

Article

A Novel Multi-Objective Algorithm for Home Health Care Location-Routing and Scheduling with Time Window and Skill Matching

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Abstract

With the accelerating global population aging process, home health care (HHC) has emerged as a promising service mode to satisfy surging elderly medical care needs and alleviate the pressure of offline medical institutions. As a core operational optimization problem in the HHC service system, the home health care routing and scheduling problem (HHCRSP) has attracted extensive research attention in recent years. Different from traditional HHCRSP research, this work proposes a bi-objective mixed-integer programming model for HHC, which integrates facility location, caregiver allocation, route planning and skill-matching rules. The model simultaneously minimizes two competing objectives: total operational cost and total penalty incurred from time window violations. To tackle the high-complexity NP-hard characteristics of this integrated optimization problem, an enhanced non-dominated sorting genetic algorithm (E-NSGA) is designed by introducing dedicated local search operators to improve solution quality. Comparative numerical experiments are carried out on 12 test instances extended from the classic Vidal benchmark, covering four patient scales of 70, 80, 90 and 100 patients. Four state-of-the-art multi-objective metaheuristics, i.e., MOEA/D, MOGWO, NSGA-II and NSGAII-MLS, are selected as baseline comparison algorithms. Experimental results reveal prominent performance advantages of E-NSGA over all comparison methods. In terms of the IGD metric, E-NSGA achieves IGD reductions of 20.19%, 86.30%, 24.98% and 37.72% against MOEA/D, MOGWO, NSGA-II and NSGAII-MLS, respectively. In terms of the Hypervolume metric, E-NSGA obtains performance improvements of 6.22%, 2019.42%, 10.36% and 18.04% relative to the four baseline algorithms. Such quantitative evidence verifies the strong comprehensive optimization capacity of the proposed E-NSGA for addressing the investigated problem.

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1. Introduction

In recent decades, population aging has become a prominent global issue, placing increasing pressure on public health systems, social welfare, and family support structures [1]. The growing number of elderly individuals has led to a surge in demand for long-term medical and nursing services, while traditional hospital-based care is gradually

becoming unsustainable due to limited beds, high operational costs, and overloaded medical staff [2]. Meanwhile, the shortage of qualified nursing professionals further exacerbates the difficulty of meeting the daily care and rehabilitation needs of the elderly. Under such circumstances, home health care (HHC) has emerged as an effective and sustainable service model, which delivers professional medical, nursing, and daily care services to patients in their own residences rather than in medical institutions [3]. By reducing hospital congestion and improving the quality of life for the elderly, HHC has been widely promoted and applied worldwide. Consequently, the scientific planning and intelligent management of HHC service networks have become critical research directions in academia and industry.

As an important branch of HHC management, home health care routing and scheduling problems (HHCRSPs) focus on rationally arranging caregivers' service sequences and travel routes to improve service efficiency, reduce operating costs, and enhance patient satisfaction [4]. In practice, HHC decision-making involves multiple stakeholders with conflicting objectives, including service providers, caregivers, and patients. From the perspective of managers, reducing total operational costs, including travel costs, labor costs, and facility construction costs, is a primary concern [5]. Caregivers pay more attention to reasonable workload allocation and balanced working hours to avoid excessive labor intensity [6]. Patients typically require timely, professional services that match their physical conditions and care needs [7]. Therefore, it is essential to establish a multi-objective decision-making framework for solving realistic HHCRSPs.

Notably, different patients often have differentiated care demands, such as postoperative rehabilitation, chronic disease management, mental counseling, and daily life assistance, which require caregivers with corresponding professional skills and qualification grades [8]. In general, caregivers with higher-grade skills can cover the service demands of patients with lower-grade requirements, whereas caregivers with insufficient qualifications are not allowed to provide services for patients with complex needs [9]. This hierarchical skill-matching constraint significantly increases the complexity of routing and scheduling decisions. In addition, the location design of HHC service centers plays a fundamental role in the entire service network. Reasonable site selection can effectively shorten travel distances, reduce response time, lower long-term operational costs, and improve the coverage and fairness of services. Therefore, the integration of location, routing, and scheduling decisions is of great practical significance for constructing an efficient and economical HHC system.

To fill the above research gaps and meet practical demands, this study investigates a multi-objective home health care location-routing-scheduling problem that simultaneously considers skill-matching and time window requirements. A bi-objective mathematical model is formulated with the goals of minimizing the total operational cost and minimizing the total penalty cost caused by time window violations. To solve the problem efficiently, an enhanced non-dominated sorting genetic algorithm (E-NSGA) is developed, in which problem-specific crossover, mutation, and local search strategies are designed to improve convergence and distribution performance. Finally, extensive numerical experiments and comparative analysis are conducted to validate the effectiveness and advantages of the proposed algorithm. We summarize the main contributions of this study as follows:

- (1) An integrated location-routing-scheduling bi-objective mixed-integer programming model is established. Distinct from existing multi-objective HHCRSP models that only optimize routing and scheduling with fixed service depots, the proposed formulation integrates facility location decisions, patient allocation, caregiver route arrangement, hierarchical skill matching, and time window penalty calculations into a single optimization framework. The total operational cost comprehensively covers facility fixed setup cost, graded skill-dependent labor service cost and travel cost.

Meanwhile, the second objective quantifies the full penalty generated by both early arrival and delayed service to patients.

- (2) An E-NSGA is proposed with problem-tailored genetic operators and local search mechanisms to improve the optimization performance for resolving the considered complex optimization problem. Differing from the greedy local search in existing non-dominated sorting genetic algorithm variants, the embedded local search introduces five simulated annealing-inspired acceptance rules to escape local optima. Meanwhile, multi-segment integer encoding and dedicated crossover operators are customized to fit the joint location-routing-scheduling decision structure of HHC services.
- (3) Comprehensive computational experiments demonstrate the superiority of the proposed algorithm, which can provide decision support for HHC service network design and daily operation management. Statistical tests verify that E-NSGA achieves better convergence and diversity than mainstream multi-objective benchmarks. The generated trade-off solutions offer flexible operation schemes for managers to balance operational costs and service punctuality.

The subsequent sections of this paper are outlined below. We review and analyze the related literature in Section 2. Then, Section 3 provides a detailed problem description and the corresponding mathematical formulation. The proposed algorithm is elaborated in Section 4. Next, we perform extensive computational experiments and offer result analysis in Section 5. Finally, the whole study is summarized and future research topics are given.

2. Literature Review

2.1. Review of Existing HHCRSP Models and Algorithms

Recently, HHCRSPs have been widely studied with various optimization objectives. Gong et al. [10] addressed an HHCRSP involving chargeable overtime and preference matching. An integer programming model was constructed to minimize the total cost composed of travel cost and overtime cost, and a matheuristic approach was developed to solve the model. Li et al. [11] formulated a mixed-integer programming model for an HHCRSP with time window constraints, reaching the minimal operation cost. A genetic algorithm (GA) was employed to obtain efficient solutions. Considering stochastic travel and service times as well as synchronized services, Bazirha et al. [12] studied an HHCRSP with the objective of minimizing total transportation cost. A GA embedded with Monte Carlo simulation was designed to handle the uncertainties. Fu et al. [13] investigated an HHCRSP with uncertain parameters and skill requirements, and built a mathematical model to realize the minimum operational time. Then, they adopted a hybrid framework combining GA and simulation optimization to solve the model. Ceschia et al. [14] studied an HHCRSP to minimize total travel time, and proposed an improved simulated annealing (SA) algorithm to obtain solutions.

In addition to single-objective scenarios, multi-objective HHCRSPs have attracted increasing research attention. Fu et al. [15] addressed an HHCRSP with workload balance considerations. A multi-objective programming model was established to simultaneously minimize operational cost and total delay time, and a problem-aware multi-objective artificial bee colony (MOABC) algorithm was developed to solve the model. Yang et al. [16] investigated a tri-objective HHCRSP aiming to reduce transportation cost, improve service consistency, and balance workload among caregivers. To tackle the problem, an enhanced MOABC algorithm was designed. Li et al. [17] studied an HHCRSP with priorities and uncertainties. To deal with the concerned problem, a multi-objective gray wolf optimizer was designed. Kordi et al. [18] considered four objectives, namely service quality, workload balance, total cost, and carbon emissions. To tackle the considered HHCRSP, they proposed an improved variable neighborhood search algorithm. Bazirha et al. [19]

aimed to minimize service tardiness and caregiver waiting time, and designed a hybrid MOEA combining GA and local search. Du et al. [20] studied a green HHCRSP aiming at reaching the minimization of total cost and carbon emissions. Afterwards, an adaptive GA was developed to solve the problem.

It is widely acknowledged that HHCRSPs belong to the class of NP-hard problems, as they represent practical extensions of the classical vehicle routing problem [21]. Given their computational complexity, heuristic and metaheuristic algorithms have become the dominant solution method in the literature. Clapper et al. [22] devised a new evolutionary algorithm for an HHCRSP to minimize the weighted sum of travel time, overtime, and waiting time. Masmoudi et al. [23] used a variable neighborhood descent algorithm to minimize patient dissatisfaction and improve workload fairness among caregivers. Kummer et al. [24] adopted an improved GA to handle an HHCRSP with the objective of reducing earliness and tardiness incurred by time window violations. Considering the skill needs of patients, Li et al. [25] developed a hybrid solution method combining SA and GA to solve a multi-objective HHCRSP. To minimize total cost and total tardiness simultaneously, Ma et al. [26] designed a cooperative evolutionary algorithm for an HHCRSP with consideration of outsourcing service and patient classification.

As we all know, the non-dominated sorting genetic algorithm II (NSGA-II) [27] serves as a classic baseline for multi-objective optimization. In the field of HHCRSPs, hybrid NSGA-II frameworks embedded with local search have gained substantial research interest in recent years. To jointly minimize caregivers' total working time and elevate service quality, Decerle et al. [28] constructed a hybrid algorithm combining NSGA-II and multi-directional local search. Taking time window constraints into consideration, Xiang et al. [29] designed a hybrid NSGA-II integrated with local search to reduce operational costs and boost patient satisfaction. Ma et al. [30] further incorporated simple swap-based local search into standard NSGA-II for HHCRSPs. Most recently, Zaghdoud et al. [31] put forward NSGAII-MLS, a variant that executes local search at middle generations to optimize travel time, caregiver waiting time and workload balance simultaneously. Nevertheless, all the above studies did not incorporate service center location into joint decision-making, and their local search modules only adopted greedy improvement strategies without multi-type neighborhood structures or simulated annealing (SA)-based probabilistic relaxation to escape local optima.

2.2. Research Gaps and Distinct Novelties

Based on the above literature analysis, we systematically summarize the research gaps of state-of-the-art HHCRSP models and algorithms, and clarify the distinct novelties of this work from two dimensions.

2.2.1. Novelty of the Developed Mathematical Model

- (1) Most existing multi-objective HHCRSP models fix service depots as pre-determined fixed nodes without introducing location selection binary variables and depot capacity constraints. This paper integrates candidate center opening decisions, patient allocation limits, and routing-scheduling variables into a single optimization framework.
- (2) Prior studies simplify skill matching to binary judgment. This work adopts hierarchical skill grade constraints, where high-skill caregivers can cover low-demand patients while low-skill staff cannot undertake complex care tasks, fitting real hierarchical nurse qualification management rules.
- (3) Few existing formulations simultaneously couple depot capacity, caregiver maximum workload, time window penalties, and location-routing joint decisions. The proposed model contains all these practical constraints and two conflicting cost objectives, forming a more realistic integrated HHC decision system.

2.2.2. Novelities of E-NSGA Algorithm

- (1) Most existing NSGA-II variants only adopt greedy local search that easily traps local optima. This paper proposes an E-NSGA whose core innovation lies in SA-driven local search. Concretely, three diversified neighborhood operators are designed, and five groups of SA-inspired solution acceptance criteria are embedded in the local search component. Enabled by the probabilistic judgment mechanism of SA, the proposed local search allows controlled acceptance of inferior candidate solutions during iterations, broadening the exploration scope of the solution space and achieving a favorable trade-off between global exploration and local exploitation. Meanwhile, customized multi-segment integer encoding, crossover, and mutation operators are tailored to match the joint location-routing-scheduling decision structure unique to our problem.
- (2) As two representative benchmark algorithms for comparative analysis, MOEA/D stands as a classic mainstream decomposition-based multi-objective optimizer widely adopted in scheduling research, while MOGWO is a swarm intelligence method that has been specially tailored and applied to solve HHCRSPs in prior studies. Different from the above two approaches, our proposed E-NSGA establishes an external archive to store all non-dominated solutions generated in the entire evolutionary process. Moreover, the embedded SA-inspired local search substantially boosts the convergence and distribution uniformity of Pareto solutions without extra computational overhead.

3. Problem Formulation

3.1. Problem Description

In the studied problem, the core decisions involve selecting an optimal set of HHC centers from a set of candidate locations, while simultaneously optimizing caregiver routing and service scheduling to meet the HHC needs of a given group of patients. Generally, each patient has two requirements. The first is the skill grade requirement, i.e., a patient can only be served by a caregiver whose skill grade is equal to or higher than the patient's required skill grade. The second is the time window requirement, where a penalty cost is incurred if service arrival violates the specified time window.

Each candidate HHC center is characterized by a fixed setup cost and a limited service capacity. Specifically, opening a candidate HHC center incurs a fixed operating cost including facility rental, equipment procurement, and daily management expenses. Additionally, each opened HHC center has a limited service capacity, meaning the total quantity of patients allocated to it cannot surpass this capacity. Once opened, each HHC center is equipped with a certain number of caregivers and medical devices to offer professional care services for assigned patients.

Each caregiver is affiliated with one opened HHC center, which serves as their departure and return point after completing all assigned patients. Caregivers are differentiated by skill grade and labor cost. Each caregiver is assigned a specific skill grade reflecting their service capabilities, which must match the patient's skill requirements. Meanwhile, the labor cost of a caregiver is determined by their skill grade, with higher skill grades corresponding to higher labor costs. Furthermore, the maximum number of patients assigned to each caregiver is restricted to realize workload balance among all staff.

For the considered problem, three decisions need to be made simultaneously: (1) Select and open appropriate candidate locations for HHC centers to provide services; (2) Assign patients to the opened centers; (3) Determine the routing and scheduling schemes for caregivers. An example is shown in Figure 1, which involves three available HHC centers and eight patients, with circles of different colors representing distinct skill requirements.

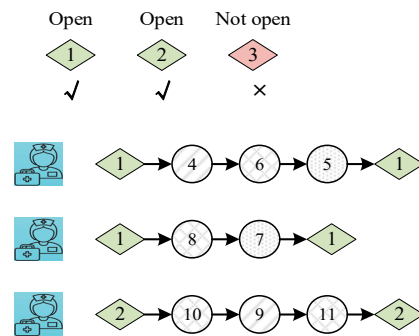


Figure 1. Diagram of the considered problem. (the diamonds represent the candidate HHC centers, the circles represent the patients, and the circles with different shadows are used to differentiate the skill grade requirements of the patients.).

3.2. Mathematical Model

In the formulated model, the used notations are given as follows:

- H : Set of available care centers, $H = \{1, 2, \dots, n\}$.
- F : Set of patients, $F = \{1, 2, \dots, m\}$.
- V : Set of nodes including centers and patients, $V = H \cup F$.
- J_h : Set of caregivers at center h , $J_h = \{1, 2, \dots, a_h\}$.
- G : Set of skill grades, $G = \{1, 2, \dots, g\}$.
- O_h : Fixed operating cost of center h .
- ϖ_h : Maximum service capacity of center h .
- Q : Maximum workload of caregivers.
- ρ_i : Required skill grade by patient i , $\rho_i \in G$.
- ς_{lh} : Skill grade of caregiver l at center h , $\varsigma_{lh} \in G$.
- r_i : Service time that patient i requires.
- η : Basic unit-time service cost.
- S_{il} : Actual unit-time service cost for patient i when served by caregiver l , $S_{il} = \varsigma_{lh}/\rho_i \cdot \eta$.
- $[e_i, d_i]$: Time window that patient i requires.
- ψ : Unit-time penalty cost.
- t_{ij} : Traveling time between two nodes.
- T : Unit-time traveling cost.
- M : A very large number.
- X_h : If center h is opened, $X_h = 1$, otherwise, $X_h = 0$.
- Y_{ilh} : If patient i is visited by caregiver l at center h , $Y_{ilh} = 1$, otherwise, $Y_{ilh} = 0$.
- Z_{ijlh} : If caregiver l at center h travels from patient i to patient j immediately, $Z_{ijlh} = 1$, otherwise, $Z_{ijlh} = 0$.
- A_{ilh} : Time when caregiver l of center h reaches patient i .
- B_{ilh} : Time when caregiver l of center h departs from patient i .
- PT_i : Early or late arrival time for patient i .

Based on the above-defined notations, we construct the multi-objective optimization model as follows.

$$\min \left(\sum_{h \in H} O_h \cdot X_h + \sum_{i \in F} \sum_{l \in J_h} \sum_{h \in H} \varsigma_{lh}/\rho_i \cdot \eta \cdot r_i \cdot Y_{ilh} + \sum_{i \in F} \sum_{j \in F} \sum_{l \in J_h} \sum_{h \in H} T \cdot Z_{ijlh} \cdot t_{ij} \right) \quad (1)$$

$$\min \sum_{i \in F} \psi \cdot PT_i. \quad (2)$$

s.t.

$$Y_{ilh} \leq X_h, \forall i \in F, \forall l \in J_h, \forall h \in H. \quad (3)$$

$$\sum_{l \in J_h} \sum_{h \in H} Y_{ilh} = 1, \forall i \in F. \quad (4)$$

$$\sum_{i \in F} \sum_{l \in J_h} Y_{ilh} \leq \varpi_h, \forall h \in H. \quad (5)$$

$$\sum_{j \in V} \sum_{l \in J_h} \sum_{h \in H} Z_{ijlh} = 1, \forall i \in F. \quad (6)$$

$$\sum_{l \in J_h} \sum_{h \in H} Y_{ilh} \cdot \varsigma_{lh} \geq \rho_i, \forall i \in F. \quad (7)$$

$$\sum_{i \in F} Y_{ilh} \leq Q, \forall l \in J_l, \forall h \in H. \quad (8)$$

$$Y_{ilh} = \sum_{j \in V} Z_{ijlh}, \forall i \in F, \forall l \in J_h, \forall h \in H. \quad (9)$$

$$Y_{jlh} = \sum_{i \in V} Z_{ijlh}, \forall j \in F, \forall l \in J_h, \forall h \in H. \quad (10)$$

$$\sum_{j \in F} Z_{ijlh} \leq 1, \forall i \in H, \forall l \in J_h, \forall h \in H. \quad (11)$$

$$\sum_{j \in V} Z_{ijlh} = \sum_{j \in V} Z_{jilh}, \forall i \in F, \forall l \in J_h, \forall h \in H. \quad (12)$$

$$Z_{ijlh} = 0, \forall i \in H, \forall j \in H, \forall l \in J_h, \forall h \in H. \quad (13)$$

$$\sum_{j \in V} \sum_{l \in J_h} z_{hjlh'} = \sum_{i \in V} \sum_{l \in J_h} z_{ihlh'} = 0, \forall h \in H, \forall h' \in H, h \neq h'. \quad (14)$$

$$A_{ilh} \geq t_{hi} - M \cdot (1 - Z_{hilh}), \forall i \in F, \forall l \in J_h, \forall h \in H. \quad (15)$$

$$A_{jlh} \geq B_{ilh} + t_{ij} - M \cdot (1 - Z_{ijlh}), \forall i, j \in F, \forall l \in J_h, \forall h \in H. \quad (16)$$

$$B_{ilh} \geq A_{ilh} + r_i, \forall i \in F, \forall l \in J_h, \forall h \in H. \quad (17)$$

$$PT_i = \sum_{l \in J_h} \sum_{h \in H} \max(e_i - A_{ilh}, 0) + \sum_{l \in J_h} \sum_{h \in H} \max(A_{ilh} - d_i, 0), \forall i \in F. \quad (18)$$

$$X_h \in \{0,1\}, Y_{ilh} \in \{0,1\}, Z_{ijlh} \in \{0,1\}, A_{ilh} \geq 0, B_{ilh} \geq 0, \forall i, j \in V, \forall l \in J_h, \forall h \in H. \quad (19)$$

Specifically, Equation (1) minimizes the total operational cost, which consists of the fixed operating cost of opened care centers, the service cost, and the traveling cost. Then, Equation (2) aims to minimize the total penalty cost arising from violations of patients' time window requirements. Equation (3) guarantees that each patient is visited by exactly one opened center. Next, Equation (4) denotes that each patient receives service from only one caregiver. Equation (5) imposes a constraint that the total quantity of patients allocated to an opened center can not surpass its service capacity. Subsequently, Equation (6) stipulates that each patient is served exactly once. Equation (7) enforces that the skill grade of the

caregiver assigned to a patient must meet or exceed the skill requirement of that patient. Afterwards, Equation (8) represents workload balance, i.e., the number of patients served by each caregiver shall not exceed a predefined threshold. Equations (9) and (10) give the relationships among the decision variables. Equation (11) means that each caregiver departs from their affiliated center at most once. Equation (12) ensures the flow conservation of routes. Equation (13) forbids any caregiver from departing a service center and returning to it without visiting patients. Equation (14) enforces that each caregiver's full route originates and terminates at an identical center. Equations (15) and (16) determine the service start time for each patient. Equation (17) formulates the time at which a caregiver leaves a patient's location after finishing the service. Equation (18) computes early or late arrival time for patients. Finally, Equation (19) defines the range of decision variables.

3.3. Roles and Functions of Proposed Mathematical Model

The constructed bi-objective mixed-integer programming model serves as a fundamental theoretical foundation for the whole study. Its core functions are summarized as three aspects:

- (1) The model uniformly quantifies practical decision constraints ignored by existing studies, including candidate center location selection, depot capacity limits, hierarchical skill-matching rules, caregiver workload upper bounds, and time window penalty calculations. It formulates cost components, i.e., facility fixed cost, skill-gradient labor cost, and travel cost, into computable objective functions, forming a complete quantitative description of the integrated location-routing-scheduling problem.
- (2) All genetic operators and local search operators in E-NSGA strictly follow the model's equality and inequality constraints. Any newly generated solution is filtered by the model's constraint set to eliminate infeasible schedules during iteration, which guarantees the validity of all Pareto solutions output by the algorithm.
- (3) The two objective functions defined in the model are the unified evaluation criteria for E-NSGA and four comparative algorithms. All metric calculations rely on the objective values derived from the model, ensuring consistent and fair performance comparisons across metaheuristics.

4. Methodology

Although both optimization objectives in the model are measured in monetary units and essentially belong to cost-type functions, the two criteria are mutually conflicting in practical HHC operations and cannot be reasonably aggregated via a static linear weighted sum. Minimizing the total operational cost restricts the number of opened service centers and caregivers' travel distances, which tends to cause more service delays and higher time window penalty costs. Conversely, reducing penalty costs requires sufficient service capacity and earlier arrival time, which significantly raises facility, travel and labor expenditures. This inherent trade-off means the two objectives are antagonistic in actual scheduling. A single-objective weighted convolution approach relies on manually predefined weight values, which cannot adapt to shifting decision preferences. Meanwhile, fixed weights only produce one optimal solution and cannot provide a full set of trade-off alternatives. In contrast, the proposed bi-objective optimization framework yields a set of non-dominated solutions, offering flexible decision options for different practical scenarios. Therefore, this study proposes a multi-criteria optimization method, i.e., E-NSGA, to resolve the considered problem.

Before elaborating on the detailed steps of the proposed algorithm, we first present the overall flowchart of E-NSGA, as shown in Figure 2. To clearly demonstrate the innovations of the proposed E-NSGA, we systematically compare it with the classic NSGA-II

as follows. The standard NSGA-II merely evolves a single population and lacks auxiliary local refinement operations, which renders it susceptible to premature convergence when tackling complex NP-hard location-routing optimization problems. In contrast, our E-NSGA establishes an external archive to store all non-dominated solutions and embeds a dedicated local search module equipped with three neighborhood operators as well as multi-objective solution acceptance policies. This embedded local search enables in-depth exploitation of high-quality solution regions and significantly improves the algorithm's search performance, representing the most prominent innovation distinguishing E-NSGA from conventional NSGA-II.

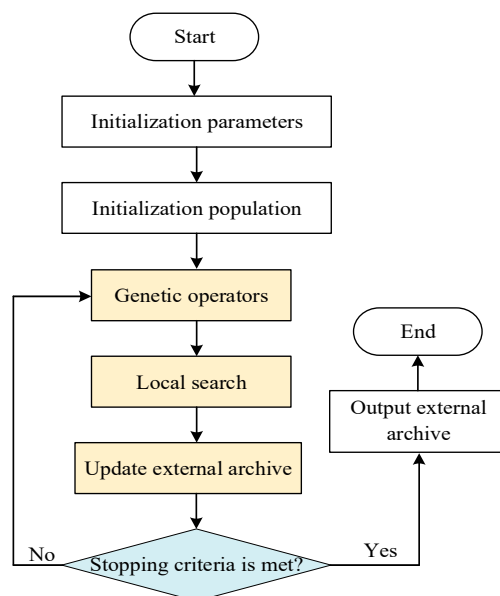


Figure 2. The overall flowchart of E-NSGA.

4.1. Encoding Approach

In the proposed E-NSGA, we use multiple routes to represent a solution (i.e., an individual). Each route corresponds to an integer sequence. Let n be the number of candidate centers and m be the number of patients. The candidate centers are indexed as $1, 2, \dots, n$, and the patients are indexed as $n + 1, n + 2, \dots, n + m$. For each route, the first position represents the index of an HHC center, followed by a sequence of patient indices, which indicates the service order of the corresponding patients. Notably, if a route contains only the index of a center without any subsequent patients, this implies that the center is not selected. For example, consider a case with three candidate centers and five patients. The centers are numbered 1, 2, 3, while the patients are numbered from 4 to 8. Based on the above encoding rule, Figure 3 shows a solution indicating that Centers 1 and 2 are open. Specifically, patients 4, 8 and 7 are assigned to Center 1 and served in this order, while patients 5 and 6 are assigned to Center 2 and served sequentially.

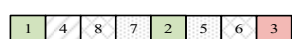


Figure 3. An example of the solution encoding method.

4.2. Population Initialization

In this study, a random method is employed to generate an initial population with PS feasible individuals. The detailed procedure is implemented through the following steps: (1) we assign all patients to the available care centers randomly; (2) we sort patients involved in the same center at random; (3) for each center, we partition the assigned

patients sequentially into multiple routes while respecting the constraint of caregiver workload balance; and (4) to guarantee the skill-matching constraint, for each constructed route, we assign a caregiver whose skill grade matches the maximum skill requirement among all patients on that route. Additionally, an external archive is constructed to preserve the non-dominated solutions obtained throughout the evolutionary process. Specifically, all newly produced individuals are adopted to update the external archive based on the Pareto criterion.

4.3. Genetic Operations

The genetic operations consist of selection, crossover, mutation and population updating, which are detailed as follows:

- (1) **Selection:** A binary tournament selection strategy [32] is adopted to choose two individuals as parent individuals.
- (2) **Crossover:** Based on the selected parents, the proposed crossover operator is implemented according to the following steps.

Step 1: One route is chosen from each parent individual randomly.

Step 2: The patients in the two chosen routes are exchanged while preserving their original service order.

Step 3: The duplicated patients are removed from the remaining routes.

Step 4: The unassigned patients are re-inserted into routes randomly while satisfying all constraints.

An illustrative example of offspring generation is displayed in Figure 4, where two parent individuals are denoted as Parent 1 and Parent 2.

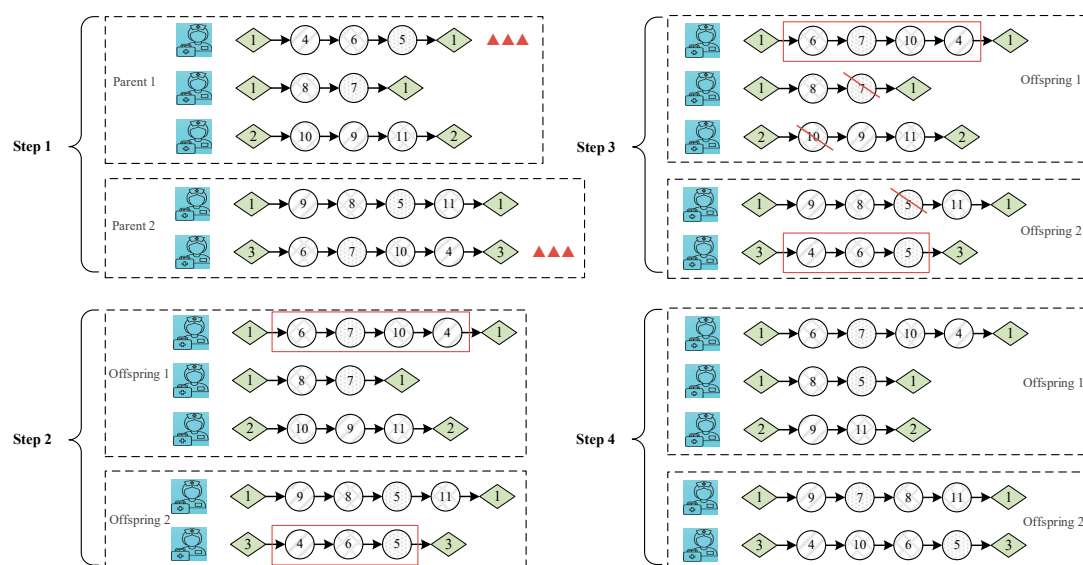


Figure 4. An example of the designed crossover method. The diamonds represent the candidate HHC centers, the circles represent the patients, and the circles with different shadows are used to differentiate the skill grade requirements of the patients.

- (3) **Mutation:** In the mutation process, a randomly selected patient is removed from its route and inserted into another randomly chosen position of the same route. After the crossover operation, this mutation operator is applied to the newly generated offspring with a mutation probability of φ .
- (4) **Population updating:** Through the above-mentioned operations, PS new individuals are generated. The individuals in the population and the newly generated individuals are combined. Then, the best PS individuals are selected using the non-

dominated sorting and crowding distance approach [26] to construct the next-generation population.

4.4. Local Search Strategy

To fully explore high-quality solution spaces and enhance optimization performance, this study designs a local search strategy (LSS) to optimize non-dominated solutions stored in the external archive. This designed strategy adopts three typical neighborhood operators to produce new candidate solutions, which are specified as follows: (1) Swap the visiting order of two randomly chosen patients within a single service route. (2) Exchange service assignments of two patients selected from distinct routes. (3) Pick out one patient from an existing route and re-insert it into any position of another route.

This local search strategy draws on the core search logic of simulated annealing (SA), while discarding the traditional temperature cooling rule used in standard SA. To help the algorithm jump out of local optimal states efficiently, five solution acceptance strategies proposed in reference [33] are applied in this work. We set ς as the initial solution and ς' as its corresponding neighboring solution. All five acceptance policies are listed in Table 1. Among them, Δf_1 and Δf_2 stand for the objective value differences between the new solution and the original one, namely $\Delta f_1 = f_1(\varsigma') - f_1(\varsigma)$ and $\Delta f_2 = f_2(\varsigma') - f_2(\varsigma)$. In addition, ϵ refers to the temperature variable randomly generated in the range $[\epsilon_1, \epsilon_2]$, λ represents a uniformly distributed random value ranging from 0 to 1, and m indicates the overall patient quantity.

Table 1. Five acceptance conditions.

(1) $\Delta f_1 \leq 0, \Delta f_2 \leq 0$
(2) $\Delta f_1 > 0, \Delta f_2 \leq 0$ and $\lambda < \exp(-\Delta f_1/\epsilon)$
(3) $\Delta f_1 \leq 0, \Delta f_2 > 0$ and $\lambda < \exp(-\Delta f_2/\epsilon)$
(4) $\Delta f_1 > 0, \Delta f_2 > 0, \Delta f_1/f_1(\varsigma') < \Delta f_2/f_2(\varsigma')$, and $\lambda < \exp(-\Delta f_2/m \cdot \epsilon)$
(5) $\Delta f_1 > 0, \Delta f_2 > 0, \Delta f_1/f_1(\varsigma') > \Delta f_2/f_2(\varsigma')$, and $\lambda < \exp(-\Delta f_1/m \cdot \epsilon)$

At each iteration, we perform the LSS on each non-dominated solution with a fixed probability α . Meanwhile, $\beta \cdot m$ neighboring solutions are generated using the aforementioned three neighborhood operators. The detailed procedure of the proposed LSS is formally described in Algorithm 1.

Algorithm 1: LSS

Input: α , β , and external archive.

Output: external archive.

Begin

$\kappa := 0; \Lambda := \emptyset;$

for (each solution ς in external archive) **do**

if ($\text{rand}(0, 1) < \alpha$) **then**

while ($\kappa \leq \beta \cdot m$) **do**

 randomly select one of the three neighborhood operators;

 generate a neighbor solution ς' of ς ;

if (any of five conditions is satisfied) **then**

$\Lambda := \Lambda \cup \{\varsigma'\};$

endif

$\kappa := \kappa + 1;$

end while

end if

end for

Update external archive by using the solutions in Λ .
End.

4.5. Complexity Analysis of E-NSGA

This section analyzes the worst-case time complexity of the proposed E-NSGA. Let PS and N_A represent population size and external archive size, respectively. Meanwhile, m is the number of patients.

The worst-case time complexity of each core module in E-NSGA is decomposed and analyzed separately as follows: (1) We select PS parent individuals via binary tournament selection, with a time complexity of $O(PS)$. (2) The crossover and mutation methods are used to generate PS offspring solutions. The overall complexity is $O(PS \cdot (m^2 + m))$. (3) We employ the non-dominated sorting and crowding distance approaches to select PS individuals, with a time complexity of $O(PS^2)$. (4) Three neighborhood operators are executed on all non-dominated solutions stored in the external archive. The corresponding worst-case complexity is $O(N_A \cdot m^2)$. Summing up the complexity of all modules, the total worst-case time complexity of E-NSGA is calculated as: $O(PS + PS \cdot (m^2 + m) + PS^2 + N_A \cdot m^2)$, i.e., $O(PS \cdot m^2)$.

5. Experiments and Discussions

To validate the effectiveness of the proposed E-NSGA, four representative multi-objective metaheuristics are selected as comparative baselines: a decomposition-based multi-objective evolutionary algorithm (MOEA/D) [34], a multi-objective gray wolf optimizer (MOGWO) [16], classic NSGA-II [26], and NSGAII-MLS [30]. MOEA/D and NSGA-II are two mainstream classic multi-objective optimizers that have been widely deployed to address various location-routing and task scheduling optimization problems [35–38]. MOGWO is a recently developed algorithm specially tailored for HHCRSPs, whereas NSGAII-MLS represents a recent improved NSGA-II local-search hybrid scheme proposed for HHCRSP scenarios. Incorporating these four comparative algorithms can fully benchmark the performance of our E-NSGA: the original NSGA-II isolates the optimization gain brought by our dedicated local search operators, NSGAII-MLS enables fair comparison against existing NSGA-II variants with local search for HHCRSPs, and MOEA/D and MOGWO provide cross-category comparisons with decomposition-based and swarm intelligence multi-objective solvers. Such a comprehensive set of closely related baselines guarantees the fairness, sufficiency and persuasiveness of our performance verification. All the algorithms are coded in the C++ programming language and run on the VC++ 2017 platform. The experiments are conducted on a computer equipped with an Intel Core i7-12700 CPU and 16 GB of RAM.

In this work, we use a Taguchi method of Design of Experiment (DOE) [39] to determine four key parameters of E-NSGA. According to the obtained results, the parameters of E-NSGA are configured as follows: $PS = 100$, $\varphi = 0.2$, $\alpha = 0.5$, and $\beta = 0.6$. To ensure fair comparisons, we also employ the DOE to determine the rivals' parameters. Specifically, the population size, mutation rate, and neighborhood size of MOEA/D are set to 100, 0.1, and 10, respectively. The population size of MOGWO is set to 100. The population size, crossover rate, and mutation rate of NSGA-II are set to 100, 0.9, and 0.15, respectively. The population size, crossover rate, mutation rate, and local search probability of NSGAII-MLS are set to 100, 0.85, 0.15, and 0.15, respectively.

5.1. Test Instances

Since there are no benchmark test problems available for the new problem considered in this study, the test instances are constructed by extending the benchmark proposed by Vidal [40]. Specifically, the original benchmark is expanded into four groups,

where each group corresponds to a different number of patients, denoted as $m = \{70, 80, 90, 100\}$. For the groups with $m = 70$ and $m = 80$, the number of available HHC centers n is set to 5. For the groups with $m = 90$ and $m = 100$, the number of available HHC centers n is set to 6. Furthermore, each group is extended to include three distinct instances, resulting in a total of 12 test instances. Each instance is named using the format $m-n-b$, where $b = \{1, 2, 3\}$ denotes the instance number within each group. We extend the classic benchmark instances to match the characteristics of the proposed problem. All standardized cost coefficients, capacity thresholds and skill-matching rules are explicitly defined below for full reproducibility of experimental results.

- (1) The Euclidean distance between any two nodes is directly adopted as travel time. The core monetary coefficients are fixed as follows: unit-time patient service cost is equal to 2, fixed setup cost for each candidate care center is set to 10, unit labor cost of caregivers is equal to 5, and unit-time time window violation penalty cost is set to 2.
- (2) The maximum number of patients that a single caregiver can serve per route is limited to 5, while the upper service capacity of each opened HHC center is restricted to 30 patients.
- (3) Three hierarchical skill grades are introduced for both patients and caregivers. Each patient is randomly assigned two skill levels, with the lower level designated as their minimum service requirement. The quantity ratio of caregivers with low, medium, and high skill grades is set as 6:3:1.

All generated benchmark instances and supporting parameter files will be made publicly available upon paper acceptance for full reproducibility of our experiments.

5.2. Performance Metrics

In our study, we employ two metrics: the IGD metric [41] and the Hypervolume metric [42], to measure the experimental outcomes. Their formal mathematical definitions and practical calculation settings are elaborated as follows.

- (1) The IGD metric simultaneously quantifies the convergence degree and distribution uniformity of a Pareto solution set. Its mathematical formula is presented below.

$$\text{IGD}(\bar{A}, A^*) = \frac{\sum_{\varepsilon \in A^*} d(\varepsilon, \bar{A})}{|A^*|}. \quad (20)$$

In the formula, $\bar{A}$ stands for the non-dominated solution set obtained by a specific algorithm, and A^* refers to the true Pareto front. The term $d(\varepsilon, \bar{A})$ denotes the minimal Euclidean distance from ε to $\bar{A}$. As the exact theoretical Pareto front of the investigated problem cannot be analytically solved in advance, we aggregate all non-dominated solutions generated by all compared algorithms across all test trials to construct an approximate reference front A^* for metric calculation. Lower IGD values correspond to better overall algorithm performance in both convergence and diversity.

- (2) The Hypervolume metric measures the dominated hypervolume bounded by the obtained Pareto set and a predefined reference point, which comprehensively reflects the quality of trade-off solutions. Before calculation, all objective values of non-dominated solutions are normalized to the interval $[0, 1]$. The coordinate point $(1, 1)$ is set as the reference point for all test instances. A larger Hypervolume value indicates that the algorithm can acquire a superior Pareto front with better convergence and wider distribution range.

5.3. Comparisons of E-NSGA with Competitive Algorithms

This section conducts comprehensive comparisons among E-NSGA, MOEA/D, MOGWO, NSGA-II, and NSGAII-MLS. To ensure the reliability and statistical significance of the comparison results, each optimizer is independently implemented for 20 runs.

The termination condition for each optimizer is set as the number of function evaluations reaching $150 \cdot m$.

Table 2 summarizes the mean IGD values and corresponding standard deviations (SDs) of all competing algorithms across all test instances. Evidently, the proposed E-NSGA yields the smallest mean IGD on every test case, which strongly evidences its outstanding convergence capability and uniform distribution of the obtained non-dominated solutions. To quantitatively compare the overall performance, we compute the average IGD of each algorithm over all test instances. The overall average IGD values for E-NSGA, MOEA/D, MOGWO, NSGA-II, and NSGAI-MLS are 0.1111, 0.1392, 0.8112, 0.1481, and 0.1784, respectively. In terms of the IGD metric, E-NSGA reduces the IGD value by 20.19%, 86.30%, 24.98%, and 37.72% relative to MOEA/D, MOGWO, NSGA-II, and NSGAI-MLS, in order, further verifying its remarkable comprehensive performance. Additionally, E-NSGA maintains comparatively low standard deviations on most test instances, revealing its stable searching behavior throughout the optimization process. Collectively, these results demonstrate that E-NSGA consistently outperforms the four peer algorithms in solving the concerned problem.

Table 2. Mean values of all compared algorithms with regard to the IGD metric.

Instance	ENSGA		MOEA/D		MOGWO		NSGA-II		NSGAI-MLS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
70-5-1	0.1030	0.0246	0.1508	0.0589	0.7218	0.0459	0.1403	0.0330	0.1620	0.0304
70-5-2	0.1284	0.0366	0.1452	0.0378	0.8954	0.0710	0.1612	0.0438	0.2115	0.0296
70-5-3	0.1110	0.0286	0.1353	0.0518	0.7697	0.0587	0.1414	0.0392	0.1639	0.0426
80-5-1	0.0900	0.0259	0.1297	0.0397	0.7162	0.0502	0.1379	0.0434	0.1594	0.0247
80-5-2	0.1036	0.0481	0.1513	0.0682	0.8873	0.0566	0.1434	0.0387	0.1997	0.0436
80-5-3	0.1143	0.0259	0.1222	0.0490	0.7544	0.0416	0.1471	0.0383	0.1791	0.0324
90-6-1	0.1215	0.0325	0.1425	0.0393	0.8525	0.0600	0.1621	0.0323	0.1938	0.0344
90-6-2	0.1211	0.0323	0.1465	0.0361	0.7510	0.0547	0.1645	0.0307	0.1904	0.0223
90-6-3	0.1230	0.0315	0.1648	0.0503	0.8529	0.0446	0.1651	0.0376	0.1888	0.0365
100-6-1	0.1037	0.0347	0.1399	0.0339	0.8576	0.0613	0.1383	0.0362	0.1737	0.0387
100-6-2	0.1103	0.0317	0.1324	0.0371	0.8018	0.0602	0.1511	0.0293	0.1699	0.0302
100-6-3	0.1038	0.0248	0.1096	0.0306	0.8739	0.0693	0.1252	0.0356	0.1484	0.0337
Average	0.1111	0.0314	0.1392	0.0444	0.8112	0.0562	0.1481	0.0365	0.1784	0.0333

Table 3 reports the mean Hypervolume values and corresponding standard deviations (SDs) of all competing algorithms across all test instances. The proposed E-NSGA consistently obtains the largest mean Hypervolume on every test case, which manifests its prominent ability to balance convergence and diversity of Pareto solutions. To quantitatively evaluate overall performance, we compute the average HV for each algorithm over all test instances. The resulting overall average Hypervolume values for E-NSGA, MOEA/D, MOGWO, NSGA-II, and NSGAI-MLS are 0.8075, 0.7602, 0.0381, 0.7317 and 0.6841, respectively. In terms of the HV metric, E-NSGA delivers performance improvements of 6.22%, 2019.42%, 10.36% and 18.04% compared with MOEA/D, MOGWO, NSGA-II and NSGAI-MLS. In addition, E-NSGA yields relatively small standard deviations across most test instances, implying stable search performance. Collectively, these outcomes demonstrate the comprehensive superiority of E-NSGA over the four baseline competitors in addressing the considered problem.

Table 3. Mean values of all compared algorithms with respect to the Hypervolume metric.

Instance	ENSGA		MOEA/D		MOGWO		NSGA-II		NSGAI-MLS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
70-5-1	0.7508	0.0530	0.6861	0.0895	0.0571	0.0316	0.6816	0.0649	0.6479	0.0580
70-5-2	0.8007	0.0654	0.7714	0.0628	0.0230	0.0176	0.7466	0.1025	0.6510	0.0638
70-5-3	0.7742	0.0602	0.6923	0.0875	0.0421	0.0323	0.7025	0.0973	0.6750	0.1067
80-5-1	0.8129	0.0534	0.7605	0.0705	0.0676	0.0406	0.7250	0.0860	0.6941	0.0847
80-5-2	0.8642	0.0789	0.7872	0.1010	0.0413	0.0300	0.7880	0.0781	0.7126	0.0873
80-5-3	0.7743	0.0515	0.7555	0.0949	0.0551	0.0318	0.7049	0.0812	0.6650	0.0857
90-6-1	0.8310	0.0735	0.8055	0.0721	0.0187	0.0200	0.7480	0.0586	0.6732	0.0734
90-6-2	0.7894	0.0651	0.7534	0.0710	0.0456	0.0296	0.6975	0.0764	0.6515	0.0544
90-6-3	0.8103	0.0900	0.7385	0.0925	0.0153	0.0129	0.7288	0.0962	0.6826	0.0720
100-6-1	0.8285	0.0700	0.7812	0.0733	0.0188	0.0172	0.7530	0.0844	0.7104	0.0704
100-6-2	0.7990	0.0520	0.7683	0.0757	0.0387	0.0268	0.7144	0.0734	0.6888	0.0766
100-6-3	0.8545	0.0607	0.8227	0.0643	0.0344	0.0319	0.7898	0.0772	0.7574	0.0698
Average	0.8075	0.0645	0.7602	0.0796	0.0381	0.0269	0.7317	0.0814	0.6841	0.0752

To comprehensively validate performance gaps from a statistical perspective, we conduct a paired-samples *t*-test [43]. Table 4 presents the statistical results, including *p*-values, Cohen's *d* effect sizes, and the corresponding 95% confidence intervals for Cohen's *d*. We observe that all *p*-values between E-NSGA and the four competitors are smaller than 0.001, far below the standard significance threshold of 0.05. This outcome verifies that the performance advantages of E-NSGA are not random. In addition, all Cohen's *d* values are greater than 0.8, indicating large meaningful performance differences between E-NSGA and each competing algorithm. Accordingly, we conclude that the proposed E-NSGA exhibits statistically significant and substantial optimization superiority over MOEA/D, MOGWO, NSGA-II and NSGAI-MLS across all test instances.

Table 4. Results of the paired samples *t*-test.

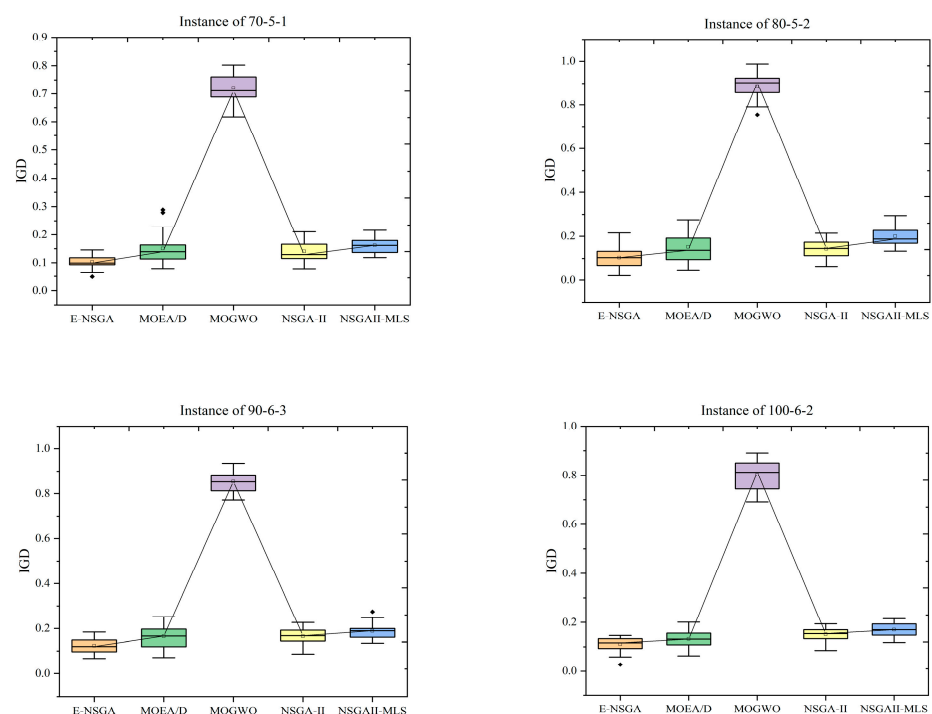
E-NSGA vs.	Metric	<i>p</i> -Value	Cohen's <i>d</i>	95% CI for Cohen's <i>d</i>	
				Lower	Upper
MOEA/D	IGD	<0.001	1.939	0.9454	2.904
	HV	<0.001	2.161	1.092	3.202
MOGWO	IGD	<0.001	11.13	6.518	15.57
	HV	<0.001	17.79	10.45	24.83
NSGA-II	IGD	<0.001	5.236	3.002	7.457
	HV	<0.001	7.075	4.106	10.04
NSGAI-MLS	IGD	<0.001	5.013	2.867	7.146
	HV	<0.001	5.775	3.327	8.213

We divide all test instances into four groups based on the number of patients *m*. Table 5 summarizes the average computational time (in seconds) consumed by E-NSGA and all comparison algorithms for each group. It can be clearly observed that E-NSGA achieves the shortest running time across all problem scales. Compared with NSGA-II and NSGAI-MLS, E-NSGA only saves several seconds under small-scale instances, yet the efficiency gap gradually expands as the number of patients rises. These experimental results demonstrate that the improved neighborhood search mechanism embedded in E-NSGA does not introduce extra computational burden. Instead, the optimized search logic accelerates the optimization process and delivers superior computational efficiency.

Table 5. Average computational time (in seconds) of the five algorithms.

<i>m</i>	E-NSGA	MOEA/D	MOGWO	NSGA-II	NSGAI-MLS
70	13.482	17.190	95.802	15.931	14.494
80	17.375	21.809	150.708	18.821	17.612
90	20.419	28.423	222.903	22.653	22.434
100	23.849	43.523	264.096	28.405	25.441

To intuitively visualize the experimental results, Figure 5 displays the boxplots of the five comparative algorithms on four instances of different sizes, based on the IGD metric. As illustrated in the figure, E-NSGA obtains notably lower median values than the other four algorithms across selected test cases. According to the above comprehensive experimental analysis, we can draw the conclusion that the proposed E-NSGA outperforms MOEA/D, MOGWO, NSGA-II, and NSGAI-MLS for dealing with the investigated problem.

**Figure 5.** Boxplot graphs of five comparative methods regarding the IGD metric.

To visualize the optimization outcomes more clearly, Figure 6 plots non-dominated solution sets derived from all compared algorithms across four distinct test instances. Evidently, the non-dominated solutions yielded by E-NSGA lie much nearer the bottom-left region of each subgraph, in contrast to the solution sets generated by MOEA/D, MOGWO, standard NSGA-II and NSGAI-MLS. Based on the comparative observations above, it can be summarized that the proposed E-NSGA algorithm achieves superior convergence performance when tackling the multi-objective optimization problem studied in this work.

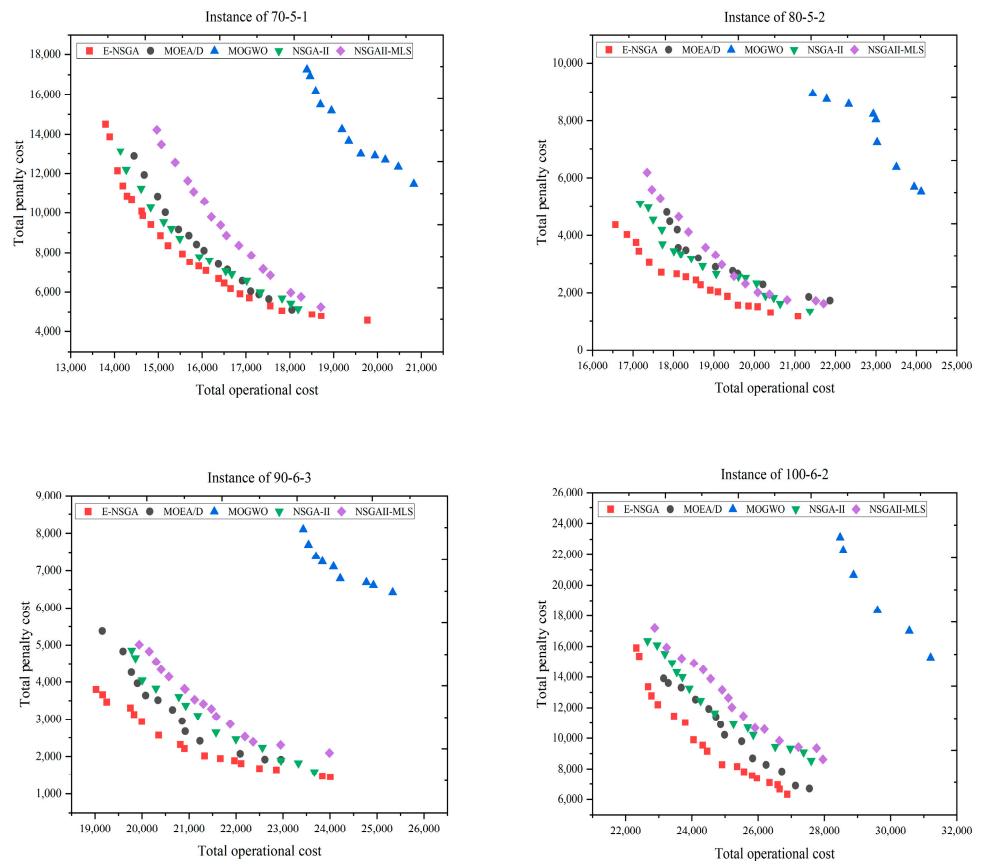


Figure 6. Non-dominated solution sets acquired by all compared algorithms.

To demonstrate the stepwise optimization process of E-NSGA, Figure 7 presents the distribution of Pareto solutions for the medium-scale instance 80-5-3 under three different total function evaluation budgets ($50 \times m$, $100 \times m$, $150 \times m$). As the number of evaluations increases, the data points gradually shift toward the bottom-left region with smaller values for both objectives, which intuitively illustrates the continuous optimization and convergence performance of the proposed algorithm.

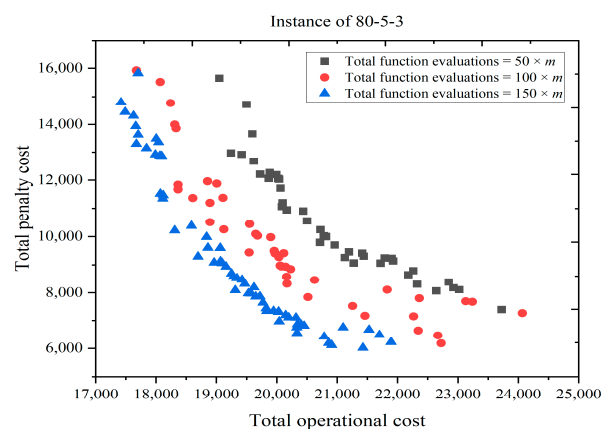


Figure 7. Pareto solutions obtained by E-NSGA under different function evaluation budgets.

6. Conclusions

This paper establishes an integrated location-routing-scheduling bi-objective mixed-integer programming model that incorporates HHC operational constraints, overcoming the separation of location and routing decisions in conventional multi-objective HHCRSP models. To efficiently solve the complex model, we propose an E-NSGA integrating customized genetic operators and SA-inspired local search strategies.

In summary, the core contributions and novelties of this work are as follows: (1) We construct a bi-objective mixed-integer programming model that integrates facility location, hierarchical skill matching, depot capacity, caregiver workload limits, and time window penalties for home health care, filling the research gap of separated location and routing decisions in existing HHCRSP formulations. The model provides a standardized quantitative benchmark for subsequent large-scale HHC scheduling optimization. (2) An E-NSGA with SA-driven local search is developed for the integrated NP-hard problem. Different from greedy local search in existing NSGA-II variants, the five groups of probabilistic solution acceptance rules effectively avoid premature convergence. Customized encoding and genetic operators are designed to adapt to the joint location-routing-scheduling decision structure. Numerical results on 12 extended benchmark instances demonstrate that E-NSGA achieves statistically significant performance improvements over four representative state-of-the-art multi-objective algorithms, while maintaining superior computational efficiency.

Furthermore, we discuss the scalability of the proposed E-NSGA to clarify its applicability beyond the bi-objective setting adopted in our numerical experiments. First, E-NSGA is built upon the standard non-dominated sorting architecture, which natively supports optimization problems with an arbitrary number of conflicting objectives. Its core modules, i.e., non-dominated sorting, external archive maintenance, and customized local search operators, require no structural modification when extended to three or more objectives. Second, all case studies in this paper adopt a bi-objective setup out of problem-driven practicality, rather than due to algorithmic limitations. The integrated home health care location-routing-scheduling problem investigated in this work intrinsically involves two core conflicting optimization targets: total operational cost and time window violation penalty, which aligns with mainstream real-world HHC operation demands. Third, the algorithm exhibits favorable scalability for many-objective scenarios. If extra optimization criteria (e.g., caregiver workload balance, carbon emission cost) are incorporated into the model, the E-NSGA framework can still efficiently explore high-quality Pareto solutions without major adjustments. In summary, the proposed method is a general multi-objective metaheuristic, rather than an algorithm restricted exclusively to bi-objective problems.

For future research, constructing many-objective test instances and conducting corresponding numerical experiments constitutes a valuable research direction. Moreover, larger instances and systematic parameter sensitivity analysis will be explored in future research.

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References

1. Fu, Y.; Dong, J.; Gao, K.; Suganthan, P.N.; Huang, M.; Zhu, L. A review on metaheuristics for solving home health care routing and scheduling problems. *Applied Soft Comput.* **2025**, *182*, 113560.
2. Masmoudi, M.; Euchi, J.; Siarry, P. Home healthcare routing and scheduling: Operations research approaches and contemporary challenges. *Annals Oper. Res.* **2024**, *343*, 701–751.
3. Atta, S.; Basto-Fernandes, V.; Emmerich, M. A concise review of home health care routing and scheduling problem. *Oper. Res. Persp.* **2025**, *15*, 100347.
4. Zhang, T.; Liu, Y.; Yang, X.; Chen, J.; Huang, J. Home health care routing and scheduling in densely populated communities considering complex human behaviours. *Comput. Indus. Eng.* **2023**, *182*, 109332.
5. Yin, Y.; Liu, X.; Chu, F.; Wang, D. An exact algorithm for the home health care routing and scheduling with electric vehicles and synergistic-transport mode. *Annals Oper. Res.* **2026**, *359*, 1661–1696.
6. Ma, X.; Fu, Y.; Gao, K.; Sadollah, A.; Wang, K. Integration routing and scheduling for multiple home health care centers using a multi-objective cooperation evolutionary algorithm with stochastic simulation. *Swarm Evol. Comput.* **2022**, *75*, 101175.
7. Oladzad-Abbasabady, N.; Tavakkoli-Moghaddam, R. Dynamic routing-scheduling problem for home health care considering caregiver-patient compatibility. *Comput. Oper. Res.* **2022**, *148*, 106000.
8. Shiri, M.; Ahmadizar, F.; Mahmoudzadeh, H. A three-phase methodology for home healthcare routing and scheduling under uncertainty. *Comput. Ind. Eng.*, **2021**, *158*, 107416.
9. Cinar, A.; Salman, F.S.; Bozkaya, B. Prioritized single nurse routing and scheduling for home healthcare services. *Eur. J. Oper. Res.* **2021**, *289*, 867–878.
10. Gong, X.; Geng, N.; Zhu, Y.; Matta, A.; Lanzarone, E. A matheuristic approach for the home care scheduling problem with chargeable overtime and preference matching. *IEEE Trans. Auto. Sci. Eng.* **2020**, *18*, 282–298.
11. Li, Y.F.; Xiang, T.; Szeto, W.Y. Home health care routing and scheduling problem with the consideration of outpatient services. *Trans. Res. Part E Logis. Trans. Rev.* **2021**, *152*, 102420.
12. Bazirha, M.; Kadrani, A.; Benmansour, R. Stochastic home health care routing and scheduling problem with multiple synchronized services. *Annals Oper. Res.* **2023**, *320*, 573–601.
13. Fu, Y.; Ding, F.; Mu, Z.; Sun, C.; Gao, K. Integrating scheduling and routing decisions into home health care operation with skill requirements and uncertainties. *J. Simul.* **2024**, *18*, 259–282.
14. Ceschia, S.; Di Gaspero, L.; Rosati, R.M.; Schaerf, A. Multi-neighborhood simulated annealing for the home healthcare routing and scheduling problem. *Int. Trans. Oper. Res.* **2026**, *33*, 38–67.
15. Fu, Y.; Ma, X.; Gao, K.; Li, Z.; Dong, H. Multi-objective home health care routing and scheduling with sharing service via a problem-specific knowledge-based artificial bee colony algorithm. *IEEE Trans. Intel. Trans. Syst.* **2023**, *25*, 1706–1719.
16. Yang, M.; Ni, Y.D.; Yang, L. A multi-objective consistent home healthcare routing and scheduling problem in an uncertain environment. *Comput. Indus. Eng.* **2021**, *160*, 107560.
17. Li, Y.; Ye, C.; Wang, H.; Wang, F.; Xu, X. A discrete multi-objective grey wolf optimizer for the home health care routing and scheduling problem with priorities and uncertainty. *Comput. Indus. Eng.* **2022**, *169*, 108256.
18. Kordi, G.; Divsalar, A.; Emami, S. Multi-objective home health care routing: A variable neighborhood search method. *Optim. Letters.* **2023**, *17*, 2257–2298.
19. Bazirha, M.; Kadrani, A.; Benmansour, R. Pareto and decomposition based approaches for the multi-objective home health care routing and scheduling problem with lunch breaks. *Eng. Appl. Artif. Intel.* **2024**, *128*, 107502.
20. Du, G.; Li, W. Multi-objective home healthcare routing and scheduling problem based on sustainability and “physician–patient” satisfaction. *Annals Oper. Res.* **2025**, *355*, 1131–1173.
21. Entezari, Z.; Mahootchi, M. Developing a mathematical model for staff routing and scheduling in home health care industries: Genetic algorithm-based solution scheme. *Scientia Iranica* **2021**, *28*, 3692–3718.
22. Clapper, Y.; Berkhout, J.; Bekker, R.; Moeke, D. A model-based evolutionary algorithm for home health care scheduling. *Comput. Oper. Res.* **2023**, *150*, 106081.
23. Masmoudi, M.; Jarboui, B.; Borchani, R. Efficient metaheuristics for the home (health)-care routing and scheduling problem with time windows and synchronized visits. *Optim. Letters.* **2023**, *17*, 2135–2167.
24. Kummer, A.F.; de Araújo, O.C.; Buriol, L.S.; Resende, M.G. A biased random-key genetic algorithm for the home health care problem. *Int. Trans. Oper. Res.* **2024**, *31*, 1859–1889.
25. Li, W.; Du, G.; Yue, X. A multi-time-window multi-objective hybrid fleet home health care routing optimization problem considering caregiver utilization and compatibility. *Comput. Oper. Res.* **2025**, *185*, 107288.

26. Ma, X.; Pu, X.; Fu, Y.; Gao, K.; Xu, Y. Home health care routing and scheduling problems considering patient classification and outsourcing: Modeling and a solution algorithm. *Comput. Oper. Res.* **2025**, *182*, 107143.
27. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T.A.M.T. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **2002**, *6*, 182–197.
28. Decerle, J.; Grunder, O.; El Hassani, A.H.; Barakat, O. A memetic algorithm for multi-objective optimization of the home health care problem. *Swarm Evol. Comput.* **2019**, *44*, 712–727.
29. Xiang, T.; Li, Y.F.; Szeto, W.Y. The daily routing and scheduling problem of home health care: Based on costs and participants' preference satisfaction. *Int. Trans. Oper. Res.* **2023**, *30*, 39–69.
30. Ma, X.; Fu, Y.; Gao, K.; Zhang, H.; Mou, J. A knowledge-based multi-objective evolutionary algorithm for solving home health care routing and scheduling problems with multiple centers. *Applied Soft Comput.* **2023**, *144*, 110491.
31. Zaghdoud, R.; Zidi, I.; Rhaïem, O.; el Khediri, S.; Mesghouni, K. A hybrid NSGA-II and delayed local search approach for home healthcare scheduling and routing optimization. *Applied Soft Comput.* **2026**, *191*, 114617.
32. Cinar, A.C. A novel adaptive memetic binary optimization algorithm for feature selection. *Artif. Intel. Review* **2023**, *56*, 13463.
33. Lin, S.W.; Ying, K.C. Minimizing makespan and total flowtime in permutation flowshops by a bi-objective multi-start simulated-annealing algorithm. *Comput. Oper. Res.* **2013**, *40*, 1625–1647.
34. Zhang, Q.; Li, H. MOEA/D: A multiobjective evolutionary algorithm based on decomposition. *IEEE Trans. Evol. Comput.* **2007**, *11*, 712–731.
35. Bai, L.; Zhang, Y.; Yang, S.; Zhang, Z.; Liu, Y. Multi-objective optimization of drone location-routing problem for photovoltaic power plant inspection: A MOEA/D-based approach with altitude coordination. *Expert Syst. Appl.* **2026**, *322*, 132407.
36. Lv, C.; Zhang, C.; Ren, Y.; Meng, L.; Wu, J. Synthetic pertinence clustering and reinforced evolutionary algorithm for the hybrid E-commerce green location routing problem. *Swarm Evol. Comput.* **2026**, *104*, 102377.
37. Song, F.; Xing, H.; Xu, L.; Xiao, M.; Liu, Y.; Deng, M.; Lei, X. Multi-objective dependent task scheduling, resource allocation, and service caching in aerial-ground integrated MEC. *IEEE Trans. Intel. Trans. Syst.* **2025**, *26*, 13489–13505.
38. Yu, C.; Yong, Y.; Liu, Y.; Cheng, J.; Tong, Q. A multi-objective evolutionary approach: Task offloading and resource allocation using enhanced decomposition-based algorithm in mobile edge computing. *IEEE Access* **2024**, *12*, 123640–123655.
39. Ma, X.; Pu, X.; Fu, Y. Multi-objective integrated harvest and distribution scheduling for fresh agricultural products with farm-to-door requirements using Q-learning and problem knowledge-based cooperative evolutionary algorithms. *Comput. Ind. Eng.* **2025**, *200*, 110755.
40. Vidal, T.; Crainic, T.G.; Gendreau, M.; Prins, C. A hybrid genetic algorithm with adaptive diversity management for a large class of vehicle routing problems with time-windows. *Comput. Oper. Res.* **2013**, *40*, 475–489.
41. Li, Y.; Wang, Q.; Wang, H.; Wang, F.; Zhao, D. A modified memetic algorithm for the home health care scheduling and routing problem considering caregiver skill deviation and synchronous service. *Comput. Ind. Eng.* **2025**, *203*, 110938.
42. Wang, Y.; Gou, M.; Luo, S.; Fan, J.; Wang, H. The multi-depot pickup and delivery vehicle routing problem with time windows and dynamic demands. *Eng. Appl. Artif. Intel.* **2025**, *139*, 109700.
43. Ma, X.; Pu, X.; Fu, Y.; Wang, Y. Integrated harvest and distribution scheduling of fresh agricultural products for multiple farms using a Q-learning-based artificial bee colony algorithm with problem knowledge. *Swarm Evol. Comput.* **2025**, *95*, 101957.

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