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Article

Enhancing disaster management through multi-objective water wave optimization for medical supplies storage and distribution

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Abstract: This paper conducts a comparative analysis of advanced methodologies aimed at addressing the intricate task of scheduling medical supplies in both civilian and military sectors for epidemic prevention and control. This study introduces a multi-objective water wave optimization (MOWWO) algorithm and enhances its efficacy by incorporating a dynamically adjusted component to the metaheuristic approach (DAMOWWO). The primary goal of this research is to assess the proposed approach in contrast to established state-of-the-art methods with similar objectives. The aim of this study is to optimize multiple aspects simultaneously, including the overall satisfaction rates of medical supply delivery and the reduction of scheduling costs, while ensuring a minimum military supply reservation ratio. This paper offers a comprehensive evaluation of the MOWWO algorithm, emphasizing its potential applications in emergency response scenarios. The DAMOWWO algorithm demonstrated the best performance outperforming state-of-art algorithms by a 10%, significantly optimizing medical supply scheduling for epidemic prevention and control.

1. Introduction

Prediction algorithms have the capabilities to address problems in various fields and sectors such as logistics, health, and social [1–3]. In the last ten years, considerable research focus has been directed towards the Healthcare Supply Chain, a domain encompassing the effective management of resources, logistics, and processes associated with the procurement and distribution of medical supplies and equipment [4]. The emphasis has predominantly revolved around investigating healthcare supply chain operations, technology integration, and best practices in routine scenarios [5]. Nevertheless, there is a noticeable gap in

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research addressing healthcare supply chain operations during abnormal conditions, such as disasters like earthquakes, floods, epidemics/pandemics, landslides, and technological accidents [6]. Further exploration in this realm is essential to enhance our understanding and preparedness for managing healthcare logistics in crisis situations [7].

The global public health landscape has faced recurring challenges from major epidemics, such as the coronavirus (COVID-19), underscoring the crucial importance of efficiently managing medical supplies, especially during disruptions caused by pandemics. The natural course of the healthcare supply chain is often disrupted during such outbreaks, impacting demand dynamics. In scenarios like the COVID-19 pandemic, the demand for essential medical resources like masks, ventilators, and hospital beds experiences an exponential surge, straining the capacities of civilian medical services [8]. Addressing this challenge involves considering the use of military medical resources as a feasible solution to bridge the supply gap and ensure comprehensive epidemic prevention and control [9]. However, integrating military and civilian resources poses its own challenges, including the need to navigate complexities such as interoperability issues, distinct operational protocols, and variations in resource availability.

Recent advancements in algorithmic approaches have shown promise in optimizing healthcare supply chains, particularly during emergencies. Particle Swarm Optimization (PSO) has been utilized for its efficiency in solving complex logistics problems by mimicking social behavior patterns. Genetic Algorithms (GA) are widely applied due to their robustness in searching large solution spaces, making them suitable for scheduling and resource allocation in healthcare. Multi-Objective Optimization algorithms, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), have demonstrated effectiveness in balancing multiple conflicting objectives, such as cost and delivery time, in healthcare logistics. Additionally, hybrid algorithms that combine the strengths of different metaheuristics have emerged. For instance, recent research has developed hybrid algorithms that combine PSO and GA to optimize medical supply distribution under uncertain demand conditions, highlighting their efficacy in addressing logistics and scheduling challenges [10, 11].

Effectively managing medical supply shortages during epidemics is crucial for protecting public health and mitigating the impact of such crises. In this context, the article titled "Multi-Objective Optimization of Integrated Civilian-Military Scheduling of Medical Supplies for Epidemic Prevention and Control" [12] serves as a foundational resource for our proposed approach. The article underscores the challenges posed by epidemics and introduces a multi-objective optimization framework. This framework aims to concurrently maximize the overall satisfaction rate of medical supplies, minimize the total scheduling cost, and adhere to constraints such as the maximum supply capacity of military medical services, the allowable number of patients for open military medical services, and the lower limit. The approach utilizes a multi-objective optimization evolutionary method based on the water wave optimization (WWO) metaheuristic to address these complex problems. Additionally, recent advancements in the field include "A Multi-objective Sustainable Medicine Supply Chain Network Design Using a Novel Hybrid Multi-Objective Metaheuristic Algorithm." This approach introduces an innovative hybrid algorithm that combines PSO and GA to attain Pareto solutions, effectively addressing logistics and scheduling challenges while optimizing various objectives within the context of an NP-hard problem [13].

In this context, the objective of this paper is to apply and build upon the strategies outlined in the referenced guide study. The focus is on improving the efficiency of storage and distribution of medical supplies within the domain of technological emergency management. The upcoming sections will provide a detailed exploration of the methodology, related work, problem statement, results, and contributions.

2. Related work

Scheduling problems in medical supply chains have been a subject of extensive research, focusing on optimizing the allocation and distribution of medical resources during disasters and emergencies. For instance, [14] introduces a stochastic multi-objective mixed-integer mathematical programming approach for logistic distribution and evacuation planning during earthquakes. Similarly, [15] proposes a two-stage stochastic emergency supply planning model for regional healthcare coalitions, aiming to minimize total cost and the maximum supply shortage rate.

Multi-objective optimization techniques have been employed to tackle complex scheduling problems in disaster scenarios. [16] presents a multi-objective optimization approach based on mathematical programming to address resource management challenges related to hospitalizing ill patients, particularly in emergency scenarios like pandemics. Additionally, [17] introduces a multi-objective optimization approach for resilient project scheduling under uncertain activity durations. Resiliency, measured by schedule adaptability to disruption, is assessed using a surrogate measure considering activity float and associated risks.

The Water Wave Optimization (WWO) algorithm has gained attention for its applicability in solving complex optimization problems [18]. Researchers have explored its use in disaster management contexts. For instance, the authors propose a multi-objective discrete water wave optimization (MODWWO) algorithm for solving the job shop scheduling problem with variable processing speeds [19]. Moreover, the paper [20] introduces a novel emergency transportation planning model that integrates rail and road transportation, addressing complex constraints and hybrid networks.The proposed hybrid algorithm combines water wave optimization (WWO) and particle swarm optimization (PSO) meta-heuristics, achieving effective exploration and exploitation in the search space.

Finally, the paper [21] introduces two Water Wave Optimization (WWO) algorithms tailored for Flow-shop Scheduling Problem (FSP). The first adapts the original evolutionary operators of WWO to the FSP solution space, while the second enhances the first by incorporating a self-adaptive local search procedure. Experimental results demonstrate the effectiveness of the proposed strategies in solving FSP. The WWO algorithm with self-adaptive local search shows significant performance advantages over other well-known metaheuristic algorithms. In other fields, while handling the scheduling problems, [22] introduces an energy-conscious FJSP model that aims to optimize the sum of energy consumption cost and completion-time cost. To address this discrete optimization problem, a discrete water wave optimization (DWWO) algorithm is proposed. The DWWO algorithm employs a three-string encoding approach and adapts discrete evolutionary operations (propagation, refraction, and breaking) tailored to the characteristics of the FJSP.

In summary, the highlighted research collectively emphasizes the importance of tackling scheduling issues in medical supply chains amidst disasters. It underscores the efficacy of employing multi-objective optimization techniques to improve disaster response strategies. Moreover, it acknowledges the promising potential of the Water Wave Optimization algorithm in addressing intricate challenges within disaster management contexts.

3. Problem statement

This study aims to tackle the scheduling complexities associated with coordinating medical resources for both civilian and military purposes, specifically in the realm of epidemic prevention and control. The objective is to efficiently allocate supplies between civilian and military services, taking into consideration the characteristics of the supplies, service capacities, and confidentiality requirements. The overarching goal is to strengthen epidemic prevention and control measures, particularly in scenarios like the COVID-19 pandemic. For instance, the satisfaction rate of the medical N95 mask was 52.57% during the pandemic in Wuhan, China. The variables for defining the problem are structured as follows [12]:

- There are m civilian and m_0 military medical services. Within a defined planning period, each service i is expected to cater to a specific number (or expected number) of individuals, including normal residents, suspected cases, mild cases, and severe cases, denoted as $i-th$ service are n_i^0, n_i^s, and n_i^v, respectively.
- The tasks encompass a variety of medical supplies, which can be categorized into K types. These supplies consisted of gK_1 non-fixed types (e.g., medical masks, protective clothing, and portable CT scanners) and gK_2 fixed types.
- Notably, non-fixed supplies, denoted as K_1, constitute the initial set among all K types. Each type of supply is associated with a weight ω_k $(1 \leq k \leq K)$, determined based on its level of significance in the context of epidemic control, subject to $\sum_{k=1}^{K} \omega_k = 1$.
- The amount of the k-th type of medical supply available at the i-th civilian medical service is a_{ik}, and the amount the k-th type of medical supply required per normal resident, suspected case, mild case, and severe case is r_k^0, r_k^s, r_k^v respectively $(1 \leq i \leq m; 1 \leq k \leq K)$.
- In epidemics, medical services might not have enough supplies. Therefore, supplies from m' military medical services are also utilized. Some military medical services can admit outside patients (open), while others cannot be due to confidentiality requirements (closed).

During an epidemic, such as the one examined in this paper (COVID-19), civilian medical services often face a shortage of essential supplies. To address this deficiency, they turned to military medical services for additional resources. Consequently, the problem at hand necessitates decision-making in three key aspects.

- How much of each non-fixed supply should be dispatched from each military medical service to each civilian medical service (x_{ijk}).
- How much of each non-fixed supply should be dispatched from each closed military medical service to each open military medical service (x_{jjk}).
- How many people from each group (normal residents, suspected cases, mild cases, severe cases) should be reallocated from each civilian medical service to each open military medical service $(y_{ij}^o, y_{ij}^s, y_{ij}^m, y_{ij}^v)$.

3.1. Supplies satisfaction rates

To address this deficiency, they turned to military medical services for additional resources. Consequently, the problem at hand necessitates decision-making in three key aspects. The primary objective function of the problem is to enhance, maximize the overall weighted satisfaction rate of all medical supplies:

$$\mathrm{MaxS}(x,y) = \frac{1}{m+m''} \left(\sum_{i=1}^{m} \sum_{k=1}^{K} \omega_k \theta(i,k) + \sum_{j=1}^{m''} \sum_{k=1}^{K} \omega_k \theta'(j,k) \right). \tag{1}$$

3.2. Scheduling costs

The second objective function is to minimize the total scheduling cost. In real-world scenarios, decision-makers usually establish an upper limit $\bar{C}$ for the total scheduling cost and a lower limit $\bar{S}$ for the overall supply satisfaction rate. In this case, $\bar{C}$ is employed to normalize the second objective, ensuring it falls within the same order of magnitude as the first objective. This normalization process is described as follows:

$$\max C'(x,y) = 1 - \frac{\min(C(x,y),\bar{C})}{2\bar{C}}. \tag{2}$$

3.3. Constraints

A valid solution $(\mathbf{x}, \mathbf{y})$ for this problem must adhere to the following set of constraints:

- A military medical service must reserve a minimum amount b_{jk} of each type of supply (e.g., for unexpected military use).
- The number of residents/patients received by an open military medical service has an upper limit (denoted by an overline).
- The overall supply satisfaction rate cannot be below the low limit: $S(\mathbf{x}, \mathbf{y}) \geq S$, where S must not fall below a predetermined lower limit.
- The total scheduling cost cannot exceed the upper limit: $C(\mathbf{x}, \mathbf{y}) \leq \overline{C}$, where $\overline{C}$ must not surpass the predefined upper limit.

4. Methodology

A Multi-objective Water Wave Optimization (MOWWO) algorithm was introduced to efficiently tackle the problem presented in the previous section, rapidly yielding an almost Pareto-optimal set of solutions. MOWWO draws inspiration from the principles of shallow water wave theory applied to the optimization of intricate systems . In this algorithm, a population of solutions is maintained, and each solution is characterized by a wavelength denoted as λ, which is inversely related to its fitness. During each generation, solutions generate offspring within a hyper-sphere defined by a radius of λ [24,25]. A Multi-objective Water Wave Optimization (MOWWO) algorithm, shown in Algorithm 1 was introduced to efficiently tackle the problem presented in the previous section, rapidly yielding an almost Pareto-optimal set of solutions.

Algorithm 1 Water Wave Optimization Metaheuristic Algorithm [20]

Randomly initialize a population P of n waves (solutions);
while stop criterion is not satisfied **do**
  for each $x \in P$ do **do**
    Propagate x to a new x' based on Equation 3;
    if $f(x') > f(x)$ **then**
      if $f(x') > f(x_*)$ **then**
        Break x' based on Equation 7;
      end if
      Update x_* with x';
      Replace x with x';
    else
      Decrease $x.h$ by one;
      if $x.h = 0$ **then**
        Refract x to a new x' based on Equation 5 and 6;
        Update the wavelengths based on Equation 4;
      end if
    end if
  end for
end while
return x_*; =0

where:

$$x'(d) = x(d) + \text{rand}(-1, 1) \cdot \Lambda L(d) \tag{3}$$

$$\lambda = \Lambda \cdot \alpha - \frac{(f(x) - f_{\text{min}})}{(f_{\text{max}} - f_{\text{min}})} \tag{4}$$

$$x'(d) = N\left(\frac{(x_*(d) + x(d))}{2}, |x_*(d) - x(d)|/2\right) \tag{5}$$

$$\lambda' = \lambda \frac{f(x)}{f(x')} \tag{6}$$

$$x'(d) = x(d) + N(0, 1) \cdot \beta L(d) \tag{7}$$

MOWWO draws inspiration from the principles of shallow water wave theory applied to the optimization of intricate systems [23]. In this algorithm, a population of solutions is maintained, and each solution is characterized by a wavelength denoted as λ, which is inversely related to its fitness. During each generation, solutions generate offspring within a hyper-sphere defined by a radius of λ [24, 25].

This strategy allows highly fit solutions to exploit local areas, whereas less fit solutions explore more extensive solution spaces, striking a balance between global and local exploration. Furthermore, MOWWO employs an intensive local search around a recently discovered optimal solution and discards the solution if it fails to produce improved offspring after a specified number of generations, thereby preventing search stagnation [26].

4.1. Solution initialization

The steps for initializing each solution in the population of solutions are presented in Table 1. These steps involve the determination of various parameters and decision variables to establish a comprehensive solution.

Table 1. Steps for initializing each solution in the population of solutions.

Step	**Description**
1	Determine Service Capacity: For each civilian medical service, calculate a percentage that represents how much of its current supplies are just enough to treat residents.
2	Allocate Resources: If the calculated percentage is less than 100% (which means the civilian medical service cannot serve all the residents/patients assigned to it), set a random ratio of residents that will be sent to open military.
3	Allocate Resources for all: Repeat the previous step for normal, suspected cases, mild cases, and severe cases. This ratio is divided into parts to obtain decision variables.
4	Calculate Supply Shortage: For each type of non-fixed supply, calculate the set of civilian medical services where the supply is not sufficient for treating the remaining residents/patients.
5	Distribute Supplies: For each open military medical service and each type of non-fixed supply, if the supply is sufficient for the residents/patients received by the service, divide the remaining amount of this supply into parts for the civilian medical services.

4.2. Solution evolution

The algorithm improves upon the original single-objective Water Wave Optimization (WWO) method to handle multi-objective optimization tasks. While initially designed for single-objective optimization, the authors of the MOWWO adapted WWO to address multi-objective optimization by incorporating an efficient non-dominated sorting technique inspired by NSGA-II [9]. This technique assigns a rank, represented by rank(X), to each solution $X = (x, y)$ within the solution population. The ranking procedure entails a sequential assignment of ranks, where the first rank is allocated to the current nondominated solutions, followed by subsequent ranks for newly identified nondominated solutions. Solutions that violate constraints and are infeasible are dominated by feasible solutions. To calculate the wavelength (λ) of each solution X, the following formula was used:

$$\lambda(x) = \alpha \frac{\text{rank}(x)}{\text{rank}_{\max}} \tag{8}$$

where rank max represents the highest rank value within the population, and α serves as a control parameter. For further details on constraint handling and comprehensive information, refer to the guide paper [8].

4.3. Algorithm Approach

Algorithm 2 provides the framework for the DAMOWWO method, specifically crafted to tackle the integrated civilian-military medical supply scheduling challenge. Termination occurs once the algorithm acquires the existing nondominated solution set. This set is then presented to the decision maker, accompanied by a visual representation illustrating the distribution of objective function values. The decision maker can subsequently opt for a final solution for implementation, aligning with their preferences regarding supply satisfaction rate and scheduling cost.

Algorithm 2 Dynamically Adjusted Multi-Objective Water Wave Optimization (DAMOWWO Algorithm)

Initialize a population of solutions.
Initialize a parameter, say λ_0, as the initial wavelength value.
while the stopping condition is not met **do**
    Perform non-dominated sorting of the solutions in the population.
    for each solution X in the population **do**
        Calculate the wavelength $\lambda(X)$ based on Equation (1) using the current λ_0 and progress metrics.
        Use the procedure described to produce a child solution X_0.
        Perform possible reparation on X_0 to ensure validity.
        if $\text{rank}(X_0) < \text{rank}(X)$ **or** ($\text{rank}(X_0) = \text{rank}(X)$ **and** $s(X_0) > s(X)$) **then**
            Replace X with X_0 in the population.
        end if
        if X is a new non-dominated solution **then**
            for $k = 1$ to K_N **do**
                Generate a neighbor X_0 of X.
                if X_0 is better **then**
                    Replace X with X_0 in the population. X has not been improved for h_{max} generations
                    Replace X with a new random solution between X and a non-dominated solution.
                end if
            end for
        end if
    end for
    Update the value of λ_0, based on the progress and convergence of the algorithm.
end while
Return the non-dominated solution set. =0

It's worth noting that both the MOWWO and DAMOWWO algorithms execute non-dominated sorting of solutions in the population, utilizing similar criteria for generating child solutions and population replacement based on dominance and performance. However, the primary distinctions arise from DAMOWWO's incorporation of wavelength dynamics, solution repair, and updates to λ_0 based on algorithm convergence.

By incorporating the parameter λ_0 and updating it dynamically in step 22, the algorithm adapts the wavelength according to the optimization progress. Different strategies to update λ_0, such as reducing it as the optimization proceeds to encourage local search or increasing it to promote exploration in stagnant regions of the solution space, are implemented. This dynamic adjustment is the approach of this study to enhance the algorithm's ability to strike a balance between exploration and exploitation, leading to improved convergence and solution quality.

5. Results

The proposed method in this investigation is tested on four problem instances that are constructed based on data from China during January and February of 2020, the peak period of COVID-19. Table 2 provides an overview of the key attributes of these instances; the main characteristics were kept consistent to enable the evaluation of the algorithms in similar environments. To assess the performance of the DAMOWWO algorithm, the results were compared with the following well-known multi-objective optimization algorithms: Multi-objective Biogeography-Based Optimization (MOBBO) algorithm [27], Multi-objective Particle Swarm Optimization (MOPSO) algorithm [28], and Guide approach MOWWO algorithm [10].

Table 2. Summary of the main characteristics of the problem instance.

ID	m	´	´´	$\sum_i n_i^o$	$\sum_i n_i^s$	$\sum_i n_i^m$	$\sum_i n_i^v$	K_1	K_2
1	39	5	3	1,602,112	1556	385	132	12	7
2	42	6	4	3,195,823	2094	297	96	12	9
3	58	8	5	6,857,710	6720	2335	416	11	8
4	58	8	6	10,693,117	8164	3566	601	13	10

In response to the urgent need for medical supplies scheduling, the study adhered to the guidelines by imposing a maximum CPU time limit of 600 seconds as the termination criterion for each algorithm. The algorithms were implemented using Python, and for each instance, 50 Monte Carlo simulation runs were conducted for each algorithm. Within these 50 runs, the best aggregated objective function value achieved by each algorithm was computed, with the aggregation weight (w) being varied from 0 to 1.

$$\max f(X) = w \cdot S(X) + (1 - w) \cdot C'(X) \tag{9}$$

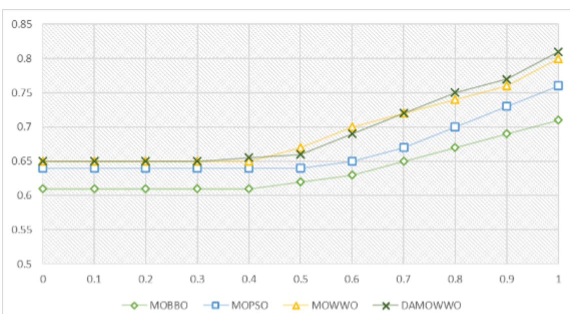
Table 3 details the results of the Best Performance Comparison and Relative Percentage Error metrics for each instance. Where the Best Performance Comparison for each instance, identifying the algorithm with the highest objective function value and calculate the percentage improvement of each algorithm compared to this best value. Respectively, the Relative Percentage Error for each instance, percentage error is calculated of each algorithm compared to the best-performing algorithm. Figure 1 depicts a comparison of the best aggregated objective function values obtained from various algorithms across four instances. The proposed DAMOWWO algorithm demonstrates robust performance, outperforming MOBO, MOPSO, and MOWWO in three out of four instances and yielding comparable results in the remaining one. Overall, DAMOWWO and MOWWO consistently outshine state-of-the-art algorithms.

Moreover, the hyper-volume of the solution set generated by both DAMOWWO and MOWWO consistently surpasses the other two algorithms across all instances. DAMOWWO consistently achieves the most favorable aggregated objective function values, showcasing its remarkable capability to provide optimal solutions that cater to diverse decision maker preferences, whether emphasizing high satisfaction rates, minimizing scheduling costs, or striking a balance between these aspects.

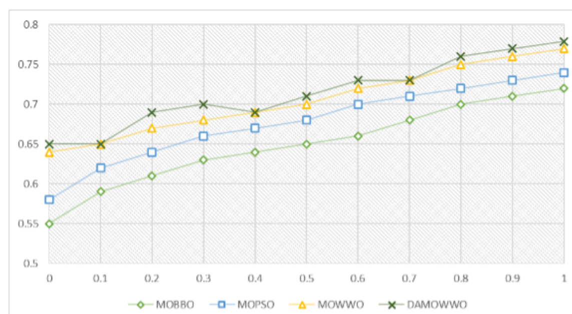
The results decisively establish DAMOWWO's excellence in addressing the integrated civilian-military medical supply scheduling problem for epidemic prevention and control, enhancing the guide-based MOWWO approach. To validate the methods' effectiveness, the overall weighted satisfaction rate of medical supplies was evaluated using solutions from each algorithm, along with a solution derived from mixed to 0-1 integer programming [6], exclusively utilizing civilian medical supplies. Supply weights were assigned based on their significance in epidemic control, as determined by public health experts.

Table 3. Results of Best performance comparison metrics.

Algorithm	Average Improvement (%)	Average Relative Error (%)
MOBBO	5.83	7.96
MOPSO	2.81	5.55
MOWWO	8.38	2.7
DAMOWWO	10.20	2.3

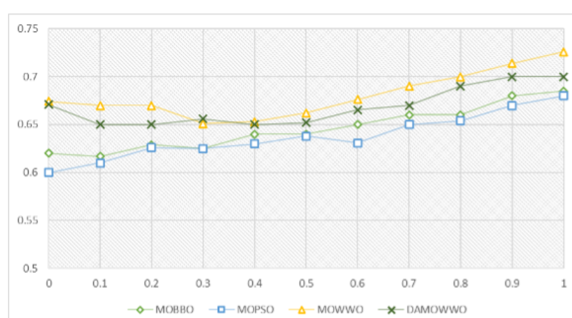


(a) First Instance



(b) Second Instance

(c) Third Instance



(d) Fourth Instance

Figure 1. Best aggregated objective function values obtained from various algorithms across four instances.

6. Conclusions

The successful implementation of the proposed approach, guided by the methodology outlined by G. Richey Jr [6], incorporated significant improvements through a dynamic-adjusted extension, resulting in enhanced performance. While subtle variations in programming environments may introduce minor distinctions, the results strongly support the potential impact of these enhancements. This study extends its relevance beyond the specific problem domain, showcasing its adaptability to a wider array of emergency management scheduling challenges.

DAMOWWO algorithm consistently demonstrated robust performance compared to alternative methods, surpassing MOBO, MOPSO, and MOWWO in three out of the four instances and achieving competitive results in the remaining ones. Across all instances, DAMOWWO and MOWWO consistently outperformed state-of-the-art algorithms, as substantiated by the results. Furthermore, the aggregated objective function value of DAMOWWO consistently ranked as superior in most scenarios, highlighting the adaptability of DAMOWWO and MOWWO in offering optimal solutions regardless of whether the emphasis is on maximizing satisfaction rates, minimizing scheduling costs, or achieving a balance between the two.

In summary, the results decisively establish the superiority of the DAMOWWO algorithm among the three approaches in addressing the integrated civilian-military medical supply scheduling problem for epidemic prevention and control. This advancement significantly enhanced the effectiveness of the guided approach introduced by MOWWO, making a substantial contribution to emergency management scheduling. Additionally, the robustness and adaptability of the DAMOWWO algorithm make it a valuable tool for a broader spectrum of emergency management scenarios.

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Author contributions: Bethsy Guerrero-Granados programmed the intelligent models and conducted the tests. Christian G. Quintero M. supervised the programming of the intelligent models and validated the relevance of the results. Cesar Viloria-Nuñez advised on the relationship between the developments and digital transformation applied to risk management. Miguel Jimeno established the mechanisms for integrating the development into other information systems.

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