

Short term load forecasting using evolutionary algorithm for Tajikistan

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Article Info

Article history:

Received Dec 27, 2022

Revised Jan 15, 2023

Accepted Feb 6, 2023

Keywords:

Load forecasting

Meteorological

Particle swarm optimization

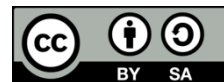
Support vector machine

Tajikistan

ABSTRACT

Load forecasting is a significant element in the energy management system of power systems. Precise load forecasting aids electric utilities to conduct decisions of unit commitment, reduction of spinning reserve capacity, and schedule device maintenance plan. Furthermore, load forecasting contributes to reducing the generation cost, and it is fundamental to the reliability of the power systems. On the other hand, short-term load forecasting is substantial for economic running. The forecasting precision directly affects the reliability, economy running and supplying power quality of the power system. Hence, finding the required load forecasting method to enhance the accuracy is valuable for forecasting precision. This paper proposed particle swarm optimization (PSO) to improve working support vector machine (SVM), SVM regression model is derived; also derived SVM with PSO. Support vector machine (SVM) model is adopted with and without PSO based on the historical load data and meteorological data of Tajikistan country, analysis the various factors affecting the forecast. The historical data and the load forecasting factors to be considered are normalized. The two parameters of SVM significantly influenced the model, and therefore it optimized using evolutionary algorithm.

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1. INTRODUCTION

Tajikistan has a population of 10 million people with total area of 143,100 km². Total installed capacity of electrical power station is 6178 MW (hydro–5578, thermal–598 MW) with annual power generation of 20 billion kW/h. Tajikistan relies almost entirely on hydropower. Tajikistan has huge reserves of hydropower resources, which is annually above 500 billion kWh. Technically, the hydropower resources of Tajikistan are promising for development and consist of 317 billion kWh yearly, of which only 4-5% have been used so far. In terms of its hydropower generation, Tajikistan ranks eighth in the world after China, Russia, the USA, Brazil, Zaire, India and Canada, and first in Central Asia. Hydropower is the foundation of Tajikistan's energy sector by 95 percent or more [1]–[3]. However, 70% of people suffer from extensive shortage in winter. Peaks demand comes during winter when the flow of river is low and people use conventional heaters. Electricity network losses are extremely high in Tajikistan amounting to more than 24%.

Compared to the Central Asia countries, Tajikistan's hydropower generation is three times the energy consumption of the other five countries. The region can be supplier by inexpensive and environmentally

friendly energy if these resources used efficiently. The main potential of hydropower electricity is concentrated around the Pyanj, Vakhsh, Kafernigan, and Zeravshan rivers [4], [5]. The energy system of Tajikistan is currently divided into three parts: Southern part, Northern part and Central part. Year after year, there is an increase in electricity consumption in all cities of the republic, especially in the northern part of the Tajikistan, especially in the Sughd region [6].

This area is industrial, in which plants and factories are built. Actual issues are forecasting the electricity consumption of consumers in the Northern part. Since the throughput of the Dushanbe-Sughd transmission lines with a voltage of 500 kV decreases year after year. It is necessary to predict the daily schedule of the electric load of the region in order to determine the peak load in winter and summer seasons. Currently, three major projects for the reconstruction of hydroelectric power plants are being implemented in the energy system of Tajikistan, including reconstruction of the Nurek hydroelectric power plant with a capacity of 3000 MW, Kairokkum hydroelectric power plant of 126 MW, and Golovnaya hydroelectric power plant with 240 MW. The reconstruction of large hydroelectric power plants complicates the task of regulating the modes of operation of the energy system of Tajikistan in the direction of electricity generation. In this direction, the implementation of forecasting the electricity consumption of the Northern and Southern parts of Tajikistan is relevant. Tajikistan is also connected with the energy systems of the neighboring countries of Afghanistan and Uzbekistan, with which it has an agreement on the transmission of electricity in the winter and summer periods of the year.

On the subject of forecasting daily schedules of electrical loads in the energy system of republic of Tajikistan, a study was carried out based on the method of principal components [7], [8]. This forecasting method is used to predict long-term daily schedules of electrical loads [8]. For the energy system of Tajikistan, current problems are short-term forecasting of daily schedules of electrical loads for consumers in the Northern part of the energy system [9]. Since in the Northern part of the energy system there is only one hydroelectric power station with a capacity of 126 MW, and the total load of the region is 980 MW.

The implementation of short-term forecasting of the daily schedule of the electrical load of consumers in the northern part of the energy system of Tajikistan based on the method of support vector machine [10]. Since this method has the least error and is widely used for short-term forecasting of consumers of power systems. Daily data of electricity consumers in the Northern part of the energy system were received from the energy company OAHK "Barki Tojik".

2. PROBLEM FORMULATION

2.1. Support vector machine

Vapnik invented the support vector machine (SVM) in 1995, which is a classification and regression technique [11]. Hence, the SVM is used for the applications of this study. A brief review to the theory beyond the utilization of SVM for function estimation is introduced next with the relevant terms and parameters, especially, the parameters whose influence load forecasting. In this context, this overview is vital to understanding the performance evaluation, and more statistical description and derivations of SVM can be found in these survey studies [12]–[14].

Suykens [15], proposed SVM and compared with other methods. SVM has less parameters candidate instead of the original inequality constraints and equality constraints, reduce some of the uncertainty factor. The loss function of SVM is defined as the sum of squared errors of the optimization of inequality constraints. Hence, the quadratic programming reduces the computational complexity and accelerate solution when using in solving such linear equation system. Minimization principle, structure, SVM optimization objectives can be formulated as (1),

$$\min J = \frac{1}{2} \|\omega\|^2 + \frac{1}{2} \gamma \sum_{i=1}^l e_i^2 - \sum_{i=1}^l \lambda_i (\omega^T \phi(x_i) + b + e_i - y_i) \quad (1)$$

where: (x_i, y_i) , $i = 1, \dots, l$, $x_i \in R^d$ is a data point set related to forecast the impact of factors such as historical load and meteorological factors, d is the number of dimensions of the selected input variables, $y_i \in R$ is the expected value of the predicted amount if the total number of points are known. $\phi(x)$ is a nonlinear mapping from input space to a high dimensional feature space, e_i error, $e \in R^{l \times 1}$ is the error vector, γ is the parameter of regularization controls error punishment. λ the lagrange multiplier, $\lambda \in R^{l \times 1}$ and b is coefficient of regression.

Nonlinear predictive model expression:

$$y = \sum_{i=1}^l \lambda_i K(x_i, x) + b \quad (2)$$

$K(x, x_i)$ is the kernel function,

$$K(x, x_i) = \exp(-\|x - x_i\|^2/\sigma^2) \quad (3)$$

where: x is the input vector (with m -dimension), x_i is the i -th center of the radial basis function, and x has the same dimension as well, σ the standardized parameter determines the width of the function, and the norm of the vector is determined by $\|x - x_i\|$, that refers to the distance of x to x_i which is the radial basis function of a high-dimensional space non-linear transformation. In addition, the simple form, only one parameter needs to be adjusted. The Kernel width coefficient σ indicates the correlation degree among the support vector learning sample input space, the larger range of the sample input space leads to greater σ value. σ make small, the support vectors relaxation, relatively complex machine learning, generalization ability is guaranteed. However, σ make large, support vector affects very strong regression model will difficulty achieved with sufficient accuracy. Also, this is same about the γ regularization parameter, which control error punishment. Therefore, appeared to need an evolutionary algorithm to optimize the values of these parameters, which is, in this paper, particle swarm optimization.

2.2. Particle swarm optimization

The PSO technique is an evolutionary algorithm that is inspired by the behavior of bird flocking, and firstly developed by Eberhart and Kennedy [16]. The PSO algorithm seeks the best solution by imitating the movement of the swarm of birds. The algorithm firstly initializes random swarm of birds as a search space, in which, every bird is a particle. Next, the particles move with a specific velocity reaching the best global position over a number of iterations. In each iteration, each particle adjusts its velocity based on the momentum, the effect of its best position, and the best position of adjacent particles. The algorithm computes the new position of that “particle” [17].

Some of the beneficial merits of the PSO may include: uncomplicated implementation, and the unconditional information of the gradient information. It is also useful in solving a large variety of different optimization problems. Some examples for the applications of SVM may include the training of neural networks and minimization of functions. In PSO technique, the number of particles is initialized randomly, which include positions, velocities, individual best fitness values ($pbest$), and global best fitness value ($gbest$). The commonly used approach of PSO employes local best fitness values ($lbest$), so the particles belong a topological neighborhood. The size of neighborhood is defined at initialization stage, and the best fitness value is achieved within any neighborhood that refers to as the local best fitness value for particles included in that definite neighborhood [18]–[20].

$$v_{i,j}(t+1) = \omega v_{i,j}(t) + c_1 r_{1,i}(t)(p_{i,j}(t) - w_{i,j}(t)) + c_2 r_{2,i}(t)(p_{i,j}(t) - w_{i,j}(t)) \quad (4)$$

The next position is obtained by adding the new velocity to the current position as follows:

$$w_i(t+1) = w_i(t) + v_i(t+1) \quad (5)$$

where the value the velocity vector v_i is ranged as $[-v_{max}, v_{max}]$ for reducing the likelihood of the particles leaving the search space. The value of v_{max} is defined as $v_{max} = k \times w_{max}$, where $0.1 \leq k \leq 1$ and w_{max} is the domain of search space. However, the values of w_i are not restricted with the domain of $[-v_{max}, v_{max}]$. Rather, it barely limits the maximum distance of the particle movement. On the other hand, the acceleration coefficients $c1$ and $c2$ control the travel distance of the particle’s movement at single iteration. Thus, both are set to a value of 2, although the setting of $c1 \neq c2$ could results in a good performance [21], [22]. The inertia weight ω in (6) is employed to drive the convergence of the PSO. Generally, the inertia weight ω is based on the following formula [23]–[25]:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} iter \quad (6)$$

where, $iter_{max}$ is the maximum iterations, and $iter$ is the number of the current iteration. Usually, small values of ω can results in a rapid convergence on a sub-optimal position. Whereas, too large values of ω might restrain divergence. The regular implementation of the PSO relays on the training stage values and linearly decreases from 1.0 to 0 over the iterative execution. Thus, convergence is ultimately obtained by fixed values.

3. CASE STUDIED

The SVM method is applicable to short-term load forecasting of power systems based on the following support vector machine regression algorithm:

- The training set is $S = \{(x_1, y_1), \dots, (x_l, y_l)\} \subset R^n \times R$.
- Select appropriate positive number σ and γ , Select the appropriate Kernel function $K(x, x')$.
- Construct and solve the optimal solution of the optimization problem.

$$\alpha = (\alpha_1, \alpha_1^*, \dots, \alpha_l, \alpha_l^*)^T$$
- Construct decision function $f(x) = \sum_{i=1}^l (\alpha_i^* - \alpha_i) K(x_i, x) + b$, b value is calculated as follows:

$$b = y_i - \varepsilon - \sum_{i=1}^l (\alpha_i - \alpha_i^*) K(x_j, x_i) \quad \alpha_j \in (0, C) \quad (7)$$

$$b = y_i + \varepsilon - \sum_{i=1}^l (\alpha_i - \alpha_i^*) K(x_j, x_i) \quad \alpha_j^* \in (0, C) \quad (8)$$

- The decision function of future load forecast.

As in the flowchart shown of Figure 1, the PSO is used to optimized SVM, by selecting the optimum values of SVM parameters [26].

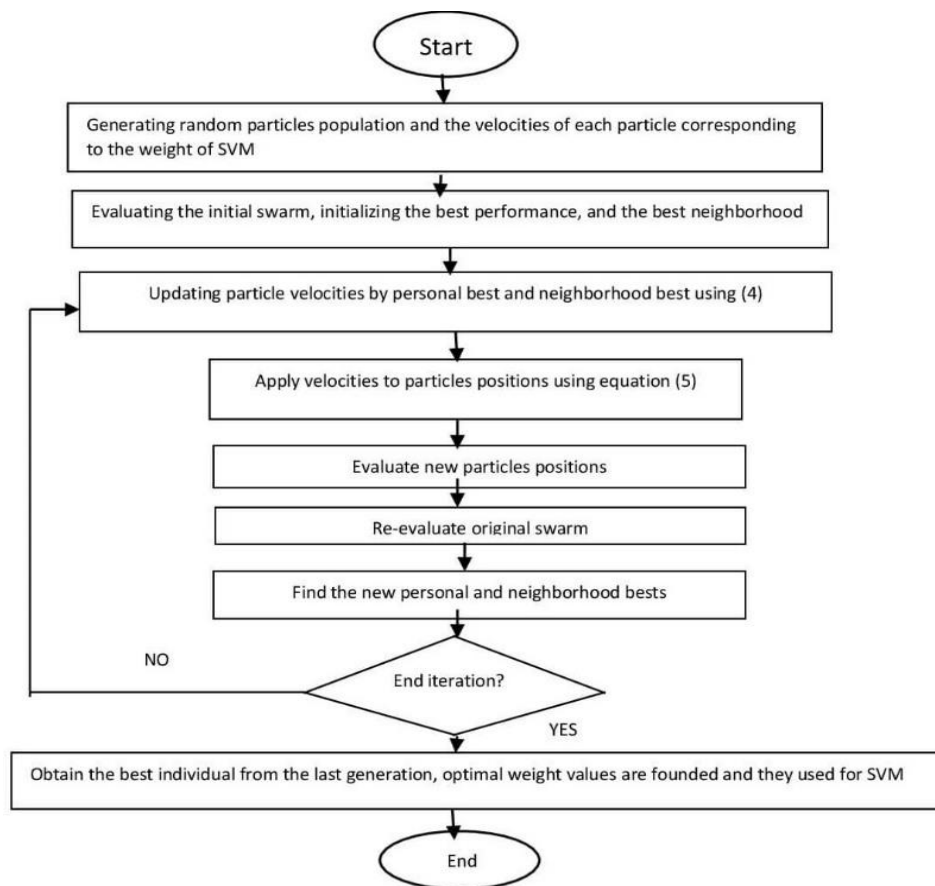


Figure 1. Flowchart of training and testing the SVM using PSO algorithm

4. SIMULATION RESULTS

The simulation environment MALAB2020a. The input data taken from the Tajikistan for the interval 2018–2020, which contain daily electrical demand, daily air temperature and type of day, while the output presented the load data for the next day. The load forecasting curve and the actual load curve for one day in different session are shown in Figures 2 to 5. In order to overcome the causal factors, Table 1 lists the predicted results of multiple samples. To estimate this method used the mean absolute percentage error (MAPE).

Table 2 lists MAPE for each session according to values of γ, σ optimized by using PSO, in fact, these values depend on data, which is clear from this table.

$$MAPE = \frac{|p^{Forecast} - p^{Actual}|}{p^{Actual}} \cdot 100\% \tag{9}$$

Where: p^{Actual} actual power, and $p^{Forecast}$ is forecasting power.

Table 1. MAPE of SVM for different year session $\gamma = 30, \sigma = 2$

Session	Sumer	Winter	Autumn	Spring
MAPE %	0.053198	0.051777	0.047826	0.059589
Average value of (MAPE) 0.0781%				

Table 2. MAPE of PSO-SVM for different year session

Session	Sumer	Winter	Autumn	Spring
γ	139.0221	76.5445	41.3709	84.321
σ	6.1524	9.564	7.5732	2.5001
MAPE %	0.051987	0.042662	0.036229	0.055634
Average value of (MAPE) 0.0691%				

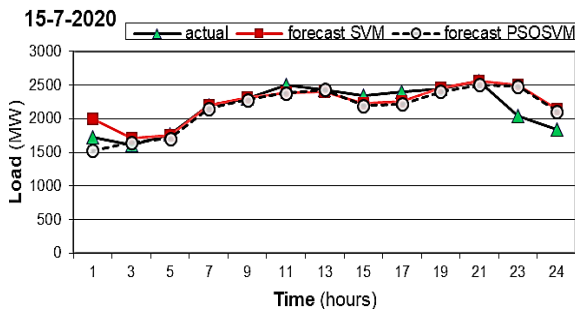


Figure 2. Load forecasting for 15.07.2020 (MAPE= 5.1987%)

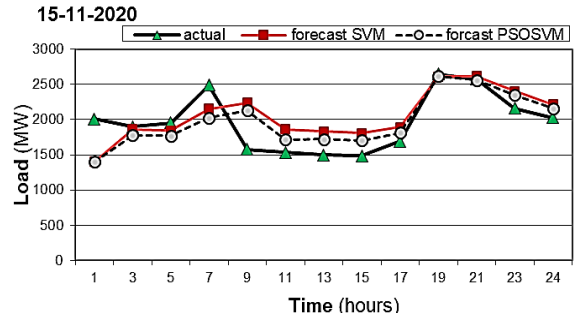


Figure 3. Load forecasting for 15.11.2020 (MAPE= 3.6229%)

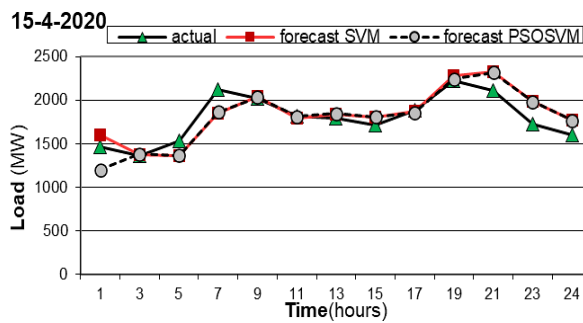


Figure 4. Load forecasting for 15.04.2020 (MAPE= 5.5634%)

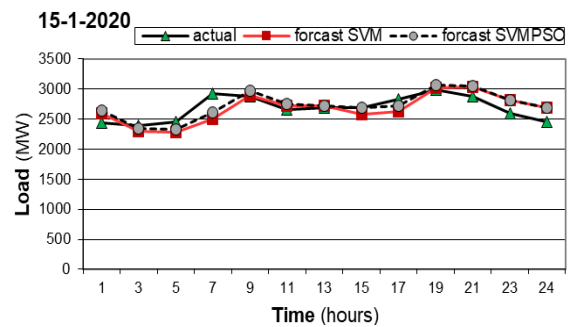


Figure 5 Load forecasting for 15.01.2020 (MAPE = 4.2662%)

5. CONCLUSION




In this paper, the SVM model is optimized using the PSO algorithm for forecasting the short-term energy consumption at the operation and control center in Tajikistan. From the results, the proposed SVM based-PSO method can be utilized successfully to provide a reliable prediction of electrical loads. The results show that the selection of the temperature as a factor with the type of the day is a successful choice, as it enhances the forecasting accuracy when using SVM with the PSO algorithm. The enhancement is clear from the predicted results. Moreover, the study indicates that the prediction error for all seasons is almost the same. This refers to the stability of the SVM model and its reliability. Also, the study shows that the PSO algorithm

improves the performance of the SVM model. Therefore, the proposed SVM method can be applied successfully for accurate and reliable load forecasting. The proposed method can be extended further by considering additional factors such as humidity.




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