Coordinated Ambulance Routing Problem for COVID-19 by Using Cloud-Theory-based Simulated Annealing to Minimize Number of Unserved Patients and Total Travel Distance

Purba Daru Kusuma, *Member IAENG*, Ratna Astuti Nugrahaeni, Dimas Adiputra

Abstract—**This work proposes a new coordinated ambulance routing model suitable for implementation during the COVID-19 pandemic. This model is different from the existing model, where it was conducted uncoordinatedly, so that mismatch between supply and demand may occur. In general, high number of unserved requests and travel distance are unwanted. Therefore, this work proposes a model consisting of three steps: hospital-patient allocation, ambulance-patient dispatching, and ambulance pickup-delivery sequencing. The proposed model consists of two objectives: minimizing the number of unserved patients and minimizing total travel distance. It is developed by using cloud-theory-based simulated annealing. The simulation result shows that the proposed model outperforms the existing uncoordinated model in number of unserved patients, total travel distance, and average travel distance. It creates zero unserved patients if the total number of patients does not surpass the total number of slots in all hospitals. It produces 12 to 19 percent lower total travel distance and 27 to 29 percent lower average travel distance than the uncoordinated model.**

Index Terms—**ambulance routing problem, COVID-19, metaheuristic, simulated annealing**

I. Introduction

THE outbreak of coronavirus disease, which began at the end of 2019, has resulted in medical facilities and equipment shortages. Many hospitals, for example, in the US, reported shortages of crucial equipment, such as ventilators and personal protective equipment for the medical staff [1], [2]. The government of Indonesia has allocated 132 referral hospitals with 1,350 isolation rooms for the infected patients. Unfortunately, this number was still not enough to cover the 267 million population [3]. China also faced a shortage of medical staff and beds, especially during the peak of the pandemic, when Wuhan Union Hospital faced approximately 800 patients every day [4]. The shortage in hospital rooms made some patients being treated in the back of the ambulance [5].

Ambulance plays a significant role during the COVID-19 pandemic. In general, the ambulance is an integral part of the emergency medical service (EMS) system [6]. This need increases during the pandemic [7]. Ambulance becomes the most critical transportation mode that takes COVID-19 patients from their houses to the hospital [8]. The advanced life support (ALS) techniques can also be performed in the ambulance while taking the patients to the hospital. In France, some mass transportation resources are transformed into collective critical care ambulances to accommodate many patients [9].

In general, the EMS is conducted centralized. A patient calls a single general number. Then, the EMS central will dispatch an ambulance to pick up this patient. Unfortunately, in some countries, this mechanism is neither centralized nor coordinated. A patient must contact the hospital directly to check whether an available bedroom or ambulance exists. In many cases, a patient must call several hospitals one by one due to the shortage of these facilities. Besides, a patient must contact several private ambulance providers one by one too due to the shortage of these facilities.

In some cases, the chartered ambulance is expensive enough and not affordable for low-income patients [8]. This uncoordinated mechanism may trigger several problems. The customer may fail to find an available hospital or ambulance, even though at least one room in the hospital or ambulance that can serve them still exists. This problem is called a mismatch problem.

A study conducted on this problem is known as the ambulance routing and allocation problem. This study is part of studies in EMS [10]. Even though many studies have been conducted on the ambulance routing problem (ARP), the model that is suitable for implementation during the COVID-19 pandemic is rare. Many studies on ambulance routing problems were implemented in the case of disasters where there are many injured people in a particular area, and an ambulance can pick up several patients simultaneously [11], [12]. In the COVID-19 pandemic, there are several unique circumstances. First, an ambulance can handle only a single patient simultaneously. This circumstance makes the shuttle one-by-one mechanism should be applied [13]. Second, many patients are spread over a wide area [8].

This work proposes a coordinated ambulance routing model suitable for the COVID-19 pandemic based on this

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problem. The objective is to minimize the number of unserved patients and travel distance. Available ambulances, as well as the hospital, can serve patients who request service. This model is developed as a multi-depot capacitated vehicle routing problem covering pick up and delivery. As for the vehicle routing problem, the circumstance is developing a route for the vehicle to visit specific nodes in the system in the most efficient way to minimize total travel distance [14] or cost [15]. It can be seen as a pickup and delivery problem (PDP) because the ambulance conducts both pickup and delivery activities during its trip [16]. It adopts a cluster-first route-second approach where in general, the model consists of clustering and routing processes [10].

Then, this model is optimized by using a cloud-theory-based simulated annealing algorithm. The reason is that the simulated annealing is a well-known metaheuristic algorithm used in many combinatorial optimization studies, especially in vehicle routing problems, such as in [11] and [14]. The cloud-theory-based simulated annealing is chosen because of the advantage of achieving a solution faster as a population-based solution than in its basic form [17]. The simulated annealing algorithm is chosen because of its effectiveness in finding the global optimization and avoiding local optimal local traps [18].

The novelties or contributions of this work are as follows.

1) This work proposes a centralized and coordinated ambulance routing problem with multiple hospitals and ambulance providers.
2) The capacity of the hospitals is considered in the decision process, where it was neglected in most studies conducting ambulance routing problems.

The remainder of this paper is organized as follows. The shortcoming studies due to the ambulance routing problem are explored in section two. Section three presents the proposed model, consisting of the system architecture and the mathematical model. The simulation scenario and the simulation result are shown in section four, while the findings and more profound analysis are discussed in section five. The conclusion and future research potentials are summarized in section six.

II. Related Works

The ambulance routing problem is a well-known study and an integral part of the emergency service. It has a critical mission to save injured people and reduce mortality when a disaster occurs [10], such as volcano eruption, flood, storm, earthquake, etc. Its main objective is transporting a set of patients or requests to appropriate emergency centers [11], such as hospitals. In other words, the main objective of ARP is determining the most effective route for the ambulance to serve a set of requests [19]. Besides locating and dispatching, the routing process is one aspect of the ambulance management system. The patient will be taken to the nearest hospital [20].

ARP is also a derivative of the vehicle routing problem [11], specifically the pickup and delivery problem [10]. In general, it is a kind of the assignment problem, in which its objective is to assign a set of jobs to a group (limited number) of resources [21]. In general, its objective parameters are time or cost [21]. Then, this problem is optimized by many well-known optimization algorithms, such as genetic algorithm [22], tabu search [23], simulated annealing [24], Dijkstra [25], particle swarm optimization [12], and so on. Many studies in ambulance routing problem are formulated by using mixed-integer linear programming (MILP) due to its characteristic as discrete combinatorial optimization, such as in [13] and [20]. This method consists of two aspects: objective and constraints.

Although ARP is similar, there are many studies on ARP due to their specific circumstances. The examples are as follows. Knyazkov et al. [25] developed an ARP model with complex road circumstances (topology, traffic jams, and so on) in Saint Petersburg, Russia. Rabbani et al. [12] developed an ARP model where the patients are classified into three categories: seriously injured, slightly injured, and dead. Zeng et al. [20] developed an ARP model for coordination among stakeholders, such as EMS providers, hospitals, and traffic operators. The summarization of the shortcoming studies in the ambulance routing problem is shown in Table 1. These studies are sorted chronologically. Moreover, the proposed work is added in the last row to state its position.

TABLE I
SHORTCOMING STUDIES IN AMBULANCE ROUTING PROBLEM

Authors	Objectives	Methods
[25]	minimize travel time	Dijkstra algorithm
[10]	minimize travel distance	petal algorithm, particle swarm optimization
[11]	minimize travel time	simulated annealing, tabu search
[23]	minimize the latest service completion time (make-span)	genetic algorithm, tabu search
[22]	maximize total served requests	genetic algorithm
[12]	minimize latest service completion time (make-span), reduce casualties	non-dominated sorting genetic algorithm (NSGA II), multi-objective particle swarm optimization (MOPSO)
[20]	minimize travel time, minimize cost, minimize late arrival penalty	mixed-integer linear programming (MILP)
[26]	maximize cured patient	multi-agent, blockchain technology
[13]	maximize the number of served requests, maximize the number of prioritized requests	0-1 knapsack problem, discrete binary gaining-sharing knowledge-based optimization
[24]	minimize total travel time	simulated annealing
this work	minimize travel distance (total and average) and minimize the number of unserved patients	cloud theory-based simulated annealing

Based on the summarization in Table 1 and the exploration before, there are three aspects in many ARP studies: circumstance, objective, and method. Every study is conducted in a specific circumstance. The circumstance becomes the main reason for every study due to the variety of circumstances in ARP.

Even though many studies on ARP already exist, the potential of studies in it is still broad, especially related to this emerging COVID-19 pandemic. Most of the studies were conducted in a disaster scenario. Meanwhile, the authors can find only two ARP studies conducted on

COVID-19. The first study used a single hospital scenario [13]. It is unclear about the implementation of this model in a multiple-hospital multiple-ambulance scenario, whether there exists coordination among parties or not. Besides, the patient's home-hospital distance and prioritization were the only parameters considered in this work [13].

The second study conducted multiple hospital scenarios and used a multi-agent system (coalition mechanism) in hospital selection [26]. Moreover, this work also has considered the ambulance and hospital capacity in the decision-making process. However, the ambulance dispatching and requests scheduling mechanism remain unclear due to the lack of a mathematical model. Besides, this work also lacked experimental or simulation results that analyze the performance of the proposed model.

Based on this explanation, there is a potential in the ambulance routing problem study, mainly conducted during the COVID-19 pandemic. In the COVID-19 pandemic, the patients are spread in a city, district, or province area. Besides, there are many hospitals with a limited number of available beds. Moreover, many ambulance providers belong to a particular hospital or independent ambulance provider. Without coordination among parties, it is difficult for patients to find the most appropriate ambulance and hospital. Ironically, the study or model in the ambulance routing problem that can solve this problem directly has not existed yet.

III. Proposed Model

The ambulance routing model can be viewed as an input and output system. This proposed model consists of three entities: hospitals, ambulances, and patients. They become the system's input. Every entity has a specific location. Each hospital consists of a certain number of available beds. This system has several outputs: the patient-hospital allocation, patient-ambulance allocation, and ambulance pickup-delivery sequence. This system is illustrated in Fig. 1.

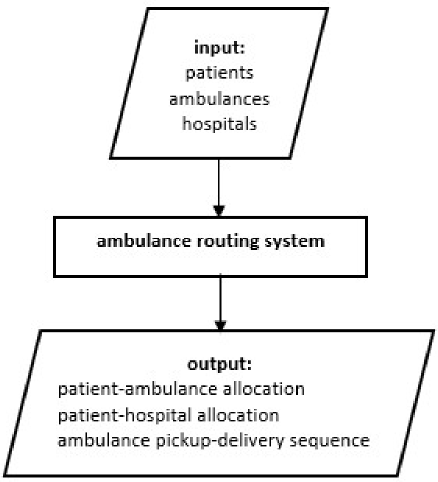

Fig. 1. System diagram.

Relation among entities is as follows. The relationship between hospitals and ambulances is many-to-many. An ambulance can take a set of patients to several hospitals. On the other hand, a hospital may receive patients from several ambulances. The relationship between ambulances and patients is one-to-many. An ambulance may serve several patients while a patient will be served by an ambulance. The relationship between hospitals and patients is one-to-many. A hospital may receive several patients while a hospital will serve a patient. This model adopts a coordinative approach.

This proposed model can be viewed as a multi-depot vehicle routing problem, especially a vehicle routing problem with mixed deliveries and pickup [16]. It also can be viewed as a shuttle ambulance [13]. As a vehicle routing problem, each ambulance will be given a set of patients that must be served. The ambulance starts from its depot, executes requests one by one, and then returns to its depot [15]. There are two processes conducted for every patient: picking up a patient from his house and then taking the patient to his selected hospital [25]. Due to the ambulance capacity being only one patient, a patient will be picked up first before being delivered.

The illustration of this process can be seen in Fig. 2. In Fig.2, there are two hospitals, two ambulances, and five patients. Every ambulance has its depot. Ambulance one serves patients one, two, and three. Patients four and five are served by ambulance two. Hospital one receives patients one and five. Hospital two receives patients two, three, and four. After patient three arrives at hospital two, ambulance one returns to depot one. After patient five arrives at hospital one, ambulance two returns to depot two.

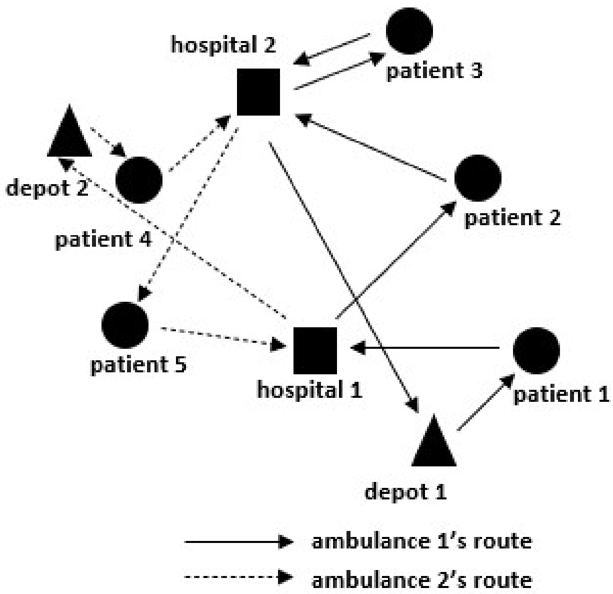

Fig. 2. Illustration of the coordinative ambulance routing model with multiple hospitals and ambulance providers.

As a vehicle routing problem, especially a multi-depot capacitated pickup and delivery problem, several assumptions used in this model are as follows.

- The number of hospitals is known at time zero [27].
- The number of ambulances is known at time zero [27].
- The number of patients is known at time zero [28].
- The capacity of every hospital is known at time zero [27].
- There is no request cancellation during the scheduling and routing process [28].
- The number of patients cannot surpass its maximum

capacity [28].
- A patient is served only by a hospital.
- All ambulances are identical in capacity and speed [29].
- Every ambulance starts from and returns to its depot [29], [30].
- A patient is served only by an ambulance [31].
- An ambulance visits a patient only once [31].

This proposed model consists of three processes. These processes are conducted sequentially. The first process is allocating the patients to the nearest possible hospital. The second process is dispatching patients to the ambulance. The third process is sequencing patients in every ambulance. In other words, this model adopts a cluster-first route-second approach. This work uses taxicab distance or Manhattan distance to calculate the distance between two objects. The reason is that the taxicab distance provides a better actual distance rather than a straight line as in the Euclidean distance [32].

There are several annotations used in the mathematical model. These variables are as follows.

a	ambulance
A	set of ambulances
A_{av}	ambulances pool
a_{se}	selected ambulance
c	hospital capacity
c_{ave}	hospital average capacity
d	distance
d_{pi}	pickup distance
d_{de}	delivery distance
d_{re}	return distance
f_h	hospital fitness function
f_a	ambulance fitness function
h	hospital
H	set of hospitals
H_{av}	hospitals pool
h_{se}	selected hospital
k	constant (Boltzmann constant)
l	location
n_{ap}	ambulance current capacity
n_{maxap}	ambulance maximum capacity
o_h	hospital clustering objective
o_a	ambulance routing objective
p	patient
P	set of patients
P_{ra}	set of randomly picked patients
p_{se}	selected patient
s	patient's status (0 = unserved, 1 = served)
sol_{best}	current best solution
sol_{cur}	current solution
T	current temperature
Δf_a	ambulance fitness gap
Δf_h	hospital fitness gap

The first process is conducted to cluster the patients to their nearest possible hospital. Its objective is to minimize the total hospital-patient distance. This objective is formalized by using (1) to (3).

$$o_h = min(f_h) \tag{1}$$

$$f_h = \sum_{\forall p \in P_s} \left| l(p) - l(h_{se}(p)) \right| \tag{2}$$

$$P_s = \{p | p \in P \wedge s(p) = 1\} \tag{3}$$

The explanation of (1) to (3) is as follows. Equation (1) states that the first process's objective is to minimize the hospital fitness function. Equation (2) explains the hospital fitness function is the total distance between the served patients and their selected hospital. Then, (3) states that the set of served patients consists of patients where their status is 1.

This mechanism is conducted stochastically. In the first process, each patient will be allocated to a hospital that is still available, and its location is the nearest to the patient. In the beginning, an available hospitals pool is generated. If the pool is not empty, a hospital is selected randomly to be allocated to the specified patient. This process is formalized by using (4) and (5).

$$H_{av} = \{h | h \in H \wedge c(h) > 0\} \tag{4}$$

$$h_{se}(p) = U(H_{av}) \tag{5}$$

Hereafter, this first process is optimized by using a cloud-theory-based simulated annealing algorithm. A specific number of patients will be picked randomly to be reallocated in every iteration. Then, the hospital fitness function is recalculated. If the new hospital's fitness is better than the hospital's current best fitness, this solution becomes the new hospital's current best solution. This reallocation and replacement mechanism is formalized by using algorithm 1.

algorithm 1: hospital reallocation and replacement

begin
  $P_{ra} = \{p | p \in P \wedge p = U(P)\}$
  for p in P_{ra} :
  begin
    reallocate(p)
  end for
  $\Delta f_h = f_h(sol_{cur}) - f_h(sol_{best})$
  if $\Delta f_h < 0$ **then**
    $sol_{best} = sol_{cur}$
  else
  begin
    if $U(0,1) < \exp(-\Delta f_h / (kT))$ **then**
      $sol_{best} = sol_{cur}$
    end if
  end if
end

The explanation of algorithm 1 is as follows. The specific number of patients are selected randomly to enter the patients' pool. This process follows a uniform distribution. The reallocation mechanism for every patient in the patients' pool follows (4) and (5). The replacement of the current best solution follows the rule in the simulated annealing algorithm. If the current solution is better than the best solution, then this current solution becomes the new current best solution. Otherwise, the replacement occurs based on the stochastic process that depends on the hospital fitness gap, constant, and current temperature. The individual (solution) with the lowest total hospital-patient distance at the end of the process becomes the final solution.

After the hospital-patient allocation process ends, the following process is the patient-ambulance dispatching process. This process is conducted simultaneously with the third process, the patient sequencing process. These processes aim to minimize the total travel distance. This objective is formalized by using (6) to (11).

$$o_a = min\left(f_a\right) \tag{6}$$

$$f_a = \sum_{\forall a \in A} d(a) \tag{7}$$

$$d(a) = \sum_{\forall p \in P(a)} \left(d_{pi}(a,p) + d_{de}(a,p)\right) + d_{re}(a) \tag{8}$$

$$d_{pi}(a,p) = \begin{cases} \left|l(b(a)) - l(p(a,i))\right|, i=1 \\ \left|l(p(a,i)) - l(h(p,a,i-1))\right|, i>1 \end{cases} \tag{9}$$

$$d_{de}(a,p) = \left|l(p) - l(h,p)\right|, p \in P(a) \tag{10}$$

$$d_{re}(a) = \left|l(h,p,i) - l(b(a))\right|, i=n(P(a)) \tag{11}$$

The explanation of (6) to (11) is as follows. Equation (6) shows that the objective is to minimize total travel distance. The total travel distance accumulates all ambulance distances, as shown by (7). Equation (8) shows that the ambulance distance consists of pickup distance, delivery distance, and return distance. Equation (9) shows that pickup distance is the distance between the ambulance depot to the first patient of the ambulance or the distance between the current patient and the previous patient's hospital. Equation (10) shows that the delivery distance is the distance between the patient location and the patient's hospital location. Equation (11) shows that return distance is the distance between the last patient's hospital location and the depot location of the ambulance.

In the beginning, the maximum ambulance capacity must be determined first. The ambulance's maximum capacity is the number of patients transported by an ambulance in a single trip. As mentioned previously, these patients are picked up and delivered one by one. This ambulance's maximum capacity is formalized by using (12). Equation (12) tries to make the number of patients carried by ambulance equal to or almost equal to other ambulances.

$$n_{maxap} = \begin{cases} \dfrac{n\left(P_s\right)}{n(A)}, n\left(P_s\right) mod\ n(A) = 0 \\ int\left(\dfrac{n\left(P_s\right)}{n(A)}\right) + 1, otherwise \end{cases} \tag{12}$$

The next step is dispatching every served patient to the ambulance. Like the first process, all available ambulances are collected into the ambulance pool for every patient. The sequence of the served patients is scrambled first. Then, an ambulance is picked up randomly to be dispatched to the specified patient. This process follows a uniform distribution. This step is determined by using (13) and (14). Equation (13) shows that the ambulance pool consists of ambulances whose current capacity is below its maximum capacity. Equation (14) shows that the selected ambulance is picked up randomly from the ambulance pool, following a uniform distribution.

$$A_{av} = \left\{a | a \in A \wedge n_{ap}(a) < n_{maxap}(a)\right\} \tag{13}$$

$$a_{se}(p) = U\left(A_{av}\right) \tag{14}$$

Hereafter, this ambulance-patient dispatch and sequence processes are optimized using cloud-theory-based simulated annealing (CSA). There are two operations in every iteration: inter-ambulance patient interchange and intra-ambulance patient interchange. The fitness value, i.e., total travel distance, is improved by conducting these operations. The inter-ambulance patient interchange is interchanging two patients' positions between two ambulances, and the intra-ambulance patient interchange is interchanging two patients' positions in the same ambulance. These processes are formalized in algorithm 2. Process in algorithm two is conducted in every iteration. At the end of the process, the individual (solution) with the lowest total travel distance becomes the final solution.

algorithm 2: ambulance-patient reallocation

1 **begin**
2 inter-ambulance_interchange()
3 intra-ambulance_interchange()
4 $\Delta f_a = f_a(sol_{cur}) - f_a(sol_{best})$
5 **if** $\Delta f_a < 0$ **then**
6 $sol_{best} = sol_{cur}$
7 **else**
8 **begin**
9 **if** $U(0,1) < \exp(-\Delta f_a / (kT))$ **then**
10 $sol_{best} = sol_{cur}$
11 **end if**
12 **end if**
13 **end**

The explanation of algorithm 2 is as follows. Line 2 represents the patients' interchange between two selected ambulances. Line 3 represents the patients' interchange inside a selected ambulance. Line 4 is used to find the fitness score gap between the current and best solutions. Lines 5 and 6 show that the current solution becomes the best solution immediately only if this current solution is better than the best solution. Line 9 and 10 show that the current solution may become the best, although its fitness is worse than the best solution by using specific probabilistic calculations.

IV. Simulation

This proposed model is implemented into ambulance routing simulation to analyze its performance. The environment is the Special Region of Yogyakarta, Indonesia. It is like a province, and its size is 3,186-

kilometer square. This region has 5 districts: Yogyakarta city, Sleman, Bantul, Kulonprogo, and Gunungkidul. At the beginning of the COVID-19 outbreak, only four hospitals were referred for COVID-19 patients. During the increase in the number of patients, there are now 25 COVID-19 hospitals in this region.

This simulation has three observed parameters: number of unserved patients, total travel distance, and average travel distance. These experimental parameters are considered due to several reasons. The first reason is that the objective of this work is to minimize the number of unserved patients and total travel distance. Besides, both minimizing total travel distance (time) [10], [11], [25] and the number of unserved patients [13], [22], [26] are used in many ambulance routing problem studies as observed parameters.

In this simulation, the proposed model is compared with the existing 0-1 knapsack ambulance routing models [13]. The reason for choosing this model is as follows. First, this model was developed to handle COVID-19 patients. Second, the ambulance could handle a patient only on a single trip, so a shuttle mechanism is conducted. Due to its simulation scenario where there was only one hospital and several patients requested this hospital [13], this model can be seen as uncoordinated. Based on this simulation, the proposed model, as a coordinated model, will be benchmarked with the uncoordinated model [13]. This model [13] becomes the only comparing model in this work because the other ambulance routing model specified for COVID-19 is hard to find.

In the beginning, a specific number of hospitals and ambulances are generated. Their location is distributed randomly around the region. It follows a uniform distribution. Meanwhile, a certain number of patients are also generated. Their location is distributed randomly. It follows uniform distribution too. The capacity of every hospital is generated randomly. It follows a normal distribution. For the uncoordinated model [13], every ambulance is dedicated to a particular hospital, and serving only this hospital.

Then, this uncoordinated model is optimized by using several well-known metaheuristic algorithms: cloud-theory based simulated annealing (CSA), simulated annealing (SA), harmony search (HS), and tabu search (TS). The reason to choose these algorithms is as follows. SA is chosen as the original form of CSA. HS represents a metaheuristic that splits the option of choosing exploration and exploitation based on stochastic calculation. TS represents a non-population-based metaheuristic algorithm that focuses on exploiting the best solution but avoids redundancy.

In the proposed model, every patient can be served by any available hospital and ambulance. Every patient also requests a particular hospital, and they will be served only by the ambulance that belongs to the hospital. The hospital preferencing is selected randomly, and it follows a uniform distribution.

The simulation is conducted to analyze the increase in the number of patients with the observed parameters. There are 25 hospitals and 50 ambulances. The hospital's average capacity is 20 patients. Meanwhile, the number of patients ranges from 250 to 450 patients. In this simulation, there are several default variables.

The parameters implemented in CSA are as follows. The population size is 5. The number of iterations is 50. The initial temperature is 10°C, while the final temperature is 1°C. Boltzmann constant is 0.001. In HS and TS, the number of iterations is 100. In HS, the harmony memory size is 5, and the harmony memory considering rate is 0.5. In TS, the number of candidates generated in every iteration, and the tabu list size is 10. The simulation result is shown in Fig. 3 to Fig. 8. The proposed model is acronymized as a prop. Meanwhile, the uncoordinated models are acronymized as uc-CSA, uc-SA, uc-HS, and uc-TS, respectively, for CSA, SA, HS, and TS models.

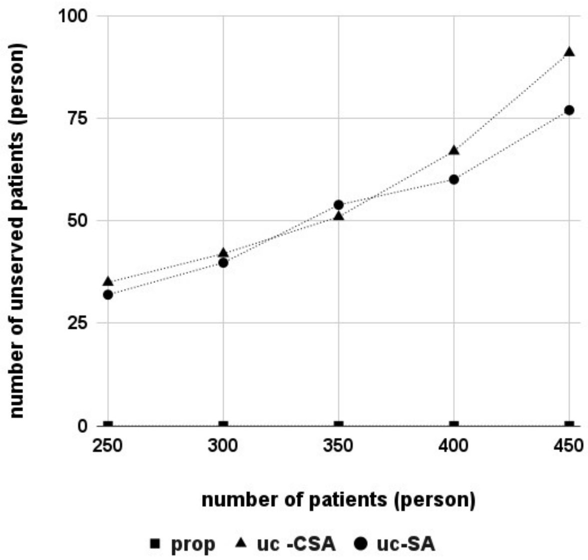

Fig. 3. Relation between the number of patients and number of unserved patients for prop, uc-CSA, and uc-SA.

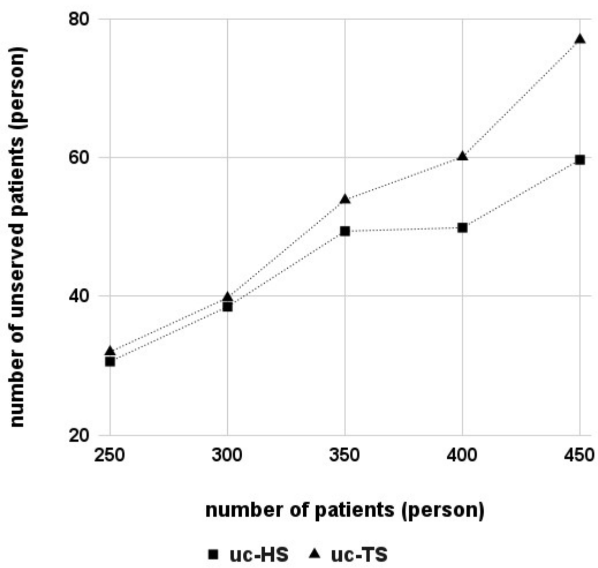

Fig. 4. Relation between the number of patients and number of unserved patients for uc-HS and uc-TS.

Fig. 3 and Fig. 4 show that the proposed model performs better than all uncoordinated models [13] in minimizing the number of unserved patients. The proposed model creates zero unserved patients in any number of patients if the number of patients does not surpass the total hospital capacity. Therefore, a patient is guaranteed to be served if at least one available hospital exists in the system. The condition is different in all the uncoordinated models [13]. There is a certain number of unserved patients, although the total patients are only approximately half of the total hospital capacity. The number of unserved patients increases due to the number of patients. When the number of patients is low (50 percent of the average total capacity), the unserved-patients rate is 13 percent. When the number of patients is high (90 percent of average total capacity), the unserved-patients rate is 17 percent.

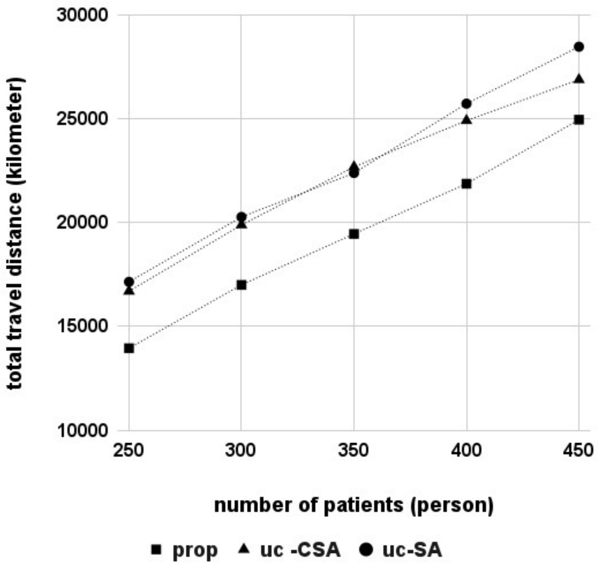

Fig. 5. Relation between the number of patients and total travel distance for prop, uc-CSA, and uc-SA.

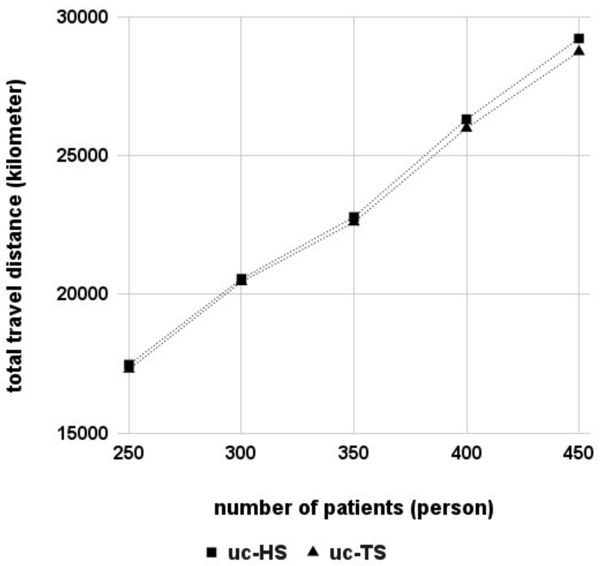

Fig. 6. Relation between the number of patients and total travel distance for uc-HS and uc-TS.

Fig. 5 and Fig. 6 show that the total travel distance increases due to the number of patients. The total travel distance rises linearly. This trend occurs in both models. Benchmarking between models, the proposed model performs better in creating a low total travel distance. When the number of patients is low (250 persons), the proposed model creates a 19 percent lower total travel distance than the uncoordinated model. When the number of patients is high (450 patients), the proposed model creates a 12 percent lower total travel distance than the uncoordinated model.

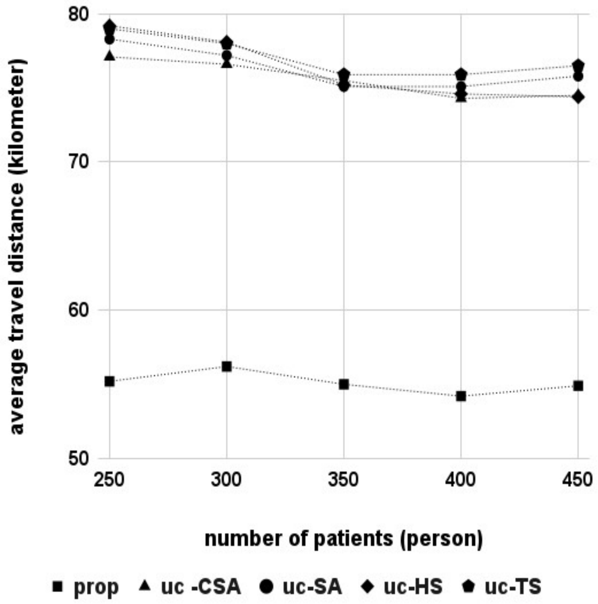

Fig. 7. Relation between the number of patients and average travel distance.

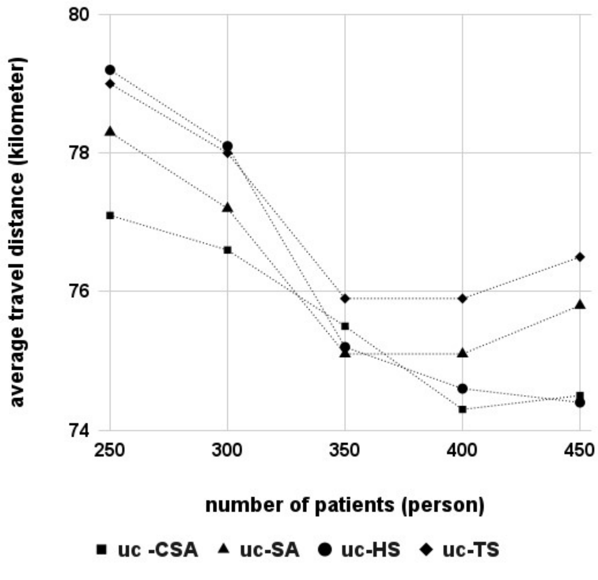

Fig. 8. Zoom view of relation between the number of patients and average travel distance for uc-CSA, uc-SA, uc-HS, and uc-TS.

Benchmarking between models, the proposed model performs better in creating a low average travel distance than the uncoordinated model [13]. Fig. 7 and Fig. 8 show that the average travel distance decreases very slowly due to the increased number of patients, which occurs in both models. When the number of patients is low (250 persons), the proposed model creates a 29 percent lower average travel distance than the uncoordinated model. Meanwhile, when the number of patients is high (450 patients), the proposed model created a 27 percent lower average travel distance than the uncoordinated model.

V. Discussion

Several findings can be obtained based on the simulation result. The coordinated model, as proposed in this work, is better than the uncoordinated model as in the benchmark model [13]. This advantage occurs in all three aspects: number of unserved patients, total travel distance, and average travel distance.

The first finding is that the proposed model can minimize the number of unserved patients compared to the uncoordinated one. This circumstance comes from the abstraction of the dedicated relation between hospital and patients and between hospital and ambulance. In the coordinated model, patients can be served by an ambulance and taken to any available hospitals in the system. This condition does not occur in the uncoordinated model [13]. In the uncoordinated model, patients cannot be taken to other available hospitals when their preferred hospital is not available. Moreover, patients will fail to be taken to the hospital although their preferred hospital is still available but does not have a relation with any ambulance in the system. The general cause is the mismatch due to the dedicated relation.

The second finding is that the proposed model is proven to minimize total travel distance. Once again, this circumstance is achieved because of the flexibility in the coordinative approach. The total travel distance reduction is achieved in three ways. The first way is by allocating patients to the nearest available hospital. The second way is by dispatching the patients to the most appropriate ambulance. The third way is arranging the patients' sequence so that the travel distance of every ambulance can be minimized.

The third finding is that the proposed model is proven to minimize average travel distance. The gap in average travel distance is more expansive than in total travel distance. This circumstance is caused by the difference in the number of served patients. The proposed model serves more patients than the uncoordinated model. It makes the gap in total travel distance narrow. Based on the average travel distance comparison, the proposed model is much more efficient rather than the uncoordinated model.

Overall, the collaborative approach is proven better than the non-collaborative approach. The collaborative method outperforms all non-collaborative methods without considering the metaheuristic algorithm chosen to optimize. The performance gap between the collaborative method and all non-collaborative methods is wide. Contrary, the gap among non-collaborative methods is so narrow. It means that choosing a collaborative approach should be more prioritized than choosing the optimization algorithm.

The benefit of the collaborative approach comes from the nature of resource sharing adopted in this approach. In general, every system will face limitations in the resources utilized. On the other hand, tasks or jobs can surpass their capacity. In the condition that there are multiple providers in the system, collaboration may benefit in several ways. First, collaboration can improve the utilization of resources. Second, collaboration can improve the quality of service. In the non-collaborative approach, a patient can only be served by their preferred hospital despite the minimum capacity and distance. There might exist a hospital near this patient that still has enough capacity to serve. This circumstance also occurs in ambulances where their availability is also limited. Through collaboration, the available ambulances can serve more customers beyond their preferred customers. The less utilized resources can be assigned to handle the over-demand circumstance through resource sharing.

Simulation result also shows that using various metaheuristic algorithms is less significant to improve the performance (travel distance and unserved patients) in the non-collaborative models. Even though these algorithms have been used widely in many optimization problems, the narrow problem space or space for improvement is limited. Meanwhile, this narrow problem space comes from the nature of the non-collaborative approach because the number of possible arrangements is less than the collaborative ones.

This work is conducted with several limitations. First, the condition of all patients is assumed to be similar so that they are treated equally. In the real world, the patient's condition can be classified into several levels to treat them differently. Second, all patients, hospitals, and ambulances are distributed uniformly. In the real world, the density in every area is different. Besides, several aspects such as time window, make-span, penalty, and others are not considered. In the future, these aspects can be included to improve the quality of the model.

VI. Conclusion

This work has demonstrated that the proposed coordinated ambulance routing model is suitable in the ambulance management system during the COVID-19 pandemic. The coordinated model has met its objective in minimizing the number of unserved patients and total travel distance. Based on the simulation result, this proposed model outperforms the existing uncoordinated model in three aspects: number of unserved patients, total travel distance, and average travel distance. It produces 12 to 29 percent lower total travel distance than the uncoordinated model, and it also produces a 27 to 29 percent lower average travel distance than the uncoordinated model. It is proven to create zero unserved patients if at least one available hospital exists.

This work can be used as a baseline for future research potential. Several studies can be conducted to improve this model by concerning the limitations of this work, such as by implementing prioritization among patients. In many studies on ambulance routing problems, patients are classified based on the urgency. Other studies can also be conducted by implementing this model in many other locations or cities where the demographic characteristics of their people are different. Several shortcoming metaheuristic algorithms can become optimization alternatives too.

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