Regional large-scale science instruments configuration efficiency evaluation method based on multi-objective optimization and fuzzy decision-making model

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Received 1 November 2014, www.cmnt.lv

Abstract

This paper concentrates on the problem of regional large-scale science instruments configuration efficiency evaluation, which is a typical multi-objective optimization problem. As large-scale science instruments have not been utilized with high efficiency, it is of great importance to promote the efficiency of large-scale science instruments configuration. Firstly, the multi-objective particle swarm optimization model is proposed, in which three objectives are considered (such as Economic benefits, Utilization rate of equipment, and Social benefits). Exploiting the proposed multi-objective particle swarm optimization model, Pareto optimal solutions can be obtained. Secondly, a fuzzy decision-making model is provided to choose an optimal solution from the set of Pareto optimal solutions by implementing the intersection of all fuzzy criteria and the related constrains. Thirdly, to make performance evaluation, we collect the data from statistical yearbooks of ten provinces in China to construct dataset. Experimental results demonstrate that the proposed method can effectively evaluate regional large-scale science instruments configuration efficiency.

Keywords: Multi-objective optimization, Particle swarm optimization, Fuzzy decision-making model, Science instruments

1 Introduction

Science and technology resources are important factors to promote economic and social development and social progress, particularly, in the era of knowledge economy, science and technology resources is more and more important to the modern society[1][2]. As is well known that science and technology is primary productive force. Therefore, how to enhance the production rate of technological products and promote the utilization of science and technology resources under limited resources is of great importance [3] [4].

The regional sharing of the large-scale scientific instruments is a service for science and technology. Thus, improving the scientific instruments allocation efficiency can effectively enhance the scientific resources utilization. In our opinion, the scientific instruments with low utilization should be provided to the Internet, and the users who want to use them can obtain this information in time. Furthermore, effectively allocating regional large-scale science instruments may promote science and technology development for the specific region.

Currently, science and technology resources, especially large-scale science instruments have not been used with high efficiency. Therefore, to study how to maximize and improve large-scale science instruments allocation efficiency is necessary. However, large-scale science instruments configuration problem is a complex problem, in which there are many influencing factors. Moreover, the relationships between these factors are also complex. Regional large-scale science instruments configuration problem is belonged to the resource allocation problems.

In strategic planning, resource allocation represents a plan to utilize available resources, such as human resources and science and technology resources. It is the process of allocating scarce resources in the different projects or business transactions [5]. There are a lot of methods to solve the resource allocation problems, which cover many application fields in both natural science and humanity science [6-8].

To tackle the resource allocation problem, the fuzzy optimization model is suitable to be exploited. Moreover, optimization problems exist in many kinds of applications [9]. As the decision makers usually state their requirements in a vague way, they may prefer to obtain more than one solutions. Therefore, the optimal solution can be used according to the state of existing decision of the production process at a specific time. Based on the above analysis, fuzzy optimization is an effective approach, because this method can represent the potential uncertainty of the optimization problem through searching for optimal solutions [10].

This paper illustrates a regional large-scale science instruments configuration efficiency evaluation approach utilizing the fuzzy multi-objective optimization decision-making model. Section 2 provides the related works of fuzzy multi-objective optimization and its applications. In section 3, a multi-objective model for the regional large-scale science instruments configuration problem is given. Section 4 proposes an evaluation approach using the fuzzy multi-objective optimization decision-making model. To demonstrate the effectiveness of the proposed algorithm,

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experiments are conducted in section 5. Finally, the conclusions are drawn in section 6.

2 Related works

The multi-objective optimization problem should satisfy several different objectives, which are characterized by distinct measures. Furthermore, there is no integration of decision variables values which can optimize all the components of the objective vector at the same time. For example, the objectives can minimize the negative environmental impact of the process, and at the same time, maximize the profit and to maximize the safety of the process. In the following parts of this section, related works about multi-objective optimization problem are given.

Siano et al. presented a novel approach to design fuzzy logic controllers for voltage-regulated DC power converters. The main idea of this paper is that multi-objective particle swarm optimization is utilized to search multiple Pareto-optimal solutions in a multi-objective optimization problem. To testify the effectiveness of the proposed method, different cases have been tested in laboratory on a buck converter prototype [11].

Hussain et al. exploited the evolutionary optimization to design and tune smart fuzzy controllers for heating, ventilation, and air conditioning systems or HVAC. The objective is to minimize energy cost when considering user comfort requirements. Particularly, the energy saving in air conditioning systems is belonged to a kind of multi-objective optimization constrained problems. To tackle this problem, a multi-objective evolutionary optimization method utilizing genetic algorithm is proposed. The main contributions of this paper lie in that a fuzzy controller is given through expert knowledge, and genetic algorithm is utilized to modify the rules and membership functions of the fuzzy controller to optimize multi-objectives [12].

Garg et al. proposed an approach to tackle the multi-objective reliability optimization model, and in this model, parameters are regarded as imprecise according to the triangular interval data. Afterwards, the proposed uncertain multi-objective optimization model is converted to a new model with left, centre and right interval functions included. Using the intuitionistic fuzzy programming technology, conflicts can be avoided through the nonlinear degree of membership and non-membership functions [13].

In paper [14], the authors concentrated on linear fractional multi-objective optimization problems exploiting the max-Archimedean triangular norm composition. The main contributions of this work lie in that the linear fractional multi-objective optimization problem is regarded as a linear problem.

Garg et al. introduced multi-objective optimization in the workflow grid scheduling, which is belonged to NP-hard problems. The proposed algorithm used a fuzzy based mechanism to achieve the best compromised solution under two objectives, that is, execution time and cost. Particularly, the authors optimized the execution time and cost at the same time considering dynamic characteristics of grid resources [15].

Routing is an important and basic problem for wireless sensor networks, and it is a typical optimization. In paper [16], Lu et al. utilized fuzzy random optimization and multi-objective optimization to represent both fuzziness and randomness of link delay, and thus presented a routing model using fuzzy random expected value and standard deviation. Furthermore, a novel fuzzy random multi-objective optimization based wireless sensor networks routing algorithm based on is given. The proposed algorithm combined fuzzy random simulation to genetic algorithm based on Pareto optimal solution [16].

Particle swarm optimization is a powerful computing tool, which has been widely used to solve the optimization problem in many different fields. In paper [17], the authors designed a Particle Swarm Optimization based fuzzy multi-objective method to tackle the optimal locating and parameter setting problem in power system. As two objectives should be optimized in this system, such as voltage violation and congestion, these objectives are fuzzified and designed to be comparable against each other. Afterwards, particle swarm optimization is exploited to search the solution which can optimize the value of integrated objective function [17].

In the field of advanced manufacturing technology, Mirakhorli et al. proposed an interactive fuzzy multi-objective linear programming approach to tackle fuzzy bi-objective reverse logistics network design problem. The main ideas of this paper are that this paper tries to minimize the system total cost and system total delivery time together. Particularly, this method can let the decision makers to change fuzzy data to obtain the optimal results [18].

Our work differs from the existing algorithms in two aspects. Firstly, we design a multi-objective particle swarm optimization model to describe the regional large-scale science instruments configuration efficiency evaluation problem. Secondly, a fuzzy decision-making model is proposed to choose final optimal solutions from the candidate Pareto optimal solutions.

3 Multi-objective optimization models for the Regional large-scale science instruments configuration problem

Multi-objective model aims to find the optimal solution which is represented as a vector of functions:

$$F(x) = \left(f_1(x), f_2(x), \cdots, f_m(x)\right)$$
$$\text{s.t. } x = \left(x_1, x_2, \cdots, x_n\right) \in \Omega \tag{1}$$

In Eq.1, the symbol Ω represents the decision space, and the mapping function $F : \Omega \to \mathbb{R}^m$ can map the decision space to m real valued objectives space. Supposing that there is a maximization problem, in which vector $x^1 \in \Omega$ determines vector $x^2 \in \Omega$ (denoted as $x^1 \succ x^2$) if and only if the following condition is satisfied.

$$\forall i=1,2,\cdots,m\ f_i\left(x^1\right)\geq f_i\left(x^2\right)\wedge\exists j=1,2,\cdots,m\ f_i\left(x^1\right)>f_i\left(x^2\right) \tag{2}$$

In addition, vector of the decision valuables $x^*\in\Omega$ refers to a Pareto optimal solution when there is no other element $x\in\Omega$, such that $x\succ x^*$. Based on the above description, the Pareto optimal set is given as follows.

$$P^*=\left\{x^*\in\Omega\middle|\neg\exists\in\Omega,x\succ x^*\right\} \tag{3}$$

Afterwards, we define the Pareto optimal set as the set of all the Pareto optimal solutions as follows.

$$Q^*=\left\{F\left(x^*\right)=\left(f_1\left(x^*\right),f_2\left(x^*\right),\cdots,f_m\left(x^*\right)\right)\middle|x^*\in P^*\right\} \tag{4}$$

Then, the aim of the multi-objective particle swarm optimization model is to pursue a setoff Pareto optimal solutions.

After studying on the characteristics of the regional large-scale science instruments configuration system, a modified multi-objective model for regional large-scale science instruments optimal configuration is constructed. Our proposed model has three objectives: 1) Economic benefits, 2) Utilization rate of equipment, and 3) Social benefits, and framework of the regional large-scale science instruments configuration efficiency evaluation system is shown in Fig.1.

In this system, multi-objective particle swarm optimazation model is a key module, which can generate a set of Pareto optimal solutions integrating three objectives together. The particle swarm optimization (PSO) refers to an evolutionary method by Kennedy and Eberhard [19]. Particle swarm optimization considers a population of randomly positioned particles, which is named a swarm, and finds the best position with best fitness. The swarm is made up of particles, which can be represented by vectors, where each particle is corresponding to a potential solution of an optimization problem [20]. The standard particle swarm optimization is represented as follows.

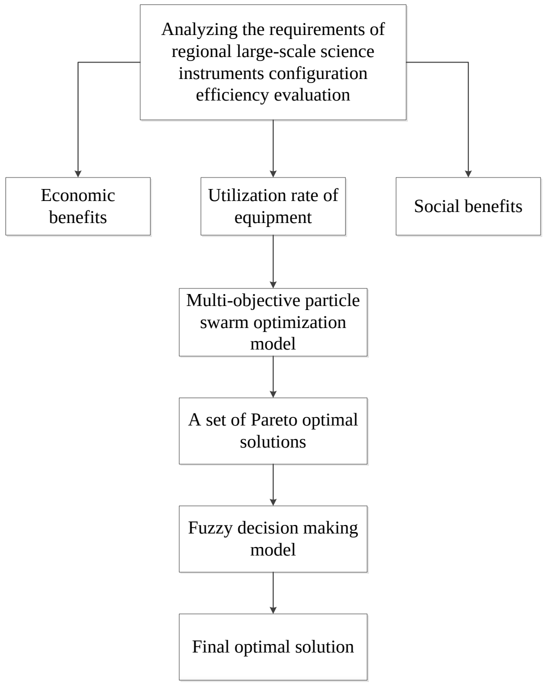

FIGURE 1 Framework of the regional large-scale science instruments configuration efficiency evaluation system

$$v_{id}\left(k+1\right)=w\cdot v_{id}\left(k\right)+c_1\cdot r_1\left(p_{id}\left(k\right)-x_{id}\left(k\right)\right)+c_2\cdot r_2\left(p_{gd}\left(k\right)-x_{id}\left(k\right)\right) \tag{5}$$

$$x_{id}\left(k+1\right)=x_{id}\left(k\right)+v_{id}\left(k+1\right) \tag{6}$$

Where i means the i^{th} particle, and d denotes the d^{th} dimension. Particularly, current velocity and position of the i^{th} particle are calculated as follows.

$$V_i\left(k\right)=\left(v_{i1}\left(k\right),v_{i2}\left(k\right),\cdots,v_{in}\left(k\right)\right) \tag{7}$$

$$X_i\left(k\right)=\left(x_{i1}\left(k\right),x_{i2}\left(k\right),\cdots,x_{in}\left(k\right)\right) \tag{8}$$

For the i^{th} particle, the best position is represented as $P_i\left(k\right)=\left(p_{i1}\left(k\right),p_{i2}\left(k\right),\cdots,p_{in}\left(k\right)\right)$, and the best position obtained by neighbors is $P_g\left(k\right)=\left(p_{g1}\left(k\right),p_{g2}\left(k\right),\cdots,p_{gn}\left(k\right)\right)$.

Particularly, c_1 and c_2 denote the acceleration constants, and r_1 r_2 mean the random numbers with uniformly distribution.

In our multi-objective particle swarm optimization model, we assume that a set of solutions are obtained in the process of Pareto optimization. Next, we will discuss how to evaluate the fitness for a decision vector S. The minimal value of $\left\{f_i\left(S\right)-f_i\left(T\right)\middle|\forall i\in\left\{1,2,\cdots,m\right\}\right\}$ is calculated as follows.

$$\min_{i\in\{1,2,\cdots,\mathrm{m}\}}\left\{f_i\left(S\right)-f_i\left(T\right)\right\} \tag{9}$$

Where m represents the number of objectives, and in this paper, m is equal to 3. To compute the new position of a particle in the objective space, the following equation is defined exploiting the fitness inheritance technology:

$$VF_i(h)=c_1\cdot r_1\left[F_{PBest(i)}\left(h\right)-F_i\left(h\right)\right]+c_2\cdot r_2\left[F_{GBest(i)}\left(h\right)-F_i\left(h\right)\right] \tag{10}$$

$$F_i(h)=F_i(h\text{-}1)+VF_i(h) \quad (11)$$

In Eq. 10 and Eq. 11, $F_i(h)$ denote the value of i^{th} objective function related to the current particle.

Moreover, $F_{PBest(i)}(h)$ and $F_{GBest(i)}(h)$ refer to the value of $PBest$ and $GBest$ respectively.

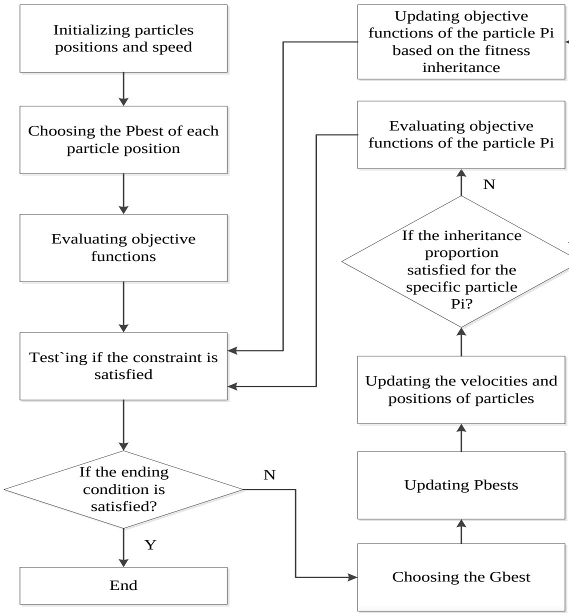

FIGURE 2 Flow chart of the multi-objective particle swarm optimization model

4 Regional large-scale science instruments configuration efficiency evaluation method

Before evaluating the resource configuration efficiency, the index system should be constructed in advance, and in this paper, we use analytical hierarchy process [21][22] (AHP) technology to compute the index weight. The index system for large-scale science instruments configuration efficiency evaluation is shown in Fig.3, and this index system considers not only the input information but also output information. In this index system, three aspects are included, that is, “Economic benefits”, “Utilization rate of equipment”, and “Social benefits”. These three aspects can cover the main objectives of regional large-scale science instruments configuration evaluation problem.

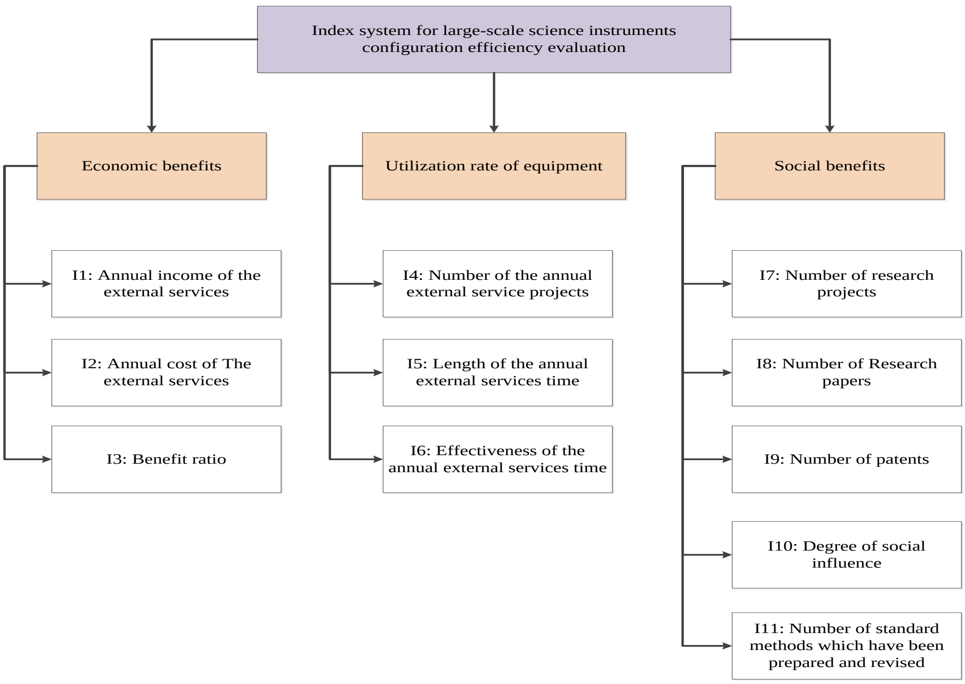

FIGURE 3 Index system for large-scale science instruments configuration efficiency evaluation

To find the final optimal solution, each $R_j(X)$ is represented by a fuzzy objective function as follows.

$$A_j = \{X, \mu_{Aj}(X)\}\ X \in L,\ j \in \{1,2,\cdots,k\} \tag{12}$$

Where $\mu_{Aj}(X)$ denotes a membership of function which is belonged to A_j. Hence, a final solution is defined as the intersection of all fuzzy constraints using the related membership function. Assuming that Z denotes the fuzzy solution, and Z is equal to $\cap_{j=1}^{k} A_j$. Next, the membership function is defined as follows.

$$\mu_Z(X) = \cap_{j=1}^{k} \mu_{A_j}(X) = \min_{j=\{1,2,\cdots,k\}} \mu_{A_j}(X),\ X \in L \tag{13}$$

The maximum value of $\mu_Z(X)$ is computed by the following equation.

$$\max \mu_Z(X) = \max_{X_L} \min_{j=\{1,2,\cdots,k\}} \mu_{A_j}(X) \tag{14}$$

$$X = \arg\max_{x \in L} \min_{j \in \{1,2,\cdots,k\}} \mu_{A_j}(X) \tag{15}$$

The optimal value of each $R_j(X)$ is computed through scalar optimization, and the optimal results are represented as $\{X_j^0, j \in \{1,2,\cdots,m\}\}$.

Afterwards, the matrix table $\{M\}$, in which the diagonal elements are optimal values, is defined in the following equation.

$$\{M\} = \begin{bmatrix} R_1(X_1^0) & R_2(X_1^0) & \cdots & R_n(X_1^0) \\ R_1(X_2^0) & R_2(X_2^0) & & R_n(X_2^0) \\ & & & \\ R_1(X_n^0) & R_2(X_n^0) & & R_n(X_n^0) \end{bmatrix} \tag{16}$$

Furthermore, the max and min bounds for the given objective are given as follows.

$$\min(R_1) = \min_j R_j(X_j^0),\ i \in \{1,2,\cdots,n\} \tag{17}$$

$$\max(R_1) = \max_j R_j(X_j^0),\ i \in \{1,2,\cdots,n\} \tag{18}$$

In our decision-making model, to maximize and minimize the objective functions, the membership functions are different.

For maximizing objective functions, the membership functions are illustrated as follows.

$$\mu_{R_i}(X) = \begin{cases} 1, & R_i(x) > R_i^{\max} \\ \dfrac{R_i - R_i^{\max}}{R_i^{\max} - R_i^{\min}}, & R_i \in (R_i^{\min}, R_i^{\max}] \\ 0, & R_i(x) \le R_i^{\min} \end{cases} \tag{19}$$

Similarly, the membership functions corresponding to the minimizing objective functions are defined as follows.

$$\mu_{R_i}(X) = \begin{cases} 0, & R_i(x) > R_i^{\max} \\ \dfrac{R_i^{\max} - R_i}{R_i^{\max} - R_i^{\min}}, & R_i \in (R_i^{\min}, R_i^{\max}] \\ 1, & R_i(x) \le R_i^{\min} \end{cases} \tag{20}$$

On the other hand, fuzzy constraints are given in the following equation.

$$C_j(X) \le C_j^{\max} + \eta_j,\ j \in \{1,2,\cdots,k\} \tag{21}$$

Where parameter η_j denotes the distance between admissible displacement of $C_j^{\max}$ and the j^{th} constraint. Accordingly, the related membership functions can be obtained:

$$\mu_{C_i}(X) = \begin{cases} 0, C_i(X) > C_i^{\max} \\ 1 - \dfrac{C_j(X) - C_j^{\max}}{\eta_i}, C_i(X) \le C_i^{\max} \\ 1, C_i(X) \in (C_i^{\max}, C_i^{\max} + \eta_i] \end{cases} \tag{22}$$

Finally, the final optimal solution can be achieved by implementing the intersection of all fuzzy criteria and the related constrains.

5 Experiments

In this section, to verify the effectiveness of the proposed model, experiments are conducted based on the real regional large-scale science instruments configuration data. As the data collection task of large-scale science instruments utilization is quite difficult, and the dataset must be authoritative. Therefore, we collect related dataset from statistical yearbooks of ten provinces in China, which are named Region #1 to Region #10. Particularly, the "Statistical yearbook of China" is exploited in this experiment as well. To make the experimental results can be compared with others; we normalize the value of each optimal objective.

As is shown in Fig.3, the problem of large-scale science instruments configuration efficiency evaluation aims to optimize three objectives: "Economic benefits", "Utilization rate of equipment", and "Social benefits". That is, we should find the optimal resource allocation scheme by integrating the multi-objectives together.

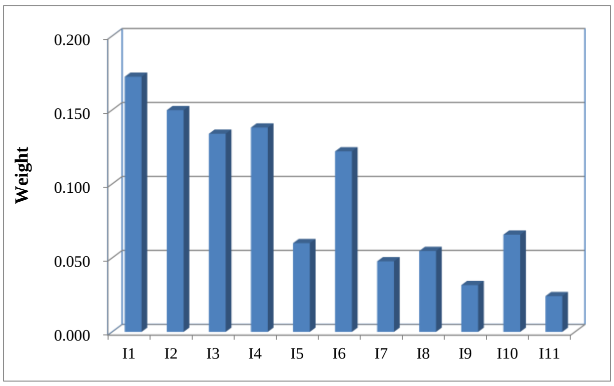

FIGURE4. Weight of each index in the index system

Next, we will show the performance of our proposed multi-objective particle swarm optimization model and the decision-making mode, and the experimental results are shown in Fig.5 – Fig.10. In the experiment, number of particles and iterations in the proposed multi-objective particle swarm optimization model are set as 120 and 300 respectively. The value of c_1 and c_2 are set to 2 and 3 respectively. In Fig.5 and Fig.6, the optimal scheme of Region #1 is described using a three dimensional scatter diagram with two different views, in which the blue asterisk and red asterisk represent Pareto optimal solutions and final optimal solution respectively. Furthermore, the final optimal solution is chosen from Pareto optimal solutions. Similarly, the optimal solution of Region #2 is illustrated in Fig. 7 and Fig. 8 in two different views as well. For the region #3, please refer to Fig. 9 and Fig.10.

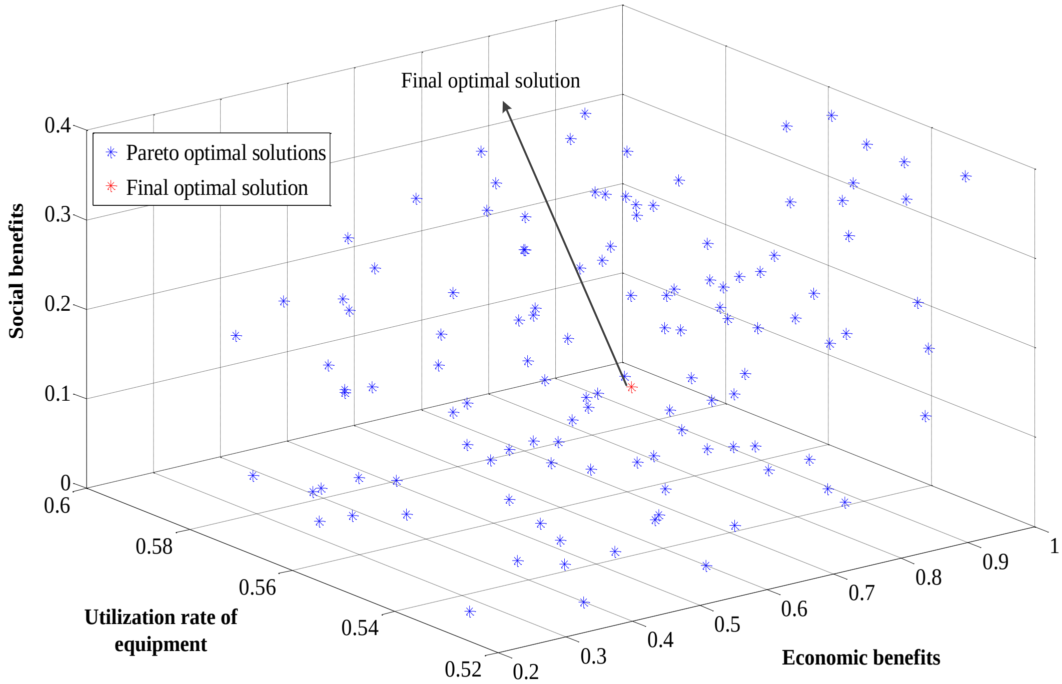

FIGURE 5 Final optimal solution obtained from the candidate Pareto optimal solutions for Region #1 (View 1)

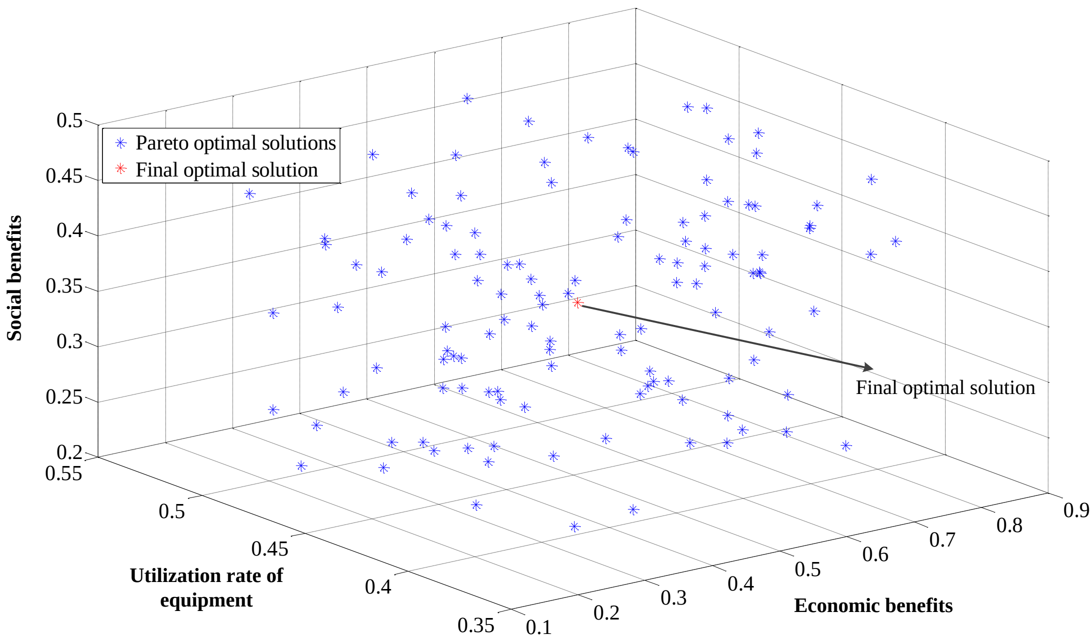

FIGURE7. Final optimal solution obtained from the candidate Pareto optimal solutions for Region #2 (View 1)

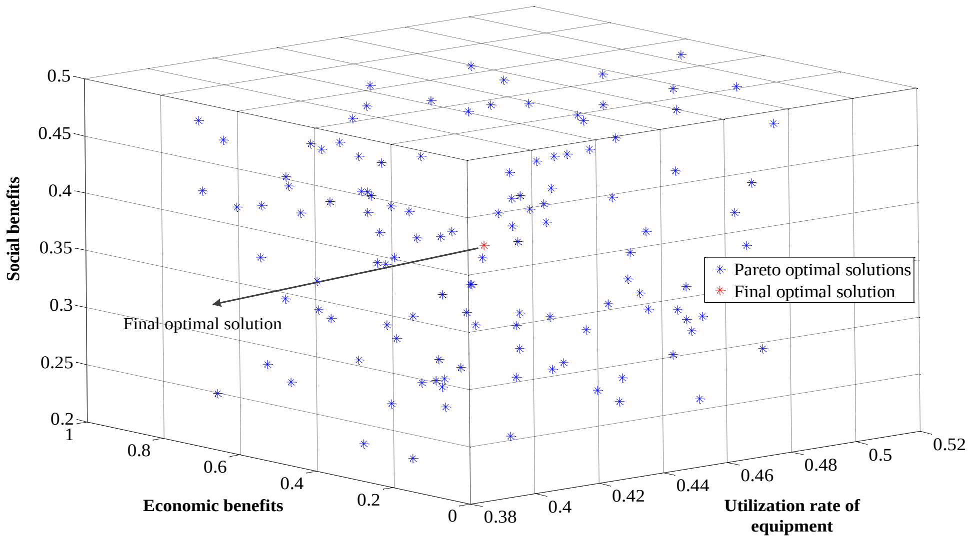

FIGURE 9 Final optimal solution obtained from the candidate Pareto optimal solutions for Region #3 (View 1)

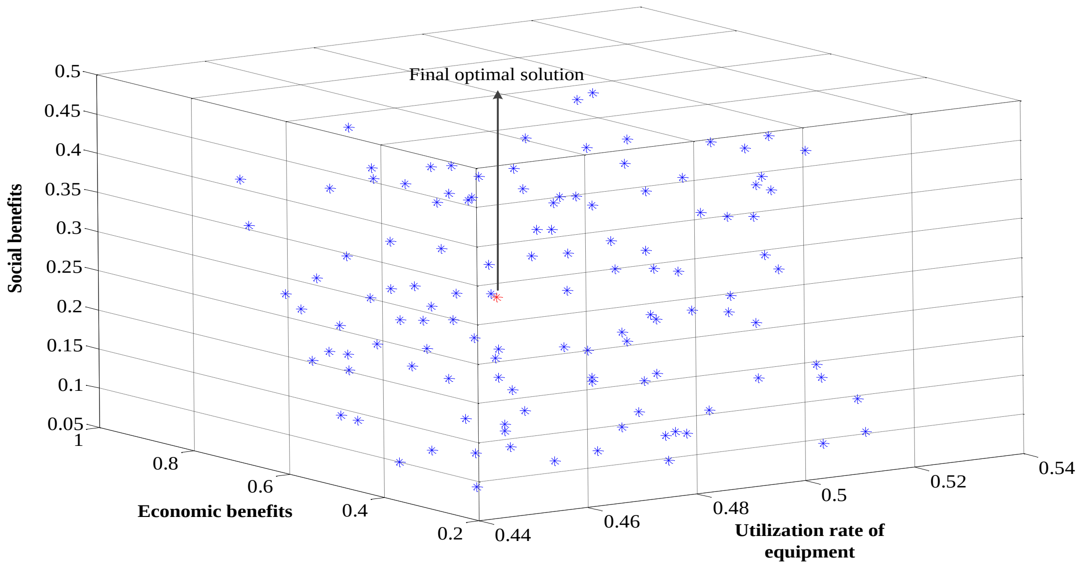

FIGURE 10 Final optimal solution obtained from the candidate Pareto optimal solutions for Region #3 (View 2)

Integrating Fig. 5 to Fig. 10, we can see that the final optimal solution is obtained by comprehensively considering "Economic benefits", "Utilization rate of equipment", and "Social benefits" of the given region. Moreover, we also find that, for both region #1, region #2 and region #3, the point of final optimal solution in the three dimensional scatter diagram almost locate in the centroid of Pareto optimal solutions distribution.

Next, the final optimal solutions of all the ten regions are given in Table. 1 as follows.

TABLE1. Final optimal solution for different regions

Region Number	Economic benefits	Utilization rate of equipment	Social benefits
Region #1	0.597	0.546	0.168
Region #2	0.482	0.442	0.363
Region #3	0.534	0.473	0.258
Region #4	0.558	0.469	0.274
Region #5	0.531	0.527	0.185
Region #6	0.537	0.472	0.314
Region #7	0.617	0.495	0.175
Region #8	0.572	0.553	0.231
Region #9	0.534	0.468	0.292
Region #10	0.539	0.519	0.235

Integrating all the experimental results above, it can be seen that the proposed model can effectively evaluate regional large-scale science instruments configuration efficiency. The reasons lie in the following aspects:

(1) As the regional large-scale science instruments configuration efficiency evaluation problem have several objectives, the proposed multi-objective particle swarm optimization model is suitable to tackle this problem. Because this model can effecttively satisfy the multi-objectives to obtain a set of Pareto optimal solutions

(2) The fuzzy decision-making model is powerful, and can select final optimal solutions from the candidate Pareto optimal solutions with high accurate rate.

(3) "Economic benefits", "Utilization rate of equipment", and "Social benefits" can cover main requirements of the proposed problem.

6 Conclusions

In this paper, we aim to evaluate the regional large-scale science instruments configuration efficiency, and effecttively large-scale science instruments allocation policy can contribute to economic development of the specific region. Particularly, to solve the proposed problem, three objecttives are considered in this paper, which are 1) Economic benefits, 2) Utilization rate of equipment, and 3) Social benefits. Afterwards, Pareto optimal solutions are obtained using the multi-objective particle swarm optimization. Next, we give a fuzzy decision-making model to select optimal solutions from the results of the multi-objective particle swarm optimization model. In the future studies, we will try to expand the proposed method to forecast the regional large-scale science instruments configuration efficiency, and then provide countermeasures for local governments.

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