand in Tunisia can be influenced by various factors, including meteorological, socio-economic, and technological variables. Based on data availability and local context, we included three climate variables (average temperature, average maximum temperature, and precipitation), four socio- economic variables (GDP per capita, inflation, population, and urbanization), and one technological variable (internet users). We anticipate that these variables will have a significant influence on Tunisian electricity demand.

As illustrated in Figure 3, there is a strong positive correlation between electricity demand and both overall population and urban population in Tunisia, with each correlation reaching a value of 0.99. This indicates that as Tunisia's population grows and more people move to cities, electricity demand will rise due to the higher energy needs of urban areas. The strong correlation between "internet users" (0.97) and electricity demand highlights the growing importance of digitalization in Tunisia, with more internet-connected households and businesses driving up electricity consumption. Additionally, "GDP per capita" correlates significantly with electricity demand at 0.83, suggesting that economic growth and rising living standards are closely linked to higher energy consumption. These factors—demographic growth, urbanization, digitalization, and economic growth—should be considered when forecasting future electricity demand in Tunisia.

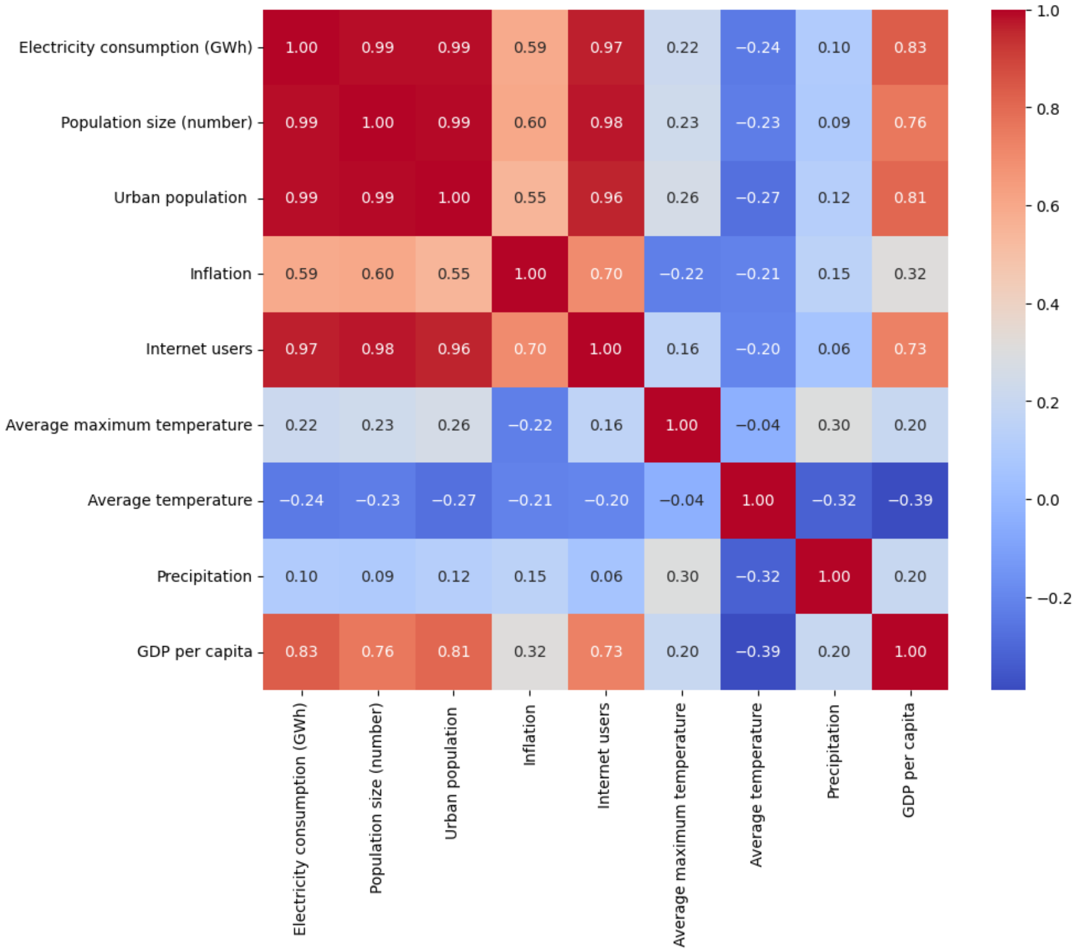


**Figure 3.** Correlation matrix with electricity consumption.

### *2.2. Selection of Forecasting Model Alternatives and Define the Final Main Performance Measures*

Our MCDM study starts by defining alternatives and their corresponding evaluation criteria. We include Tunisian electricity experts from different institutions and organizations: Tunisian Company of Electricity and Gas (STEG), National Agency for Energy Management (ANME), and Green Power Energy (GPE). Their contributions have been indispensable during the initial stages of the current research. Additionally, this team of experts will also be involved in evaluating and approving the final ranking results.

- Forecasting models alternatives

Selecting too many alternatives is not advised because it makes conducting pairwise comparisons challenging, especially with a large number of alternatives and criteria. A widely accepted rule of thumb suggests selecting between five and nine alternatives to enhance the effectiveness of judgment-based decision making. Based on interviews with key experts, decision-makers affirmed that six alternatives are the most representative and suitable for forecasting electricity demand in Tunisia.

The ARIMA model is a time series forecasting method introduced in 1976 by Box and Jenkins [24]. ARIMA is defined by ARIMA (p, d, q), where 'p' signifies the count of autoregressive components, 'd' indicates the number of non-seasonal differences required to achieve model stationarity, and 'q' denotes the quantity of lags considered in the forecast error equation. ARIMA is renowned for its forecasting accuracy and ability to adapt to various time series situations [25]. While the ARIMA model is highly effective for analyzing time series data, it is limited to one variable. Therefore, it is necessary to develop a multivariate ARIMAX (Auto Regressive Integrated Moving Average with Exogenous Variables) model that can include other variables related to the target series as input variables to improve prediction accuracy [26].

Electricity consumption highlights periodic fluctuations resulting from seasonal changes, which can be addressed using the SARIMA model. The general form of the SARIMA model is expressed as (p, d, q) ∗ (P, D, Q). In this mathematical expression, 'p' denotes the autoregressive order, 'P' designates the seasonal autoregressive order, 'd' indicates the order of differencing, 'D' conveys the seasonal differencing, and 'q' and 'Q' correspond to the order of the moving average (MA) and seasonal moving average (SMA), respectively. 'S' characterizes the seasonality [27]. Similar to ARIMAX, we propose SARIMA with exogenous influencing factors (SARIMAX: Seasonal Auto Regressive Integrated Moving Average with Exogenous Variables) to reduce the error values and enhance model accuracy.

The Holt–Winters exponential smoothing method is a highly regarded approach for forecasting seasonal time series data. Exponential smoothing methods are extensively adopted due to their robustness and precision in applications requiring automated procedures. However, exponential smoothing, with its single component, is not well-suited for data exhibiting consistent trends. Double exponential smoothing (DES) introduces a second component, the trend, to better capture and forecast data with linear or exponential trends.

Regression models enable predictions about future events using information from past or present events [28]. They investigate the relationship between the endogenous variable (dependent variable) and several exogenous variables (independent variables) [29].

Decision trees (DT) are widely utilized for classification and prediction [30]. They provide visual and interpretable solutions for complex decision making processes by optimizing the attribute splits at each node.

The random forest (RF) is an ensemble learning algorithm that utilizes decision trees as base learners. It is prevalent in both classification and regression tasks [31] due to its robustness and ease of hyperparameter adjustment. RF combines the Bagging algorithm and the Random Subspace algorithm to construct multiple decision trees and determine the best feature splits [32].

- Performance Evaluation Metrics

The accuracy of the employed forecasting models is evaluated by extracting pertinent statistical performance indicators. Six evaluation measures were used: ME, MPE, RMSE, MAPE, MAE, and $R^2$. These criteria were finalized through expert surveys and categorized into four groups: absolute error, quadratic error, relative error, and overall quality. The mathematical representation of the evaluation measures is provided in Equations (1)–(6).

$$ME = \frac{\sum F_i - O_i}{N} \tag{1}$$

$$MPE = \frac{\sum F_i - O_i / O_i}{N} * 100 \tag{2}$$

$$RMSE = \sqrt{\frac{\sum (F_i - O_i)^2}{N}} \tag{3}$$

$$MAPE = \frac{\sum \left| \frac{(F_i - O_i)}{O_i} \right|}{N} \tag{4}$$

$$MAE = \frac{\sum |(F_i - O_i)|}{N} \tag{5}$$

$$R^2 = 1 - \frac{\sum (O_i - F_i)^2}{\sum (O_i - \overline{O})^2} \tag{6}$$

In the above formula, $N$ is the size of the dataset, $O_i$ is the actual value, and $F_i$ is the forecasted value [25].

### 2.3. MCDM Procedure for Selection Forecasting Model

Once alternatives and criteria are defined, the MCDM framework is introduced. MCDM consists of two main phases: calculating criteria weights and ranking alternatives. The hierarchical structure of the MCDM problem is built with different levels (goal, main criteria, sub-criteria, and alternatives), as portrayed in Figure 4. This research proposes a hybrid MCDM to select the best electricity forecasting model.

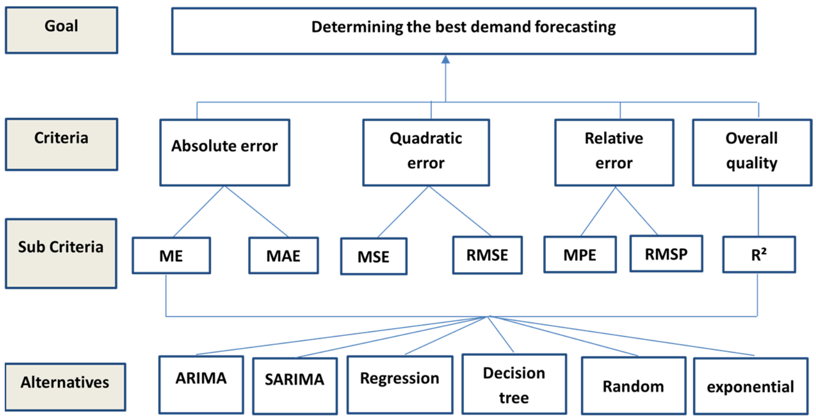


**Figure 4.** Hierarchical structure of MCDM.

Over the past three decades, a multitude of methods and tools have been employed within the field of MCDM [33]. Our review of the MCDM literature reveals that the combined ANP–TOPSIS approach is popular and widely applied in several fields [34]. The ANP method is used to determine the weight of the criteria, while the TOPSIS method aims to rank the forecasting models.

The high similarity in the calculation of many error measures leads to their interdependence. In this line, the ANP approach offers the advantage of incorporating the interdependence among evaluation criteria, including error measures, in the calculation of criteria weights. Therefore, we propose ANP as a well-known multicriteria decision making method capable of improving prediction accuracy with better priority calculations in cases of networks with dependent criteria [35].

In our implementation, the team proceeds to compare these criteria using Saaty's scale to determine the relative significance of one criterion in comparison to another [36]. The pairwise comparison matrix of evaluation criteria (error measures) is presented in Table 1.

**Table 1.** Criteria priorities.

| Criteria | ME | MAE | RMSE | MPE | RMSPE | MAPE | $R^2$ |
|---|---|---|---|---|---|---|---|
| ME | 1 | 1/5 | 1/4 | 1/3 | 1/5 | 1/5 | 1 |
| MAE | 5 | 1 | 1/3 | 1 | 1/3 | 1/3 | 1 |
| RMSE | 4 | 3 | 1 | 3 | 1 | 1/3 | 1 |
| MPE | 3 | 1 | 0 | 1 | 1/3 | 1/5 | 1 |
| RMSPE | 5 | 3 | 1 | 3 | 1 | 1/3 | 1 |
| MAPE | 5 | 3 | 3 | 5 | 3 | 1 | 1 |
| $R^2$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

In Table 2, the supermatrix of the network is computed, where each column represents the normalized eigenvectors calculated for each criterion. The final column, denoted as the normalized weight vector $\omega_{ANP}$, is derived by multiplying the supermatrix with the priority weight vector w.

**Table 2.** Normalized interdependences and weights.

| Criteria | ME | MAE | RMSE | MPE | RMSPE | MAPE | $R^2$ | Weight (w) |
|---|---|---|---|---|---|---|---|---|
| ME | 1 | 0 | 0.106 | 0 | 0 | 0 | 0 | 0.064 |
| MAE | 0 | 1 | 0.100 | 0 | 0 | 0 | 0 | 0.184 |
| RMSE | 0 | 0 | 0.745 | 0 | 0.138 | 0 | 0 | 0.148 |
| MPE | 0 | 0 | 0 | 1 | 0.172 | 0.200 | 0 | 0.171 |
| RMSPE | 0 | 0 | 0 | 0 | 0.690 | 0 | 0 | 0.119 |
| MAPE | 0 | 0 | 0 | 0 | 0 | 0.600 | 0 | 0.185 |
| $R^2$ | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.129 |

To check the coherence of the matrix of comparisons, Saaty proposed the calculation of the coherence index consistency ratio (CR). This measure is based on a comparison of the consistency index (CI) to the random consistency index (RI). In ANP, pairwise comparisons of a judgment matrix are considered sufficiently consistent if the CR is less than 10%. The CR is given by CI/RI. The CI is calculated using Equation (7).

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{7}$$

where $\lambda_{max}$ refers to the maximum eigenvalue of the supermatrix. The present study has CR = 0.0935 which is within the acceptable range.

After obtaining the weight vector of criteria by the ANP process, we proceed to implementing the steps of TOPSIS to evaluate the forecasting models. The TOPSIS method, first introduced by Hwang and Yoon in 1981 [37], is one of the most well-known MCDM methods and it is applied to many decision making problems [38]. The concept of TOPSIS is to find the alternative with the shortest distance from the positive ideal solution as well as the longest distance from the negative ideal solution. It has been selected for this study because it simultaneously considers both the ideal solution and the worst possible non-ideal solution.

Figure 5 shows comparisons of the actual and predicted values from different algorithms (ARIMA, SARIMA, MLR, DT, RF, and ES).

After executing the discussed models, we have generated the decision matrix D = $(x_{ij})_{m*n}$ with $m$ alternatives and $n$ criteria, as presented in Table 3. This matrix comprehensively encompasses the error measures for each of the alternative forecasts.

**Table 3.** Decision matrix: evaluation criteria per forecasting models.

| | ARIMA | SARIMA | Regression | DT | RF | ES |
|---|---|---|---|---|---|---|
| ME | −159.845 | 183.664 | −280.687 | −476.428 | −687.403 | 167.768 |
| MAE | 399.492 | 521.4334 | 463.583 | 696.428 | 950.479 | 444.221 |
| RMSE | 523.081 | 668.185 | 555.395 | 807.334 | 1316.559 | 614.910 |
| MPE | −0.96% | 1.38% | 1.8% | −5.207% | −10.421% | 0.97% |
| RMSPE | 3.2% | 4.51% | 3.4% | 9.1% | 19.7% | 3.9% |
| MAPE | 2.503% | 3.568% | 2.942% | 7.639% | 12.065% | 2.905% |
| $R^2$ | 0.569 | 0.808 | 0.514 | 0.934 | 0.869 | 0.837 |

Then, we calculate the normalized decision matrix to obtain $R = \left(r_{ij}\right)_{m*n}$ using the following equation.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m}\left(x_{ij}\right)^2}} \text{ , } i = 1, \ldots, n \text{ } et \text{ } j = 1, \ldots, m \tag{8}$$

Thereafter, the normalized matrix $R$ was integrated to determine the weighted normalized decision matrix V = R * W (see Table 4) using the weights calculated by ANP.

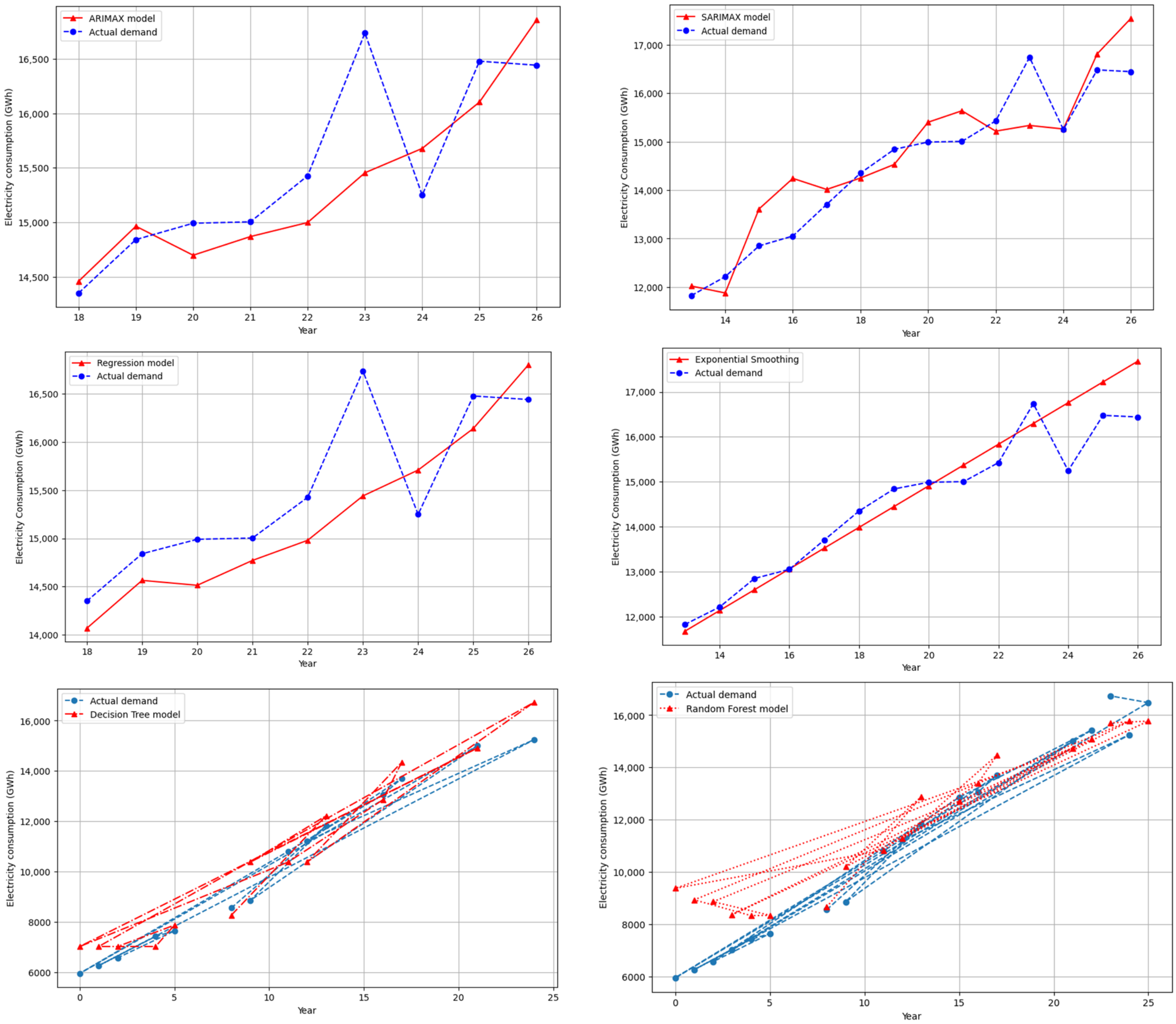


**Figure 5.** Visualizations of actual and forecasted values from six forecasting models.

**Table 4.** The weighted normalized decision matrix.

| | ARIMA | SARIMA | Regression | DT | RF | ES |
|---|---|---|---|---|---|---|
| ME | −0.011 | 0.013 | −0.019 | −0.033 | −0.047 | 0.012 |
| MAE | 0.049 | 0.064 | 0.057 | 0.086 | 0.117 | 0.055 |
| RMSE | 0.040 | 0.020 | 0.026 | −0.075 | −0.149 | 0.014 |
| MPE | 0.014 | 0.020 | 0.026 | −0.075 | −0.149 | 0.014 |
| RMSPE | 0.017 | 0.023 | 0.018 | 0.047 | 0.102 | 0.020 |
| MAPE | 0.030 | 0.043 | 0.035 | 0.091 | 0.144 | 0.035 |
| $R^2$ | 0.039 | 0.055 | 0.035 | 0.064 | 0.059 | 0.057 |

After computing the weighted normalized decision matrix, we proceed to calculate the positive and negative ideal solutions (FPIS and FNIS) denoted as $A^+$ and $A^-$, respectively, using the following equations.

$$A^+ = \left(v_1^+, v_2^+, v_i^+, \ldots, v_m^+\right) = \left\{\left\{\max_j v_{ij} \middle| iCP\right\}, \left\{\min_j v_{ij} \middle| iCN\right\}\right\} \tag{9}$$

$$A^- = (v_1^-, v_2^-, v_i^-, \ldots, v_m^-) = \left\{ \left\{ \min_j v_{ij} \middle| i \in P \right\}, \left\{ \min_j v_{ij} \middle| i \in N \right\} \right\} \quad (10)$$

where $P$ represents the positive criteria and $N$ represents the negative criteria.

In our case, the creation of the positive ideal solution vector (designated as $A^+$) involves identifying the minimum values among the cost-based criteria, where lower error results are considered superior (e.g., ME, MAE, RMSE, MPE, RMSPE, and MAPE), and the maximum values among the benefit criteria, which emphasize higher values, as exemplified in the case of $R^2$. Conversely, in establishing the negative ideal solution vector ($A^-$), we select the maximum values for the cost-based criteria and the minimum values for the benefit criteria. Table 5 presents the positive and negative ideal solutions.

**Table 5.** Positive and negative ideal solution for each criterion.

| | ME | MAE | RMSE | MPE | RMSPE | MAPE | $R^2$ |
|---|---|---|---|---|---|---|---|
| $A^+$ | 0.047 | 0.049 | 0.040 | 0.149 | 0.017 | 0.030 | 0.064 |
| $A^-$ | 0.013 | 0.117 | 0.1 | 0.026 | 0.102 | 0.144 | 0.035 |

Furthermore, the distances, $d_j^+$ and $d_j^-$, which represent the ratings of each forecasting model concerning $A$+ and $A$-, are determined in accordance with the calculations provided in Equations (11) and (12).

$$d_j^+ = \sqrt{\sum_{i=1}^{m} (A_i^+ - v_{ij})^2}, \ j = 1, \ldots, n \quad (11)$$

$$d_j^- = \sqrt{\sum_{i=1}^{m} (A_i^- - v_{ij})^2}, \ j = 1, \ldots, n \quad (12)$$

The final ranking of the forecasting models is calculated from the closeness coefficient $CC_i$. The forecasting model with the highest $CC_i$ represents the best model and the most suitable choice for accurately predicting the Tunisian electricity demand (Table 6).

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}, i = 1, \ldots, m \quad (13)$$

**Table 6.** Ranking of forecasting models.

| | $CC_i$ | Rank |
|---|---|---|
| ARIMA | 0.501 | 3 |
| SARIMA | 0.522 | 2 |
| MLR | 0.534 | 1 |
| DT | 0.367 | 4 |
| RF | 0.344 | 5 |
| ES | 0.534 | 1 |

### 2.4. Robustness Analysis

In this phase, we perform a robustness analysis to test the stability of the forecasting model. Therefore, we suggest carrying out a validation and sensitivity study.

**Validation of ranking with VIKOR method**

As discussed in the previous section, it is challenging to determine the best forecasting model because no option has the best parameters. All of the MCDM have strengths and weakness in terms of ranking and the accuracy of results [39]. It should be noted that the choice of multicriteria decision-support method can influence the ranking of the alternatives. As illustrated in Table 6, exponential smoothing and multiple linear regression are the best forecasting models for our case study, followed by SARIMA. To confirm the consistency of these results, the VIse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) method is used.

The VIKOR method was introduced by [40] to solve multicriteria decision making problems. It is widely used to rank alternatives. The main concept of VIKOR is based on the particular measure of "closeness" to the "ideal" solution. It calculates the best $f_i^*$ and $f_i^-$ ($f_i^* = \max_j f_{ij}$, $f_i^- = \min_j f_{ij}$) values of all criteria functions (j = 1,2, 3...J) to be able to calculate $S_i$ (refers to the maximum group utility) and $Ri$ (refers to the individual regret of opponent) values for final $Q_i$ rankings [26]. The results from applying the VIKOR method are presented in Table 7.

**Table 7.** Ranking of forecasting models obtained by VIKOR.

| | $Q_i$ | Rank |
|---|---|---|
| ARIMA | 0.178 | 4 |
| SARIMA | 0.033 | 2 |
| MLR | 0.000 | 1 |
| DT | 0.574 | 5 |
| RF | 1 | 6 |
| ES | 0.066 | 3 |

Due to inherent subjectivity in expert judgement, a sensitivity analysis is carried out to examine how the ranking of alternatives changes due to the variation of criteria weights. We apply a few perturbations to the experts' evaluations to test the consensus on the results. Equal weights and an additional seven scenarios are analyzed. In scenario 1, each criterion is considered equally important. The following scenarios show the ranking results when the weight of a specified criterion is augmented by 50% and the weight of the other criteria is decreased proportionally to make the sum of the normalized weights equal to 1. Table 8 presents the ranking based on the relative closeness of the forecasting models for each scenario.

**Table 8.** Ranking of the forecasting models according to the different sensitivity cases.

| | S1: Equal Criteria | S2: ME +50% | S3: MAE +50% | S4: RMSE +50% | S5: MPE +50% | S6: RMSPE +50% | S7: MAPE +50% | S8: $R^2$ +50% |
|---|---|---|---|---|---|---|---|---|
| ARIMA | 4 | 4 | 3 | 4 | 4 | 4 | 4 | 4 |
| SARIMA | 2 | 2 | 2 | 2 | 3 | 2 | 2 | 2 |
| MLR | 3 | 3 | 4 | 3 | 1 | 3 | 3 | 3 |
| DT | 5 | 4 | 5 | 5 | 5 | 5 | 5 | 5 |
| RF | 6 | 5 | 6 | 6 | 4 | 6 | 6 | 6 |
| ES | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 |

To evaluate the effectiveness of the proposed model, we conduct a comparative analysis with similar studies from the existing literature. It can be observed that limited research has been dedicated to developing models for predicting long-term electricity consumption in Tunisia. A summary of these comparative findings is provided in Table 9. The validation results indicate that the proposed hybrid approach is highly effective in predicting long-term net electricity consumption and demonstrates strong generalization in terms of accuracy. The results outperform those from studies conducted by Lahouar and Jaleleddine [41] and Essallah and Khedher [42]. A comparison of the various techniques examined shows that the proposed approach achieves a lower MAPE than previous studies using different methods.

**Table 9.** Comparison with similar studies in the literature.

| References | [41] | | [42] | | Current Paper | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Methods | ANN | SVM | Box–Jenkins | MLR | ES | MLR | ARIMA | SARIMA | DT | RF |
| Accuracy Measure MAPE (%) | 3.2641 | 3.6765 | 4.76 | 3.26 | 2.905 | 2.942 | 2.503 | 3.568 | 7.639 | 12.065 |

## 3. Results and Discussions

This section summarizes the research outcomes and presents additional discussion points related to the proposed methodology. To forecast electricity demand in Tunisia, we consider six forecasting models (ARIMAX, SARIMAX, MLR, ES, DT, and RF).

These models are employed to estimate the intercept and the slope of the trend component, the seasonal coefficient, and to determine the relationship between electricity consumption and influential factors. After running the models, the actual and forecast values of the total electricity demand are reported in Figure 5. It is apparent that the values obtained through exponential smoothing provide the most accurate projections. Using the error metrics provided in Section 2, we compare the performance of the proposed forecasting models. The ARIMA model performed better than other models, giving the smallest ME, MAE, RMSE, MPE, RMSPE, and MAPE. However, the $R^2$ measure of 0.569 indicates that the regression is lower compared to others. Therefore, to support the selection of the most appropriate forecasting model with these conflicting performances, ANP–TOPSIS is applied. Based on the experts' judgments, the weights of the evaluation criteria are obtained, as shown in Table 2. The results illustrate the importance assigned to MAPE, MAE, and MPE as the top three main criteria with the priority level of 0.185, 0.184, and 0.171, respectively. RMSE also has a considerable weight of 0.148. $R^2$ and RMSPE criteria, respectively, achieved 0.129 and 0.119 weights. ME obtained the least weight of 0.064. The ranking of alternatives, obtained using the TOPSIS method, are presented in Table 6. As a result, we conclude that multiple linear regression and exponential smoothing are the best models for forecasting electricity consumption. This ranking is similar to the VIKOR method (Table 7). The final ranking of both methods coincides with the first and second forecasting models. Therefore, the results from this comparison can validate the robustness of the selected models. Additionally, the sensitivity analysis also demonstrates its robustness. As shown in Table 8, each scenario presents how the ranking changes following the adjustment of one criterion weight. The findings show that the exponential smoothing forecasting model is always selected first except in the case of scenario 3 (MPE + 50%), where it is classified second. Moreover, the ranking of regression, ARIMA, and SARIMA switch between each other. These results are in line with the initial results and confirm that the forecast selection process is robust in selecting the best forecast from a set of alternatives.

## 4. Conclusions

Energy security is a critical issue worldwide. For effective decision making in the energy sector, long-term load forecasting plays a decisive role in cost-effective, $CO_2$ reduction, and reliable planning and operation of the power system. This paper introduces an innovative integrated methodological approach for annual electricity demand forecasting, incorporating a robust multicriteria decision making framework. In fact, the MCDM approach serves as a powerful tool for selecting a resilient electricity forecasting model from various alternatives across different classes, considering conflicting error measures.

An empirical case study in Tunisia validates the effectiveness of the proposed methodology. For long-term electricity demand forecasting, several factors can affect future energy demand growth, including climatic, technological, demographic, and socioeconomic variables. These factors are often chosen based on the author's knowledge, but this approach does not ensure that all variables are explanatory and significant. Based on correlation analysis, the case study results imply that population, urban population, internet users, GDP per capita, and inflation are significant variables that directly influence the electricity demand evolution in Tunisia and were considered as input in the forecasting models. Six forecasting models of different classes (ARIMAX, SARIMAX, MLR, DT, RF, and ES) were used and evaluated with several error measures (ME, MAE, RMSE, MPE, RMSPE, MAPE, and $R^2$). However, the results revealed contradictory performance. Therefore, the decision maker found it difficult to choose a model for forecasting electricity consumption based solely on the results of error measurements. To address this complex problem, we adopted two well-known decisions making methods, namely ANP and TOPSIS, to select the best alternative forecasting model with respect to several evaluation criteria. By considering all seven error measures and their interdependencies, ES and MLR are the best alternatives, followed by SARIMA.

In this paper, we also complement our research with two robustness analyses: comparison with the VIKOR method and a sensitivity analysis. Our findings indicate that the final ranking is resilient. The results obtained from the comparison with the other MCDM method (VIKOR) validate the robustness of the final ranking. Moreover, our sensitivity analysis reveals that, in all scenarios, perturbations in criteria weighting do not significantly impact the ranking of forecasting models.

Therefore, this study provides an important reference for Tunisian policymakers and offers a robust methodology for selecting the best forecasting models for other cities. For future research, we aim to extend our study by applying Fuzzy MCDM, which can better handle vagueness in the decision making process.

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## Appendix A. Historical Data Used in This Study from 1995 to 2021

| Year | Electricity Consumption (GWh) | Population Size | Urban Population | Inflation | Internet Users | Average Maximum Temperature | Average Temperature | Precipitation | GDP Per Capita |
|---|---|---|---|---|---|---|---|---|---|
| 1995 | 5944 | 9,294,102 | 61,474 | 6.244 | 0.011 | 40.747 | 20.21 | 371.077 | 1,940,034 |
| 1996 | 6254 | 9,430,550 | 61,87 | 3.725 | 0.028 | 42.187 | 20.309 | 297.7 | 2,076,990 |
| 1997 | 6563 | 9,557,948 | 62,262 | 3.652 | 0.044 | 41.856 | 20.935 | 293.396 | 2,170,571 |
| 1998 | 7015 | 9,677,148 | 62,653 | 3.125 | 0.108 | 42.661 | 20.661 | 313.452 | 2,253,029 |
| 1999 | 7415 | 9,788,067 | 63,043 | 2.690 | 1.602 | 44.749 | 21.761 | 389.261 | 2,343,997 |
| 2000 | 7637 | 9,893,316 | 63,432 | 2.962 | 2.751 | 43.264 | 21.068 | 244.668 | 2,170,508 |
| 2001 | 7866 | 9,995,123 | 63,818 | 1.983 | 4.298 | 42.8 | 21.388 | 237.748 | 2,207,661 |
| 2002 | 8259 | 10,094,561 | 64,202 | 2.721 | 5.253 | 42.327 | 19.887 | 297.265 | 2,292,483 |
| 2003 | 8548 | 10,193,798 | 64,585 | 2.713 | 6.491 | 45.885 | 20.031 | 540.007 | 2,693,196 |
| 2004 | 8848 | 10,292,225 | 64,95 | 3.632 | 8.529 | 40.392 | 18.692 | 353.896 | 3,029,850 |
| 2005 | 10,374 | 10,388,344 | 65,237 | 2.018 | 9.655 | 44.408 | 19.396 | 341.658 | 3,106,576 |
| 2006 | 10,800 | 10,483,558 | 65,524 | 3.225 | 12.986 | 44.285 | 19.938 | 380.923 | 3,279,103 |
| 2007 | 11,212 | 10,580,395 | 65,809 | 2.967 | 17.100 | 45.127 | 18.377 | 384.342 | 3,678,062 |
| 2008 | 11,826 | 10,680,380 | 66,093 | 4.345 | 27.530 | 42.3 | 16.2 | 390 | 4,200,174 |
| 2009 | 12,215 | 10,784,504 | 66,376 | 3.665 | 34.070 | 44.45 | 17.75 | 320 | 4,029,461 |
| 2010 | 12,850 | 10,895,063 | 66,657 | 3.339 | 36.800 | 43.131 | 21.862 | 322.9 | 4,241,012 |
| 2011 | 13,053 | 11,032,528 | 66,938 | 3.240 | 39.100 | 43.058 | 19.658 | 393.677 | 4,361,948 |

| Year | Electricity Consumption (GWh) | Population Size | Urban Population | Inflation | Internet Users | Average Maximum Temperature | Average Temperature | Precipitation | GDP Per Capita |
|---|---|---|---|---|---|---|---|---|---|
| 2012 | 13,705 | 11,174,383 | 67,218 | 4.612 | 41.442 | 44.411 | 20.204 | 324.904 | 4,233,917 |
| 2013 | 14,350 | 11,300,284 | 67,495 | 5.316 | 43.800 | 41.644 | 19.86 | 353.464 | 4,308,337 |
| 2014 | 14,841 | 11,428,948 | 67,772 | 4.626 | 46.160 | 43.4 | 20.328 | 343.676 | 4,398,639 |
| 2015 | 14,991 | 11,557,779 | 68,056 | 4.437 | 46.500 | 42.772 | 19.864 | 349.16 | 3,960,925 |
| 2016 | 15,004 | 11,685,667 | 68,346 | 3.629 | 49.600 | 42.552 | 20.524 | 323.288 | 3,796,109 |
| 2017 | 15,427 | 11,811,443 | 68,642 | 5.309 | 55.500 | 44.592 | 19.816 | 282.464 | 3,569,719 |
| 2018 | 16,738 | 11,933,041 | 68,945 | 7.308 | 64.191 | 42.236 | 20.06 | 404.208 | 3,577,169 |
| 2019 | 15,249 | 12,049,314 | 69,254 | 6.720 | 66.700 | 44.26 | 18.292 | 416.932 | 3,477,844 |
| 2020 | 16,479 | 12,161,723 | 69,568 | 5.634 | 72.807 | 43.3 | 19.938 | 311.415 | 3,497,733 |
| 2021 | 16,442 | 12,262,946 | 69,888 | 5.706 | 78.990 | 44 | 20 | 312 | 3,807,185 |

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