J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 5177--5195

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Optimization study of urban elderly manpower resource development strategy based on differential evolutionary algorithm

Yanping Yang[1], Peng Zhao[2,✉]

[1] *Nanjing Tech University Pujiang Institute, Nanjing, Jiangsu, 210000, China*

[2] *Purple Mountain Laboratories, Nanjing, Jiangsu, 210000, China*

ABSTRACT

In the context of urban elderly human resource development, differential evolutionary algorithms can be used to optimize the development strategy and improve the efficiency of resource utilization. The study constructs a multi-objective scheduling optimization model for human resources based on an improved differential evolutionary algorithm, which searches for the optimal development strategy by simulating the mutation, crossover, and selection operations in the process of biological evolution. In addition, the model combines a multi-objective feature selection algorithm to capture the data information of urban elderly resource development more accurately and ensure the scientific and practicality of the strategy. The pareto front of this paper's algorithm on the optimal solution test function is more in line with the real frontier, and the GD value is between 0.00171 and 0.0325, which has better convergence. The execution time of this algorithm for elderly manpower resource scheduling is shortened compared to the comparison algorithm, and the convergence of different task sizes is accomplished when iterating to 110~150 rounds. The ADE-MOFS algorithm has the lowest running cost and the shortest completion period on elderly manpower resource scheduling. The research in this paper shows new ideas and methods for the rational development and utilization of urban elderly manpower resources, which has important theoretical and temporal significance.

Keywords: differential evolutionary algorithm, scheduling optimization model, feature selection algorithm, elderly manpower resources

1. Introduction

Since the reform and opening up, the demographic dividend has become one of the important factors for China's great economic achievements. However, with the aggravation of China's current population

✉ Corresponding author.
E-mail address: yyplucky2024@126.com (P. Zhao).
Received 05 March 2024; Revised 25 May 2024; Accepted 05 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-292

aging, the labor force will eventually experience a serious shortage, so tapping the potential demographic dividend is an important initiative for China to cope with population aging, in which the development of the elderly manpower resources is not a proactive and positive countermeasures [1-4].

Comprehensively implementing the national strategy of actively coping with population aging is a key part of supporting China's modernization with high-quality population development, and the development and utilization of elderly human resources is an important part of it [5-6]. Elderly human resource development refers to the process of improving the labor and employment and social activity ability and social quality of life of the elderly through skills training, re-education, etc., and exploring the potential of elderly human resources into human resources [7]. Elderly human resources development to promote the withdrawal of social production activities of the elderly re-entry into social activities to play a value, the population burden into dividends, not only help to improve the living standards of low-income elderly groups, but also help the elderly better integration into society, to solve the psychological problems of the elderly after the withdrawal of social production [8-12]. It also helps to reduce the burden of social old-age, finance and family, alleviate the shortage of talents and sustainable development in the social transition period, and is an important initiative to solve the problem of population aging [13-16]. Therefore, exploring countermeasure suggestions for the development of human resources for the elderly and encouraging the re-employment and social participation of the elderly are important topics faced in the context of population aging.

Along with the rapid and massive growth in the number of elderly people, it will certainly bring about significant changes in China's economic and social development. Cai, F. showed that China's demographic structure has entered a new stage characterized by population aging, which means that China's first demographic dividend will disappear permanently, and it is crucial to grasp the new sources of economic growth generated by demographic change to cultivate the second demographic dividend [17].Ye, J. et al. studied the impact of population aging on China's GDP growth and found that aging shapes labor market performance and human capital, which reduces labor force ratios and productivity and slows China's economic growth [18]. Taketoshi, K. holds a different view, stating that China's rapid economic development due to demographic transition is more influenced by the population “capital effect” than the “labor effect”, and that the decrease in the working-age population in an aging society reduces the capital formation rate and weakens the growth rate of the Chinese economy. In the aging society, the decrease of the working age population makes the capital formation rate lower, which is an important reason for weakening the development momentum of the Chinese economy [19]. Meng, X. further pointed out that the expansion of the proportion of the working population to the total population (WAPS) is the key factor influencing the growth of China's economy, which explains why China's economy is still slowing down under the circumstances of a higher number of labor force supply and a lower labor force participation rate [20]. Therefore, fully developing and utilizing the human resources of the elderly is not only a good way to improve the ability of the elderly to provide for themselves, but also a good way to transform China's potential demographic dividend into a real demographic dividend, and thus to alleviate the pressure on economic growth brought about by population aging.

Some scholars have studied how to create a favorable employment environment for the elderly and establish human resource practices for older employees.Pahos, N. et al. examined the growth-related needs of older employees throughout the lifecycle of their human resource practices, and found that a certain percentage of participating older employees are of outstanding value to the work organization, which provides valuable insights into the development of human resources for the elderly [21]. Hlatká, M . et al. designed a human resource management methodology including age management principles to develop more effective and sustainable talent recruitment strategies for organizations by measuring the level of decline in employees' work capacity under different age categories [22]. Dorokhov, O. et al. used a fuzzy logic approach to explore age-friendly human resource practices in the context of active aging, which provided a quantitative assessment of the majority of human resources including workplace practice aspects were quantitatively assessed [23]. Martin, L. et al. analyzed the link between employees' perceived external employability and the propensity to leave from an age perspective, showing that flexibility-enhancing HR practices are more effective in retaining highly employed older employees [24]. Berti, N. et al. found that aging employees, despite the presence of declining physical abilities, have more productive experience and thus used a dual resource constraint model and heuristic algorithms to allocate work tasks between workers and machines to promote the joint realization of corporate performance and employee well-being [25]. Peruzzini, M. et al. explored the problem of aging workers' adaptation to modern intelligent systems and used information-physical systems and pervasive technologies to design an adaptive manufacturing system that responds to the needs of the elderly, adapting machines to the aging workers' working conditions and improved the quality of human-machine interaction in smart factory environments [26]. It can be found that re-employment of the aging labor force is not only a personal problem of the elderly, but also a social problem, which requires the coordination of all aspects of the enterprise, and jointly turn the aging pressure into the elderly force resource power. Therefore, there is an urgent need to propose an optimization model of elderly manpower resources that includes multiple perspectives to provide feasible suggestions for enterprises to recruit elderly employees.

In this paper, a multi-objective scheduling optimization model for urban elderly manpower resources is designed based on the differential planning algorithm and the SPEA2 multi-objective feature selection algorithm. The model uses the multi-objective feature algorithm to remove the irrelevant features of the elderly manpower resources, randomly generates the individuals of the elderly population, and realizes the initialization of the population in the form of vectors. New variation vectors are generated from the population individuals, and then the variation vectors are mixed with the current individuals to generate new research vectors to increase the diversity of optimal solutions. Finally, according to the fitness function, the more available individuals are selected to enter the next generation to ensure that the quality of the population is constantly improving.

2. Study on strategies for the development of urban geriatric resources

2.1. Definition of the research base

2.1.1. Manpower resources for older persons. Older people's human resources refer to the sum of physical, mental and spiritual energy that older people with a certain working capacity can directly invest in the process of labor and production, and it is an important part of human resources. The recognition that “the human resources of older persons are part of human resources” is also based on a shift in the understanding of older persons from a “wealth theory” to a “resource theory”. Older people's human resources are distinguished from the wealth theory of old age by five different characteristics: creative, dynamic, exploitative, social and developmental. In addition, from the perspective of productive resources, the human resources of older persons engaged in productive activities (i.e., all activities that directly or indirectly create social value, including the three dimensions of paid employment, unpaid social work and unpaid family work) are considered to be an important component of human resources.

2.1.2. Development of human resources for the elderly. The development of human resources for the elderly is defined as the process of studying the situation of retired persons and then formulating a program for their reconfiguration, use and training, as well as providing all the possible conditions for people to leave their jobs without losing their wisdom and talents to society. The so-called development of human resources for the elderly means the formation of new concepts, the creation of new environments, and new mechanisms to promote the sustainable development and utilization of human resources for the elderly. It is an activity that utilizes, shapes, transforms, and develops the potential human resources of the elderly through a series of organized, purposeful, and planned learning, education, training, management, and cultural construction activities in order to cope with the future of a shrinking workforce of the appropriate age, and to realize the development strategy of "a society for all ages".

Based on the understanding of the development of human resources for older persons in existing studies, and on the basis of the concept of human resources for older persons that has been sorted out and defined in the previous article, this paper uses the following definition: the development of human resources for older persons refers to the process of improving the talents of older persons through a series of measures such as security, education and training, and creating an age-adapted social environment in which older persons are able to continue to create social wealth and promote physical and mental health.

2.2. Differential Evolutionary Algorithm

Differential evolutionary algorithm [27] has four steps: initialization, crossover, mutation, and selection, and the flow of the algorithm is shown in Fig. 1.

The DE algorithm has its unique evolutionary approach, i.e., it amplifies the differences between individuals in the current population to construct new variant individuals, and uses operations such as crossover and mutation to expand the distribution of the solution. In the traditional DE algorithm, F and CR are the important mutation and crossover parameters in the algorithm, respectively, and at each iteration, F is a random value selected in the interval (0, 2], and CR is a random value selected in the interval [0, 1], which has a certain probability of enabling the algorithm to jump out of the local optimum but does not have the optimization effect as the evolutionary process of the population advances. Therefore, in this paper, for the defects of the traditional DE algorithm parameter updating strategy, a new parameter adaptive mechanism is proposed to enrich the diversity of the population, so that the solution set obtained by the algorithm has a wider distribution and can optimize the performance of the solution with the increase of the number of iterations.

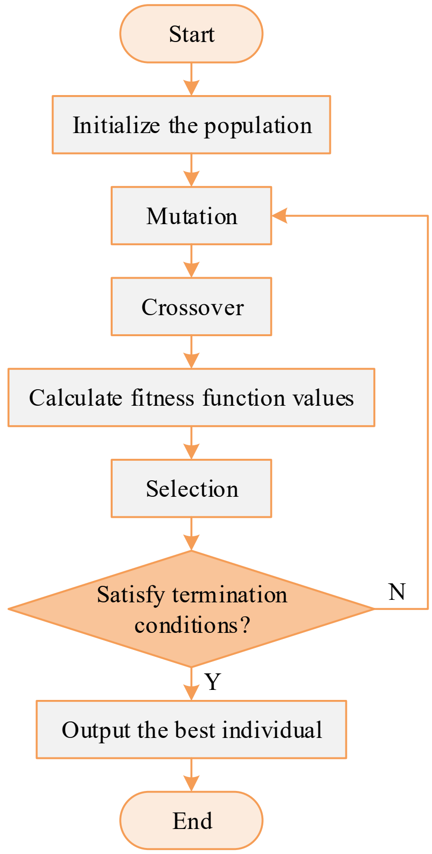

Fig. 1. Flow chart of difference evolutionary algorithm

2.3. SPEA2 multi-objective feature selection algorithm

Strength Pareto Evolutionary Algorithm [28] (SPEA2), many researchers combined external archives in their Multi-Objective Evolutionary Algorithms [29] (MOEA), and this elite retention strategy began to be the focus of the second phase of MOEA design, where the algorithm's search efficiency was significantly improved.

The main process of the SPEA2 algorithm is described:

1) Initialize population P_0, empty external file A_0, order $t = 0$.

2) Calculate the fitness values of individuals P_t and A_t.

3) If the number of individuals in A_{t+1} is greater than N, prune A_{t+1}. If the number of individuals in A_{t+1} is less than N, add the dominated solutions in P_t and A_t to A_{t+1} until its number of individuals is equal to N. If $t > T$, output the external file A_{t+1} and stop the search.

4) Select individuals into the mating pool using a binary tournament method for external profile A_{t+1}.

5) Apply mutation and crossover operations to the individuals in the mating pool and to the individuals of population P_{t+1}, order $t = t+1$, and go to step (1).

The best time complexity of the SPEA2 algorithm is $O\left(M^2 \log M\right)$ and the worst time complexity is $O\left(M^3\right)$.

2.4. Improved differential evolutionary algorithm based on multi-objective feature selection

2.4.1. Improved Differential Evolution Algorithm. To address the shortcomings of the traditional differential evolution algorithm, an improved differential evolution algorithm (ADE) is proposed in this paper, in which the expressions of the variation operator F_g and the crossover probability CR_g are as follows:

$$F_g = F + F \cdot \frac{(G-g)}{G} \tag{1}$$

$$CR_g = \begin{cases} CR - CR \cdot \frac{g}{G}, \frac{g}{G} > 0.8 \\ 0.1, otherwise \end{cases} \tag{2}$$

where g represents the current number of generations and G represents the total number of updates. The larger the values of F_g and CR_g, the richer the population diversity, but it will be unfavorable to the population convergence, after a lot of research and experiments, the values of F and CR are taken 0.5 in the ADE algorithm.

2.4.2. Algorithm operation flow:
1) Population initialization. N D-dimensional population individuals are randomly generated in the initialization phase as in Eq:

$$X_{i,g} = \left(x_{i,g}^1, x_{i,g}^2, \ldots, x_{i,g}^j\right), j = 1, 2, \ldots, D \tag{3}$$

where D denotes the number of individual dimensions of the population, $g = 0, 1, \ldots, G$ denotes the number of evolutionary generations, and j denotes the jth dimension of the current individual. $i = 0, 1, \ldots, N$ denotes the ith individual in the current population.

The individual dimensions are initialized as in Eq:

$$x_{i,g}^j = x_{\min}^j + rand_i^j[0,1] \cdot \left(x_{\max}^j - x_{\min}^j\right) \tag{4}$$

Where $rand_i^j[0,1]$ denotes a random number uniformly distributed in the interval $[0,1]$, and $x_{\max}^j$ and $x_{\min}^j$ denote the upper and lower bounds of the jth dimension of the individual optimization variable $X_{i,g}$.

According to the above equation, a “matrix” of features is initialized by real number coding, where each row vector $X_{i,g}$ represents a population individual, and each column $x_{i,g}^j$ in each row represents the value of the jth feature of vector $X_{i,g}$.

2) Variation. Mutation is for each individual $X_{i,g}$ in the current population, three randomly selected individuals to perform linear operations to generate new individuals $V_{i,g}$, as in Eq:

$$V_{i,g} = X_{r_1,g} + F_g \cdot \left(X_{r_2,g} - X_{r_3,g}\right) \tag{5}$$

Where, $X_{r_1,g}$, $X_{r_2,g}$, $X_{r_3,g}$ are three individuals selected using a randomized strategy in the current population, and $r_1 \neq r_2 \neq r_3$, F_g are parameters that amplify the difference between two individuals and control the search step size by deflating the difference between $X_{r_2,g}$, $X_{r_3,g}$. In the ADE algorithm, the deflation factor $F_g = F + F \cdot \frac{(G-g)}{G}$.

3) Crossover. The target vector $X_{i,g}$ and the corresponding dimensions in the obtained variation vector $V_{i,g}$ are crossed to obtain the new test individual $U_{i,g}$ as in Eq:

$$u_{i,g} = \begin{cases} v_{i,g}^{j}, if\ randd_{i}^{j}[0,1] \leq CR_{g} or j = r \\ x_{i,g}^{j}, otherwise \end{cases} \tag{6}$$

$$U_{i,g} = \left(u_{i,g}^{1}, u_{i,g}^{2}, \ldots, u_{i,g}^{j}\right), j = 1, 2, \ldots, D \tag{7}$$

where CR_g is the crossover probability and r is a random index to ensure that $U_{i,g}$ always receives at least one element from $V_{i,g}$ and thus avoids being identical to the individual vector. In the ADE algorithm, the crossover probability $CR_g = \begin{cases} CR - CR \cdot \frac{g}{G}, \frac{g}{G} > 0.8 \\ 0, otherwise \end{cases}$.

4) Selection. The value on the optimization objective directly selects the individual and retains the child individual into the next iteration only if the classification error rate of the child individual $U_{i,g}$ and the number of selected features are less than that of the parent individual $X_{i,g}$, otherwise discards the child individual and selects the parent individual into the next iteration. The selection manipulation rule is shown in Eq:

$$X_{i,g+1} = \begin{cases} U_{i,g} if\ f_1\left(U_{i,g}\right) < f_1\left(X_{i,g}\right) and f_2\left(U_{i,g}\right) < f_2\left(X_{i,g}\right) \\ X_{i,g}, otherwise \end{cases} \tag{8}$$

Where, $f_1\left(U_{i,g}\right)$ denotes the classification error rate of individual $U_{i,g}$, $f_1\left(X_{i,g}\right)$ denotes the classification error rate of individual $X_{i,g}$, $f_2\left(U_{i,g}\right)$ denotes the number of features selected by individual $U_{i,g}$, and $f_2\left(X_{i,g}\right)$ denotes the number of features selected by individual $X_{i,g}$.

After completing the last iteration, specific features are to be selected in the optimal individual vector, following the principle as in Eq:

$$z_{i,g}^{j} = \begin{cases} 1, x_{i,g}^{j} \geq \theta \\ 0, otherwise \end{cases} \tag{9}$$

Where, θ is a pre-set threshold that determines whether the features of each dimension are selected or not, and when the value of $x_{i,g}^{j}$ is greater than θ, $z_{i,g}^{j}$ is assigned a value of 1, indicating that the jth feature is selected.

2.4.3. Algorithm design and implementation. The ADE algorithm proposed in this paper, which uses a stochastic search strategy, is fused with the SPEA2S algorithm and applied to the multi-objective feature selection problem, named Improved Differential Evolution-based Multi-Objective Feature Selection Algorithm (ADE-MOFS). Firstly, the individual beginnings are represented in the form of vectors and each individual is regarded as a kind of solution, and then the population is formed by multiple individuals, and the population is updated according to the new parameter adaptive strategy using differential evolution, which can make the algorithm have a certain probability of jumping out of the limitation of the local optimization, enriching the diversity of the population, and optimizing the performance of the solution with the increase of the number of iterations.

ADE-MOFS algorithm design:

1) Perform an initialization operation on the feature set of dimension D, using real number encoding, to generate N D-dimensional vector sets (populations with N individuals).

2) For each individual in population $1 \sim N$, randomly select three individuals in the population, use one of them as the basis vector, find the difference between the other two individuals, and multiply by the improved variation operator F_g to generate a new individual.
3) For each dimension of the new individual and its corresponding parent individual, perform the crossover operation according to the improved crossover probability CR_G to generate the child individual.
4) For both parent and child individuals, select them according to their values on the two objectives of classification error rate and number of selected features to ensure that the population evolves in the optimal direction.

2.5. Multi-objective scheduling optimization model based on urban elderly manpower resources

2.5.1. Coding scheme. A multidimensional chromosome coding scheme is designed to address the characteristics of the project planning and scheduling model based on urban elderly people, which excludes most of the infeasible solutions without reducing the search space of the algorithm. What's more, when human resource conflict occurs, that is, when two parallel tasks request the same staff, it is necessary to convert parallel activities into serial tasks. And the order of execution between serial tasks is uncertain, therefore, a priority coding scheme is introduced into the original coding scheme to identify the priority of each activity so that the order of execution will be determined. Each complete chromosome consists of a priority chromosome and a senior citizen assignment chromosome.

Priority chromosome: one gene of the priority chromosome represents a priority decision variable.

Priority is represented by a randomly generated integer between 1 and m (m is the number of activities), with smaller values prioritizing task scheduling. In the event of human resource conflicts, activities with high priority are prioritized for human resources.

Elderly Assignment Chromosome: Each elderly person in the Elderly Assignment Chromosome corresponds to one row of the chromosome, and the corresponding value represents the decision variable; if an elderly person does not master the skills required for a task, the corresponding value is assigned to -1, indicating that the task will not be assigned to this elderly person. If an older person who has mastered the skills required for the task is assigned to the activity, the value is assigned to 1, otherwise the value is assigned to 0. When the algorithm is terminated, the priority chromosome as well as the older person assignment chromosome are decoded, respectively. The priority of the task for each activity and the number of the older person involved in the construction are obtained sequentially to obtain a feasible solution to the multi-skilled older person based multi-objective project planning and scheduling model.

2.5.2. Adaptation function. The fitness function is varied by the objective function, and according to the optimization objectives of this paper: the lowest human resource cost as well as the shortest duration, the fitness function $Fit(x)$ of the chromosome can be obtained following the following computational rules:

When $f_1(x) < C_{\max}$ and $f_2(x) < T_{\max}$, $Fit(x) = \left[C_{\max} - f_1(x)\right] + \left[T_{\max} - f_2(x)\right]$.

Otherwise, $Fit(x) = 0$.

Where f_1 is the value of the human resource cost function, f_2 is the value of the project duration function, $C_{\max}$ is the maximum estimated value of the human resource cost, and $T_{\max}$ is the maximum specified period of the project duration.

2.5.3. Genetic manipulation:
1) Adaptive parameter selection. The use of adaptive genetic algorithms whose probability can change with the value of the fitness function can effectively address the impact of convergence speed. The core

idea of the algorithm is: in order to realize the global search for the best, when there is little difference in the fitness values of the individuals in the population, the probability of cross-variation is increased. In order to preserve the good individuals, when an individual fitness function value is higher than the average value of the population, the probability of cross mutation is reduced. The cross-mutation probability of the adaptive genetic algorithm varies according to the following pattern.

For the mutation probability P_m:

When $f \geq f_a$,

$$P_m = \frac{k_3\left(f_{\max} - f\right)}{f_{\max} - f_a} \tag{10}$$

When $f < f_a$:

$$P_m = k_4 \tag{11}$$

Where $f_{\max}$ denotes the maximum value of the fitness function in the current population, f_a denotes the mean value of the fitness of the population, f denotes the value of the fitness function of the variant individuals, and k_3 and k_4 are taken as constants in the open interval between 0 and 1.

2) Selection operation. Selection operation refers to somehow selecting the excellent individuals with higher fitness according to the size of individual fitness function value, and this study invokes the roulette method to select the individuals' selection probability. The functional expression of roulette method is:

$$P(i) = \frac{F(i)}{\sum_{1}^{m} F(k)} \tag{12}$$

where $P(i)$ is the probability that an individual with the ind gene is passed on to the next generation, $F(i)$ is the fitness value of an individual with the ith gene, and m is the population size.

3) Crossover and Mutation. The crossover operation uses random crossover method. Two chromosomes are selected and random breakpoints are generated to cut the chromosome into several gene segments, which are then combined accordingly. Mutation is done by reverse mutation. Two neighboring genes are randomly selected on the collaborating chromosome of the parent, the corresponding values are exchanged, and the other gene values are copied to the offspring in the original order to generate the offspring chromosome [30].

2.6. Optimization of the development strategy of urban elderly manpower resources

How to assign the urban elderly and achieve the synergistic optimization of multiple objectives such as schedule and human resource cost has become a major challenge for managers. Therefore, this paper establishes the mechanism of elderly resource development with appropriate mathematical models and optimization methods, and at the same time, uses computer as an auxiliary tool to provide a series of Pareto solutions for decision makers to choose programs based on their preferences.

After several rounds of iterative optimization of the model above, the optimal combination of strategies for the development of urban elderly manpower resources is obtained. Based on the optimal combination of strategies, specific development plans are formulated, including training programs, employment guidance, policy support and other aspects.

The optimized development strategies are put into practice to promote the development and utilization of urban elderly human resources through the establishment of employment service centers for the elderly, the development of targeted training courses, and the improvement of laws and regulations. At the same time, an evaluation mechanism will be set up to assess the effectiveness of the development strategy, and the strategy will be adjusted and optimized according to the results of the evaluation.

3. Evaluation of geriatric resource planning performance and applications

The experimental design in this section includes experimental environment setup, task and virtual machine setup, and control group setup. The implementation of the core code of the algorithm is completed in Matlab and the cloud task scheduling simulation experiment is conducted in CloudSim 3.0 platform. The hardware configuration of the experimental computer is as follows: windows 11.21H2.22000.1574. RAM 16.0 GB. SSD 512 GB. AMD Ryzen 7 6800H with Radeon Graphics 3.20 GHz. to ensure a consistent experimental environment, all simulations were performed on the same computer.

3.1. Evaluation of model resource scheduling optimal solution search performance

Based on the description above, a program was written to set the parameters of the algorithm: the population size was NP300, the dimension of the decision variable was 20dim, the maximum number of iterations was 300max Gen, the preset Euclidean distance L5.1, and the penalty function was 3010Penalty.Three classical multi-objective test functions ZDT1, ZDT2, and ZDT6 were used to compare the improved algorithm of this paper with the multi-objective Genetic Algorithm (NSGA-II), Strength pareto Evolutionary Algorithm (SPEA-II) for comparison.

Figure 2 shows a comparison plot of the pareto front generated by this paper's model, NSGA-II, SPEA-II and the true curve TRUE under three classical unconstrained test functions. As can be seen from the figure, the algorithm in this paper is always the closest to the true front, performs smoothly throughout the search process, and also compensates for the weakness of the lack of pre-search ability in single-objective algorithms.

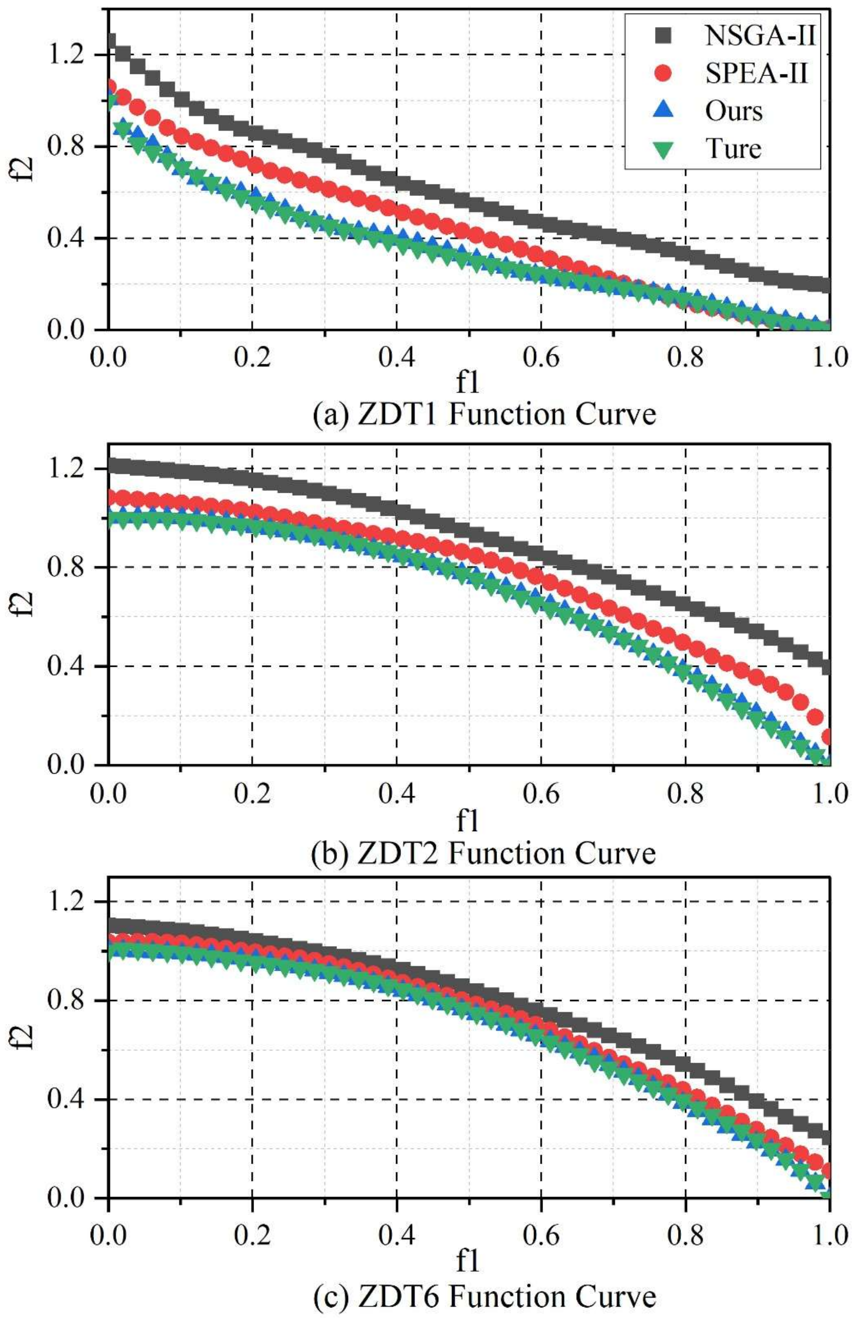

Fig. 2. The model is born in pareto front, which is born in three test functions

In order to be able to visualize the performance of the compared algorithms from the data, the convergence evaluation metric Generation Distance GD and the distribution evaluation metric SP are used.

1) Convergence. The larger the value of the convergence index GD, the farther it deviates from the actual optimal boundary, and the worse the convergence is. The calculation formula is:

$$GD = \frac{(\sum_{i=1}^{n} d_i^2)^{1/2}}{n} \tag{13}$$

Where: d_i denotes the Euclidean distance, i.e., the smallest Euclidean distance between the pareto optimal solution and each of the solutions in the set of non-inferior solutions computed in the algorithm being used. n denotes the number of non-inferior solutions.

2) Distributability. The distributivity metric SP is used to indicate the distributivity of the optimal solution set of the algorithm within the pareto frontier region and is calculated as:

$$SP = \left(\sum_{i=1}^{n} (\bar{d} - d_i)^2 / (n-1) \right)^{1/2} \tag{14}$$

Where: d_i denotes the Euclidean distance between each solution in the set of non-inferior solutions and its neighbor with the smallest distance. $\bar{d}$ is the mean of all individuals in the non-inferior solution set. n denotes the number of solutions in the non-inferior solution set found by the algorithm.

Figure 3 shows the performance of the GD and SP evaluation algorithms in the three test functions ZDT1, ZDT2, and ZDT6. From the corresponding data, the algorithm of this paper is lower than the algorithms it compares in the comparison of the mean values of GD and SP, and the calculated values of GD, for example, are in the range of 0.00171~ 0.03253, which indicates that the convergence of the algorithm is better than that of NSGA-II and SPEA-II. From the above performance, it can be concluded that the algorithm proposed in this paper outperforms the compared algorithms in terms of convergence and distribution.

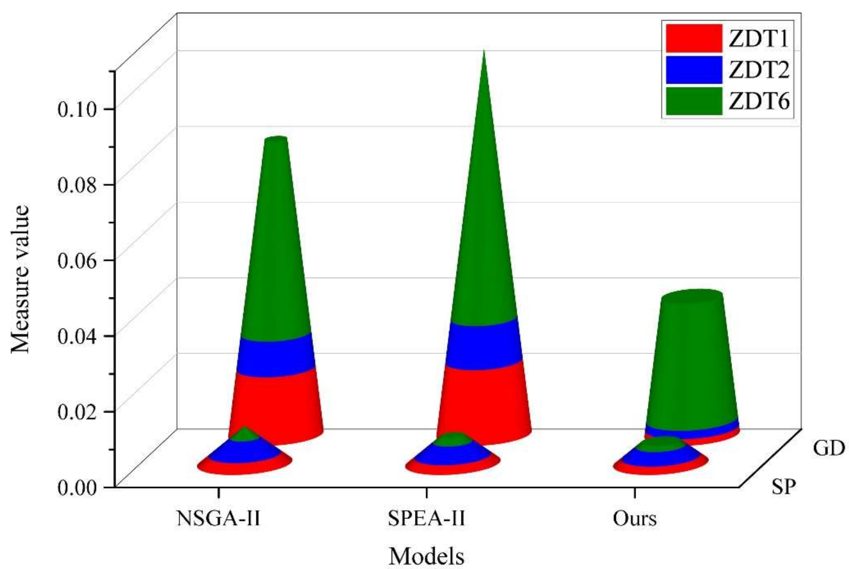

Fig. 3. The GD and SP evaluation algorithm performs in three test functions

3.2. Analysis of the efficiency of manpower resource mobilization for the elderly

The purpose of the efficiency experiment of the algorithm is to evaluate the total execution time of the two-stage algorithm. Specifically, the population size and the number of iterations are kept constant, and the number of iterations and the population size of the elderly force resource scheduling algorithm are changed and the total running time of the two-stage algorithm is counted. At this time, the number of iterations are set to 300, and the population size is set to 300. The experiment is run for 5 cycles, keeping the number of application instances entered into the scheduling framework in each cycle to 50, the number of equipment resource service points set to 50, and the number of workers set to 30.

Figure 4 demonstrates the effect of the initial population size on the running time of the elderly force resource scheduling algorithm, with the horizontal coordinate being the initial population size of the algorithm. From the figure, it can be seen that as the initial population size increases, the running time of the elderly manpower resource scheduling algorithm increases linearly. From the results, both this paper's algorithm and the comparison algorithm are affected by the number of iterations and the population size, and the effect is generally linear. This is because the time complexity of the algorithm is linearly related to the number of iterations and population size. The execution time of this paper's algorithm is significantly shorter than that of the comparison algorithm, which has a certain time advantage.

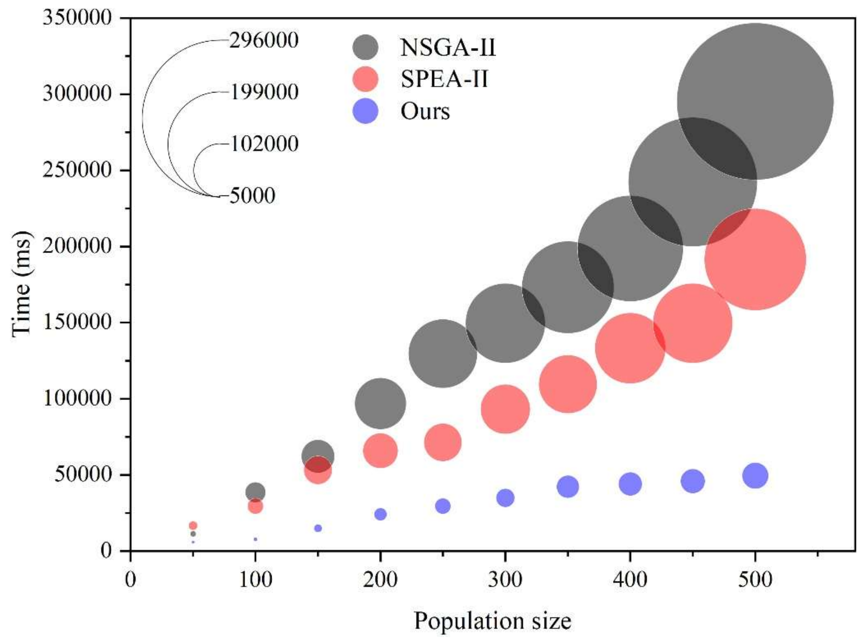

Fig. 4. The impact of initial population size on operating duration

Three algorithms based on different strategies were experimented under 2 groups of task sizes of 200 and 500, and each group of experiments was conducted for 20 times, and the convergence curves of each algorithm were calculated and plotted. The convergence of each algorithm under different task sizes is shown in Fig. 5, with the horizontal coordinate indicating the number of iterations of the algorithm and the vertical coordinate indicating the value of the best fitness of each algorithm. As can be seen from the figure, NSGA-II exhibits the worst convergence effect among all task sizes, which is because although population evolution is related to the initial population distribution, but this weak correlation has a relatively limited effect on the algorithm. In contrast, the algorithm in this paper achieves the best convergence speed and convergence accuracy, and the convergence is completed when iterating up to 110~150 rounds under 200 and 500 group task sizes, stabilizing at around 55 and 150, respectively.

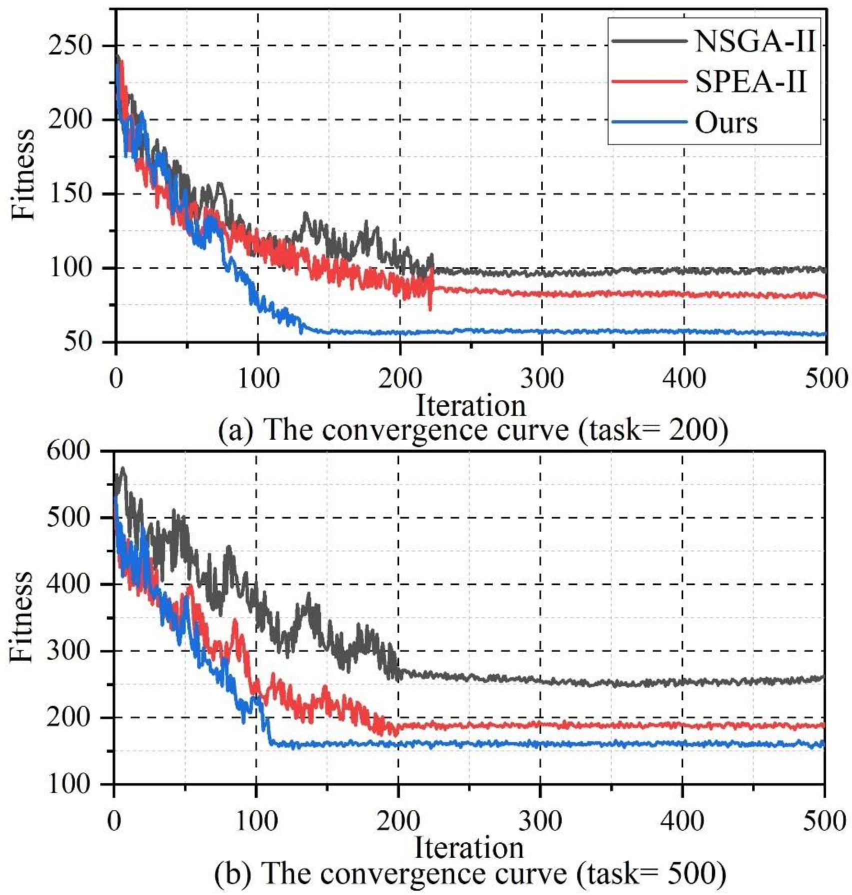

Fig. 5. The convergence of algorithms in different tasks

In the research of this paper, the maximum completion time (Makespan) of cloud tasks is used as a metric to measure the merits of scheduling schemes. The meaning of Makespan in task scheduling of elderly force resources is that when a batch of cloud tasks is scheduled to be executed on a batch of VMs, the total time span from the start of the VMs' work until all the work is processed is denoted as the Maximum Completion Time of Cloud Scheduling, which is calculated as follows:

$$makespan = \max(\tau_j) \tag{15}$$

Where τ_j denotes the time span of task execution on a single VM V_j, calculated as follows:

$$\tau_j = \sum (A_{j,i} \times \Gamma_{i,j}), i \in \{1,2,...,n\}, j \in \{1,2,...,m\} \tag{16}$$

where $A_{j,i}$ marks whether task i is executed on VM j, $\Gamma_{i,j}$ is the execution time of task i on VM j, and n and m denote the number of cloud tasks and VMs, respectively.

The Makespan results for different strategies are shown in Table 1. The table records the completion time statistics of different improvement strategies under 20 experiments, including the best, worst, average, and standard deviation results under four groups of task sizes. Calculations from the table show that compared with the comparison algorithms, the average Makespan of this paper's algorithm is reduced by 18.46% to 41.76%. The comprehensive experimental results show that this paper's algorithm elderly force resource task scheduling gets the best performance.

Table 1. The Makespan results of different improvement strategies

Tasks	Models	Best	Worst	Average	Std
200	NSGA-II	97.54	100.64	95.253	1.14

	SPEA-II	81.17	83.62	82.23	1.39
	Ours	54.59	56.788	55.48	0.75
500	NSGA-II	250.25	261.54	255.63	1.09
	SPEA-II	189.51	196.92	193.4	0.74
	Ours	154.79	160.14	157.69	0.56

3.3. Resource Development Scheduling Example Validation

A textile enterprise is selected as an example analysis object, and the method of this paper is used to optimize the scheduling of elderly manpower resources for a project of this enterprise, which contains six activities. NSGA-II and SPEA-II models are selected to compare with the cost of elderly manpower resources and project completion time results of this paper's algorithm, to analyze the practical application effect of this paper's urban elderly manpower resource development strategy based on differential evolutionary algorithm.

Figure 6 shows the comparison results of the cost of scheduling elderly manpower resources and the project completion time. As can be seen from the figure, comparing with the other 2 methods, the total cost of the elderly force resources of this paper's design method is lower, and the total cost of each activity is less than 230,000 yuan after adopting this paper's elderly force resource development method, while the cost of the other 2 methods is much higher than the design method of this paper. Then we analyze the completion period of the 6 activities of the scheduling of elderly manpower resources, and we can see that: after adopting the method of this paper, the completion period of each activity is shorter than that of the comparison method, and the longest completion period is 24 d. And the completion period of the other 2 methods is more than 25 days, which proves the effect of this paper's method.

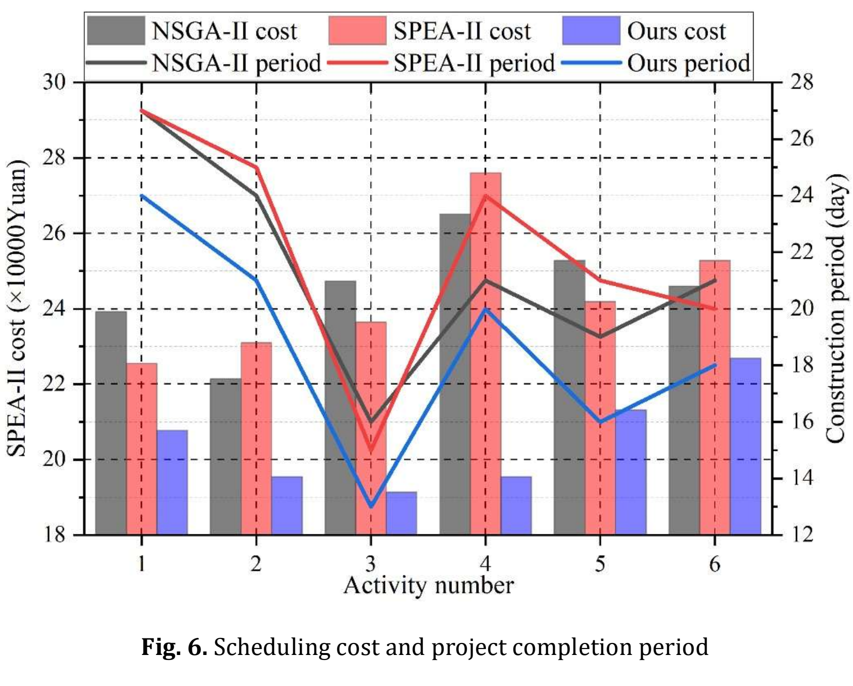

Fig. 6. Scheduling cost and project completion period

In addition, this section uses indicators in the above project activity 2 to evaluate this paper's urban elderly manpower resource development strategy based on differential evolutionary algorithm for different elderly sizes (12, 16, 20, 24, 28, and 32) under different processes (4, 6, 8, and 10), to further test the efficiency of this paper's strategy for the development of elderly manpower resources. The indicators are as follows:

1) Approximation ratio (γ): this is the main indicator to test the efficiency of elderly manpower resource development. The calculation formula is as follows:

$$\gamma = \frac{T}{T^*} \tag{17}$$

where T is the completion time and T^* is the global optimal solution. Obviously, the closer the value of γ is to 1, the better the algorithm's optimization ability.

2) Standard deviation (SD): given the size of the algorithm, this indicator is used to assess the stability of the solution obtained by the strategy in this paper.

3) Execution Time (ET): this metric is the total time spent by this paper's strategy to find the optimal solution.

Figure 7 shows the evaluation results of finding the optimal solution for the development of elderly force resources for the strategy proposed in this paper in Activity 2. From the figure, it can be seen that the γ value of the solution obtained by this paper's strategy is closer to 1 in all the examples, which means that this paper's strategy can obtain a more optimal elderly manpower scheduling solution. Further it can be observed that the γ value of this paper's strategy fluctuates between 1.0025 and 1 as the size of the elderly grows. In the case of the same process, the SD shows a decreasing trend in overall as the number of elderly grows. The reason is that the more the number of seniors, the less the impact of adjusting seniors on the completion time. The computational efficiency of the strategy in this paper is high, and the ET grows from 20s to about 30s with the growth of the size of the elderly, with a small change. In summary, it verifies the value of this paper's urban elderly manpower resource development strategy based on differential evolutionary algorithm in practical applications.

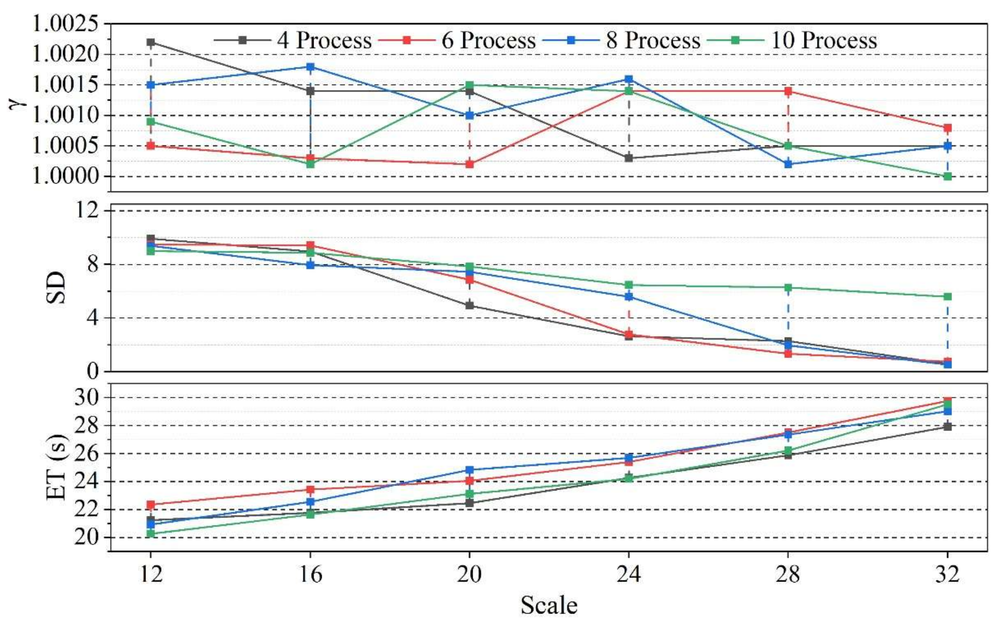

Fig. 7. The optimal solution in activity 2 is looking for the evaluation results

4. Conclusion

The article explores the research on the application of differential evolutionary algorithm based on human resources multi-objective scheduling model in the development strategy of urban elderly human resources by constructing a human resources multi-objective scheduling model. The model starts from randomly generating the initial population, and uses the improved differential evolutionary algorithm to update the population. Through continuous iterative mutation, the mutated individuals adapted to the environment are allowed to be retained, and the global optimal solution is finally approached. Through the experiments of convergence, distribution, and optimality seeking performance test, the efficiency of this paper's model in the optimization of urban elderly resource development strategy is proved.The pareto front of the ADE-MOFS model is consistent with the performance of the real frontier, and has more convergence and distribution. The scheduling time of elderly manpower resources of this paper's algorithm is shortened by 48% to 287% compared with the comparison algorithm, and the average Makespan is reduced by 18.46% to 41.76%. The running cost of each activity under this algorithm is less than 230,000 RMB, and the longest completion period is 24d, which are better than the comparison algorithm. In addition, the γ value of this algorithm is at around 1.0 under different elderly force sizes, which has better stability.

Acknowledgements

This work was supported by the General Project for Philosophy and Social Science Research in Jiangsu Universities (2023SJYB0684).

References

[1] Zhou, J., Deng, J., Li, L., & Wang, S. (2023). The demographic dividend or the education dividend? evidence from China's economic growth. Sustainability, 15(9), 7309.

[2] Froidevaux, A., Alterman, V., & Wang, M. (2020). Leveraging aging workforce and age diversity to achieve organizational goals: a human resource management perspective. Current and emerging trends in aging and work, 33-58.

[3] Von Bonsdorff, M. E., Zhou, L., Wang, M., Vanhala, S., von Bonsdorff, M. B., & Rantanen, T. (2018). Employee age and company performance: An integrated model of aging and human resource management practices. Journal of Management, 44(8), 3124-3150.

[4] Fadaei, M. A., & Mansoori, H. (2023). Identifying specific human resource management practices for aging workforce in public organizations. Elderly Health Journal, 9(2), 92-102.

[5] Soong, J. J. (2020). EMPOWERING THE ELDERLY TO PROMOTE ACTIVE AGEING IN THE LABOUR MARKET: A NEW STRATEGIC SCHEME TO IMPROVE AGEING HUMAN RESOURCE AND TO SOLVE SHORTAGE OF LABOUR FORCE IN TAIWAN. Jebat: Malaysian Journal of History, Politics & Strategy, 47(1).

[6] Segel-Karpas, D., Bamberger, P. A., & Bacharach, S. B. (2015). The prevalence and distribution of aging-friendly human resource practices. The International Journal of Aging and Human Development, 81(1-2), 120-148.

[7] Mok, I., Mackenzie, L., & Thomson, K. (2021). Career development and human resource management of older workers: A scoping review. Australian Journal of Career Development, 30(3), 226-239.

[8] Jung, Y., & Takeuchi, N. (2018). A lifespan perspective for understanding career self-management and satisfaction: The role of developmental human resource practices and organizational support. Human Relations, 71(1), 73-102.

[9] Boehm, S. A., Schröder, H., & Bal, M. (2021). Age-related human resource management policies and practices: Antecedents, outcomes, and conceptualizations. Work, Aging and Retirement, 7(4), 257-272.

[10] Van der Heijden, B. I., Veld, M., & Heres, L. (2022). Does age matter? Examining career commitment as a moderator in the relationship between age - related HR/D practices and subjective career success for younger versus older academic staff. Human Resource Development Quarterly, 33(4), 405-425.

[11] Kaur, S. (2024, July). How does age and gender of the employees influence human resource practices–employee competencies relationship?. In Evidence-based HRM: a Global Forum for Empirical Scholarship (Vol. 12, No. 3, pp. 683-703). Emerald Publishing Limited.

[12] Salomão Filho, A., Tillmanns, T., & Corrigan, T. (2023). Ageing Organizations: Reviewing the Literature and

Making a Few Recommendations for Human Resource Management. Merits, 3(4), 640-653.

[13] Farr-Wharton, B., Bentley, T., Onnis, L. A., Caponecchia, C., Neto, A. D. A., O'Neill, S., & Andrew, C. (2023). Older worker-orientated human resource practices, wellbeing and leave intentions: A conservation of resources approach for ageing workforces. International Journal of Environmental Research and Public Health, 20(3), 2725.

[14] Chand, M., & Markova, G. (2019). The European Union's aging population: Challenges for human resource management. Thunderbird International Business Review, 61(3), 519-529.

[15] Bogataj, D., & Bogataj, M. (2017). Age management of human resources. SOR '17 proceedings, 235-241.

[16] Mok, I., Mackenzie, L., & Thomson, K. (2022). The experiences of human resource professionals in managing career development of an ageing workforce: a narrative thematic analysis. Qualitative Research in Organizations and Management: An International Journal, 18(1), 67-83.

[17] Cai, F. (2020). The second demographic dividend as a driver of china's growth. China & World Economy, 28(5), 26-44.

[18] Ye, J., Chen, Z., & Peng, B. (2021). Is the demographic dividend diminishing in China? Evidence from population aging and economic growth during 1990–2015. Review of Development Economics, 25(4), 2255-2274.

[19] Taketoshi, K. (2020). How and to what extent has the demographic dividend affected China's economic growth?. International Journal of Economic Policy Studies, 14(2), 337-350.

[20] Meng, X. (2023). The People's Republic of China's 40-Year Demographic Dividend and Labor Supply: The Quantity Myth. Asian Development Review, 40(02), 111-144.

[21] Pahos, N., Galanaki, E., & van Der Heijden, B. I. (2024). Multi‐level effects of human resource bundles on the performance of aging employees. Human Resource Development Quarterly, 35(2), 165-188.

[22] Hlatká, M., Stopka, O., Bartuška, L., Stopková, M., Yordanova, D. N., Gross, P., & Sádlo, P. (2021). Draft methodology of the age management implementation in human resource management in a transport company. Journal of risk and financial management, 14(4), 183.

[23] Dorokhov, O., Jaakson, K., & Dorokhova, L. (2024). Age-friendly human resource practices: a comparison of Baltic and Nordic countries. Baltic Journal of Management, 19(6), 133-153.

[24] Martin, L., Nguyen-Thi, U. T., & Mothe, C. (2021). Human resource practices, perceived employability and turnover intention: does age matter?. Applied economics, 53(28), 3306-3320.

[25] Berti, N., Finco, S., Battaïa, O., & Delorme, X. (2021). Ageing workforce effects in Dual-Resource Constrained job-shop scheduling. International Journal of Production Economics, 237, 108151.

[26] Peruzzini, M., & Pellicciari, M. (2017). A framework to design a human-centred adaptive manufacturing system for aging workers. Advanced Engineering Informatics, 33, 330-349.

[27] Zhenghao Song,Liangliang Sun,Natalja Matsveichuk & Yuri Sotskov. (2025). Diversity enhancement-based Differential Evolution with a novel perturbation strategy. Swarm and Evolutionary Computation101822-101822.

[28] Hanting Wang,Yugen Du & Fan Chen. (2024). A Hybrid Strategy Improved SPEA2 Algorithm for Multi-Objective Web Service Composition. Applied Sciences(10).

[29] Keyu Zhong,Fen Xiao & Xieping Gao. (2025). A multi-population competitive evolutionary algorithm based on genotype preference for multimodal multi-objective optimization. Swarm and Evolutionary Computation101826-101826.

[30] Binanda Maiti,Saptadeep Biswas,Absalom El Shamir Ezugwu,Uttam Kumar Bera,Ahmed Ibrahim

Alzahrani,Fahad Alblehai & Laith Abualigah. (2025). Enhanced crayfish optimization algorithm with differential evolution's mutation and crossover strategies for global optimization and engineering applications. Artificial Intelligence Review(3),69-69.