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Retraction

Retracted: Research on Human Resource Management Performance Evaluation Method Based on Chaos Optimization Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] H. Wang, "Research on Human Resource Management Performance Evaluation Method Based on Chaos Optimization Algorithm," *Security and Communication Networks*, vol. 2022, Article ID 9201618, 8 pages, 2022.

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Research Article

Research on Human Resource Management Performance Evaluation Method Based on Chaos Optimization Algorithm

Hailin Wang

Rizhao Polytechnic, Rizhao, Shandong 276826, China

Correspondence should be addressed to Hailin Wang; rzwhl@rzpt.edu.cn

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All enterprise components and business activities are centered on the customer. Whether human resource management is reasonable and effective not only is a matter of human resource management, but also directly influences whether other resources can be used reasonably and effectively, and determines the efficiency of business operations. In human resource management, perfect performance evaluation criteria are developed based on the actual situation in order to evaluate employee productivity and work ethic. Nonetheless, in the process of actual enterprise HR management performance evaluation work, there are not only imperfect performance evaluation standards, but also relatively objective evaluation standards, and HR cannot conduct a comprehensive analysis of each position, which has a negative impact on the quality of enterprise HR management work. This paper improves the performance evaluation model for the original data mining and proposes a human resource management performance evaluation method based on chaotic optimization algorithm, which generates the initial values of evaluation data through chaotic logistic mapping, bringing the initial data closer to the optimal value, reducing the impact of random initialization on the algorithm's performance, and when the model is trained, it can make the algorithm's performance more stable. Capability thereby addresses the flaws in the original evaluation method. Experiments demonstrate that our method significantly improves the precision of model training and prediction.

1. Introduction

The process of enterprise production and management is an input-output process that cannot be separated from the use of human, material, and monetary resources. Human resources are active and subjective resources, initiating, manipulating, and controlling other resources, and occupying a preeminent position among productivity elements [1]. Therefore, whether human resource management is reasonable and effective not only is a matter of human resource management, but also directly influences whether other resources can be used reasonably and effectively and determines the effectiveness of business operations.

Human resource management's objective is to effectively exploit the potential and current energy of people [2]; its subject is all enterprise employees. Whether it is recruitment, hiring, promotion, training, or evaluation of employees, or adjustment of labor organization, reasonable division of labor and collaboration, improvement of working environment and labor conditions, or organization of wages, rewards, insurance, and welfare, the goal is to use labor force economically and rationally, reduce consumption, and increase work efficiency.

In enterprise development, performance evaluation is a routine examination of the daily work of enterprise employees, which can effectively motivate staff to work. In the work of performance evaluation, human resource management must develop a flawless evaluation standard based on the actual situation in order to evaluate staff productivity and work ethic [3]. Through the development of a performance evaluation mechanism, enterprise managers can effectively and fundamentally improve the level of human resources management of band enterprises, achieve a reasonable allocation of resources, and enhance the productivity of the staff of work enterprises. On the other hand, scientific and reasonable performance evaluation can motivate employees, improve their sense of belonging, and facilitate the enterprise's sustainable development.

Currently, the issues with human resource management performance evaluation work are as follows:

(1) Failure to conduct exhaustive analyses for each position. Prior to evaluating the performance of enterprise human resources management, personnel must actively comprehend the various positions within the organization and perform a thorough job analysis to ensure that the appropriate measures are implemented [4]. Nonetheless, in the actual work, some enterprises in China do not analyze the jobs based on the actual situation in human resource management, which results in the staff not having clear work objectives in the actual work, thereby causing the performance evaluation to have large errors and lose its meaning, which has a negative impact on the development of related work.

(2) Not possessing flawless performance evaluation criteria. The fundamental guarantee of the quality of performance evaluation work is the use of flawless evaluation standards. However, there is no perfect evaluation mechanism for the development of performance evaluation work in Chinese enterprises, resulting in a disconnect between the evaluation work and the actual circumstances of employees. Moreover, there are no designated perfect system implementation efforts, etc., in the process of performance rating operation, which negatively impacts the quality of enterprise human resource management work.

In order to address the aforementioned issues, this paper proposes a human resource management performance evaluation model based on data mining KNN algorithm. During the construction of the data mining model, we discovered that, due to the unique nature of human resource management performance evaluation, the problem of KNN algorithm based on data mining KNN algorithm is that KNN algorithm has the disadvantage of long classification time, as each test sample must be compared with all training samples. Specifically, the dimensionality of the feature vector in the evaluation classification is frequently thousands or even tens of thousands of dimensions, which requires a great deal of computation time.

This paper proposes a chaotic optimization algorithm for selecting the optimal feature terms from the training text set in order to form the feature subspace and then implementing KNN classification on the feature subspace.

2. Related Work

2.1. Comparative Analysis of Common Tools for Performance Appraisal

2.1.1. Key Performance Indicator (KPI) Appraisal Method. Key performance indicators are derived from the performance evaluation of construction projects in the UK and refer to a goal-based quantitative management tool used to measure process performance by setting, sampling, calculating, and analyzing key parameters on the input side (inputs) and output side (outputs) of processes within an organization [5].

The KPI appraisal method has the following advantages: clear objectives; grasp of key; objective and comparable results; and high operability. The KPI appraisal method has the following disadvantages: relatively difficult to determine the indicators and inflexible after the indicators are determined.

2.1.2. 360-Degree Appraisal Method. The "360-degree appraisal method" was first proposed and implemented by Intel Corporation. This method refers to understanding the performance of employees through different subjects such as themselves, supervisors, colleagues, subordinates, and customers [6]. Hsiao-Ho [7] conducted a detailed study of the 360-degree appraisal method and found that this assessment method can fully reflect the employee's achievements, but at the same time, there are also shortcomings in that the entire 360-degree assessment method depends on the degree of objectivity self-reported by all parties involved. The method would be worthless if it did not allow subordinates, leaders, and peers of the surveyed employees to make fair, honest, and open evaluations.

Advantages of the 360-degree appraisal method: the information obtained is more comprehensive, involving different levels of people; the results tend to be objective; the operation is simpler. Disadvantages of 360-degree appraisal method are a s follows: high qualitative components; quantitative components less; easy to appear "good old boy" results; subjective factors have a greater impact; and participation in a wide range of workload.

2.1.3. Balanced Scorecard (BSC) Method. The balanced scorecard is a strategic management method proposed by Professor Robert S. Kaplan of Harvard Business School and David P. Norton, founder and president of Renaissance Global Strategy Group [8]. It goes beyond the traditional approach of measuring business performance from a financial perspective only and examines a company comprehensively in four dimensions: financial, customer, internal operations, and learning [9], translating an organization's strategy into daily actions through a system of cause-and-effect indicators [10]. Indicators are both interdependent and interactive, and are an important tool for performance management.

Advantages of the balanced scorecard are as follows: comprehensive assessment with four dimensions of performance; balanced indicators; conducive to fostering organizational values; operable and applicable; and objective results. Disadvantages of the balanced scorecard are as follows: high information requirements and relatively heavy workload.

2.2. Analysis of the Traditional KNN Algorithm Prediction Model.

The K-nearest neighbor (KNN) algorithm is the simplest unsupervised learning algorithm in data mining classification techniques and a machine learning algorithm. The main idea of this method is to calculate the distance between the current sample data and the data points in the historical statistics, and to classify the current sample data based on the difference of the distance. K historical samples searched in a sample space belong to a certain category [11]. This paper summarizes the traditional KNN travel time prediction algorithm idea, considering domestic and foreign research.

Step 1: To predict the travel time of road section li, first determine the feature vector $(\alpha_i, \beta_i, \ldots, \mu_i)$ of road section l_i at time t_i travel time prediction, and initialize the historical dataset of road section l_i.

Step 2: Determine the appropriate k values.

Step 3: Narrow the search space by classifying the road segment li historical dataset (based on morning and evening peaks, holidays, etc.) or performing cluster analysis using k-means algorithm.

Step 4: Specify the similarity measure (e.g., Euclidean distance), and calculate the similarity between the road segment l_i feature vectors $(\alpha_i, \beta_i, \ldots, \mu_i)$ and the road segment l_i historical dataset metrics.

Step 5: Select the most similar K samples of the historical training set of road segment li, and predict the travel time of road segment l_i by combining and weighting the historical training set samples.

Since the prediction results of the KNN method are related to the K samples with the highest similarity, the KNN method is more suitable than other methods for the set of samples to be divided with more crossover or overlap of class domains. The main limitation of this method is that when there is a large variability in the capacity of each type of historical samples, it will make a larger proportion of individuals with larger sample capacity in the nearest neighboring samples and affect the classification results [11]. It is also necessary to calculate the distance of each sample, which leads to low efficiency of the algorithm when the historical samples are large. In the traditional KNN prediction model, in order to avoid the similarity calculation with each sample in the historical sample pool and to improve the speed of the model, on the one hand, the historical samples are classified by Step 3 to remove the samples that have little or no influence on the prediction results. This classification method is not targeted and lacks objective analysis and proof, while the computational effort after classification is still relatively large. On the other hand, when the k-means clustering algorithm is used for clustering, the target feature vector is compared with the cluster center, which simplifies the calculation process but ignores the uniqueness of each historical sample itself. As can be seen from Step 5, when the traditional KNN algorithm is used for search prediction, it is mostly based on the state vector of the current performance evaluation without considering the influence of others, and the prediction results do not have dynamicity.

2.3. Chaotic Optimization Algorithm. In 1997, Bing Li et al. [12] introduced chaotic sequences into the optimization algorithm and successfully solved the convergence to local minima in the optimization algorithm with great success. In recent years, some results have been obtained. The problem of search speed of optimization algorithms has been a hot spot and a difficult problem in optimization. The basic idea of using chaotic sequences for optimization search is to linearly map chaotic variables to optimization variables for searching. The optimization results are highly dependent on the search space and often fail to achieve satisfactory solutions when the search space is large. Moreover, the randomness of the chaotic motion makes it possible to jump far away when approaching the global optimal solution, resulting in a waste of optimization time. The search process based on chaotic dynamics is divided into two stages: first, the entire solution space is examined based on an iterative traversal track generated deterministically [13]. When certain termination conditions are met, the best state found during the search process or the best solution to the problem is approached, and this is used as the starting point for the second phase of the search. Then, using the results obtained in the first stage as the center, the search is further refined by adding small perturbations in the local area until the termination criterion is satisfied. The "coarse search" plus "fine search" secondary carrier method thus establishes the basic methodology for the optimization method based on chaotic search. Since then, much of the work on the optimization method based on chaos search has been carried out on the basis of this research and improvement, or in combination with other methods, to form a hybrid chaos optimization method.

The gradient descent algorithm is a commonly used optimization method with strong local search capability, but the drawbacks are large computational effort, long learning period, slow convergence, and tendency to fall into local minima. Choi et al. [14] introduced chaotic dynamics into the steepest descent method for function optimization and adopted a parallel search structure, in which chaotic dynamics is used to jump out of local minima and steepest descent is used to perform fine search in local minima. Taking advantage of the speed of the gradient descent algorithm and the global nature of chaos search, Hu et al. [15] first used the gradient descent method for "coarse search" and then used the chaos search to continuously expand the scale of the variable scale chaos for "fine search." The two methods are combined in an iterative combination.

The basic idea of chaotic genetic algorithm (CGA) is to load the chaotic variables into the variable population of the legacy algorithm and then use the chaotic variables to make small perturbations to the offspring population and adjust the perturbation magnitude gradually as the search process progresses. Yadong Li et al. [16] proposed a new legacy chaos optimization combination method, which can improve the legacy algorithm's local search capability and search accuracy while also proving that the algorithm can converge to the global optimum with probability.

3. Method

3.1. Definition of Chaos. A mathematical definition of chaos was given by Li T.Y. and Yorke J.A. in a short paper published in the American Mathematical Monthly in 1975 and is now called the Li–Yorke definition [17].

Definition 1. A continuous self-map $f: I \longrightarrow I \subset R$, where I is a subinterval in R, is located. There exists an uncountable set $S \subset I$ satisfying

(1) S does not contain a periodic point.

(2) Any $x_1, x_2 \in s(x_1 \neq x_2)$, and there is

$$\begin{aligned} &\lim_{t\longrightarrow\infty} \sup\left|f^t(x_1) - f^t(x_2)\right| > 0, \\ &\lim_{t\longrightarrow\infty} \sup\left|f^t(x_1) - f^t(x_2)\right| = 0. \end{aligned} \tag{1}$$

Here, $f^t(\cdot) = f(f(f(\cdot)))$ denotes the relation of t-heavy functions.

(3) Given any $x_1 \in S$ and any periodic point $p \in I$ of f, $x_1 \neq p$ has

$$\lim_{t\longrightarrow\infty} \sup\left|f^t(x_1) - f^t(p)\right| > 0. \tag{2}$$

Defining f is said to be chaotic on S.

In this definition, since the first two limits state that the subset of $x_1, x_2 \in S$ is fairly decentralized and fairly central, the third limit states that the subset does not converge to any periodic point, so the theorem itself predicts the existence of nonperiodic trajectories, neither whether the set of these nonperiodic points has a nonzero measure, nor which cycles are stable. Thus, the flaw in the Li–Yorke definition is that the Lebesgue measure of the set S may be zero; i.e., chaos is not observable at this time, whereas what is of interest is the observable situation; i.e., S has a positive measure at this time.

Definition 2. Let V be a tight metric space and the continuous map $f: V \longrightarrow V$ if the following three conditions are satisfied:

(1) Sensitive dependence on the initial value: there exists $\delta > 0$ for any $\varepsilon > 0$ and any $x \in V$, in the ε-neighborhood of x memory in y and the natural number n such that $d(f^n(x), f^n(y)) > \delta$.

(2) Topological transitivity: for any pair of open sets X, Y on V, there exists $k > 0$ such that $f^k(X) \cap Y \neq \phi$.

(3) The set of periodic points of f is dense in V.

Then, f is said to be a chaotic map or chaotic motion on V in the Devaney sense.

3.2. Chaos Optimization Theory. To a certain extent, optimization algorithms are operational research; i.e., they address the problem of optimal choice of decision problems [18]. With appropriate mathematical modeling, the decision problem can be equated to the study of finding the global minimum or maximum value in the state space (although the maximum value can be handled by transforming to the minimum value), i.e.,

$$\begin{aligned} &\min f(X), \\ &\text{st.}\, g(X) \leq 0, \\ &X \in \Omega, \end{aligned} \tag{3}$$

where X is the decision variable, a vector whose dimensionality is equal to the number of parameters of the decision problem. $f(X)$ is the mathematical model of the decision problem and the objective function of the decision problem. $g(X) \leq 0$ is the constraint of the decision problem, and Ω is the feasible domain of the problem.

Chaos is a seemingly irregular, random-like phenomenon that occurs in a deterministic system, and is a more common phenomenon in nonlinear systems. Chaos is not a chaotic mess, but a class of phenomena with a refined internal structure. Chaos is a form of operation of a nonlinear kinetic system under certain conditions, a random behavior of the system in a nonequilibrium process, and the mechanism for generating chaos is often simply nonlinear, a fixed rule without any random element [19]. Therefore, nonlinearity is a necessary condition for chaos to arise, but not all nonlinear systems will generate chaos, and chaos is generally considered to occur when the system has the following numerical characteristics:

(1) The motion of the system is characterized by strange attractor phenomena.

(2) The power spectrum of the system motion is characterized by the superposition of spikes on a continuous spectrum.

(3) There is at least one Lyapunov exponent in the system that is greater than zero.

If the decision problem is a convex problem, it can be solved using linear programming, nonlinear programming, and so on. However, a large number of problems are nonconvex, and it is necessary to find the global optimal solution among a large number of locally optimal solutions. It is customary to classify optimization algorithms into two categories: local optimization algorithms and global optimization algorithms. The former can be called classical optimization algorithms, which have been extensively studied and published in many research papers [20], and the latter is customarily called modern optimization algorithms, which is a new type of global optimization algorithm emerging in the 1980s, mainly for the intractable problems in optimization problems, i.e., the NP-HARD problem [21].

Typically, deterministic search strategies such as the simplex method, gradient descent method, and greedy method are employed by local optimization algorithms to solve convex or single-peaked problems. In the state transfer process, the fundamental idea is to accept only the superior states and reject the inferior ones [22]. Global optimization algorithms are typically employed to solve convex or multipeaked problems utilizing probabilistic search strategies, i.e., state transfer rules, as actual global optimization problems typically lack analytical expressions or have expressions that are too complex for theoretical analysis. The basic idea is to search from one or more random initial points in the feasible domain, to search for new better points using appropriate state transfer rules and reasonable probabilistic state reception rules, and to terminate the operation after a predetermined amount of time or searches. Typically, local optimization algorithms can quickly converge to a locally optimal solution, whereas global optimization algorithms are less capable of searching for locally optimal points but can obtain the best possible global optimal solution region through probabilistic search. The basic solution lies in combining the two, i.e., using a global optimization algorithm to search the optimal solution domain in the entire feasible domain and a local search algorithm to search the optimal solution in the optimal domain; the so-called memetic algorithm is the basic embodiment of this concept.

3.3. Classical Chaos Optimization Algorithm. The basic steps of the classical chaos optimization algorithm are as follows [23]:

Step 1: Initialize the algorithm. By setting $k=1$ and assigning x_i in equation to each of the ix initial values with small differences, we obtain f chaotic variables with different trajectories $x_{i,n+1}$.

Step 2: Using the carrier method, the selected i chaotic variables $x_{i,n+1}$ are turned into i optimization variables $x'_{i,n+1}$, and the variation range of the chaotic variables is "scaled up" to the value range of the corresponding optimization variables.

$$x'_{i,n+1} = c_i + d_i x_{i,n+1}, \tag{4}$$

where c_i, d_i are constants, which are equivalent to the "magnification" multiplier, and the above equation is an algebraic sum.

Step 3: Iterative search with chaotic variables.

Let $x_i(k) = x'_{i,n+1}$ and calculate the corresponding performance index $f_i(k)$. Let $x^* = x_i(0) f^* = f(x(0))$; if $f_i(k) < f^*$, then $x^* = x_i(k)$, $f^* = f_i(k)$; otherwise, give up.

Step 4: If the optimal value remains unchanged after several searches, proceed to the next step; otherwise, go back to Step 3.

Step 5: Perform the second carrier.

The second carrier is the one in which the optimal value of the second waveform is the same as that of the second waveform.

$$x'_{i,n+1} = x'_i + a_i x_{i,n+1}, \tag{5}$$

where $a_i x_{i,n+1}$ are chaotic variables with very small traversal intervals, x'_i is the modulation constant, which can be smaller than 1, and x^* is the current optimal solution.

Step 6: Continue the iterative search with the chaotic variables after the quadratic carrier wave.

Step 7: If the termination criterion is satisfied, the search is terminated and the optimal solution is output. If not, return to step 6.

3.4. Our Chaos Optimization Algorithm

3.4.1. Chaotic Mapping with Inertia Weights. In the PSO algorithm, large inertia weights favor global search while small inertia weights favor local search. The inertia weight w influences the convergence of the problem-solving and PSO search processes, which impacts classification precision. PSO is susceptible to local optimums, which leads to early convergence. The chaotic mapping is added to PSO to create CPSO so that the CPSO algorithm can overcome premature convergence and guarantee the search to the global optimum, but also guarantee the search speed, so that the classification algorithm's performance is enhanced.

Chaos is a nondeterministic state of random motion generated by deterministic equations. The characteristics of chaos are randomness, ergodicity, and regularity. Consequently, the chaotic mapping is utilized during each iteration of the BPSO algorithm to determine the value of the inertia weights. According to the logistic mapping [24] of equation (6), the values of the inertia weights are calculated as follows:

$$\omega(t+1) = u \times \omega(t) \times (1 - \omega(t)), t = 0, 1, 2, \ldots n, \tag{6}$$

where $\omega(t)$ is a chaotic sequence (0, 1), u is the control parameter, and the logistic mapping is in a chaotic state when $3.6198 \le u \le 4$. When $u = 4$, it is completely chaotic. When the inertia weight is close to 1, the CPSO algorithm strengthens the search ability of global optimum; when the value of inertia weight is close to 0, the search ability of local optimum is enhanced.

3.4.2. Description of CPSO-Based KNN Classification Algorithm. The basic idea of the new algorithm is that the CPSO algorithm generates P particles at each iteration, selects the corresponding feature terms on the feature space set according to the position value of each particle to form the corresponding feature term subset, and then performs KNN classification on these feature term subsets for the test text separately to obtain P groups of K-nearest neighbors, compares the fitness values of all particles, and obtains the current optimal particle, i.e., the current global most K-nearest neighbors that are most similar to each other. After continuous iterations of the CPSO algorithm, the K-nearest neighbors with the highest fitness are finally found, and then the class to which the test text should belong is calculated according to the KNN classifier method (Algorithm 1).

4. Experimental and Analysis

4.1. Data Preprocessing. The data preprocessing methods we use in the experiment are data missing value supplementation and normalization, PCA dimensionality reduction, and other elements [24]. Among them, we supplemented the values with missing value processing, after which the range of values made the data normalized, and we avoided the phenomenon of slowing down or even failing to converge the network due to too much difference in the values taken. We normalize the data by transforming them into a range of [0, 1] to obtain better learning efficiency and prediction accuracy. As shown in the figure below, we compare the

Input:
Text set D
Text X
Nombre de texts de formation
K- nearest neighbors NUMBER OF FEATURE TER
Particles P
Lower and upper limits of particle velocity V_{min} and V_{max} MAXIter iterations.
Output:
K-nearest neighbors with the best F1 value and the test category.
1. Preprocess the data of the training set, including downscaling and outlier removal
2. The VSM model of the training set is constructed.
3. Calculate the TF-IDF value of each feature item according to the feature item set, and build the VSM vector of X.
4. Initialize the particle swarm. The positions X_i, velocity V_i, particle optimal position pbesti, and global optimal position gbest of P particles are randomly generated, each of the particle positions is 0 or 1, and the velocity is a random number within (0, 1); the current iteration number $t = 0$.
5. For $i = 1$ to P
(a) Evaluate the fitness F (X_i) of particle i. Here, the K-nearest neighbors of the test text X are calculated according to the KNN classification method, the value of the classification evaluation criterion F1 is calculated, and the F1 value is used as the fitness of the particle. Globally, optimal particle has the highest F1 value.
(b) Calculate chaotic inertia weight
(c) Update the particle's speed and position.
(d) Calculate the optimal position pbesti of particle i; calculate the global optimal position gbest of the particle population.
(e) If F(X_i) > F(pbesti), then pbesti = xi.
(f) If F(Xi) > F(gbest), then gbest = xi.
(g) END
6. $T = T+1$
7. Check whether the termination condition is satisfied; if so, then turn (8); otherwise, go to (5). The termination condition is that the number of iterations exceeds MAXIter.
8. Calculate X's category based on its K-nearest neighbors and output it.

Algorithm 1: Algorithm of CPSO-based KNN classification.

learning performance of the model with and without data normalization.

As shown in Figure 1, the prediction results of the neural network are more accurate and within the error value after unifying the values of the group sample data into one order of magnitude, which indicates that the robustness and accuracy of the network learning are significantly improved after unifying the field values of the sample data into one order of magnitude.

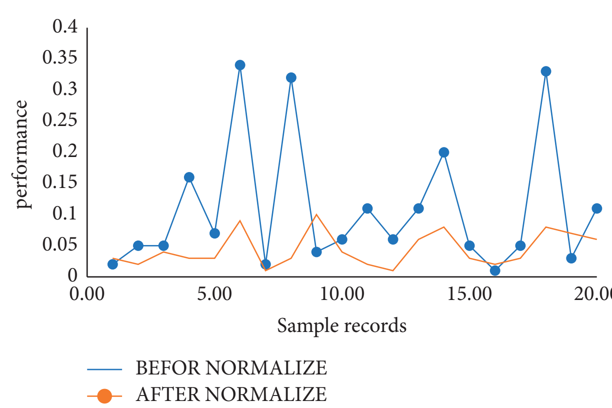

Figure 1: Learning performance comparison using preprocessed sample data.

4.2. Feature Dimension. In order to verify the effect of different feature dimensions on the classification effect, the feature dimensions are taken as 100, 200, 500, 1000, 3000, and 5000, as shown in Figure 2, the distribution of F1 values obtained from the experiment. For the CPSO–KNN algorithm, the F1 value changes most significantly when the feature dimension reaches 500, and the F1 value does not change much when the feature dimension is greater than 500, indicating that the larger the feature dimension is, the better the classification effect is, but it increases the computation time.

4.3. Convergence Process. The following figure shows the convergence process of the optimized solution. As shown in Figure 3, the global fitness of CPSO–KNN is stable after 120 iterations of the algorithm. In contrast, the global fitness of the ordinary KNN algorithm is stable after 180 iterations, which shows that the optimized model converges better during training.

4.4. Accuracy Comparison. We used 800 performance evaluation data for testing. The classification accuracies of the simple KNN algorithm and the algorithms in this paper are measured using the cross-validation method, as shown in Table 1, which shows the specific results.

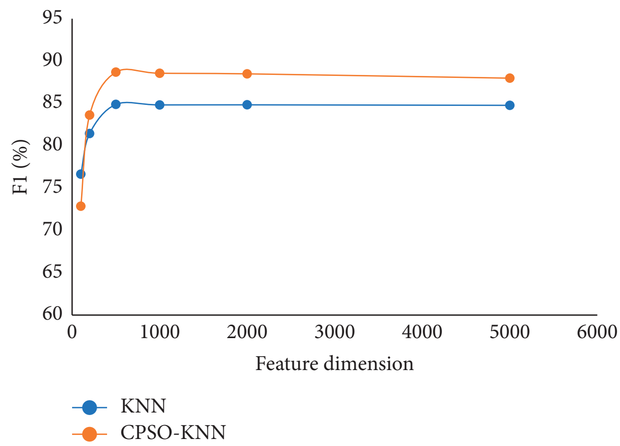

Figure 2: Effect of feature dimension on F1.

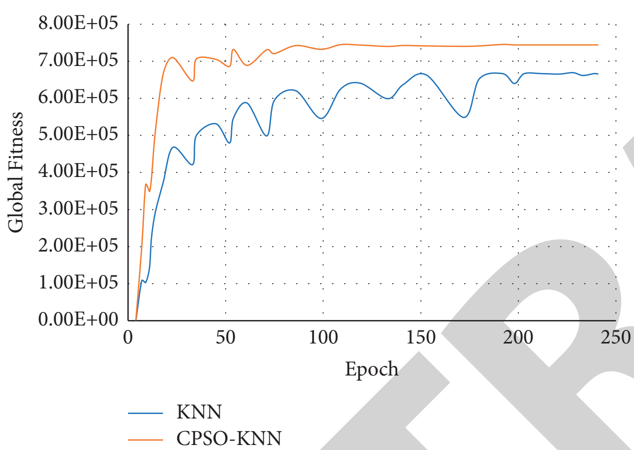

Figure 3: Convergence of the algorithm.

Table 1: Accuracy comparison.

Algorithm	Epoch	Accuracy
KNN	180	0.848
CPSO–KNN	120	0.872

The average classification accuracy of each KNN algorithm on this dataset is 0.848, while the average is 0.872. Overall, the CPSO–KNN classification accuracy is better than the traditional KNN algorithm on the performance evaluation dataset.

5. Conclusion

Due to the unique nature of HRM performance evaluation, this paper proposes a data mining-based model for HRM performance evaluation that is based on chaos optimization. Due to the incorporation of chaos mapping, the effect of random initialization on the performance of the algorithm can be mitigated during model training, and model training can eliminate local optimum and increase the algorithm's capacity to find the global optimum solution. The experimental results demonstrate that the data mining evaluation model utilizing chaos is quantitative and specific with a high degree of accuracy, and can be used as a benchmark by enterprise HR departments for performance evaluation.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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