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Uncertain Machine Load Forecasting Based on Least Squares Support Vector Machine

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Abstract. Machine state is a very important constraint for job shop scheduling. For the uncertainty machine state, the paper proposes a machine load forecasting method based on support vector machine. The method reduces complexity and improves efficiency by eliminating a large number of unrelated input factors and selecting a small number of input parameters with strong correlation. The efficiency of the algorithm is verified by the production workshop instance.

Keywords. Machine load forecasting, support vector machine, particle swarm optimization

1. Introduction

Based on past machine load data, predicting machine load data for a certain day in the future is a short-term forecast problem. Traditional load forecasting methods such as trend extrapolation [1], time series method [2], exponential smoothing method [3], regression analysis [4] And the gray model method [5], etc., usually need to establish a mathematical model, which is more difficult to solve complex problems [6]. The load forecasting method based on time-frequency analysis classifies the load by frequency variation, including Fourier analysis method [7] and wavelet analysis method [8]. The load prediction methods described by the dynamic process include chaos theory [9] and Kalman filter algorithm [10]. The knowledge-based expert system [11] generalizes the factors affecting the load into knowledge and predicts future loads through some rules. The knowledge and rules of this method are more difficult to determine, the model is more relevant to specific problems, and the model is not easy to popularize and apply. The artificial neural network [12] is a nonlinear system composed of a large number of simple neurons. But the forecasting process of it is easy to fall into local minimum values. And the learning process is time consuming and easy to cause over-fitting[13]. The support vector machine can predict small sample data, the method is simple and has high efficiency, and the structured learning unit is adopted, thus avoiding the over-fitting problem and receiving extensive attention and research.

In this paper, the least squares support vector [14] machine nonlinear regression is used to predict the machine load. Compared with the standard support vector machine [15], the least squares support vector machine has the following characteristics[16]: the

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equality constraint replaces the inequality constraint; There are fewer model parameters required and the model is easier to determine[17].

The next section of the paper proposes an uncertain machine load forecasting scheme including forecasting process. The third section is the simulation experiment with actual production workshop data. In the fourth section the full paper is summarized.

2. Uncertain Machine load forecast

The machine load in this paper is defined as the sum of the processing times of all the processes assigned to a machine. A very critical step in the flexible job shop scheduling problem is to arrange the process onto the right machine. In the actual production workshop, some machines have more work-pieces to be processed, while some machines have fewer tasks or even idle for a long time. On the one hand, the completion time of the operation is prolonged, and on the other hand, other problems are caused. More power consumption and wear and tear of some machines are serious. To solve these problems, it is necessary to consider the load of the machine when arranging the process to the machine, and to balance the load of each machine as much as possible to achieve maximum production efficiency. Actual production is a real-time dynamic process, and there are many uncertainties. For example, orders can come at any time in the customized production mode. This requires the scheduling system to consider the instantaneous static machine load and possible future orders when arranging the work-piece processing machine. The dynamic load enhances the robustness of the scheduling system and reduces the number of rescheduling.

The prediction model of the least squares support vector machine is shown by the formula 1, where α_i is Lagrange multiplier, $K(x, x_i)$ is a function of the mapping from low-dimensional space to high-dimensional feature space,The calculation method of α_i, b is as described in the paper[18].

$$y = \sum_{i=1}^{l} \alpha_i K(x, x_i) + b. \tag{1}$$

The machine load consists of two parts: one is the existing work, and the other is the job that arrives randomly in the future. Since the arrival of the job is random, the real-time machine load is also uncertain. This paper predicts the future machine load based on known machine load data. When the machine is assigned, the current determined machine load and the predicted machine load are considered. The rule-based method, such as the machine with less total machining time, is more likely to be selected. To generate a robust scheduling scheme. For uncertain machine load factors, such as the arrival of random orders, etc. have a greater impact on scheduling, this paper predicts the uncertainty of machine load.

The key steps of the NPSO-SVM algorithm presented in this paper are described below.

Step 1. Preprocess historical data to generate training data according to the principle of similarity;

Step 2. Initialize. Select the radial basis kernel function, initialize the regularization parameter γ, the kernel function width σ, local Search threshold L_1 ;

Step 3. Using the improved PSO algorithm for parameter optimization;

1) initialization;

2) Calculate the individual fitness values in the population, and update the global optimal value and the individual optimal value;

3) Calculating the variance of the fitness value of the population Var;

4) If $Var < L_1$, perform a local search;

5) The population evolved to the next generation;

6) Repeat (2)-(5) until the end condition is met.

Step 4. Calculate α_i , b, construct the prediction function $f(x)$, and predict the machine load with the prediction function.

3. Simulation

The improved particle swarm optimization algorithm was used to perform optimization experiments on the regularization parameter and the kernel width coefficient.

The optimal regularization parameter γ and the kernel width coefficient σ is set as follows.

Single shift: $\gamma = 100, \sigma = 3.3$. Double shift 1: $\gamma = 120, \sigma = 1.8$. Double shift 2:$\gamma = 118, \sigma = 7.9$. Overtime shift 1:$\gamma = 100, \sigma = 4.5$. Overtime shift 2: $\gamma = 100, \sigma = 4.2$. Three shifts: $\gamma = 100, \sigma = 3.8$.

The machines in the actual production workshop usually work according to the shifts of the operators. The shifts for each machine in this paper:

1) Single shift (08:30-12:00, 13:00-17:30)

2) Double shift 1 (07:00-15:00, 15:00-22:00)

3) Double shift 2 (07:00-19:0 0, 19:00-07:00)

4) Overtime 1 (08:30-12:00, 13:00-19:30)

5) Overtime 2 (08:30-12:00, 13:00-21:30)

6) Three shifts (07:00-15:00, 15:00-23:00, 23:00-07:00)

The daily shift of the equipment is set to one of six shifts, and the processing of the work-pieces is arranged according to the shift of the equipment. Shifts have a significant impact on machine load, so this article is tested separately for each shift.

In order to evaluate the quality of the solution, the average relative prediction error at t moment and the average relative prediction error shown in the formula 2 and formula 3 are used as Evaluation criteria, where *MAE(t)* represents the average relative prediction error at t moment, *MAE* is the average relative prediction error, and $L_k(t)$ is the load of k for the machine predicted at t moment, $\hat{L}_k(t)$ is the actual load of the machine k, l is the number of machines, and N is the predicted number of moments.

$$MAE(t) = \frac{1}{n}\sum_{k=1}^{l} \frac{\left|L_k(t) - \hat{L}_k(t)\right|}{\hat{L}_k(t)} \times 100\%. \tag{2}$$

$$MAE = \sum_{t=1}^{N} MAE(t). \tag{3}$$

In order to verify the effectiveness of the NPSO-SVM algorithm proposed in this paper, the algorithm is proposed by the hybrid wavelet transform, artificial neural network algorithm (WT-ANN)[19] and the hybrid wavelet and support vector machine (C-WSVM) algorithm were compared[20]. The three algorithms were optimized for 30 experiments. According to the data of a factory from May 1, 2017 to December 1, 2017, the machine load at each hour of the day on December 2 is predicted, and the forecast is performed according to the shift. The single shift prediction result using the WT-ANN algorithm is shown in the figure 1, and the average relative error is 1.83%. The single-shift prediction result using the C-WSVM algorithm is shown in the figure 2, and the average relative error is 1.44%. The single-shift prediction result using the NPSO-SVM algorithm proposed in this paper is shown in the figure 3, and the average relative error is 1.09%. The average relative error of the double shift 1 is 3.31% using the WT-ANN algorithm. The average relative error of the double shift 1 is 2.04% using the C-WSVM algorithm. The average relative error of the double shift 1 is 0.76% using the NPSO-SVM algorithm. The average relative error of the double shift 2 is 3.52% using the WT-ANN algorithm. The average relative error of the double shift 2 is 2.57% using the C-WSVM algorithm. The average relative error of the double shift 2 is 1.25% using the NPSO-SVM algorithm. The average relative error of the overtime 1 is 3.32% using the WT-ANN algorithm. The average relative error of the overtime 1 is 2.17% using the C-WSVM algorithm. The average relative error of the overtime 1 is 1.41% using the NPSO-SVM algorithm. The average relative error of the overtime 2 is 3.37% using the WT-ANN algorithm. The average relative error of the overtime 2 is 2.35% using the C-WSVM algorithm. The average relative error of the overtime 2 is 1.42% using the NPSO-SVM algorithm. The average relative error of the three shifts is 5.05% using the WT-ANN algorithm. The average relative error of the three shifts is 3.3% using the C-WSVM algorithm. The average relative error of the three shifts is 1.9% using the NPSO-SVM algorithm. It can be seen from the figure and the experimental data that the prediction error of the NPSO-SVM algorithm proposed in this paper is better than the prediction error of WT-ANN algorithm and C-WSVM for the six shifts.

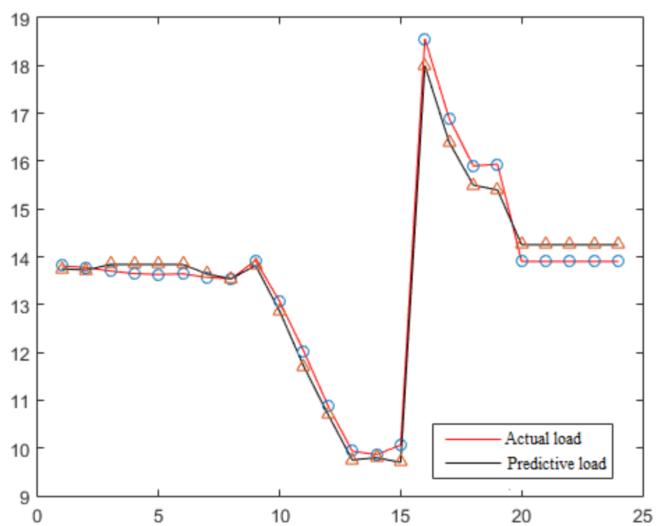

Figure 1. Prediction results using WT-ANN of Single shift.

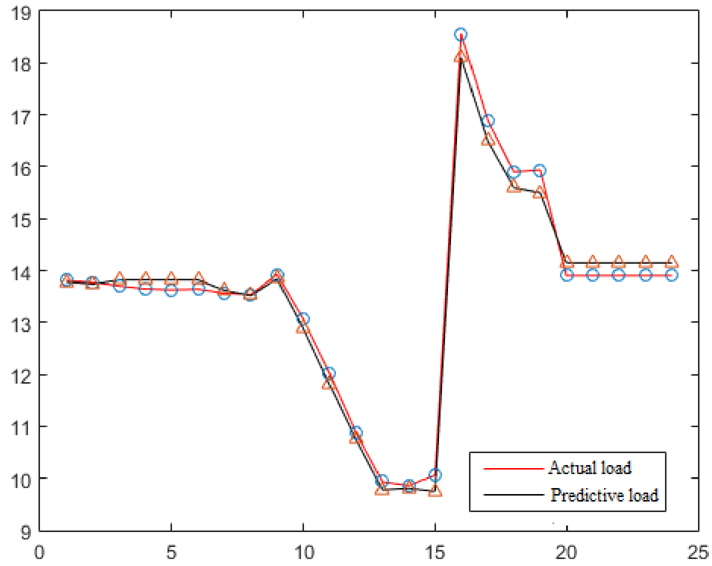

Figure 2. Prediction results using C-WSVM of Single shift.

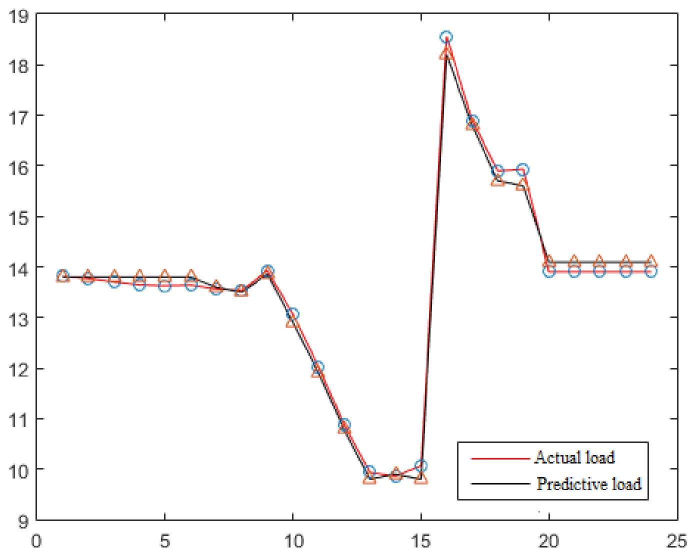

Figure 3. Predictin results using NPSO-SVM of Single shift .

The algorithm performance of the NPSO-SVM algorithm proposed in this paper, the WT-ANN algorithm and the C-WSVM algorithm are shown in the Table 1. As can be seen from the table, the NPSO-SVM algorithm proposed in this paper in the predicted average relative error *MAE* and the time performance is superior to the WT-ANN algorithm and the C-WSVM algorithm.

Table 1. Algorithm performance comparison

Shift type	WT-ANN		C-WSVM		NPSO-SVM	
	MAE(%)	Time(s)	*MAE*(%)	Time(s)	*MAE*(%)	Time(s)
Single	1.83	1468	1.44	1255	1.09	1163
Double1	3.31	1389	2.04	1219	0.76	1109
Double2	3.52	1393	2.57	1276	1.25	1187
Overtime1	3.32	1428	2.17	1302	1.41	1210
Overtime2	3.37	1430	2.35	1295	1.42	1196
Three shifts	5.05	1485	3.3	1356	1.9	1276

4. Summary

Aiming at the uncertain machine load, a machine uncertainty load forecasting method based on least squares support vector machine is proposed. The improved particle swarm optimization algorithm is used to predict the machine load. The results of simulation shows that this method is more effective than the other two popular methods.

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