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Shearer reliability prediction using support vector machine based on chaotic particle swarm optimization algorithm

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ABSTRACT

Shearer reliability is considered as one of the most important indexes in longwall mining production. However, the traditional reliability methods are based on the specific distribution of the failure parameters, which are incongruent in the actual practice. Therefore, a novle shearer reliability prediction method based on support vector machine (SVM) with chaotic particle swarm optimization (CPSO) is proposed. It combines the advantages of the high accuracy of SVM and the fast convergence of CPSO, where the chaos idea is introduced to particle swarm optimization for the particle initialization, inertia weight coefficient optimizing and premature convergence treatment. Then this CPSO is used to select and optimize the important parameters of SVM. Ultimately, the optimized parameters are used to obtain a superior CPSO-SVM method for reliability prediction. To show the effectiveness of the proposed method, two numerical comparisons are designed respectively using the literature data and the actual shearer data from the coal mine enterprise. The research results reveal the prediction accuracy and validity of the proposed method.

Keywords: Reliability prediction; Support vector machine; Particle swarm optimization; Chaotic mapping.

1. INTRODUCTION

The shearer is known as the key equipment in longwall mining production. The basic structure of shearer is shown in Figure 1. Its reliability is important for keeping the mine production at the desired level and preventing unplanned operation stops. Any unexpected failure of the shearer may cause serious casualties and property losses. Therefore, it has great significance to predict the shearer reliability so as to implement a timely maintenance before the sudden failure occur. So, more and more studies have focused on the shearer reliability. Various theories and methods have been proposed to solve this problem. ESHAGHIAN *et al.* [1] investigated the failures of coal shearer picks in order to enhance the lifetime of cutting picks. CHEN *et al.* [2] used nonlinear dynamics and Runge-Kutta method to predict the reliability of shearer gear transmission system. ZHU *et al.* [3] used probability perturbation theory and the fourth-order moment method to design the shearer cutting arm. MA *et al.* [4] revealed the failure mechanism of the walking wheel and improve the haulage reliability of the shearer. GAO and ZHANG [5] presented a method of radial size design of the relief groove of torque shaft based on combining positive reverse reliability with unloading coefficient. PENG *et al.* [6] designed a simulation cutting experiment system to test the reliability of shearer spiral cutting drum. YANG *et al.* [7] analyzed the dynamic characteristics of key parts of shearer under different working conditions in order to optimize the shearer hardware structure. LIU *et al.* [8] investigated the vibration properties of a double drum coal shearer in order to improve the design reliability.

All of these researchers promote the theoretical and experimental developments of the shearer reliability prediction, however they are based on the specific distribution of the failure parameters, which are incongruent in the actual practice. According to the prediction research of the author's group [9–13] and considering the excellent performance on learning and generalization [14, 15], this paper plans to predict the shearer reliability using SVM with small samples. In order to overcome the weakness caused by artificial selected SVM parameters [16, 17], this paper plans to obtain the optimal results directly using the particle swarm optimization (PSO) algorithm. However, when handling the complex function, the PSO algorithm easy to fall into local optimum, having inferior local search ability and low precision [18]. Therefore, this paper proposes an SVM-based shearer reliability prediction method which combines the SVM and the CPSO. This CPSO-SVM method can avoid premature result and local optimum [19], so as to improve the prediction accuracy of shearer reliability.

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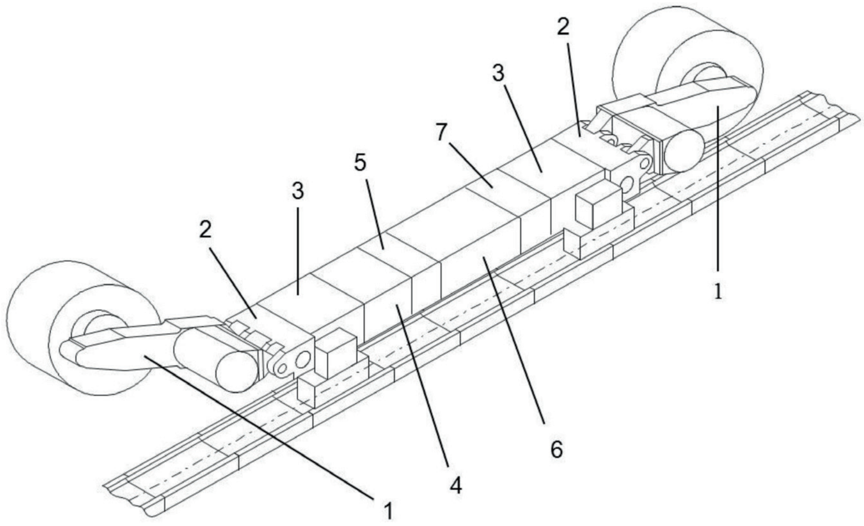

Figure 1: Basic structure of shearer.

1- cutting unit, 2-body connecting bracket, 3- haulage unit, 4- hydraulic tank, 5- high voltage switch tank, 6- inverter tank, 7- transformer tank

2. THEORY MODEL

2.1. SVM

The SVM is firmly grounded in the framework of statistical learning theory and Vapnik-Chervonenkis (VC) theory [20], which has been developed over the last three decades by VAPNIK and CHERVONENKIS [21]. The goal of SVM is to minimize the structural risk instead of the usual empirical risk by minimizing an upper bound of the generalization error [22]. Moreover, SVM is especially suitable for solving problems of small sample size and has already been used for classification, regression and time series prediction. Given training sample $\{(x_i, y_i), i = 1, 2, \cdots, l\}$, where $x_i \in R^n$ is the input vector, $y_i \in \{+1, -1\}$ is the expected output vector, l is the number of samples. Using the nonlinear mapping function $\varphi(\cdot)$ to map lower dimensional input vector to higher dimensional hyperplane. The separating hyperplane can be derived in Eq. (1).

$$f(x) = \omega\varphi(x) + b = \sum_{k=1}^{1} \omega_k \varphi(x_k) + b = 0 \tag{1}$$

where ω is the weight vector, the real b is called the bias. The ω and b determine the position of the optimal hyperplane which has to ensure the following constraint.

$$y_i f(x_i) = y_i(\omega\varphi(x_i) + b) \geq 1, \quad i = 1,\ 2,\ ...\ I \tag{2}$$

Introducing the surplus variable ξ_i as the error associated with the margin of the ith sample relative to the separating hyperplane. It is equivalent to solving the following optimization problem.

$$\min \frac{1}{2} \| \omega \|^2 + c \sum_{i=1}^{I} \zeta_i, \quad i = 1,\ 2,\ ...,\ I \tag{3}$$

subject to

$$\begin{cases} y_i(\omega x_i + b) \geq 1 - \zeta_i \\ \zeta_i \geq 0 \end{cases} \tag{4}$$

where c is called penalty factor, which used to control the tradeoff between margin maximization and error minimization. This problem can be solved by means of Lagrange multipliers as follows.

$$\max L(\alpha) = \sum_{i=1}^{I} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{I} \alpha_i \alpha_j y_i y_j k(x_i x_j),\ i = 1,\ 2,\ ...,\ I \tag{5}$$

subject to

$$\begin{cases} \sum_{i=1}^{I} \alpha_i y_j = 0 \\ \alpha_i \geq 0 \end{cases} \tag{6}$$

where α_i is the Lagrange multiplier. $k(x_i, y_i) = \varphi(x_i)\ \varphi(x_j)$ is kernel function through some another mapping function $\varphi\,(x)$. Thus, the classification decision function can be obtained by solving the Eq. (5).

$$f(x) = \mathrm{sgn}(\sum_{i,j=1}^{m} \alpha_i y_i k(x_i,\ x_j) + b) \tag{7}$$

where $f(x)$ is the classification decision function. The samples can be put into the well trained SVM, and get the classification results from $f(x)$. Some common kernel functions are liner: $k(x, y) = x{\cdot}y + 1$, polynomial: $k(x, y) = (x{\cdot}y + 1)^{\sigma}$, radial basis: $k(x, y) = \exp(-||x - y||/(2{\cdot}\sigma^2))$, sigmoid: $k(x, y) = \tanh(\kappa(x, y) - \delta)$, where κ and δ is the sigmoid parameters, and σ should be optimally tuned with c.

2.2. PSO algorithm

Presented by Kennedy and Eberhart in 1995, The PSO algorithm is good at solving optimization problems [23]. In PSO algorithm, each individual is a potential solution moving through a D-dimensional search space [24]. After the initialization of the population, the particle seeks the optimal solution by changing its velocity and position at each iteration according to two factors: its own best previous experience (Pbest) and the best experience of all particles (Gbest). At the end of each iteration, the performance of all particles will be evaluated by predefined fitness functions. Suppose there are n particles in a D-dimensional space. The positions of the particles are $X = (X_1, X_2, \cdots X_n)$. For the ith particle, its position is $Xi = (x_{i1}, x_{i2}, \cdots x_{iD})^{\mathrm{T}}$, and its velocity is $V_i = (v_{i1}, v_{i2}, \cdots v_{iD})^T$. At each iteration, all the particles update their positions and velocities through the Pbest indicated as $P_i = (p_{i1}, p_{i2}, \cdots p_{iD})^T$ and Gbest indicated as $P_g = (p_{g1}, p_{g2}, \cdots p_{gD})^T$. Eqs. (8) and (9), respectively represents how to update the position and velocity of each particle at the k + 1th iteration.

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 (p_{id}^{k} - x_{id}^{k}) + c_2 r_2 (p_{gd}^{k} - x_{gd}^{k}) \tag{8}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{9}$$

where $d = 1, 2, \cdots$D, D is the dimension of the search space. and are velocities of the ith particle in the dth dimension at the kth and k + 1th iterations. and are positions of the ith particle in the dth dimension at the kth and k + 1th iterations. represents the best position in the dth dimension that particle i has obtained until iteration k. represents the previous best position of whole particle in the dth dimension until iteration k. $c1$ and $c2$ are positive acceleration coefficients which respectively called cognitive parameter and social parameter. $r1$ and $r2$ are positive random numbers between 0 and 1. w is the inertia weight coefficient which balance the search range and the convergence rate. In order to prevent the blind search of the particle swarm, the position is limited to the range of $[-X_{max}, X_{max}]$, and the velocity is limited to $[-V_{max}, V_{max}]$.

2.3. CPSO algorithm

The performance of the PSO depends on the preset parameters, and it often suffers the problem of being trapped in local optima [25]. If the PSO falls into the local extremum, the velocities of all particles are easy to rapidly decrease to zero and stop flying, which causes the premature convergence [26]. However, characterized as ergodicity, randomicity and regularity [27], the chaotic search can experience all positions in a specific area without repeat. So, the chaos idea is introduced to PSO algorithm (CPSO) to enhance the performance of PSO.

Logistic mapping is a typical chaotic model which was presented by ROBERT [28]. This paper uses Logistic mapping to optimize the PSO algorithm, which is represented as follows:

$$x_{k+1} = ux_k(1 - x_k) \tag{10}$$

where k is the iterations, u is the control parameter. When $u = 4$ and $x_0 \in [0,1]$ the system of (10) has been proved to be entirely chaotic. The basic ideas of chaos are adopted in this paper are described as follows:

(1) Particle initialization. Using cubic mapping to get the chaotic variables which can be applied to chaotic initialization and chaotic perturbation.

$$z_{n+1} = 4z_n^3 - 3z_n \tag{11}$$

where $-1 \leq z_n \leq 1$ and $z_n \neq 0$. The chaotic variable z_n can be converted to the position of the ith particle in the dth dimension at the kth iteration. The convert equation can be presented as follows:

$$v_{id}^k = d_{i\min} + (1 + z_{id}^k)\frac{d_{i\max} - d_{i\min}}{2} \quad (i = 1, 2, ..., N) \tag{12}$$

where N is the size of the particle swarm, D is the dimension of the search space, d_{imax} and d_{imin} are the decision variables of the ith particle.

(2) Inertia weight coefficient optimization. In the PSO algorithm the inertia weight coefficient w is very important. In order to effectively balance the local search and the global search, improve the performance of algorithm optimization, enhance the convergence rate, chaos is employed to optimize the coefficient w as follows:

$$w_{k+1} = 4w_k(1 - w_k) \tag{13}$$

where k is the iterations, and w_k is the inertia weight coefficient at the kth iteration.

(3) Premature convergence treatment. The PSO algorithm is easy to fall into the local extremum, and casuse premature convergence. However, the swarm fitness variance δ^2 can be utilized as the judgment of the premature and calculated as follows:

$$\delta^2 = \sum_{i=1}^{N}\left(\frac{f_i - f_{avg}}{f}\right)^2 \leq H \tag{14}$$

$$f = \max\,(1, \max(abs(f_i - f_{avg}))) \tag{15}$$

$$f_{avg} = \frac{1}{N}\sum_{i=1}^{N} f_i \tag{16}$$

where f_i is the fitness of the ith particle at current iteration, f_{avg} is the average fitness of all particles, H is the premature judgment threshold. When $\delta^2 \leq H$, it can be predicted that the swarm has fell into stagnant state, the algorithm has been premature. However, the chaos can be employed to make the particles escape from the local optimum area by replacing the velocity according to following equation.

$$v_{id}^{k+1} = 4v_{id}^k(1 - v_{id}^k) \tag{17}$$

3. OPTIMIZE THE SVM PARAMETERS BY CPSO

In the SVM, the penalty factor c is used for keeping a proper balance between the calculation complexity and the separating error. If the value of c is too small, it is prone to be "lack of learning". Otherwise, if the value of c is too large, the situation of "over learning" will occur. The kernel parameter σ affects the complexity of the

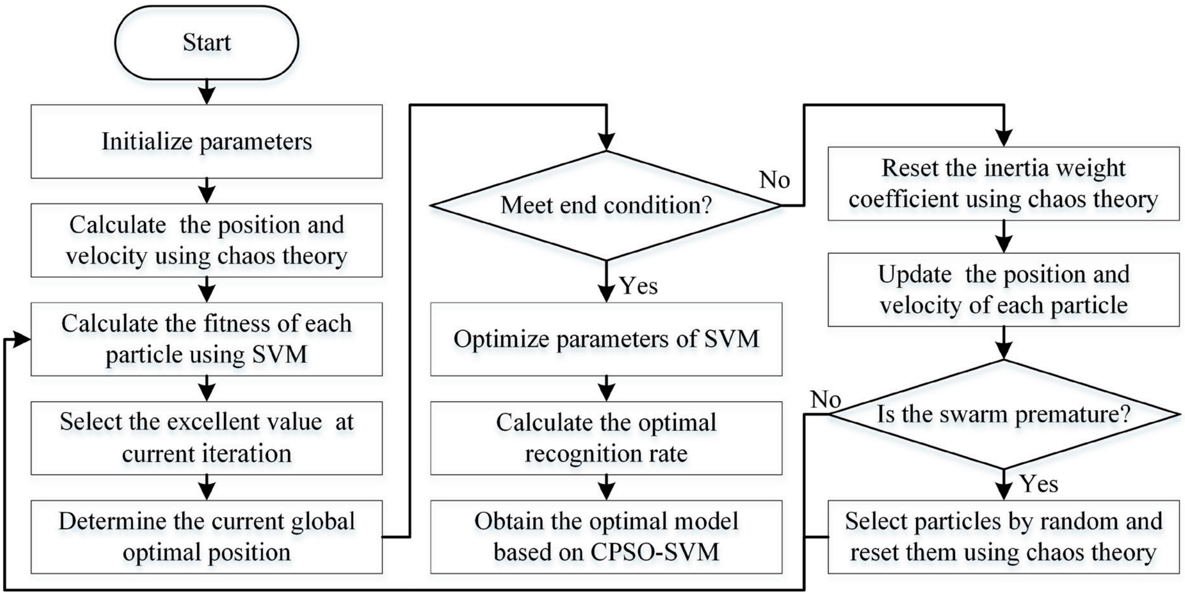

Figure 2: Framework of the proposed CPSO-SVM algorithm.

distribution for the sample data in the high-dimensional space. When $\sigma^2 \to \infty$, all the training samples identified as the same class, the generalization ability of the SVM is almost 0, which means serious "lack of learning". Otherwise, when the value of σ^2 is too small, it is prone to be "over-learning". However, in the SVM classification model, the parameter c and σ are affected by each another. So, these parameters cannot be optimized alone, they should be comprehensively considered at the same time in order to find the optimal combination values. The CPSO algorithm is not affected by the number of particle dimensions, and can optimize several parameters at the same time. Therefore, the CPSO algorithm with better optimization performance is proposed to find the optimized combination values of parameters in SVM model. Then an optimized SVM (CPSO-SVM) method is proposed in this paper, and its specific steps and framework are described as follows, and the framework is shown in Figure 2.

Step1: Parameter initialization. Initialize the parameters of the CPSO-SVM, including the population size N, the maximum number of iteration T, the inertia weight coefficient range $[w_{min}, w_{max}]$, the acceleration coefficient range $[c_{min}, c_{max}]$, the velocity range $[v_{min}, v_{max}]$, the premature judgment threshold H, the criterias of global convergence and premature convergence.

Step2: Particle chaotization. Initialize N chaotic sequences according to Eqs. (11), then convert them to particle velocities and particle positons by Eqs. (8) and Eqs. (9). Evaluate the fitness of each particle. Calculate the best previous experience of each particle P_i and the best experience of all particles P_g.

Step3: Data update. Update the inertia weight coefficient w according to Eqs. (13). Update the positon and velocity of each particle by Eqs. (8) and (9). Recalculate the fitness of each particle, and update P_i and P_g.

Step4: Premature judgment. Calculate the swarm fitness variance δ^2 according to Eqs. (14). If $\delta^2 \leq H$, it is predicated that the swarm has fell into stagnant state, and the algorithm has been premature, then perform Step 5, otherwise go to Step6.

Step5: Premature treatment. Rebuild some new particles according to Eqs. (11) and Eqs. (12). Evaluate the fitness of the new particles, and find the excellent ones, then use them to replace the previous particles randomly.

Step6: Program skip. If the stopping criteria is satisfied, or the program has reached the maximum iterations, then output the optimum solution and stop the program, otherwise loop to Step3.

4. APPLICATION EXAMPLES AND NUMERICAL COMPARISON

In this section, one literature case and one actual case of coal mine are presented to demonstrate the prediction performance of the proposed CPSO–SVM method. Firstly, reliability data of a turbocharged diesel engine, from XU *et al.* [29], are used to evaluate the superiority of the proposed method by being compared with other prediction methods. Then, actual failure data of a shearer, from XiShan Coal Electricity Group Co., LTD, are analyzed to verify the suitability of the CPSO–SVM method for the shearer reliability prediction. In this paper, the following measures are used for model evaluation: the mean absolute error (MAE), the root of mean square error (RMSE), the normalized root mean square error measure (NRMSE) and the Theil's inequality coefficient (TIC). These error indicators are defined as following:

$$\mathrm{MAE} = \frac{1}{N} \sum_{i=1}^{N} | y_i - \hat{y}_i | \tag{18}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{19}$$

$$\mathrm{NRMSE} = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} y_i^2}} \tag{20}$$

$$\mathrm{TIC} = \frac{\sqrt{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}}{\sqrt{\sum_{i=1}^{N} y_i^2} + \sqrt{\sum_{i=1}^{N} \hat{y}_i^2}} \tag{21}$$

where y_i and $\hat{y}$ denote the measured value and predicted result respectively.

4.1. Reliability prediction of the turbocharger

4.1.1. Data set

As shown in Table 1, the system reliability data of the turbocharger [29] are used to verify the effectiveness of the proposed method. In this example, data 1 to 35 are used for modeling and the rest 5 data are used for testing. Setting i as failure index, n as the data sample size, then the reliability $R(T_i)$ can be calculated by Eqs. (22).

$$R(T_i) = 1 - \frac{i - 0.3}{n + 0.4} \tag{22}$$

4.1.2. Performance of different optimization algorithms for SVM

The prediction results of turbocharger reliability based on SVM, PSO-SVM and CPSO-SVM are shown in Table 2. It is seen that the SVM gives an MAE of 0.0036, a RMSE of 0.0039, an NRMSE of 0.0063, and a TIC of 0.0031. The PSO-SVM has an improved prediction performance than SVM, with an MAE of 0.0031, a RMSE of 0.0033, an NRMSE of 0.0053, and a TIC of 0.0026. However, the CPSO-SVM achieves even better performance, with percentage decreases of 47.22% on MAE, 43.59% on RMSE, 44.44% on NRMSE, and 45.16% on TIC compared to prediction results of the SVM.

Figure 3 shows the reliability curves of turbocharger predicted by SVM, PSO-SVM and CPSO-SVM, respectively. Obviously, the CPSO-SVM has a better performance than the other two algorithms. It is because the parameters for SVM model are randomly specified which greatly affect the generalization performance. Although the PSO algorithm can optimize the parameters of the SVM, but it easy fall into local optimum. However, the CPSO algorithm can overcome the disadvantage of the PSO and find the global optimum of the SVM parameters. Therefore, the performance of the CPSO-SVM is greatly improved.

4.1.3. Comparison with literatures

Three previous literature methods: the MLP method, the RBF method by XU et al. [29], and the GRN method are used to compare with the proposed CPSO-SVM method. The parameters of CPSO are assigned as follows: $N = 100$, $T = 20$, $c_1 = 1.5$, $c_2 = 1.7$, $v_1 = 3.0$, $c \in (0, 100)$, $\sigma \in (0, 100)$, $H = 2.0$, $w_0 = 0.8$, and using the optimized SVM parameters $c = 9.4632$, $\sigma = 0.9989$ according to the framework of CPSO-SVM.

Table 1: Reliability of turbochargers.

I	*TI*/1000 h	R(TI)	*I*	*TI*/1000 h	R(TI)
1	1.6	0.993	21	6.5	0.7938
2	2.0	0.9831	22	6.7	0.7839
3	2.6	0.9731	23	7.0	0.7739
4	3.0	0.9631	24	7.1	0.7639
5	3.5	0.9532	25	7.3	0.754
6	3.9	0.9432	26	7.3	0.744
7	4.5	0.9333	27	7.3	0.7341
8	4.6	0.9233	28	7.7	0.7241
9	4.8	0.9133	29	7.7	0.7141
10	5.0	0.9034	30	7.8	0.7042
11	5.1	0.8934	31	7.9	0.6942
12	5.3	0.8835	32	8.0	0.6843
13	5.4	0.8735	33	8.1	0.6743
14	5.6	0.8635	34	8.3	0.6643
15	5.8	0.8536	35	8.4	0.6544
16	6.0	0.8436	36	8.4	0.6444
17	6.0	0.8337	37	8.5	0.6345
18	6.1	0.8237	38	8.7	0.6245
19	6.3	0.8137	39	8.8	0.6145
20	6.5	0.8038	40	9.0	0.6046

Table 2: Performance of the different optimization algorithms for SVM.

NO.	ACTUAL DATA	SVM	PSO-SVM	CPSO-SVM
36	0.6444	0.6508	0.6482	0.6461
37	0.6345	0.6376	0.6393	0.6383
38	0.6245	0.6224	0.6273	0.6263
39	0.6145	0.6174	0.6156	0.6142
40	0.6046	0.6083	0.6074	0.6064
MAE		0.0036	0.0031	0.0019
RMSE		0.0039	0.0033	0.0022
NRMSE		0.0063	0.0053	0.0035
TIC		0.0031	0.0026	0.0017

The prediction data listed in Table 3 indicates that the proposed CPSO-SVM method has the best performance overall on the dataset of turbochargers reliability. In details, MLP method gives an MAE of 0.0145, a RMSE of 0.0156, an NRMSE of 0.0250, and a TIC of 0.0123. For GRN method, obtains an MAE of 0.0062, a RMSE of 0.0068, an NRMSE of 0.0108, and a TIC of 0.0054. It is seen that RBF method has an improved prediction accuracy than MLP and GRN method, with an MAE of 0.0025, a RMSE of 0.0029, an NRMSE of 0.0046, and a TIC of 0.0023. However, the proposed CPSO-SVM method achieves even better performance. The MAE, RMSE, NRMSE, and TIC are 0.0019, 0.0022, 0.0035 and 0.0017, with percentage decreases of 24.00%, 24.13%, 23.91%, and 26.09% compared to that of the RBF method, respectively. These error indicators prove that the CPSO-SVM method provides wonderful prediction accuracy on the dataset of turbochargers reliability.

A more explicit illustration in Figure 4 shows how better the CPSO-SVM works than other compared methods do on the dataset of turbochargers reliability. The curve without mark is the actual reliability data which obtained from literature [29], whereas the curve marked with crosses is the reliability that predicted by CPSO-SVM. The results predicted by MLP, GRN, and RBF are represented by the curves marked with triangles, diamonds and circles respectively. It is clear that the result of the CPSO-SVM is best and nearly being the actual

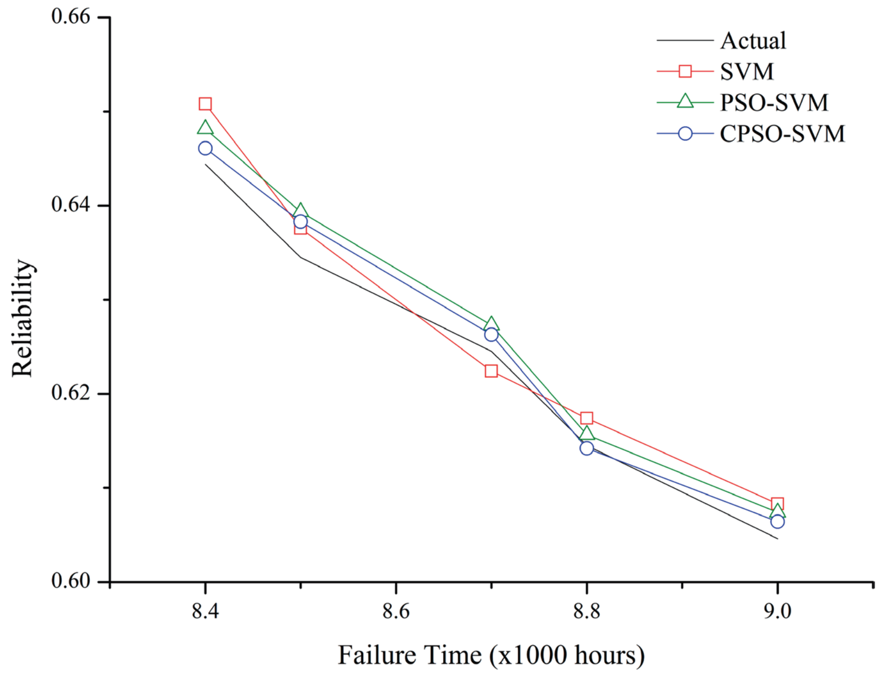

Figure 3: Performance of the different optimization algorithms for SVM.

Table 3: Performance of the methods on turbochargers reliability prediction.

METHOD	MAE	RMSE	NRMSE	TIC
MLP [29]	0.0145	0.0156	0.0250	0.0123
RBF [29]	0.0025	0.0029	0.0046	0.0023*
GRN	0.0062	0.0068	0.0108	0.0054
CPSO-SVM	0.0019	0.0022	0.0035	0.0017#

* The best literature result; # the best result; MLP: he multilayer perceptron network based method; GRN: generalized regression neural network based method; RBF: the radial basis function network based method.

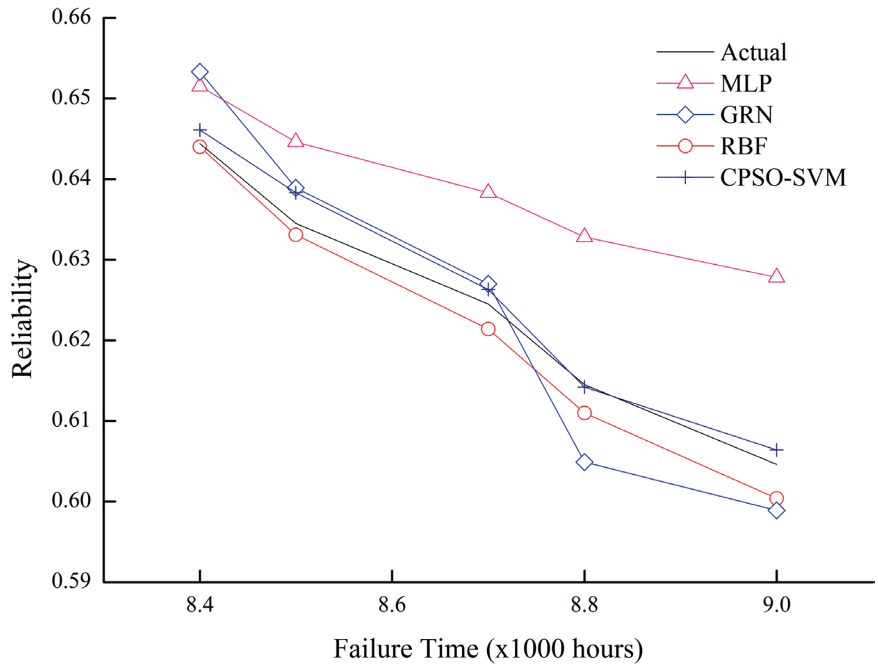

Figure 4: Performance of the methods on turbochargers reliability prediction.

value on most data points. Moreover, the RBF method has a best prediction result in these three literature methods, but not as good as that of the CPSO-SVM method. Therefore, this visual comparison proves the superior prediction accuracy of the proposed method.

4.2. Reliability prediction of the shearer

4.2.1. Data set

In this example, the shearer of Xiqu coal mine in Shanxi province of China is selected for data collection. The total power of the shearer is 600 kW, the supply voltage is 1.14 kV, and the hauling speed is 0–7.7–12.8 m/min. The diameter of the cutting head is 1800mm and the cutting depth is 800mm.

The required data, such as failure occurrence time, failure reason and type of repair action, are collected from maintenance reports over a period of nine months. Therefore, the reliability data that time to failures (TTF) are calculated as shown in Table 4. The objective of this paper is to predict the TTF of the shearer based on past failure data. Hence, using the reliability method explained earlier, the data are divided into two parts: training samples and testing samples. In this example, data 1 to 26 are the training samples and data 27 to 31 are the testing samples.

4.2.2. Parameter optimization

As mentioned before, the performance of the SVM is mainly affected by the penalty factor c and the kernel parameter σ. Therefore, this paper employs the CPSO algorithm to obtain the optimized parameters. However, the CPSO algorithm needs a suitable searching area for the parameter optimization. If the area is too small, the optimal result may be out of it. Otherwise, if the area is too large, the searching result may only be a suboptimal solution.

In order to confirm the suitable search area for the SVM parameters, this paper divides the entire searching area into many small pieces equally. Then search local optimal NRMSE in each small area. The local optimum points are shown in Figure 5, where c and σ are all within the range of (0, 50). As it is seen, the NRMSE is sensitive to the parameter σ, and is affected by the parameter c when $c \to 0$. Furthermore, the local optimal NRMSE achieves optimum value 0.0096 when σ within the range of (2, 6.5). Therefore, in this example the parameters of CPSO are assigned as follows: $N = 100$, $T = 20$, $c_1 = 1.5$, $c_2 = 1.7$, $v_1 = 3.0$, $c \in (0, 50)$, $\sigma \in (2, 6.5)$, $H = 2.0$, $w_0 = 0.8$.

4.2.3. Comparison with other methods

In this example, wavelet neural network (WNN) based method, GRN method, and SVM method are used to compare with the proposed CPSO-SVM method. The prediction data listed in Table 5 indicates that the CPSO-SVM method still has the best performance overall on the dataset of shearer reliability. In details, WNN method gives a MAE of 0.0761, a RMSE of 0.0809, an NRMSE of 0.0144, and a TIC of 0.0066. For GRN method, obtains a MAE of 0.0682, a RMSE of 0.0711, an NRMSE of 0.0127, and a TIC of 0.0064. It is seen that SVM method has an improved prediction accuracy than WNN and GRN method, with a MAE of 0.0536, a RMSE of 0.0536, an NRMSE of 0.0096, and a TIC of 0.0048. However, the proposed CPSO-SVM method achieves even better performance. The MAE, RMSE, NRMSE, and TIC of CPSO-SVM method are 0.0416, 0.0423, 0.0075 and 0.0038, with percentage decreases of 22.39%, 21.08%, 21.88% and 20.83% compared to that of the SVM method, respectively. These error indicators prove that the proposed CPSO-SVM method has a wonderful performance for shearer reliability prediction.

Table 4: TTF of the shearer (×1000h).

NO.	TTF	NO.	TTF	NO.	TTF	NO.	TTF
1	0.2492	9	1.9350	17	4.0913	25	5.2213
2	0.4685	10	2.2680	18	4.3437	26	5.3525
3	0.7290	11	2.6735	19	4.5478	27	5.4540
4	0.9180	12	3.0236	20	4.6152	28	5.5108
5	1.1354	13	3.3425	21	4.7998	29	5.6085
6	1.4038	14	3.5050	22	4.9113	30	5.6998
7	1.6080	15	3.7030	23	4.9765	31	5.7617
8	1.7900	16	3.8470	24	5.0775		

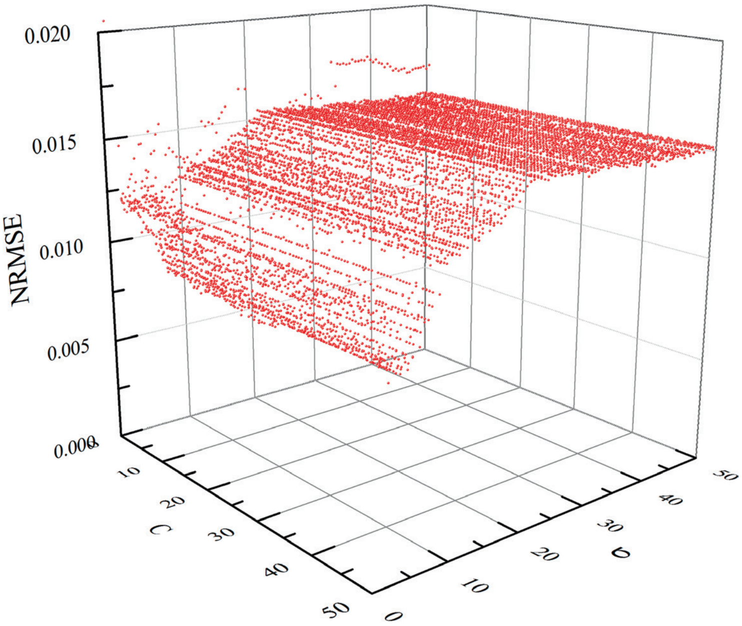

Figure 5: Local optimum discrete points of *c* and *σ*.

Table 5: Performance of the methods on shearer reliability prediction.

NO.	ACTUAL DATA	WNN	GRN	SVM	CPSO-SVM
27	5.4540	5.5771	5.3651	5.3993	5.4215
28	5.5108	5.5949	5.4806	5.5648	5.5451
29	5.6085	5.6511	5.5333	5.5564	5.5547
30	5.6998	5.7567	5.6289	5.6454	5.6582
31	5.7617	5.8356	5.6857	5.7090	5.7157
MAE		0.0761	0.0682	0.0536	0.0416
RMSE		0.0809	0.0711	0.0536	0.0423
NRMSE		0.0144	0.0127	0.0096	0.0075
TIC		0.0072	0.0064	0.0048	0.0038

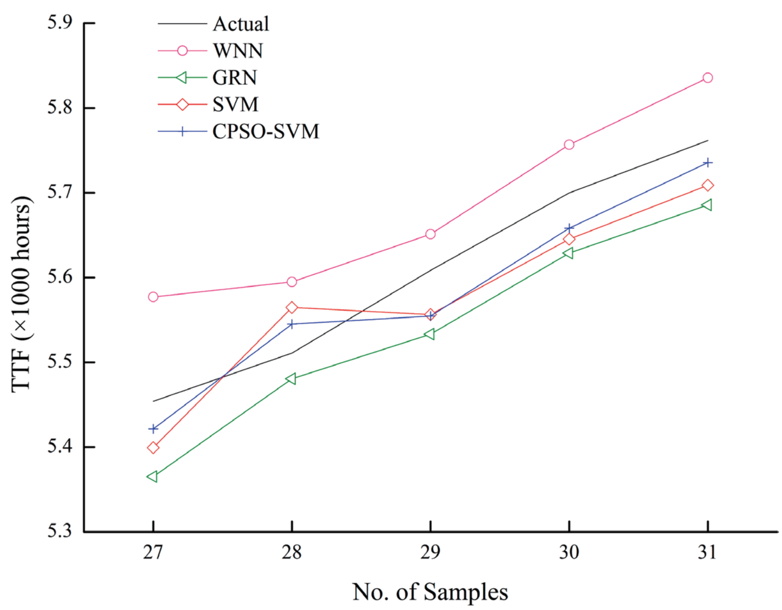

Figure 6: Performance of the methods on shearer reliability prediction.

Figure 6 gives a more explicit illustration in how better the CPSO-SVM works than other compared methods do on the dataset of shearer reliability. The curve without mark is the actual TTF of the shearer, whereas the curve marked with crosses is the TTF that predicted by CPSO-SVM. The results predicted by WNN, GRN, and SVM are represented by the curves marked with circles, triangles, and diamonds respectively. It is seen that the SVM method is superior to the WNN and GRN methods in forecasting performance. That is because SVM has an excellent performance on learning and generalization with small size sample. Moreover, the proposed CPSO-SVM method has better predictive performance than SVM method, and this can be attributed to the optimized SVM parameters which obtained by CPSO algorithm. Therefore, this visual comparison verifies the great suitability and prediction accuracy of the proposed method on the dataset of shearer reliability.

5. CONCLUSION

The prediction of shearer reliability in actual production process using CPSO-SVM method is presented in this paper. To avoid the deficiency of the SVM, the CPSO is proposed, which can get the optimal penalty factor c and kernel parameter σ, avoid premature result and local optimum. To show the effectiveness of the proposed method on reliability prediction, a numerical comparison using the turbocharger reliability data taken from the previous literature is designed. The results indicate that the proposed CPSO-SVM method is much better than the literature results using MLP, GRN and RBF method with the increase of 86.00%, 67.59%, and 23.91% on the indicator of NRMSE. To verify the applicability of the proposed method on shearer reliability prediction, a numerical comparison using the shearer reliability data taken from the coal mine enterprise is designed. The results show that CPSO-SVM method predicts shearer reliability with NRMSE of 0.0075, which reduces reliability prediction error about 47.92%, 40.94% and 21.88% compared to WNN, GRN and SVM methods,showing the accuracy and validity of the proposed method on practical industrial shearer reliability prediction.

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