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A hybrid data mining driven algorithm for long term electric peak load and energy demand forecasting

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A B S T R A C T

Load forecasting is one of the main required studies for power system expansion planning and operation. In order to capture the nonlinear and complex pattern in yearly peak load and energy demand data, a hybrid long term forecasting method based on data mining technique and Time Series is proposed. First, a forecasting algorithm based on the Support Vector Regression (SVR) method is developed. The parameters of the SVR technique along with the dimension of input samples are optimized using a Particle Swarm Optimization (PSO) method. Secondly, in order to minimize the forecasting error, a hybrid forecasting method is presented for long term yearly electric peak load and total electric energy demand. The proposed hybrid method acts based on the combination of Auto-Regressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN) and the proposed Support Vector Regression technique. The parameters of the ARIMA method are determined based on the autocorrelation and partial autocorrelation of the original and differenced time series. The proposed hybrid forecasting method prioritizes each forecasting method based on the resulted error over the existing data. The hybrid forecasting method is used to forecast the yearly peak load and total energy demand of Iran National Electric Energy System.

1. Introduction

1.1. Background and literature review

Nowadays, electricity plays an undeniable role in human life and electric energy systems are an essential part of our lives. Many human activities need to access electricity as their primary energy. The main goal of constructing national electric energy systems is to meet the yearly peak load and energy demand in a reliable and sustainable way [1]. The first stage of designing an adequate and secure electric power system is the yearly peak load and energy demand forecasting. Without accurate load and energy forecasting, the expansion of national electric energy systems is underestimated or overestimated, resulting in unwanted loss of load or unnecessary investment decisions. In this regard, one of the main responsibilities of the electric utilities is to forecast the peak load and energy demand at all times, accurately. Load forecasting is used in power short term energy system operation and long term expansion planning studies. In fact, the long term load forecasting (e.g. forecasting the yearly peak load and yearly energy demand for future years) is conducted to optimize the expansion decisions, while short term load forecasting is used for economic dispatch or unit commitment studies in hour-ahead, day-ahead or week-ahead horizons. The main focus of this paper is the long term yearly peak load and energy demand forecasting for expansion planning or refurbishment of large scale electric energy systems. The yearly or annual electric peak load refers to the maximum value of the load curve in a given year. It is actually difficult to forecast the load and energy demand over a long term horizon because the longer prediction horizons come up with significant uncertainty in load and energy demand and their driving parameters [2]. Indeed, the electric load and energy demands are affected by numerous factors, such as social welfare, economic issues, and irregular behaviors [3].

Due to economic growth and appearing in new human activities and processes, in many national energy systems around the world, especially in developing countries, both load and energy demand are increasing [4]. For example, the total annual energy consumption of Iran's national grid has been increased from 240043 GWh in 2011–304400 GWh in 2018 [5]. The aim of this paper is to address the long-term annual peak load and energy forecasting in Iran's

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national grid. The Iranian national grid struggles with a low reserve during peak hours in summers over recent years. Although such recent generation deficiency has occurred due to the reduction of hydropower plants generation caused by dry hydro seasons in the country; however, this deficiency highlights the importance of accurate forecasting of yearly peak load as well as the yearly total energy demands.

Many researchers have developed various kinds of load forecasting approaches to improve forecasting accuracy [3]. Generally, the load forecasting methods are categorized into univariate and multivariate methods. The most commonly used univariate method is the Times Series approach [6]. In univariate methods, the amount of load or energy demand in a given year is assumed as a function of the load and energy demand in past years. In multivariate methods, the amount of load and energy demand is assumed to be a function of other driving parameters such as population growth and Gross Domestic Production (GDP). In Refs. [7], the application of Box-Jenkins, as a time series method, using an ARIMA model has been addressed for mid-term and long term energy forecasting. In Ref. [7], the parameters of the ARIMA model are determined using the least square approach. Since the Box-Jenkins method assumes a linear model for the forecasting problem, it is not able to capture all nonlinearity and complexity of load and energy data. To this end, the artificial intelligence and evolutionary algorithms are used to obtain accurate forecasting results in the presence of inherent nonlinearity of load and energy time series. In Ref. [8], the Artificial Neural Network (ANN) is utilized for long term load forecasting. In Ref. [9], a knowledge-based expert system is developed for long term load forecasting. The basic concentration of [10] is to propose an energy prediction model employing the machine learning-based technique including artificial neural network, linear and nonlinear autoregressive multivariable models, and the adaptive boosting model. Authors in Ref. [11], utilize the Particle Swarm Optimization (PSO) algorithm for long term load forecasting. In another application of evolutionary algorithms for load forecasting, in Ref. [12], a short-term electric load forecasting model based on the Back Propagation Neural Network (BPNN) algorithm is proposed. The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used to optimize the parameters of BPNN. In Ref. [13] an ANN-based model is developed for Iran's and the U.S. energy consumption forecasting. Moreover in Ref. [14], the forecasted results using ANN and time series methods are compared and an error criterion is used for determining the accuracy of models. Similarly, in Ref. [15], the short-term load forecasting (STLF) is performed by combining the convolutional neural networks and fuzzy time series methods with automated feature extraction on the basis of a hybrid model of convolutional neural networks (CNN) and the fuzzy time series (FTS). In Ref. [15], some error criteria are utilized for validation of the results. In Ref. [16], a new technique is proposed to forecast hourly and peak loads in a medium-term span. The proposed method implements a new combination of some existing and well-established techniques. The proposed method is applied to the Jordanian power system. In Ref. [17], the combination of genetic algorithm (GA) and ANN is utilized to forecast the electrical energy consumption (EEC) from 2006 to 2008, in the Iran agriculture sector, using input data from 1981 to 2005. In Ref. [18,19], ANN is used to forecast Japan's peak loads.

The Support Vector Regressor (SVR) technique has been an appealing tool for both short term and long term load forecasting. SVR as a machine learning method is able to deal with a limited number of input samples and dominate the local optimal solution problem [20]. Authors in Ref. [21], has proposed an SVR algorithm for short term load forecasting. In Refs. [22], a forecasting approach based on the Support Vector Machine (SVM) is presented to enable the load aggregators to forecast the aggregated smart households' demand response capacity in the day-ahead market. A major problem in load forecasting using SVR is the proper adjustments of parameters [23]. Heuristic search approaches like GA and PSO algorithms can be used for optimal selection of SVR parameters [24]. In Ref. [24], the ability of the data decomposition is tested to predict near-infrared non-invasive glucose detection with the PSO-SVR model. In Ref. [25], the authors proposed a hybrid model that is designed by integrating a robust and efficient PSO-SVR technique with the ICEEMDAN (i.e. integrated with an improved version of empirical mode decomposition with adaptive noise) algorithm. In Ref. [25], authors construct a two-phase hybrid ICEEMDAN-PSO-SVR model where the model inputs are firstly decomposed by the ICEEMDAN algorithm for better frequency resolution within the predictor data, and then the PSO algorithm is used to tune the weights based on input samples. In Refs. [25], the dimension of the input-output vector for training and test purposes is not optimized. Also, the number of input samples is 12 which is not enough for an accurate forecast. In Ref. [26], a chaotic particle swarm optimization (CPSO) algorithm is developed to choose the suitable parameter combination for an SVR model. The empirical load forecasting results in Ref. [26], reveal that the proposed model outperforms the other two models applying other algorithms including GA and the simulated annealing (SA) algorithm.

Recently, new hybrid methods based on the combination of different forecasting methods have been developed. In Ref. [27], a hybrid model based on the least-square support vector machine and an autoregressive integrated moving average has been presented. The proposed model is used to forecast the future net electricity consumption for Turkey until 2022. In Ref. [28], a new hybrid seasonal approach is proposed for short-term load forecasting (STLF) in Assam, a state situated in the North-Eastern part of India. The proposed approach is based on the firefly algorithm (FA), support vector machine (SVM), and the season specific similarity concept (SSSC). The results of [28] are evaluated by the mean absolute percentage error (MAPE) metric. In Ref. [29], a hybrid model called ANN-IEAMCGM-R is proposed for short-term load forecasting. For finding the optimal network weights, the ANN is integrated with an enhanced evolutionary algorithm (IEAMCGM-R). The electric load data of the New England Power Pool and Australian Energy Market Operator have been utilized.

There are some other methods for peak load and energy forecasting. In Ref. [30] a framework based on the combination of the Kalman filter and regression methods is proposed for short term load forecasting.

In [31], the current status of energy policies is used to create a framework for the development and application of a LEAP (Long-range Energy Alternate Planning) model of Pakistan's electric power sector. Authors in Refs. [32] propose a long-term electricity demand forecasting model using the system dynamics method. This method is used to predict the electricity demand of Tianjin in China. In Refs. [33], a forecasting procedure is presented to combine both long and short-term features by employing temporal disaggregation techniques. The proposed method in Ref. [33] is applied to forecast electricity load for Spain and its performance is compared to a nonlinear autoregressive neural network with exogenous inputs. In Ref. [34], three forecast methods based on multiple linear regression, random forest, and gradient boosting are utilized to forecast hourly (i.e. next 24-h) load in the southern California network. The proposed method in Ref. [34] is a multivariate method that uses air temperature as the most important meteorological variable, along with the time of consumption and past load data as the most important non-meteorological variables.

In load forecasting, some researches focus on the day-ahead short-term forecast of photovoltaic power generation. In Ref. [35] a data-driven generative model named generative adversarial networks is used to augment the training dataset for the weather classification problem. Then the convolutional neural networks-based weather classification model was trained by the augmented dataset including both original and generated solar irradiance data. In Ref. [36], a novel day-ahead Photo-Voltaic power forecasting model assembled by fusing deep learning modeling and time correlation principles is proposed. The proposed model in Ref. [36] is developed using the long-short-term memory recurrent neural network (LSTM-RNN).

A detailed comparison between different forecasting approaches is given in Table 1.

1.2. Research gap

Long term peak load and energy are conventionally forecasted using Trend Curves or ARIMA methods. The traditional forecasting methods have some disadvantages. Trend Curves have been initially proposed for the growth processes such as population growth that exhibit a different rate of exponential growth as initiation, acceleration, deceleration, and saturation. Such S-shape variations may not fit the peak load and energy demand forecasting problems especially in developing countries where their load and energy growths may not enter the saturation phase. ARIMA method as a most popular forecasting method, mainly due to its flexibility and simplicity, is utilized for stationary time series. ARIMA method is very sensitive to noise and seasonal trends in time series. Also for non-stationary time series (e.g. load and energy time series) identification of ARIMA orders and parameters is not an easy task. Also, the ARIMA method is based on linear analysis and they may fail to give an accurate forecast for non-linear time series. Several studies have demonstrated that the ARIMA model tends to generate large errors for long-range forecasting horizons. Regarding these issues, ARIMA methods may result in an undesired overestimated or underestimated forecast. Also, in previous SVR-based methods, the dimension of the input-output vector for training and test purposes has not been optimized. Additionally, the number of input samples in previous SVR-based methods is not enough for an accurate forecast. Also, most of the previous forecasting approaches are just capable of short term load forecasting which is suitable for short term operational studies such as optimal power flow, economic dispatch and unit commitment. However, few studies have been made to develop the long term load forecasting methods. The simultaneous prediction of long-term yearly peak load and energy demands and their verification using the load factor is missing in previous long term forecasting methods. Estimation of load factor is an adequate tool that gives the power system planners the capability to verify the load and energy demand forecast, assuming that the load factor has small variations. This issue was not addressed in most of the previous works. Finally, a major gap in previous research works is that majority of previous methods rely on just one forecasting method without benefiting from all forecasting methods including ARIMA, ANN, and SVR methods based on their performances.

1.3. Contributions

In this paper, first, an SVR algorithm is proposed for long term load and energy demand forecasting. The Particle Swarm Optimization (PSO) algorithm is utilized to optimize the parameters of SVR. Then, a hybrid method based on time series or ARIMA method, ANN method, and the developed PSO-SVR forecasting method is proposed for long term load and energy forecasting of Iran's national grid. A major advantage of the proposed hybrid method is the combination of analytic time series method and the data mining approach which can handle the nonlinearity and seasonal trends in input samples (i.e. input observations). The main contributions of this paper are summarized as follows:

1: Since the Box-Jenkins (i.e. ARIMA) model as the major forecasting tool is very sensitive to the noise and seasonal trends in time series, in this paper, a data mining method based on the SVR algorithm is proposed to forecast the long term load and energy demands. Unlike the ARIMA methods, the proposed PSO-SVR algorithm utilizes the information of all samples without assuming any predetermined S-shape or linear model for the forecasting process. The parameters of the SVR algorithm are optimized using the PSO algorithm.

Table 1
Comparison of previous load forecasting approaches.

Approaches of forecasting	References	Description
Bayesian theory and expert prediction	[1]	The proposed multivariate method forecast the long term per-capita consumption through an econometric methodology using fuzzy Bayesian theory and expert's experiences.
Machine learning, deep learning, and knowledge-based expert system	[2,4,9,10,36]	Machine learning techniques are used to capture the nonlinearities and de-noising input data noise. The uncertainties are taken into account, These methods can be univariate ([2,4]) or multivariate ([9,10]). In multivariate methods in addition to historical load data, environmental and climate data are used. These methods can be combined with ANN-based approaches.
Artificial Neural Networks (ANNs)	[3,8,12–15,17–19,29,35]	The ANN models are considered more accurate rather than nonlinear methods, one of the disadvantages of ANN is that it is essentially a black box, not a causal model.
Combined Bootstrap Aggregating (Bagging), The gradient boosting model	[7,34]	The ARIMA-based Bootstrap aggregating is used to obtain more accurate demand forecasts. This multivariate method can promote forecasting accuracy. In Ref. [34], this method is applied over the California grid.
Support Vector Machine and Support Vector Regressor	[11,20–28]	SVM-based and SVR-based methods are employed to solve nonlinear regression and time series problems. Evolutionary algorithms can minimize the forecasting error and remove noise in input data.
Polynomial regression and Singular value decomposition	[16]	The hourly loads are forecasted in the medium-term using a new combination of different univariate methods. SVD is used to de-noising the input data.
The EnKF (ensemble Kalman filter) technique	[30]	The proposed univariate model combines the Kalman Filter and Shrinkage regression methods. The Kalman filter estimates loads and the Regression model promotes accuracy.
Long-range energy alternatives planning (LEAP)	[31]	The future load demand is forecasted using analysis of supply policy and demand assumptions for future power generation systems. This multivariate forecasting method depends on energy policies.
System Dynamics	[32]	In order to forecast the load demand, the relationship between electricity demand and driving factors is quantified using the system dynamics method. The proposed multivariate method is suitable for long term electricity demand.
Using causal models by temporal disaggregation techniques	[33]	This multivariate model is able to combine long and short-term features by employing temporal disaggregation techniques.

2: In order to achieve a robust forecast and benefit from the Box-Jenkins and the proposed data mining techniques, a hybrid method is developed. The proposed hybrid approach prioritizes each algorithm based on its error over the input observations. The proposed hybrid method gives robust and accurate forecasting results.
3: The proposed PSO-SVR and the hybrid methods are implemented in the real-life case of the Iran national grid. The separate forecasting is done for both the load and energy demands. Based on the forecasted peak load and energy demand, the load factors are then calculated and utilized for additional verification of the forecasting results.
4: The obtained forecasts for Iran's national grid are compared with the previously proposed forecasting methods to show the higher accuracy of the proposed method in peak load and energy demand forecasting. Moreover, the proposed hybrid method is tested on different datasets (i.e. other real cases) to verify the performance of the proposed method.

Actually, the focus of this paper is to propose a hybrid method for both the peak load and energy demand forecasting. The proposed hybrid method acts based on the combination of Auto-Regressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN) and a new proposed Support Vector Regression technique (PSO-SVR). The proposed method is used to forecast yearly peak loads and the energy demand of real case studies.

The rest of the paper is organized as follows. Section 2 introduces the proposed methodology including the formulation of the proposed PSO-SVR and the hybrid methods. In sections 3 and 4, simulation results of the proposed method over Iran's national grid and other networks are presented. Finally, the paper is concluded in section 5.

2. Methodology

Univariate forecasting methods consist of the Trend-Curve and Time-series or Box-Jenkins approaches [6]. The other categories of peak load forecasting methods are machine learning approaches such as the SVR technique. The hybrid load forecasting methods use the weighted combination of the load forecasting approaches to reduce the error of the final estimation as much as possible [6]. The comprehensive structure of the proposed load forecasting method has been illustrated in Fig. 1. The main parts of the proposed method will be described.

2.1. Time series or Box-Jenkins method

Box-Jenkins method is realized in three steps including step 1: Identification of the adequate model, step 2: Estimating the model parameters, and step 3: Model diagnostic checking. The details of each step will be illustrated.

Step 1:

The aim of this step is to identify the proper order of the model. In this step, an adequate model should be selected by using available data. Here, two functions including Autocorrelation Function (ACF) and Partial ACF (PACF) are utilized to determine if the times series is stationary or dynamic. As given by (1), ACF shows the autocorrelation between the original series and a series where its samples have a time lag of k, denoted by (X_{t+k}, X_t). According to (2), PACF shows the autocorrelation between two variables, regardless of the effects of other variables. For a given time series, PACF gives the partial correlation of a stationary time series with its own lagged samples (i.e. (X_{t+k}, X_t)), without considering the effect of correlation at all shorter lags.

$$r_k = \frac{\sum_{i=1}^{N-k}(x_i - \overline{x})(x_{i+k} - \overline{x})}{\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{1}$$

$$\pi_k = \frac{r_k - \sum_{j=1}^{k-1}\left(\pi_{(k-1,j)} \times r_{(k-j)}\right)}{1 - \sum_{j=1}^{k-1}\left(\pi_{(k-1,j)} \times r_{(k-j)}\right)} \tag{2}$$

where, in (1) and (2), r_k is the autocorrelation of a signal with a delay of k, x_i is the i^{th} sample of the original series (i.e. load and energy data), x_{i+k} is the delayed signal, N is the number of samples, $\overline{x}$ is average of signals and π_k refers to the PACF of that signal. When ACF is damped in primitive lags, it means that the correlation between samples of the time series is not significant and it can be assumed as an stationary signal, otherwise, it is a dynamic signal. The dynamic time series should be differentiated to make sure that the ACF has negligible variation [6].

2.1.1. Auto-Regressive Integrated Moving Average (ARIMA) model

In the ARIMA model, two types of linear-regressions including the AR and MA models are integrated [37].

The ARIMA model is defined as in (3).

$$W_t = \Phi_1 w_{t-1} + \Phi_2 w_{t-2} + \ldots + \Phi_p w_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \tag{3}$$

In (3), p and q are the orders of autoregressive and moving average terms, respectively. In the ARIMA model, W_t is the d^{th} difference of the original time series (i.e. $\overline{Y}_t$) as shown in (4).

$$W_t = \nabla^d(\overline{Y}_t) \tag{4}$$

Finally, if the ACF of the differenced time series tails-off while the PACF cut-off after lag p, the suitable model is AR(p). If the PACF of the differenced time series tails-off but the ACF cut-off after lag q, the suitable model is MA (q), otherwise the ARIMA (pq) is preferred.

Step 2:

The parameters of the ARIMA model (i.e. $\Phi(B)$,$\theta(B)$) can be estimated by minimizing the mean square of errors (MSE) as illustrated in (5).

$$\underset{\theta,\Phi}{\mathrm{Min}} f = \sum_{t=1}^{N} e_t^2 \tag{5}$$

Considering the θ, Φas the optimization variables, the optimality conditions of (5) gives a set of non-linear equations that can be solved using gradient-based methods. In this paper, these parameters are estimated using the ARMAX approach [38].

Step 3:

The third step is the diagnostic checking to verify the adequacy of the obtained forecasting model. If the errors of the model are random or the autocorrelation of the residuals indicates a random series, the estimation model is correct and can be used for load forecasting, otherwise, the model parameters and orders must be changed with the same procedure.

Finally, by determining the model parameters and order, the forecasting model is obtained.

2.2. Support Vector Regression (SVR)

An SVR model can provide solutions to the regression problems with multiple predictors. Based on the SVR model, a non-linear regression problem is defined as given in (6) [39].

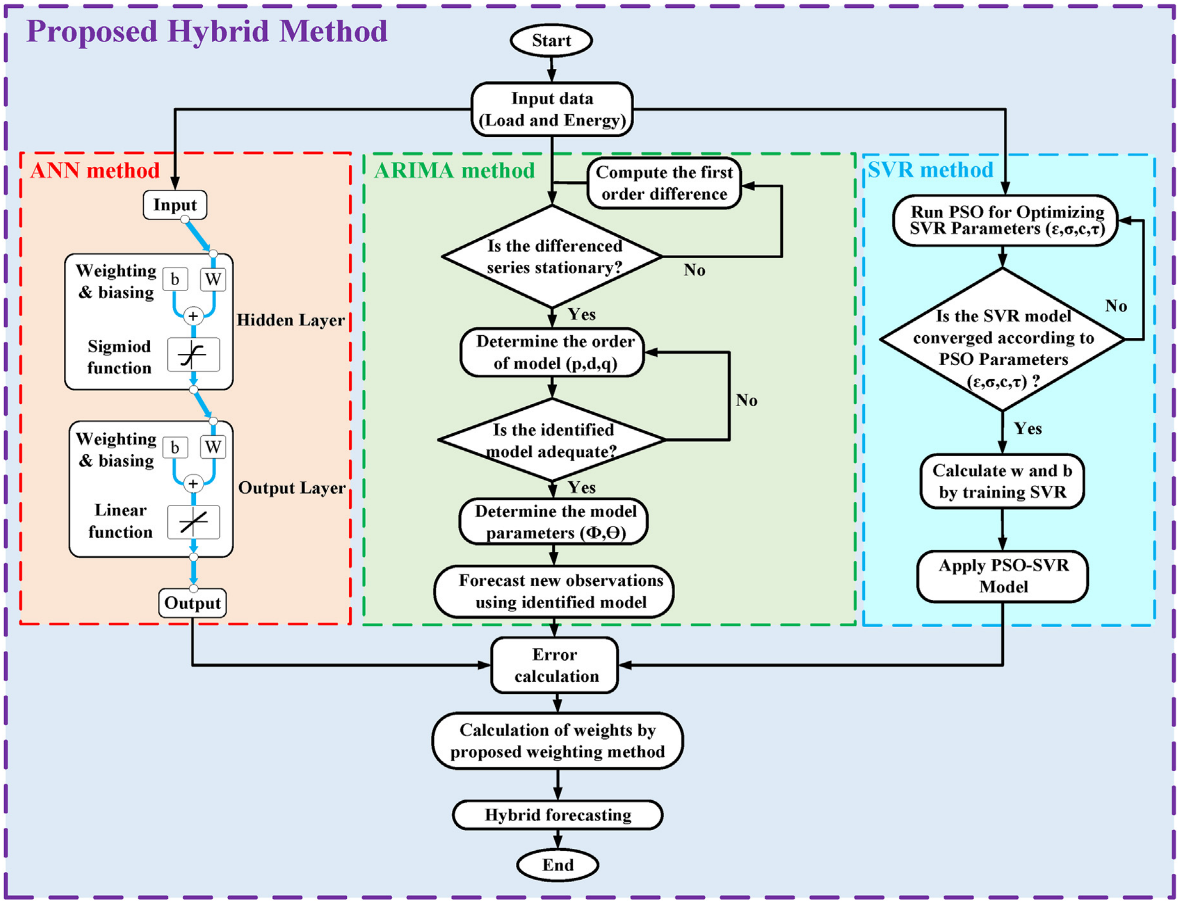

Fig. 1. The overall structure of the proposed forecasting method.

$$y = f(X) = \omega.\varphi(X) + b \quad (6)$$

In (6), b is a constant parameter or bias, ω is the weighting vector, and φ(X) denotes the mapping function applied in the feature space. The coefficients of ω and b are estimated by the minimization problem as given by (7)–(10).

$$Minimize : 0.5\ \omega^2 + c\frac{1}{N}\sum_{i=1}^{N}(\xi_i + \xi_i^*) \quad (7)$$

$$y_i - (\omega, x_i + b) \geq \varepsilon + \xi_i \quad (8)$$

Subject to:

$$(\omega, x_i + b) - y_i \geq \varepsilon + \xi_i^* \quad (9)$$

$$\xi, \xi_i^* \geq 0 \quad (10)$$

In (7)–(10), c and εare the model's parameters. As shown in Fig. 2, the term $0.5\omega^2$ measures the smoothness of the function and c evaluates the trade-off between the empirical risk and smoothness. Also, ξ_i And ξ_i^* are the positive slack variables that measure the distance between real and corresponding boundary values in the ε-tube model of function approximation.

Based on the Lagrange function, the optimality conditions result in a non-linear regression function is as (11) [39].

$$f(X) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(x_i, x_j) + \mathrm{b} \quad (11)$$

where, α_i and α_i^* are Lagrangian multipliers and $K(x_i, x_j)$ refers to the kernel function showing the inner product of x_i and $x_j$in D-dimensional feature space [39]. Under Karush-Kuhn-Tucker conditions, a limited number of α_i and α_i^* coefficients are non-zero. The data points, with the closest distance to the decision hyper-plane, are called the "support vectors" [40]. In this study, a polynomial kernel function is employed to develop the SVR forecasting model as given in (12).

$$K(x_i, x_j) = \left(1 + x_i^T.x_j\right)^\sigma \quad (12)$$

Where, x_i and x_j are the inputs in the i^{th} and j^{th}dimensions and σ is the kernel width. During SVR training, the support vector's area of influence with respect to input data space is specified by the Kernel width and the parameter c.

PSO can efficiently find optimal or near-optimal solutions in optimization problems. In PSO, the swarm X consists of N particles in an m-dimensional search space. Each particle has two vectors including the swarm position as $x_i = (x_{i1}, x_{i2}, \ldots, x_{im})$ and swarm velocity as $v_i = (v_{i1}, v_{i2}, \ldots, v_{im})$. Each particle is accelerated while searching for the particles in the locally best (i.e. $P_i^{best}(k)$ of i^{th} swarm at iteration k) and globally best (i.e. G_{best}^k at iteration k)

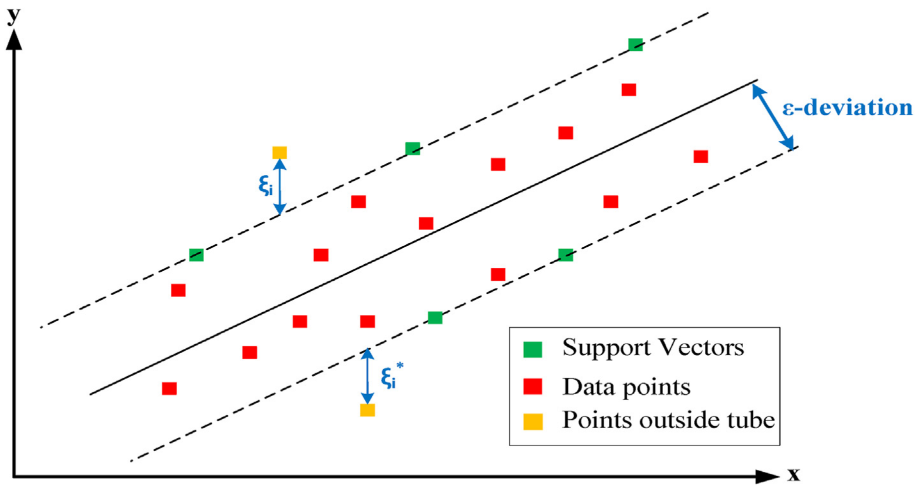

Fig. 2. Linear regression with epsilon intensive band in SVR algorithm.

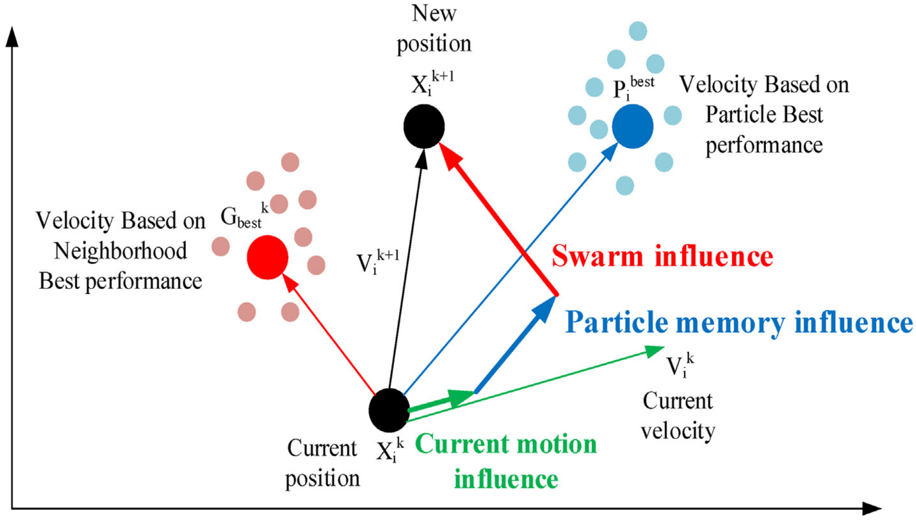

Fig. 3. Conceptual update of the position and velocity of a searching point by PSO.

positions as illustrated in Fig. 3. It is assumed that p_i^{best} is the locally best position, whereasG_{best} is the globally best position. During the iterative process, each particle updates its velocity and location. The velocity and position for each particle (i.e. $i = 1, 2, \ldots., N$) can be updated using (13) and (14), respectively.

$$\left(V_i(k+1) = w \times V_i(k) + c_1 \times r_1 \times \left(p_i^{best}(k) - x_i(k)\right)\right. \\ + c_2 \times r_2 \times (G_{best}(k) - x_i(k)) \tag{13}$$

$$x_i(k+1) = x_i(k) + V_i(k+1) \tag{14}$$

where, w is the inertia weight, which provides a balance between local and global explorations, where a larger w facilitates the global search, whereas a smaller w facilitates the local search. The parameter k is the counter of iterations, N is the total number of particles, c_1 and c_2 are acceleration positive numbers, r_1 and r_2 are random values in the range of (0,1) [41], [42].

According to (13) and (14), the objective function of the proposed PSO-SVR algorithm is defined as (15).

$$Min\ obj = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{Y_t^a - Y_t^f}{Y_t^a} \right| \tag{15}$$

In (15), Y_t^a and Y_t^f are actual and forecasted values. The pseudo-code of the proposed PSO- SVR algorithm is given in Fig. 4.

The input-output pairs of existing samples are constructed as given in Fig. 5. At first, the historical data including the yearly peak load and total yearly energy demand are entered into the initialization stage. In this stage, using the PSO algorithm, the dimension of input-output pairs is determined. In other words, in a time series vector as $P = (P_1, P_2, \ldots, P_n)$, an input-output sample can be considered as $[(P_k, P_{(k+1)}, \ldots, P_{(k+\tau)}), P_{(k+\tau+1)}]$. Also, other settings of SVR algorithm such as (C, σ, ε) are optimized using PSO. It is noted that, each sample or pair includes $(P_k, P_{(k+1)}, \ldots, P_{(k+\tau)})$ 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 $[1 \times 1]$. It should be added that the dimension of input vector (i.e. τ) is a decision variable and obtained by the PSO algorithm, but the dimension of output is always one.

Start

Parameters:
MaxIt-Maximum Number of iterations
NP-Number of particles
W-Inertia weight
$\mathbf{W_{damp}}$- Inertia weight damping ratio
$\boldsymbol{C_1}$- Personal learning coefficient
$\boldsymbol{C_2}$- Global learning coefficient

Variables:
$\boldsymbol{X_i}$-The i^{th} particle's position
$\boldsymbol{BX_i}$-The best particle's position of i^{th} particles
$\boldsymbol{F_i}$-The i^{th} particle's fitness function
$\boldsymbol{BF_i}$-The best fitness function of i^{th} particle
Gbest-Vector for determining the global best position and particles

Outputs:
(C, σ, ε, τ) - SVR parameters

/*Set the PSO parameters*/
/*Initialize particles' (C, σ, ε, τ) positions and their velocities randomly*/
FOR each particle **DO**
  Randomly initialize the particle's position according to (14);
  Randomly initialize the particle's velocity according to (13);
End FOR
Evaluate the objective function of each particle according to (15);
Calculate the local or personal best position according to ($BX_i = X_i$);
Calculate the local or personal best fitness according to ($BF_i = F_i$);
Calculate the global best according to ($BX_i = X_i$) and ($BF_i = F_i$);
FOR EACH i: 1 ≤ i ≤ MaxIt **DO**
  FOR EACH j: 1 ≤ j ≤ NP **DO**
    Update the position and velocity of particles (according to (14) and (13));
    Evaluate the objective function of the new particles according to (15);
    If ($\boldsymbol{F_i < BF_i}$)**THEN**
      Calculate the new position as personal best (i.e. $\boldsymbol{X_i}$);
      Calculate the new objective function value (i.e. $\boldsymbol{F_i}$);
    End If
  End FOR
  Determine the particle with minimum objective function and store its position as global best (i.e. **Gbest**);
End FOR

Fig. 4. The pseudo-code of the proposed PSO-SVR algorithm.

According to Fig. 5, it should be said that a four-step procedure is followed to determine the required input data using the original time series of yearly peak load and energy demands. In the first step, which is named by the historical data step, all the original data of the load and energy time series are provided. In the second step or the initialization part, it is assumed that the input-output pairs are constructed using the original time series. Indeed, for each input-output pair, a given number of subsequent data with a length of τ are assumed as the input and the output data will be the $(\tau+1)^{th}$ sample. In the third step, the optimal value of τ is determined using the PSO algorithm. Finally, after determining the length of input data, the set of input-output pairs are determined in the fourth step. It is noted that the objective function of the PSO algorithm is the MAPE (the mean absolute percentage of errors) error criterion.

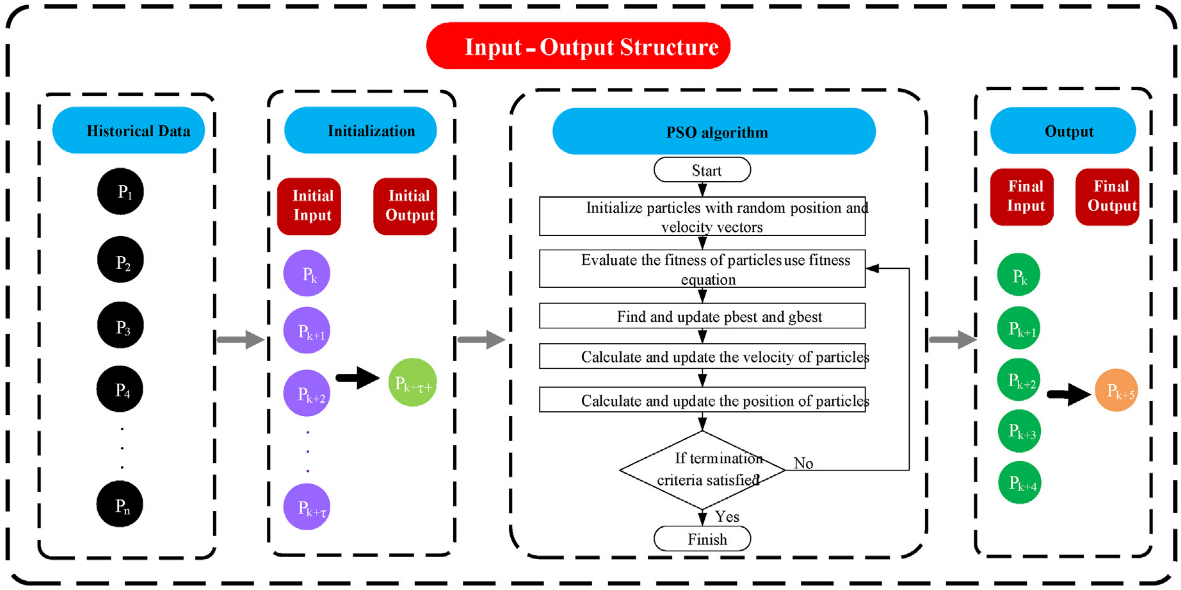

Fig. 5. Structure of the procedure utilized for determining the dimension of input pairs.

2.3. Hybrid method

In order to benefit from the results of all individual forecasting methods and achieve robust forecasting results, a weighted forecasting method is proposed. Based on the forecasted results of each method, the final weighted forecasting results are obtained.

$$Y_t^H = \sum_{i=1}^{k} W_i^m . Y_{i,t}^f \tag{16}$$

In (16), W_i^m is the weight of i^{th} forecasting method, $Y_{i,t}^f$ is the value of forecasting using the i^{th} method at t^{th} year and Y_t^H is the value of hybrid forecasting method at t^{th} year. The weight of each forecasting method is determined based on the error of forecasting. The proposed hybrid approach acts based on the electrical circuit known as the current division in parallel circuits as shown in Fig. 6. According to Fig. 6, each branch of the circuit belongs to a forecasting method. The resistors and their related currents are interpreted as analogs of the error and weight of each forecasting method, respectively. Therefore, the weight of the i^{th}forecasting method is obtained.

$$I_i = \frac{V}{R_i}, \; aV = R_{eq}.I, \; R_{eq} = \frac{1}{\sum_{j=1}^{n} \frac{1}{R_j}} \tag{17}$$

Using the current division rule, the current of each resistor is obtained in (18).

$$I_i = I\frac{\frac{1}{\sum_{j=1}^{n} \frac{1}{R_j}}}{R_i} \tag{18}$$

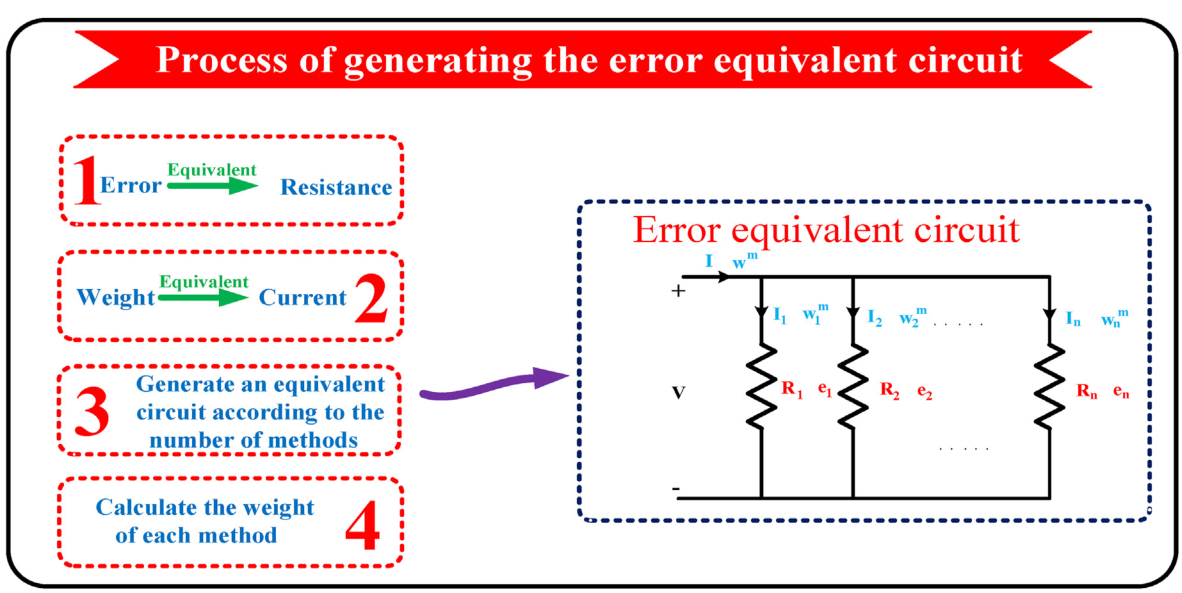

Fig. 6. The overall structure of the proposed hybrid method based on current division rule.

The current division rule is expressed as: “The higher the value of the resistor, the lower the current value”. This is equivalent to “The higher the error of forecasting method, the lower the weight factor”. In this regard, according to (18), the weight of each method in each year is obtained as given in (19). In (19), n refers to the number of forecasting methods.

$$w_{i,t}^{e} = w_{t}^{e}\frac{\frac{1}{\sum_{j=1}^{n}\frac{1}{e_{j,t}}}}{e_{i,t}} \tag{19}$$

where;

$$e_{i,t} = \left|\frac{Y_t^a - Y_{i,t}^f}{Y_t^a}\right| \tag{20}$$

$$W_i^m = \frac{1}{N_t}\sum_t w_{i,t}^e \tag{21}$$

$$w_t^e = \sum_{i=1}^{N_w} w_{i,t}^e = 1 \tag{22}$$

In (19), $w_{i,t}^e$ is the weight of i^{th} method in existing t^{th} year, $e_{i,t}$ is the error of i^{th} method in existing t^{th} year. In (20)Y_t^a is the value of historical (i.e. actual) data in t^{th} year, $Y_{i,t}^f$ is forecasting value obtained by i^{th} method in existing t^{th} year and finally, in (21), N_t is the number of existing years. It is noted that the error is calculated over the existing data using standard criteria that will be presented in the next part.

3. Simulation results

The aim of this section is to forecast the yearly peak load and the yearly electric energy demand of Iran national grid for a ten-year horizon ahead from 2017 to 2026. The yearly peak loads and the total yearly energy demand have been reported in Table 2 From 1991 to 2016. Obviously, the actual values of the yearly peak loads and the total energy for 2017–2018 are known. However, in this paper, these two years (i.e. 2017 and 2018) are considered as a part of the forecasting horizon to make a fair comparison [5]. In part A, the results of load and energy forecasting using the time series method are given. In part B, the results of load and energy demand forecasting using the ANN method are presented and in part C, the results of the proposed PSO-SVR method are discussed. Finally, in part D, the load and energy demand are forecasted using the proposed hybrid method. Also, all forecasting methods are compared in this part. The simulation platform of the proposed method is MATLAB (R2018a) [43]. All simulation codes have been created using MATLAB.

3.1. Part A: ARIMA method

In order to identify the order of the ARIMA model, the ACF and PACF of original and differenced time series of load and energy demand are shown in Fig. 7 and Fig. 8. According to Fig. 7, at the second difference, the ACF is damped sinusoidally, so it tails off, and the PACF after the second time lag remains inside the significance bound, so it cuts off after the second lag. Therefore, the proper Box-Jenkins model for the load demand is identified as ARIMA (2,2,0). With the same procedure and according to Fig. 8, the appropriate model for the energy demand is identified as ARIMA (1,2,0). Since identifying the order of the ARIMA model is not a clear task; two other recommended models are assumed for both peak load and energy forecasting which are ARIMA (2,2,1) and ARIMA (1,2,1), respectively. Now, the parameters of the identified model are determined using the least square technique and also the final load energy forecasting models are reported in Table 3. For diagnostic checking, the autocorrelation of the resulted errors is illustrated in Fig. 9. Since the autocorrelation remains inside the thresholds, both estimated ARIMA models are adequate. Finally, according to the load and energy forecasting models given in Table 3, the values of forecasted load and energy demand are illustrated in Fig. 10. Using ARIMA (2,2,0), the yearly peak load of the year 2019 and the final year 2026 is forecasted as 59726.5 MW and 74871.5 MW, respectively. Using ARIMA (2,2,1), the peak load value.

increases from 59016.1 MW in 2019–72694.4 MW in 2026. The energy demand of the year 2019 and 2026 is forecasted as 311161.5 GWh and 364017.6 GWh, respectively based on ARIMA (1,2,0). Using ARIMA (1,2,1), the energy demand increases from 310448.2 GWh in 2019–362053.2 GWh in 2026.

3.2. Part B: ANN method

Here, the Multi-Layer Perceptron (MLP) is used as a popular ANN model. Using the ANN technique, as one part of the proposed hybrid method, the yearly peak load of the current year (i.e. 2019) and the final year (i.e. 2026) is forecasted as 60339.2 MW and 76127.0 MW, respectively. Also, the energy demand of the year 2019 and 2026 is forecasted as 315923.2 GWh and 385593.1 GWh, respectively.

3.3. Part C: PSO-SVR method

In order to achieve an optimal SVR algorithm, it is required to

Table 2
Existing yearly peak load and energy demand of Iran National Grid [5].

Year	Peak load (MW)	Energy (GWh)	Year	Peak load (MW)	Energy (GWh)
1991	11209	59710	2004	29267	162871
1992	12065	63982	2005	32253	178072
1993	13384	71335	2006	34269	192535
1994	14369	77086	2007	34983	203983
1995	15251	80044	2008	37651	214280
1996	16109	85825	2009	37878	221314
1997	17513	92310	2010	40239	232994
1998	18821	97862	2011	42367	240063
1999	19805	107207	2012	43459	257265
2000	21347	118441	2013	46474	262192
2001	23062	127169	2014	48937	274480
2002	24750	137814	2015	50321	280689
2003	27107	149676	2016	53198	289196

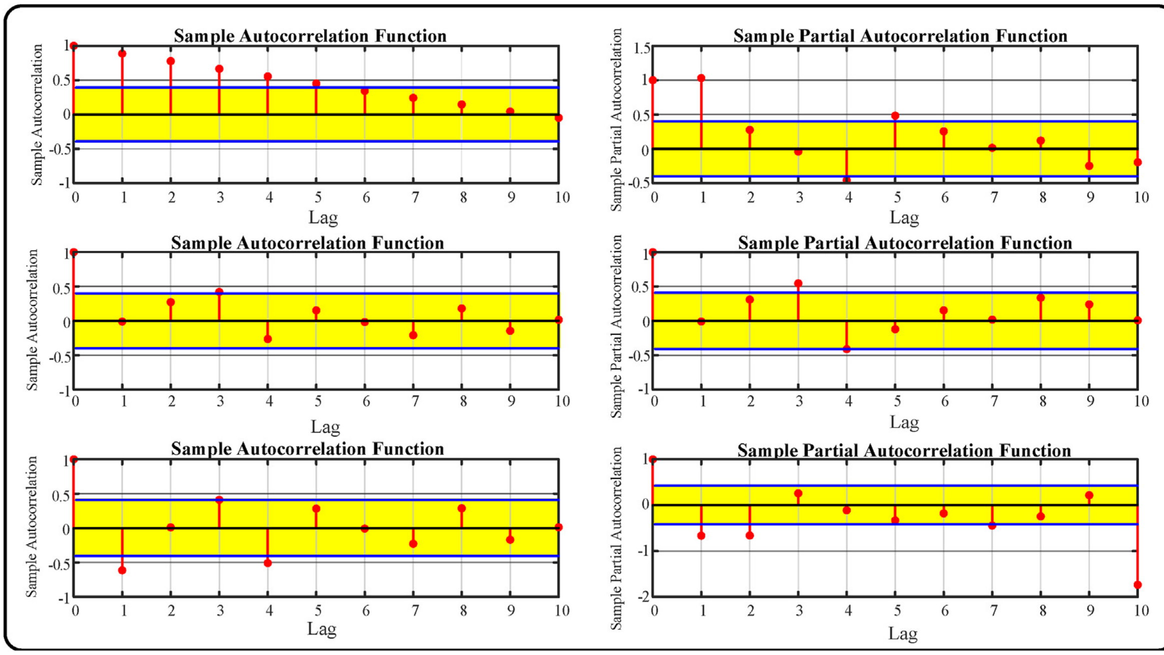

Fig. 7. ACF and PACF of the original and differenced time series of yearly peak load.

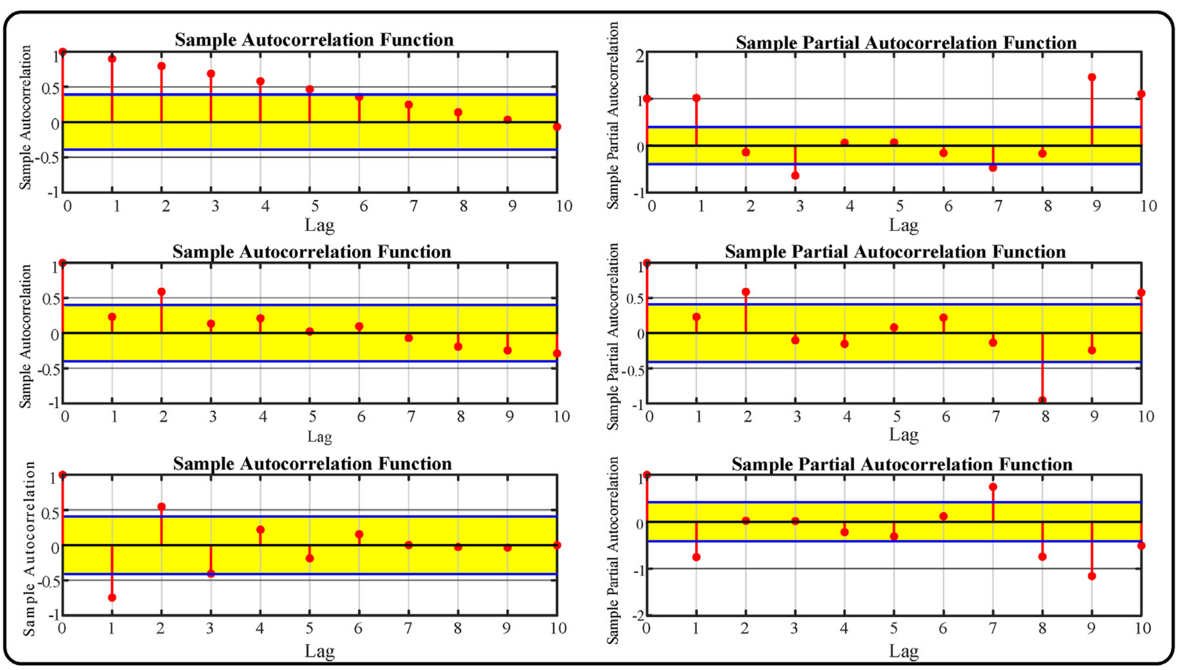

Fig. 8. ACF and PACF of the original and differenced time series of yearly energy demand.

optimize the SVR parameters using an evolutionary optimization method such as the PSO algorithm. In this paper, these parameters are optimized as given in Table 4 and SVR parameters are obtained as given in Table 5. Now, using the optimized SVR, the load and energy demand are forecasted. The yearly peak load of the current year (i.e. 2019) and the final year (i.e. 2026) is forecasted as 59956.2 MW and.

77353.4 MW, respectively. The energy demand for the year 2019 and 2026 is forecasted as 314128.7 GWh and 374298.8, respectively.

3.4. Part D: hybrid method

Each forecasting method has its own advantages and surely a single method is not enough to capture all characteristics and complexity of a time series. Therefore, a hybrid method is required to combine the forecasting results of all individual methods, properly. Regarding these issues, in addition to the proposed PSO-SVR method, a hybrid approach is developed to achieve reliable forecast results. A major advantage of the proposed hybrid method is the combination of analytic time series method and the data

Table 3
Identified parameters and models for the peak load and energy demand time series.

Load	Model type	φ		θ		Energy	Model type	φ		θ	
	ARIMA (2,2,0)	1.055	0.6461	–	–		ARIMA (2,2,0)	0.7502	–	–	–
	ARIMA(2,2,1)	1.271	0.7881	0.3492	–		**ARIMA(2,2,1)**	0.7721	–	0.0476	–

Load	Model type	**Forecasting Model**	**Energy**	Model type	**Forecasting Model**
	ARIMA(2,2,0)	$Y_t = 0.945 \times Y_{t-1} + 0.4639 \times Y_{t-2} + 0.2372 \times Y_{t-3} - 0.6461 \times Y_{t-4} + e_t$		**ARIMA(2,2,0)**	$Y_t = 1.2498 \times Y_{t-1} + 0.5004 \times Y_{t-2} - 0.7502 \times Y_{t-3} + e_t$
	ARIMA(2,2,1)	$Y_t = 0.729 \times Y_{t-1} + 0.7539 \times Y_{t-2} + 0.3052 \times Y_{t-3} - 0.7881 \times Y_{t-4} + e_t + 0.3492 e_{t-1}$		**ARIMA(2,2,1)**	$Y_t = 1.2279 \times Y_{t-1} + 0.5442 \times Y_{t-2} - 0.7721 \times Y_{t-3} + e_t + 0.04764 e_{t-1}$

mining approach which can handle the nonlinearity and seasonal trends in input samples (i.e. input observations). The hybrid proposed method acts based on the standard error criterion of each method.

One of the most important achievements of this research work is the development of a robust hybrid method to maximize the accuracy of peak load and energy demand of the network. This method consists of combining several methods, two of them are the ANN method and the proposed PSO-SVR. In the hybrid proposed method, all methods including the ANN, ARIMA, and the PSO-SVR, have their own weights according to their errors. All the forecasting methods are optimized separately, and then based on their errors, the forecasts are combined to achieve a robust method, named the proposed hybrid method.

In this part, the results of the proposed hybrid method are presented. According to the proposed procedure, the weight of each method for both load and energy demand series is obtained as reported in Table 6. Also, the results of load and energy demand forecasting using the hybrid method are obtained as presented in Table 7. It should be added that in this paper, ARIMA1 and ARIMA2 refer to ARIMA (2,2,0) and ARIMA (2,2,1) in load forecasting and ARIMA (1,2,0) and ARIMA (1,2,1) in energy demand forecasting, respectively.

Both the peak load and energy demand are related to each other by the load factor (LF) which is defined according to (23) and it is around 0.6 in Iran national grid. It is expected to have the approximately same load factor for future or forecasted values of load and energy demand. To this end, the load factors over some existing and the forecasted samples have been illustrated in Fig. 11.

$$Annual\ Load\ Factor = \frac{Yearly\ Total\ Energy\ Demand\ in\ MWh}{Yearly\ Peak\ Load\ in\ MW * 8760\ hour} \tag{23}$$

The computational time of the proposed algorithm over the time series of peak load and energy demand should be investigated. Using a PC with Intel Core i7, 2.8 GHz 7700 CPU, and 16 GB DDR4 RAM, the simulation time of the PSO-SVR algorithm is 0.1221 s. The computational time of the proposed hybrid method is 0.8344 s. It can be seen that the time complexity of the proposed PSO-SVR and the hybrid forecasting methods are acceptable. It is noted that the proposed method is applied for the long term forecasting of yearly peak loads and energy demands in future years and these computational time are acceptable.

3.5. Part E: accuracy validation

In order to assess the performance of the proposed forecasting model, different error measures have been used as the performance criteria. In this part, the mean absolute error (MAE), the mean absolute percentage error (MAPE) and the root mean square error (RMSE) are utilized to assess the performance of forecasting methods [44]. Detailed formulations of error criteria have been given in Refs. [45].

According to Table 8, in the IA error metric, Y_t^a is the actual value of the time series and Y_t^f is the forecasted value. Also, $\overline{Y^a}$ refers to the average of the actual value of the time series (i.e. the existing values), and T represents the total number of existing data [46]. According to these four criteria, errors are given in Table 9.

For calculating these indices, data length was assumed 24 years from 1993 to 2016 for peak load time series and 21 years from 1996 to 2016 for energy demand time series.

According to Table 9, the values of standard error criteria using the hybrid method are significantly lower than other methods. After the hybrid method, the proposed PSO-SVR method gives an acceptable forecasting error. In Table 9, the ANN and PSO-SVR methods give acceptable levels of error but according to the utilized objective function (i.e. MAPE error criterion), the proposed hybrid method is significantly better than the other utilized methods.

Also, because of the inability of the Box-Jenkins (i.e. ARIMA) model in dealing with nonlinearity in input samples, this conventional method, which has been widely used in previous research works, gives higher forecasting error. It should be noted that the incapability of the ARIMA method is due to the sensitivity of this method to noise and seasonal trends.

To investigate the performance of the error criteria in forecasting procedure (i.e. as given in Table 8), the errors of the forecasting models over the existing years (i.e. 1991-2015 for load and 1996–2015 for energy forecasting) have been illustrated in Fig. 12. As expected, the proposed hybrid method gives the highest precision, while the well-known ARIMA method has the lowest accuracy. Also, the PSO-SVR and ANN give acceptable performance in comparison with both ARIMA methods. In order to compare the accuracy and validity of different load and energy demand forecasting methods, the forecasting results over the existing years are plotted in Fig. 13. It can be seen that the proposed SVR-based method, ANN approach, and the hybrid method present the negligible difference between the existing (i.e. actual data) and the forecasting data. Moreover, the MAPE variation is shown in the bottom right of Fig. 13. According to the MAPE index, the proposed hybrid method is the most accurate method with respect to other methods.

4. Discussion

In this part, the obtained load and energy demand forecasting results using all methods are altogether presented in Fig. 14. The yearly peak load of the current year (i.e. 2019) is forecasted as 59726.5 MW, 59016.1 MW, 60339.2 MW 59956.2 MW, and 60055.2 MW using ARIMA (2,2,0), ARIMA (2,2,1), ANN, PSO-SVR,

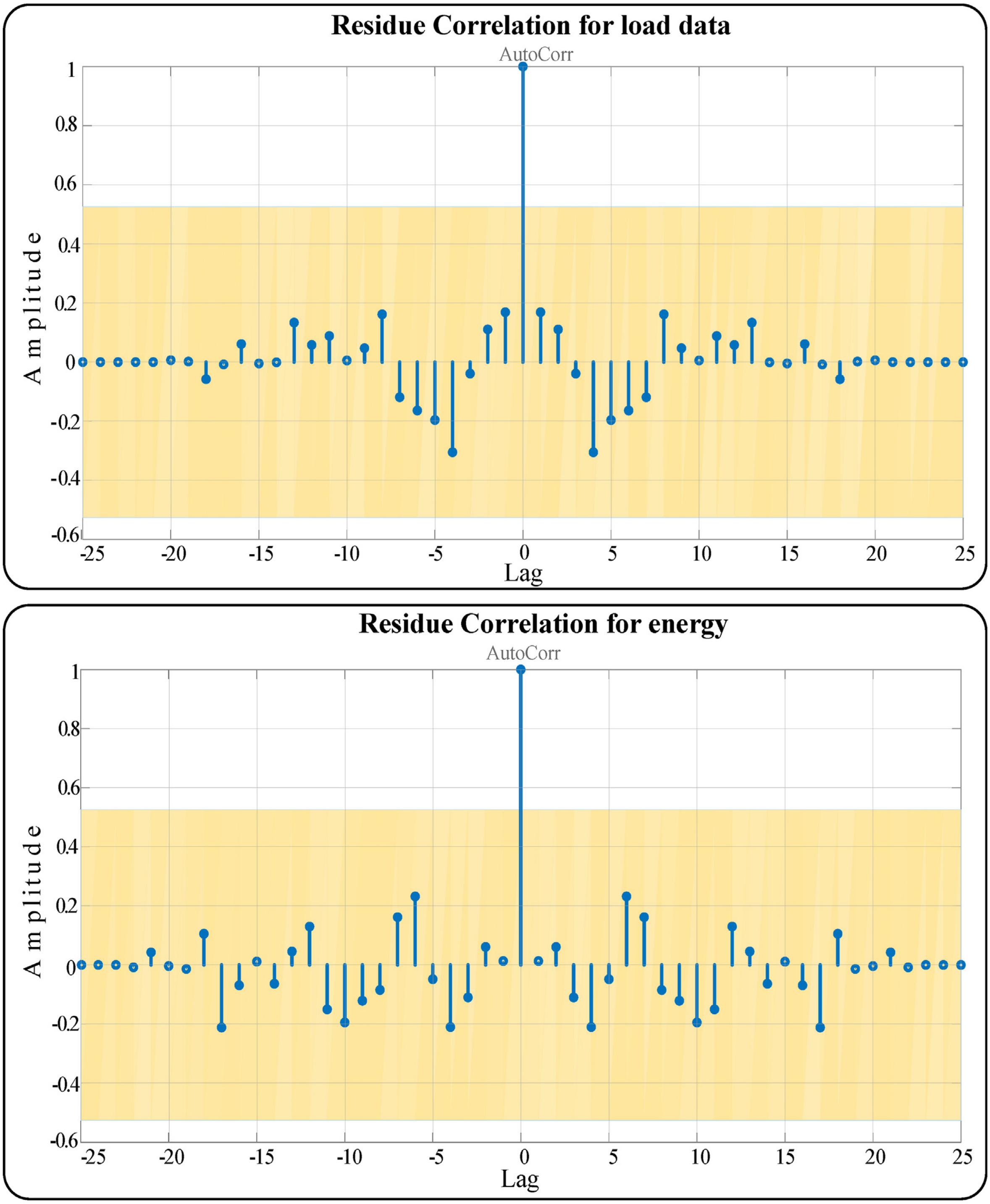

Fig. 9. Autocorrelation of errors of the estimated ARIMA model for peak load and energy demand series.

and hybrid methods, respectively. These forecasts are highly close to the actual peak load occurred in Summer 2019. The peak load at the final year (i.e. 2026) is forecasted as 74871.5 MW, 72694.4 MW, 76127.0 MW, 77353.4 MW, and 76425.0 MW, using ARIMA (2,2,0), ARIMA (2,2,1), ANN, PSO-SVR, and hybrid methods, respectively. The energy demand of the year 2026 is forecasted as 364017.6 GWh, 362053.2 GWh, 385593.1 GWh, 374298.8 GWh, and 383985.1 GWh, respectively. This summer (i.e. 2019), the Iran national grid touched the 60000 MW peak load. As the Iran national grid has a very small capacity reserve during peak hours, assuming a 10% reserve capacity, it is required to construct a generating capacity of 24012 MW (i.e. (76425.0*1.10−60055.2) MW) up to the year 2026. The presented forecast caution that, during the next years the power deficiency or scheduled load interruption is expected in Iran national grid especially during the summer season. Also, due to climate change and global warming, the future summers, all the records of peak loads and energy demand are broken that in turn results in a sharp rise in electricity consumption. Additionally, in the Iran national grid, there is a unique mutual interaction between the gas and electric sectors. The peak of the national electric grid is

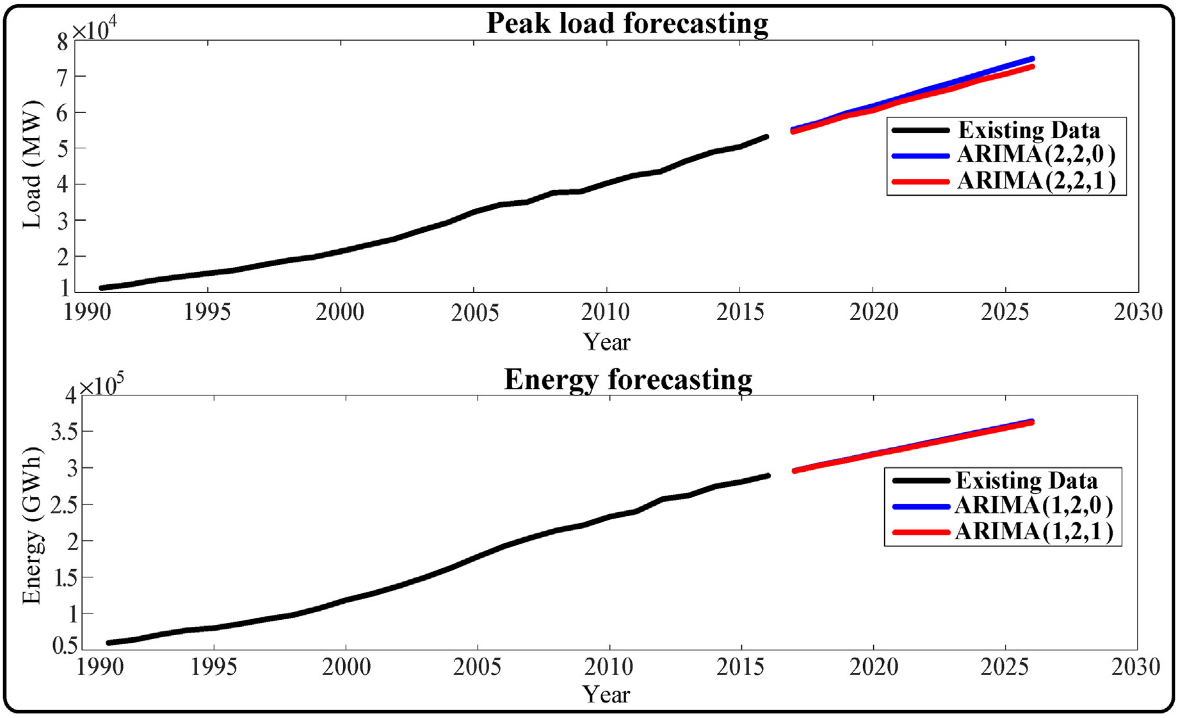

Fig. 10. Peak load and energy demand forecasting using the ARIMA method.

Table 4
Parameters of particle swarm optimization algorithm.

Metric	Definition	Value
N	Number of particles	40
W	Inertia Weight	1
W'	Inertia Weight Damping Ratio	0.99
$C1$	Personal Learning Coefficient	2
$C2$	Global Learning Coefficient	2

Table 5
Parameters of the support vector regression algorithm.

Metric	Definition	Load	Energy
C	Weight coefficient	3763	1000
σ	Kernel width	1	1
ε	Admissible error	9.41	39.48
τ	Number of predictors	5	5

Table 6
wt of different methods in the hybrid method for peak load and energy demand forecasting.

	Weight			
	ARIMA1	ARIMA2	ANN	PSO-SVR
Peak Load	0.0955	0.0396	0.4517	0.4131
Energy	0.0065	0.1188	0.4825	0.3921

occurred during summer, while the peak of natural gas consumption occurs in winter. Most of the natural gas production in Iran is consumed by the domestic sector, while the thermal power plants are the second largest consumers of natural gas. During cold winter, the access of thermal power plants to natural gas is limited due to the priority of other sectors such as household consumption for heating purposes. Therefore, during cold winter, some of the thermal power plants must either switch to alternative fuels (e.g. gasoil, mazut, or heavy oil) or shut down. Due to air pollution regulations and natural gas shortage, the electric sector is affected by the gas sector, significantly. To this end, it seems that most of the required generation capacity to meet the forecasted load and energy demand should be provided by clean renewable resources such as wind and solar power.

In [13], the long-term electrical energy consumption of the Iran national grid has been forecasted. In Ref. [13] a multivariate method is applied for forecasting energy consumption including historical Electrical Energy Consumption (EEC) and socio-economic indicators. In Ref. [13], the energy demands of the period 2010 to 2016 is forecasted using the historical data from 1967 until 2009. For making a clear and fair comparison, the proposed method is used to forecast the energy demand at the same horizon (i.e. from 2010 to 2016). In Fig. 15, the results of the proposed method and the proposed method in Ref. [13] are compared with the actual energy demands.

Also, the standard errors of both methods are reported in Table 10. It can be seen that the proposed method gives more accurate results, while the results reported in Ref. [13] are far from the actual values.

The proposed hybrid method is applied over another existing grid named Tehran Regional Electric Company (TREC) as the largest electric company in Iran.

In TREC, the long-term peak load is forecasted from 2018 till 2027 using five similar methods including the ARIMA method, the PSO-SVR method, the ANN method and finally the proposed hybrid method. It should be added that ARIMA1 and ARIMA2 refer to ARIMA (2,2,0) and ARIMA (2,2,1). The forecasting results are given in Table 11. It can be seen that the peak load of TREC reaches to 14012.10 MW in 2027. According to Table 11 and Fig. 16, the proposed hybrid method results in the least possible error. As given in Table 12, the proposed hybrid method has the lowest error.

As it is shown in Fig. 16, the years from 2002 until 2016 are

Table 7
Results of yearly peak load and energy demand forecasting using different methods.

		Year									
		2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
Load (MW)	**ARIMA1**	55197.5	57157.9	59726.5	61678.9	63888.2	66224.7	68261.1	70531.8	72749.3	74871.5
	ARIMA2	54553.8	56666.8	59016.1	60468.3	62874.7	64775.1	66566.7	68895.4	70627.1	72694.4
	ANN	55751.7	57954.6	60339.2	62754.5	65078.9	67375.6	69648.4	71866.5	74026.2	76127.0
	PSO-SVR	55134.2	57168.7	59956.2	61917.9	64455.6	67100.4	69339.6	72155.1	74762.5	77353.4
	Hybrid	55372.3	57472.4	60055.2	62183.2	64596.2	67038.2	69254.2	71751.6	74102.1	76425.0
Energy (GWh)	**ARIMA1**	295979.1	304055.4	311161.5	318995.5	326283.5	333981.1	341371.3	348992.2	356440.0	364017.6
	ARIMA2	295622.6	303655.4	310448.2	318198.3	325209.3	332791.0	339932.0	347413.3	354631.8	362053.2
	ANN	298580.7	307526.1	315923.2	325087.4	334510.1	343594.2	352944.6	363258.3	374137.7	385593.1
	PSO-SVR	297202.3	305212.9	314128.7	322571.0	331555.0	340195.5	348903.8	357455.7	365903.5	374298.8
	Hybrid	303376.4	312251.9	321575.5	330636	339895.6	348925.9	357882.9	366705.1	375381.6	383985.1
Load Factor	**PSO-SVR**	0.6153	0.6094	0.5981	0.5947	0.5872	0.5787	0.5744	0.5655	0.5586	0.5523
	Hybrid	0.6133	0.6084	0.5986	0.5955	0.5895	0.5829	0.5793	0.5733	0.5690	0.5655

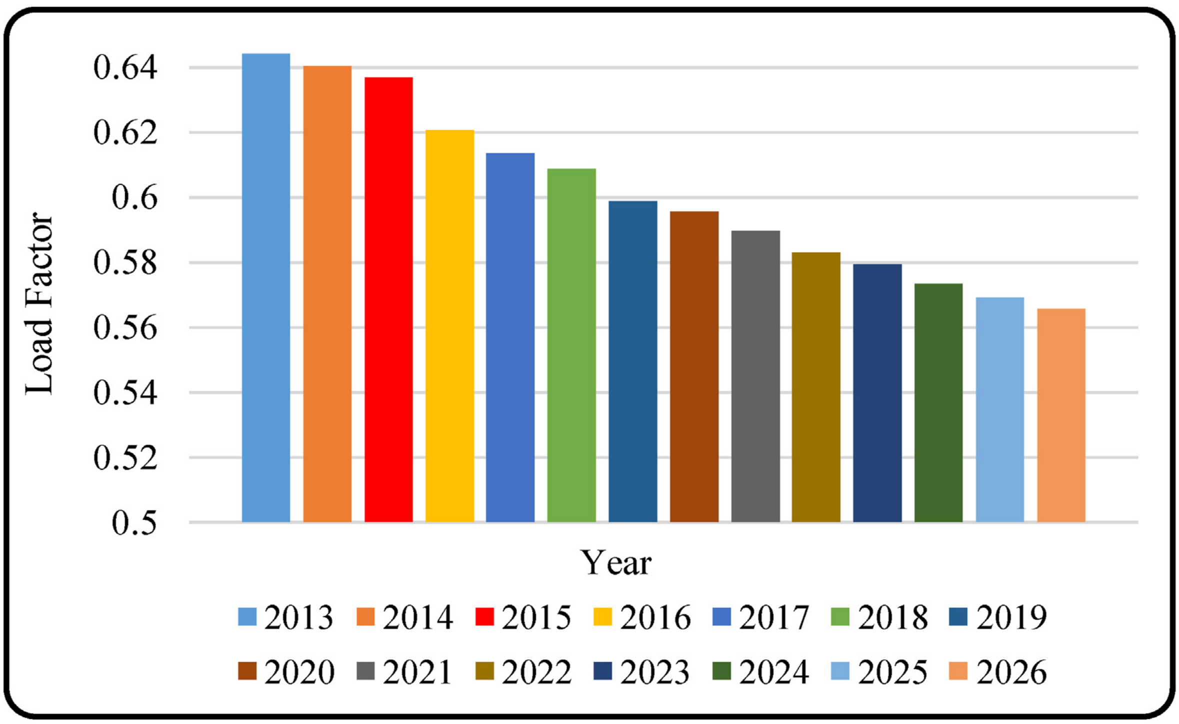

Fig. 11. Load Factor of the hybrid method for some of the existing and forecasting years.

Table 8
Definitions and formulation of different metrics utilized for error calculation.

Metric	Definition	Equation
MAE	The mean absolute of errors	$\textbf{MAE} = \frac{1}{T}\sum_{t=1}^{T}\left\|Y_t^a - Y_t^f\right\|$
RMSE	The root mean square of errors squares	$\textbf{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^a - Y_t^f\right)^2}$
MAPE	The mean absolute percentage of errors	$\textbf{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\left\|\frac{Y_t^a - Y_t^f}{Y_t^a}\right\| \times 100\%$
IA	Index of Agreement	$\textbf{IA} = 1 - \frac{\sum_{t=1}^{T}\left(Y_t^a - Y_t^f\right)^2}{\sum_{t=1}^{T}\left(\left\|Y_t^f - \overline{Y^a}\right\| + \left\|Y_t^a - \overline{Y^a}\right\|\right)^2}$

Table 9
Results of errors for both peak load and energy demand forecasting.

	PEAK LOAD				ENERGY			
	MAE	**RMSE**	**MAPE%**	**IA**	**MAE**	**RMSE**	**MAPE%**	**IA**
ARIMA1	6371.43	8392.84	16.29	0.83	160884.2	171618.3	85.3	0.39
ARIMA2	7159.99	9209.98	18.79	0.80	44609.25	54988.54	19.97	0.76
ANN	476.90	691.61	1.50	0.99	3510.59	4321.50	2.51	0.99
PSO-SVR	416.07	567.37	1.44	0.99	2234.89	2697.76	1.40	0.99
Hybrid	294.00	573.01	0.97	0.99	1558.51	3243.86	0.87	0.99

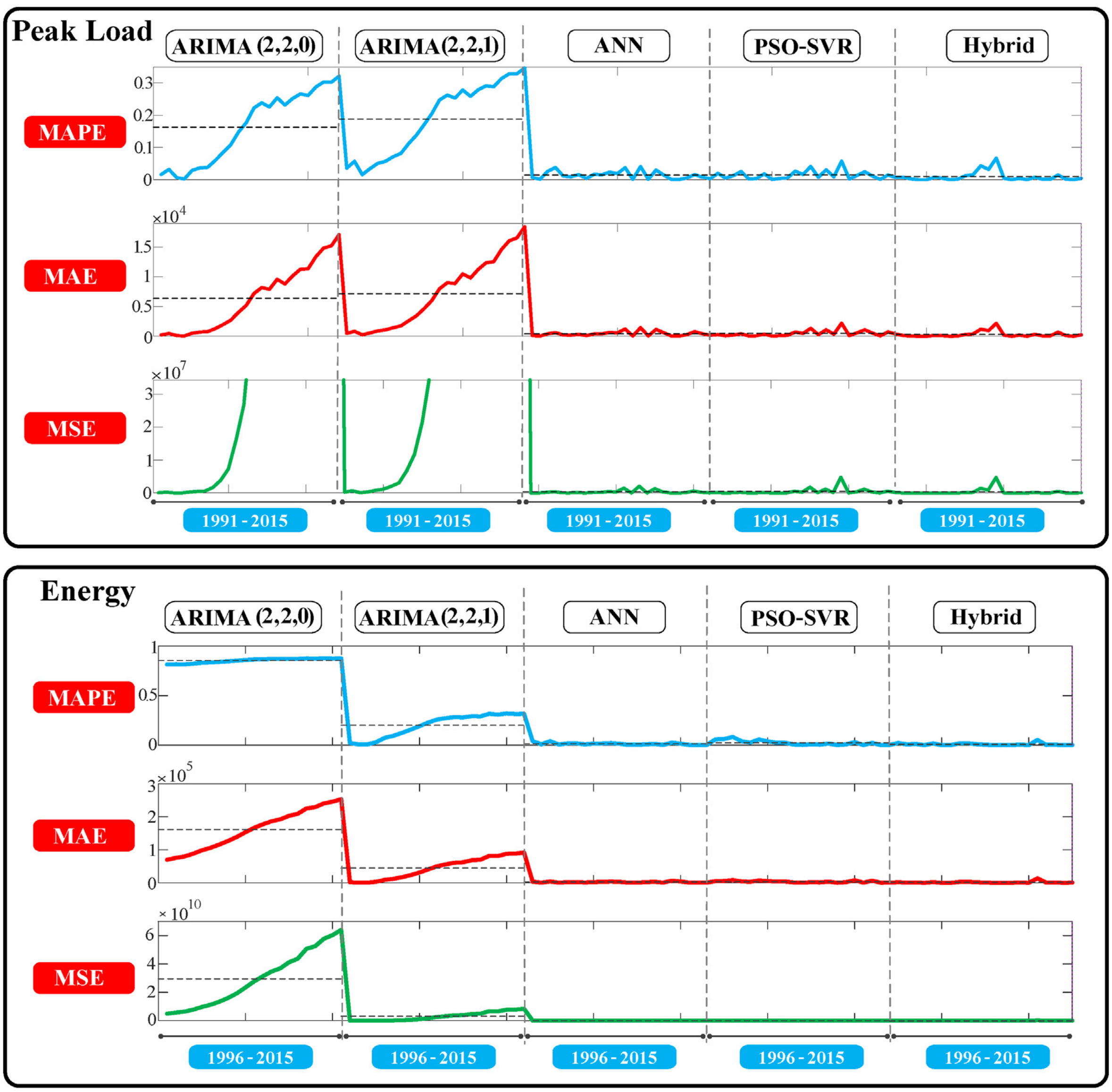

Fig. 12. Errors comparison for peak load and energy demand.

assumed to check the accuracy of the utilized methods. According to Fig. 16, the results of the proposed hybrid method is close to the actual data. Indeed, the lowest value of the MAPE index is achieved using the proposed hybrid method. It can be concluded that the proposed method keeps its performance regardless of the utilized test case.

In another study, the results of the proposed forecasting method are compared with the grey method as proposed in Ref. [47].

In order to give a fair comparison between the proposed hybrid method and the grey method, the input data related to the grain production of China in ten thousand tons (as given in Ref. [47]), are used as the dependent variable (i.e $\boldsymbol{X}_1^{(0)}$ as given in Ref. [47]). This dependent variable is affected by many factors such as the irrigated area ($\boldsymbol{X}_2^{(0)}$, Thousand hectares), the total mechanical power ($\boldsymbol{X}_3^{(0)}$, Ten thousand kilowatts), the amount of fertilizer ($\boldsymbol{X}_4^{(0)}$, Ten thousand tons) and the sown area ($\boldsymbol{X}_5^{(0)}$, Thousands of hectares). These

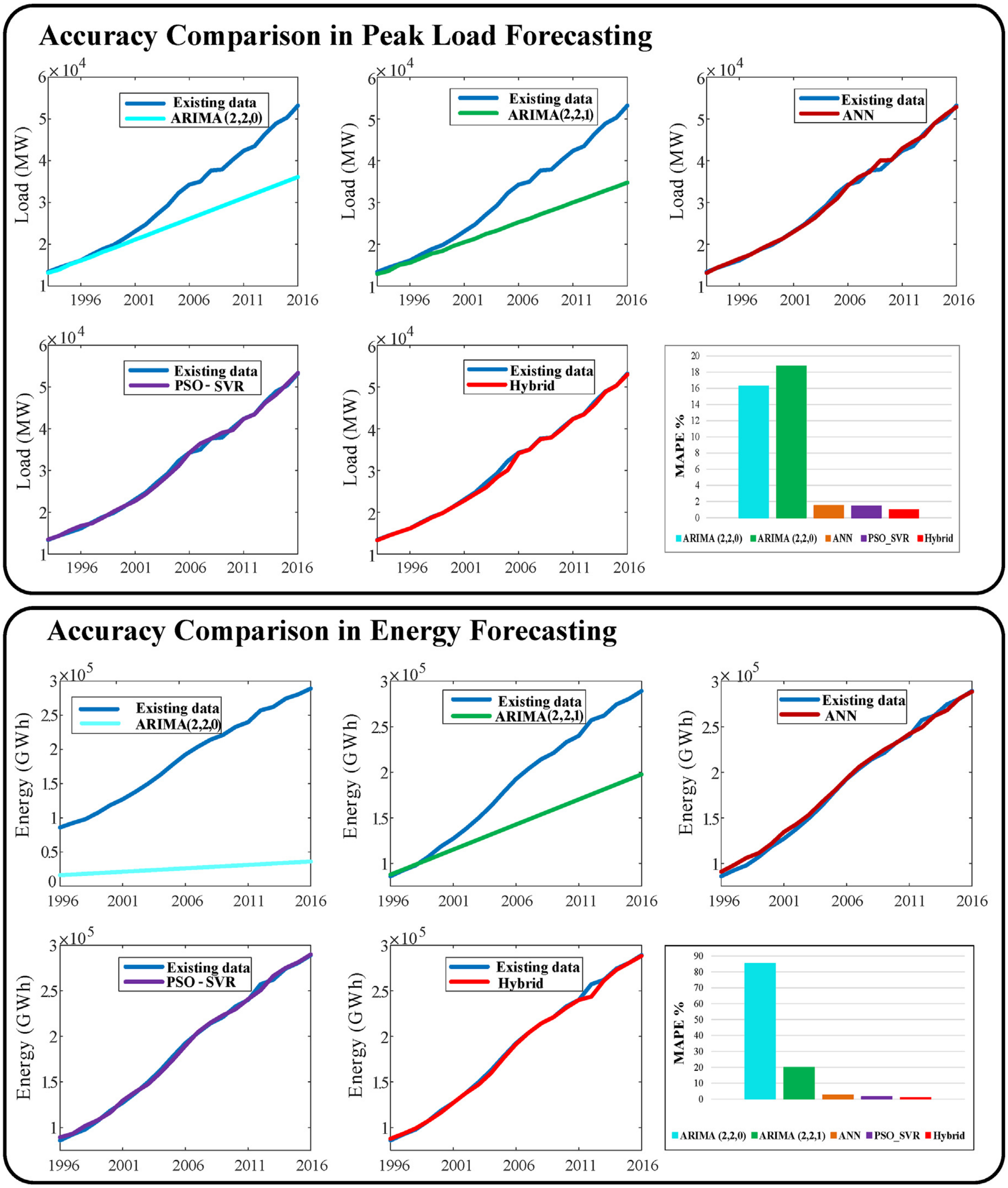

Fig. 13. Comparison of forecasting accuracies for peak load and energy demand.

data are used as the input of the forecasting model from 2003 till 2015. Then, the future ten years are assumed as the forecasting horizon for grain production forecasting from 2016 till 2025.

The forecasting results using the proposed methods of the present paper are given in Table 13. Also, by considering the years from 2007 until 2015 the accuracy of all methods is checked in Fig. 17. According to Fig. 17, the proposed hybrid method gives the highest accuracy. This can be verified according to the MAPE index that is illustrated in the bottom right of Fig. 17.

5. Conclusions

In this paper, a comprehensive univariate model was presented for long term yearly peak load and energy demand forecasting. It was shown that the proposed PSO-SVR and hybrid methods give more accurate results rather than ARIMA and ANN methods. The proposed algorithm is a general approach that can be applied to any other electric energy system. The major findings of this paper are summarized as follows: 1) The ARIMA methods may results in undesired overestimation or underestimation in load and energy demand forecasting results. 2) The PSO-SVR method is capable to

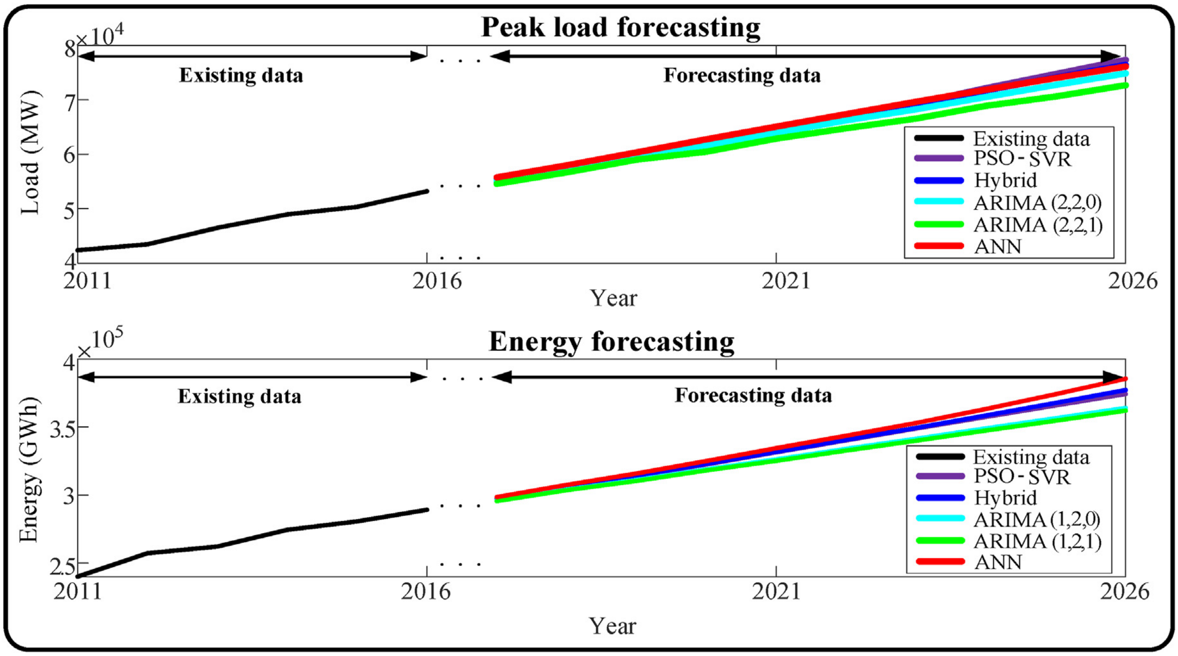

Fig. 14. Results of all utilized methods for peak load and energy demand forecasting.

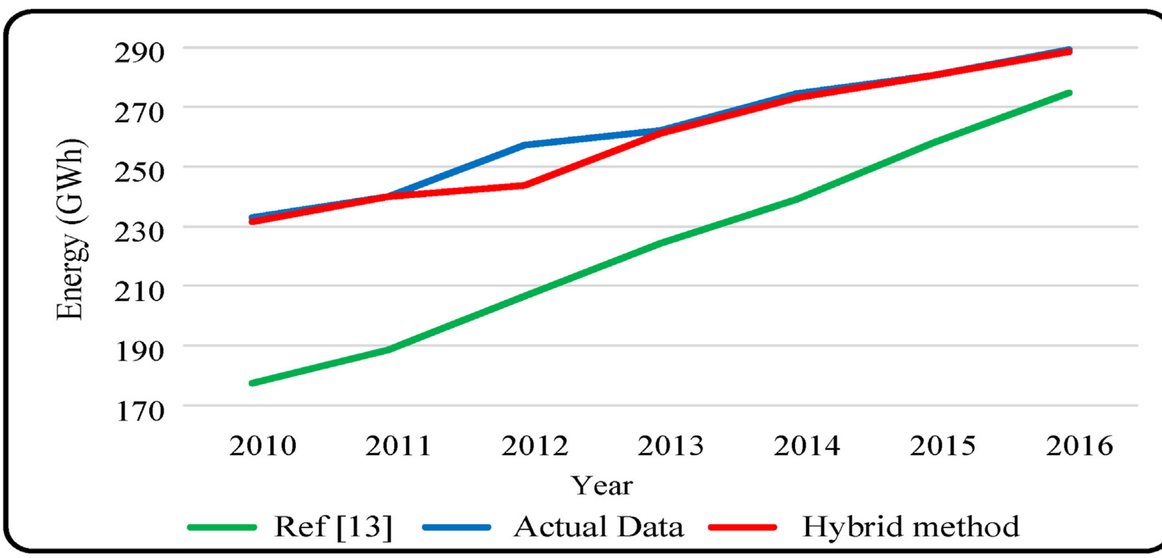

Fig. 15. A comparison between the results of this paper and ref [13].

Table 10
Comparison of error criteria for hybrid method and ref [13].

	Error Criteria for Energy		
	MAPE%	MAE	RMSE
Hybrid method	0.8761	1558.51	3243.86
Ref [13]	15.06	38325.76	40925.49

Table 11
Results of yearly peak load forecasting in TREC in MW.

	Methods				
Year	ARIMA1	ARIMA2	ANN	PSO-SVR	Hybrid
2018	9680.70	9670.42	9901.81	9521.31	9821.10
2019	10020.58	10000.19	10347.58	9789.11	10228.18
2020	10364.24	10339.39	10787.73	10007.00	10627.86
2021	10708.55	10673.25	11236.25	10304.03	11040.47
2022	11051.70	11010.13	11809.95	10515.14	11533.57
2023	11395.51	11345.31	12340.18	10795.42	12002.36
2024	11739.09	11681.45	12876.17	10977.99	12466.17
2025	12082.71	12017.04	13436.79	11235.03	12954.27
2026	12426.34	12352.94	14066.08	11386.50	13481.04
2027	12769.96	12688.67	14691.56	11612.95	14012.10

forecast the load and energy demand with small errors without any sensitivity to seasonal trends in the original time series. The reliable forecasts are obtained provided that the SVR parameters are set optimally using an optimization method such as the PSO algorithm.
3) The hybrid forecasting method based on the circuit current division rule is a powerful method to benefit from all forecasting

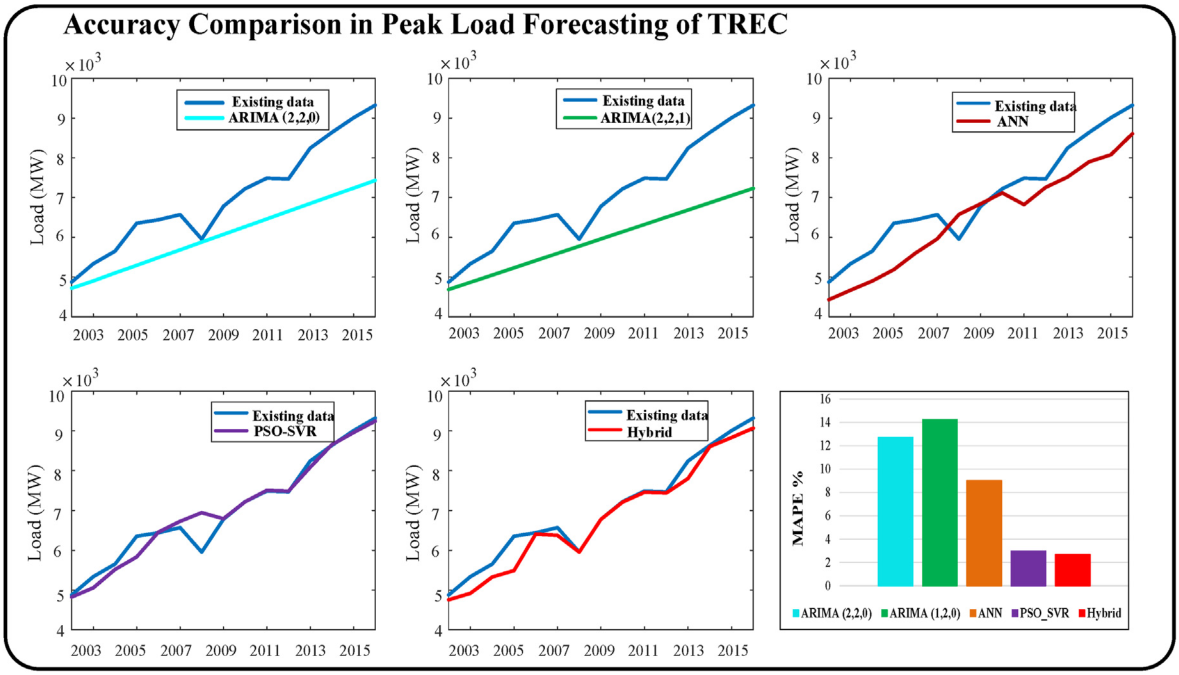

Fig. 16. Comparison of forecasting accuracy for the peak load of TREC.

Table 12
Results of errors for peak load forecasting in TREC.

Method	Error criteria MAE	RMSE	MAPE%	IA
ARIMA1	950.03	1084.25	12.70	0.7907
ARIMA2	1064.40	1205.80	14.24	0.7489
ANN	616.10	681.18	9.01	0.9307
PSO-SVR	194.99	302.81	2.96	0.9868
Hybrid	166.49	306.52	2.68	0.9860

methods based on their errors. 4) The MAPE percentage error metric is a suitable performance criterion for load and energy forecasting. 5) Since the load factor has small variations during the forecast horizon, the peak load and energy demand forecasts can be verified regarding the load factors over the existing years. 6) The presented forecast warns that during the next years the power deficiency or scheduled load interruption is expected in Iran national grid especially during summer seasons and it is required to accelerate the generation expansion plans. The primary fuel in thermal power plants in Iran's national grid is natural gas. Due to the priority of household gas consumption, the access of thermal power plants to natural gas is limited during cold winter. Due to air pollution regulations and natural gas shortage during the winter season, the electric sector is affected by the gas sector, significantly. To this end, it seems that most of the required generation capacity to meet the forecasted load and energy demand should be provided by clean renewable resources such as wind and solar power. The multivariate methods consider other important factors in load forecasting such as climate changes and global warming. The enhancement of the hybrid univariate method using a multivariate method is an open question that can be addressed in our future research works.

Table 13
The grain production forecasting results of China by the utilized methods of the paper.

$X_1^{(0)}$ (Ten thousand tons)					
Year	ARIMA1	ARIMA2	ANN	PSO-SVR	Hybrid
2016	63004.24	63268.47	63353.12	63418.13	63288.01
2017	64164.89	64500.61	64307.39	64704.29	64480.36
2018	65183.01	65696.22	65652.58	65973.25	65692.77
2019	66265.63	66904.24	66660.13	67229.94	66859.27
2020	67319.92	68108.05	67845.44	68473.69	68043.00
2021	68386.40	69313.28	69009.42	69704.75	69220.52
2022	69447.71	70518.03	70096.14	70923.24	70378.06
2023	70511.19	71722.95	71312.11	72129.26	71552.56
2024	71573.77	72927.80	72420.01	73323.02	72703.04
2025	72636.72	74132.68	73612.65	74504.55	73862.57

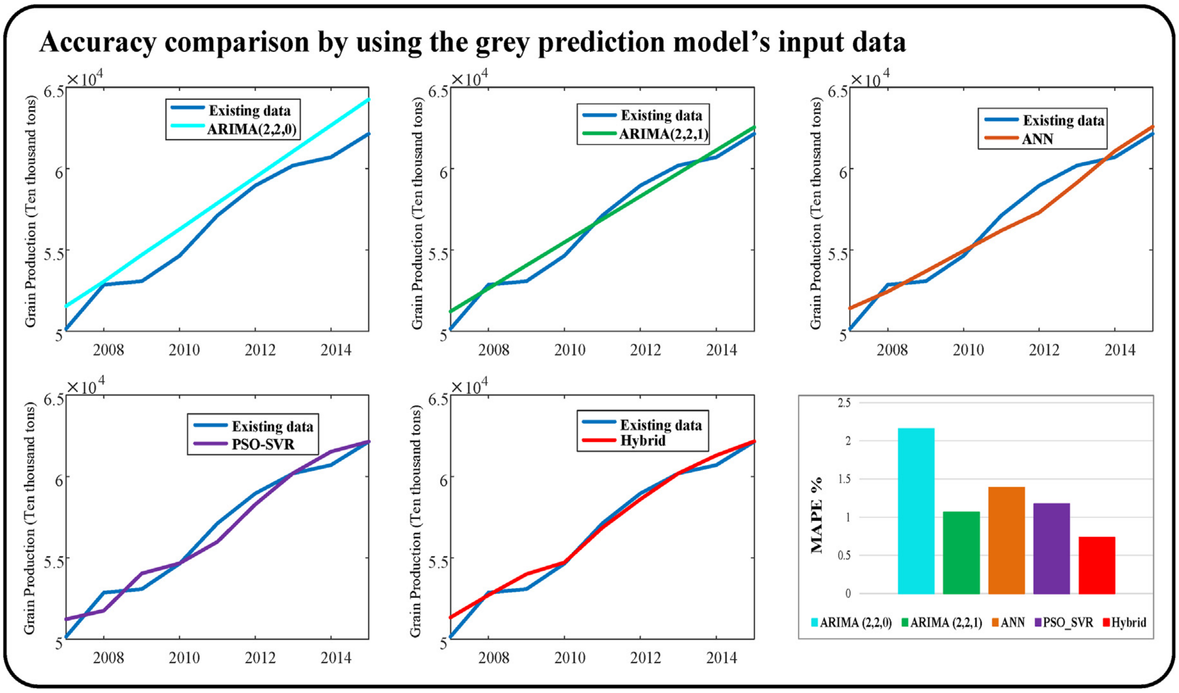

Fig. 17. Comparison of forecasting accuracy for grey model's input data.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Mohammad-Rasool Kazemzadeh: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Ali Amjadian:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Turaj Amraee:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization.

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