A bi-objective Medical Sampling Service System

Tran Thi Hue
huett@hvnh.edu.vn
Banking Academy of Vietnam
School of Information and Communications Technology,
Hanoi University of Science and Technology
Hanoi, Vietnam

Hoang Tuan Ky
kyhoanghust@gmail.com
School of Information and Communications Technology,
Hanoi University of Science and Technology
Hanoi, Vietnam

Nguyen Khanh Phuong
phuongnk@soict.hust.edu.vn
School of Information and Communications Technology,
Hanoi University of Science and Technology
Hanoi, Vietnam

Huynh Thi Thanh Binh
binhht@soict.hust.edu.vn
School of Information and Communications Technology,
Hanoi University of Science and Technology
Hanoi, Vietnam

Abstract

Drones are increasingly adopted in logistics due to their flexibility and efficiency, presenting novel solutions for complex service systems. This study develops a bi-objective optimization model for medical sampling service systems, where technicians and drones independently collect samples from patient locations. The model addresses critical challenges by simultaneously minimizing system completion time and patient test kit waiting duration, while incorporating realistic constraints, such as technicians' dynamic velocity variations reflecting traffic conditions and drone energy consumption dependent on load. A hybrid algorithm combining Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Tabu Search is proposed, ensuring elite solution preservation and genetic diversity. Experimental validation demonstrates better performance compared to NSGA-II, Tabu Search, and Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) across hypervolume and non-dominated solution metrics, highlighting the approach's effectiveness in optimizing medical sampling logistics with disease outbreaks serving as a compelling use case.

Keywords

Drone delivery, Health care, Multi-objective, NSGA-II

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1 Introduction

Remarkable advances in robotics over the past decade have driven the widespread adoption of drones in various sectors including logistics, healthcare, disaster management, agricultural operations, and security surveillance systems. In particular, the e-commerce boom has especially accelerated research into drone-based last-mile delivery, with industry leaders in the logistics sector like Amazon, DHL, Alibaba pioneering drone delivery trials to enhance their logistics networks. The implementation of drone-based delivery systems demonstrates the potential for a paradigm shift in logistics, offering threefold benefits: reduced operational expenditure for service providers, enhanced delivery speed for consumers, and minimized environmental impact through reduced carbon emissions.

In addition, drones have emerged as a critical tool in healthcare logistics, enabling rapid delivery of essential medical supplies including first aid equipment, medical devices, biological materials, and protective gear during emergencies [1]. In academia, researchers have begun developing frameworks for drone-based medical services. For instance, in 2022, Manh et. al [2] expanded on the parallel drone scheduling Traveling Salesman Problem (PDSTSP) model proposed by Murray and Chu [3] to develop an innovative system where drones and technicians work collaboratively to collect patient test kits. This study extends the framework of Manh et. al [2] by introducing the Medical Sampling Service System with Variable Technician Speed and Drone Energy Consumption (MSSVTDE). The proposed framework incorporates three extensions: the integration of time-dependent speed constraint for technicians, a drone energy consumption model, and a bi-objective optimization approach that simultaneously minimizes system completion time and patient test kits waiting duration, striving to balance operational efficiency with service quality. Our contributions are both in adapting NSGA-II and tabu search operators to the particular requirements of the MSSVTDE and in designing the overall organization of the hybrid algorithm to answer the challenges of this problem setting. Experimental results validate the approach's efficacy, demonstrating better performance compared to NSGA-II, Tabu Search, and MOEA/D across hypervolume and non-dominated solution metrics.

Previous multi-objective vehicle routing studies primarily emphasized economic benefits, such as minimizing delivery costs or total travel times. For instance, Das et al. [4] proposed a bi-objective model balancing costs and customer service through timely deliveries. Despite these contributions, minimizing total waiting time as a primary objective remains unexplored. Our work distinctly addresses both operational efficiency and patient satisfaction by simultaneously minimizing completion time and total waiting time,

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presenting a novel multi-objective optimization perspective in the drone-integrated logistics domain.

2 Problem description

The medical sampling service system in MSSVTDE includes a medical center housing a set of technicians $k \in \mathcal{K}$ and a set of homogeneous drones $d \in \mathcal{D}$. Patients requiring sample collection are located at various points C and categorized into two groups: those serviced exclusively by technicians due to complex sampling requirements, and those serviceable by either technicians or drones. Technicians perform a single round-trip starting and ending at the medical center, visiting multiple patients. Drones, however, may undertake multiple trips, each directly linking the medical center and one or more patient locations. Service durations for technicians and drones at patient $i \in C$ are denoted by σ_i and σ'_i, respectively, while the sample weight from each patient is w_i.

All technicians and drones depart simultaneously at time 0. The optimization aims to minimize both system completion time and total waiting time for patient samples, defined as the duration between sample collection and return to the medical center. Upon arrival at a patient's location, sample collection is immediate. Each patient is visited exactly once. Technicians are unaffected by sample weight, but their travel speed varies by time interval to reflect real-world traffic conditions. We adopt a time-dependent speed model, which divides the day into L intervals $[T_l, T_{l+1}]$, $l = 0, \dots, L-1$, and models technician speed in each interval as $v_{ijl} = \theta V$, where V is the base speed and $\theta \in [F_L, F_U]$ reflects traffic congestion. Lower θ values correspond to heavier traffic.

Drones, fully recharged before departure with energy level E, operate at fixed speeds: v_t (takeoff), v_c (cruise), and v_l (landing). Their energy consumption follows a linear model from Dorling et al.[5], dependent on payload mass ω: $P(\omega) = \beta\omega + \gamma$, where β is the consumption per unit mass and γ is the base consumption for an empty drone.

3 The proposed hybrid NSGA-II and tabu search

The proposed HNSGAII-TS algorithm employs a hybrid evolutionary approach, as depicted in Algorithm 1. The method commences with the initialization of N feasible solutions comprising the initial population. During each generational iteration, genetic operators are applied to produce an offspring pool $\mathcal{P}'$ of equivalent size N, followed by the implementation of repair mechanisms when required to maintain solution feasibility (lines 4-10). The subsequent generation is determined through a selection procedure that operates on the unified population $\mathcal{P} \cup \mathcal{P}'$, utilizing non-dominated sorting in conjunction with crowding distance metrics (line 12). A notable enhancement to the traditional NSGA-II framework is introduced through the integration of tabu search: when the Pareto front exhibits stagnation for *nonImp* consecutive generations, the algorithm activates a tabu search procedure to intensify the exploration of solutions within the current Pareto set. These solutions are subsequently integrated into the current population $\mathcal{P}$ (lines 14-17). The selection process is then reapplied to maintain the prescribed population size N (line 18). This algorithmic cycle persists until predetermined termination criteria are satisfied.

Algorithm 1 Hybrid NSGAII-TS metaheuristic

```
1:  Generate an initial population 𝒫 of N individuals
2:  repeat
3:      New population 𝒫′ ← ∅
4:      repeat
5:          Select two parents from 𝒫
6:          A crossover operator is selected randomly and applied
    to procedure offspring O with probability p_c
7:          Apply mutation to O with probability p_m
8:          Repair O if it is infeasible
9:          Add O to 𝒫′
10:     until the number of individuals in 𝒫′ equals N
11:     Update Pareto set of the problem based on 𝒫 ∪ 𝒫'
12:     𝒫 = Select(𝒫 ∪ 𝒫′, N)            ▷ Generation replacement
13:     if Pareto set is not improved for nonImp generations then
14:         for each individual x in the Pareto set do
15:             T(x) ← Tabu search on x
16:             𝒫 ← 𝒫 ∪ T(x)
17:         end for
18:         𝒫 = Select(𝒫, N)
19:     end if
20: until termination criteria are satisfied
```

3.1 Initial population

The initial population consists of N feasible solutions generated through a simultaneous assignment of patients to technicians and drones. The process begins with random patient selection and iteratively builds routes using a nearest-ranking strategy based on temporal proximity. At each step, the technician/drone with the lowest current travel time is selected to expand its route. To select the next patient j from the set of unserved patients S for a vehicle currently at patient i, we use a composite ranking function $R(i, j, S) + R(j, i, S \cup i)$, where $R(a, b, S)$ returns the rank of point b with respect to a among all candidates in S, based on travel time or distance. The patient j minimizing this composite score is selected, ensuring all operational constraints are satisfied. If a drone violates energy or load limits, it returns to the medical center to start a new trip. This procedure continues until all patients are assigned, forming complete routing solutions.

3.2 Parent selection

We adopt a hybrid selection strategy combining truncation and tournament selection to select parent individuals. First, the top 50% of the current population, based on Pareto ranking, are selected to form an elite pool. Within this pool, tournament selection is performed using a normalized objective function defined as:

$$f(x) = \frac{x.obj1 - bestobj1}{worstobj1 - bestobj1} + \frac{x.obj2 - bestobj2}{worstobj2 - bestobj2}$$

where $x.obj1$ and $x.obj2$ are the objective values of individual x, and $bestobj_i$, $worstobj_i$ $(i = 1, 2)$ represent the best and worst values for each objective in the current population. The individual with the lowest $f(x)$ value is selected as a parent.

To maintain diversity, the selection is repeated to choose a second parent, with the constraint that it must differ from the first. This ensures genetic diversity in the offspring generation.

3.3 Offspring generation

Crossover and mutation operators. A probabilistic multi-operator crossover strategy is used, with crossover probability p_c. For each offspring, one of three classical operators (PMX, POS, OX) is randomly applied. Mutation follows with probability p_m by swapping two patient positions in the chromosome.

Chromosome repair mechanism. To ensure feasibility, a repair mechanism is applied when genetic operators create infeasible solutions. For drones, constraint-violating patients are pushed to later trips, and any remaining violations are resolved by inserting those patients into technician routes in positions that preserve feasibility and minimize added cost.

3.4 Education

When the Pareto front stagnates for *nonImp* generations, a Tabu Search is triggered to refine all individuals in the current population $\mathcal{P}$. For each solution x, the search runs up to IT_{TS} iterations. In each iteration, a neighborhood type is randomly chosen, and feasible neighbors $N(x)$ are explored. The first Pareto front F in $N(x)$ is identified, and a candidate x' is randomly selected from F. It is accepted if it dominates x or is not in the tabu list. All such accepted x' solutions are collected into a set $T(x)$. After processing all $x \in \mathcal{P}$, the solutions in $T(x)$ are added to $\mathcal{P}$, and the population is resized using the replacement strategy to maintain size N.

We define four neighborhoods in the Tabu Search: (1,0) move (inserting patient x after patient y), (1,1) move (swapping patients x and y), (2,0) move (relocating consecutive patients x, x' after y), and (2,1) move (swapping x, x' with y). Each move type is supported by a dedicated tabu list: newly assigned positions or swaps are marked tabu to prevent cycling and encourage diversification.

4 Computational results

The algorithm is implemented in C++ and tested on GitHub Actions using Ubuntu-latest runners (4 CPU, 16GB RAM, 14GB SSD). The dataset from Sacramento et al.[6] includes 60 instances with 20 to 200 patients uniformly distributed around a central depot at $[0, 0]$ over grids from 5×5 to 40×40 miles. Technicians have a base speed of $V = 35$ mph with variability $[F_L, F_U] = [0.4, 0.9]$. Test kit weights range from 10 to 100 grams. Drone configurations follow Murray and Chu [7], with 563 KJ energy, flight speeds (takeoff: 17.5 mph, cruise: 35 mph, landing: 8.75 mph), energy model parameters $\beta = 210.8$ (w/kg), $\gamma = 181.2$ (w), and a cruising altitude of 50 meters. The instance set and results can be accessed via https://github.com/phuongnkHUST/VRP_MSS.

4.1 Analysis of design decisions

A hybrid meta-heuristic like HNSGAII-TS involves critical design decisions regarding algorithm structure, components, and parameters. Due to page limitations, this study focuses on three primary design components: crossover operators, population size and number of tabu search iterations. Other parameters were fixed as follows: crossover rate $p_c = 0.9$, mutation rate $p_m = 0.05$, and tabu search activation set at 30 unimproved generations.

4.1.1 Variants of crossover operators. The initial experiment assessed crossover operators' impact on solution quality by investigating several combinations of four crossover operator types (PMX, CX, OX, POS) using NSGA-II for 1500 generations with a population size of 200. The results showed comparable computation times across most combinations, with PMX+POS+CX being a notable exception in demonstrating significantly reduced computational time at the cost of markedly inferior solution quality. The combination PMX+POS+OX achieved the best performance with a mean hypervolume value of 0.82 and demonstrated superior results across the majority of test instances, leading to its selection for subsequent experimental phases based on its consistent performance advantages across the evaluated dataset.

4.1.2 Calibration of population size. This experiment examines population size impact from 200 to 350 using HNSGAII-TS across 1500 generations with 10 tabu search iterations. The result shows that, for instances with 20 and 50 patients, population size 200 outperformed larger sizes across three criteria: lower average time, better average hypervolume, and more instances with improved hypervolume. Conversely, for instances with larger patient numbers, higher population sizes enhanced solution quality, though each 50-generation increase required approximately 30% more computational time. Consequently, the population size of 200 was selected, providing optimal results for instances while maintaining relatively good performance for larger instances with less time consumed.

4.1.3 Calibration of tabu search iterations. This experiment was conducted by varying the number of tabu search iterations from 10 to 50 per execution, with computational time constraints standardized across configurations based on problem size for the fairness: 20 seconds for 20-customer instances, 200 seconds for 50-customer instances, 1000 seconds for 100-customer instances, and 2000 seconds for 200-customer instances. The experimental result shows that the 10-iteration configuration achieves an average hypervolume of 0.79 and ranks second highest among all tested variants, demonstrating superior performance compared to configurations with 30 or more iterations in the majority of the 60 test instances. However, the 20-iteration configuration emerged as the optimal choice, achieving the highest average hypervolume and outperforming the reference configuration in 30 out of 60 instances, leading to its selection for subsequent HNSGAII-TS experiments.

4.2 Performance of HNSGAII-TS

The performance of HNSGAII-TS was evaluated through comparisons with established approaches including NSGA-II, Tabu Search (TS), and MOEA/D (Multi-Objective Evolutionary Algorithm based on Decomposition). All algorithms were executed under standardized computational time limits based on problem size to ensure fair comparison as indicated in section 4.1.3. MOEA/D, introduced by Zhang and Li [8] which decomposes multi-objective optimization problems into collaborative scalar optimization subproblems, was configured with population sizes matching HNSGAII-TS and NSGA-II to ensure equitable resource allocation. The experimental results demonstrated the proposed HNSGAII-TS's superior performance across multiple metrics. The hypervolume comparison is displayed in Table 1 including hypervolume value (HV), hypervolume difference (GapHV, positive values indicating superior solutions), and distribution of performance outcomes (+/=/-, representing instances where combinations performed better, equally, or worse than the HNSGAII-TS). The result shows that HNSGAII-TS achieved an average value of 0.87 for 50-patient instances, outperforming NSGA-II, TS, and MOEA/D by 7.05%, 34.66%, and 42.86% respectively. This dominance extended to larger instances (100 and 200 patients), although for 20-patient instances, MOEA/D showed better performance while HNSGAII-TS still surpassed NSGA-II and TS.

Table 1: Performance comparison among algorithms

Dataset		HNSGAII-TS	NSGA-II		TS		MOEA/D	
Patients	Grid size	HV	GapHV (%)	+/=/-	GapHV (%)	+/=/-	GapHV (%)	+/=/-
20	5	0.73	-4.45	0/1/3	-4.68	1/1/2	9.03	3/1/0
	10	0.89	-3.70	0/0/4	-2.72	1/0/3	-7.47	3/0/1
	20	0.85	-1.69	2/0/2	-18.38	0/0/4	1.66	2/0/2
	Average	**0.82**	**-3.28**	**2/1/9**	**-8.59**	**2/1/9**	**1.07**	**8/1/3**
50	10	0.93	-1.23	1/0/3	-39.58	0/0/4	-41.72	2/0/2
	20	0.83	-2.86	0/0/4	-46.35	0/0/4	-10.21	1/0/3
	30	0.82	-7.84	0/0/4	-40.28	0/0/4	-51.92	0/0/4
	40	0.88	-16.29	0/0/4	-12.44	0/0/4	-67.58	0/0/4
	Average	**0.87**	**-7.05**	**1/0/15**	**-34.66**	**0/0/16**	**-42.86**	**3/0/13**
100	10	0.98	-9.61	0/0/4	-51.93	0/0/4	-71.99	0/0/4
	20	0.94	-18.21	0/0/4	-49.42	0/0/4	-26.92	0/0/4
	30	0.92	-24.82	0/0/4	-34.83	0/0/4	-60.82	0/0/4
	40	0.85	-39.15	0/0/4	-26.92	0/0/4	-90.15	0/0/4
	Average	**0.92**	**-22.95**	**0/0/16**	**-40.78**	**0/0/16**	**-62.47**	**0/0/16**
200	10	0.97	-11.40	0/0/4	-19.79	0/0/4	-11.04	0/0/4
	20	0.99	-8.14	0/0/4	-22.68	0/0/4	-8.34	0/0/4
	30	0.99	-19.95	0/0/4	-40.26	0/0/4	-41.88	0/0/4
	40	0.96	-32.20	0/0/4	-14.75	0/0/4	-94.55	0/0/4
	Average	**0.98**	**-17.92**	**0/0/16**	**-24.37**	**0/0/16**	**-38.95**	**0/0/16**
Summary		**0.90**	**-13.43**	**3/1/56**	**-28.33**	**2/1/57**	**-38.26**	**11/1/48**

In terms of solution quality and quantity, Table 2 indicates that HNSGAII-TS generated 12.70, 29.90, 54.35, and 41.44 solutions on average for instances with 20, 50, 100, and 200 patients respectively, with a high proportion remaining non-dominated when compared against other algorithms. While MOEA/D produced more solutions across all instance sizes (21.27, 50.16, 132.94, and 214.81), most were dominated by HNSGAII-TS solutions, as evidenced by their low non-dominated solution counts (15.38, 18.73, 5.19, and 16.29). Similar patterns emerged with NSGA-II (5.32, 10.25, 7.83, 4.58 non-dominated solutions) and TS (2.32, 0.39, 0.36, 2.31 non-dominated solutions). Visualization of results for a 100-patient instance 100.10.1 from Figures 1 further confirmed HNSGAII-TS's effectiveness, showing superior Pareto front coverage and consistently lower values in both objectives compared to other algorithms' more scattered and less optimal solution distributions.

5 Conclusions

The MSSVTDE framework demonstrates a new variant in medical sampling service systems by integrating time-varying technician constraints, drone energy consumption modeling, and bi-objective optimization. Our hybrid algorithm, combining NSGA-II and tabu search, effectively addresses complex operational challenges. Experimental validation confirms better performance across multiple computational metrics, highlighting the approach's potential to enhance efficiency and service quality in medical sampling logistics.

Table 2: Summary (average) of non-dominated solutions for each algorithm

	Size of instances			
Average	20	50	100	200
HNSGAII-TS solutions	12.70	29.90	54.35	41.44
HNSGAII-TS solutions not dominated by NSGA-II	8.68	24.23	50.11	37.93
HNSGAII-TS solutions not dominated by TS	10.70	29.53	54.16	40.18
HNSGAII-TS solutions not dominated by MOEA/D	5.87	27.94	53.99	40.78
NSGA-II solutions	11.80	23.78	32.28	27.65
NSGA-II solutions not dominated by HNSGAII-TS	5.32	10.25	7.83	4.58
TS solutions	10.82	23.38	26.78	45.33
TS solutions not dominated by HNSGAII-TS	2.32	0.39	0.36	2.31
MOEA/D solutions	21.27	50.16	132.94	214.81
MOEA/D solutions not dominated by HNSGAII-TS	15.38	18.73	5.19	16.29

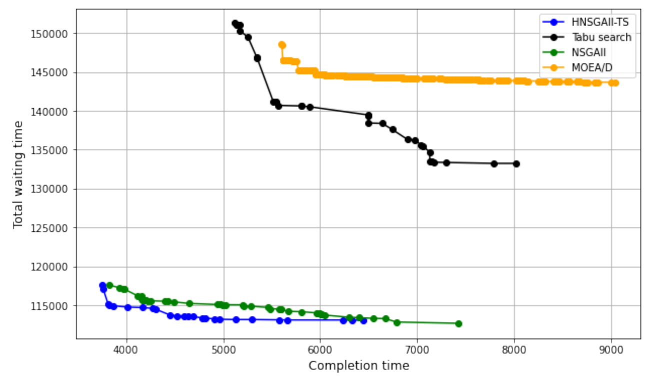

Figure 1: Performance comparison on instance 100.10.1.

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