Research on the construction of enterprise human resource allocation model based on multi-objective particle swarm optimisation algorithm

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Abstract: The irrationality of human resource allocation and the unfitness of talent positions make it difficult for the original human resource management model of the enterprise to give full play to its actual effect to a certain extent, which has a negative impact on the overall economic benefits of the enterprise. Therefore, this research combines the perspective of multi-objective problems and the particle algorithm with the characteristics of fast convergence, simplicity and parallel search, makes a systematic study of multi-objective optimisation and introduces matrix criteria to the configuration model for testing. The results show that, the improved multi-objective particle swarm optimisation algorithm has the highest accuracy of 98.54% on the data set, and the classification performance and combination mode of the algorithm have good application results. At the same time, the human resource model under the algorithm makes the maximum enrolment rate reach 9% and the maximum decline of turnover intention reach 10%. The optimisation of enterprise human resource allocation model can realise the high efficiency of the overall system of the enterprise and promote its long-term benign development.

Keywords: multi-objective particle swarm optimisation algorithm; enterprise development; human resource allocation model; employee satisfaction evaluation.

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1 Foreword

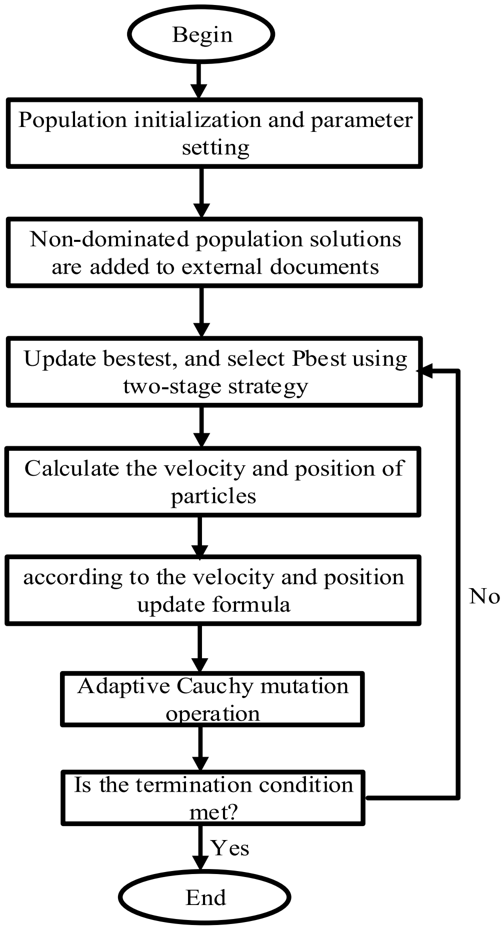
As the most dynamic and innovative factor of production, people can bring great positive guiding ability to the development of enterprises and the income generation of social economy. The optimal allocation of human resources in enterprises is conducive to reducing the time cost, avoiding the waste of resources and reducing the employment risk of enterprises (Li et al., 2018). Particle Swarm Optimisation (PSO) has certain advantages in data processing, but it inevitably has the problems of falling into local optimum and premature, which affects the efficiency and integrity of data running algorithm (Wang et al., 2018). Most scholars have put forward their own views on the allocation of human resources. Bao et al. (2020) analysed the influencing factors of enterprise human resources allocation based on the data envelopment method; Wang and Srivastava (2020) and Chen et al. (2021) used grey correlation analysis and fuzzy system to evaluate the risk factors and conduct qualitative and quantitative treatment on the influencing factors of enterprise human resources, in order to improve the efficiency of enterprise human management. However, the above methods are difficult to detect HR management changes synchronously to a certain extent, and are vulnerable to subjective factors. Alkebsi and Du (2020) proposed to use fitness sharing technology to select the optimal value and introduce the external centralised elite particles into the group, so as to realise the real-time update and processing of archives. Tang et al. (2019) realised the optimisation of particle swarm by quantum behaviour, so that particles can appear in the whole feasible search space with a certain probability, effectively avoiding the problem that particles are easy to fall into local optimisation, and can better determine the numerical value. Multi-objective particle algorithm has a good range of applications, and can filter and extract data information. Therefore, in terms of the structure arrangement of the paper, the research first optimises the multi-objective particle swarm optimisation algorithm, that is, assigns different weight values to the objective function value, and carries out iterative particle screening when designing the multi-objective evolution mechanism and selection strategy, and selects the screened non-dominated solution set to improve the search ability of particles. Then, the optimised particle algorithm is applied to the construction of enterprise human resource model, and the multi factors that affect human resource management are compared to the multi-objective function values. At the same time, the suitability of Posts and human resources is considered by the evaluation matrix standard. Then, the application effect of the established human resource model is tested in order to provide various achievable solutions for the decision-making objectives. The model construction method proposed in the study meets the needs of dynamic human resource management mode, and can further improve the ability of enterprises to appoint, hire and retain personnel and promote their long-term stable development.

2 Optimisation and improvement of multi-objective particle swarm optimisation algorithm and construction of enterprise human resource allocation model

2.1 *Optimisation of multi-objective particle swarm optimisation and establishment of model*

Multi-objective optimisation refers to choosing between a group of at least two or more conflicting objectives, which involves maximising or minimising multiple conflicting objective functions (Nabavi et al., 2021). Particle Swarm Optimisation (PSO) evaluates the performance of each potential solution through fitness function, which makes the particles representing the global optimal solution or the particles representing the local optimal solution converge to the optimal solution continuously (Aparicio and Pastor, 2018; Feng et al., 2019). The multi-objective problem can be widely used in the fields of information processing and decision-making, and combined with particle algorithm to explore the enterprise human resource allocation model, which can effectively grasp the individual diversity of employees and the effectiveness of human management mode, and improve the efficiency of resource allocation. Multi-objective particle swarm optimisation algorithm gives different weights to the objective functions and combines them to find the Pareto optimal solution in the running process. The improved flow chart of multi-objective particle optimisation algorithm is shown in Figure 1.

Figure 1 Improved flow chart of multi-objective particle swarm optimisation algorithm



In Figure 1, first initialise the population particles and set the parameters, then import the relevant human resources data, select the global optimal particles according to the stage strategy, update the particles according to the position and speed formula and evaluate and adjust the particle function value with the adaptive Cauchy mutation operation until the termination condition is reached, then the optimal solution is output. In the traditional particle swarm optimisation algorithm, the population is composed of a collection of particles and each particle in the population represents a feasible solution in an optimisation problem (Yang and Li, 2018). That is, the dimension of particles in the population is set as d, and the population size in the search space is set as n, which makes the position of particles change after iteration. The calculation formula of particle algorithm is shown in Formula (1).

$$\begin{cases} v_i(t+1) = w \cdot v_i(t) + c_1 r_1(t)\left[pbest_i(t) - x_i(t)\right] \\ +c_2 r_2(t)\left[pbest_i(t) - x_i(t)\right] \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{cases} \tag{1}$$

In formula (1), $v_i(t+1)$ is the velocity of the particle, $x_i(t+1)$ is the position of the particle and the $pbest_i$ is optimal position obtained by the particle according to its own experience during flight, that is, the local optimal solution. t is the iteration number, w is inertia weight, c_1, c_2 are individual learning factor and social learning factor, and r_1, r_2 is a uniform random number within the range of [0, 1]. The transformation of multi-objective optimisation problem into mathematical problem is the minimisation problem of multi-objective function, namely formula (2).

$$\begin{cases} \min imizeF(x) = \left[f_1(x), f_2(x), ..., f_k(x)\right] \\ s.tg_i(x) \le 0, i = 1,2,...,m \\ h_i(x) = 0, i = 1,2,...,l \end{cases} \tag{2}$$

In formula (2), D is the decision vector representing one dimension $fi(x)$ is the objective function of the decision vector, $gi(x)$ is the constraint condition of equation, m is the maximum number of inequality constraints, $hi(x)$ is the constraint condition of equation and l is the maximum number of equality constraints.

The improvement of multi-objective particle optimisation algorithm lies in the selection of global optimal solution, the avoidance of Pareto method falling into local optimal solution and the improvement of external document updating strategy, that is, the convergence and distribution of the screened non-dominated solution set are evaluated by the formula of average similar distance, so as to use the optimal solution with the largest distance in the screened non-dominated solution set to guide particles to fly, so as to improve the exploration ability and dominant convergence efficiency of particles in the population.

$$\begin{cases} d(x_i, y_j) = \sqrt{\sum_{k=1}^{N}(x_{i,k} - y_{j,k})^2} \\ SD_i = \left\{d(x_i, y_1), d(x_i, y_2), ..., d(x_i, y_Q)\right\} \\ ASD_i = \dfrac{\sum_{j=1}^{Q} SD_{i,j}}{Q} \end{cases} \tag{3}$$

In formula (3), SD_i is the similarity distance between the iteration position of particles and the position of external particles, ASD_i is the average similarity distance, x_i indicates the i particle in the population and y_j is the non-dominant solution in j external document, N is the dimension of particles and Q is the number of non-dominant solutions in the external document.

$$\begin{cases} d(A,L) = \dfrac{|ax_A + by_A + c|}{\sqrt{a^2 + b^2}} \\ X_{i,j} = x_{i,j} + F_n Cauchy(X_{\min}, X_{\max}) \end{cases} \tag{4}$$

In formula (4), $d(A,L)$ is the improved calculation method and $X_{i,j}$ is the improved Cauchy variation calculation formula. According to the formula of average distance, A is the non-dominated solution , x_A, y_A are the two target values from the non-dominated solution to the straight line, and $Gbest$ is the solution with the largest distance from each point to the straight line is taken as. $x_{i,j}$ Is the value of dimension of particle, $X_{\min}, X_{\max}$ is the maximum and minimum value of problem definition domain interval, and F_n is the control factor based on the change of iteration times, a and b are parameter values in the linear equation.

2.2 Optimisation algorithm of enterprise human resource allocation model

Under the background of social and economic development, the important position of knowledge economy and human resources has gradually become prominent, and human resources, as the lifeline of enterprise development, to a certain extent, have highlighted the enterprise management philosophy and development needs (Aparicio and Pastor, 2018). However, some enterprises have some problems, such as brain drain, imperfect management system and lack of corresponding supporting facilities, which make it difficult to retain and recruit people a development problem, which is not only unfavourable to the long-term healthy development of enterprises, but also easy to cause certain waste of resources and time cost (Feng et al., 2019; Yang and Li, 2018; Jonathan et al., 2020). The introduction of the multi-objective particle optimisation algorithm into the enterprise human resource training mode and the establishment of a new human resource allocation mode means that the multi-objective factors affecting human resource management are compared to the objective function value of the multi-objective algorithm. Through the iterative analysis and screening of the influencing factors, and considering the actual needs, the human resource allocation is conducive to comprehensively considering the selection, training to establish a benign and optimised human resource allocation in terms of evaluation, rewards and punishments. The human resource allocation model of the enterprise is shown in Figure 2.

Figure 2 Optimal allocation model of human resources

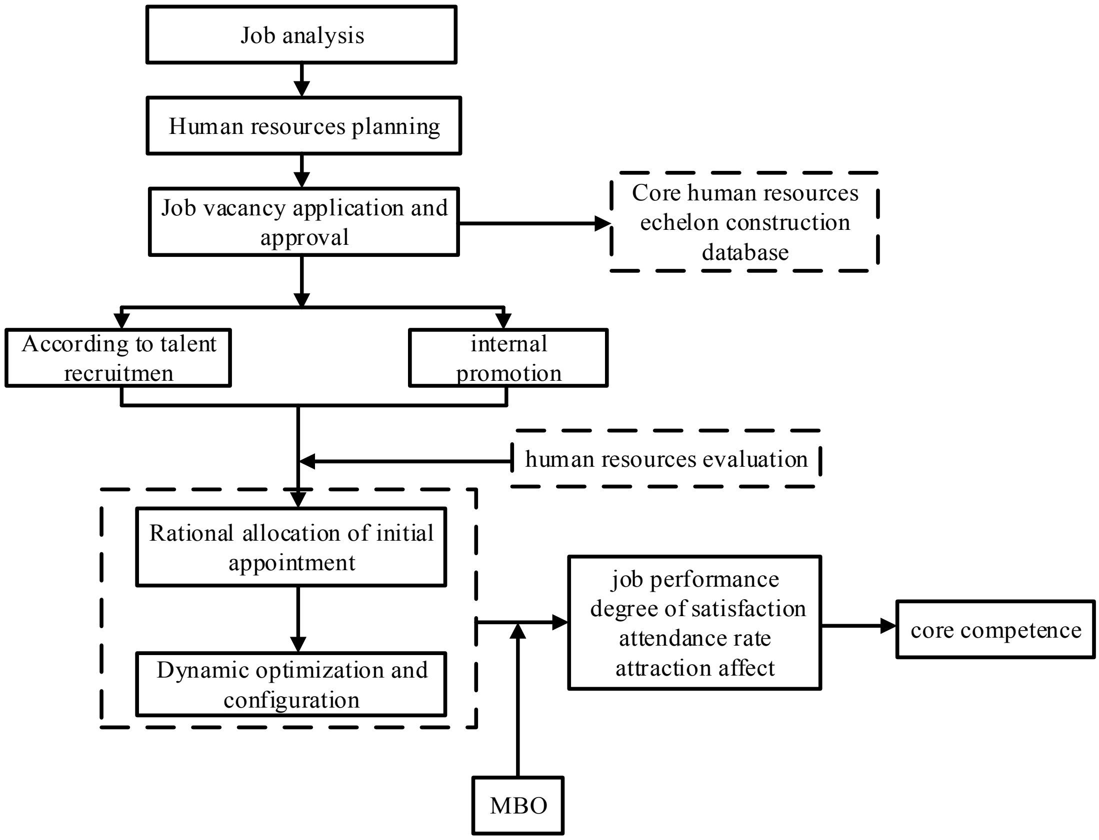


Figure 2 shows that the diversity of occupations and the adaptability of employees to positions are fully taken into account when formulating the human resources plan, and the rationality of human resources allocation is evaluated by indicators such as job performance, satisfaction and attendance. The multi-objective particle algorithm is used to evaluate the rationality of human resource allocation, which can realise the optimal allocation and dynamic adjustment of personnel. The enterprise human resource model is extracted from the representation of human resources, and it is a planning form with deep connotation under the combination of enterprise culture and management system, while the optimal allocation of human resources needs to be selected and configured according to the long-term development demands of the enterprise, the specific situation of its own organisational structure and the emphasis of the post on the needs of staff (Ai et al., 2019). That is, the suitability and stability of personnel can be comprehensively evaluated by establishing the evaluation matrix standard of personnel quality.

$$(Sij)n\times m = \{p_1(aij)n + p_2(b_{ij})n + p_3(c_{ij})n + p_4(d_{ij})n(v_{ij})m\} \tag{5}$$

Among them, s_{ij} is the comprehensive scores of the personnel M_i on the W_j post are the scores of the work return rate, the work itself, the degree of work cooperation and the weight in the evaluation of the working environment, which should be determined according to the specific situation of the organisational structure and the quality of the evaluation personnel.

Introducing the evaluation matrix standard can make it easier to examine the adaptability of individual ability and post in human resources, and can initially form human resource gradients at different levels. While optimising production factors, targeted management standards can be adopted (Kim, 2019). On the dynamic adjustment and positioning of the latter structure, a comprehensive investigation is made by combining various indexes, and the search and optimisation performance of the multi-objective particle swarm optimisation algorithm is utilised to make the personnel's appointment tend to the optimal solution, thus ensuring the reasonable mobility of the internal personnel of the enterprise and the virtuous circle of the mode.

3 Algorithm optimisation and application effect test of human resource allocation model

3.1 *Results test of improved multi-objective particle swarm optimisation algorithm*

The diversity of information increases the difficulty for decision-makers to deal with data, and the data sets with different characteristics make it difficult to select the optimal subset. The selection of features is mainly aimed at minimising the classification error rate and the number of features. As an effective data dimension reduction technique, feature selection can remove irrelevant, redundant and unobvious data with different features, thus reducing the work intensity (Antipova, 2020; Wang et al., 2018). The particle optimal solution is selected from the decision space and the target space, and the Cauchy mutation operation is improved to make the particles jump out of the local optimal. In addition, the particle dimension is reduced to make the particle distribution more uniform. Then, the relevance between numerical feature points is filtered by mutual information, and the selected high-quality particle feature combination is included in the classifier for performance evaluation, so as to obtain the classification accuracy of the algorithm. The accuracy of the sample data set is trained and tested with the cross-validation method. Seven data sets are selected to compare the classification accuracy of the three algorithms. 60% of the samples in the data set are selected as the training set. 40% of the samples are taken as the test set, the population size is set to 800, each data set is run independently for 30 times, and the simulation environment is matlabr2018b. The results are shown in Table 1.

It can be seen from Table 1 that the Improved-MOPSO algorithm has the best classification effect on WBCO, ZOO, Wine and Sonar data sets and its accuracy has reached more than 80%, among which the accuracy on WBCO data sets has reached 98.54%, while the accuracy on Glass (70.73%) and Vehicle (64.68%) is still higher than MOPSO and NSGA II algorithms, which. Generally speaking, the average accuracy of the improved multi-objective particle optimisation algorithm on the data sets in Wine, WBCO, ZOO and Sonar groups is better and the values are all above 85%. In order to further explore the combination mode and application effect of the algorithm in the number of features, the algorithm is simulated and the results are shown in Figure 3.

Table 1 Average classification accuracy of three algorithms for seven data sets

Average classification accuracy classification accuracy data set	*Wine*	*WBCO*	*Glass*	*Vehicle*	*ZOO*	*Spect*	*Sonar*
Improved-MOPSO	89.02%	98.54%	70.73%	64.68%	87.92%	78.54%	85.43%
MOPSO	87.79%	97.02%	63.84%	58.55%	78.91%	82.65%	83.99%
NSGAII	88.07%	94.25%	64.21%	52.32%	80.17%	74.55%	73.57%

Figure 3 Equivalent feature combination of three algorithms in different data sets

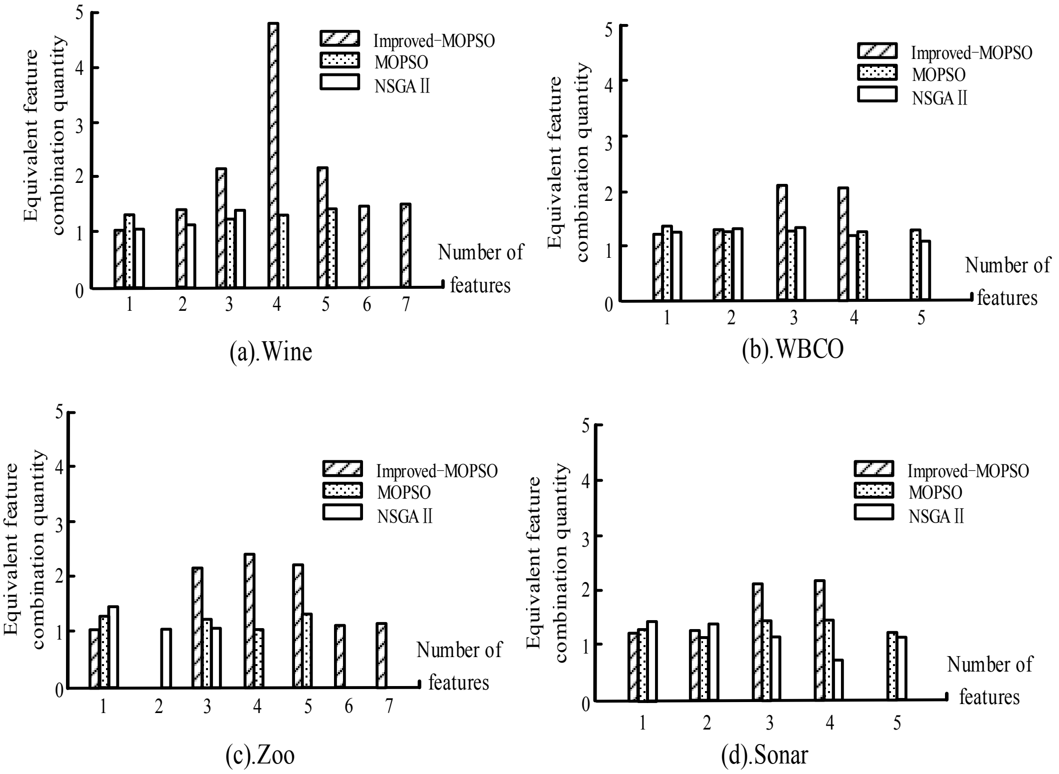


Figure 3 shows the combination modes of the equivalent feature quantity of the three algorithms on Wine, WBCO, ZOO and Sonar data sets. It can be seen that the Improved-MOPSO algorithm has more diversified combinations modes in the equivalent feature quantity, and there are five combinations modes with the feature quantity of 4 on Wine data sets, while MOPSO and NSGA II do not have the equivalent feature quantity combination modes on some data sets when the feature quantity reaches 5 or more. Traditional PSO and NSGA-II belong to single-mode and multi-objective optimisation algorithms, and their evaluation strategies make it difficult to guarantee the integrity of the searched equivalent feature combinations. However, the Improved-MOPSO algorithm can comprehensively consider the diversity of solutions in target space and decision space, and its richness and integrity of equivalent feature combinations can provide decision makers with various choices.

Figure 4 shows the Pareto front results of three algorithms on Wine, WBCO, ZOO and Sonar data sets. In the figure, the abscissa indicates the number of selected features, and the ordinate indicates the classification error rate. The closer the Pareto front is to the lower left corner of the coordinate axis, the better the algorithm performance. From Figures 4(a) to 4(d), it can be seen that the performance of the Improved-MOPSO algorithm is running well, and the Pareto front on the Wine data set is closer to the coordinate axis, the classification performance is improved to a certain extent, which is helpful for decision makers to extract appropriate subsets according to the needs of the problem or the requirements of the goal, and improves the efficiency. To sum up, the classification performance of Improved-MOPSO has been improved to a certain extent, which is beneficial for decision makers to extract suitable subsets according to the needs of problems or objectives, saving time and cost and improving efficiency.

3.2 Research on the application results of human resource allocation model

In this experiment, the actual operation mode and effect of human resources in an enterprise are taken as the experimental object, and the working attitude and enthusiasm of employees in this mode are investigated in two months, and the actual human resources cost of enterprises under this mode is tested in the third quarter. The human resources allocation mode supported by this algorithm is taken as the experimental group, and the experimental data of the control group are the performance appraisal of the enterprise in previous years and the work summary and self-evaluation data of employees, and the results are shown in Figures 5 and 6.

Figure 4 Pareto frontiers of three algorithms on data sets

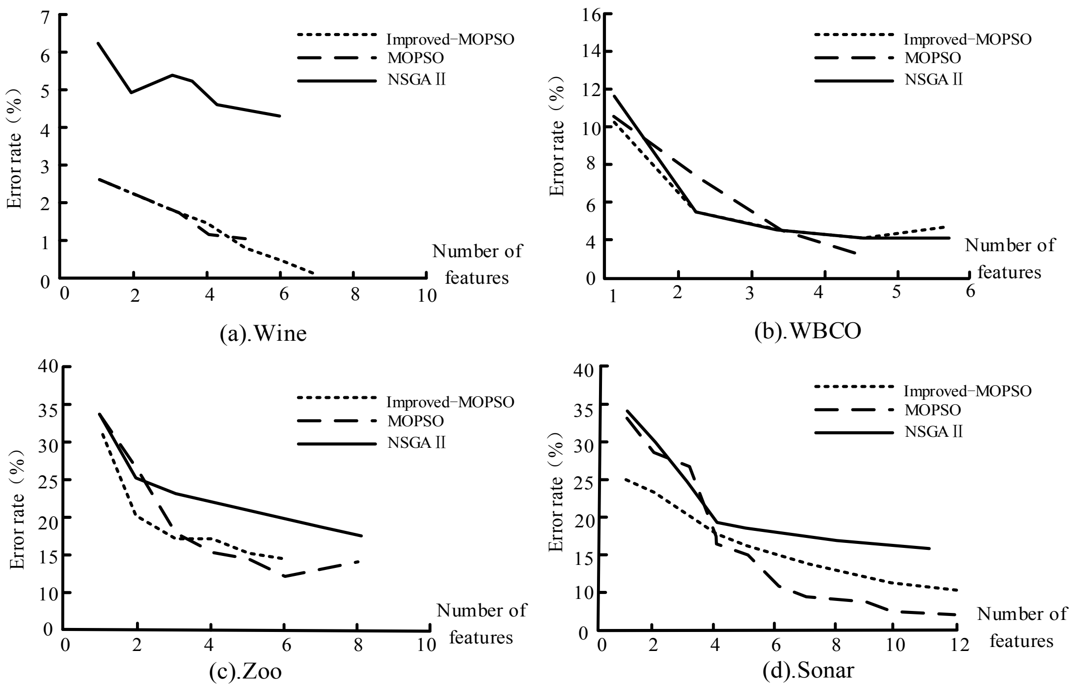


Figure 5 Statistical chart of employees' job satisfaction and attitude changes before and after the experiment

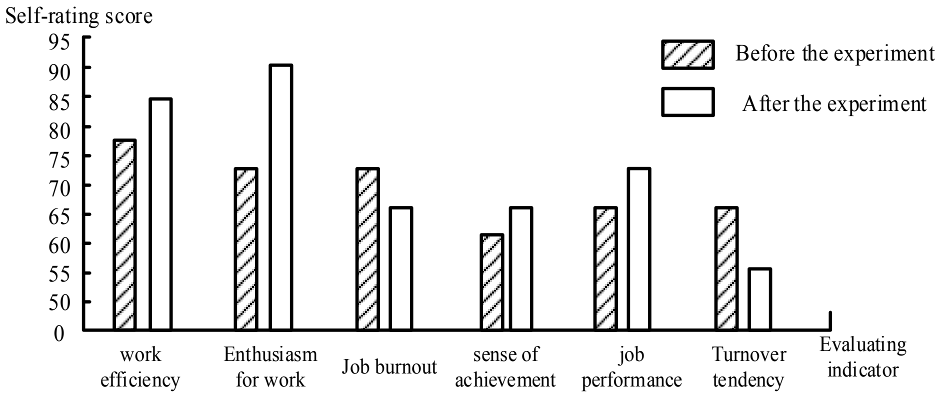


Figure 5 is a statistical chart of employees' job satisfaction and work attitude changes before and after the experiment. The abscissa is the evaluation index, and the ordinate is the self-evaluation score. The evaluated indexes include work efficiency, work enthusiasm, job burnout, sense of accomplishment, work performance and turnover intention. It can be seen from the figure that since the operation of the human resource mode based on the multi-objective particle optimisation algorithm, the work efficiency and enthusiasm have been greatly improved and the self-rating has reached 85 points and 90 points, and the increase has changed greatly. Since the operation of the human resources model under the improved PSO algorithm, employees' work efficiency and enthusiasm have been greatly improved, and employees' Job Burnout and turnover intention have decreased to varying degrees, with a decrease of 10%, which reflects employees' affirmation of the operation effect of the model and their recognition of their own work content. In order to further explore the relationship between employees' wishes and demands and the existence of each embodied dimension under the human resource model, correlation regression analysis was conducted and the results are shown in Table 2.

Table 2 is the regression analysis table of employees' wishes and demands and various dimensions in human resource mode. In the table, '*' means significant at $P<0.05$ and '* *' means significant at $P<0.01$. There is a positive correlation between the quality of human resource model and the company's operating costs and benefits. It can be seen from the table that employees' emotional input is greatly influenced by the relationship between superior and subordinate, reward and punishment system and training, which has certain significance ($P<0.01$) and also has certain relationship with the years of the enterprise ($P<0.05$). However, the requirements of employees to strengthen their work ability and improve their enthusiasm are also significantly higher than those of reward and punishment system and promotion mechanism ($P<0.01$). At the same time, in order to evaluate the overall human resource cost consumption of the enterprise, the turnover rate and entry rate of last year and three quarters of this year are statistically analysed, and the results are shown in Figure 6.

Figure 6 shows the change trend of turnover rate and entry rate under the operation of human resource mode. The abscissa in the figure is the month, the time is three quarters, and the ordinate is the ratio. The recruitment of human resources is the golden time in June and September of each year, while May and August are the hesitation periods when people quit their jobs. It can be seen from the figure that the phenomenon of human resources recruitment in this enterprise has improved compared with last year's epidemic situation, showing an upward trend from March to August, with the enrolment rate reaching 9% in July to August, and the turnover rate also declined to varying degrees, with a maximum drop of 1.2%. At the same time, fewer people who joined the enterprise left the company, further avoiding the waste of human cost. By improving the structure mode of human resources, optimising the internal welfare and recruitment screening process, more humanised service management mode and more fair reward and punishment competition mechanism, more and more people join and stay, which is more conducive to the long-term development of the company (Hanushchak and Maistrenko, 2020).

Table 2 Regression analysis table of employees' willingness and demands and all reflected dimensions in human resource mode

	Reward and punishment system	*Job promotion training*	*Positive subordinate relationship*	*Enterprise life*	*Scale*	*corporate culture*
Emotional-involvement	0.015**	0.026**	0.13	0.227*	0.113	0.012
Improvement of working ability	0.385**	0.153	0.0147	0.220*	0.056	0.066
Enthusiasm for work	0.244**	0.53	0.01**	0.027	0.049	0.621
Collective sense of honour in work	0.110	0.192*	0.063	0.164	0.084*	0.131
Personal career planning	0.015	–0.1612	0.0013	0.153	0.041*	0.279

Figure 6 Statistical comparison of turnover rate and entry rate before and after the experiment

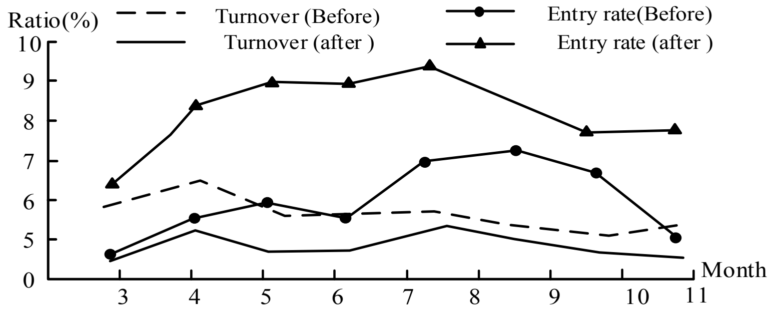


Table 3 Employee satisfaction evaluation index system and index weight

Factor	*Weight*	*Subfactor*	*Weight*
Satisfaction with job returns	0.276	salary	0.43
		Recognition	0.42
		promote	0.16
Job satisfaction	0.19	Competency level	0.52
		sense of responsibility	0.36
		sense of security	0.23
Enterprise satisfaction	0.183	corporate culture	0.25
		rules and regulations	0.18
		Sense of participation	0.28
		Development prospect	0.25
Satisfaction with job collaboration	0.265	Degree of trust	0.38
		Colleague harmony	0.37
		Information openness	0.24
Satisfaction with working conditions	0.141	working hours	0.37
		working environment	0.40
		Work equipment	0.25

Table 3 is the employee satisfaction evaluation index system and index weight analysis table. The employee satisfaction evaluation index system is divided into job return rate, satisfaction, enterprise satisfaction, cooperation degree satisfaction and working conditions and environment satisfaction. Each dimension can be divided into 3–4 sub-factors in detail. The overall grasp of the index system of employee satisfaction can better understand the employees' work ideas and opinions on the enterprise management system, and help to promote the perfection and improvement of the management system. It can be seen from Table 3 that the rate of return on work and the cooperation and coordination relationship with colleagues are the most important aspects for employees to evaluate a job, in which the recognition of salary and work can bring the most important value affirmation to employees, which has a certain positive incentive effect, and its weight reaches 0.277 and 0.269. Secondly, although the proportion of working environment is relatively low, the proportion of environmental security has reached 0.40, which shows that the spiritual support brought by job security will also affect their future career planning. After all, working for a long time will inevitably cause people to have the illusion of doubting and denying the meaning of their work, and then affect the correct judgment of employees on their work.

4 Conclusion

How to make efficient use of human resources is of great significance to improve the enthusiasm and innovation of employees and create benefits for enterprises. In this paper, the improved multi-objective particle swarm optimisation algorithm is introduced into the construction of enterprise human resources allocation model, and its algorithm performance and the actual effect of model application are studied. The results show that the improved MOPSO algorithm has a good precision operation effect on data sets, among them, the accuracy of WBCO data set has reached 98.54%, while the accuracy effect of glass (70.73%) and vehicle (64.68%) is still better than the other two algorithms, and their combination methods of equivalent feature quantity are more diverse, while the classification accuracy of MOPSO and NSGA II algorithms is mostly at the medium and lower levels except WBCO data set. Similarly, the requirements for employees to strengthen their work ability and improve their enthusiasm were significantly better than the reward and punishment system and promotion mechanism ($p<0.01$), and the maximum decrease in turnover rate reached 1.2%. While paying attention to the change and innovation of the enterprise's human resource model, paying attention to the employees' work needs and future planning direction and adopting appropriate incentive mechanisms are conducive to the long-term sustainable development of the enterprise.

References

Ai, H., An, S. and Zhou, J. (2019) 'A new perspective of enterprise human resource management', *International Journal of Human Resource Management and Service*, Vol. 1, No. 1, pp.1–7.

Alkebsi, K. and Du, W. (2020) 'A fast multi-objective particle swarm optimization algorithm based on a new archive updating mechanism', *International Journal of IEEE Access*, Vol. 7, No. 99, pp.1–1.

Antipova, O. (2020) 'Model of development of competences of workers and experts as element of personnel marketing in the personnel management system', *International Journal of Management of the Personnel and Intellectual Resources in Russia*, Vol. 8, No. 6, pp.38–43.

Aparicio, J. and Pastor, J.T. (2018) 'New centralized resource allocation DEA models under constant returns to scale', *International Journal of Boletin de Estadistica e Investigacion Operativa*, Vol. 28, No. 2, pp.110–130.

Bao, G., Zeng, F. and Wang, M. (2020) 'Study on human resource allocation efficiency based on DEA analysis', *International Journal of Circuits*, Vol. 14, No. 1, pp.826–832.

Chen, Z., Ye, X. and Tong, N. (2021) 'Enterprise human resource management index based on fuzzy system', *International Journal of Intelligent and Fuzzy Systems*, Vol. 40, No. 2, pp.3137–3146.

Feng, L., Yang, Q. and Park, D. et al. (2019) 'Energy efficient nano-node association and resource allocation for hierarchical nano-communication networks', *International Journal of IEEE Transactions on Molecular, Biological and Multi-Scale Communications*, Vol. 4, No. 4, pp.208–220..

Hanushchak, T. and Maistrenko, Y. (2020) 'Situational management of human resources as a basis for ensuring the economic security of the enterprise', *International Journal of Economics Finances Law*, Vol. 12, No. 3, pp.16–20.

Jonathan, V., Adruce, S. and Stephen, D. et al. (2020) 'Socially responsible human resource management practices from employees' perspective: a study in a Malaysian GLC, *International Journal of Psychosocial Rehabilitation*, Vol. 24, No. 6, pp.11021–11032.

Kim, Y.H. (2019) 'Social enterprise, social economy, social entrepreneurship, human resource development, *International Journal of Lifelong Education and HRD*, Vol. 15, No. 1, pp.29–53.

Li, L.I., Cheng, F. and Cheng, X. et al. (2018) 'Enterprise remanufacturing logistics network optimization based on modified multi-objective particle swarm optimization algorithm', *International Journal of Jisuanji Jicheng Zhizao Xitong/Computer Integrated Manufacturing Systems*, Vol. 24, No. 8, pp.2122–2132.

Nabavi, S.R., Eraghi, N.O. and Torkestani, J.A. (2021) 'Wireless sensor networks routing using clustering based on multi-objective particle swarm optimization algorithm', *International Journal of Intelligent Procedures in Electrical Technology (JIPET)*, Vol. 12, No. 47, pp.49–67.

Tang, W., Hao, C. and Wei, M. et al. (2019) 'Atmospheric refractivity estimation from AIS signal power using the quantum-behaved particle swarm optimization algorithm', *International Journal of Open Geosciences*, Vol. 11, No. 1, pp.542–548.

Wang, C., Thanh, N.V. and Hung, D.D. et al (2018) 'A hybrid fuzzy analytic network process (FANP) and data envelopment analysis (DEA) approach for supplier evaluation and selection in the rice supply chain', *International Journal of Symmetry*, Vol. 10, No. 6, pp.221–221.

Wang, D., Tan, D. and Lei, L. (2018) 'Particle swarm optimization algorithm: an overview', *International Journal of Soft Computing*, Vol. 22, No. 2, pp.387–408.

Wang, W. and Srivastava, G. (2020) 'Enterprise human resource quality management model based on grey relational analysis', *International Journal of Performability Engineering*, Vol. 16, No. 3, pp.419–419.

Yang, W. and Li, L. (2018) 'Efficiency evaluation of industrial waste gas control in China: a study based on data envelopment analysis (DEA) model', *International Journal of Cleaner Production*, Vol. 179, No. 1, pp.1–11.