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Research on Quantitative Analysis and Calculation Methods for Dynamic Optimization of Human Resources in Hospitals

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Abstract Traditional human resource allocation methods often rely on empirical judgments and lack the support of scientific quantitative analysis, making it difficult to find a balance between cost control and benefit maximization. Aiming at the cost-benefit balance problem in hospital human resource allocation, this study proposes a multi-objective optimization model based on the improved NSGA-II algorithm. By introducing the cosine similarity to adjust the congestion distance ranking, the multi-objective decision-making model with the objectives of minimizing human resource costs and maximizing project benefits is constructed, and the multi-dimensional chromosome coding and adaptive parameter selection strategy are used to solve the problem. An empirical study is conducted in three departments of respiratory medicine, neurology and orthopedics in a hospital, and the results show that the improved algorithm reduces the human resource cost by 6.81% to 23.90%, improves the project benefit by 10.95% to 41.07%, and converges to the optimal distance of about 20 at the 150th iteration cycle. Compared with the traditional NSGA-II algorithm, the improved algorithm shows significant advantages in both Pareto frontier quality and convergence performance, and provides an effective quantitative analysis method for the dynamic optimization of hospital human resources.

Index Terms Multi-objective optimization, NSGA-II algorithm, human resource allocation, Pareto frontier, cosine similarity, hospital management

I. Introduction

According to the data of the 2018 China Health Care Development Statistical Bulletin, by the end of 2018, there were a total of 997,434 healthcare organizations in China [1]. However, the progress of healthcare has also brought about a series of problems, such as the low efficiency of healthcare resource allocation and the unfair allocation of health resources between regions [2]. In particular, there are a series of problems such as unbalanced allocation of health human resources, low quality, and irrational structural layout, and the main contradiction is that the existing health public resources are unable to adapt to the growing health needs of the people [3], [4]. Under the tense situation of medical reform, the arrangement of hospitals in the development and management of human resources is extremely important for the current and future development of hospitals [5]. How to enhance the core competitiveness of hospitals and how to optimize the allocation of human resources are the main issues that hospitals need to think about in their current and future development and growth.

The reform of the healthcare system, changes in the personnel system, updates in medical technology, and the promulgation of government policy norms and guidance initiatives have had an impact on the organizational configuration of hospitals [6]. The innovative iteration of medical technology, the promulgation of policy norms and supportive policies, etc. have brought about an impact on the management structure of hospitals. At present, hospitals in the field of human resources allocation management, there are some backward management mode and management system can not adapt to the current talent needs, personnel management work is not perfect, personnel recruitment and hiring work is not scientific and reasonable, personnel treatment management is unreasonable and other problems [7]-[9]. At the same time, the hospital's management structure is not flexible enough, the medical staff's work pressure, heavy personal burden, temporary staff with different pay for the same work and other problems also come to the fore [10].

Human resources as one of the core resources of hospitals, how to ensure that local people have full access to quality medical services at the same time, so that the personal value of medical professionals is fully apparent, the development of individual capacity in order to promote the development of the organization better [11]-[13]. Currently China's health human resource allocation of the main problem is focused on the number, especially the regional differences are large, the same population structure and pay and treatment, resulting in many high-quality medical personnel often prefer to choose the city. In the level of health staffing, its quantity, quality and structure will affect the medical service capacity and level of local medical institutions [14], [15]. Scientific and reasonable optimization of health staffing can alleviate the contradiction between the growing demand for medical services and the supply of residents, promote the development of the regional health economy, and also have a certain reference value for the governmental departments in the formulation and improvement of health decision-making [16].

As an important part of the national economy, the service quality and operational efficiency of the medical industry are directly related to the well-being of society and people's livelihood. In the operation and management of hospitals, human resources, as the most core production factors, have a decisive impact on the overall performance of hospitals in terms of their allocation efficiency. Currently, hospitals are generally facing challenges such as continuous growth in medical demand, relative scarcity of professionals, and rising operating costs, and the traditional human resource management model has been difficult to adapt to the requirements of modern hospitals' refined management. The parallel operation of multiple projects is a typical feature of modern hospitals, and the demand for human resources in different departments and different medical projects presents dynamic, complex and cross-cutting characteristics, which makes the human resource allocation decision-making extremely complex. At the same time, hospital managers need to seek the best balance between controlling manpower costs and enhancing service benefits, which is essentially a multi-objective optimization problem. Therefore, it is of great significance to construct a scientific human resource allocation optimization model to improve the management level and service quality of hospitals.

Based on the above analysis, this study adopts the multi-objective optimization theory to construct a mathematical model with the objectives of minimizing human resource costs and maximizing project benefits. By improving the traditional NSGA-II algorithm, introducing cosine similarity to adjust the congestion distance calculation, and designing a multidimensional chromosome coding scheme and an adaptive parameter selection strategy, a quantitative analysis framework for the dynamic optimization of hospital human resources is established. The study utilizes empirical research methods to verify the validity and practicality of the model in a real hospital environment, providing scientific decision support for hospital human resource management.

II. Human resources calculation methodology based on the improved NSGA-II algorithm

Non-dominated Sorting Genetic Algorithm (NSGA), which can be searched in the feasible domain to find Pareto solutions by parallel and combinatorial methods. Based on previous research, the Non-dominated Sorting Genetic Algorithm with Elite Strategy (NSGA-II) [17] is proposed to further improve the efficiency and diversity of the search for the set of Pareto solutions. The basic flow of the NSGA-II algorithm is shown in Fig. 1.

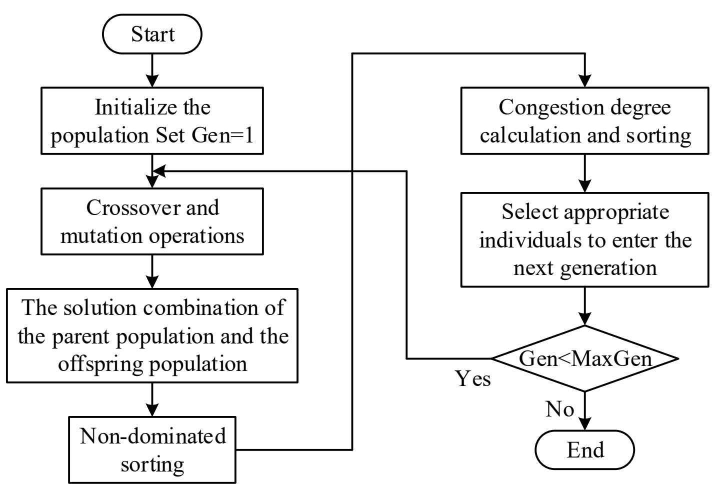

Figure 1: The basic flowchart of NSGA-II

To improve the performance of NSGA-II, this paper proposes a method to adjust the ordering of the crowding distances in order to make the solution set more centralized in the direction preferred by the researcher while maintaining the non-dominated nature of the solution set.

(1) Initializing the population

In this paper, the search fields of the processing parameters are bounded positive integers or positive floating point numbers. Therefore, binary codes are chosen for initialization. The genotypes of the initial individuals are used to randomly generate codes for many individuals whose values need to be restricted to the size of the previously defined search field.

(2) Crossover and mutation operations

In each evolutionary process, two different individuals (denoted as parent_one and parent_two) from the current population are selected for crossover. Before crossover is performed on each binary bit, a random number rand is generated between 0 and 1. The crossover probability is denoted as P(cross). If rand ⩽ P(cross), the crossover is applied. Otherwise, nothing is done. Cyclic crossover is used here as the crossover function since binary coding is used in the initialization of groups and individuals.

(3) Fast non-dominated sorting

The most important difference between the improved NSGA-II and the single-objective optimization algorithm is the selection operator. Specifically, for the calculation of the ranking, the fitness value of each individual in the current population needs to be calculated first. Next, all individuals in the current population that are not dominated by any other individual are selected and the rank of these individuals is set to zero. Subsequently, after removing all these individuals from the current population, all remaining individuals that cannot be dominated by any other individual are considered and their rank is set to 1. And so on, according to the dominance relationship, all individuals in the population are ranked to obtain their rank.

(4) Improved congestion distance ranking

In order to make the results of multi-objective optimization more compatible with different design preferences, this paper proposes a method with directional bootstrapping to improve the congestion distance. The basic idea is to introduce preference bootstrapping in the computation of congestion distance, where preferences are introduced as vectors. The cosine similarity [18] is used as a measure of similarity between two non-zero vectors. The degree of similarity between two non-zero vectors is measured by calculating the cosine of the angle between them, which is equivalent to normalizing to the inner product of identical vectors both of length one. The definition is shown below:

$$\cos(A,B)=\frac{A\cdot B}{\|A\|\|B\|}=\frac{\sum_{i=1}^{n}A_iB_i}{\sqrt{\sum_{i=1}^{n}A_i^2}\sqrt{\sum_{i=1}^{n}B_i^2}} \tag{1}$$

Therefore, the value of cosine similarity ranges from 0 to 1. The closer the value is to 1, the more similar the two vectors are. Where A_i and B_i are the components of vectors A and B respectively. By calculating the cosine similarity between the preference vector A and the individual target value vector B and incorporating it into the individual's crowding distance calculation, the preference of the optimization result can be adjusted in the subsequent crowding distance ranking and screening process. The improved crowding distances for the top of the form bottom of the form can be described as:

$$D_i=\alpha\times\cos(A,B)+\sum_{m=1}^{n}\frac{f_m(i+1)-f_m(i-1)}{f_m^{\max}-f_m^{\min}} \tag{2}$$

where α is a weighting factor to balance the preferences and dispersion of individuals in the same layer. The part after the “+” sign is the same as in the traditional congestion distance calculation.

(5) Selection operator and elite strategy

Parent individuals will generate child individuals through crossover and mutation operators. The use of elite strategy makes the parent and offspring individuals compete together to select quality individuals from them into the next generation. In this figure, all the individuals of the parent and offspring form the population Rt, which has a scale of 2N. In Rt, N of the individuals are selected based on non-dominated sorting and crowding order to form a new next generation population Pt+1.

III. Multi-objective decision-making model for optimizing redeployment

The dynamic and optimal deployment of hospital human resources is a complex issue, and the demand between projects and personnel presents a multi-dimensional cross state, and the competition for hospital human resources among multiple projects can lead to chaos in hospital management.

Analyzed from a systemic perspective, the goals to be achieved by human resource allocation among multiple projects in hospitals are often diversified, and hospitals hope to complete the project work with lower human resource costs and achieve the maximization of project benefits, the optimal quality of the project, and the shortest project duration, etc. The achievement of these goals is usually subject to the influence of the hospitals' human resource management. Achieving these goals is usually subject to the limitations of the internal and external environments of the hospital. Therefore, hospital multi-project staff deployment can actually be regarded as a multi-objective planning problem to achieve the optimization of multiple objectives under certain constraints, and the multi-objective decision-making of multi-project staff deployment is shown in Figure 2.

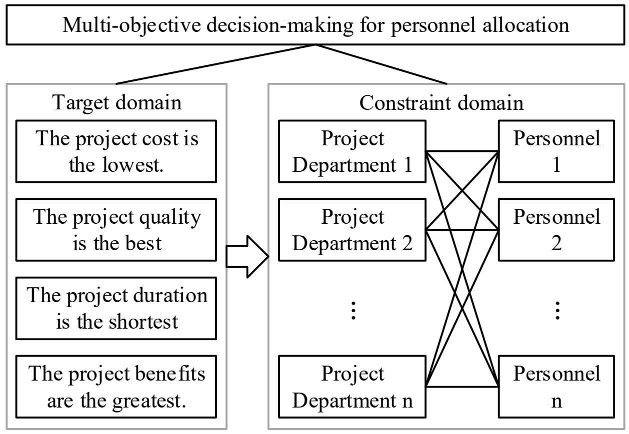

Figure 2: Multi-objective decision making

The set of projects that need to be staffed in the current phase of the hospital is defined as $W=\{w_i \mid 0<i\leq n\}$, where w_i denotes the i rd project or process that needs to be staffed, and n denotes the total number of sub-projects in the project set that need to be staffed. The hospital's current set of deployable staff is $P=\{p_j \mid 1<j\leq m\}$, p_j represents the j th employee to be deployed, and the total number of employees to be deployed is m. Each employee may be assigned to complete one or more tasks, $x_{ij}: p_j \to w_i, p_j \in P, w_i \in W$ means that employee p_j is assigned to work on project w_i, and x_{ij} can only take the value of 0 or 1. Taking the value of 1 means that p_j is assigned to work on project w_i, and taking the value of 0 means that he or she is not assigned p_j to work on project w_i. Employees assigned to complete the work need to incur a certain human resources costs, so that $C(x_{ij})$ represents the deployment of staff p_j to work on the project w_i costs, $L(x_i)$ represents the deployment of staff p_j to work on the project w_i can produce the benefits. It is stipulated that each employee can only undertake one project task in each round of deployment, while the same project task can be undertaken by more than one employee at the same time. The multi-objective decision making for staffing decisions can be modeled as follows:

$$\min \sum_{i=1}^{n}\sum_{j=1}^{m} C(x_{ij}) \tag{3}$$

$$\max \sum_{i=1}^{n}\sum_{j=1}^{m} L(x_{ij}) \tag{4}$$

$$s.t \quad \sum_{i=1}^{n} x_{ij}=1, j=1,2,...,m \tag{5}$$

$$\sum_{j=1}^{m} x_{ij} \leq m, i=1,2...,n \tag{6}$$

Equations (3) and (4) constitute multiple decision objectives for the staffing decision, which are to minimize the cost of deploying staff to complete the project and to maximize the benefit of deploying staff to complete the project, respectively. Formula (5), (6) represents the decision-making problem of the two constraints, formula (5) that each employee can only and must undertake a task, formula (6) that each task can be redeployed up to the number of personnel for the completion of the $m-n$ and each task must be at least one person to complete, that is, the deployment of all the hospital personnel to complete a task.

IV. Optimizing human resources dynamics for deployment solutions

This section uses the improved NSGA-II algorithm above to solve the objective function of dynamic optimal deployment of human resources in hospitals.

(1) Algorithm flow

1) Coding to randomly generate an initial population P_t of size N.

2) Adaptation evaluation to obtain the corresponding objective function value.

3) Perform selection, crossover and mutation operations to obtain a new population C_t.

4) Merge P_t with C_t to obtain population N_p of size $2N$.

5) Perform fast nondominated sorting on population N_p to obtain nondominated set $\{F_1, F_2, ...\}$, set $P_{i+1} = \varnothing, i = 0$, and when $|P_{i+1}| + |F_i| \le N$, copy $|F_i| - 1$ individuals from F_i to $P_{i+1}, i = i+1$. Otherwise, calculate the crowding distances of the individuals in F_i, and select $N - |P_{t+1}|$ individuals to be copied to P_{t+1} according to the principle of sparsity to density, until the size of P_{t+1} is N.

6) Gen=Gen+1, if $Gen \le Gen_{\max}$, skip to step 3. otherwise, proceed to step 7.

7) Save the results of the run, output the Pareto frontier image of the multi-objective optimization problem, and the decision maker outputs the results of the corresponding scheduling plan based on the problem environment as well as the preferences, and the algorithm terminates.

(2) Coding scheme

A multi-dimensional chromosome coding scheme is designed for the characteristics of the HR project-based planning and scheduling model, which excludes most of the infeasible solutions without reducing the search space of the algorithm. When a human resource conflict occurs, parallel activities need to be converted into serial tasks, and the execution order 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 is determined. Each complete chromosome consists of a priority chromosome and a staff assignment chromosome.

Priority chromosome: a 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, so that in the event of a human resources conflict, activities with a higher priority are given first access to human resources.

Staff assignment chromosome: each staff member in the staff assignment chromosome corresponds to a row of the chromosome, and the corresponding value represents the decision variable. At the termination of the algorithm, the priority chromosome as well as the staff assignment chromosome are decoded separately. The priority of each activity task and the number of staff involved in the project are obtained in turn, thus obtaining a feasible solution to the hospital multi-objective project planning and scheduling model.

(3) Adaptation function

Adaptation function has an objective function variation, according to the optimization objectives of this study: the lowest human resources costs and the highest benefits, we can get the chromosome of the adaptability to follow the following rules of calculation:

$$Fit_1[t] = \sum_{i=1}^{n}\sum_{j=1}^{m} C(x_{ij}), x_{ij} \in X_t, t = 1,2,...,N \tag{7}$$

$$Fit_2[t] = -\sum_{i=1}^{n}\sum_{j=1}^{m} L(x_{ij}), x_{ij} \in X_t, t = 1,2,...,N \tag{8}$$

where $Fit_1[t]$ denotes the t nd particle with the cost function as the fitness function, similarly the benefit function fitness can be calculated for each particle.

(4) Genetic operation

1) Adaptive parameter selection

In order to realize the global optimization search, the cross variance probability is increased when there is not much difference in the fitness values of individuals in the population. In order to enable the preservation of good individuals, reduce the cross variance probability when there is an individual fitness function value higher than the population average. The cross variance probability of the adaptive genetic algorithm varies according to the following pattern.

For crossover probability P_c:

When $f \ge f_a$:

$$P_c = \frac{k_1(f_{\max} - f)}{f_{\max} - f_a} \tag{9}$$

When $f < f_a$:

$$P_c = k_2 \tag{10}$$

where $f_{\max}$ denotes the maximum value of the fitness function in the current population, f_a denotes the mean value of fitness in the population, f denotes the value of the fitness function that is larger in the crossover individuals, and k_1, k_2 is taken as a constant in the open interval from 0 to 1.

For the probability of variation p_m:

When $f \geq f_a$:

$$P_m = \frac{k_3(f_{\max} - f)}{f_{\max} - f_a} \tag{11}$$

When $f < f_a$:

$$P_m = k_4 \tag{12}$$

where $f_{\max}$ denotes the maximum value of the fitness function in the current population, f_a denotes the mean value of fitness in the population, f denotes the value of the fitness function for the variant individuals, and k_3, k_4 takes a constant in the open interval from 0 to 1.

2) Selection operation

Selection operation refers to somehow selecting the excellent individual with higher adaptation according to the size of the value of the individual's fitness function, and in this study, the roulette method is invoked to select the individual's selection probability. It is set that the probability of each individual to be selected is proportional to the size of its fitness, if the trait of an individual gene is better adapted to the problem environment, the value of the fitness function will be bigger and the probability of being selected will be higher, thus it is also known as the proportional selection method. The functional expression for the roulette method is:

$$P(i) = \frac{F(i)}{\sum_{1}^{m} F(k)} \tag{13}$$

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

3) Crossover and Mutation

Crossover operation is done by 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 chromosome of the offspring.

V. Quantitative analysis of the dynamic optimization of human resources in hospitals

V. A. 5.1 Optimal Pareto Frontier for HR Programs

Programs were written separately for the optimized NSGA-II algorithm and the traditional NSGA-II algorithm described in this paper using Matlab R2019b. The number of individuals per population was set to 20, 150 iterations were calculated, and the crossover probability of the two algorithms was set to 0.5 and the variance probability was set to 0.1. The computer parameters were Windows 10 operating system, 16G RAM, and Intel(R) Core(TM) i7-11370H CPU.

Two algorithms were used to calculate the values of two objective functions for the dynamic and optimal allocation of human resources in hospitals, i.e., the minimum cost of human resources and the maximum project benefit, respectively. The multi-objective approximate Pareto frontiers of the two algorithms are shown in Figure 3. From the figure, it can be seen that the quality of the optimization algorithm solution is overall better than the standard algorithm. Under the same constraints, the solution of the optimization algorithm performs better in terms of minimum resource cost of human resources and maximum project benefit of the hospital. And in terms of the two optimization objective function values, the optimization NSGA-II algorithm occupies a greater advantage and the average solution is better than the traditional NSGA-II algorithm, which proves the superiority of the optimization algorithm.

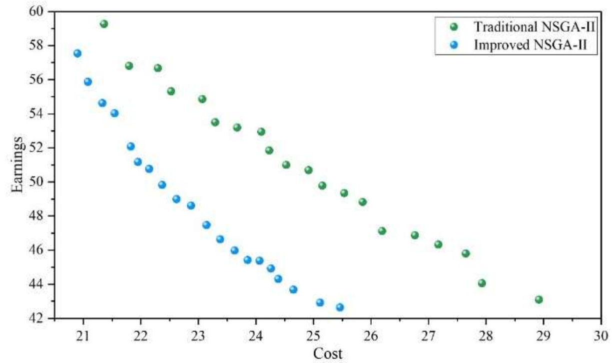

Figure 3: More likely to approximate the front edge of the pareto

In addition, this subsection measures the intermediate results of the optimized NSGA-II algorithm, i.e., the distance from the origin of the individual closest to the origin among all individuals in each generation, d. From the Pareto solution in the previous section, it can be seen that the values of the objective function are all non-negative, and therefore a smaller distance to the origin represents a better solution, and this holds in any multidimensional space. Figure 4 shows how the optimal distance of the test case changes under different number of iterations. Where the first generation of individuals is randomly generated, which can be approximated as human resources autonomously participating in the hospital program. It can be seen that as the number of iterations increases, the allocation scheme gradually converges to the optimal, and finally the optimal distance converges to about 20 at about the 150th epoch. In this paper, based on the optimization NSGA-II multi-objective optimization algorithm model, the best matching between hospital human resources and projects is quantitatively achieved, and the feasibility of the model and the solution method is verified.

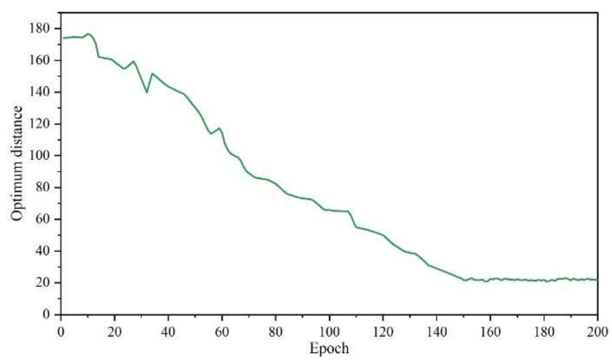

Figure 4: The optimal distance of the test case in different iterations

V. B. 5.2 Example of optimization of human resource allocation in hospitals

In order to verify whether the above optimization model is effective, the model is used to optimize the staffing of a hospital. The hospital includes major departments such as respiratory medicine, neurology, orthopedics, etc., with a total of 53 attending physicians, 27 associate physicians, 10 chief physicians, and the rest such as several nurses and security guards. For the three departments of respiratory medicine, neurology and orthopedics in this hospital, three human resource dynamic optimization projects were designed to optimize the allocation of human resources using the traditional NSGA-II algorithm and the improved NSGA-II algorithm, respectively, and compared with the manpower costs and project benefits before human resource optimization. The results of the manpower cost and project benefits of the theoretical allocation schemes obtained according to the multi-objective optimization model are shown in Table 1.

From the table, it can be seen that in this hospital under the new human resource allocation scheme in respiratory medicine, neurology, orthopedics, the human resource cost as well as the project benefits have been optimized to different degrees, but the optimization of the human resource allocation scheme using the improved NSGA-II algorithm is better than that of the traditional NSGA-II algorithm. Specifically, in the above three departmental projects, the traditional NSGA-II algorithm's human resource allocation scheme reduces the labor cost by 2.65% to 12.03% and improves the project revenue by 5.84% to 16.96% compared with the pre-optimization period. In contrast, the improved NSGA-II algorithm provides a human resource allocation scheme that reduces the labor cost by 6.81%~23.90% and improves the project benefits by 10.95%~41.07%. The results of the study prove the effectiveness of the improved NSGA-II algorithm of this paper for dynamic optimization of human resources in hospitals.

Table 1: Human cost and project earnings results

Project	Target function	Pre-optimize	Traditional NSGA-II		Improved NSGA-II	
			Post-optimize	Improved (%)	Post-optimize	Improved (%)
Respiratory medicine	Cost	3.85×105	3.53×105	-8.31	2.93×105	-23.90
	Earning	1.12×106	1.31×106	16.96	1.58×106	41.07
Neurology	Cost	1.58×106	1.39×106	-12.03	1.25×106	-20.89
	Earning	2.78×106	3.05×106	9.71	3.22×106	15.83
Orb	Cost	5.29×105	5.15×105	-2.65	4.93×105	-6.81
	Earning	1.37×106	1.45×106	5.84	1.52×106	10.95

For the 10 chief physicians of the hospital, the corresponding worker scheduling Gantt chart is shown in Fig.5 by choosing the improved NSGA-II algorithm to give the corresponding worker scheduling Gantt charts for the medical activities in the three departments mentioned above. The lengths on the crosswalks in the graph indicate the length of time that the hospital workers work, and the labels indicate the activities that the hospital workers are engaged in at that point in time. From the figure, it can be seen that the algorithm in this paper can reasonably schedule human resources in different time periods, making the labor cost minimum while ensuring the maximum benefit of the project.

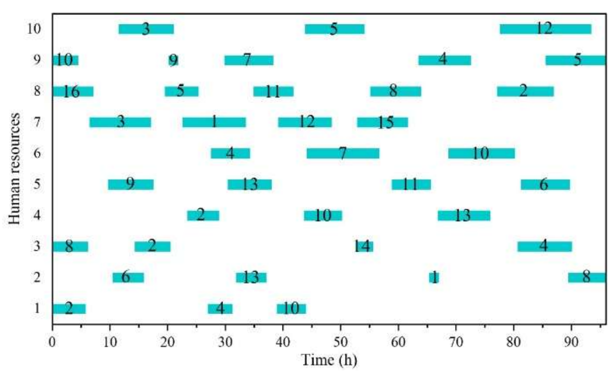

Figure 5: Manual dispatch of Gantt chart

VI. Conclusion

In this paper, by constructing a multi-objective optimization model of hospital human resources based on the improved NSGA-II algorithm, the efficiency and cost balance problem in traditional human resource allocation is successfully solved. Empirical analysis shows that the improved algorithm achieves 23.90% labor cost reduction and 41.07% project revenue enhancement in the respiratory medicine project, which is significantly better than the 8.31% cost reduction and 16.96% revenue enhancement of the traditional NSGA-II algorithm. The convergence performance of the algorithm is good, and the optimal distance stably converges to about 20 in 150 iteration cycles, which proves the computational efficiency and stability of the model. The introduction of cosine similarity effectively improves the congestion distance ranking mechanism, which makes the quality of the Pareto frontier solution set significantly improved, and provides richer and better-quality options for decision makers. The design of multidimensional chromosome coding and adaptive parameter selection strategy enhances the algorithm's ability to handle complex constraints and improves the solution accuracy. This study provides a scientific quantitative analysis tool for the dynamic optimization of human resources in hospitals, which has an important practical value for improving the operational efficiency and service quality of hospitals.

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