Long-term Electric Peak Load Forecasting of Tehran Regional Electric Company using a Combinatorial Artificial Intelligence Approach

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Abstract: Forecasting the long-term electrical yearly peak load is pivotal in power system expansion planning. The accuracy of the forecasting method holds immense significance in preempting economic losses and budgetary issues arising from unwarranted or inadequate investments. Although conventional techniques like time-series methodologies such as Auto-Regressive Integrated Moving Average (ARIMA) are extensively employed for long-term electrical peak load and energy demand forecasts, their limitations in dealing with inefficiencies, nonlinearity, and seasonality trends present considerable challenges. This paper proposes a novel approach that leverages the ARIMA method, incorporating Support Vector Regression (SVR) and the Genetic Algorithm (GA) technique. This approach aims to forecast the long-term yearly peak load of the Tehran Regional Electric Company (TREC), Iran's largest regional electric company. The SVR algorithm parameters are fine-tuned to minimize forecasting errors using a combination of GA and the ARIMA method. The resulting optimized forecasting approach, ARIMA-GA-SVR, is applied in a real-life case study network within TREC. Comparative analysis with existing forecasting methods is conducted. The ARIMA-GA-SVR approach is a reliable and accurate forecasting solution based on established error criteria and simulation outcomes.
Keywords: ARIMA; Long-term Peak Load Forecasting; ARIMA-GA-SVR; Tehran Regional Electricity Company (TREC).

Nomenclature

Sets and Indices	
N	The number of predictor variables of the SVR model
t	Number of years
T	Total number of existing data in the long-term peak load forecasting time horizon
Parameters	
$\bar{Y}_i$	The average of i^{th} epoch of past long-term electrical peak load data of the grid
Φ_p	Unknown parameters of the ARIMA approach
θ_q	Unknown parameters of the ARIMA approach
W_t	The d^{th} difference of the original time series (i.e., $y(t)$)
b	Constant parameter or bias of the SVR model
ω	Weighting vector of the SVR model
ε	Loss function
σ	Kernel width for SVR model
C	Regulation for SVR model
α_i, α_i^*	Lagrangian multipliers
x_i, x_j	The inputs in the i^{th} and j^{th} dimensions of Kernel function
$\bar{R}$	The average of the real amount of long-term electrical peak load of the time series
Variables	
Y(t)	The forecasted long-term electrical peak load of the t^{th} year
ξ_i, ξ_i^*	The positive slack variables showing the distance between real and corresponding boundary values in the ε-tube model of function approximation
$\phi(X)$	The applied mapping function in the feature space of the SVR model
$\frac{1}{2}\lVert \omega \rVert^2$	Smoothness of the objective function
$K(x_i, x_j)$	Refers to the Kernel function for showing the inner product of x_i and x_j in D-dimensional feature space
F_t	The forecasted value of long-term electrical peak load

1. Introduction

In today's world, the quality of human life relies heavily on the assurance of a consistent and dependable electricity supply. In pursuit of this, precise forecasting of long-term electrical peak load is paramount in planning a robust and secure power infrastructure. Given the ongoing surge in electrical demand, the significance of precise long-term electrical peak load forecasting has grown even more critical within power networks.

1.1. Research motivation

The initial phase of planning a robust and secure electric power system hinges on accurately forecasting the peak load. Failure to ensure the proper design of power networks will result in substantial challenges. Hence, electric utilities must forecast peak load and energy demand consistently and accurately. This paper addresses one of the crucial steps of accurately forecasting the yearly peak load in the design of power networks. It presents a highly accurate method, offering valuable insights into this important issue.

1.2. Literature review

Long-term load forecasting is a critical step in power system planning as input for both generation expansion planning (GEP) and transmission expansion planning (TEP) investigations [1]. On the other hand, one of the priorities of planning the power networks is supplying the loads efficiently [2], which depends on accurate planning. Electrical load forecasting involves over different time frames, including short-term, mid-term, and long-term periods. Long-term forecasting involves higher levels of uncertainty compared to shorter-term forecasting. Given the economic and societal significance of long-term forecasting and the inherent challenges posed by this extended time frame, this paper's primary objective is to introduce a precise and dependable long-term forecasting methodology. It is important to note that as the forecasting horizon extends, the complexity of the forecasting task increases, which in turn directly impacts the accuracy of the results, as discussed in references [3] and [4].

Over the years, numerous research endeavours have been dedicated to the field of long-term electrical peak load forecasting. These forecasting methodologies can be broadly categorized into two groups: univariate and multivariate approaches. In the univariate approach, future electrical peak load levels are predicted based solely on historical peak load data. This category encompasses techniques like Modified Exponential, Gompertz, and Logistic methods, which utilize past peak load data to project future trends [5]. On the other hand, the multivariate forecasting approach considers long-term electrical peak load as a dependent variable influenced by a range of external factors. These factors may include population growth rates, Gross Domestic Product (GDP), unemployment rates, social welfare, and other relevant driving parameters, all of which contribute to a more comprehensive forecasting model [6]. In [7], the impact of independent inputs on peak load forecasting through various combinations and subsets using multilinear regression (MLR) equations is examined.

Most existing methods for long-term peak load forecasting have primarily centered around traditional techniques, including trend curves and ARIMA models. Despite their simplicity in implementation, these methods suffer from various drawbacks. Notably, they lack a well-founded approach for parameter selection, particularly in the case of the ARIMA method. Furthermore, their incapacity to capture nonlinearity restricts them from relying solely on historical peak load data. For instance, in [8], electric energy consumption is predicted using the ARIMA method for both mid-term and long-term forecasts. In [9], electric load forecasting is accomplished through a combination of clustering and ARIMA models, with [9] indicating superior performance of the combined forecasting method compared to using the ARIMA model in isolation. In [10], an ensemble hybrid forecasting model is introduced to address data scarcity issues, offering a suitable approach for forecasting annual energy consumption in Iran. Additionally, the findings from [4], which encompass long-term electric peak load and energy demand in Iran's national grid, underscore that both ARIMA models utilized therein exhibit higher error rates and inaccuracies compared to alternative approaches. On the other hand [11], the Advanced Autoregressive Moving Average (AARMA) model, is proposed. AARMA is designed to detect the possible intrusion of the given data set.

Recognizing the limitations of ARIMA methods, researchers have pursued the development of alternative approaches, particularly those grounded in Machine Learning (ML) and Artificial Intelligence (AI) techniques, to attain more precise forecasting outcomes. In [12], statistical, machine learning, and deep learning techniques in the energy forecasting field, highlighting both traditional and cutting-edge methods that advance the industry are examined. In [13], an energy forecasting model was introduced, harnessing machine learning-based methodologies, including Artificial Neural Networks (ANNs), linear and nonlinear autoregressive multivariable models, and the adaptive boosting model. [14] conducted a comparative study on aggregated short-term load forecasting, employing various data strategies. The simulation results in [14] revealed that the mean absolute percentage error criterion (MAPE) ranged from 1.67% to 4.80%, contingent on the ML algorithm and the chosen forecasting horizon. In [15], long-term electric energy consumption spanning from 2010 to 2030 was predicted using a blend of optimization methodologies and ANN models, encompassing both Iran's and the U.S.'s energy consumption. [15] also corroborated the high accuracy of AI-based methodologies. Additionally, [16] conducted a comparison between ANN and a hybrid technique known as wavelet decomposed Artificial Neural Networks (WANN). In [17], a novel hybrid predictive method using multivariate empirical mode decomposition (MEMD) and SVR with parameters optimized by PSO, which can capture precise electricity peak load is proposed. For mid-term daily peak load forecasting, [18] introduced an approach utilizing recurrent artificial neural networks (RANN). The outcomes, using peak load data from South Korea, underscored the performance and effectiveness of the proposed RANN approach. Moreover in [19], a comparative analysis to determine the best peak load-forecasting model for Korea, by comparing the performance of time series, machine learning, and hybrid models is proposed. In [20], monthly peak load forecasting using all essential information for good long-term strategic planning is addressed. In [21], the authors presented a methodology for forecasting solar energy, employing machine and deep learning techniques. In [22], utilizing a deep learning approach, the peak load of Panama is forecasted, as a real-life case study. Another illustration of the ANN method's application in peak load forecasting can be found in [23]. In this case, [23] employed two ANN-based models: a three-layered back-propagation network and a recurrent neural network. These models were tested for forecasting peak electric loads in Japan up to the year 2020. In [24], a monitoring and peak load forecasting system was designed and tested on the experimental open pit mine.

To optimize SVR performance, heuristic search methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) can be employed for parameter selection [25]. In the study presented in [25], the PSO-SVR model was assessed for its capacity to forecast near-infrared non-invasive glucose detection. The findings validate that meticulous parameter tuning in SVR leads to minimized forecasting errors. Additionally, [26] introduces recurrent support vector machines with genetic algorithms (RSVMG) for peak load forecasting, where genetic algorithms are utilized to determine support vector machine parameters. In [27], a novel approach using chaotic particle swarm optimization (CPSO) is proposed for selecting appropriate SVR model parameters. Simulation results indicate the superior performance of the CPSO-based model when compared to other algorithms such as GA and simulated annealing (SA). Furthermore, [28] explores the optimization of SVM and neural network (NN) parameters, including network structures, penalty parameters, and kernel function widths, through a dedicated optimization program. This optimization enhances the forecasting accuracy. The effectiveness of SVM in short-term peak load forecasting is underscored in [29], where a new SVM kernel function, the Gaussian wavelet kernel, is introduced. Simulation results demonstrate that this novel approach not only improves forecasting accuracy but also accelerates the forecasting process.

Support Vector Regression (SVR), a subset of Support Vector Machine (SVM) techniques, proves to be another instance of employing evolutionary algorithms for forecasting can be found in [30]. In [30], a novel concept called the Season-Specific Similarity Concept (SSSC) is employed to capture the season-specific meteorological requirements (seasonality effect) and incorporate them into the short-term load forecasting (STLF) process in Assam, India. This innovative approach combines the Firefly Algorithm (FA), Support Vector Machine (SVM), and the newly introduced SSSC. The simulation results convincingly demonstrate significantly higher forecasting accuracy compared to traditional forecasting methods. In the same geographic region in India, as described in [31], the Grey Wolf Optimizer (GWO) is utilized to identify suitable parameter combinations for SVM in power system load forecasting (PSLF) during regional special event days (RSEDs). In [32], an SVR-based model is applied to predict the short-term electric load of office buildings. In [33], long-term load forecasting for large residential communities including smart homes with energy storage is performed. Meanwhile, in [34], a novel SVR-based load forecasting model is proposed. Here, the PSO, known for its global optimization capabilities, is used to determine the higher-frequency parameters of the SVR model. Conversely, for lower frequencies, the GA, based on evolutionary selection and crossover rules, is employed to select appropriate parameter values. The integrated energy system, which includes electricity, heat, cooling, and gas loads, is the subject of forecasting [35]. The proposed approach, rooted in multi-task learning theory and the Least Squares Support Vector Machine (LSSVM) algorithm, demonstrates its effectiveness. Furthermore, [36] adopts a novel multi-task learning approach to simultaneously forecast both active and reactive power in smart grids. The results presented in [36] affirm the robustness and reliability of this method for practical applications in power systems.

In [37], Genetic Programming (GP) is introduced as a tool for predicting electricity consumption in China based on data spanning from 1991 to 2019. The simulation results demonstrate that the proposed Multi Expression Programming (MEP) method outperforms both Gene Expression Programming (GEP) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in terms of power and accuracy. In [38], smart grid loads are accurately forecasted using a fuzzy logic approach within short-term time horizons. Furthermore, in [39], one-day-ahead energy using a deep learning approach is proposed.

The literature review has been summarized in Table 1, providing an overview of common and widely used methodologies for electricity demand forecasting.

1.3. The necessity of the research based on challenges of the literature

Iran's power sector comprises 16 regional electricity companies, and TREC is the country's largest sector. TREC relies heavily on imported power from other regional electricity companies to meet its energy demands. Given the critical nature of the power supply in Tehran REC, it is imperative to address its electrical peak load, which has experienced significant fluctuations in recent years. Factors contributing to this change include a growing population, ongoing urban development projects, and the concentration of industries in Tehran province, such as automotive manufacturing. Long-term load forecasting for Tehran is indispensable to ensure the effective planning of power generation technologies and transmission lines. On the other hand, power deficit or scheduled load interruptions in TREC in the coming years is one of the main challenges that necessitates conducting research in the field. Tehran, being the capital city with numerous large industries, is expected to witness significant electrical demand growth. Another noteworthy challenge in reshaping load consumption is the emergence of Bitcoin mining in Iran's power industry. Given these factors and the anticipation of hot summers due to climate change, accurate peak load forecasting becomes crucial to prevent power outages in Tehran province.

As indicated in Table 1, there is a noticeable absence of accurate hybrid methods aimed at reducing errors in long-term peak load forecasting of real-life case studies. Therefore, this paper introduces a comprehensive combined approach with the primary objective of minimizing peak load forecasting errors. This means this paper proposes an ARIMA-GA-SVR method that leverages several tools, including GA, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF) functions, to enhance the accuracy of forecasting. These tools are employed to preprocess the input data and refine the model dimensions, ultimately reducing forecasting errors.

1.4. Novelty and main contributions of the paper

This paper introduces a novel approach for forecasting the long-term electrical peak load over ten years, employing the ARIMA-GA-SVR method. In this methodology, we not only employ the ARIMA method to set SVR parameters but also utilize the GA to optimize the SVR parameters further. The historical peak load data for the TREC from 1996 to 2019 (corresponding to the Persian solar calendar years 1375-1398) is the basis for our analysis. Subsequently, we extend our forecasts to predict TREC's peak load from 2020 to 2029 (Persian solar calendar years 1399-1408). As of mid-2024, we possess known values for TREC's peak loads for the years 2020 to 2023, which we use to verify and validate our forecasting results. Additionally, we employ four commonly accepted error criteria to evaluate the accuracy of our forecasting approaches. The proposed method's performance is then benchmarked against the ARIMA model, the GA-SVR approach, and the Multilayer Perceptron Artificial Neural Network (MLP-ANN) method. The noteworthy novelties and contributions of this study can be summarized as follows:

1. Forecasting the long-term electrical peak load by four approaches including the proposed ARIMA-GA-SVR method in TREC as a real-life case study is presented. The proposed method optimizes SVR model parameters using ARIMA and GA, enhancing forecasting accuracy.

2. Utilization of standard error criteria to assess the accuracy of long-term electrical peak load forecasts, demonstrating the effectiveness and potency of the proposed approach in this domain.

3. Implementation of the proposed approach on the existing data from previous years to demonstrate the accuracy and validity of the results obtained from the proposed method.

1.5. Organization and structure of the paper

The paper is divided into four main sections. The first section is the introduction, which includes the research motivation, the literature review consisting of the explanation of related research and papers in the field of peak load forecasting, the necessity of the research based on the challenges of the literature, the novelty and main contributions of the paper, and the organization and structure of the paper. The second section explains the proposed approach of the paper as the most accurate method for forecasting the long-term electrical peak load and energy demand. The third section presents the simulation results, including the outputs of the models and their validations to illustrate the accuracy of the model. Finally, the paper concludes in the conclusion section by presenting the achievements of the paper and future works of the research.

2. Proposed Methodology

Univariate methods for long-term electric peak load forecasting rely on historical data and observations as their foundation. In this paper, we utilize three existing peak load forecasting approaches alongside our proposed ARIMA-

GA-SVR method to forecast the long-term electrical peak load of TREC. In this section, we introduce these various methods.

2.1. Autoregressive Integrated Moving Average (ARIMA) approach

In the context of time series forecasting, historical data observations are interrelated, signifying that past data points are essential for projecting future values using ARIMA models. Consequently, a vital prerequisite for applying ARIMA models is the requirement for the series to exhibit stationarity and to be free from any trends. Stationarity is attained when statistical characteristics remain consistent over time. The ARIMA approach comprises three fundamental steps: model identification, estimation of model parameters, and model diagnostic verification. The ARIMA model is formally presented in equation (1).

$$W_t = \Phi_1 w_{t-1} + \Phi_2 w_{t-2} + \ldots + \Phi_p w_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q} \tag{1}$$

W_t as the d^{th} difference of the original time series (i.e., $y(t)$)is defined in (2).

$$W_t = \nabla^d (\bar{Y}_t) \tag{2}$$

Then, the model parameters (i.e., $\Phi(B)$, $\theta(B)$) are estimated by minimizing the mean square of errors (MSE) as (3).

$$Min_{\theta,\Phi} f = \sum_{t=1}^{N} a_t^2 \tag{3}$$

Given the nonlinearity conditions outlined in equation (3), these parameters are estimated through the ARMAX approach, as detailed in [40]. In the final step, during the diagnostic checking phase, the estimation model is deemed valid if the model errors exhibit randomness or if the autocorrelation of the residuals suggests a random pattern.

2.2. Multi-Layer Perceptron Artificial Neural Network (MLP-ANN)

In contemporary times, one of the most robust and precise approaches for peak load forecasting involves artificial intelligence methods. Artificial Neural Network (ANN) models have gained significant traction in producing accurate long-term load forecasts. In this study, for the sake of a comprehensive comparison, we not only employ conventional peak load forecasting methods like the ARIMA approach but also integrate ANN-based techniques, including the Multi-Layer Perceptron Artificial Neural Network (MLP-ANN). Consequently, this paper employs the MLP-ANN approach to predict the electric peak load of TREC.

2.3. Proposed GA-SVR approach

Support Vector Regression (SVR) model can solve the regression problems with multiple predictors such as $X = \{X_i, i = 1,..., N\}$, where N denotes the number of predictor variables and each X_i has N variables. The predictors as the inputs are linked to the output as $Y = \{Y_i, i = 1,..., N\}$. The matrix X is mapped into a higher-dimensional feature space using a proper function [41]. Based on this methodology, a non-linear regression problem is defined as given in (4) [42].

$$y = f(X) = \omega \cdot \phi(X) + b \tag{4}$$

By solving the minimization problem as given in (5)-(8), the coefficients of ω and b in (4), are determined.

$$Minimize: \frac{1}{2} \| \omega \|^2 + c \frac{1}{N} \sum_{i=1}^{N} (\xi_i + \xi_i^*) \tag{5}$$

$$y_i - (\omega \cdot x_i + b) \geq \varepsilon + \xi_i \tag{6}$$

Subject to:

$$(\omega \cdot x_i + b) - y_i \geq \varepsilon + \xi_i^* \tag{7}$$

$$\xi, \xi_i^* \geq 0 \tag{8}$$

According to the Lagrange function, the optimality conditions make a non-linear regression function [43].

In this paper, a polynomial kernel function is utilized to expand the SVR forecasting methodology as given in (9) and (10).

$$f(X)=\sum_{i=1}^{N}(\alpha_i-\alpha_i^*)K(x_i,x_j)+b \tag{9}$$

$$K(x_i,x_j)=\left(1+x_i^T x_j\right)^{\sigma} \tag{10}$$

The GA is employed to fine-tune the SVR parameters. GA is designed to comprehensively explore the entire search space in pursuit of the global minimum. Consequently, in this paper, we propose the GA-SVR method as the approach for long-term electrical peak load forecasting.

Equation (11) introduces the objective function of the proposed GA-SVR algorithm, aimed at minimizing the disparity between actual and predicted values.

$$\text{Min } obj=\frac{1}{T}\sum_{t=1}^{T}\left|\frac{R_t-F_t}{R_t}\right| \tag{11}$$

The dimension of input-output pairs is determined by utilizing the GA. In a time series vector as $P=(P_1,P_2,...,P_n)$, an input-output sample can be considered as , $[(P_k,P_{(k+1)},...,P_{(k+n)}),P_{(k+\tau+1)}]$, where the τ is determined using the GA along with other settings of SVR algorithm such as (C , σ , ε). Each sample or pair includes $(P_k,P_{(k+1)},...,P_{(k+n)})$ as the input and $P_{(k+\tau+1)}$ as the output. In each pair of samples, the dimension of the input vector is $[1\times\tau]$, while the output dimension is one (i.e. $[1\times1]$).

2.4. Proposed ARIMA-GA-SVR approach

In this proposed approach, like the GA-SVR approach, the parameters of the SVR algorithm are optimized by the GA. However, the main difference between these approaches is that in addition to the GA, the ARIMA approach is also utilized to optimize one of the parameters. In other words, three SVR parameters (C, σ, ε) are optimized by the GA, and the other variable (τ) is determined by the ARIMA. Unlike the GA-SVR approach, in the ARIMA-GA-SVR approach, this parameter of (τ) is not optimized by GA. Instead, τ is determined using the ACF and PACF analysis according to the ARIMA approach.

Following the proposed ARIMA-GA-SVR model, input-output pairs for existing samples are generated. The schematic representation of the proposed ARIMA-GA-SVR flowchart is illustrated in Fig 1.

The flowchart in Fig 1 takes historical electrical peak load data from 1996 to 2019 for the TREC as input. It then forecasts the long-term electrical peak load for TREC over the next ten years, from 2020 to 2029. The flowchart uses an ARIMA model to determine how many past inputs (historical data points) are needed for accurate future estimations. After that, the SVR parameters are optimized using the GA. This entire process allows for the accurate forecasting of TREC’s long-term electrical peak load. The flowchart in Fig 1 provides a comprehensive demonstration of how the historical data is processed through the ARIMA model to determine necessary inputs, followed by the optimization of SVR parameters using GA, ultimately leading to the accurate forecast of TREC’s long-term electrical peak load.

This comprehensive approach ensures the accurate forecasting of TREC’s long-term electrical peak load.

3. Simulation results

3.1. Outputs

The primary objective of this study is to employ both traditional and data mining methods to achieve the most accurate forecast possible for the long-term electrical peak load of TREC. This forecasting exercise covers ten years, from 2020 (equivalent to 1399 in the Persian solar calendar) to 2029 (equivalent to 1408 in the Persian solar calendar). To accomplish this, historical data spanning the last 24 years, from 1996 (equivalent to 1375 in the Persian solar calendar) to 2019 (equivalent to 1398 in the Persian solar calendar), has been utilized as input for all forecasting methods. The annual long-term electrical peak load data for TREC during this period is provided in Table 2. It is worth noting that the actual values for the electrical peak loads of 2020 to 2023 are known and available. However, for the sake of comparison and validation, these years (i.e., 2020 to 2023) are considered part of the forecasting time horizon in this paper.

The simulation results for the long-term electrical peak load of TREC are detailed in Table 3. As per the findings in Table 3, it is observed that in most instances, the ARIMA method tends to yield the lowest annual peak load forecasts for the same year. Conversely, the proposed ARIMA-GA-SVR method consistently delivers the highest peak load forecasts compared to the other methods.

As illustrated in Table 3, the electrical peak load projections for TREC in the summer of 2023 stand at 11,600.27 MW, 11,733.08 MW, and 12,214.41 MW when employing the ARIMA, MLP-ANN, and GA-SVR methods, respectively. Conversely, for the final year within the forecasted time horizon (i.e., 2029), the electrical peak loads are estimated at 13,616.25 MW, 13,444.98 MW, and 15,011.38 MW utilizing the ARIMA, MLP-ANN, and GA-SVR methods, respectively. Notably, the ARIMA-GA-SVR method predicts peak loads of 12,225.65 MW during the 2023 summer and 15,550.64 MW in the summer of the concluding forecast year.

The appropriate ARIMA model for forecasting TREC's electrical peak load is determined to be ARIMA (1,2,0), as established through an examination of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), as depicted in Fig 2. Subsequently, the parameters of the selected model are estimated employing the least square technique, resulting in the final load forecasting model presented in equation (12). As indicated by equation (12), the annual peak load for a given year relies on the values from past years along with an associated error term.

$$Y_t = 1.3974 \times Y_{t-1} + 0.2052 \times Y_{t-2} - 0.6026 \times Y_{t-3} + e_t \tag{12}$$

The schematic depiction of the forecasted long-term electrical peak loads using the ARIMA method is presented in Fig 3. As illustrated, the ARIMA approach indicates an upward trajectory in TREC's long-term electrical peak load, ascending from 11,600.27 MW in 2023 to 13,616.25 MW in 2029. In simpler terms, the electrical peak load for the final year within the forecasting horizon is estimated to be 17.37% higher than the peak load observed during the summer of 2023.

In the MLP-ANN approach, the projected peak load for the concluding year (i.e., 2029) is anticipated to be 14.59% higher, equivalent to 1,711.9 MW, than the peak load observed in the summer of 2023. The graphical representation of the forecasted long-term electrical peak loads using this method is depicted in Fig 4.

Under the GA-SVR approach, the predicted peak load for the concluding year (i.e., 2029) is expected to be 22.89% higher, equivalent to 2,796.97 MW, than the peak load observed during the summer of 2023. The graphical representation of the forecasted long-term electrical peak loads using this method is depicted in Fig 5.

Within the proposed ARIMA-GA-SVR approach, it is projected that the peak load for the concluding year (i.e., 2029) will register a notable increase, specifically 27.19%, amounting to 3,324.99 MW, in comparison to the peak load recorded during the summer of 2023. The graphical representation of the forecasted long-term electrical peak loads using this method is presented in Fig 6.

Finally, the results suggest that TREC's yearly peak load may surge to 15,000 MW, signifying a 50% load growth over a ten-year horizon.

3.2. Validation of results

The forecasted results are subject to evaluation using two distinct methods. Firstly, consider previous years for which the long-term electrical peak load is known (i.e., 2020 to 2022). Secondly, error indices quantify the disparities between actual values and forecasts.

The error metrics utilized for performance evaluation are detailed in Table 4, including the mean absolute error (MAE), the mean absolute percent error (MAPE), the root mean square error (RMSE), and the index of agreement (IA).

The outcomes derived from the employed error criteria are summarized in Table 5. As per the findings in Table 5, all three methods—MLP-ANN, GA-SVR, and ARIMA-GA-SVR—exhibit an acceptable level of forecasting error. The ARIMA-GA-SVR approach is the method with the lowest error values, thus validating its accuracy in long-term electrical peak load forecasting for TREC. Specifically, higher levels of accuracy are indicated by lower values for MAE, RMSE, and MAPE, and an IA index value of one signifies a closer match between forecasts and actual data.

Notably, all of these favorable characteristics are exhibited by the proposed approaches. In contrast, despite being a well-known approach in peak load forecasting, the ARIMA method demonstrates the highest error level.

Furthermore, the error indices used in the evaluation are visualized in Fig 7 and Fig 8. The consistently low values across all error indices when employing the proposed methods underscore their efficiency. These results collectively serve as compelling evidence for the effectiveness of the proposed methodologies in forecasting the long-term electrical peak load of TREC.

The error indices employed in various peak load forecasting approaches are presented in Fig 9. As depicted in Fig 9, the proposed methods yield results that closely align with the actual data.

Another way to assess the accuracy of the results and outputs is to test existing data. As indicated by the outcomes depicted in Fig 10, the proposed SVR-based methods consistently deliver the most favorable results, whereas the ARIMA method is less effective in providing valuable forecasts.

Furthermore, for a fair comparison, as indicated in [44], the electrical peak load of TREC increased from 7471 kW in 2012 to 11525 kW in 2021. The forecasted peak load using different methods of the paper is as follows: ARIMA method: 10950.18 kW, MLP-ANN method: 11023.86 kW, GA-SVR method: 11250.62 kW, and the proposed ARIMA-GA-SVR method: 11232.06 kW.

As shown in Table 3, the difference between the forecasted amount of electrical peak load and the real amount of electrical peak load in 2021 of the paper is 574.82 kW, 501.14 kW, 274.38 kW, and 292.94 kW, respectively. This demonstrates the superiority of the GA-SVR and ARIMA-GA-SVR methods.

3.3. Sensitivity Analysis

In this section, the impact of an independent variable on specific dependent variables is investigated.

In this paper, the independent variable is the long-term electrical peak load of TREC. This is influenced by the SVR parameters optimized by the GA, as well as the long-term electrical peak load of TREC in previous years, etc. To evaluate the ARIMA-GA-SCR approach, the input of the problem is changed to Iran's long-term electrical peak load. The long-term electrical peak load of Iran's grid is considered as input from 1986 (7464 kW) to 2016 (53198 kW) [44].

Therefore, the ARIMA-GA-SVR method is used to determine the peak load amount in Iran's network over a ten-year time horizon (۲۰۱۷-۲۰۲۶). According to the results, the forecasted long-term electrical peak load for Iran in 2023 is 71216 kW, and it is forecasted to be 80123 kW in 2026. To validate the proposed method of this paper, the long-term forecasted electrical peak load can be compared with the actual peak load in 2023, which was recorded at 73463 kW. In other words, the ARIMA-GA-SVR method of this paper forecasts that Iran's network will have a peak load of 2,247 kW lower than its actual value in the summer of 2023. The forecasting of the ARIMA-GA-SVR method using Iran's network data and its comparison with real values is presented in Fig 11.

4. Conclusions

This paper introduced a novel approach for long-term yearly peak load forecasting in power networks. The study demonstrated that traditional methods like the ARIMA approach often led to overestimations or underestimations in long-term electrical peak load forecasts, which creates challenges in the network. Consequently, the GA-SVR and ARIMA-GA-SVR approaches were proposed to enhance accuracy compared to conventional methods. These approaches are considered hybrid methods because they optimize SVR parameters through a combination of GA and ARIMA. Given the versatility of this method, it can be readily applied to long-term peak load forecasting in various networks. Furthermore, the paper employed error criteria for validating the accuracy of the proposed approach.

4.1. Main findings of the research and comparison of results

The paper introduced the ARIMA-GA-SVR approach as a hybrid method with high accuracy for long-term electrical peak load forecasting. The main accomplishment of this research is the forecasting of the long-term electrical peak load of Iran's most important regional electricity company (TREC) over ten years. This was achieved using ARIMA, MLP-ANN, GA-SVR methods, and the ARIMA-GA-SVR method. According to the results, the ARIMA-GA-SVR method demonstrated the highest degree of closeness to the actual peak load values and the lowest error criteria. The main discoveries of this paper can be summarized as follows:

1) The ARIMA methods may result in unreliable outputs for peak load forecasting.

2) The GA-SVR method can effectively forecast the electrical peak load with minimal errors, provided that the SVR parameters are optimally set using an optimization method such as the PSO algorithm. In the proposed ARIMA-GA-SVR method, the parameters of the SVR model are optimized using ARIMA and GA to enhance the accuracy of the forecasting.
3) Four error criteria, including MAE, RMSE, MAPE, and IA, are utilized to evaluate method accuracy. The comparison of error criteria demonstrates that the ARIMA-GA-SVR approach delivers more accurate results.
4) The forecast indicates a potential power shortage or scheduled load interruption in TREC over the next few years.

4.2. Bridging the gap and future directions

Future research in electrical peak load forecasting should focus on improving the accuracy of forecasting techniques to the highest possible level. Addressing these concerns could assist network planners in developing a more reliable and adequate power network. This paper could be enhanced by investigating the following aspects:

- The multivariate methods consider other important factors in load forecasting, such as climate changes, GDP growth, population rate, and global warming. Exploring the potential enhancement of the hybrid univariate method using a multivariate approach can be addressed in future research.
- Utilizing innovative combined approaches with artificial intelligence can significantly minimize forecasting errors.
- The implementation of the proposed method in this paper on other real networks in Iran and around the world can be considered one of the future goals.
- The presented methods of this research can also be used to forecast peak load and energy demand for power network design in shorter time frames such as mid-term and short-term. This can be considered as one of the future directions of this research.

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Table 1 Summary of some prior load forecasting methods
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Fig. 2. Autocorrelation function (ACF) and partial autocorrelation function (PACF) of the long-term electrical peak load of TREC
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Table 1 Summary of some prior load forecasting methods

Approach / Reference	Artificial Intelligence (AI), Machine learning models, and deep learning approaches	Hybrid Methods	Unsupervised learning method called SOMN (Self-Organizing Mixture Network)	Bootstrap aggregating (Bagging) and forecasting methods	Clustering, ARIMA, and AARMA model	ANNs, Wavelet Decomposed Artificial Neural Network (WANN), Improved Wavelet Neural Network (IWNN), RANN (Recurrent Artificial Neural Network), and CNN-LSTM algorithm	PSO-SVR, RSVMG (Recurrent Support Vector Machines with Genetic algorithms), Wavelet SVM, Gaussian Wavelet SVM, FA-SVM (Firefly Algorithm-SVM), GWO-SVM (Grey Golf Optimizer-SVM), Least Square-SVM	Multi-task learning	Multi Expression Programming (MEP) and fuzzy logic approach
[1]	✓	×	×	×	×	×	×	×	×
[3]	✓	×	×	×	×	×	×	×	×
[4]	×	✓	×	×	×	×	×	×	×
[6]	×	×	✓	×	×	×	×	×	×
[7]	✓	×	×	×	×	×	×	×	×
[8]	×	×	×	✓	✓	×	×	×	×
[9]	×	×	×	×	✓	×	×	×	×
[10]	×	✓	×	×	×	×	×	×	×
[11]	×	×	×	×	✓	×	×	×	×
[12]	✓	×	×	×	×	✓	×	×	×
[13]	✓	×	×	×	×	×	×	×	×
[14]	✓	×	×	×	×	✓	×	×	×
[15]	×	×	×	×	×	✓	×	×	×
[16]	×	×	×	×	×	✓	×	×	×
[17]	×	✓	×	×	×	×	×	×	×
[18]	×	×	×	×	×	✓	×	×	×
[19]	✓	✓	×	×	×	×	×	×	×
[20]	×	×	×	×	×	✓	×	×	×
[21]	✓	×	×	×	×	✓	×	×	×
[22]	✓	×	×	×	×	×	×	×	×
[23]	×	×	×	×	×	✓	×	×	×
[24]	✓	×	×	×	×	×	×	×	×
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[38]	×	×	×	×	×	×	×	×	✓
[39]	✓	×	×	×	×	×	×	×	×
[41]	×	×	×	×	×	×	✓	×	×
[43]	×	×	×	×	×	×	✓	×	×
[45]	×	✓	×	×	×	×	×	×	×
[46]	✓	×	×	×	×	×	×	×	×

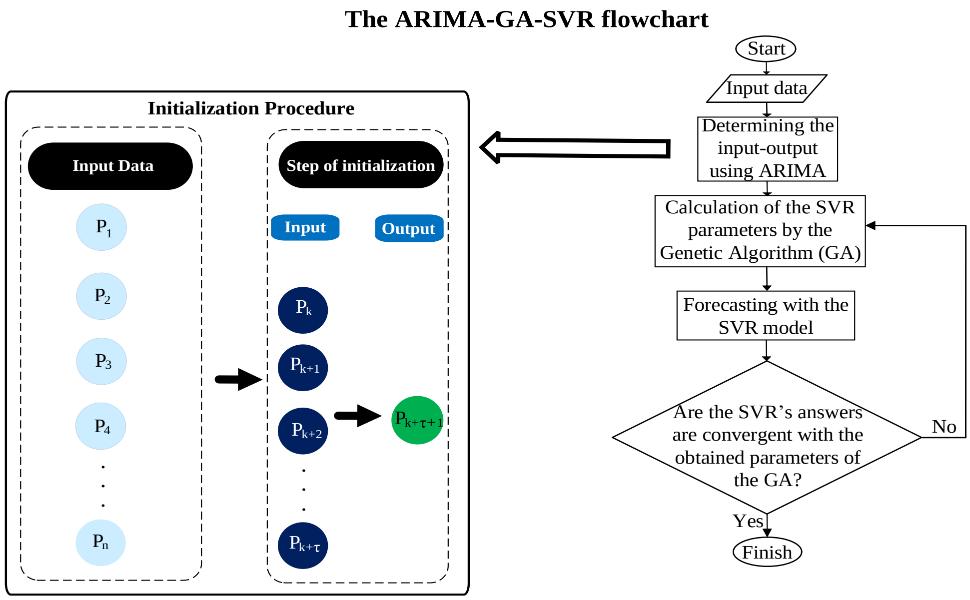

Fig. 1. Flowchart of the ARIMA-GA-SVR approach for initialization procedure and determining the optimum parameters

Table 2 Electrical peak loads of TREC in previous years [44]

Year	Peak load (MW)	Year	Peak load (MW)
1996	3487	2008	5956
1997	3876	2009	6779
1998	4014	2010	7223
1999	4090	2011	7491
2000	4351	2012	7471
2001	4597	2013	8244
2002	4876	2014	8757
2003	5337	2015	9007
2004	5652	2016	9364
2005	6356	2017	9873
2006	6442	2018	9701
2007	6572	2019	10347

Table 3 The forecasted electrical peak load of TREC in MW

Year	The approach of long-term electrical peak load forecasting			
	ARIMA	MLP-ANN	GA-SVR	ARIMA-GA-SVR
2020	10500.07	10724.56	10889.73	10879.08
2021	10950.18	11023.86	11250.62	11232.06
2022	11221.29	11382.91	11595.64	11709.64
2023	11600.27	11733.08	12214.41	12225.65
2024	11914.24	12056.94	12551.29	12720.25
2025	12267.39	12368.89	12971.70	13241.47
2026	12596.93	12666.66	13502.60	13791.52
2027	12940.70	12945.44	14021.80	14356.39
2028	13275.89	13204.92	14451.80	14941.58
2029	13616.25	13444.98	15011.38	15550.64

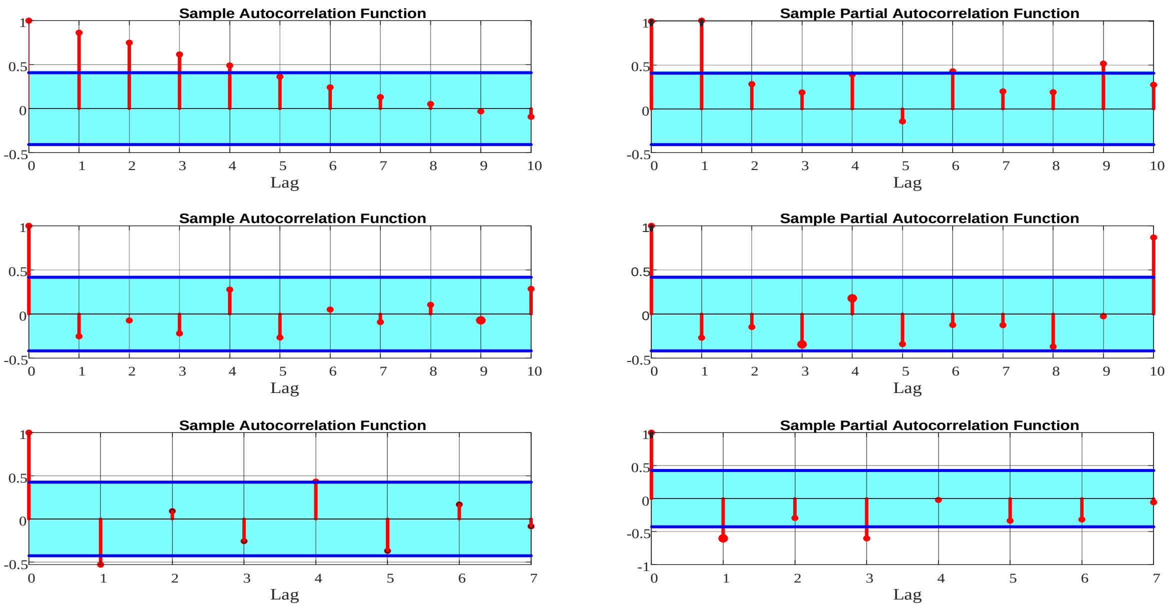

Fig. 2. Autocorrelation function (ACF) and partial autocorrelation function (PACF) of the long-term electrical peak load of TREC

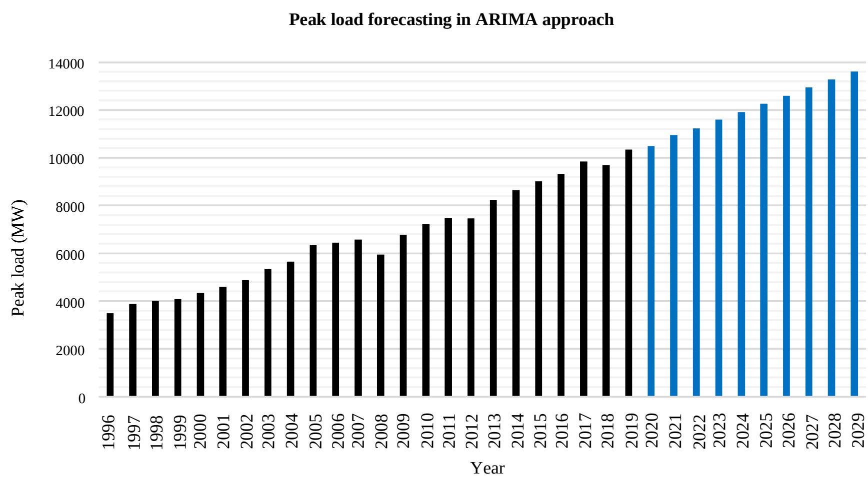

Fig. 3. Long-term electrical peak load forecasting of TREC using the ARIMA approach

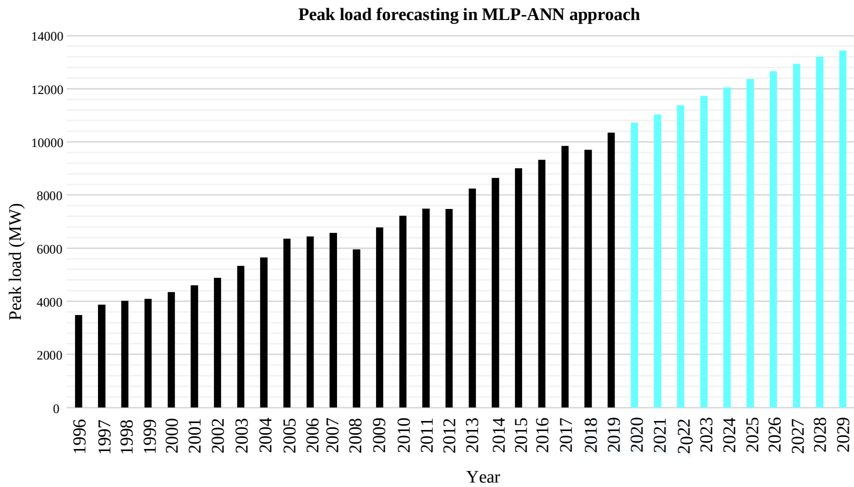

Fig. 4. Long-term electrical peak load forecasting of TREC using the MLP-ANN approach.

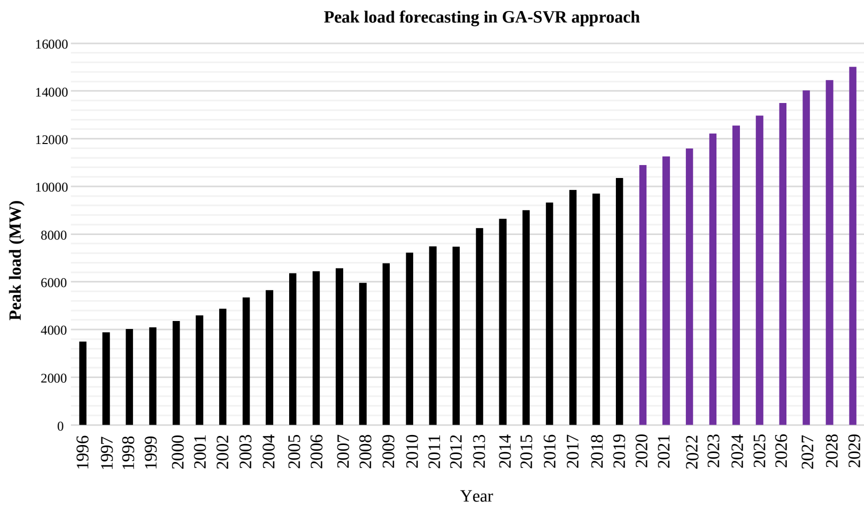

Fig. 5. Long-term electrical peak load forecasting of TREC using the GA-SVR approach.

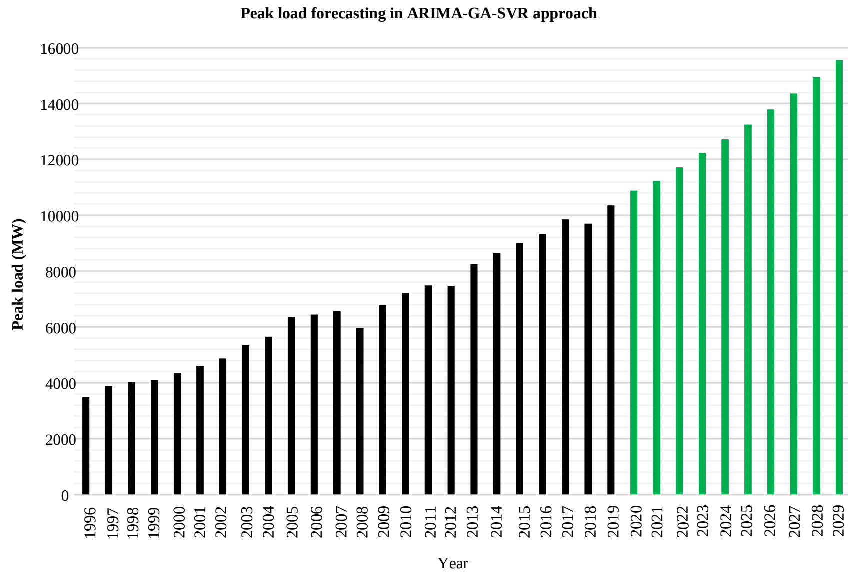

Fig. 6. Long-term electrical peak load forecasting of TREC using the ARIMA-GA-SVR approach.

Table 4 Definitions of error criteria [45], [46]

Metric	Definition	Equation
MAE	The mean absolute of T forecasting results	$\frac{1}{T}\sum_{t=1}^{T}\lvert R_t - F_t\rvert$
RMSE	The Root Mean Square Error	$\sqrt{\frac{1}{T}\sum_{t=1}^{T}(R_t - F_t)^2}$
MAPE	The average of T absolute percentage errors	$\frac{1}{T}\sum_{t=1}^{T}\left\lvert\frac{R_t - F_t}{R_t}\right\rvert \times 100\%$
IA	Index of Agreement	$1-\frac{\sum_{t=1}^{T}(R_t - F_t)^2}{\sum_{t=1}^{T}(\lvert F_t - \overline{R}\rvert + \lvert R_t - \overline{R}\rvert)^2}$

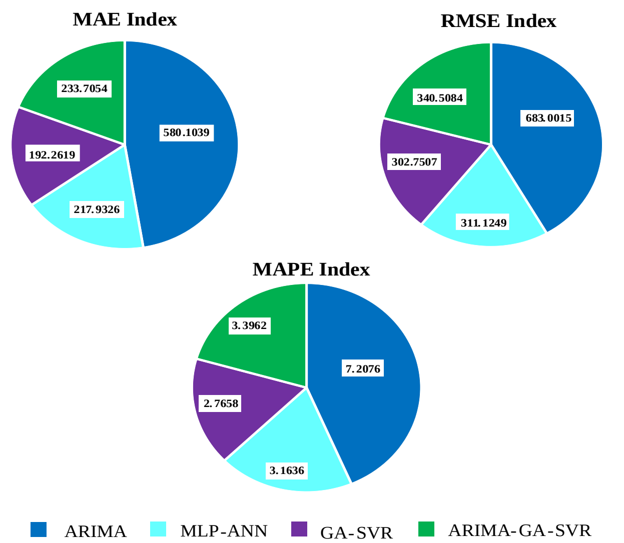

Fig. 7. Schematic of error indices for long-term peak load forecasting approaches

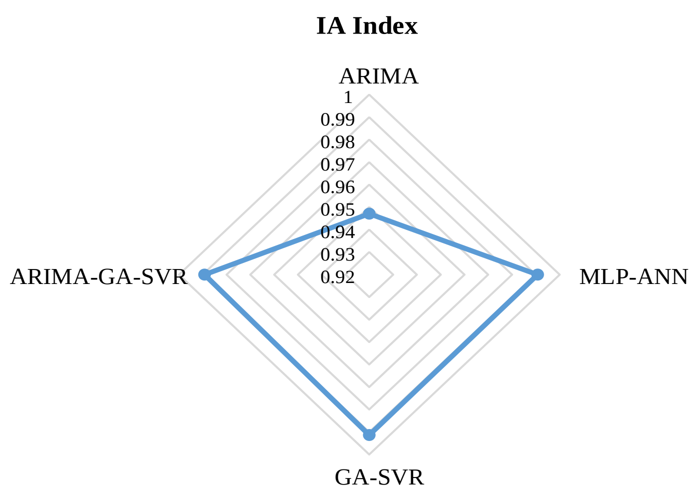

Fig. 8. Schematic of the IA index for long-term peak load forecasting approaches

Table 5 Error criteria results using different forecasting approaches and the proposed methods.

Approach	Error Criteria			
	MAE	**RMSE**	**MAPE %**	**IA**
ARIMA	580.1039	683.0015	7.2076	0.9471
MLP-ANN	217.9326	311.1249	3.1636	0.9907
GA-SVR	192.2619	302.7507	2.7658	0.9914
ARIMA -GA-SVR	233.7054	340.5084	3.3962	0.9893

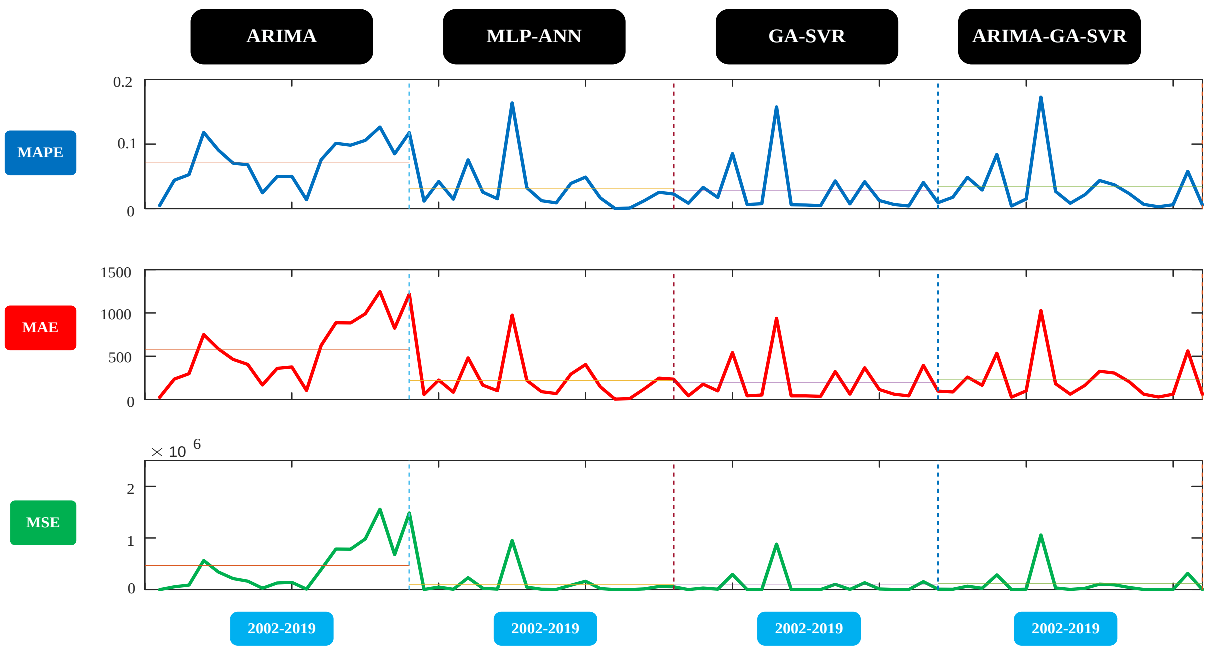

Fig. 9. Validation of electrical long-term peak load forecasting approaches

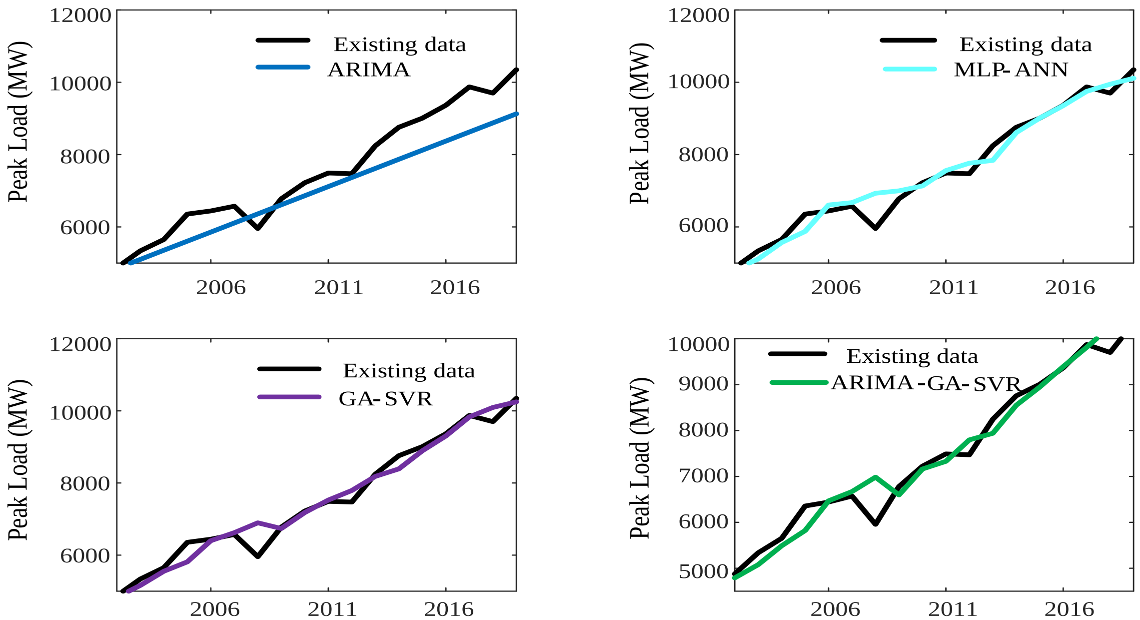

Fig. 10. Testing the electrical long-term peak load forecasting on the existing data

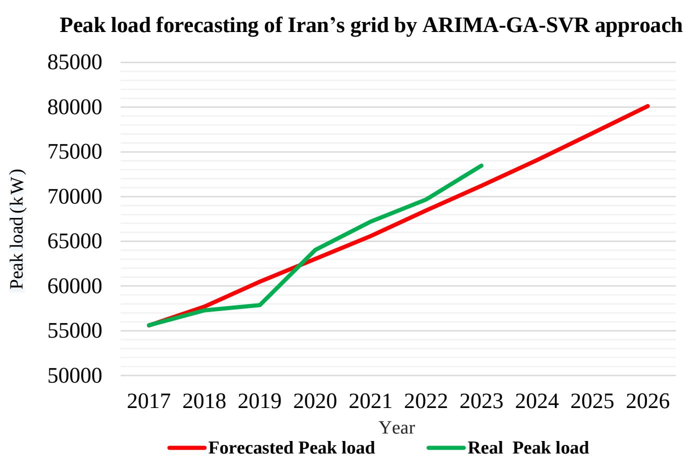

Fig. 11. Long-term electrical peak load forecasting of Iran's grid using the ARIMA-GA-SVR approach.

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