Power Load Forecasting Based on Wireless Sensor Networks

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Abstract—At present, wireless sensor networks (WSN) technology is a field of much research interest in the area of information technology. The application of wireless sensor networks is expected to be very broad. With the development of communication protocol and their corresponding components, wireless sensor networks technology plays an increasingly important role in the power industry. The analysis and forecast of electric power data is essential to the construction and operation of the power network. Through the wireless sensor networks, we can obtain comprehensive power data. Then we can better forecast the power load through the data we obtain from the wireless sensor networks. In this paper, we propose an improved LSSVM method. We collect the power data by the wireless sensor networks and use the improved LSSVM method to forecast the power load. Experimental results demonstrate the effectiveness of the proposed method.

Keywords— LSSVM; WSN; power data

1 Introduction

With the advent of wireless sensor networks, networking and intelligent information gathering technology replace the independent single model. Wireless sensor networks have become an important research focus in the IT field [1-2].

Power energy is the primary energy supply form in modern society. Power systems has become a lifeline for the whole society [3-4]. With the development of the national economy, the demand for electricity in both urban and rural areas is increasing in China contiguously. By the end of the year 2016, Chinese annual electricity generation was 5 trillion and 920 billion kw/h, ranking first in power output globally.

The production, transmission and use of electric energy constitute a complex, time-varying and stochastic dynamic process. As such, the enormous energy demands must be distributed and consumed by the facilities of power generation, transmission and distribution to numerous users [5].

Any fault in the power network may cause a chain reaction and may result in collapse. This will have disasterous results to the national economy and national security [6]. Therefore, the modern power network must use advanced monitoring, control and scheduling mechanism to maintain its stability and optimal operation. The expansion of the power network to accomidate the increasing demand will lead to the continuous improvement in the automation level of power network management and automatic level of operation [7-8].

In the power system automation field, the existing research applies the wireless sensor networks to remote meter reading [9], substation automation [10], transmission line real-time monitoring [11] and early warning [12], etc. At the same time, the data collected by the wireless sensor networks can also be used to forecast the power load and provide a powerful guarantee for the electrical needs of both daily life of the society and industry.

The least squares support vector machine replaces the inequality constraints of standard support vector machines with equality constraints [13]. The two programming problem is transformed into the problem of solving linear equations by quadratic optimization index [14]. The computational complexity is reduced, the speed of the solution is improved and the ability of anti-jamming is enhanced. This is an extension of the standard SVM [15].

In this paper, we combine the wireless sensor networks with the power load forecasting, and propose an improved LSSVM method. Firstly, we use the wireless sensor networks to collect the input data of power load forecasting. Then, we use the modified LSSVM method to forecast the demand on the power load. The first part of this paper introduces the research background. In the second part, we introduce the combination of wireless sensor networks and power system. In the third part, we propose an improved LSSVM method. In the experimental stage, we use the improved LSSVM method to forecast the demand on the power load. Finally, the experimental results demonstrate the accuracy of the improved LSSVM method for power load forecasting based on wireless sensor networks.

2 Power data acquisition based on wireless sensor networks

The internet of things architecture is divided into three levels of perception, network and application [16]. The perception layer is the bottom layer of the internet of things. Its main function is to collect data through various types of sensors data, such as RFID (radio frequency) data, video capture equipment data, etc [17]. The network layer is the second layer, which is built on the basis of communication technology and the internet.

The network layer can accurately transmit data through the combination of wired and wireless technology. The application layer is the ultimate goal of the internet of things. The function is to solve the problem by the collection and transmission of information data. Typical applications include intelligent signal processing [18], data mining technology [19], and cloud computing technology [20].

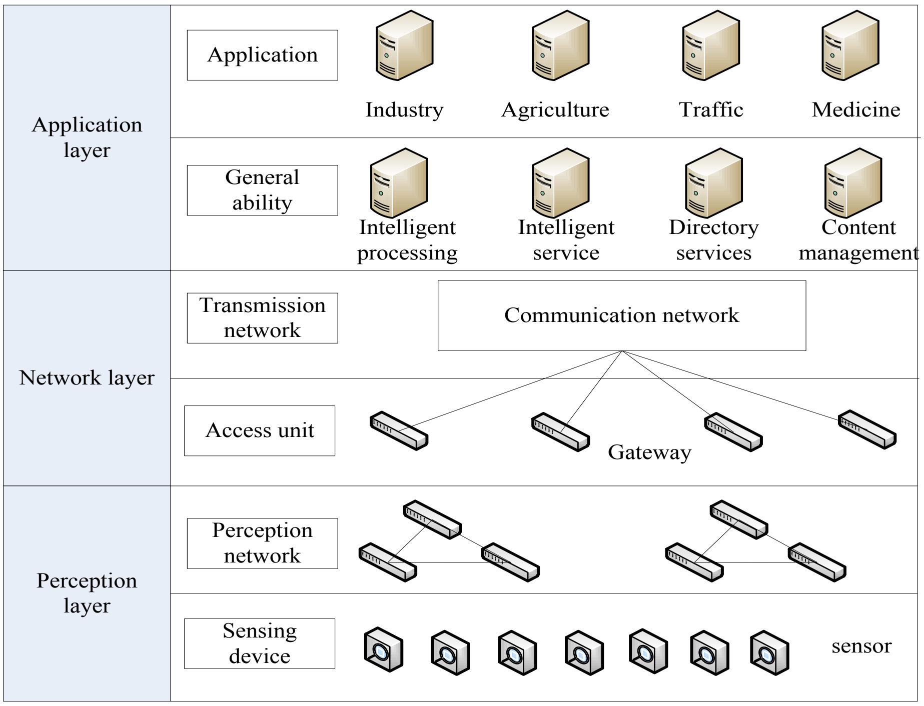

Fig. 1. Three layer architecture of Internet of things.

The design of the wireless sensor networks node unit is the key to data acquisition and transmission. The node unit is the smallest unit in the network, but also an essential link. The wireless sensor networks node unit often has the following characteristics.

1. Data processing and storage. Wireless sensor network nodes collect data through different front-end sensors. The different types of sensors collect different data. So, it is required that the processing module of the sensor node can be able to process and store the different signals.
2. High reliability. The transfer of the power load forecasting input data must be exact. Otherwise it will affect the predicted results.
3. Low energy consumption. We must consider the problem of the service life of the node. We also consider how to improve the use time of the node and how these nodes can have a long and stable operation.
4. Low cost. The engineering must consider the overall cost.

In the practical application, the design of wireless sensor network nodes should save energy and reduce cost. In existing wireless sensor networks, wireless sensor network nodes are generally composed of four modules which include data acquisition module, communication module, etc.

The main function of the wireless sensor network nodes is energy supply and data transmission. The wireless sensor network node is constituted of energy supply, sensors, processors, wireless communications and other components.

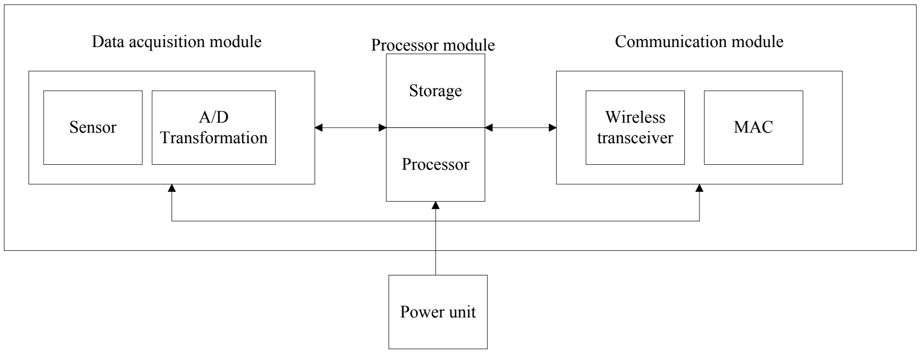

Fig. 2. Wireless sensor network node structure

3 PSO Algorithm.

Particle Swarm Optimization (PSO) is proposed by American scholars Kennedy and Eberhart in 1951[21]. This is a global search optimization algorithm. Based on swarm intelligence theory, the PSO algorithm uses the simple particle position and velocity operation to optimize the search by swarm intelligence [22].

In the PSO algorithm, a particle in the population is a solution to the optimization problem. The algorithm initializes the particle. In the search space, we initialize *m* particles and get a new population as follows:

$$X = (x_1, x_2, \cdots, x_m) \tag{1}$$

The position of particles is:

$$x_i = (x_{i1}, x_{i2}, \cdots, x_{iN})^T \tag{2}$$

This is a solution of the optimization problem. The fitness value of each particle is determined by the objective function. Each particle will then iterate through the solution space. This position is changed by updating the particle velocity as follows:

$$v_i = (v_{i1}, v_{i2}, \cdots, v_{iN})^T \tag{3}$$

In the iterative process, the particle will adjust itself according to the global extreme value and the individual extreme value. The individual extremum is the optimal position of the individual particle p_{id}. Global extremum is the optimal location of the whole population p_{gd}. The speed and the position of the particle are updated by type (4) and type (5).

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 (p_{id}^{k} - x_{id}^{k}) + c_2 r_2 (p_{gd}^{k} - x_{id}^{k}) \quad (4)$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \quad (5)$$

v_{id}^{k} is the velocity of *i-th* particle in the (k+1)-*th* iteration at the d dimension. x_{id}^{k+1} is the position of $i-th$ particle in the (k+1)-*th* iteration at the d dimension.. c_1 and c_2 are the acceleration constant. w is the weight. r_1 and r_2 are the independent functions. The range is $(0,1)$.

When

$v_{id}^{k} > v_{\max}$, $v_{id}^{k} = v_{\max}$; When $v_{id}^{k} < -v_{\max}$, $v_{id}^{k} = -v_{\max}$.

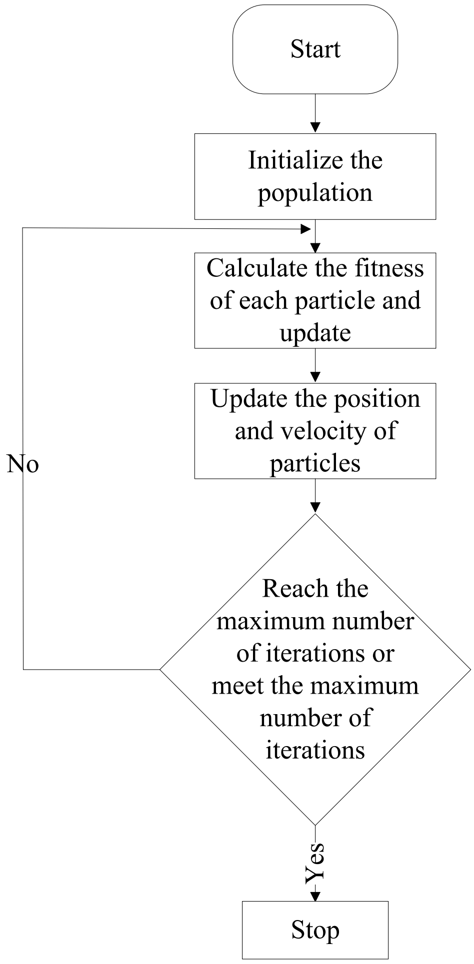

Fig. 3. Flow chart of PSO algorithm

4 improved LSSVM method

SVM theory is based on structural risk minimization and VC dimension. This is the most frequently used and the most successful algorithm in machine learning. SVM has a unique way to deal with the related problems of small samples, nonlinear and high dimension space. In recent years, SVM has been used in classification and regression computation. This method is becoming increasingly popular over others. The principle of two-dimensional space linear separation of SVM is shown in Fig. 4.

LSSVM and SVM have a same structure. They have the input layer and the output layer. But the working principle of LSSVM is different from SVM. LSSVM is based on the idea of equality of constraints, and SVM is based on inequality of constraints. LSSVM transforms the original problem from the two programming problem into a set of linear equations for linear KKT systems. The error processing principle of LSSVM is shown in Fig. 5.

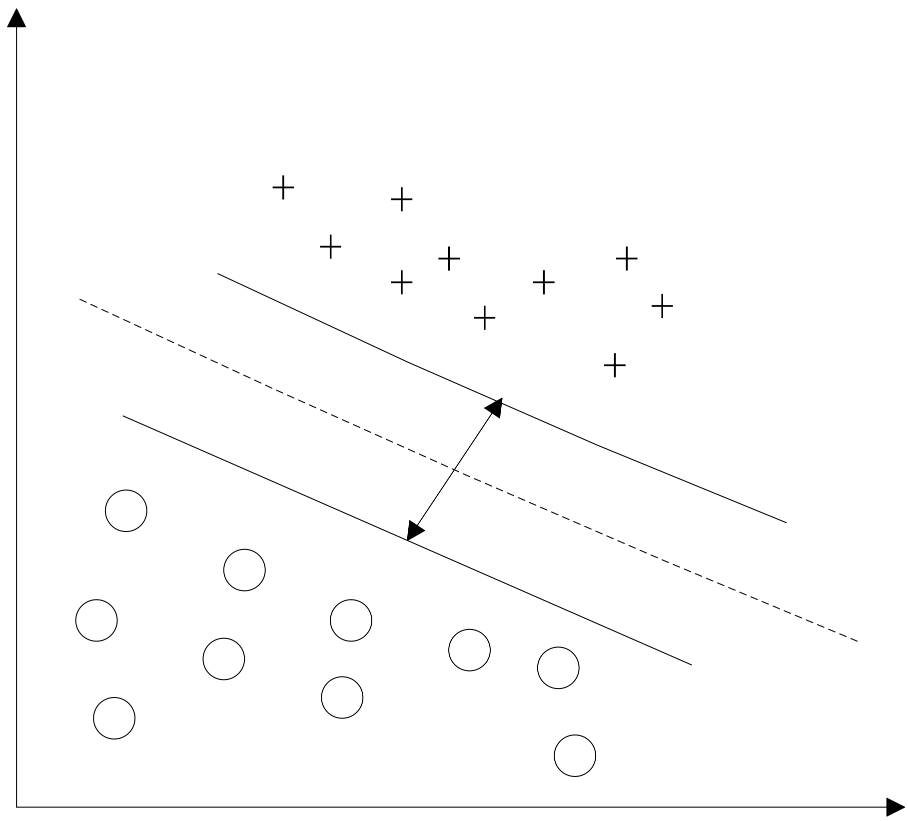

Fig. 4. Two-dimensional space linear separation of SVM

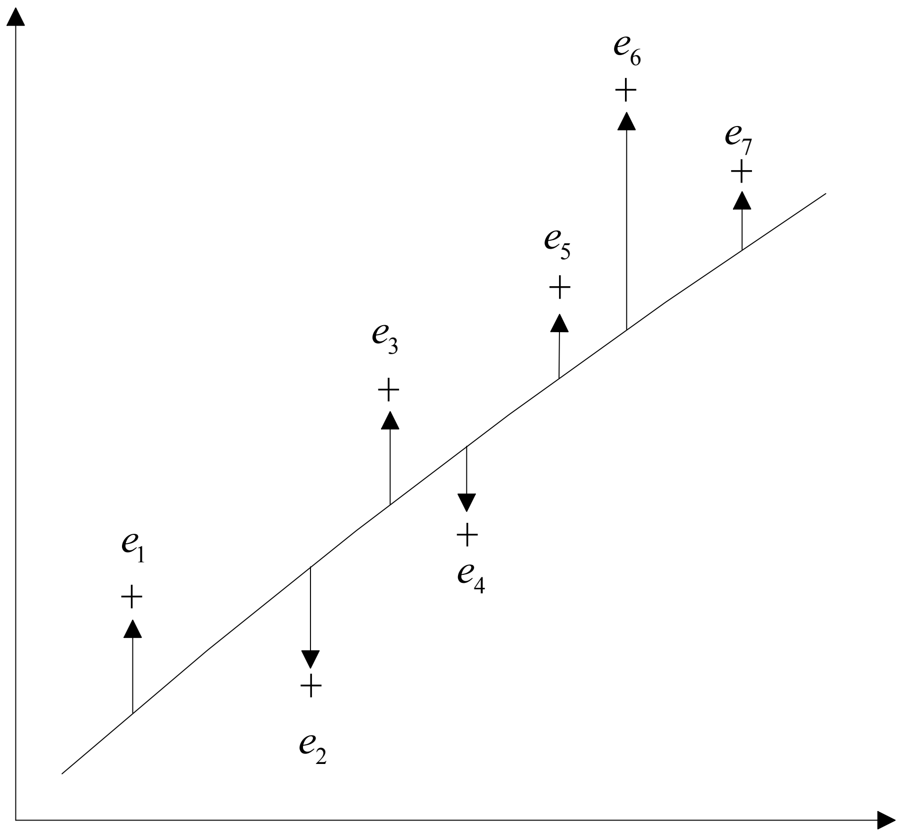

Fig. 5. Error processing principle of LSSVM

As the improvement of the standard SVM model, the Lagrange multiplier and the error are proportional to the model that will lead to the noise sensitivity and robustness, although LS-SVM has inherited the advantages of SVM. In order to enhance the ability of the model to deal with the noise data, the improved LSSVM algorithm is proposed. The principle structure diagram of the LSSVM is as follows.

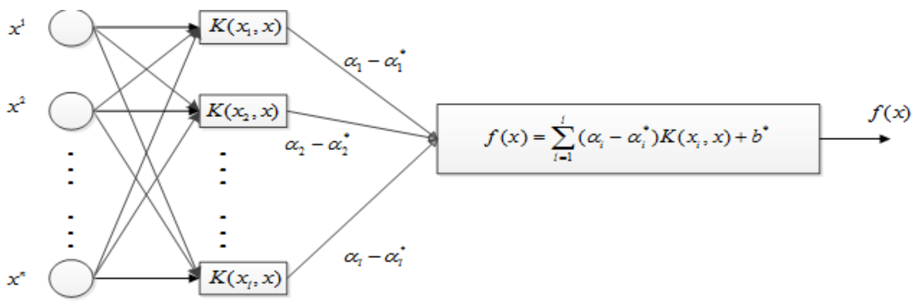

Fig. 6. Principle structure diagram of LSSVM

In the LSSVM algorithm, we set:

$$\min_{\omega^*,b^*,e^*} J(\omega^*,e^*) = \frac{1}{2}\left\|\omega^*\right\|^2 + \frac{1}{2}\gamma\sum_{k=1}^{N}\nu_k e_k^{*2} \tag{6}$$

subject to:

$$y_k = \omega^{*T}\varphi(x_k) + b^* + e_k^*, k = 1,2,\cdots,N \tag{7}$$

The lagrange function is:

$$\begin{aligned} &L(\omega^*,b^*,e^*,\alpha^*) = J(w^*,e^*) \\ &-\sum_{i=1}^{N}\alpha_k^*\{\omega^{*T}\varphi(x_k) + b^* + e_k^* - y_k\} \end{aligned} \tag{8}$$

The derivation is:

$$\begin{cases} \dfrac{\partial L}{\partial \omega^*} = 0, \omega^* = \sum_{i=1}^{N}\alpha_k^*\phi(x_k) \\ \dfrac{\partial L}{\partial b^*} = \sum_{i=1}^{N}\alpha_k^* = 0 \\ \dfrac{\partial L}{\partial e_k^*} = 0, \alpha_k^* - \gamma e_k^*\nu_k = 0 \\ \dfrac{\partial L}{\partial \alpha_k^*} = \omega^{*T}\varphi(x_k) + b^* + e_k^* - y_k = 0 \end{cases} \tag{9}$$

Delete the ω^* and e^*

$$\begin{bmatrix} 0 & 1^T \\ 1_v & \Omega + \dfrac{1}{V\gamma}l \end{bmatrix}\begin{bmatrix} b^* \\ \alpha^* \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{10}$$

where:

$$V = dig(\nu_1,\nu_2,\cdots,\nu_N) \tag{11}$$

$$y = (y_1,y_2,\cdots,y_N)^T \tag{12}$$

$$\alpha^* = (\alpha_N^*,\alpha_N^*,\cdots,\alpha_N^*)^T \tag{13}$$

$$1 = [1,1,\cdots,1]^T \tag{14}$$

$$\Omega_{ij} = K(x_i, x_j), i, j = 1,2,\ldots, N \tag{15}$$

The kernel function is used to support the vector machine, which can enhance the ability to deal with nonlinear and high dimensional space. The choice of the kernel function will affect the performance of support vector machine. If the support vector machine has a well performaning kernel function, it will have excellent generalization ability. Commonly used kernel functions include the Gauss radial basis function, polynomial kernel function and Sigmiod kernel function.

(1) Gauss radial basis function:

$$K(x, x_k) = \exp(-\|x - x_k\|^2 / 2\sigma^2) \tag{16}$$

(2) Polynomial kernel function:

$$K(x, x_k) = [(x, x_k) + 1]^q \tag{17}$$

where q is the order of a polynomial.

(3) Sigmiod kernel function:

$$K(x, x_k) = \tanh(v(x \cdot x_k) + c) \tag{18}$$

$v > 0, c < 0$

In this paper, the Gauss radial basis function (RBF) $K(x, x_k) = \exp(-\|x - x_k\|^2 / 2\sigma^2)$ with global convergence is used as the kernel function. σ is core width. The RBF kernel function reduces the influence of the abnormal data on the overall performance of LS-SVM and improves the robustness of the model.

$$v_k = \begin{cases} 1, if \left| e_k / \hat{s} \right| < \xi \\ \dfrac{\xi}{\left| e_k / \hat{s} \right|}, if \left| e_k / \hat{s} \right| \geq \xi \end{cases} \tag{19}$$

Weight parameter ξ must be determined. $\hat{s}$ is used to measure the degree of deviation between the distribution of unweighted error variable e_k and Gaussian distribution. $\hat{s}$ is determined by the following:

$$\hat{s} = 1.483 med(\left| e_k - med\{e_k\} \right|) \tag{20}$$

where med is median

The function estimation is:

$$y = \sum_{k=1}^{N} \alpha_k^* K(x, x_k) + b^* \tag{21}$$

In order to enhance the robustness of the LSSVM model, we add weight e_k to adjust the number of iterations.

Then, we improve the PSO part.

The particle swarm optimization with extended memory records the pre-global extreme position.

The individual extreme position and pre self-position through extended memory. The significance of extended memory is that the search experience which is accumulated by the individual particles can help the algorithm to more quickly converge. Compared with traditional PSO algorithms, the improved PSO algorithm has the advantages of fast convergence speed and simple implementation. This method maintains the advantages of the swarm intelligence, parallelism, and fewer adjustment parameters of the PSO algorithm. The speed and the position update types are:

$$\begin{aligned} v_{id}^{k+1} = wv_{id}^{k} &+ c_1 r_1 [\xi_l (p_{id}^{k} - x_{id}^{k}) + \xi_{l-1} (p_{id}^{(k-1)} - x_{id}^{k-1})] \\ &+ c_2 r_2 [\xi_l (p_{gd}^{k} - x_{id}^{k}) + \xi_{l-1} (p_{gd}^{k-1} - x_{id}^{k-1})] \end{aligned} \tag{22}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{23}$$

where $\xi_1, \xi_{l-1} \in R^+, \sum_{i=1}^{1} \xi_{i-1} = 1$, ξ_1 is current effective factor, ξ_{l-1} is extended memory effective factor.

The flow chart of the algorithm is as follows:

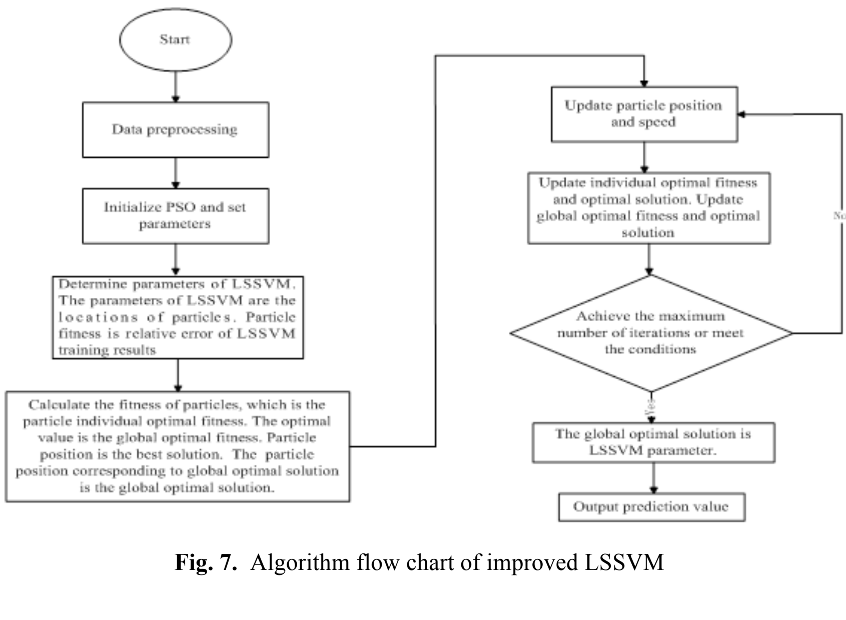

Fig. 7. Algorithm flow chart of improved LSSVM

The steps are as follows.

(1) Calculate the Lagrangian multipliers α_k of LSSVM. We can obtain the unweighted LSSVM error variable $e_k = \alpha_k / \gamma, k = 1,2,\cdots,N$.

(2) Calculate weight coefficient v_k

(3) Obtain $(V\gamma)^{-1} I$, where $V = (v_1, v_2, \cdots, v_N)$. Update the α_k.

(4) Solve partial derivative e^* to obtain $e_k = e_k^{*(i)}, i = 1$. We set $i = i+1$ and return to step (2).

(5) When $i = M$ or $\left|\alpha_k^{*(i+1)} - \alpha_k^{*i}\right| \le 10^{-4}$, the algorithm ends.

(6) Take the updated α_k^* and b^* into type (1) to obtain the forecasting value.

Firstly we use the LSSVM model to fit the training data. Then, we use the PSO algorithm to search the parameters of the model in the fitting process to determine the parameters of the LSSVM model. Lastly, we use the improved LSSVM model to determine the forecasting value after the parameters of the LSSVM model have been determined.

5 Experiment

In the power industry, the use of wireless sensors to collect data has become the standard. Firstly, we use the wireless sensor to collect the power load data in a certain area. The specific data is shown in the following table.

After that, we compare the proposed method with the traditional LSSVM method and the PSO method. We selected the first 20 data points as the training set, and the last four data points as the prediction value. The prediction results are as shown in Figure 9.

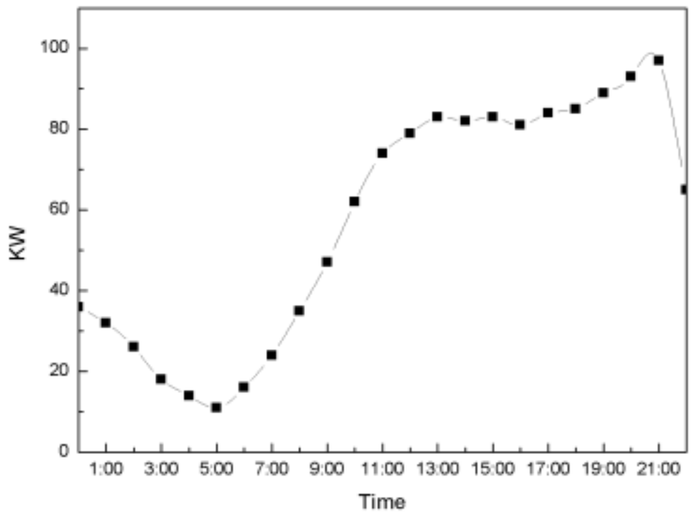

Fig. 8. Specific power data

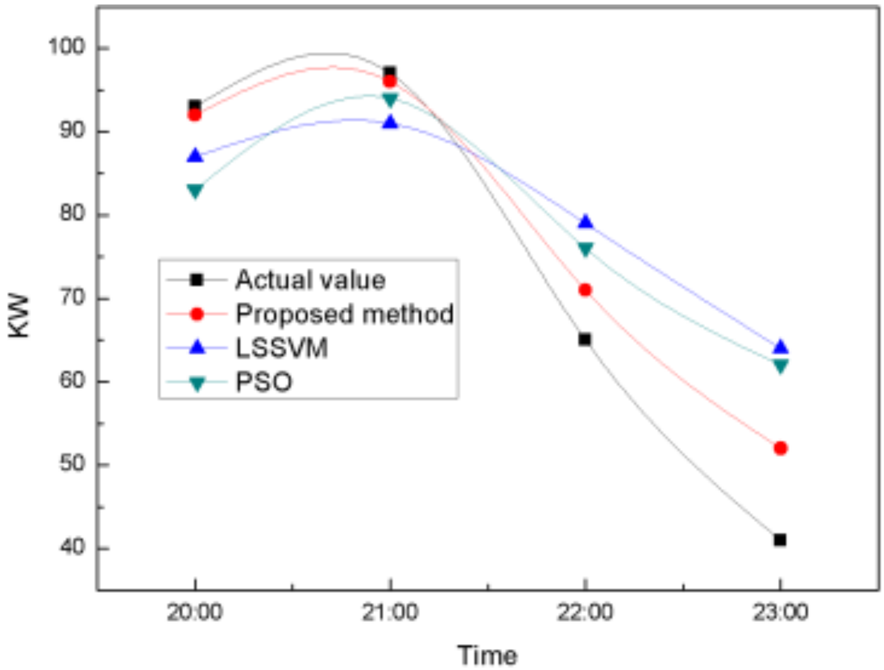

Fig. 9. Comparison result

From the above, we can see that the improved method proposed in this paper has a good prediction result in power load forecasting based on wireless sensor networks. Compared with the traditional LSSVM and PSO methods, this method has higher prediction accuracy. The experimental results show that the method is feasible and effective.

6 Conclusion

As a new technology in the communications field, wireless sensor networks have the advantages of high precision, high fault tolerance, large coverage area, remote telemetry and remote control, self-organization, multi-hop routing, etc. Wireless sensor networks have been widely used in multi-object communication. Electric power is the main energy supply form in modern society. The power system has become a lifeline of modern society. With the continuous development of the national economy, China's demand for electricity is also increasing. Using the wireless sensor networks to collect power data and forecast the power load will be the future development trend. In this paper, we first introduce the method through which wireless sensor networks collect power data. After that, we introduce the PSO method. Finally, we propose an improved LSSVM method by combining the PSO method with the LSSVM method. The experimental results demonstrate the feasibility and effectiveness of the proposed method for power load forecasting based on wireless sensor networks.

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