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Research article

A sustainable scheduling system for medical equipment: Towards net zero goals for green healthcare

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Abstract: Shortages of medical equipment, growth in medical waste and carbon emissions have increased healthcare pressures and has a huge impact on the environment. An efficient scheduling of medical equipment will effectively reduce the pressure on healthcare and improve the healthcare system's ability to respond to unexpected disasters. A medical equipment scheduling system was established to improve the sustainable utilization of medical equipment within the healthcare network and to reduce the carbon emissions of the healthcare process. First, this paper combines medical equipment information to establish a medical equipment scheduling decision model that considers pollution to filter qualified medical equipment for scheduling. Then, this paper constructs and solves a multi-objective robust optimization model by collecting the patient's travel information and the medical pressure information of each region. In addition, to meet dynamic healthcare needs, a dynamic medical equipment configuration framework was constructed to enhance the flexibility of equipment scheduling and the resilience of the healthcare network. Combined with case studies, the results show that the medical equipment scheduling system can help decision makers make quick scheduling decisions and achieve sustainable use of medical equipment, with a corresponding increase in medical equipment utilization of 12.25% and a reduction in carbon emissions of 26.50%. The study will help enhance healthcare resource utilization and contribute to the net-zero goal of green healthcare.

Keywords: medical equipment; net-zero emissions; medical resource scheduling; medical network; sustainable development

1. Introduction

In the wake of the global pandemic, countries around the world have realized the deficiencies in their health care systems and have improved them, to some extent, to deal with unexpected medical problems. It is worth noting that while healthcare systems operate well to safeguard human health, a large amount of healthcare waste is also generated. During global pandemics, outbreaks lead to an exponential increase in medical waste due to increased demand for medical products such as masks and protective clothing [1]. Medical waste is highly infectious and poses a significant threat to human health. Common medical waste treatment methods are mainly divided into autoclaving, incineration, and landfills; of these three technologies, 91% of countries use the incineration method for medical waste treatment, resulting in serious pollution of the atmosphere [2]. Countries have taken measures to address pollution during epidemics, such as improving monitoring systems for medical waste and wastewater discharges, and enhancing the ability to predict and prevent medical pollution [3]. However, some countries are unable to provide enough medical equipment to meet the needs of patients, leading to a growing problem of contamination associated with medical equipment. First, the lack of data-based information leads to an increase in the number of ineffective patients trips to the hospital, and consequently to the emission of vehicle emissions. Second, the production process of medical equipment is often accompanied by the generation of a large number of pollutants; for example, in the process of welding, electroplating, spraying, etc. Therefore, due to the special characteristics of medical equipment, the manufacturing companies need to use cleaning agents that cause pollution to the environment (i.e., chlorinated solvents, fluoride solvents, etc.) several times during the production process. In addition, the operation of medical equipment usually produces pollution phenomena, such as radiation pollution [4,5], noise pollution [6], emission of exhaust gases [7], etc. In a medical response to a major emergency, decision-makers may overlook the importance of risk management because of a shortage of medical equipment, which greatly increases the probability of uncertain risk factors in the medical process. The risk of radiation [8], fire [9], electricity [10] and chemical risks [11] will cause irreversible medical accidents to healthcare workers and patients, in addition to environmental pollution [12]. Therefore, choosing the appropriate medical equipment and reducing the number of hospital trips for patients will help reduce carbon emissions. In addition, the process of scheduling medical equipment resources between regions may face different linguistic and semantic issues, which increases the difficulty of circulating medical data. Multimodal models can effectively integrate different linguistic and semantics to harmonize the corresponding medical reports [13]. Advances in vision-language pretraining (VLP) help healthcare professionals extract critical information from medical graphics to improve healthcare efficiency [14,15]. In recent years, as a new medical method, telemedicine has effectively alleviated this problem [16]. Telemedicine and health information technology can help save time, energy and fuel and thus reduce carbon emissions [17]. However, when major disaster problems occur, some patients need immediate treatment. In some regions, the shortage of medical equipment and the confusion of information and data [18] are likely to confuse the medical process, which will lead to an increase of carbon emissions and a decrease of the utilization rate of medical equipment. The improvement of the hospital's medical treatment capacity and the reduction of carbon emissions in the process of medical treatment are preconditions for realizing efficient, sustainable and green healthcare.

The shortage of medical resources caused by sudden disasters often makes it difficult to promptly meet the medical needs of patients, causing some patients to miss the best time for medical treatment [19].

In response to the shortage of medical resources, some scholars have improved the efficiency of resource utilization by optimizing the allocation of medical resources. For example, [20] improved resource utilization and built a multi-objective function solution to minimize the average hospital stay of patients and the waste of medical resources. [21] proposed a dynamic allocation strategy of medical resources to maintain the stability of the medical system by establishing a multi-stage and multi-type medical service network model. In addition, some scholars believe that the coordination between the prediction of public health emergencies and the allocation of medical resources will help improve the capability of medical responses. [22] improved the efficiency of emergency medical resource allocation decisions by building a predictive optimization framework. [23] predicted the patient's clinical condition to determine the optimal number of medical resources. The prediction method can effectively improve the efficiency of resource planning in advance and realize the preparation of medical resources. At the same time, there is no doubt that the process of medical resource allocation is usually accompanied by the generation of carbon emissions. Regarding the carbon emissions generated during the allocation of medical resources, some scholars have studied medical site selection [24], patient travel times [25–27], low-emission medical equipment [28], medical pharmaceuticals [29,30], etc. to reduce the carbon emissions generated during the medical process. Combined with computer technologies, medical decision-makers can realize two-way information connections through the collection of patient information and medical information in order to make reasonable medical decisions. The medical system can effectively avoid unnecessary carbon emissions by providing patients with the best personalized medical services to reduce the number of trips and overall travel distances [31].

Combining previous research and discussions, we found that when the travel of medical patients matches the best medical capabilities, the hospital's medical processing capacity and carbon emissions will be effectively resolved. When the medical pressure on the hospital is high, one of the prerequisites for whether an advanced medical system can exert medical effects lies in the rapid circulation of medical resources in the medical network. However, for the issue of scheduling medical equipment between regions, coordination between the medical processing capacity and carbon emissions is rarely studied. In response to the aforementioned problems, we built a sustainable medical equipment scheduling system within the medical network to achieve medical equipment scheduling between regions. The scheduling of medical equipment resources within the medical network will effectively increase the medical capacity in regions with high medical pressure. After the scheduling of medical equipment, the medical capacity of the region will be improved, and patients will be able to prioritize local hospitals to receive treatment, thus reducing unnecessary travel. In addition, we included the fuzzy theory to help decision-makers select suitable medical equipment for the environmental pollution problems generated during the operation of medical equipment. To solve this problem, this paper highlights a multi-objective optimization model is constructed based on the carbon emissions generated by patients in vehicles and combined with a swarm intelligence algorithm. This research enables the sustainable scheduling of medical equipment within the healthcare network and contributes to the net-zero goal of green healthcare. The relevant contributions of this paper are as follows:

- This study establishes risk system evaluation indicators related to medical equipment to ensure that the decision-making and scheduling of medical equipment are more in line with actual needs.
- This paper establishes the medical equipment scheduling scheme by simulating the digital scheduling of medical equipment and by utilizing the multi-objective swarm intelligent

algorithm. This paper considers the issue of carbon emissions while considering medical equipment scheduling to minimize the number of times patients travel to the hospital.

The article is structured as follows. Section 2 highlights the problem description, which includes the introduction for the environment with limited medical equipment resources, the construction of the dynamic equipment scheduling model, the introduction of the dynamic medical equipment configuration framework and the construction of the scheduling decision model based on fuzzy theory. Section 3 describes a sustainable scheduling system for medical equipment, which includes the construction of a multi-objective model which considers carbon emissions and the introduction of the non-dominated sorting genetic algorithm-II-multiple objective particle swarm optimization (NSGA-II-MOPSO algorithm). Section 4 describes a case study combining the medical equipment scheduling of several hospitals. Section 5 discusses the application cases and a future development direction of medical equipment scheduling system.

2. Model description

2.1. Medical environment with limited medical equipments

In a normal medical diagnostic environment, hospitals can maintain good medical services to complete the patient's treatment process. However, when a major medical incident is caused by natural environment or human factors, hospitals usually lack sufficient equipment and resources to provide medical services [32]. Within the medical network, appropriate medical equipment from other hospitals needs to arrive in a timely manner to relieve the medical pressure in the region. In addition to disaster issues affecting the stability of medical services, it is difficult for regional hospitals to have enough medical equipment to provide real-time treatment to patients due to the high price of some medical equipment. In order to avoid further transmission of the virus, when a large-scale infectious disease is prevalent, some governments will restrict patients from taking public transportation. Most patients will choose to travel to hospitals by private cars. This will increase the carbon emissions generated by patients traveling to hospitals. The new approach of “equipment-based scheduling of hospitals to proactively serve patients” will be more popular with patients than the traditional “patients travel to hospitals with medical capacity” approach to healthcare. Therefore, in an environment where medical equipment is limited, hospitals within a medical network should coordinate well and provide available medical equipment to hospitals with medical needs in a timely manner. In Figure 1, green represents the area with a low number of patients and red represents the area with a high number of patients. The green and red color shades represent the degree of the number of patients.

At the same time, in order to realize the net zero concept of green healthcare, the scheduling of equipment resources within the healthcare network can effectively avoid unnecessary carbon emissions. When local hospitals are unable to meet patients' medical needs, patients often choose to travel to other hospitals with medical capacity. This process will result in continuous and significant environmental pollution. In addition, when the demand for patients in a region exceeds the capacity of the regional hospital, it will also result in significant carbon emissions from the medical process. This use of dispatching medical equipment to cater to medical needs will greatly facilitate patient travel and provide more convenient and personalized medical services. The corresponding carbon emission differential is schematically shown in Figure 2. In the case of insufficient medical capacity in Region 1, patients travel to hospitals in Region 2 for treatment. When medical equipment is dispatched from

Region 2 to a hospital in Region 1, patients in Region 1 can go directly to a local hospital for treatment. Additionally, patients will travel less for medical treatment, thereby effectively reducing carbon emissions. In addition, for the convenience of the presentation, we divide a region into subregions. The medical capacity of all hospitals within a subregion is expressed as the medical capacity of the subregion. The notations are listed in the supplement.

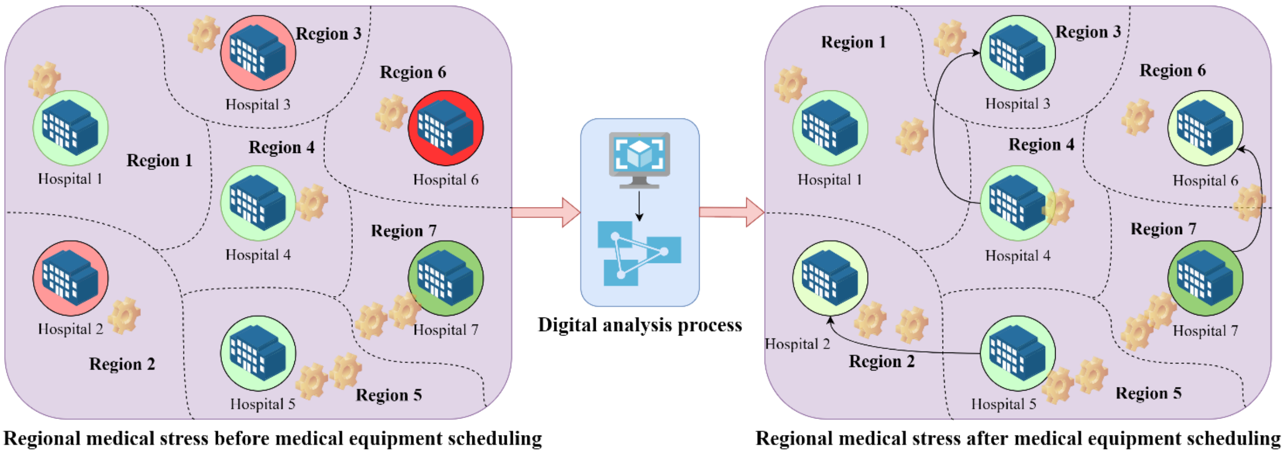


Figure 1. Equipment resource scheduling graph within the medical network.

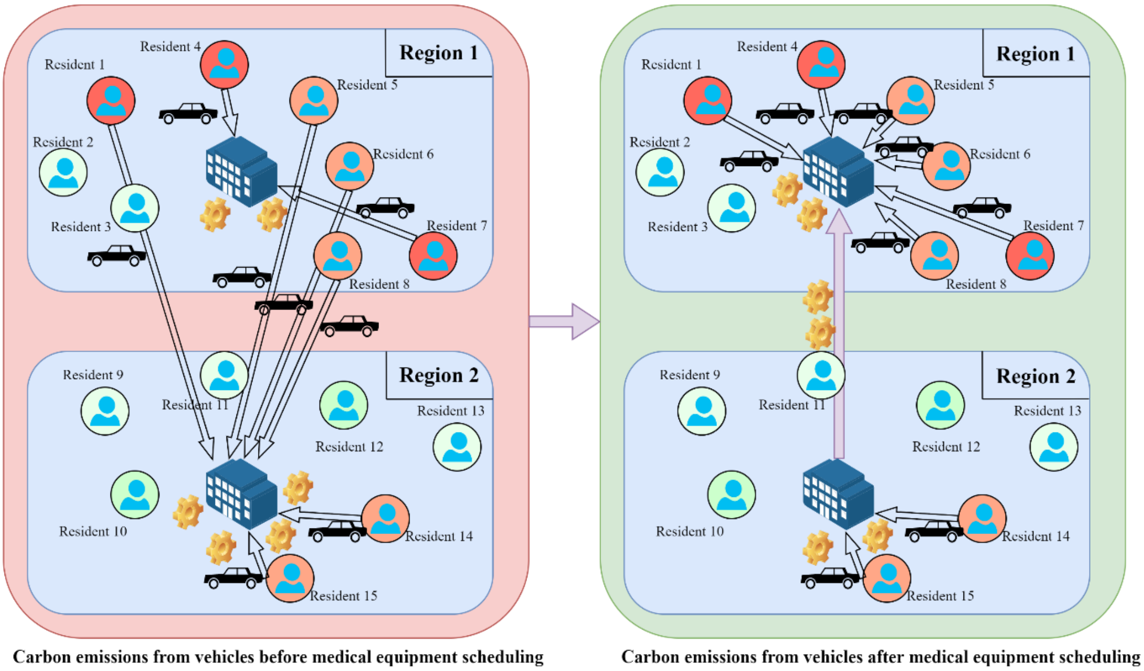


Figure 2. Carbon emission mitigation graph before and after medical equipment scheduling.

2.2. Carbon emission difference model within the healthcare network

Combining Figure 2 and Table 1, a reduction in carbon emissions is achieved through the scheduling of medical equipment. Among them, carbon emissions change from the high emissions of patients traveling to hospitals in other areas for treatment previously to the low emissions of patients traveling to local hospitals. After the medical equipment scheduling occurs, the number of patient trips to the hospital and the amount of travel within the healthcare network will be reduced. At the same time, the process of medical equipment scheduling will generate some carbon emissions. Thus, we made the following definition:

Definition 1. Let $\left(\Delta_{12}^{emission}, \Delta_{13}^{emission}, \Delta_{14}^{emission}, \dots, \Delta_{i'i}^{emission}\right)$ denote the reduction in carbon emissions after medical equipment scheduling between regions.

Definition 2. Let $\left(C_{12}^{emission}, C_{13}^{emission}, C_{14}^{emission}, \dots, C_{i'i}^{emission}\right)$ denote the carbon emissions generated during the scheduling of hospital equipment between two regions. Thus, the carbon emission reduction before and after medical equipment scheduling between the two regions is as follows:

$$\Delta_{i'i}^{emission} = C_{ir}^{emission,total} - C_{ir}^{emission,scheduling,total} \tag{1}$$

where:

$$C_{ir}^{emission,total} = C_{ir}^{emission} + C_{i}^{emission,operation} + C_{i}^{emission,production}$$

$$C_{ir}^{emission,scheduling,total} = C_{ir}^{emission,scheduling} + C_{i}^{emission,operation,scheduling} + \sum_{a\in A} C_{i'i}^{emission} x_{i'i}^{a}$$

$$C_{ir}^{emission,scheduling} = \sum_{d\in D} Q_{ir}^{d} C_{ir}^{emission,travel,scheduling,d}$$

The total carbon emission reduction within the healthcare network is shown in Equation (2).

$$\begin{aligned}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R}\Delta_{i'i}^{emission} = &\left[\sum_{i\in I}\sum_{r\in R} C_{ir}^{emission} + \sum_{i\in I} C_{i}^{emission,operation} + \sum_{i\in I} C_{i}^{emission,production}\right] \\ &- \left[\sum_{i\in I}\sum_{r\in R} C_{ir}^{emission,scheduling} + \sum_{i\in I} C_{i}^{emission,operation,scheduling} + \sum_{a\in A}\sum_{i\in I}\sum_{i'\in I} C_{i'i}^{emission} x_{i'i}^{a}\right]\end{aligned} \tag{2}$$

In order to achieve the goal of green healthcare, we should reduce the carbon emissions within the healthcare network. Thus, we construct the following objective function and constraints:

Objective function:

$$C_{network}^{emission,scheduling} = \sum_{i\in I}\sum_{r\in R} C_{ir}^{emission,scheduling,total} + \sum_{i\in I} C_{i}^{emission,production} \tag{3}$$

Subject to:

$$C_{ir}^{emission,scheduling,total} = C_{ir}^{emission,scheduling} + C_{i}^{emission,operation,scheduling} + \sum_{a\in A} C_{i'i}^{emission} x_{i'i}^{a} \tag{4}$$

$$C_{ir}^{emission,scheduling} = \sum_{d\in D} Q_{ir}^{d} C_{ir}^{emission,travel,scheduling,d} \tag{5}$$

$$\sum_{a\in A}\sum_{i\in I}\sum_{i'\in I} x_{i'i}^{a} \le A \tag{6}$$

$$x_{i'i}^{a} = \begin{cases} 1, \ if \ \ medical \ equipment \ a \ in \ region \ i' \\ \quad is \ scheduled \ to \ region \ i. \\ 0, \ Otherwise. \end{cases} \tag{7}$$

2.3. Dynamic medical capacity model within a healthcare network

The scheduling of medical equipment within the medical network will relieve the medical pressure on the demanding hospitals. Hospitals can achieve rapid patient care by enhancing medical capacities combined with digital technology. Hospitals use digital health platforms to personalize patient care plans in advance to ensure time savings and reduce unnecessary medical travel for patients [33]. Thus, we defined and inferred the following changes in the hospital medical capacity before and after scheduling:

Definition 3. Let $\left(\Delta_{12}^{hospital}, \Delta_{13}^{hospital}, \Delta_{14}^{hospital}, \dots, \Delta_{i'i}^{hospital}\right)$ denote the amount of medical capacity improvement after medical equipment scheduling between regions. Thus, the amount of medical capacity improvement before and after medical equipment scheduling between two regions is as follows:

$$\Delta_{i'i}^{hospital} = Q_i^{hospital,scheduling} - Q_i^{hospital} \tag{8}$$

Corollary 1. After medical equipment scheduling, the medical capacity of each hospital will change as the medical equipment is transferred in and out. Based on the transfer of medical equipment out and in, the following two main scenarios can be distinguished:

If medical equipment is transferred out of the hospital, the hospital's medical capacity will be reduced.

$$Q_i^{hospital,scheduling} = Q_i^{hospital} - \sum_{a\in A}\sum_{i'\in I}\Delta_{i'i}^{hospital} x_{i'i}^{a} \tag{9}$$

The medical equipment was transferred to the hospital and the hospital's medical capacity was enhanced.

$$Q_i^{hospital,scheduling} = Q_i^{hospital} + \sum_{a\in A}\sum_{i'\in I}\Delta_{i'i}^{hospital} x_{i'i}^{a} \tag{10}$$

In summary, we derive the following equation:

$$Q_i^{hospital,scheduling} = Q_i^{hospital}\begin{cases} +\sum_{a\in A}\sum_{i'\in I}\Delta_{i'i}^{hospital} x_{i'i}^{a}, \quad if \text{ equipments are} \\ \qquad\qquad\qquad\qquad \text{transferred to the hospital} \\ -\sum_{a\in A}\sum_{i'\in I}\Delta_{i'i}^{hospital} x_{i'i}^{a}, if \text{ equipments are} \\ \qquad\qquad\qquad\qquad \text{transferred out of the hospital} \end{cases} \tag{11}$$

In addition, the scheduled hospital's medical capacity should be no less than the maximum patient demand that the hospital can handle.

$$Q_i^{hospital,scheduling} \ge \sum_{r\in R} Q_{ir} \tag{12}$$

To maintain stability in the process of scheduling equipment within the medical network, the maximum value of the scheduled equipment should be greater than the sum of the medical equipment occurring in the network for scheduling.

$$\sum_{a\in A}\sum_{i\in I}\sum_{i'\in I} x_{i'i}^{a} \le A \tag{13}$$

Based on a dynamic medical equipment scheduling environment, this study takes the uncertainty of the number of patients in the actual process into account. Telemedicine and other means can be used to determine the number of patients. However, in some regions, we still face the problem of inadequate data-based equipment. Thus, we construct robust optimization models to reduce the impact of dynamic patient volumes. This will meet the dynamic medical needs of patients, in addition to enhancing the robustness and resilience of the healthcare network.

The relatively robust model proposed by Vairaktarakis [34] will effectively reduce the conservatism of the model while considering the worst case:

$$\min_{x} \max_{\xi \in U} \left\{ \frac{f\left(x,\xi\right) - f\left(x^{*},\xi\right)}{f\left(x^{*},\xi\right)} \middle| g_i\left(x^{*},\xi\right) \le 0, \forall \xi \in U, i = 1,\ldots,m \right\} \tag{14}$$

where $f(x^{*},\xi)$ is the true optimal output of the system and $g_i(x^{*},\xi) \le 0$ represents the relevant equality and inequality constraints in actual production. Based on the benefits and usage scenarios of the model, we construct a healthcare capacity optimisation model for healthcare networks to improve network resilience:

Objective function:

$$\min_{x} \max_{\xi \in U} \left\{ \frac{Q_i^{hospital,scheduling} - Q_i^{hospital,scheduling,*}}{Q_i^{hospital,scheduling,*}} \middle| s.t., \forall \xi \in U, i = 1,\ldots,m \right\} \tag{15}$$

Subject to:

$$Q_i^{hospital,scheduling} \ge \sum_{r \in R} Q_{ir} \tag{16}$$

$$Q_i^{hospital,scheduling} = Q_i^{hospital} \begin{cases} +\sum_{a \in A} \sum_{i' \in I} \Delta_{i'i}^{hospital} x_{i'i}^{a}, \; if \text{ equipments are} \\ \qquad \text{transferred to the hospital} \\ -\sum_{a \in A} \sum_{i' \in I} \Delta_{i'i}^{hospital} x_{i'i}^{a}, if \text{ equipments are} \\ \qquad \text{transferred out of the hospital} \end{cases} \tag{17}$$

$$\sum_{a \in A} \sum_{i \in I} \sum_{i' \in I} x_{i'i}^{a} \le A$$

$$x_{i'i}^{a} = \begin{cases} 1, \; if \;\; medical \;\; equipment \;\; a \;\; in \;\; region \;\; i' \\ \quad is \;\; scheduled \;\; to \;\; region \;\; i. \\ 0, \;\; Otherwise. \end{cases}$$

In addition, equipment scheduling based within the healthcare network will help maximize the utilization of equipment resources. Frequent equipment scheduling will effectively reduce the frequency of patient trips to different regions. This process allows medical equipment to accurately identify the dynamic needs of patients and make the best scheduling decisions through the rapid flow of digital technology within the network. To combat the difficulty in balancing medical cost and medical capacity, hospitals with scheduling needs can enhance the medical capacity and reduce the purchase cost of medical equipment through medical equipment scheduling. This will indirectly reduce the carbon emission of the medical equipment manufacturing process.

2.4. Multi-resource scheduling model based on fuzzy system

The epidemic has swept across the globe and has had an enormous impact on the functioning of societies around the world, posing a major challenge to disease prevention and control [35]. The shortage of medical equipment in the emergency situation brought about by the epidemic has caused an increased medical burden. This burden can be effectively reduced by scheduling medical equipment resources within the healthcare network. However, the operation of medical equipment is often accompanied by the generation of large amounts of contaminants, which can be harmful to patients and medical staff [36]. In addition, the operation of medical equipment is often accompanied by the generation of carbon emissions and other types of pollution, and the selection of qualified equipment will help improve the stability of medical care. We construct a scheduling decision model based on the characteristics of medical equipment to decide the qualified medical equipment for scheduling. The initial screening of medical equipment is achieved by constructing corresponding risk indicators to ensure that the scheduled medical equipment can perform better and avoid unnecessary medical risks. The model is based on the interval-valued intuitionistic fuzzy-technique for order preference by similarity to an ideal solution (IVIF-TOPSIS), which reduces the emission of pollutants while meeting the needs of medical equipment, and finally achieves the matching process of medical equipment. In the face of medical contamination in the medical process, we construct interval-valued intuitionistic fuzzy (IVIF) sets to solve the problem of excessive subjectivity in decision making and the difficulty of quantifying some of the indicators.

Definition 4. Let Q be a nonempty set and $A = \{\langle x, \mu_A(x), \nu_A(x)\rangle, x \in Q\}$ is IFS, $\mu_A: x \to [0,1], \nu_A: x \to [0,1]$ and $0 \le \tilde{\mu}_A(x) + \tilde{\nu}_A(x) \le 1$.

Definition 5. An IVIF set in $\tilde{A}$ over X is an object given as in Equation (18):

$$\tilde{A} = \left\{\left\langle x, \tilde{\mu}_A(x), \tilde{\nu}_A(x)\right\rangle, \forall\, x \in X\right\} \tag{18}$$

The membership and non-membership function of the element x of the set A are represented as the intervals $\tilde{\mu}_A(x)$ and $\tilde{\nu}_A(x)$, respectively. Then, each $x \in X$, $\tilde{\mu}_A(x)$ and $\tilde{\nu}_A(x)$ are represented using closed intervals and their lower and upper end values are shown by $[\tilde{\mu}_{ij}^-, \tilde{\mu}_{ij}^+], [\tilde{\nu}_{ij}^-, \tilde{\nu}_{ij}^+]$ [37]:

$$\tilde{A} = \left\{\left\langle x, \left[\tilde{\mu}_{ij}^-, \tilde{\mu}_{ij}^+\right], \left[\tilde{\nu}_{ij}^-, \tilde{\nu}_{ij}^+\right]\right\rangle, \ x \in X\right\} \tag{19}$$

where $0 \le \tilde{\mu}_{ij}^- + \tilde{\mu}_{ij}^+ \le 1, 0 \le \tilde{\nu}_{ij}^-, 0 \le \tilde{\mu}_{ij}^-$.

Based on the literature on medical equipment management [38-41], we selected six indicators related to medical equipment: equipment radiation (C1), equipment depreciation (C2), microbial contamination (C3), exposure to machinery-related noise (C4), respiratory problems due to chemical substances (C5), and thermal risk (C6). Decision makers use the seven levels of language terms defined in interval valued intuitionistic fuzzy set (IVIFS) to evaluate medical equipment based on metrics. IVIFS helps to apply and handle many decision problems in an uncertain environment [42]. Table 1 presents the linguistic terms and their corresponding IVIFS.

The IVIF-TOPSIS-based scheduling decision model which considers contamination in a major emergency medical setting is expressed in Figure 3. The content in Figure 3 will show how the scheduling decision model can be used to help decision makers select medical equipment with the same function but containing different characteristics in a major emergency medical environment in detail.

Table 1. Linguistic terms and IVIFS. (The first column represents the Linguistic Term and its corresponding abbreviation, and the second column represents the IVIF Number corresponding to the Linguistic Term.)

Linguistic Term	IVIF Number
Very Low (VL)	([0.00,0.12], [0.80,0.90])
Low(L)	([0.14,0.23], [0.65,0.70])
Medium Low (ML)	([0.33,0.42], [0.45,0.50])
Medium(M)	([0.44,0.61], [0.20,0.30])
Medium High (MH)	([0.67,0.73], [0.15,0.25])
High (H)	([0.71,0.82], [0.10,0.15])
Very High (VH)	([1.00,1.00], [0.00,0.00])

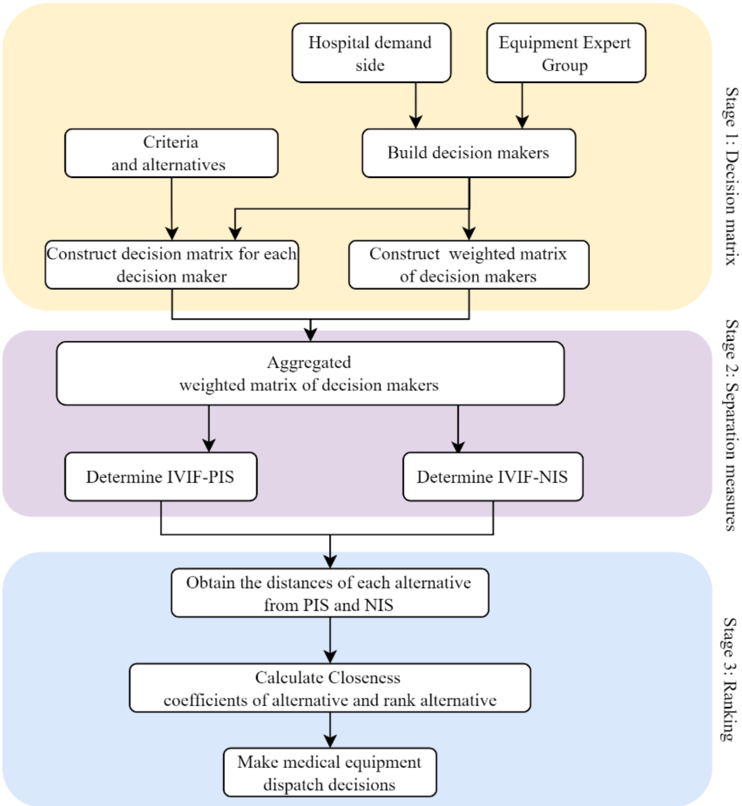


Figure 3. Decision model for medical equipment scheduling considering contamination.

The steps of the IVIF-TOPSIS method based on medical equipment scheduling are as follows:

Step 1: A questionnaire survey of multiple hospitals was used to establish the basic needs for medical equipment and common medical contamination in a major emergency medical setting. Suppose that there are m feasible alternatives, denoted by $A = \{A_1, A_2, \dots, A_m\}$ and n criterions be $C = \{C_1, C_2, \dots, C_n\}$.

Step 2: Establish equipment expert groups and hospital demand side related to equipment performance. Suppose that there are k decision makers, denoted by $D = \{D_1, D_2, \dots, D_m\}$.

Step 3: Construct an aggregated IVIF decision matrix Y_p of the pth decision maker and the average decision matrix $\bar{Y}$.

$$Y_p = \left(f_{ij}^{p}\right)_{m\times n} = \begin{bmatrix} f_{11}^{p} & f_{12}^{p} & \cdots & f_{1n}^{p} \\ f_{21}^{p} & f_{22}^{p} & \cdots & f_{2n}^{p} \\ \cdots & \cdots & \cdots & \cdots \\ f_{m1}^{p} & f_{m1}^{p} & \cdots & f_{mn}^{p} \end{bmatrix} \tag{20}$$

$\bar{Y} = \left(f_{ij}\right)_{m\times n}$, where $f_{ij} = \left(\frac{f_{ij}^{1} \oplus f_{ij}^{2} \oplus \dots \oplus f_{ij}^{k}}{k}\right)$.

Step 4: Construct a weighting matrix W of k decision maker and the average weighting matrix $\bar{W}$.

$$W_p = \left(\omega_i^{p}\right)_{1\times m} = \begin{array}{c} \begin{matrix} C_1 & C_2 & \dots & C_m \end{matrix} \\ \begin{bmatrix} \omega_1^{p} & \omega_2^{p} & \dots & \omega_m^{p} \end{bmatrix} \end{array} \tag{21}$$

where, $\bar{W} = (\omega_i)_{1\times m}$, and $\omega_i = \frac{\omega_i^{1} \oplus \omega_i^{2} \oplus \dots \oplus \omega_i^{k}}{k}$.

Step 5: Construct the aggregated weighted interval valued intuitionistic fuzzy decision matrix, D'.

$$D' = D \otimes W = \left(r'_{ij}\right)_{m\times n}, r'_{ij} = \left(\left[a'_{ij}, b'_{ij}\right], \left[c'_{ij}, d'_{ij}\right]\right) \tag{22}$$

Step 6: Determine the positive and negative ideal solution by using Equations (23) to (24).

$$\begin{gathered} D'^{k+} = \left(D_1'^{k+}, D_1'^{k+}, \dots, D_m'^{k+}\right) = \\ \left(\left\langle\left[a_1^{k+}, b_1^{k+}\right], \left[c_1^{k+}, d_1^{k+}\right]\right\rangle, \left\langle\left[a_2^{k+}, b_2^{k+}\right], \left[c_2^{k+}, d_2^{k+}\right]\right\rangle, \dots, \left\langle\left[a_m^{k+}, b_m^{k+}\right], \left[c_m^{k+}, d_m^{k+}\right]\right\rangle\right) \end{gathered} \tag{23}$$

$$\begin{gathered} D'^{k-} = \left(D_1'^{k-}, D_1'^{k-}, \dots, D_m'^{k-}\right) \\ = \left(\left\langle\left[a_1^{k-}, b_1^{k-}\right], \left[c_1^{k-}, d_1^{k-}\right]\right\rangle, \left\langle\left[a_2^{k-}, b_2^{k-}\right], \left[c_2^{k-}, d_2^{k-}\right]\right\rangle, \dots, \left\langle\left[a_m^{k-}, b_m^{k-}\right], \left[c_m^{k-}, d_m^{k-}\right]\right\rangle\right) \end{gathered} \tag{24}$$

where,

$$D_j'^{k+} = \left\langle\left[a_j^{k+}, b_j^{k+}\right], \left[c_j^{k+}, d_j^{k+}\right]\right\rangle = \left\langle\left[\max_i a_{ij}^{k}, \max_i b_{ij}^{k}\right], \left[\max_i c_{ij}^{k}, \max_i d_{ij}^{k}\right]\right\rangle, i = 1, \dots, n,\ j = 1, \dots, m, k = 1, \dots, K$$

$$D_j'^{k-} = \left\langle\left[a_j^{k-}, b_j^{k-}\right], \left[c_j^{k-}, d_j^{k-}\right]\right\rangle = \left\langle\left[\max_i a_{ij}^{k}, \max_i b_{ij}^{k}\right], \left[\max_i c_{ij}^{k}, \max_i d_{ij}^{k}\right]\right\rangle, i = 1, \dots, n,\ j = 1, \dots, m, k = 1, \dots, K$$

Step 7: Calculate the distance of each factor to the IVIF-PIS (IVIF-TOPSIS positive ideal solution) and IVIF-NIS (IVIF-TOPSIS negative ideal solution) in Equations (25) to (26).

$$\begin{gathered} S_i^{+}\left(D_i, A^{+}\right) = \left\{\frac{1}{4}\sum_{j=1}^{n}\left[\left(a_{ij} - a_j^{+}\right)^2 + \left(b_{ij} - b_j^{+}\right)^2 + \left(c_{ij} - c_j^{+}\right)^2 + \left(d_{ij} - d_j^{+}\right)^2\right]\right\}^{1/2} \\ , i = 1, \dots, n,\ j = 1, \dots, m, k = 1, \dots, K \end{gathered} \tag{25}$$

$$\begin{gathered} S_i^{-}\left(D_i, A^{-}\right) = \left\{\frac{1}{4}\sum_{j=1}^{n}\left[\left(a_{ij} - a_j^{-}\right)^2 + \left(b_{ij} - b_j^{-}\right)^2 + \left(c_{ij} - c_j^{-}\right)^2 + \left(d_{ij} - d_j^{-}\right)^2\right]\right\}^{1/2} \\ , i = 1, \dots, n,\ j = 1, \dots, m, k = 1, \dots, K \end{gathered} \tag{26}$$

Step 8: Combine $S_i^+(D_i, A^+)$ and $S_i^-(D_i, A^-)$ to calculate the closeness coefficient(RC_i) for each medical equipment scheduling alternative by using Equation (27).

$$RC_i = \frac{S_i^-}{S_i^- + S_i^+}, i = 1, 2, ..., n \tag{27}$$

Step 9: Rank the preference of alternatives according to the ascending order of closeness coefficients. Decision makers decide on the better-performing medical equipment for medical network scheduling.

3. Sustainable medical equipment scheduling system

The main factors affecting the scheduling of medical equipment within a healthcare network are categorized into three parts: the number and types of medical equipment, the pressure of medical care in each region, and the carbon emissions generated by patients traveling to hospitals for treatment. The sustainable scheduling system for medical equipment improves the utilization of medical equipment by building a medical equipment configuration framework. When a region within a healthcare network is under high medical pressure, a sustainable scheduling system for medical equipment can quickly make medical equipment scheduling decisions. By scheduling medical equipment resources from other regions to areas with a higher medical pressure, the medical capacity of the region will be significantly enhanced. This will effectively reduce unnecessary travel and save patients' travel time to the hospital. In addition, the system is solved by constructing a multi-objective robust optimization model and combining it with the NSGA-II-MOPSO algorithm. Ultimately, the system enables the efficient scheduling of medical equipment resources within the healthcare network, thereby reducing the number of patient trips and time, subsequently reducing carbon emissions.

Combined with the IVIF-TOPSIS method, we will effectively select the right equipment for scheduling to ensure the reduction of environmental pollution and the appropriate operation of the equipment. The process of scheduling medical equipment between subregions within the healthcare network will facilitate the improvement of the healthcare capacity in subregions with a high medical pressure. By scheduling medical equipment, patients in sub-regions with a high medical pressure can reduce their carbon footprint by travelling directly to the subregion for treatment, thereby reducing the number of trips to hospitals in other subregions. Thus, the scheduling of medical equipment will effectively reduce the carbon emissions generated during the patient's travel to the hospitals and will save a significant amount of medical equipment manufacturing costs. This will effectively achieve the goal of green healthcare. At the same time, the improvement of medical capacities within the medical network will effectively achieve the improvement of medical services. Thus, we construct a multi-objective model which combines carbon emissions and the overall level of care within the healthcare network.

Objective function:

$$C_{network}^{emission,scheduling} = \sum_{i \in I} \sum_{r \in R} C_{ir}^{emission,scheduling,total} + \sum_{i \in I} C_i^{emission,production}$$

$$\min_{x} \max_{\xi \in U} \left\{ \frac{Q_i^{hospital,scheduling} - Q_i^{hospital,scheduling,*}}{Q_i^{hospital,scheduling,*}} \middle| s.t., \forall \xi \in U, i = 1, ..., m \right\}$$

Subject to:

$$C_{ir}^{emission,scheduling,total} = C_{ir}^{emission,scheduling} + C_{i}^{emission,operation,scheduling} + \sum_{a\in A} C_{i^{'}i}^{emission} x_{i^{'}i}^{a}$$

$$C_{ir}^{emission,scheduling} = Q_{ir} C_{ir}^{emission,travel,scheduling}$$

$$Q_{i}^{hospital,scheduling} \geq \sum_{d\in D}\sum_{r\in R} Q_{ir}^{d}$$

$$Q_{i}^{hospital,scheduling} = Q_{i}^{hospital} \begin{cases} +\sum_{a\in A}\sum_{i^{'}\in I} \Delta_{i^{'}i}^{hospital} x_{i^{'}i}^{a}, \quad \textit{if} \text{ equipments are} \\ \qquad\qquad\qquad\qquad \text{transferred to the hospital} \\ -\sum_{a\in A}\sum_{i^{'}\in I} \Delta_{i^{'}i}^{hospital} x_{i^{'}i}^{a}, \textit{if} \text{ equipments are} \\ \qquad\qquad\qquad\qquad \text{transferred out of the hospital} \end{cases}$$

$$x_{i^{'}i}^{a} = \begin{cases} 1, \ \textit{if medical equipment a in region } i^{'} \\ \quad \textit{is scheduled to region i.} \\ 0, \ \textit{Otherwise.} \end{cases}$$

$$\sum_{a\in A}\sum_{i\in I}\sum_{i^{'}\in I} x_{i^{'}i}^{a} \leq A$$

The above multi-objective model was constructed to effectively implement the decision process for equipment scheduling. However, with the appropriate operation of the medical equipment, there will be other areas within the medical network where medical needs will arise at residential sites. Hospitals within a healthcare network are faced with continuously changing medical demands. Therefore, in order to balance the medical needs of patients in each region and to reduce the pressure of medical care in each region, we have built a dynamic medical equipment configuration framework to enhance the dynamic processing capacity of the medical network. By establishing termination conditions, the medical equipment configuration framework will enable medical resource allocation on a continuous basis until the medical resources within the healthcare network are adequately utilized. This will improve the utilization of medical equipment resources. In addition, through the medical equipment configuration framework, the medical pressure in individual regions is shared by the entire medical network. This will increase the overall risk tolerance and resilience of the medical network. When single or multiple regions within a medical network experience a high level of medical pressure, idle resources from other regions within the medical network can enable rapid resource allocation. Figure 4 shows the dynamic medical equipment configuration framework. In this framework, we have divided the basic framework into three parts according to the process: digital statistics, scheduling decision process and medical equipment scheduling program implementation. Furthermore, we categorize the framework into a digital medical scheduling system construction, which is a dynamic configuration decision process combined with digital information based on the different functions within the framework. The framework operates with a variety of functions aimed at realizing the dynamic configuration of medical equipment resources.

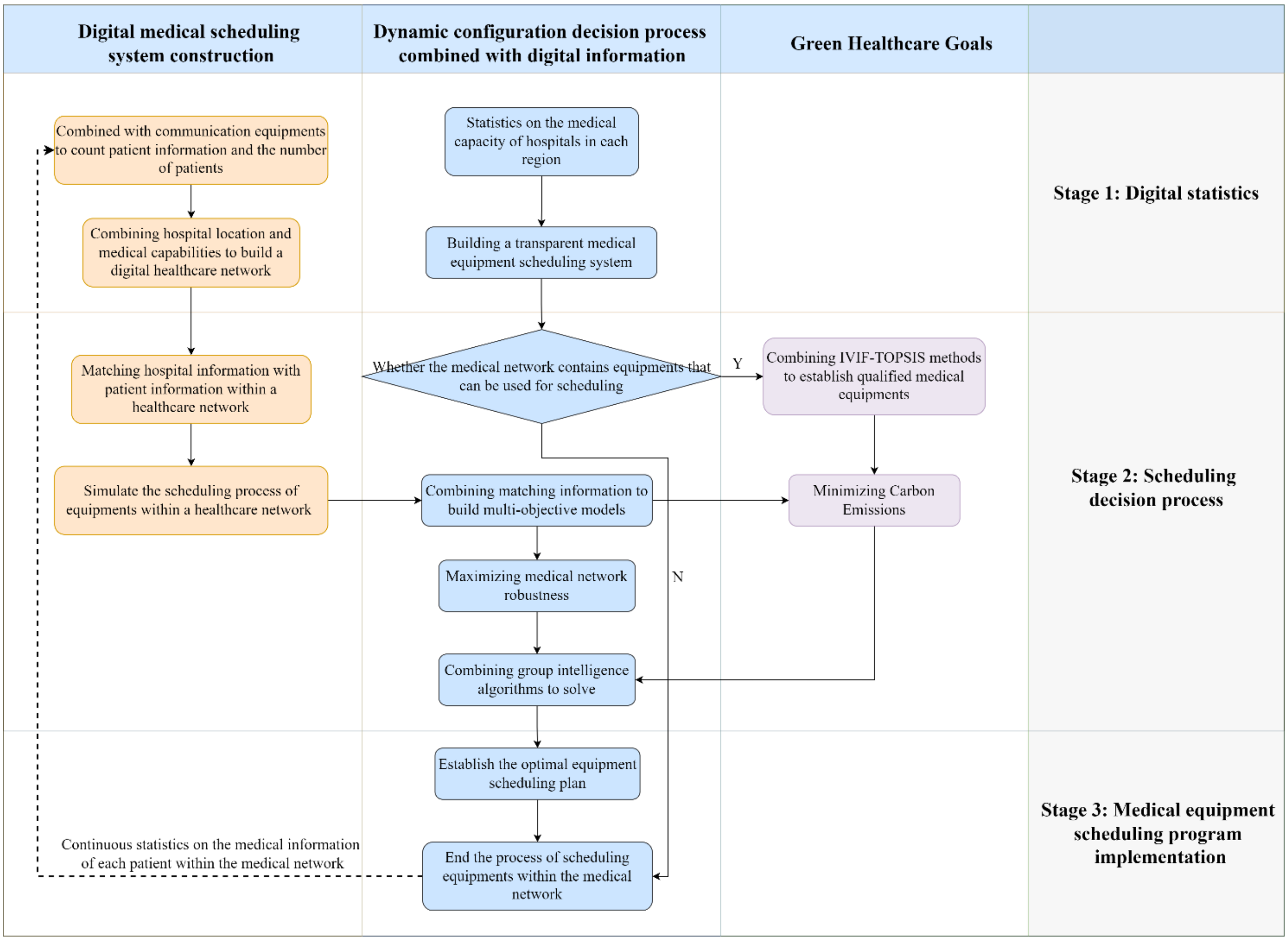


Figure 4. Dynamic medical equipment configuration framework.

The corresponding framework operation process is shown below:

Step 1: Obtain statistics of the medical capacity and the operating parameters of medical equipment in each region. Hospitals in each region upload various types of information into the transparent digital platform.

Step 2: Combine digital technology to count the patient information and the number of patients in each region. We build personalized medical plans for different patient states.

Step 3: Construct an index system for contamination and operational risk during the operation of medical equipment. Combined with the IVIF-TOPSIS method, the screening of each equipment in the medical network is realized to determine the qualified medical equipment that can operate well.

Step 4: A digital healthcare platform simulates the scheduling process of each medical equipment within the healthcare network. Different scheduling environments are generated by combining various simulated scheduling scenarios.

Step 5: A multi-objective model is constructed and solved to establish the scheduling results for each scenario. Based on this, the medical capacity of each region is analyzed to ensure that each region can meet sufficient patient demand and monitor patient information in real time.

Step 6: Select a better alternative from the multiple scheduling options as the decision solution for the final scheduling solution. This solution will ensure that the medical dispatch will be robust to patient demand and minimize the carbon emission during the patient's travel to the hospital.

Step 7: Implementation of the program and ongoing statistics on patient information and hospital capacity in each region of the healthcare network.

Based on our previous studies [43-44], the NSGA-II-MOPSO algorithm is an efficient algorithm. The set non-dominated solution has a better performance in convergence, uniformity and diversity. Thus, we adopt the NSGA-II-MOPSO algorithm for problem solving.

4. Case study and discussion

In order to demonstrate the effectiveness of sustainable medical scheduling systems in improving medical capacities and reducing carbon emissions, we analyze the process of scheduling medical equipment in a major emergency medical situation with specific examples. We interviewed several provincial hospitals in China during the March 2022 outbreak to obtain data. In addition, due to the rapid spread of the new coronavirus, the Chinese government restricted public transportation for infected and febrile patients to avoid mass transmission. As a result, most febrile patients chose to travel to the hospital by private car. After a 2-year-long outbreak, some hospitals within the region had the capacity to treat critically ill patients. Each hospital was responsible for the care of local patients and some hospitals found it difficult to supply the needs of patients in their regions. Thus, combined with the emergency medical environment, some hospitals with insufficient medical capacity requested the required medical equipment and established an emergency procurement plan based on the "Notice on the Recommendation of Urgent Medical Equipment for the Prevention and Treatment of the New Hall Pneumonia Epidemic" as issued by the China Medical Equipment Association and the published "Catalogue of Urgent Medical Equipment for the Prevention of the New Hall Pneumonia Epidemic (First Batch)", with the corresponding equipment names, manufacturers and reference models shown in the supplement. The main medical equipment purchased were as follows: non-invasive ventilator, transnasal high-flow oxygenator, extra-corporeal membrane oxygenator (ECMO), infusion pump, etc. Although the way hospitals purchase medical equipment effectively reduces the medical pressure of some hospitals, it increases the cost of purchasing a lot of equipment and increases the environmental pollution during the manufacturing process of the equipment. In the face of the reality of a gradually decreasing epidemic pressure environment, the role of additional medical equipment will gradually decrease in the future. This will increase the waste of medical equipment and raw materials. We constructed a healthcare network between provinces in China, with the major cities within each province responsible for the major healthcare needs of their provinces. In particular, we subdivided each province into five patient areas based on their size and population. Table 2 shows the number of patients in each province within the healthcare network in China. As shown in Table 2, there was no large-scale infection in March 2022 within China. However, small-scale epidemics were found in many regions. Some of these regions faced a high medical pressure. After a large number of sample surveys and data comparisons, we selected a few provinces as the main reference examples. In March 2022, coronavirus infections only occurred in some areas due to good health policies of the Chinese government and a high awareness of virus protection among the population. When severe infections occur in some regions, local people often consciously avoid unnecessary travel to prevent the spread of the virus. This effectively reduces the probability of people being infected with the virus.

We have built a digital platform that combines the medical capacity needs of each hospital with patient information. In addition, we built a Chinese healthcare network based on the number of patients in each region of China during the March 2022 outbreak. For example, the main demand for noninvasive ventilators came from hospitals in four provinces: Liaoning, Hubei, Sichuan, and Zhejiang.

Figure 5 plots the colors of different regions within China according to the number of patients in the corresponding region. The red color indicates that the number of patients in the region is high, while the green color indicates that the number of patients in the region is low.

Table 2. Statistics of the number of patients by province in China (Columns 1 and 3 represent different regions and columns 2 and 4 represent the number of patients).

Region	Number of patients	Region	Number of patients
Hebei	195	Zhejiang	393
Shanxi	23	Anhui	4
Shaanxi	192	Fujian	112
Liaoning	154	Jiangxi	0
Jilin	6063	Shandong	1110
Heilongjiang	46	Henan	46
Jiangsu	185	Hubei	39
Hunan	7	Hainan	3
Guangdong	1734	Sichuan	152
Guizhou	4	Gansu	183
Xinjiang	0	Xizang	0
Yunnan	30	Qinghai	2
Taiwan	6630	Guangxi	294
Inner Mongolia	45	Ningxia	0

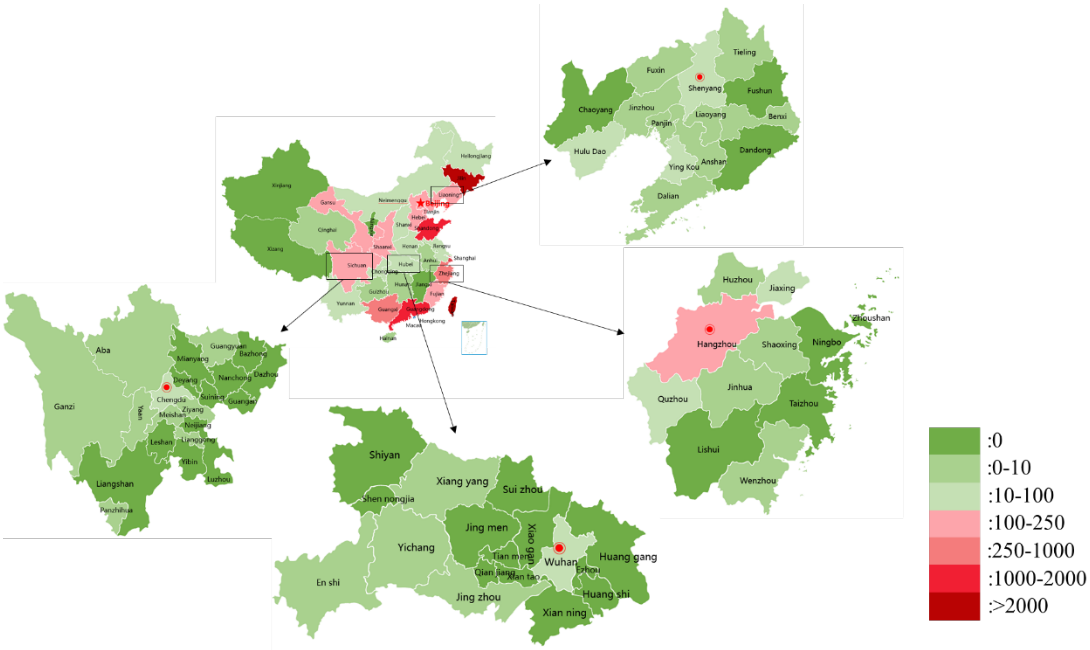


Figure 5. Distribution of patients by region within the medical network.

The epidemic situation in Zhejiang province was serious, with a large number of asymptomatic patients in addition to diagnosed patients. Therefore, we analyzed the medical capacity and medical equipment of hospitals in Zhejiang Province. For illustrative purposes, we analyzed non-invasive ventilators based on the dynamic medical equipment configuration framework. The computational procedures of the case are implemented as follows:

Step 1: First, we establish the corresponding expert group members for the non-invasive ventilators. A total of two medical equipment demanders and three equipment experts together formed a five-member expert decision group. Meanwhile, five expert decision-making groups established six indicators for the pollution problems faced during the use of medical equipment, which are: equipment radiation (C1), equipment depreciation (C2), microbial contamination (C3), exposure to machinery-related noise (C4), respiratory problems due to chemical substances (C5), and thermal risk (C6). Generate all possible alternatives and criteria. Alternatives are $A = \{A_1, A_2, \ldots, A_6\}$ and criterion are $C = \{C_1, C_2, \ldots, C_6\}$.

Step 2：Generate a set of decision makers: $D = \{D_1, D_2, \ldots, D_4\}$. Construct an aggregated IVIF decision matrix and the average decision matrix $\bar{Y}$. First, the language terms were established according to Table 2, and the corresponding results are shown in supplementary.

All individual decision opinions are fussed into a group of opinion. Then, the aggregated matrices from each decision maker are averaged to construct an aggregated group decision matrix. The average of the group decision matrix is denoted as $\bar{Y}$.

Thus, we can obtain $\bar{Y}$:

$$\bar{Y}=\begin{bmatrix} ([0.72,0.76],[0.12,0.20]) & ([0.94,0.96],[0.02,0.03]) & ([0.74,0.80],[0.10,0.16]) & ([1.00,1.00],[0.00,0.00]) & ([0.69,0.78],[0.11,0.17]) & ([0.72,0.76],[0.12,0.20]) \\ ([0.70,0.80],[0.10,0.15]) & ([0.65,0.70],[0.15,0.25]) & ([1.00,1.00],[0.00,0.00]) & ([0.72,0.76],[0.12,0.20]) & ([1.00,1.00],[0.00,0.00]) & ([0.69,0.78],[0.11,0.17]) \\ ([0.93,0.94],[0.03,0.05]) & ([0.66,0.72],[0.14,0.23]) & ([0.67,0.74],[0.13,0.21]) & ([0.80,0.84],[0.08,0.13]) & ([0.69,0.78],[0.11,0.17]) & ([1.00,1.00],[0.00,0.00]) \\ ([0.81,0.86],[0.07,0.11]) & ([0.81,0.86],[0.07,0.11]) & ([0.68,0.76],[0.12,0.19]) & ([0.87,0.90],[0.05,0.08]) & ([1.00,1.00],[0.00,0.00]) & ([0.72,0.76],[0.12,0.20]) \\ ([0.66,0.72],[0.14,0.23]) & ([0.79,0.82],[0.09,0.15]) & ([0.75,0.82],[0.09,0.14]) & ([0.73,0.78],[0.11,0.18]) & ([0.68,0.72],[0.04,0.06]) & ([0.74,0.80],[0.10,0.16]) \\ ([0.88,0.92],[0.04,0.06]) & ([0.88,0.92],[0.04,0.06]) & ([0.67,0.74],[0.13,0.21]) & ([0.73,0.78],[0.11,0.18]) & ([0.80,0.84],[0.08,0.13]) & ([0.79,0.82],[0.09,0.15]) \end{bmatrix}$$

Step 4: Construct a weighting matrix W of four decision makers and the average weighting matrix $\bar{W}$. The weighting matrix W of the four decision makers is constructed and the average weighting matrix $\bar{W}$ is calculated in the supplement.

Step 5: Construct the aggregated weighted interval valued intuitionistic fuzzy decision matrix, D'. Then, the aggregated weighted interval valued intuitionistic fuzzy decision matrix, D', is computed. The aggregated weighted interval valued intuitionistic fuzzy decision matrix is shown below：

$$D^{'}=D\times W==\begin{bmatrix} ([0.5904,0.6688],[0.0072,0.0180]) & ([0.7708,0.8448],[0.0012,0.0027]) & ([0.6068,0.7040],[0.0060,0.0144]) & ([0.8200,0.8800],[0.0000,0.0000]) & ([0.5658,0.6864],[0.0066,0.0153]) & ([0.5904,0.6688],[0.0072,0.0180]) \\ ([0.5040,0.6080],[0.0120,0.0300]) & ([0.4680,0.5320],[0.0180,0.0500]) & ([0.7200,0.7660],[0.0000,0.0000]) & ([0.5184,0.5776],[0.0144,0.0400]) & ([0.7200,0.7660],[0.0000,0.0000]) & ([0.4968,0.5928],[0.0132,0.0340]) \\ ([0.7533,0.8084],[0.0021,0.0055]) & ([0.5346,0.6192],[0.0098,0.0253]) & ([0.5427,0.6364],[0.0091,0.0231]) & ([0.6482,0.7224],[0.0056,0.0143]) & ([0.5589,0.6708],[0.0077,0.0187]) & ([0.8100,0.8600],[0.0000,0.0000]) \\ ([0.7047,0.7740],[0.0035,0.0088]) & ([0.7047,0.7740],[0.0035,0.0088]) & ([0.5916,0.6840],[0.0060,0.0152]) & ([0.7596,0.8100],[0.0025,0.0064]) & ([0.8700,0.9000],[0.0000,0.0000]) & ([0.6264,0.6840],[0.0060,0.0160]) \\ ([0.5742,0.6480],[0.0070,0.0184]) & ([0.6873,0.7380],[0.0045,0.0120]) & ([0.6525,0.7380],[0.0045,0.0112]) & ([0.6351,0.7020],[0.0055,0.0144]) & ([0.5916,0.6480],[0.0020,0.0048]) & ([0.6438,0.7200],[0.0050,0.0128]) \\ ([0.5896,0.6808],[0.0052,0.0126]) & ([0.5896,0.6808],[0.0052,0.0126]) & ([0.4489,0.5476],[0.0169,0.0441]) & ([0.4891,0.5772],[0.0143,0.0378]) & ([0.5360,0.6216],[0.0104,0.0273]) & ([0.5293,0.6068],[0.0117,0.0315]) \end{bmatrix}$$

Step 6: Determine the positive ideal partner solution and the negative ideal partner solution by using Equations (25) to (26).

$$A^{+}==\big(([0.8200,0.8800],[0.0000,0.0000]),([0.7200,0.7660],[0.0000,0.0000]),([0.8100,0.8600],[0.0000,0.0000])$$
$$([0.8700,0.9000],[0.0000,0.0000]),([0.8091,0.8460],[0.0015,0.0040]),([0.5896,0.6808],[0.0052,0.0126])\big)$$

$$A^{-}==\big(([0.5658,0.6864],[0.0066,0.0153]),([0.4680,0.5320],[0.0180,0.0500]),([0.5346,0.6192],[0.0098,0.0253])$$
$$([0.5916,0.6840],[0.0060,0.0152]),([0.5742,0.6480],[0.0070,0.0184]),([0.4489,0.5476],[0.0169,0.0441])\big)$$

Step 7: Calculate the separation measure between the candidates and NIPS for each decision maker. Results are as shown in the supplement.

Step 8: Calculate the closeness coefficient. Table 3 shows the corresponding closeness coefficient of the different schemes, thus indicating the advantages and disadvantages of the alternatives $(A_1, A_2, A_3, A_4, A_5, A_6)$.

Table 3. Statistics of RC_i results. (Columns 2-7 represent the corresponding RC_i values for each alternative).

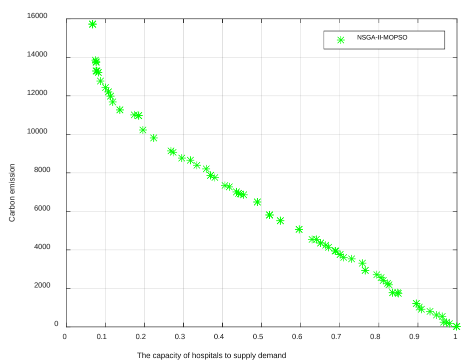
	A1	A2	A3	A4	A5	A6
RC_i	0.3261	0.3110	0.2572	0.4611	0.4713	0.3236

Step 9: Rank the preference order of all alternatives.

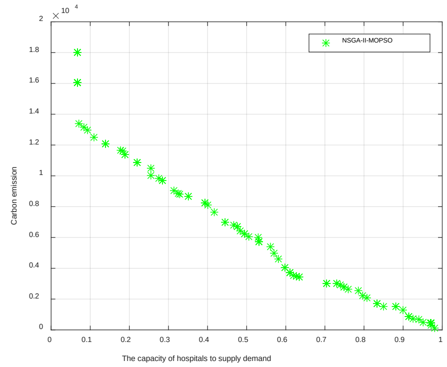
$$Rank(5) > Rank(4) > Rank(1) > Rank(6) > Rank(2) > Rank(3)$$

Step 10: With Step 1-9, we combine a fuzzy theory-based scheduling decision model to establish lower-risk medical equipment for collaborative scheduling within the healthcare network. Based on the actual medical capacity and patient needs in each region, we finalized four qualified NIVs (i.e., 1, 4, 5, and 7) for the equipment scheduling process within the medical network.

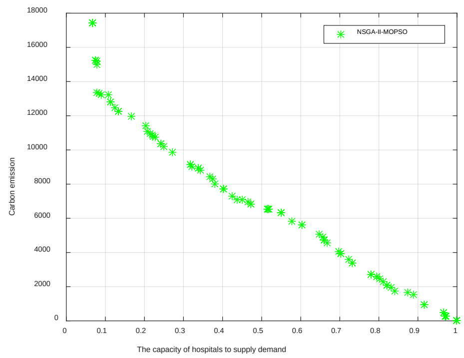
Step 11: We construct a multi-objective model based on patient profiles and carbon emissions in Zhejiang province and combine it with the NSGA-II-MOPSO algorithm to solve the scheduling results of noninvasive ventilators, as shown in Figure 6(a). Accordingly, we solved the multi-objective model for three provinces-Liaoning, Hubei, and Sichuan-after the non-invasive ventilator was scheduled and solved, as displayed in Figure 6(b) to (d). Decision makers can choose different equipment scheduling schemes based on Figure 6(a) to (d) to achieve equipment resource scheduling and to determine the carbon emissions generated by patients traveling to the hospital.



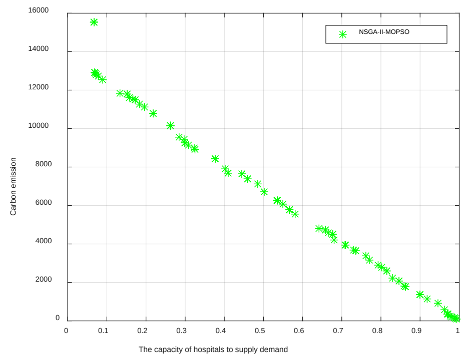
(a). The pareto surface of Zhejiang Province.



(b). The pareto surface of Hubei Province.



(c). The pareto surface of Liaoning Province.

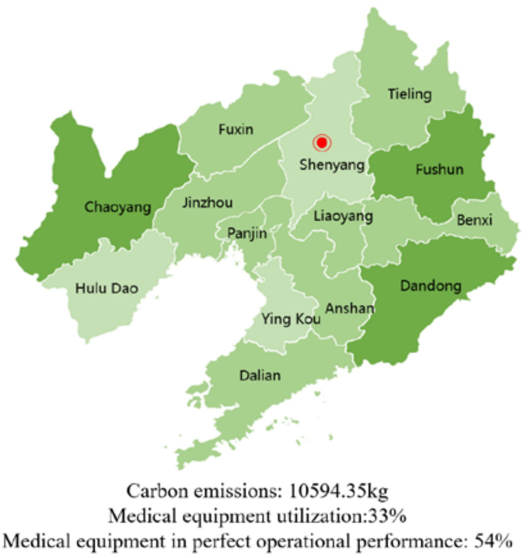


(d). The pareto surface of Sichuan Province.

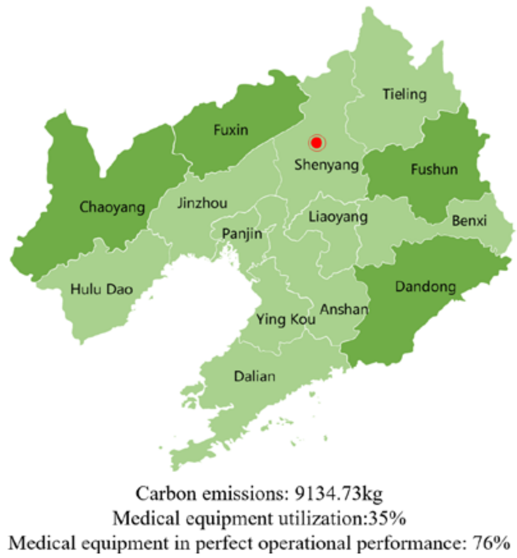
Figure 6. The pareto surfaces of Provinces.

In the case study, we combine IVIF-TOPSIS, NSGA-II-MOPSO and a method that integrates the two methods to verify the effectiveness of a sustainable scheduling system for medical equipment. After seeking the agreement of hospitals and patients in Liaoning Province, we selected four cases for comparison to show the effectiveness of a sustainable scheduling system for medical equipment. They are as follows:

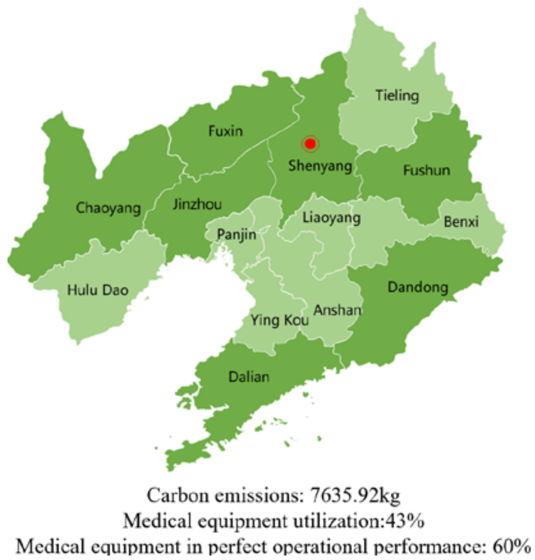
- Natural situation.
- Medical equipment decision making within the healthcare network.
- Medical equipment scheduling within the healthcare network.
- Medical equipment decision making and medical equipment scheduling within the healthcare network.



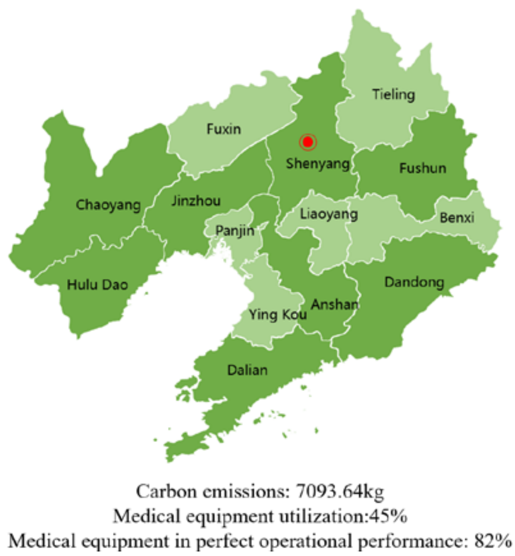
(a). Natural situation.



(b). Medical equipment decision making (IVIF-TOPSIS) within the healthcare network.



(c). Medical equipment scheduling (NSGA-II-MOPSO) within the healthcare network.



(d). Medical equipment decision making (IVIF-TOPSIS) and medical equipment scheduling (NSGA-II-MOPSO) within the healthcare network.

Figure 7. Carbon emissions, medical equipment utilization, rate of medical equipment in perfect operational performance under four cases.

Combined with the comparison of the four sets of the simulation results within Figure 7(a) to (d), we found that IVIF-TOPSIS can effectively save the time of medical equipment decision-making and guarantee the operational performance of medical equipment. However, this method is not suitable for large-scale medical device scheduling decision-making processes within the healthcare network. In addition, this approach makes it difficult to make medical equipment scheduling decisions that balance the carbon footprint and relieve the pressure on healthcare. NSGA-II-MOPSO can quickly make medical equipment scheduling decisions that balance medical equipment utilization with the carbon emissions of patients traveling to the hospital. However, this method cannot ensure the operational performance of the scheduled medical equipment. The sustainable scheduling system that incorporates both approaches is beneficial in ensuring equipment operational performance, relieving regional healthcare pressures, reducing the carbon footprint of patient travel to hospitals, and improving medical equipment utilization. Combined with a sustainable medical equipment scheduling system, carbon emissions were reduced by 3500.71kg (33% reduction in carbon emissions), which is a 45% increase of medical equipment in a perfect operational performance.

Combined with the dynamic medical equipment configuration framework, we implemented the medical equipment scheduling process within the medical network. At the end of medical equipment scheduling, Figure 8 shows the comparison of the number of patients and carbon emissions of the four provinces before and after medical scheduling. Table 4 shows the data related to medical equipment utilization and carbon emissions during the epidemic. Combined with Figure 8 and Table 4, we found that the number of patients in the four provinces was reduced through the sustainable scheduling system for medical equipment. In addition, the carbon footprint of patients traveling to hospitals was reduced because most patients only needed to travel to local hospitals for treatment.

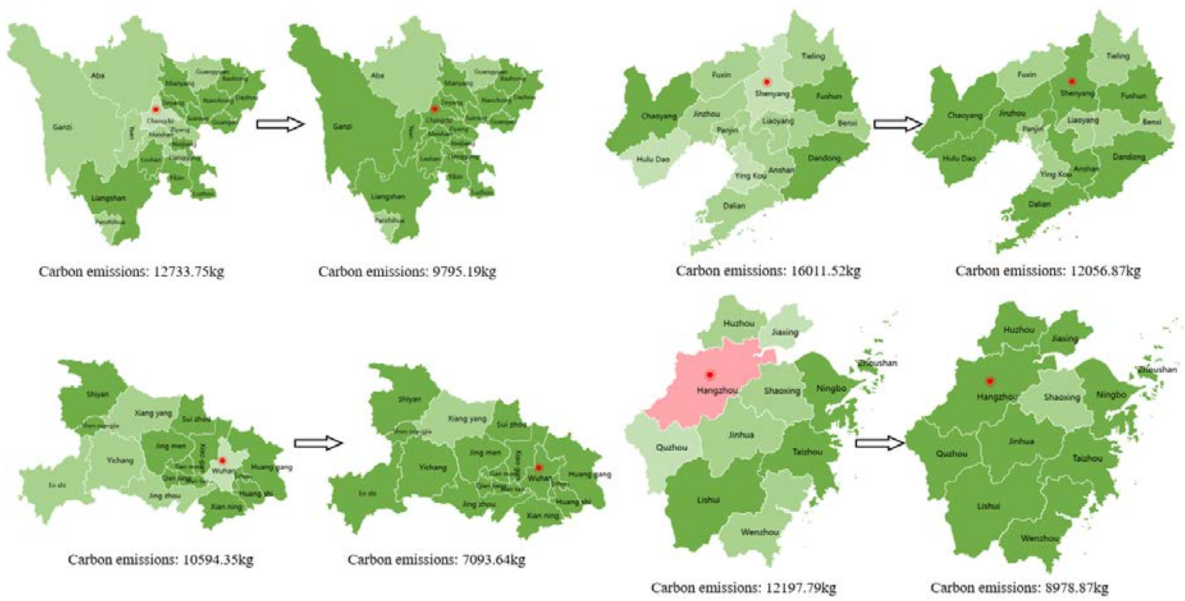


Figure 8. Comparison of the number of patients and carbon emissions before and after medical scheduling.

The continuous scheduling process of medical equipment will effectively solve the previous model of medical equipment fixed in a hospital. Flexible and continuous scheduling will increase the utilization of medical equipment and reduce environmental pollution. In the past, medical equipment was often hampered by the lack of information and data flow. While hospitals in one region are already under a lot of pressure, hospitals in other regions are just beginning to implement medical equipment scheduling. This does not make for good healthcare and still results in a higher carbon footprint due to the high number of patient trips to hospitals. Combined with Figure 8 and Table 4, we found that the four provinces increased the utilization of medical equipment by 11%, 14%, 12% and 12%, respectively. Sichuan, Liaoning, Hubei, and Zhejiang provinces all showed reductions in carbon emissions from patients traveling to hospitals. The reduction of carbon emissions generated by patients traveling to hospitals in the four provinces was 2938.56kg, 3954.65kg, 3500.71kg, and 3220.92kg, respectively.

Table 4. Comparison of Medical Equipment Utilization and Carbon Emissions (Columns 2-3 represent patient carbon emissions for the four provinces before and after scheduling. Columns 4-5 represent medical equipment utilization before and after scheduling.)

Region	Patient carbon emissions in March 2022 (kg)	Patient carbon emissions after medical equipment scheduling (kg)	Medical equipment utilization in March 2022	Utilization of medical equipment after medical equipment scheduling
Zhejiang	12733.75	9795.19	35%	46%
Hubei	16011.52	12056.87	24%	38%
Liaoning	10594.35	7093.64	33%	45%
Sichuan	12197.79	8976.87	21%	33%

The carbon emission reduction rates of the four provinces are 23%, 24%, 33% and 26% respectively. At the same time, the number of patient trips to hospitals and the probability of medical risks were also reduced. Combined with a sustainable scheduling system for medical equipment, the number of patients in the four provinces was reduced and time spent traveling to hospitals for treatment was saved. The time for patients to travel to hospitals within the four provinces was reduced by 27%, 34%, 19% and 29%, respectively. In addition, the pressure on healthcare in some regions is shared by the entire healthcare network. In summary, we have found that the system can help to reduce patient care time within the healthcare network, regional healthcare pressures, the carbon emissions of patients travelling to hospitals and improve the utilization of medical equipment.

Combining the above case results, we believe that sustainable medical equipment scheduling systems can effectively enhance the medical processing capacity of hospitals within a healthcare network. With limited healthcare resources, the rapid flow of resources within a healthcare network will stimulate the greatest healthcare potential. On the one hand, the continuous scheduling of medical equipment within the system will enable centralized treatment to meet patient needs in the fastest way possible. On the other hand, this sustainable scheduling will effectively reduce the number of patient travels to the hospital and avoid unnecessary environmental pollution. In addition, we realized the improvement of medical equipment reliability by utilizing IVIF-TOPSIS, which guarantees the safety of patients and reduces medical risks. The medical data-based service system will better realize green healthcare and avoid a lot of environmental pollution.

5. Conclusion and future work

In a healthcare environment where healthcare resources are limited, the scheduling of medical equipment resources within a healthcare network consisting of individual hospitals plays a significant role. Hospital information systems facilitate the exchange of information between hospitals and patients, which will enhance the sustainability of the healthcare service system [45]. While considering the hazards to the medical environment caused by the waste generated in the medical process, the medical equipment scheduling decision model constructed in this study that considers pollution will help realize the initial screening of equipment resources to ensure the safety and reliability of dynamic medical equipment within the scheduling network. The sustainable scheduling system for medical equipment is realized by combining the IVIF-TOPSIS methodology to screen medical equipment to ensure that the medical equipment available for scheduling can exert a stable medical capability. In addition, the health and safety of patients and healthcare workers can be effectively safeguarded by the relevant indicators. Combined with the medical equipment selected by IVIF-TOPSIS method, we constructed a corresponding multi-objective model and solved it with the NSGA-II-MOPSO algorithm to discover the accurate scheduling of medical equipment in the medical network. The dynamic medical equipment configuration framework can simulate the scheduling process of equipment within a healthcare network and combine it with a multi-objective model based on the concept of green healthcare to achieve a balance between patient needs and carbon emissions. Combined with case studies, a sustainable medical equipment scheduling system can effectively improve the utilization of medical equipment resources. This will reduce carbon emissions from unnecessary medical equipment production, medical equipment operation and patient travel to the hospital. However, the methods presented in the paper still have some limitations. First, the paper only focuses on how to solve the medical pressure in the sub-region as quickly as possible, rather than considering the upper limit of the number of equipment schedules. The frequent scheduling process of medical equipment resources requires some scheduling time. In addition, the frequent medical equipment scheduling process may reduce the medical equipment utilization rate. Thus, the issue of how to establish a medical equipment scheduling system to achieve a balance between scheduling time and medical equipment utilization requires more research and analysis. Second, the method proposed within the paper can improve the solution quality through more accurate multi-objective algorithms. In addition, a huge number of medical equipment resources can be accurately screened for qualified medical equipment for scheduling using methods such as machine learning. Third, the article did not fully consider the transfer of healthcare data between subregions and real-time information statistics of patients. It is difficult to collect personal information about patients in time for the selection and pre-scheduling of medical equipment. Thus, a transparent, comprehensive, and convenient healthcare platform is needed, which will function as a real-time interaction between patient information and hospital information.

In a future healthcare network system, multiple hospitals can jointly purchase urgently needed medical equipment to relieve the pressure of healthcare within the network, and the continuous scheduling of medical equipment within the healthcare network will effectively enhance the digital healthcare service capacity. In addition to a well-functioning hospital dispatch system, medical staff and government can make more flexible judgments to resolve major medical emergencies. While patients are traveling to the hospital, paramedics need to transmit real-time and uninterrupted patient information to the hospital to inform doctors of the situation, and some of the closer medical equipment resources can be scheduled close to the hospital to prioritize the sudden medical needs. In addition, the government should set reasonable and dynamic standards for emergency medical care. In the actual application scenario, the medical equipment sustainable scheduling system can be applied not only to the decision-making process of medical equipment in the epidemic environment, but also to other scenarios, such as flood disasters; earthquake disasters; typhoon disasters and other natural disasters, saving decision making time for decision makers while maximizing the decision results to meet actual needs. It is worth noting that when combining different emergency scenarios, reasonable and comprehensive factor indicators should be constructed to ensure that medical equipment resources are more relevant to actual needs. For future research, we propose the suggestions as follows:

- Based on the uncertain medical situation, future research can respond to the complex emergency medical environment by building more accurate patient prediction models. In addition, hospitals can achieve early scheduling of medical equipment in a way that alleviates the stress of the upcoming medical response.
- Future research can realize the rapid recycling of medical waste within the closed-loop supply chain based on digital technology to further reduce the problem of environmental pollution from medical waste [46].
- Hospitals can develop advanced medical information systems to provide real-time statistics on patient information, medical equipment information, etc [47]. This will help connect patients with hospitals and reduce unnecessary travel for greener healthcare.
- Hospitals can improve the proficiency of medical staff through training to avoid the risk of medical errors caused by the lack of proficiency in operating equipment. Meanwhile, with the improvement of digital information, hospitals can enter the proficiency level of medical personnel and other information into the medical platform to realize the matching of human resources and medical equipment resources.

Use of AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare there is no conflict of interest.

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