Measurement of Train Rim Thickness by Machine Learning

Bing Song¹, Haiping Wei¹, Yu Cao¹*, Xu Cheng² and Xiwang Guo¹

¹Computer and Communication Engineering College, Liaoning Shihua University, Fushun, China
²Economics and Management College, Agriculture University, Shenyang, China

*Corresponding author email: yucao Lnshu@163.com

Abstract. The train wheel rim thickness is always manually measured by using handheld devices or in a non-contact way by using laser and image techniques. To reduce the operating costs, this work studied some soft measurement methods with classical machine learning algorithms including neural network (NN), locally weighted linear regression (LWLR), and support vector machine (SVM). By analyzing the correlation between features, it can improve the efficiency of the model. Some approaches were used to optimize the number of hidden layer neurons in NN, parameters in LWLR and SVM. Experiments on real data are conducted, and the results show that the proposed methods can ensure high precision and accuracy, while NN has the highest accuracy.

1. Introduction

Industry 4.0 accelerates the industrial revolution and construction of modern industry [1-5]. Some soft measurement methods have been proposed for industrial measurement [6]. With the rapid development of machine learning algorithms, many researchers are using machine learning algorithms to solve measurement problems in production [7]. At present, many methods have been used to measure the rim thickness of the wheels based on images and the laser sensors [8-12]. There is little research on the measurement of the wheel rim thickness using soft measurement techniques. This paper uses the classical machine learning algorithms to establish the soft measurement models for the essential parameters of the wheel of a train wheel factory in Shenyang, China. The accuracy of this data analysis model meets the needs of enterprises and saves a lot of personnel costs for the enterprise [13].

Train wheels need to be inspected regularly, and faulty wheels need to be repaired. The width, diameter and thickness of rim after the processing are the same with data in the lathe system before the processing. The rim thickness can be obtained with the manual measurement. The measurement of rim thickness includes non-contact measurement and contact measurement. The non-contact detection includes the display of the wheelset profile with the double laser source and the single-camera image detection system [14], the light-cutting method of the direct light vertical imaging screen [15], the camera image acquisition technology and the wheelset parameter detection [16], and the measurement method of the semiconductor laser sensor [17].

The railway department publishes the vehicle wheelset maintenance document. It defines in detail the geometric parameters of wheel shape: rim area of standard LM type wheel rim tread is composed of circular segments, and their radii are R12, R18, and R24. The connection area between rim and tread is composed of a circular segment with a radius of R14, and the tread area consists of segments with different concave and convex directions of R100, R220, and R500. Contour shape of LM and the fourth type of measuring tool is shown in figure 1.
Figure 1. The diagram of LM contour outline and the forth inspector

1. Tread rolling circle: The circumference of the wheel tread at a distance of 70mm from the inner side of the rim.
2. Rim thickness: The length from the outside of the rim to the side of the rim at any point of the circumference at 12mm from the tread baseline.
3. Rim height: The vertical distance from the rim apex to the tread baseline.
4. Rim thickness: Make a vertical line from the tread base point to the inside. The external endpoint of the rim thickness is the intersection of the perpendicular and the inside.

The device does not need to remove the wheelset. There are two working hours every day, and three workers need to work at the same time. It takes a lot of human and financial resources. Different inspectors may cause various errors, so the results are difficult to achieve the desired accuracy.

Compared with the existing research, we have made three contributions:
1. Soft-Measuring technology improves the automation degree of the industrial production process.
2. A new rim measurement method is proposed, and it is based on machine learning.
3. The error of the prediction results in this study meets the industrial requirements, and it can replace manual measurement.

2. Data Preprocessing

There are 37626 groups of the original sample. To improve the efficiency of modeling, we reduce the number of features entered, and the number becomes from 18 to 16. Randomly select two sets of data from the initial data provided by the implementing unit is shown in Table 1.

Table 1. Original sets of data

| Tag | Physical name                | Measured value(mm) | Tag | Physical name                | Measured value(mm) |
|-----|------------------------------|--------------------|-----|------------------------------|--------------------|
| T1  | Left Rim thickness           | 35.7               | T11 | Left Rim thickness           | 34.0               |
|     | Right Rim thickness          | 35.5               | T12 | Right Rim thickness          | 34.0               |
| T2  | Left Treadwear               | 3.3                | T13 | Left Treadwear               | 0.0                |
|     | Right Treadwear              | 3.9                | T14 | Right Treadwear              | 0.0                |
| T3  | Left Wheel diameter          | 811.7              | T15 | Left Wheel diameter          | 808.0              |
|     | Right Wheel diameter         | 811.5              | T16 | Right Wheel diameter         | 808.0              |
| T4  | Left Rim thickness           | 30.9               | T17 | Left Rim thickness           | 31.0               |
| T5  | Left Rim thickness           | 29.7               | T18 | Right Rim thickness          | 29.0               |
| T6  | Left Rim thickness           | 138.2              | T19 | Left Rim thickness           | 138.2              |
| T7  | Right Rim thickness          | 139.7              | T20 | Right Rim thickness          | 139.0              |

We intend to adopt offline modeling. Equipment wear in the later stage may cause accuracy deviation. Through correlation analysis, relevant features are retained to improve modeling efficiency. The correlation analysis method is Spearman analysis, and the tool is SPSS24.0. The analysis results are shown in Table 2.
Table 2. The correlation analysis by spearman

|     | T1   | T2   | T3   | T4   | T5   | T6   | T7   | T8   | T9   | T10  | T11  | T12  | T13  | T14  | T15  | T16  | T17  | T18  | T19  | T20  |
|-----|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| T1  | 1.00 | .969 | -.110 | -.037 | .968 | .946 | .263 | .286 | .025 | .035 | .967 | .966 | .948 | .948 | .386 | .386 | .025 | .035 |
| T2  | .969 | 1.000 | -.052 | -.119 | .944 | .968 | .249 | .319 | .034 | .018 | .971 | .971 | .951 | .951 | .351 | .428 | .034 | .018 |
| T3  | -.110 | -.052 | 1.000 | .680 | -.046 | .500 | .399 | .139 | .118 | -.042 | -.041 | -.037 | .177 | .191 | .139 | .119 |
| T4  | -.037 | -.119 | .680 | 1.000 | -.023 | -.108 | .456 | .343 | .103 | .152 | -.049 | -.049 | -.038 | .247 | .083 | .103 | .153 |
| T5  | .968 | .944 | -.106 | -.023 | 1.000 | .974 | .283 | .294 | .070 | .079 | .948 | .948 | .975 | .975 | .408 | .395 | .070 | .079 |
| T6  | .946 | .968 | -.046 | -.108 | .974 | 1.000 | .267 | .330 | .081 | .067 | .954 | .954 | .979 | .979 | .373 | .439 | .080 | .067 |
| T7  | .263 | .249 | .500 | .456 | .283 | .267 | 1.000 | .342 | .118 | .121 | .292 | .292 | .307 | .307 | .690 | .285 | .118 | .121 |
| T8  | .286 | .319 | .399 | .343 | .294 | .330 | .342 | 1.000 | .091 | .101 | .343 | .344 | .352 | .352 | .284 | .758 | .091 | .101 |
| T9  | .025 | .034 | .139 | .103 | .070 | .081 | .118 | .091 | 1.000 | .630 | .046 | .046 | .081 | .081 | .060 | .051 | 1.000 | .630 |
| T10 | .035 | .018 | .118 | .152 | .079 | .067 | .121 | .101 | .630 | 1.000 | .047 | .047 | .081 | .081 | .082 | .042 | .629 | .999 |
| T11 | .967 | .971 | -.042 | -.049 | .948 | .954 | .292 | .343 | .046 | .047 | .999 | .999 | .974 | .974 | .378 | .427 | .046 | .047 |
| T12 | .966 | .971 | -.041 | -.049 | .948 | .954 | .292 | .344 | .046 | .047 | .999 | .999 | 1.000 | 1.000 | .378 | .428 | .046 | .047 |
| T13 | .948 | .951 | -.037 | -.038 | .975 | .979 | .307 | .352 | .081 | .081 | .974 | .974 | 1.001 | 1.000 | .397 | .436 | .081 | .081 |
| T14 | .948 | .951 | -.037 | -.038 | .975 | .979 | .307 | .352 | .081 | .081 | .974 | .974 | 1.001 | 1.000 | .397 | .436 | .081 | .081 |
| T15 | .936 | .951 | -.037 | -.038 | .975 | .979 | .307 | .352 | .081 | .081 | .974 | .974 | 1.001 | 1.000 | .397 | .436 | .081 | .081 |
| T16 | .936 | .951 | -.037 | -.038 | .975 | .979 | .307 | .352 | .081 | .081 | .974 | .974 | 1.001 | 1.000 | .397 | .436 | .081 | .081 |
| T17 | .386 | .351 | .177 | .247 | .408 | .373 | .690 | .284 | .060 | .082 | .378 | .378 | .397 | .397 | 1.000 | .373 | .060 | .081 |
| T18 | .386 | .428 | .191 | .083 | .395 | .439 | .285 | .758 | .051 | .042 | .427 | .428 | .436 | .436 | .373 | 1.000 | .051 | .042 |
| T19 | .025 | .034 | .139 | .103 | .070 | .080 | .118 | .091 | 1.000 | .629 | .046 | .046 | .081 | .081 | .060 | .051 | 1.000 | .630 |
| T20 | .035 | .018 | .119 | .153 | .079 | .067 | .121 | .101 | .630 | .999 | .047 | .047 | .081 | .081 | .081 | .042 | .630 | 1.000 |

From Table 2, first, T11 is the target output, and it is related to T1, T2, T5, T6, T15, and T16. T12 is the target output, and it is related to T1, T2, T5, T6, T15, and T16. Second, there is a coupling relationship between the features, and the traditional linear regression method cannot be used to establish a data analysis model. Input and output features after dimensionality reduction of the model are shown in Table 3.

Table 3. The output and input of model after dimensionality reduction

|     | Input                          | Output                          |
|-----|-------------------------------|---------------------------------|
| T1  | (input of left rim thick)     | T2 (input of right rim thick)   |
| T5  | (input of left wheel diameter)| T6 (input of right wheel diameter) |
| T15 | (output of left wheel diameter)| T16 (output of right wheel diameter) |

3. Algorithm and Methods

3.1. BP Neural Network Model
The BP neural network is a model trained by the error back-propagation[18]. It consists of input, hidden, and output layers. The singular data in the sample affect the performance of the model. The data needs to be normalized. The formula is $Y = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$. The number of neurons in the hidden layer is defined as $M = \sqrt{N + L + a}$, where $N$ is the number of nodes in the input layer, $L$ is the number
of nodes in the output layer, and a is a constant between [1,10]. The experiment is repeated 10 times for each model, and the final result is the average value of 10 times to ensure a better precision.

3.2. Locally Weighted Linear Regression
The input is coupled, so local linear regression is more suitable. The locally weighted linear regression algorithm assigns different weights to each point near the prediction point for local fitting. Let the input values be \( x(i) \), the Gaussian kernel function is the basis of assignment, as follows:

\[
\omega(i,i) = \exp\left(\frac{|x(i) - x|^2}{-2k^2}\right).
\]

The current prediction point is \( \beta \) where

\[
\beta = \left(X^T X\right)^{-1} X^T Y
\]

3.3. Support Vector Machine
Support Vector Machine \([19]\) maps data to the high-dimensional feature space by a nonlinear mapping. The minimum objective function can be used to find the optimal fitting function. The Lagrange equation can optimize the objective function, and the obtained support vector machine model is:

\[
f(x) = \sum_{i=0}^{l} \left( \delta_i - \delta_j \right) k(x_i, x_j) + b.
\]

The Kernel function is radial basis function where

\[
k(x_i, x_j) = \exp\left\{-\frac{|x_i - x_j|^2}{2\sigma^2}\right\}.
\]

Grid Search Method \([20]\) is a parameter optimization algorithm. It can optimize the accuracy of the SVM model by selecting penalty factors and proportional parameters \([21]\). \( c \) and \( g \) are the model parameters, and their values range from -10 to 10, the value of each change is 0.5. By calculating each intersection point and comparing the error, the most suitable intersection point is selected.

4. The Modeling by Machine Learning

4.1. BP Neural Network Model

4.1.1. Modeling by BP neural network. The inputs of the full-featured BP neural network model are T1-T10, T15-T20, and the outputs are T11, T12. The output and input of the reduce-dimension model are shown in Table 3. We construct a BP neural network model by a neural network toolkit in Matlab, and choose 37386 sets of samples randomly as training data, and the remaining 240 for testing. Set the parameters: the maximum number of iterations is 1000, the learning rate is 0.1, and the accuracy to be achieved is 0.00004. The formula for MSE is

\[
\text{MSE} = \frac{1}{m} \sum_{i=1}^{m} \left( y^{(i)} - \hat{y}^{(i)} \right)^2.
\]

\( y^{(i)} \) is the calculated result and \( \hat{y}^{(i)} \) is the actual value. The results of (MSE) after testing are shown in Table 4.
Table 4. The BPNN models and MSE

| Reduced-dimensional BP neural network model | the first layer | 7 | 8 | 9 | 10 | 11 |
|-------------------------------------------|----------------|---|---|---|----|----|
| MSE                                       | 0.3068         | 0.3156 | 0.3044 | 0.3129 | 0.3133 |
| the second layer                          | [9,3]          | [9,4] | [9,5] | [9,6] | [9,7] |
| MSE                                       | 0.3001         | 0.2995 | 0.3099 | 0.3032 | 0.2999 |
| the third layer                           | [9,4,3]        | [9,4,4] | [9,4,5] | [9,4,6] | [9,4,7] |
| MSE                                       | 0.3064         | 0.3013 | 0.2986 | 0.3023 | 0.3018 |
| the fourth layer                          | [9,4,5,3]      | [9,4,5,4] | [9,4,3,5] | [9,4,5,6] | [9,4,5,7] |
| MSE                                       | 0.3042         | 0.3016 | 0.3028 | 0.3003 | 0.3051 |

| Full-feature BP neural network model       | the first layer | 5 | 6 | 7 | 8 | 9 |
|-------------------------------------------|----------------|---|---|---|---|---|
| MSE                                       | 0.3269         | 0.3181 | 0.3190 | 0.3145 | 0.3243 |
| the second layer                          | [8,3]          | [8,4] | [8,5] | [8,6] | [8,7] |
| MSE                                       | 0.3274         | 0.3104 | 0.3071 | 0.3155 | 0.3127 |
| the third layer                           | [8,5,7]        | [8,5,8] | [8,5,9] | [8,5,10] | [8,5,11] |
| MSE                                       | 0.3156         | 0.3145 | 0.3144 | 0.3106 | 0.3184 |
| the forth layer                           | [8,5,10,4]     | [8,5,10,5] | [8,5,10,6] | [8,5,10,7] | [8,5,10,8] |
| MSE                                       | 0.3169         | 0.3177 | 0.3077 | 0.3155 | 0.3190 |

From Table 4, the Reduced-dimensional BP neural network model with three hidden layers has the highest accuracy, and the numbers of neurons are 9, 4, and 5, respectively. Its MSE value is 0.2986. The Full-feature BP model with two hidden layers has the highest accuracy, and the numbers of neurons are 8 and 5, respectively. Its MSE value is 0.3071. Measuring 240 sets of test data by the model with the highest accuracy, the results are shown in figures 3-4.

4.1.2. Simulation analysis. From figures 3-4, in the dimension reduction BPNN model, the percentage error of T11 ranged from -0.04952 to 0.1078, and the percentage error of T12 ranged from -0.04903 to 0.1006. In the full-feature model, the percentage error of T11 ranged from -0.04714 to 0.09984, and the percentage error of T12 ranged from -0.04599 to 0.1049. The industrial error range is 5%, and one of the test samples failed to fall within the error band.

We delete the abnormal data. In the dimension reduction BPNN model, the percentage error of T11 ranged from -0.04952 to 0.04375, and the percentage error of T12 ranged from -0.04903 to 0.04468. In the full-feature model, the percentage error of T11 ranged from -0.04714 to 0.04252, and the percentage error ranged from -0.04599 to 0.04188.
4.2. Locally Weighted Linear Regression

4.2.1. Modeling by locally weighted linear regression. The data of training set and testing set are the same as BP neural network. When the Gaussian kernel parameters are 1, 5, 10, the square error (MSE) is shown in Table 5.

| Classification of model | 1     | 5     | 10    |
|-------------------------|-------|-------|-------|
| reduction-Dimension LWLR| 71.3888 | 103.8594 | 123.0213 |
| Full-feature LWLR       | 198.6037 | 98.7409 | 114.1078 |

From Table 5, for the Reduced-dimensional LWLR model, when the k is 1, the model’s MSE value is 71.3888 with the highest accuracy. For the Full-feature model, when k is 5, the model has the highest accuracy, and its MSE value is 98.7409. Measuring 240 sets of test data by the model with the highest accuracy, the results are shown in figures 5-6.

4.2.2. Simulation analysis. From figures 5-6, in the dimension reduction LWLR model, the percentage error of T11 ranged from -0.05346 to 0.0856, and the percentage error of T12 ranged from -0.06587 to 0.07894. In the full-feature model, the percentage error of T11 ranged from -0.05781 to 0.08776, and the percentage error of T12 ranged from -0.05214 to 0.07479. Two of the test samples failed to fall within the error band, and one set of data is identified to the abnormal sample in the BPNN model. We delete the abnormal data. In the dimension reduction LWLR model, the percentage error of T11 ranged from -0.04658 to 0.04039, and the percentage error of T12 ranged from -0.04961 to 0.04261. In the full-feature model, the percentage error of T11 ranged from -0.04906 to 0.04245, and the percentage error ranged from -0.04906 to 0.04245.

4.3. Support Vector Machine Model

4.3.1. Modeling by support vector machine. The data of training set and testing set are the same as BP neural network. Through comparison, the optimal parameters of the dimensionality reduction SVM model are \( c = -0.5, g = 4 \). The optimal parameters of the full feature input model are \( c = -4.5, g = 0.5 \). Measuring 240 sets of test data by the model with the highest accuracy, the results are shown in figures 7-8.
4.3.2. Simulation analysis. From figures 7-8, in the dimension reduction SVM model, the percentage error of T11 ranged from -0.05443 to 0.0933, and the percentage error of T12 ranged from -0.04948 to 0.09713. In the full-feature model, the percentage error of T11 ranged from -0.04852 to 0.09815, and the percentage error of T12 ranged from -0.04325 to 0.09622. Two of the test samples failed to fall within the error band, and two sets of data are identified to the abnormal sample in the LWLR model. We delete the abnormal data. In the dimension reduction SVM model, the percentage error of T11 ranged from -0.04444 to 0.04014, and the percentage error of T12 ranged from -0.04948 to 0.04257. In the full-feature model, the percentage error of T11 ranged from -0.04852 to 0.04018, and the percentage error ranged from -0.04325 to 0.04624.

5. The Comparison of Three Machine Learning Models

The characteristics of the data are the basis for the study. The model selects three machine learning methods. And they have good predictive effects. According to the error of manual measurement results in the historical data, the enterprise stipulates that the error of measurement results is qualified if it is less than 5%. The relevant conclusive data for modeling and After removing the data out of the 5% error band is shown in Table 6.

| Model | Reduction-dimension | Full-feature | prediction error results in 5% error |
|-------|---------------------|--------------|-------------------------------------|
|       | Non-5% error band   | the rate of passing | Non-5% error band                  | the rate of passing | Reduction-dimension | Full-feature               |
| BPNN  | T11 1 0.99583 1 0.99583 | [-0.04952,0.04375] | [-0.04714,0.04252] |
|       | T12 1 0.99583 1 0.99583 | [-0.04903,0.04468] | [-0.04599,0.04188] |
| LWLR  | T11 2 0.99167 2 0.99167 | [-0.04658,0.04039] | [-0.04961,0.04261] |
|       | T12 2 0.99167 2 0.99167 | [-0.04871,0.04009] | [-0.04906,0.04245] |
| SVM   | T11 2 0.99167 1 0.99583 | [-0.04444,0.04014] | [-0.04852,0.04018] |
|       | T12 1 0.99583 1 0.99583 | [-0.04948,0.04257] | [-0.04325,0.04624] |
6. Conclusion
This work studies the measurement of train rim thickness, analyses in detail the original data, and shows the online correction efficiency of subsequent models. It uses BPNN, LWLR and SVM models, respectively, to predict train rim thickness, and get good accuracy. In addition to abnormal sample data, it can meet the requirements of the error range from industry perspective. Future work will study intelligent measurement models by considering the characteristic curve of machining equipment.

Acknowledgments
Thanks to the Professor Haiping Wei and Teacher Yu Cao for the instruction, also thanks to the lab students for the help. Thank you for your helpful insights when research is difficult. We also thank the fund for its support of the project. Research is supported by Liaoning Education Science “Thirteenth Five-Year Plan” Project of China under Grant No. JG18DA031; Liaoning Education Science “Thirteenth Five-Year Plan” Project of China under Grant No. JG18DB306. 2018 Liaoning University of Petroleum and Chemical Technology Graduate Education and Teaching Reform Research Project of China under Grant No.2018Y25. Liaoning Revitalization Talents Program under Grant No. XLYC1907166; Liaoning Province Department of Education Foundation of China under Grant No. L2019027; Liaoning Province Dr. Research Foundation of China under Grant No. 20170520135. The Natural Science Foundation of Shandong Province under Grant ZR2019BF004.

References
[1] R F Luo, H H Shao and Z J Zhang 1994 A new soft measurement method and its industrial application. (Journal of Shanghai Jiao tong University vol S1) pp 50-55
[2] M J Zhang and Y X Sun 1996 Soft measurement method and its industrial application. (Journal of Test and Measurement Technology vol 03) pp 126-131
[3] E F Yang, Q Zhou and Y F Hu 2001 On-line prediction soft measurement method for industrial cracking furnace yield based on PCA-RBF neural network (Journal of system simulation vol 13) pp 194-197
[4] R L Liu 2004 Research and industrial application of some problems in soft measurement technology (Zhejiang University) pp1-3
[5] R Y Li and G H Qi 2017 Soft measurement modeling based on the CSSE-OSELM algorithm and its industrial application (Acta Metrological Sinica vol 38(05)) pp 650-655
[6] B Bidar, J Sadeghi and F Shahraki 2017 Data-driven soft sensor approach for online quality prediction using state-dependent parameter models (Chemometrics and Intelligent Laboratory Systems vol 162) pp 130-141
[7] X F Yuan, B Huang, Y L Wang, C H Yang and W H Gui 2018 Deep learning-based feature representation and its application for soft sensor modeling with variable-wise weighted SAE (IEEE Transactions on Industrial Informatics) p 99
[8] X Q Shao 2015 Research on wheel rim thickness parameter detection technology (Hangzhou University of Electronic Science and Technology) p 14
[9] J Bi, H Yuan and M Zhou 2019 "Temporal Prediction of Multiapplication Consolidated Workloads in Distributed Clouds (IEEE Transactions on Automation Science and Engineering vol 16, no. 4, pp. 1763-1773
[10] J Bi, H Yuan, L Zhang and J Zhang 2019 "SGW-SCN: An integrated machine learning approach for workload forecasting in geo-distributed cloud data centers (Information Sciences vol, 481) pp. 57-68
[11] J Bi, T Feng and H Yuan 2018 "Real-time and short-term anomaly detection for GWAC light curves (Computers in Industry vol. 97) pp. 76-84
[12] H Yuan, J Bi, W Tan and B H Li 2017 "CAWSAC: Cost-Aware Workload Scheduling and Admission Control for Distributed Cloud Data Centers (IEEE Transactions on Automation Science and Engineering vol. 13, no. 2) pp. 976-985
[13] J Zhao, S X Liu, M C Zhou, X W Guo and L Qi 2018 Modified Cuckoo Search Algorithm to Solve Economic Power Dispatch Optimization Problems (IEEE/CAA Journal of Automatic Sinica vol 5(4)) pp. 794-806
[14] S Y Shao, J Y Cui, S Q Chen and Q Guo 2007 Research on on-line detection system of wheelset geometric parameters (Modern instrument vol 04) pp. 39-41
[15] Z F Zhang, Y Gao, Y F Ren and S Zhan 2010 Application of non-contact measurement in wheelset parameter detection technology (Laser and infrared vol40(10)) pp 1125-1130
[16] J K Wang 2008 A detection system of train wheel based on CCD imaging of technology (Dalian Jiao tong university) pp. 3-9
[17] J Y Zuo, W X Zhou, J Zeng and P B Wu 2002 Experimental study on measuring rim size with laser sensor (Railway Vehicles vol 02) pp. 11-13
[18] D E Rumelhart 1986 Learning representations by Back-Propagating errors (Nature vol 321) pp. 533-536
[19] C Cortes and V Vapnik 1995 Support-Vector networks (Machine Learning vol 20(3)) pp. 273-297
[20] V V Chemyshev 2001 Potentialities of grid search method (Acta Crystallographica vol 56(Suppl)) p 132
[21] X W Guo, M C Zhou, S X Liu and L Qi 2020 Multi-resource Constrained Selective Disassembly with Maximal Profit and Minimal Energy Consumption (IEEE Transactions on Automation Science and Engineering) accept