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Coordinated COVID-19 vaccination scheduling model by using nearest distance-single course timetabling method

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Article Info	ABSTRACT
	This work proposes a new coordinated vaccine scheduling model suitable for the city size COVID-19 vaccination program. It is different from the existing COVID-19 vaccination scheduling mechanism where there is no coordination among endpoint providers. On the other side, the vaccine stock in every provider is limited, so that this mismatch creates many unserved participants. Moreover, studies on the COVID-19 vaccination scheduling problem are hard to find. This work aims to solve this mismatch problem. It is developed by combining the nearest distance and the single course timetabling. It is then optimized by using a cloud theory based-simulated annealing algorithm. The simulation result shows that the proposed model outperforms both the uncoordinated and basic course timetabling models. It can minimize the number of unserved participants, total travel distance, and the number of participants with missed timeslot. It produces zero unserved participants if the total vaccine quantity is at least equal to the total number of participants. The proposed model creates lower total travel distance than the uncoordinated or basic course timetabling adopted model. It is also better than the basic course timetabling model in creating a low number of participants with missed timeslot.

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1.   INTRODUCTION

The outbreak and spread of COVID-19, which was initially detected in Wuhan in late 2019, have caused the multidimensional global crisis, especially in health, social, and economic aspects. There were 375,000 COVID-19 deaths in the United States in the year 2020 [1]. Another study estimated 766,611 deaths related to the COVID-19 from March 2020 to May 2021 in the same country [2]. In general, the government in many countries launched quarantine and lockdown policies to reduce the spread of this disease [3]. This policy has triggered domestic and international economic contraction due to the reduction of the production and demand of some goods [3]. This circumstance also caused massive unemployment and left millions of individuals and families with uncertainty [4]. COVID-19 also became a game-changer in the education area. The rapid shift from face-to-face teaching to the online platform occurred due to the closure of schools and universities [5].

Fortunately, the rapid development of the COVID-19 vaccine gave better opportunities to face this pandemic. Global scientific communities agreed that mass vaccination would become the most effective solution in solving this pandemic [6], [7], especially for the long term [8]. It is different from the non-pharmaceutical intervention (NPI) policies that have been implemented from the earlier of the outbreak until

now, such as mask-wearing, social distancing, lockdown, and travel restriction [9]. Vaccination also has a positive impact on the social and economic aspects rather than the NPI policy.

There are several challenges due to the implementation of the massive vaccination program. First, there is a shortage problem due to the limited production and delay in shipment [10]. This problem occurs mainly in low-income countries, which collectively received only 0.2% of all worldwide delivered vaccines [11]. The second one is the public trust and acceptance toward the COVID-19 vaccines. The third one is the distribution strategy [12]. Although the distribution strategy becomes critical in rolling out the massive COVID-19 vaccination program, studies related to it are hard to find. Many studies in COVID-19 vaccination focused on public perception and acceptance [7]-[9].

In Indonesia, besides the vaccine shortage, there is a mismatch problem in distributing the vaccine to the people. In general, this distribution is conducted by public health service providers, such as hospitals, health clinics, public health service centers, and other non-health-related institutions, such as schools, banks, state-owned companies, social organizations, and so on. Ironically, this mechanism is not well coordinated. Every eligible person makes a direct appointment with the vaccination provider. Then, this provider makes the schedule due to the registrars, and it cannot be changed. Based on this problem, this work aims to develop a novel COVID-19 vaccination scheduling model. The objective is to minimize the number of unserved participants and allocate them to their nearest possible provider. This model is designed to be implemented in a city or district size area with a certain number of vaccination providers. Besides, this model also allows participants to choose their preferred timeslots, and the model will give the best effort. However, it does not guarantee to give vaccines within their preferred timeslots.

The novelties or contributions of this work are as: i) this model adopts a coordinated/centralized approach rather than the existing uncoordinated approach; ii) this model offers the participants to be vaccinated within their preferred timeslots, although it is not guaranteed; iii) this model offers the participants to be vaccinated at their nearest possible provider. This model is developed by combining the nearest distance method and the course timetabling model. The reason for choosing these two methods is as follows. The nearest distance method is widely used in many spatial models that allocate objects to their nearest objects, such as in taxi dispatching systems [13], [14] or vehicle routing problems [15], [16]. The course timetabling model is adopted due to its similarity in allocating requests into limited resources (timeslots and providers) with a limited capacity [17], [18]. This model is then optimized by using a cloud-theory-based simulated annealing (CTA) algorithm. As a derivative of simulated annealing, this model is chosen due to its characteristics in finding global optimal faster and it is better than the basic form of simulated annealing, which use single instance only [19].

The remainder of this paper is organized as; the recent studies conducted on COVID-19 vaccination were explored in section 2. The proposed model and the research method are explained in section 3. The simulation, result, and more profound analysis of the result and the findings are discussed in section 4. The conclusion and the future research potential are summarized in section 5.

2. RELATED WORKS

There are plenty of studies related to the COVID-19 pandemic from 2020 until today. This huge number of studies is the consequence of its massive and vast impact on human being. Several studies focused on the impact of this pandemic in many sectors, while other studies focused on the governments' policies and strategies in solving this problem. Today, as the vaccine is proven effective and has long-term solutions, there are many studies concerning the COVID-19 vaccination program. Some studies were conducted in specific countries, while others generalized the locus. Several shortcomings studies related to the COVID-19 vaccination program are shown in Table 1. The position of this proposed model is shown in the last row.

More detail description of these studies is as; DeRoo *et al.* [8] proposed the planning for the COVID-19 vaccination program. They highlighted the objection of this program will come from the misconception about the impact and the safety risk of the vaccine. Therefore, education plan should be delivered first to gain the public acceptance before the vaccine rollout. El-Elimat *et al.* [9] investigated the acceptance of the COVID-19 vaccination program in Jordan and its predictors. They showed that the acceptance is low, 36.3% people refused to be vaccinated while 26.3% people were not sure [9]. Coudeville *et al.* [20] identified the plausible scenarios for the impact of the COVID-19 vaccination program in France, especially the short-term impact. This study suggested that the vaccination program may reduce the further needs of NPI. Paul *et al.* [7] investigated the peoples' knowledge, perception, and acceptance of the COVID-19 vaccination in Bangladesh. This study was conducted by using the online survey and face-to-face interview. The result indicated about mixed responses regarding the acceptance and knowledge of this vaccination program.

Table 1. Shortcomings studies in COVID-19 vaccination program

References	Focus	Related to computer science
[8]	Education plan for public acceptance	no
[9]	Public acceptance toward vaccine in Jordan	no
[20]	Assessment of the short-term impact of vaccination program in France	no
[7]	Public understanding and acceptance in Bangladesh	no
[21]	The key factor in successful vaccination rollout in Israel	no
[22]	Behavioral nudges to improve vaccination uptake in the United States	no
[12]	Targeted vaccine strategy in Indonesia	no
[23]	Public acceptance and perception in Vietnam	no
[24]	Vaccine distribution strategy in the United States	no
[10]	Cause and implications of vaccine shortage in the United Kingdom	no
[25]	Prioritization strategy toward vaccination in the United States	no
[26]	Assessment of national vaccine distribution strategy in the United States	no
[27]	Optimization model for single-dose vaccination	no
This work	Developing vaccination scheduling model	yes

Several studies were conducted in Southeast Asia. Fuady *et al.* [12] analyzed several scenarios regarding the COVID-19 vaccine delivery in Indonesia, especially in West Java. This study highlighted the needs for systematic distribution, reliable logistic, and good public acceptance to make this program successful. Khuc *et al.* [23] analyzed the public perception of the COVID-19 vaccination in Ho Chi Minh City, Vietnam. This study showed that the young adults in Vietnam were satisfied with the strict regulations and enforcement conducted by government [23]. There is difference between male and female due to this acceptance.

Rosen *et al.* [21] analyzed the strategy conducting the rapid rollout of COVID-19 vaccination program in Israel. There are several critical aspects to this success. First, Israel conducted a centralized national system with a well-developed infrastructure to face any large-scale emergencies. Second, it has a robust health system which includes organization, information technology, and logistical capabilities. Third, the government has mobilized special funding for vaccine purchase and distribution. Fourth, there is effective coordination among parties due to a national emergency.

Several studies investigated the COVID-19 vaccination program in United States. Eshun-Wilson *et al.* [24] conducted survey and choice experiment to evaluate the US public preference regarding COVID-19 distribution campaign. It is because in United States, public can choose many locations, such as local pharmacies, health services, local pop-up vaccination services, home, or national guard supported large vaccination sites. The reservation can be conducted by using an online website, phone call, or immediate drop-in. There are several findings due to this study. First, public preferred to be vaccinated in single dose rather than multiple doses. Second, public tends to avoid mass vaccination site. Third, all campaigns were negatively preferred for those who were hesitant.

Bubar *et al.* [25] evaluated the prioritization strategy regarding the vaccination program. Based on infection-minimizing strategy, adults with age ranges from 20 to 49 years are highly prioritized. Kim and Youn [26] investigated the COVID-19 vaccine distribution strategy in United States. They noted that massive rolling out program in United States was supported by good coordination among distribution channels, colossal government funding, and a huge vaccine supply. They also highlighted the critical role of accurate information sharing, such as distribution allocation, vaccination site, and vaccine availability to prevent vaccine wasting, deserts, and inequity [26].

This exploration shows that no study focused on the scheduling model for the COVID-19 vaccination program as the endpoint of the distribution strategy, even though this aspect is important and critical. Many studies focused on public acceptance, and others focused on the distribution strategy in the context of prioritization or national distribution. Moreover, these studies were not related to operational research or computer science (CS). This exploration shows that there is an opportunity to develop a COVID-19 scheduling model based on mathematical and computational methods.

3. METHOD

The vaccination scheduling model consists of three entities: participants, providers, and timeslots. Participants are the citizen who registers to be vaccinated, and providers are institutions that have the authorization to deploy the COVID-19 vaccination. They can be hospitals, clinics, public health service centers, and so on. Timeslots are time windows within a week that are allocated to vaccination. Each timeslot has limited capacity to make sure the social distancing is still conducted. In the existing mechanism, especially in Indonesia, it is conducted uncoordinatedly. It means a participant makes an appointment directly to a particular provider [28]. A participant cannot make multiple appointments at the same time. Then, the

provider will schedule this appointment based on their vaccine stock and the queue list. There are several problems due to this mechanism. First, a participant does not know the capacity and the queue length of every provider. Sometimes, a participant must check several providers one by one to find the most available. This circumstance may trigger the increase in the number of unserved participants due to the supply-demand mismatch, although totally, the vaccine stock is available. Second, the participant cannot choose their preferred time to be vaccinated. For example, some participants prefer to be vaccinated in the morning, while others prefer to be vaccinated in the afternoon. This mechanism is shown in Figure 1. In Figure 1, there are four participants and two providers. Participant one and participant two make an appointment with provider one. Meanwhile, participant three and participant four make an appointment with provider two.

There is a significant difference between the proposed model and the existing solution. In the proposed model, the system is centralized. All participants make an appointment through a single door. Then, the system will allocate the participants to the available provider. During the appointment process, the participant informs the system about their location and preferred timeslots. A participant can choose a certain number of timeslots. The system then tries to allocate the participant to the nearest possible available provider due to the participants' preferred timeslots. This process adopts a best-effort approach. It means the system cannot guarantee that the participant will be vaccinated within his preferred timeslots. If this participant cannot be vaccinated within his preferred timeslots, then he will be vaccinated at the nearest provider at any timeslot. This mechanism is illustrated in Figure 2. In Figure 2, there are four participants. Participant one prefers timeslots one and three. Participant two prefers timeslots two and six. Participant three prefers timeslots four and five. Participant four prefers timeslots three and six.
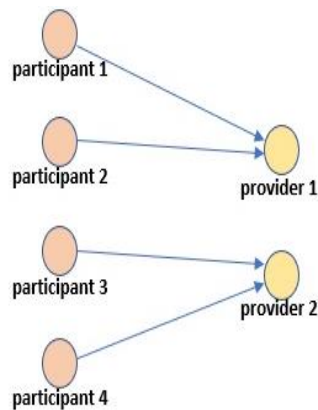

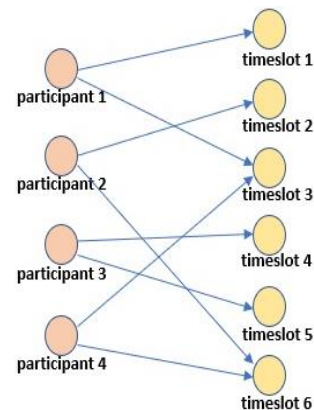Figure 1. Existing vaccination appointment system

Figure 2. Proposed vaccination appointment system

This timeslot-based mechanism is like the course timetabling problem, and in general, the assignment problem. An assignment problem can be defined as the process of allocating a certain number of tasks or jobs to a certain number of limited resources [29]. In this vaccination context, the participants represent the tasks. The timeslots and providers represent the resources. The capacity in every timeslot of every provider is limited. In the course timetabling problem. there are a certain number of students, courses, lecturers, classes, classrooms, and timeslots [30]. In this context, the participants represent the students.

Meanwhile, due to the general type of vaccine in one scheduling horizon, this system can be viewed as a single course timetabling problem. In a single course timetabling, all classes deliver the same course and can be taught by any lecturers. A class can be held in any available classroom and any timeslot. Based on it, the vaccine providers represent the classrooms.

As an assignment problem, there are hard constraints and soft constraints in this model. Hard constraints are constraints or rules that cannot be violated. Soft constraints are constraints that should be concerned to improve the system's performance [31]. The soft constraint applied in this model is that the participant should be served within his preferred timeslots. The hard constraints in this vaccination scheduling model are as:
− A participant cannot be served at more than one provider.
− A participant cannot be served in more than one timeslot.
− Participants' preferred timeslots must be within the provided timeslots.
− The vaccination must be conducted within provided timeslots.

- The number of participants in a timeslot in a provider cannot surpass the maximum capacity.
- The participants' preferred timeslots are known in advance, and they do not change during the scheduling process.

     This model has three objectives that are leveled as primary, secondary, and tertiary. The primary objective is to minimize the number of unserved participants. A participant must be served if there is an available slot in a system. The secondary objective is to minimize the number of participants served outside their preferred timeslots (missed timeslot). The tertiary objective is to minimize the total travel distance. These objectives are then transformed into fitness functions. After the general model is explained, the next step is explaining the mathematical model. The annotations used in it are as:

c	:	participant or customer
C	:	set of participants
C_u	:	set of unserved participants
C_{mt}	:	set of participants with missed timeslot
c_{se}	:	selected participant
f_d	:	distance fitness function
f_t	:	timeslot fitness function
f_u	:	unserved participant fitness function
k	:	coefficient
o_{pr}	:	primary objective
o_{sd}	:	secondary objective
o_{tr}	:	tertiary objective
p	:	provider
P	:	set of providers
P_{ca1}	:	providers pool in the first round
P_{ca2}	:	providers pool in the second round
p_{se}	:	selected provider
p_{se1}	:	selected provider during the first round
p_{se2}	:	selected provider during the second round
q	:	vaccine stock
s	:	participant's status (0 = unserved, 1 = served)
sol	:	solution
t	:	timeslot
t_{se1}	:	selected timeslot during the first round
t_{se2}	:	selected timeslot during the second round
T	:	set of timeslots
T_{pr}	:	set of preferred timeslots
T_{ca1}	:	first-round timeslots pool
T_{ca2}	:	second-round timeslots pool
t_{se}	:	selected timeslot
$temp$	:	current temperature
U	:	uniform random
Δ_f	:	fitness difference

     As it is mentioned above, the model consists of three objectives: primary, secondary, and tertiary. These objectives are formalized by using (1) to (8).

$$o_{pr} = min\ (f_u) \tag{1}$$

$$o_{sd} = min(f_t) \tag{2}$$

$$o_{tr} = min(f_d) \tag{3}$$

$$f_u = n(C_u) \tag{4}$$

$$f_t = n(C_{mt}) \tag{5}$$

$$f_d = \sum_{\forall c_s} \|c - p_{se}(c)\| \tag{6}$$

$$C_u = \{c | c \in C \wedge s(c) = 0\} \tag{7}$$

$$C_{mt} = \{c | c \in C \wedge t(c) \notin T_{pr}(c)\} \tag{8}$$

The explanation of (1) to (8) is as; (1) states that the primary objective is minimizing the fitness function related to the number of unserved participants; (2) states that the secondary objective is minimizing the fitness function related to the missed timeslot; (3) states that the tertiary objective is minimizing distance fitness function; (4) states that the unserved participant fitness function equals the number of unserved participants; (5) states that the missed timeslot fitness function equals the number of participants whose vaccination timeslot is outside their preferred timeslots; (6) states that the distance fitness function is obtained by accumulating all travel distances between participants and their selected provider; (7) states that the set of unserved participants consists of all participants that fail from being allocated; (8) states the set of missed timeslot participants consists of all participants whose allocated timeslot is outside their preferred timeslots.

The model consists of two rounds. In the first round, the system tries to allocate all participants to their preferred timeslots. The system iterates from the first participant to the last participant. This process is formalized by using (9) to (13).

$$p_{se1}(c) = p, p \in P_{ca1}(c) \wedge min(\|c - p\|) \tag{9}$$

$$t(c) = t_{se1}\big(c, p_{se1}(c)\big) \tag{10}$$

$$P_{ca1}(c) = \{p | P \wedge \exists t \in T_{pr}(c) \wedge q(t) > 0\} \tag{11}$$

$$t_{se1}(c,p) = U\big(T_{ca1}(c,p)\big) \tag{12}$$

$$T_{ca1}(c,p) = \{t | t \in T_{pr}(c) \wedge q(t) > 0\} \tag{13}$$

The explanation of (9) to (13) is as; (9) shows that the system allocates providers from the provider candidates pool whose participant distance is minimal; (10) shows that the participant's timeslot is the selected timeslot related to the selected provider; (11) shows that the provider candidates pool consists of providers with a timeslot within the participant's preferred timeslots with positive quantity; (12) shows that the timeslot for the participant related to the provider is picked randomly from the timeslot candidates pool and follows a uniform distribution; (13) shows that the timeslot candidates pool consists of provider's timeslots within the participant's preferred timeslots with positive quantity.

There is a possibility that there will be unserved participants after the first round. It is caused by there is not any available timeslot that matches with the participant's preferred timeslots. This problem will be solved in the second round. In the second round, the participant's preferred timeslots are neglected. The system will allocate the participants to their nearest available provider. This process is formalized by using (14) to (18).

$$p_{se2}(c) = p, p \in P_{ca2}(c) \wedge min(\|c - p\|) \tag{14}$$

$$t(c) = t_{se2}\big(c, p_{se2}(c)\big) \tag{15}$$

$$P_{ca2}(c) = \{p | P \wedge \exists q(t) > 0\} \tag{16}$$

$$t_{se2}(c,p) = U\big(T_{ca2}(c,p)\big) \tag{17}$$

$$T_{ca2}(c,p) = \{t | t \in T \wedge q(t) > 0\} \tag{18}$$

The explanation of (14) to (18) is as; (14) shows that the provider is selected from the second-round provider candidates pool whose participant distance is minimal; (15) shows that the participant's timeslot is the selected timeslot related to the selected provider; (16) shows that the second-round provider candidates pool consists of providers who still have positive quantity in their timeslots; (17) shows that the selected timeslot related to the provider is picked randomly from the second timeslot candidates pool and follows a uniform distribution; (18) shows that the second timeslot candidates pool consists of timeslots of the provider that still have positive quantity.

This model is then optimized by using a cloud theory-based simulated annealing algorithm (CTA). The CTA is a derivative and the improvement of the basic simulated annealing (SA). Rather than conducting a single solution, the CTA is a population-based optimization algorithm [32]-[34]. The objective is to improve the possibility of achieving a better solution [32]. Moreover, CTA is proven in finding the near

optimal solution, for example, in solving the scheduling problem [33]. The process of the CTA implemented into this proposed model is shown in Figure 3. In Figure 3, both first round and second round plotting are conducted sequentially in all participants-providers plot processes, whether they are conducted in the initialization and iteration.
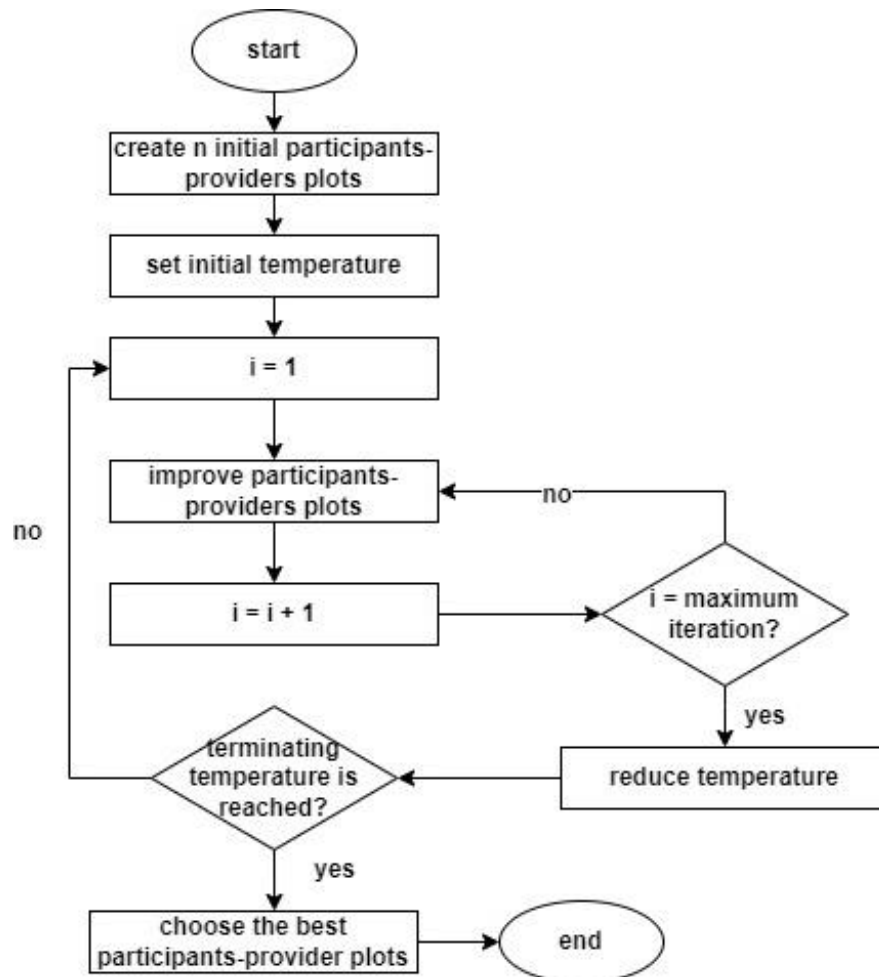

Figure 3. CTA optimized proposed model

The objectives of this optimization process are to minimize the number of participants that are served outside their preferred timeslots and minimize the total travel distance. The first objective is prioritized more than the second one. The result is that in this system, the participants choose their preferred timeslots and not the provider. The consequence of this strategy is as follows. In every iteration, the current solution will replace the current best solution only if the timeslot fitness function of the current solution is less than or equal to the current solution. It means the algorithm will not tolerate a worse timeslot fitness value. After that, the system will check the distance fitness function. If the distance fitness value of the current solution is better than the current best solution, then the current solution becomes the current best solution. Otherwise, the current best solution replacement is determined by using the probability factor. This mechanism is formalized by using algorithm 1.

During the initialization process, in every solution, the sequence of the participants is randomized. This process is conducted to ensure that the results among the solutions will be different in the initialization process. After the initialization process, the following process is the iteration. In every iteration, a certain number of participants are picked randomly for reallocation to improve the solution. This process consists of two steps. In the first step, these selected participants are released from their providers, and it means that the capacity of these related providers increases. In the second step, all these participants are reallocated based on a randomized sequence.

```
algorithm 1: current best solution replacement
1     begin
2       if fₜ(sol_cur) ≤ fₜ(sol_curbest) then
4         Δ_f ← f_d(sol_cur) - f_d(sol_cur)
5         if Δ_f < 0 then
7           sol_curbest ← sol_cur
8         else
9           if U(0,1) < exp(-Δ_f/(k . temp)) then
10            sol_curbest ← sol_cur
11          end if
12        end if
13      end if
14    end
```

4.   RESULTS AND DISCUSSION

This proposed model is then implemented into vaccination scheduling simulation to observe its performance. The scenario of this simulation is in Sleman district, Indonesia. The district size is approximately 575 square kilometers. There are 25 public health service centers in this district. These public health service centers represent the vaccination providers. In the beginning, these 25 public health service centers were generated. Their location is distributed randomly in the district, and it follows a uniform distribution. Besides that, a certain number of participants are also generated. These participants' location is also distributed randomly, and it follows a uniform distribution. The scheduling horizon consists of 10 timeslots. The vaccine quantity is equal to the number of participants. These vaccines are distributed equally among providers and timeslots.

This proposed model is compared with the uncoordinated model and the basic course timetabling model. The uncoordinated model is adopted based on [28], where every provider conducts its reservation and scheduling process. In this uncoordinated model, participants cannot choose the timeslot. The second comparing model adopts the simplification of the course timetabling model in [17], where there is only a single course, and the lecturers are abstracted. Meanwhile, in this model, the optimization method is modified so that it uses CTA too. The coordinated approach is applied in this second model.

In this simulation, the observed parameters are the number of unserved participants, the total travel distance, the average travel distance, and the number of missed timeslots. The adjusted parameter is the number of participants. The number of participants ranges from 2,500 to 5,000 persons. In the proposed model, each participant can choose three preferred timeslots. The uncoordinated model [28] is acronymized as UC. The coordinated basic course timetabling model [17] is acronymized as CTM. In both proposed model and the CTM model [17], the population size is 10. The initial temperature is 100, and the terminated temperature is 1. There are 10 iterations in every temperature value. The simulation result is shown in Table 2 and visualized in Figure 4.

Table 2. Simulation result

Number of participants (person)	No. of unserved participants			Total travel distance (kilometer)			Average travel distance (kilometer)			Number of Missed Timeslots	
	Prop.	CTM [17]	UC [28]	Prop.	CTM [17]	UC [28]	Prop.	CTM [17]	UC [28]	Prop.	CTM [17]
2,500	0	0	86	6,765	29,673	31,424	2.71	11.87	13.02	0.00	0.00
3,000	0	0	106	8,495	40,857	38,683	2.83	13.62	13.37	0.00	0.00
3,500	0	0	113	9,242	43,624	44,488	2.64	12.46	13.13	0.00	0.10
4,000	0	0	135	11,357	52,346	51,373	2.84	13.09	13.29	0.00	0.30
4,500	0	0	135	13,076	63,089	58,819	2.91	14.02	13.48	0.00	0.40
5,000	0	0	126	14,465	63,004	63,450	2.89	12.60	13.02	0.00	0.40

The relation between the number of participants and the number of unserved participants is shown in Figure 4(a). Figure 4(a) shows that the proposed model and the CTM model [17] produce zero unserved participants if the total quantity of the vaccines is enough. This circumstance occurs in all numbers of participants. Meanwhile, the number of unserved participants is high for the uncoordinated model [28], and it ranges from 86 to 135 persons. This number of unserved participants tends to increase due to the increase in the number of participants. This circumstance occurs due to the mismatch between supply and demand in the uncoordinated model [28]. The relation between the number of participants and the total travel distance is shown in Figure 4(b). Figure 4(b) shows that the total travel distance increases due to the increase in the number of participants, and this circumstance occurs in all models. Comparing among models, the proposed

model performs as the best model in creating low total travel distance. Meanwhile, the total travel distance between the uncoordinated model [28] and the CTM model is almost equal. The proposed model creates a 77 to 78 percent lower total travel distance than the uncoordinated model [28].

The relation between the number of participants and the average travel distance is shown in Figure 4(c). The average travel distance is obtained by dividing the total travel distance by the number of served participants. Figure 4(c) shows that the number of participants does not affect the average travel distance. The average travel distance tends to be stagnant, and it occurs in all models. Comparing among models, the proposed model becomes the best model in creating a low average travel distance. Meanwhile, the average travel distance of both existing models [17], [28] is almost equal. The proposed model creates a 77 to 79 percent lower average travel distance than the uncoordinated model [28]. The relation between the number of participants and the number of participants with missed timeslot is shown in Figure 4(d). Figure 4(d) shows two circumstances related to the number of participants with missed timeslot due to the increase in the number of participants. The proposed model still produces zero number of participants with missed timeslot in all ranges of the number of participants. On the other hand, the number of missed timeslots in the CTM model tends to increase [17]. This result shows that the proposed model is better than the existing CTM model [17] in creating a low number of participants with missed timeslot. Nevertheless, the number of participants with a missed timeslot of the CTM model [17] is very low.
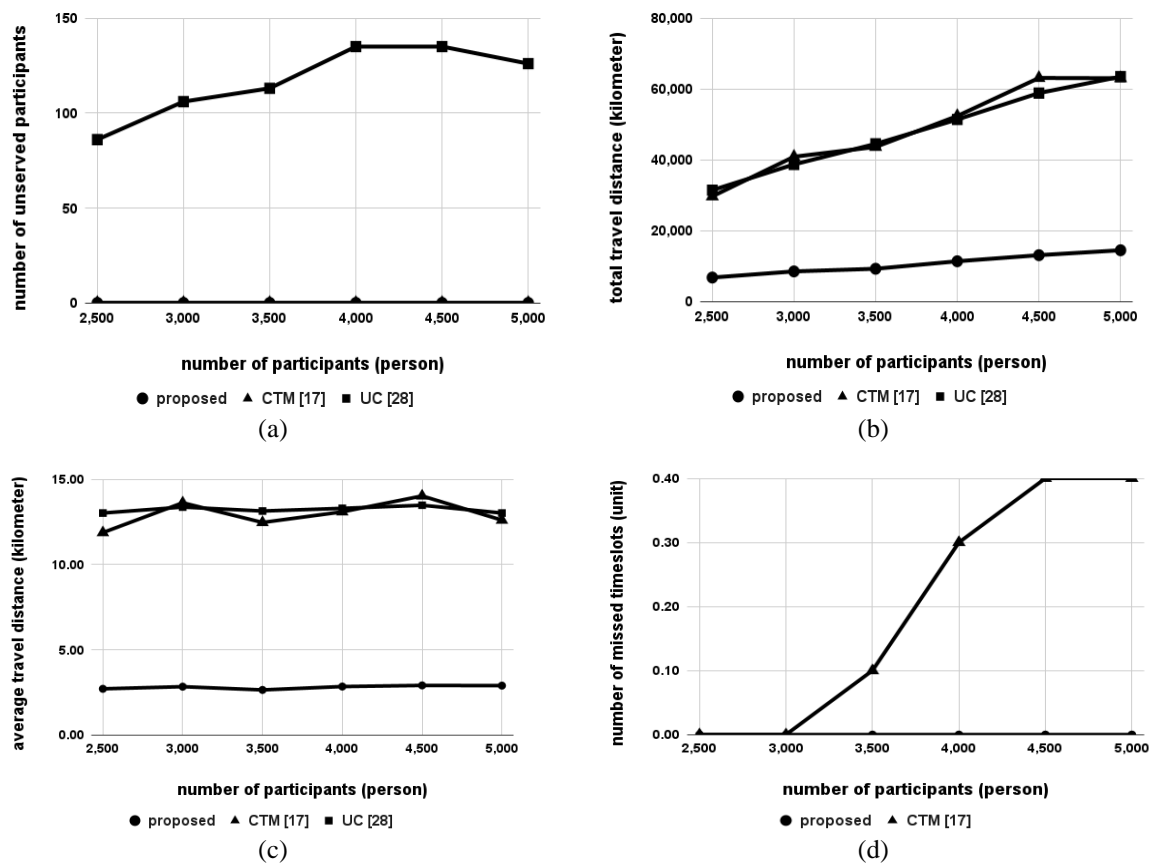

Figure 4. Relation between number of participants and observed parameters; (a) number of unserved participants, (b) total travel distance, (c) average travel distance, and (d) number of participants with missed timeslots

There are several findings due to the simulation result. First, the coordinated (centralized) approach is proven in solving the mismatch problem rather than the uncoordinated one. This condition is achieved because the system will allocate participants if there is at least one available provider with any timeslot. It is different from the uncoordinated model [28] because in the uncoordinated model, the participants cannot be reallocated although their preferred provider is not available anymore and there is at least one other available provider.

Second, the proposed model becomes the best model in creating a low total travel distance. This performance is achieved because the proposed model tries to allocate the participants to the available provider whose location is the nearest. Meanwhile, the uncoordinated model [28] does not do that because the participants choose the provider directly. They cannot be switched to another provider even if their location is closer than the chosen provider. The proposed model also outperforms the CTM model because the CTM model focuses on allocating the participants based on their preferred timeslots only. The travel distance does not become a concern in the CTM model [17].

5. CONCLUSION

This work has demonstrated that the proposed model has solved the mismatch problem in COVID-19 vaccination scheduling successfully. This coordinated approach produces zero unserved participants if the total number of vaccines is enough to cover all participants. The simulation result shows that the proposed model creates lower total travel distance rather than the uncoordinated model or the basic course timetabling adopted model. It is also better than the basic course timetabling model in creating a low number of participants with missed timeslot.

This work has demonstrated that operational research is essential in managing resources during the COVID-19 pandemic. Besides the vaccination program, many activities or resources can be optimized so that government can handle this emergency better. These resources include the ambulance, hospital, medical workers, drug, and medical equipment. In the future, this model can be explored and improved in facing other kinds of emergencies, such as distributing food or equipment in the disaster zone.

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