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Research on Computational Intelligence in Medical Resource Allocation Based on Mass Customization

Yang Xu
(Peking University, Beijing, China
yang.xu@pku.edu.cn)

Shuwen Liu
(Peking University, Beijing, China
imerlsw@pku.edu.cn)

Binglu Wang
(Peking University, Beijing, China
maplewang@pku.edu.cn
Corresponding author)

Abstract: In this era characterized by rapid improvements in the quality of living, people are eager to seek better medical services. However, the medical resource shortage threatens people's daily lives and has become an important factor causing dissatisfaction. Furthermore, as a sub-branch of artificial intelligence, computational intelligence is widely used to solve real-world problems like resource allocation. This paper proposes a medical resource allocation model based on mass customization, considering parameters such as doctors' professional level, patient preferences, and the medical station distribution. This model aims at optimizing and balancing the uneven distribution of medical resources by taking into account the patient requirements and medical costs. Moreover, a genetic algorithm is applied to improve the computational efficiency of the proposed method. The results show that the medical resource allocation model based on mass customization can lead to a higher profit. Suggestions are also discussed for sustainable development in medical service based on mass customization.

Keywords: mass customization, medical resources, computational intelligence, allocation model, willingness to pay
Categories: H.4.0

1 Introduction

In China, with the rapid economic growth and accelerated transformation of society, people's living standards continue improving. Therefore, we need to develop public services that are compatible with the level of economic and social development. In the past few years, the Chinese government has put forward a series of policies to promote equalization of the public service [Office of the State Council, 15]. As an important part of public service, the public health services reflect the public welfare of medical services. Additionally, they provide opportunities for the progressive realization of accesses to basic health services for all people, which is also the key to improving the health conditions of Chinese nationals and extending their average life expectancy.

Currently, China has established a coverage of the urban and rural health service system, which is comprised of hospitals, primary healthcare institutions, and professional public health institutions. However, in some cases, medical resource allocation is unreasonable and affects the fairness and efficiency of medical services. The service capacity of the medical institutions at the grassroots level is insufficient. Additionally, their utilization efficiency is not high [Office of the State Council, 15]. To solve these problems, Li Bin, Director of the National Health Program in China, proposed that China form a 15-minute medical service circle by 2030. That is to say, wherever we are, we can easily reach a healthcare institution within 15 minutes, making it more convenient for patients to see a doctor [Li, 16]. Furthermore, the concept of mobile medical services is proposed to settle the uneven medical resource distribution in China. The advantages of mobile medical services are to help patients make use of medical resources thoroughly and to promote the rational allocation of these resources.

With the continuous increase in people's income, their medical needs are gradually diversified. Some tend to see a doctor whenever they want, while some hope to get more professional medical services, etc. However, because of the limited medical resources and input costs, the demands of all patients cannot be fully met. We can only reduce the costs and provide the medical services to meet most patients' needs.

Moreover, the optimization of resource allocation requires high time complexity, for it is regarded as an NP-hard (Nondeterministic Polynomial time) problem. There is not any effective algorithm for this kind of problem for the time being. Nevertheless, it is easy for us to calculate the result for any one of the scheme. If we traverse all of the schemes, we may get the best solution, which will, however, lead to an exponential growth for the calculation time. To improve its computational efficiency, we applied the genetic algorithm to the calculation.

In this paper, we apply mass customization (MC) in the public medical model, aiming to balance costs and services provided by the public medical system for a 15-minute medical service circle. The literature review is elaborated in the following section, and the model construction is demonstrated in the third section. Additionally, the case study is discussed in the fourth section, while the summary is illustrated in the fifth section.

2 Literature Review

2.1 Medical resources allocation base on MC

MC is currently a very popular production or service mode. Customers can no longer be lumped together in a vast homogeneous market, but are individuals whose individual wants and needs can be ascertained and fulfilled. Fragmenting demands can yield powerful advantages. Leading companies have created processes for low-cost, volume production of great variety, and even for individually customized goods and services. They have discovered the new frontier in business competition: MC [Joseph, 92]. It seeks to both meet individual needs and achieve the low costs brought about by mass production as much as possible [Daaboul, 11]. Although mass production and personalized requirements seem to be a paradox, its trend is already recognized by researchers and enterprises [Bonev, 15]. One of the effective means to reduce costs is to improve the economies of scale. Currently, MC is widely applied throughout the world. For example, in the Korean housing market, additional manpower for site management is reduced through MC [Shin, 08]. While the dominance-based rough set approach (DSRA) is used to achieve MC in the area of airline services [Liou, 10].

From the patient's point of view, care customization has always been an important aspect of healthcare quality. Patients want to feel that they are getting the care tailored to their particular needs [Minvielle, 14]. Personalized healthcare (PHC) can be defined as a customization of the medical provision that accommodates individual differences in all stages in the process, from prevention to diagnosis and treatment, to post-treatment follow-up [Boccia, 12]. PHC is gaining popularity globally to combat clinical complexities underlying various metabolic or infectious disorders including diabetes, cardiovascular diseases, communicable diseases etc. [Kuldeep, 17]. As part of PHC, personalized medicine contains personal health planning, early diagnosis, the right drug for the right patient, and predictable side effects [Fierz, 04] [Cutica, 14] [Abrahams, 09]. Furthermore, personalization in nutritional needs is an emerging trend, whereby food and drink products are scientifically formulated to address consumers' individual nutritional needs, arising from key lifestyle health conditions, such as heart disease, diabetes, and bone/joint health [Jane, 08]. An emerging goal of medical nutrition therapy is to tailor dietary advice to an individual's genetic profile [Vakili, 07]. The principles of PHC are summarized in regards to several aspects, such as treatment, risk control, and lifestyle refinement [Salvi, 12].

However, the high cost of customization in medical services makes its weakness more and more obvious: the limited medical resources cannot meet all personal needs. Thus, MC is a key method to solve this problem appropriately. In further detail, MC aims to provide clients with an adequate diversification of products and services, as well as ensuring that consumers can get a particular product and/or service they need at a relatively low price. The balance between costs and requirements is the focus of MC research [Wang, 14]. Additionally, there are several key decision factors in an MC strategy: customer sensitivity, process amenability, and competitive environment [Hart, 95]. However, adopting MC successfully in healthcare requires overcoming several barriers. First, because it defies traditional cost analysis, it requires innovative business models in which customization and cost control are jointly optimized. Second, it requires an understanding of how the viewpoint of the service beneficiaries (patients and their relatives) can be taken into account. Next, it requires an understanding of how to combine the use of information technologies and the workforce in the same work organization to re-engineer the care process. Finally, it requires wisdom in the choice of the criteria on which care customization is based, as care customization is subject to opposing objectives [Minvielle, 14].

In this paper, an MC model on medical resource allocation is proposed, aiming to consider both cost and personalized requirements. By quantifying the customers' demands, this model seeks maximized profit in both economization and customization effects.

2.2 Computational intelligence in medical resource allocation

Computational intelligence (CI) is a sub-branch of AI, which is characterized by the capability to make computational adaptions, fault tolerance, high computational speed, and less error-prone to noisy information sources. Furthermore, CI represents algorithms for solving real-world problems somewhat intelligently, as similar problems are solved by natural systems [Konar, 06]. This class of CI algorithms encompasses algorithms like artificial neural networks (NNs), evolutionary computation (EC), swarm intelligence (SI), artificial immune systems (AISs) and fuzzy systems (FSs). A commonality of all these algorithms is that the principles for their operations are borrowed from natural systems [Engelbrecht, 07]. For instance, a genetic algorithm (GA) is inspired by the process of natural selection. In detail, computational technology can be applied in several fields, such as sports [Fister, 15], medicine [Wiwanitkit, 16], and detection system [Wu, 10].

For special elaboration, the medical resource allocation problem is interpreted as a constraint satisfaction problem (CSP) [Tsai, 09], which is demonstrated as a set of variables and a set of constraints on the value of the variables. CSPs on finite domains are typically solved using search algorithms. There are five basic search algorithms for CSPs: Naive Backtracking (BT), Back Jumping (BJ), conflict-directed Back Jumping (CBJ), Back Marking (BM), and forward checking (FC) [Prosser, 93]. Furthermore, allocation issue is an NP-hard problem, which can also be solved by a genetic algorithm. Genetic algorithms are widely used in optimization and search problems by relying on bio-inspired operators, such as crossover, mutation, and selection. [Mitchell, 96].

In further detail, Valouxis and Housos [Valouxis, 03] proposed a refined model and an efficient solution methodology for the monthly work shift and rest assignment of hospital nursing personnel. The integrated model utilizing the strengths of operational research and AI was applied to the solution. Similarly, more and more scholars have focused on the nurse allocation model [Oughalime, 08] [Dowsland, 98]]. Tsai and Li [Tsai, 09] developed a two-stage mathematical modelling for a nurse scheduling system by applying a GA wherein hospital management requirements, government regulations, and nursing staff's shift preferences are incorporated. Furthermore, a refinement of the CSP technique is proposed, which is applied to reduce hospital costs [Costa, 12].

Based on previous sections discussed before, a medical resource allocation model is proposed in the following section, aiming to settle the problem caused by the paradox of costs and individual demands. Additionally, the GA is applied to solve the NP-hard problem.

3 MC Modelling

3.1 Assumptions

People tend to see a doctor near their residence for convenience when diseases are neither severe nor difficult to handle. Otherwise, they will select large-scale hospitals in the central part of the city for better medical treatment. Besides, doctors belonging to mobile medical stations are flexible to be assigned according to various reservations in different regions.

This proposed allocation model aims at maximizing the revenue and customization simultaneously. To simplify the model and to seize the main issues to be concerned in the paper, several assumptions are proposed before the modelling process as follows:

Assumption 1. Doctors can be grouped into several types according to their different professional skills. To maximize their efficiency, one doctor would be allocated to treat one type of disease.

Assumption 2. To optimize the resource allocation, patients should select their treatment in advance. Meanwhile, patients are able to select multiple treatments one day to save their time and payment on transportation.

Assumption 3. To standardize the process of treatment, each type of disease would take a same duration of time, thereby normalizing each doctor's timetable. Moreover, costs and payment for the identical treatment would be fixed.

Assumption 4. Doctors can treat only one patient at a time to ensure the effect of the treatment. Similarly, patients can select only one treatment at a time.

Assumption 5. Doctors, assigned to one mobile medical station, would receive a fixed basic salary and bonus according to the number of patients they treated. Additionally, senior professional-level doctors can obtain a higher basic salary than junior ones.

Assumption 6. Considering the selected time slot of a patient would be the best choice for a hospital to increase patients' willingness to pay, while any adjustment of time would decrease their willingness to pay. Furthermore, patients tend to select those doctors with a senior professional level and regard it worthy of paying more for their professional skills.

It is commonly known that the uneven distribution of medical resources between rural and urban areas has been a subject of public criticism. Particularly, non-mobile large-scale hospitals attract the most talented doctors, thus widening the gap. This paper proposed a mobile medical allocation model, aiming to narrow the gap between prosperous regions and backward ones by moving medical resources including doctors and equipment.

However, because of the limited medical resources and doctor shortage, patients' demands would not be totally satisfied. That is to say, we would allocate doctors according to maximized revenue and satisfaction rather than simply considering everyone's demands. Only in this way can the utilization of medical resources be maximized in practice.

Table 1 shows the critical parameters used in this model, including variables and constants.

Symbol	Definition	Unit
w	Number of mobile medical stations	
C_i	The ith mobile medical station	
M_i	Number of patients in the i^{th} station	patient
k	Number of disease types	
DN_{if}	Number of doctors who are allocated to the i^{th} station and treat the f^{th} disease	doctor
DP_{ij}	A Boolean value (if the j^{th} doctor in i^{th} station is professional, $DP_{ij} = 1$; or, $DP_{ij} = 0$)	
C_f	Cost of the f^{th} disease	\$
T_f	Treatment time consumed for the f^{th} disease	minute

P_f	Payment for the fth disease	\$
AR_{im}	Amount of treatments ordered by the mth patient in the ith station	
AR_{imf}	A Boolean value (if the mth patient in the ith station ordered the fth treatment, $AR_{imf} = 1$; or, $AR_{imf} = 0$)	
T_{imf}	A Boolean value (if the fth treatment ordered by the mth patient in the ith station is available, $T_{imf} = 1$; or, $T_{imf} = 0$)	
S	Basic salary for all allocated doctors	\$
AS	Additional basic salary for senior doctors	\$
B	Bonus from per treatment	\$
AB	Additional bonus from treatment given by senior doctors	\$
PP_{imf}	A Boolean value (if the doctor treat the fth disease reserved for the mth patient in the ith station is a senior professional doctor, $DS_{imf} = 1$; or, $DS_{imf} = 0$)	
OT_{imf}	Ordered time for the fth treatment selected by the mth patient in the ith station	minute
AT_{imf}	Actual reserved treatment time for the fth treatment ordered by the mth patient in the ith station	minute
FP	Marginal payment on professional level, i.e., increase in the amount of willingness to pay for reserved senior professional doctors	\$
TP	Marginal payment on time, i.e., reduce the amount of willingness to pay for the adjusting time compared with the ordered time	\$
PX_{im}	Willingness to pay for actual treatment	\$
PY_{im}	Increased willingness to pay caused by the doctor's professional level	\$
PZ_{im}	Reduction in the willingness to pay caused by time	\$
AC_{im}	Marginal cost for each additional patient	\$
a	Scale of attention to professional level for patients	
b	Scale of attention to time for patients	
M_i	Cost for equipment maintenance in a station	\$
TC_i	Total cost in a station	\$
FC_i	Total fixed cost for a station	\$
R_i	Total revenue in a station	\$
P_i	Total profit in a station	\$

Table 1: Model parameters

3.2 Modelling process

To maximize the profit of the MC model, the following is shown as an objective function where the problem is to be solved:

$$\underset{\sum C_i}{argmax}(P_i) = \underset{\sum C_i}{argmax}(R_i - TC_i)$$

The total profit can be calculated by the total revenue minus the total costs; the parameters impacting on profit are depicted in Figure 1.

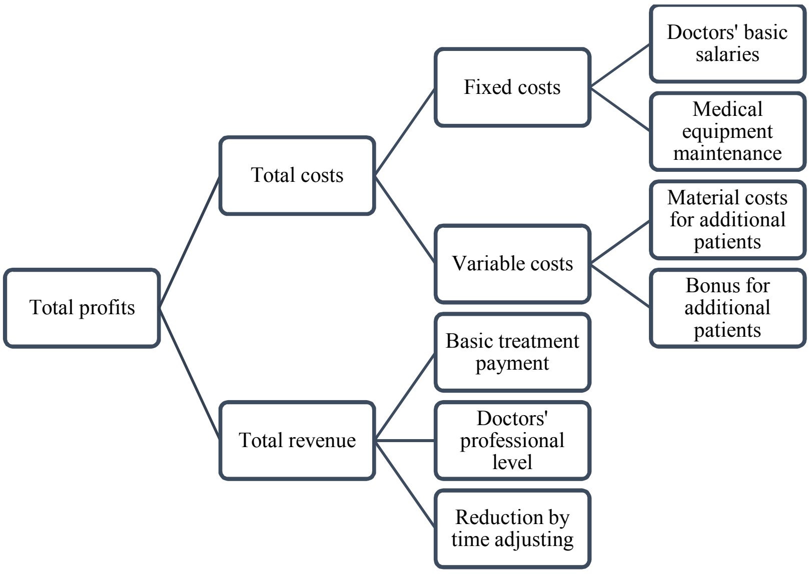

Figure 1: Basic parameters comprising total profits

To explain this in greater detail, this paper divides the MC medical costs $\sum_{i=1}^{w} TC_i$ into two parts: fixed costs and variable costs based on the assumptions above. The fixed costs include doctors' basic salaries and medical equipment maintenance, and the variable costs relying on the patients include the actual material costs and bonus for doctors. Thus, we have

$$\sum_{i=1}^{w} TC_i = \sum_{i=1}^{w} (FC_i + \sum_{m=1}^{Mi} \mathrm{AC}_{im})$$

where FC_i contains the total basic salaries for both junior and senior professional-level doctors as well as the costs for equipment maintenance, noted as:

$$FC_i = S * \sum_{f=1}^{k} DN_{if} + AS * \sum_{j=1}^{\sum_{f=1}^{k} DN_{if}} DP_{ij} + M_i$$

Furthermore, AC_{im} is the combination of actual costs and additional bonuses for both junior and senior professional-level doctors. Additionally, PP_{imf}, a Boolean value for whether the doctor is senior professional level for each treatment, means nothing when the selection is unavailable, noted as:

$$PP_{imf} = \begin{cases} 0, & T_{imf} = 0 \\ 0, & T_{imf} = 1 \text{ } and \text{ doctor with junior professional level} \\ 1, & T_{imf} = 1 \text{ } and \text{ doctor with senior professional level} \end{cases}$$

Under this circumstance, AC_{im} is calculated as:

$$AC_{im} = \sum_{f=1}^{k} (AR_{imf} * C_f * T_{imf} + B * AR_{imf} * T_{imf} + AB * PP_{imf})$$

As mentioned above, the total cost $\sum_{i=1}^{w} TC_i$ is calculated as follows:

$$\sum_{i=1}^{w} TC_i = \sum_{i=1}^{w} (S * \sum_{f=1}^{k} DN_{if} + AS * \sum_{j=1}^{\sum_{f=1}^{k} DN_{if}} DP_{ij} + M_i + \sum_{m=1}^{Mi} \sum_{f=1}^{k} (AR_{imf} * C_f * T_{imf} + B * AR_{imf} * T_{imf} + AB * PP_{imf}))$$

Compared with non-mobile hospitals, a key issue with MC medical modeling is how patients can reasonably share the relatively high operating costs that may be incurred in customization. We should first discuss and identify potential patients' willingness to pay for treatment. Different patients have different expectations based on their various needs, and thus different functions of willingness to pay correspond to different patients. The key elements of willingness to pay to be considered are time and professional level, as different patients are assigned a various scale of attention to time and professional level parameter.

Specifically, the total revenue in a station R_i consists of the basic treatment payment (PX_{im}), the additional willingness to pay for the professional level (PY_{im}), and the reduction of the willingness to pay caused by time adjusting (PZ_{im}).

$$\sum_{i=1}^{w} R_i = \sum_{i=1}^{w} \sum_{m=1}^{Mi} (PX_{im} - PY_{im} + PZ_{im})$$

Among the above-mentioned parameters, PX_{im} relies on whether the patient's order for the treatment at the specific station is available, which is calculated as:

$$PX_{im} = \sum_{f=1}^{k} AR_{imf} * P_f * T_{imf}$$

Additionally, PY_{im} demonstrates the professional-level influence on the willingness to pay. To refine the different scale of attention to the professional level, we set a as the parameter to depict various patients:

$$PY_{im} = a * FP * \sum_{f=1}^{AR_{im}} PP_{imf}$$

Furthermore, PZ_{im} indicates the willingness to pay on time adjusting, where the adjusting degree is calculated by $|OT_{imf} - AT_{imf}|$. Similar to PY_{im}, we set b as the parameter to indicate the different scale of attention to time adjusting, thereby facilitating the model effect:

$$PZ_{im} = b * TP * \sum_{f=1}^{MNim} (|OT_{imf} - AT_{imf}| * T_{imf})$$

In sum, the total revenue considering PX_{im}, PY_{im}, PZ_{im} is calculated in detail as follows:

$$\sum_{i=1}^{w} R_i = \sum_{i=1}^{w} \sum_{m=1}^{Mi} (\sum_{f=1}^{k} AR_{imf} * P_f * T_{imf} - a * FP * \sum_{f=1}^{AR_{im}} PP_{imf} + b * TP * \sum_{f=1}^{MNim} (|OT_{imf} - AT_{imf}| * T_{imf}))$$

This is a typical NP-hard combinatorial optimization problem, for the function is influenced by the order of different stations and medical resources, which is not monotonic. However, if the function P_{ij} can be determined, the enumeration method can be used to get the global optimal solution at a small calculation scale, when at a larger scale, computational intelligence can be applied to find approximately optimal solutions.

3.3 CI application in the model

The optimization of the objective function above is a non-linear and discrete combinatorial optimization problem. The most basic characteristic of such problems is that the variables are discrete, which leads to the fact that the objective function and the constraint function in the mathematical model are discrete in their feasible domain. Many of the real-world problems are essentially discrete events rather than continuous events. The methods for solving such problems are divided into two types: exact and approximate algorithms. Exact algorithms are generally used to solve small-scale problems with an acceptable computation time. Approximation algorithms are widely adopted to solve large-scale problems to obtain a satisfying solution with an acceptable computation cost. This is a commonly accepted compromise in practice when facing large-scale problems in computational intelligence. Using the enumeration method is not suitable for large-scale problems. Therefore, to be generic, approximate algorithms are preferred.

Approximation algorithms usually include mathematical programming algorithms, heuristic algorithms, and evolutionary algorithms. Among these algorithms, evolutionary algorithms have an advantage in that they use a common algorithm framework but are not limited to problem contexts, which is convenient for adaptation with minimum local changes based on the algorithm framework. Hence, a popular tool for solving integer programming problems, an evolutionary algorithm (EA), is proposed to deal with this example for demonstration due to their advantages over other algorithms [Dorigo, 99].

In this paper, a GA, a representative method of an EA, is designed using integer encoding and implemented to solve an optimization problem for model testing. Moreover, the specific steps of GA is generally listed as follows.

```
Algorithm: Genetic Algorithm
Input: A initial population P(0), Number of individuals in P(0):  M
Output: All the populations P
Procedure:
    initialize P(0);
    t = 0;
    while (t <= T)  do
        for i = 1 to M  do
            Evaluate fitness of P(t)
        end for
        for i = 1 to M  do
            Select operation of P(t)
        end for
        for i = 1 to M/2  do
            Cross over operation of P(t)
        end for
        for i = 1 to M  do
            Mutation operation to P(t);
        end for
        for i = 1 to M  do
            P(t+1) = P(t)
        end for
        t = t + 1
    end while
    return  P
```

To design a GA, the most important step is to design a chromosome that represents a valid solution structure for a targeted optimization problem. Then, the fitness function is usually derived from an objective function. This fitness function should be set to evaluate alternative solutions from the solution options during the evolutionary procedure. To advance the global searching by improving the diversity of alternative solutions and improving local searching, genetic operators, including crossover, mutation, and selection operators, should be designed.

The designed chromosome is a sequence of integers that contains the complete variables of the objective function. For a chromosome, each variable takes up a fixed gene position to represent a gene type, and each gene's phenotypes are integer values.

In a GA, the fitness function is used to evaluate alternative solutions. For many optimization problems, the objective function can be directly used as the fitness function. However, to facilitate the design of the selection operator, the fitness function value should fall within the interval of [0, 1]. Hence, in this paper, the objective function is standardized as $fit(j) = \frac{\Pi(j)}{\sum_{k=1}^{n}(\Pi(k))}$, which enables the fitness value to be within [0, 1]. In the formula, $fit(j)$ is the j^{th} individual's (alternative solution's) fitness value, where $j = 1,2,3,\dots,n$, and n is the number of a population (one generation's individuals). $\Pi(j)$ is the j^{th} individual's objective value.

In our case, there is only one objective function in the optimization process. Therefore, the Roulette selection operator, which is widely used in single-objective optimization problems, is adopted for selection operation. Furthermore, the details of crossover and mutation operations are elaborated upon in the subsequent paragraphs.

The crossover operation is used to improve the diversity of the population to further the global searching in the evolutionary optimization. This operation applies different rules to identify a cross point of two selected individuals and exchange their segments of chromosomes. By doing this operation, two parent chromosomes can generate a pair of child chromosomes. However, when dealing with classical TSP or other combinatorial optimization problems, one of the main difficulties of applying EA methods is the design of a suitable crossover operator. This is because it cannot be guaranteed that the child chromosomes, which are directly generated by exchanging a set of genes, are valid chromosomes representing valid alternative solutions. Hence, an additional operation to check and correct invalid individuals within a population after crossover operation should be designed. In this paper, two methods were tested. The first one is to check all the child chromosomes after the crossover operation and then use the original population-generation method, which can generate valid chromosomes, to generate a new chromosome to replace any one that is invalid. This method can simplify the GA program by improving code reuse and improve the population diversity. However, it would result in some children chromosomes missing the potential good "patterns" from their parent chromosomes. To compensate for its weakness, another method is designed. The main idea is to reset only one or several variables' values. When a child chromosome is invalid following crossover operation, its variable is reset to the maximum value. If the reset chromosome is still invalid, two or more variables are then reset in the order of their values until the variables reach the constraint. By doing this, good "patterns" of parent chromosomes have more chance to be passed to their child chromosomes. Finally, to conduct the crossover operation, a crossover point on the chromosome structure is randomly selected, then the two segments of the parent chromosomes after the crossover point will exchange with each other to generate two new child chromosomes.

The mutation operation is conducted by applying a mutation operator. This operator is mainly used to improve the local searching during the evolutionary procedure. It differs from crossover selection, which is used to improve the global search by changing a large part of the genes of chromosomes. While the mutation operation only slightly changes the genes of a chromosome, which can protect good "patterns" to help convergence and avoid being trapped by the local optimal. In this paper, a single-point mutation operator is adopted. At first, a mutation point is randomly selected; then, the gene's value is reset after the selected point. To ensure that the newly generated chromosome is valid, a value is randomly selected from an integer set with a dynamic up boundary (maximum integer value), for the gene on the mutation position.

3.4 A Combination of MC and a GA

In essence, MC involves choosing the most profitable solution among all possible solutions. One way is to exhaust all the solutions, calculate their profits, and then find the best choice. However, the number of solutions increases exponentially corresponding to the basic parameters of each solution, thus making the calculation quite complex. As metioned before, the medical resources allocation problem is a typical NP-hard problem. The final profit for each solution can be easily calculated, while the global optimal solution, which is time-consuming, is difficult to obtain with high computational complexity. However, each allocation solution for medical resources can be regarded as a chromosome. By constructing the crossover, mutation, and selection operators, a GA can greatly improve the computational efficiency. In the real world, we do not need to obtain the best results as long as there is little profit gap between the optimal and suboptimal schemes. The difference in the profitability of suboptimal schemes can be accepted compared to the time cost of calculating the optimal solution. Therefore, we use such an optimization algorithm, GA, to acquire the approximate optimal results.

Coding is the primary and crucial problem to be solved when applying GAs. The method of coding affects the operation of genetic operators, such as crossover and mutation operators, which determines the efficiecncy of genetic evolution in a high degree. In the actual operation of the GA, we use the binary code, where the medical resource allocation problem requires quadratic coding. Therefore, we need to convert from quadrature to binary, so that the problem can be changed into a more typical one that a GA can solve.

For an MC model, the ultimate goal is not to obtain the highest income or to pay the lowest cost, but to obtain the highest profit. Therefore, when we apply the GA to the MC model, we need to use the profit as an indicator of the individual in the population. By finding the best individual, we can obtain the optimal or suboptimal scheme in MC. Thus, the combination of MC and a GA can effectively improve the efficiency of calculation, reduce the computational complexity, and reduce the time cost.

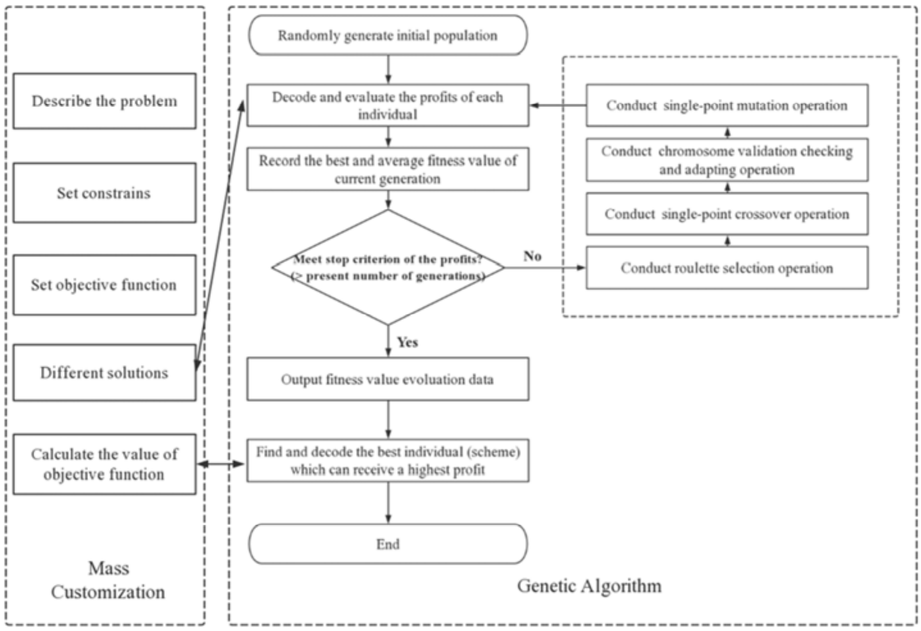

Figure 2: The flowchart of applying the GA to MC

4 Case Study

To verify the model's reliability and accessibility, data are collected to imitate the real world for medical resource allocation based on MC. As depicted in Figure 2, there are 3 mobile medical stations with 10 patients in Station A, 20 patients in Station B, and 30 patients in Station C in the chosen region. Furthermore, 12 doctors with different treatment domains as well as professional levels belonging to this region are waiting for an assignment, aiming to obtain the maximized profit based on MC for the government.

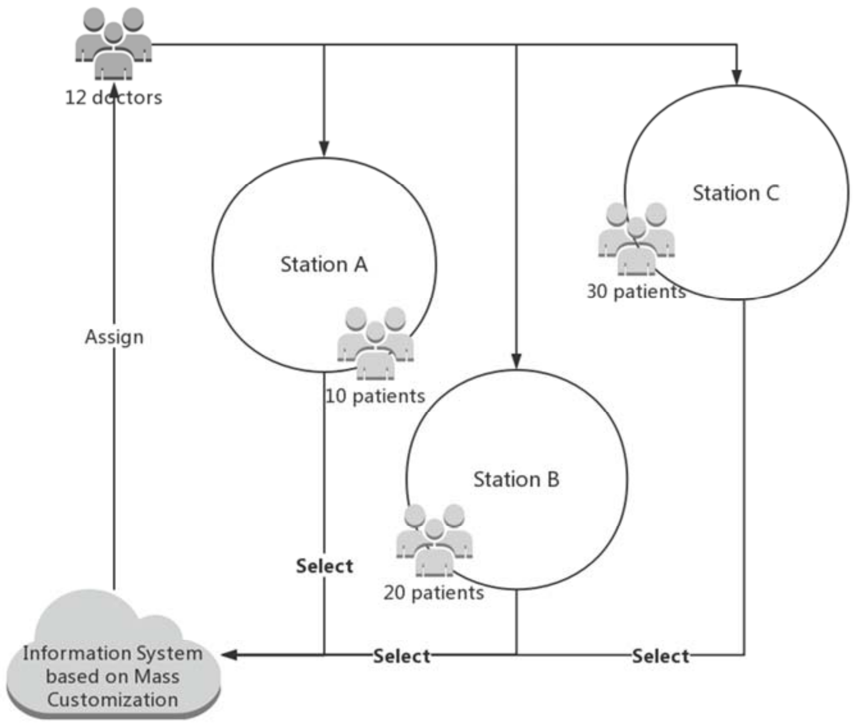

Figure 3: Construction of the allocation system

In further detail, the treatment domain and professional-level conditions of the 12 doctors in this region are illustrated in Table 2, where 1 represents their ability to handle the disease, while 0 indicates that they are unable to operate. Moreover, in the row of the professional level, 1 shows the doctor with a senior professional level, and 0 indicates the junior professional level.

Doctor No.	#1 Disease	#2 Disease	#3 Disease	Professional Level
000001	0	1	0	0
000002	1	0	0	1
000003	0	0	1	0
000004	0	0	1	1
000005	0	0	1	0
000006	1	0	0	0
000007	1	0	0	1
000008	0	1	0	1
000009	1	0	0	1
000010	1	0	0	0
000011	0	0	1	1
000012	0	1	0	1

Table 2: The treatment domain and professional-level conditions of doctors

Furthermore, selections in Stations A, B, and C are illustrated in detail in Tables 3, 4, and 5. 1 represents diseases treatments that are selected by patients. Simultaneously, patients are supposed to provide their preferred time, which is divided into 12 sessions per day. In a case in which the patient did not select one treatment, it is assigned 0 for both the disease and time rows in the case study to simplify the calculation process.

Patient No.	#1 Disease	#1 Session	#2 Disease	#2 Session	#3 Disease	#3 Session
100001	1	4	0	0	1	5
100002	0	0	1	4	1	5
100003	0	0	0	0	1	9
100004	1	1	1	2	0	0
100005	1	4	0	0	0	0
100006	1	5	1	9	1	10
100007	1	8	0	0	0	0
100008	0	0	0	0	1	11
100009	0	0	1	11	1	12
100010	1	6	0	0	0	0

Table 3: The reserved treatment and the time of patients around Station A

Patient No.	#1 Disease	#1 Session	#2 Disease	#2 Session	#3 Disease	#3 Session
200001	0	0	1	2	0	0
200002	1	1	1	3	0	0
200003	1	4	1	6	1	9
200004	1	5	0	0	1	4
200005	0	0	0	0	1	7
200006	0	0	0	0	1	8
200007	1	4	0	0	0	0
200008	0	0	0	0	1	3
200009	1	2	0	0	0	0
200010	0	0	0	0	1	4
200011	0	0	1	6	1	5
200012	1	4	0	0	0	0
200013	0	0	0	0	1	9
200014	0	0	0	0	1	10
200015	1	1	1	3	0	0
200016	1	7	0	0	0	0
200017	1	6	1	8	1	11
200018	1	3	0	0	0	0
200019	0	0	0	0	1	10
200020	0	0	1	10	0	0

Table 4: The reserved treatment and the time of patients around Station B

Additionally, the values for the basic parameters are shown in Table 6. For parameter S (basic salary for all allocated doctors), it is assigned \$100 or \$150, respectively, in two allocation tests, to contrast the profits of optimized solutions under different basic salaries.

Patient No.	#1 Disease	#1 Session	#2 Disease	#2 Session	#3 Disease	#3 Session
300001	0	0	0	0	1	2
300002	1	12	1	4	0	0
300003	1	5	0	0	1	6
300004	0	0	0	0	1	10
300005	0	0	0	0	1	6
300006	1	2	0	0	0	0
300007	0	0	0	0	1	8
300008	1	5	0	0	1	4
300009	0	0	0	0	1	7
300010	0	0	0	0	1	8
300011	1	4	0	0	0	0
300012	0	0	0	0	1	2
300013	1	4	0	0	0	0
300014	0	0	0	0	1	11
300015	0	0	0	0	1	10
300016	1	10	0	0	0	0
300017	1	11	1	12	1	10
300018	1	12	0	0	0	0
300019	0	0	0	0	1	5
300020	0	0	1	1	1	4
300021	1	8	0	0	0	0
300022	1	7	0	0	1	4
300023	0	0	0	0	1	7
300024	0	0	0	0	1	8
300025	1	6	0	0	0	0
300026	0	0	0	0	1	2
300027	1	5	0	0	0	0
300028	0	0	0	0	1	2
300029	0	0	0	0	1	10
300030	0	0	0	0	1	12

Table 5: The reserved treatment and the time of patients around Station C

Symbol	Definition	Value	Unit
$\boldsymbol{C_f}$	Cost of the fth disease	{9,15,2}	$
$\boldsymbol{P_f}$	Payment for the fth disease	{42,55,31}	$
$\boldsymbol{S}$	Basic salary for all allocated doctors	100/150	$
$\boldsymbol{AS}$	Additional basic salary for senior doctors	30	$
$\boldsymbol{B}$	Bonus per treatment	6	$
$\boldsymbol{AB}$	Additional bonus per treatment given by senior doctors	5	$

Table 6: The allocation results of doctors in this region

By conducting the parameter sensitivity analysis, we amend parameters such as the individual crossing probability and gene mutation possibility. The parameters we selected for the final calculation are listed in Table 7.

Parameters	Test set	Selected value
Size of the population	-	50
Length of the gene fragment	-	24
Probability of individual crossing	[0, 1, 0.1]*	0.6
Probability of gene mutation	[0, 0,2, 0.01]*	0.01
Number of breeding iterations	-	500

*[x, y, z] means that, ranging from x to y, test numbers are selected at the interval of z.

Table 7: The value of the parameters in the GA

In particular, in the MC model, the calculation objective function uses quaternary coding. When assigned, there are 12 doctors, and each doctor has 4 possible situations: Station A, Station B, Station C, or none. Consequently, the result for each doctor can be encoded as a number from 0 to 3 and the code for all 12 doctors ranges from $\underbrace{(0000 \ldots 0000)_4}_{12}$ to $\underbrace{(3333 \ldots 3333)_4}_{12}$. When applying the GA for the MC model, we use binary coding, and $\underbrace{(3333 \ldots 3333)_4}_{12}$ is equal to $\underbrace{(1111 \ldots 1111)_2}_{24}$, thus making the length of the gene fragment is 24.

First, we calculate the objective function value. Second, we calculate the individual fitness value, and then select the best individual and its corresponding function values, recording the best results. Next, by natural selection, some of the low adaptive individuals are eliminated, crossed, and mutated. After breeding iterations, the final result is obtained.

When MC is not considered, people sometimes tend to allocate an equal number of doctors to each station, which means 4 doctors per station in this case (Method 1). Doctors can also be prorated according to the proportion of patients, which results in 2 doctors for Station A, 4 doctors for Station B, and 6 doctors for Station C (Method 2).

By adjusting a doctor’s basic salary, the profits gained from different approaches are demonstrated in Tables 8 and Table 9.

Solution*	Profit	Doctor Allocation											
	$	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12
Solution 1	738	C	C	C	C	B	B	B	B	A	A	A	A
Solution 2	694	B	B	A	C	B	A	C	B	A	C	B	A
Solution 3	278	C	C	C	C	C	C	B	B	B	B	A	A
Solution 4	533	C	C	C	B	C	B	C	B	A	C	B	A
Solution 5	**1172**	C	C	-	C	A	-	B	C	B	A	A	B

*Solution 1, 2, 3, 4 and 5 corresponds to Method 1, Method 1, Method 2, Method 1 and MC Model respectively.

Table 8: The allocation results for the doctors in the region with a $100 basic salary

Solution*	Profit	Doctor Allocation											
	$	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12
Solution 6	138	C	C	C	C	B	B	B	B	A	A	A	A
Solution 7	94	B	B	A	C	B	A	C	B	A	C	B	A
Solution 8	-322	C	C	C	C	C	C	B	B	B	B	A	A
Solution 9	-67	C	C	C	B	C	B	C	B	A	C	B	A
Solution 10	**747**	-	C	-	C	-	-	B	C	B	-	A	B

Table 9: The allocation results for the doctors in the region with a $150 basic salary

Both Tables 8 and 9 show that the maximized output is obtained via the MC Model (Solutions 5 and 10). One possible reason is that traditional methods ignore the match degree between doctors and patients, thereby randomly allocating the doctors and only focusing on the number of doctors in each station. Moreover, the difference among diverse methods manifests that the appropriate allocation would profoundly optimize the medical resources' distribution and maximize the profit. From Table 8 and 9, we can easily conclude that the increase of costs significantly influences the final profit. Moreover, aiming at the maximized profit, MC model would rather reduce the number of assigned doctors, thus making some patients' not be served. As illustrated in Table
10, the number of actual treatments decreased as the doctor's basic salary increased.

Doctor No.	**Disease No.**	**Solution 5**		**Solution 10**	
		Allocation	Patient No.	Allocation	Patient No.
000001	2	C	{20, 2, 17}	-	
000002	3	C	{28, 26, 22,19,23, 24,29,15,30}	C	{28,26,22,19,23, 24,29,15,30}
000003	1	-		-	
000004	1	C	{25,6,11,8,3,13, 22,21,18,16,17,2}	C	{25,6,11,8,3,13, 22,21,18,16,17,2}
000005	2	A	{4, 2, 6, 9}	-	
000006	1	-		-	
000007	1	B	{2,9,7,3,4,12,15, 16, 17, 18}	B	{2,9,7,3,4,12,15, 16, 17, 18}
000008	3	C	{12,1,20,8,5,3,9, 7,10,4,14,17}	C	{12,1,20,8,5,3,9, 7,10,4,14,17}
000009	3	B	{19, 8, 4, 10, 11, 5, 6 ,3 ,13 ,14 ,17}	B	{19, 8, 4, 10, 11, 5, 6, 3, 13, 14, 17}
000010	3	A	{1, 2, 3, 6, 8, 9}	-	
000011	1	A	{4, 1, 5, 6, 10, 7}	A	{11, 5, 6, 10, 7}
000012	2	B	{1, 2, 15, 11, 3, 17, 20}	B	{1, 2, 15, 11, 3, 17, 20}

Table 10: The allocation details for Solutions 5 and 10

A suitable allocation of doctors can balance patients' requirements and human resource costs, thereby gaining the highest profit among the possible solutions. Furthermore, the government's subsidy for a doctor's salary can allow more patients to be treated, and thus largely improving the medical quality. With the constantly changing situation, the proposed allocation model based on MC can adjust doctors' assignment to increase profits.

5 Summary

This paper proposed a medical resource allocation model based on MC, aiming to alleviate the medical resources shortage as well as to function in accordance with the concept of a 15-minute medical service circle. In the modelling process, we take into account both costs and personalized demands, including time requirements and professional level. However, because the medical resource allocation problem is an NP-hard problem, it is challenging to list all the options and then find the optimal solution. In the real world, the suboptimal scheme, which is not the scheme to get the best result but is able to get a result better than most of the others, can be received. Therefore, we need to optimize the algorithm to find the optimal solution. To reduce the computational complexity and improve the computational efficiency, we use a GA and use the profit as the criterion for assessing the optimal individual in each population. The results show that the combination of MC and a GA can effectively improve the computational efficiency. Moreover, the results indicate that more patients' needs are satisfied and costs of the medical resource are reduced.

The essence of MC is to integrate the same needs of different customers to achieve both economization and customization effects. From the government's point of view, costs can be reduced by making doctors mobile, thus maximizing the utilization of medical resources. From the patients' point of view, personal preferences, such as treatment time and doctors' professional level, are better satisfied.

However, several problems still remain unsettled both in practice and related research. If the system is put into practice, the government is supposed to gather as many people's demands as possible, thereby facilitating the integration of similar requirements. Besides, publicizing the allocation system to more citizens can benefit collecting relevant information.

Additionally, assumptions are proposed in this paper to simplify the modelling process and to concentrate on crucial issues. That is to say, more parameters should be taken into account in future studies, such as doctors' flexibility, i.e., some doctors are reluctant to frequently move among mobile stations. Furthermore, with the rapid development of society, 15-minute medical service circles may be refined into 10- or 5-minute medical service circles, which requires the model to keep pace with the times. To conclude, more research should focus on the practical demands of people and policy adjustments in the future.

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