



A novel scheduling method for reduction of both waiting time and travel time of patients to visit health care units in the case of mobile communication

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ABSTRACT

This paper proposes a new scheduling problem for patient visits with two objectives: minimizing patient waiting time and travel time. It also presents a novel encoding method for Genetic Algorithms (GA) that is well-suited for this problem. Experiments demonstrate that the proposed encoding method reduces optimization iterations by 17% compared to conventional methods, and the GA can decrease waiting time by up to 58.2% and travel time by up to 89.3% for specific examples. The novel scheduling problem and the encoding method are two main contributions of this work.

ARTICLE HISTORY

Received 11 August 2022
Accepted 2 March 2023

KEYWORDS

Discrete event simulation;
Genetic algorithms; Health
care; Optimization;
Scheduling; Multi-objective
optimisation

1 Introduction

Long waiting time and extensive travel time are two of the major barriers for outpatients to access health care services (Allen et al. 2017; Ahmed et al. 2001; Leung et al. 2020). Outpatients must wait for hours or days for getting healthcare services in some regions and countries. Examples of such services are patient tests such as e.g. COVID-19 tests, imaging tests, colonoscopy examinations, etc. (Puzhko 2017; Niklas, Lasserson, and Briggs 2017; Gudivada, Philips, and Tabrizi 2020). It is found that excessive waiting time is an important reason for outpatient dissatisfaction (Clague et al. 1997). Waiting time is a non-value-added time in the health service system (Barlow 2002; Sayantan et al. 2020); besides, a longer waiting time may complicate outcomes for patients (Kaushal et al. 2015; Zhuang et al. 2020; Zhan et al. 2021; Zou, Wang, and Cheng 2022). During the ongoing COVID-19 pandemic, the waiting time problem has worsened, because of the reduced resources available for non-contagious patients (Jeffery et al. 2020). Elsewhere, the increase in non-value-added time may increase the total cost of a service or manufacturing organisation significantly (Adeyemi, Ogbeyemi, and Zhang 2021).

In addition, travel between a patient's location (i.e. home, office, etc.) to a health care unit is an important factor for patients to access proper health care services. In the past, scheduling problems only considered patient wait time and overlooked patient travel time due to potential conflict between those two. Researchers (Smith et al. 2003; Detro

et al. 2020; Lancharoen, Suksawang, and Naenna 2020) found that greater travel time for accessing services can result in a reduced number of physician visits, increased rates of attrition, and inadequate management of chronic conditions. Prolonged travel time is considered a major barrier to healthcare access. It doesn't only involve time consumption but is also related to cost, public transit safety, vehicle access, etc (Syed, Gerber, and Sharp 2013). Although telemedicine can eliminate part of the problems (Sarivougioukas and Vagelatos 2020; Wan and Chin 2021), it can only be used in cases that do not require in-person physical examinations. Additional barriers to telemedicine are lack of adequate equipment, or insufficient internet bandwidth.

The problem we investigate can be defined with the help of Figure 1. The scenario in Figure 1 is as this: there are multiple health care units in a region, and there are a few professionals (doctors, nurses) in different departments of one unit. Patients are looking for booking health care services, e.g. COVID-19 testing, through phone calls or online (Lin et al. 2021; Wan and Chin 2021). It is reasonable to assume that patients want to have short waiting time and short travel time. Waiting time in this study is defined as the interval between the time that a patient desire to have a health care service and the time the patient has actually received the service. When there is no time slot available for the patient's desired time, the patient's appointment will be postponed to the next available one; as such, waiting time occurs. The travel time is the time that a patient travels from a patient's location to a health care unit. This situation can also be described as a service

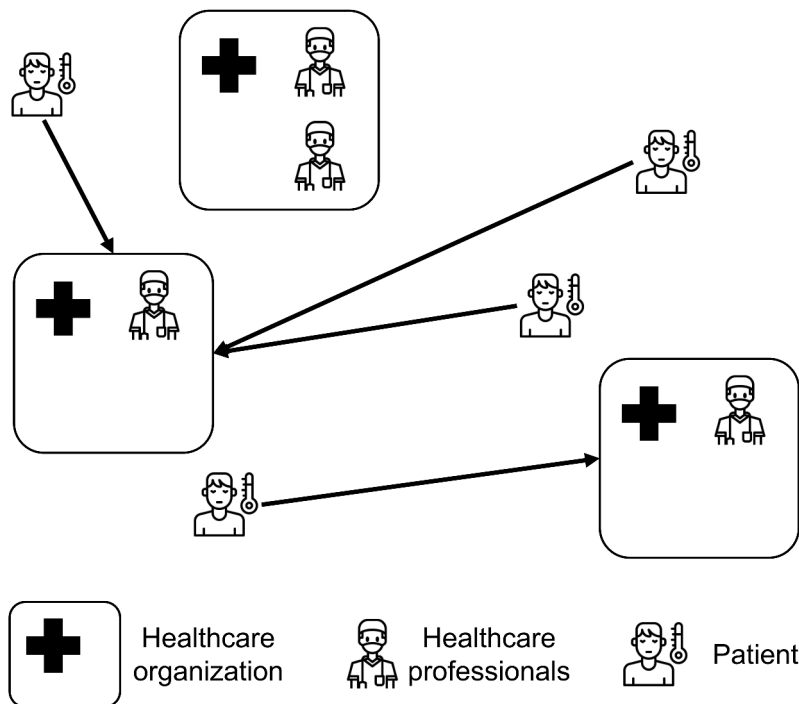


Figure 1. A general situation of the problem. There are multiple health care units in a region. Each of them has multiple health care professionals. When patients are looking for health care, they want to minimize their waiting time and travel time.

system (Wang et al. 2013, 2016), where patients are clients, and health care professionals & health care units are services.

Currently, most studies in the literature have only focused on reducing waiting time within health care units (Ahmadi-Javid, Jalali, and Klassen 2017). To the best of our knowledge, nobody has studied the problem of waiting time from the point of time that a patient books an appointment outside health care units, and naturally nobody has studied the method of reducing both the waiting time and travel time simultaneously. During the COVID-19 pandemic period, remote scheduling with simultaneous consideration of travel time and waiting time make sense for the problem such as scheduling COVID-19 testing. In this study, the problem is formulated as a multi-objective optimisation problem and solved with a Genetic Algorithm (GA). In this connection, a novel encoding method, Discrete Event Encoding (DEE), is proposed for GA as well as any evolutionary computing algorithms. As an example, DEE is implemented as a part of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) in this study. The simulated experiment demonstrates the effectiveness of the proposed method. This paper has two contributions. The first one is in the field of health care service management, specifically, a new problem has been defined and its mathematical model has been developed. The second contribution is in the field of GA, namely the novel encoding method, DEE, which can represent candidate solutions without causing violations of constraints or resource wastes. Further explanations are given in the literature review section.

The remainder of this paper is organised as follows. In Section 2, a literature review is provided on the problem of patient waiting time reduction and encoding methods used in multi-objective optimisation algorithms. In Section 3, the model along with the algorithm for scheduling is presented. The performance of the algorithm is illustrated through simulated experiments in Section 4. Finally, Section 5 concludes the paper with a discussion of future work.

2 Literature review

2.1 The existing approaches to reduce patients waiting time

The outpatient scheduling problem has received attention from health care researchers and practitioners. Extensive reviews of appointment scheduling literature can be found in the study conducted by Cayirli and Veral (2003) and Ahmadi-Javid, Jalali, and Klassen (2017). The approach can be divided into three levels: strategic, tactical, and operational (Ahmadi-Javid, Jalali, and Klassen 2017). Strategic decisions are long-term decisions that determine the main structure of an outpatient appointment system. Tactical decisions are medium-term decisions related to how patients as a whole are scheduled, or how groups of patients are processed. Operational decisions are short-term and are concerned with efficiently scheduling individual patients.

At the strategic decision level, Robinson and Chen (2010) compared the performance of the pre-scheduled policy, which schedules patients in advance of their appointment days, and the open-access policy, which schedules patients on the same day that they call for an appointment. In their study, the number of appointments was given, the service time was deterministic, and the arrival of patients was assumed to be punctual. Their numerical analysis revealed that the open-access policy can significantly outperform the

pre-scheduled policy in most cases including patients' waiting time, doctor's idle time, and doctor's overtime. Dobson, Hasija, and Pinker (2011) also compared a pre-scheduled policy with an open-access policy; they found that when there were a lot of urgent walk-in patients, the open-access policy performed better than the pre-scheduled policy. It is worth mentioning that both online¹ (appointments are scheduled immediately upon their request) and offline (appointments are scheduled after a batch of requests has been received) problems have been studied in the literature, see (Wang and Gupta 2011; Weiner et al. 2009). Indeed, the use of personal mobile devices, instant messages and notifications have made offline scheduling more efficient. The offline scheduling system collects patient requests electronically (e.g. via email or Web-based portal) first, and then advises their appointment time using text messages. Kuiper, Kemper, and Mandjes (2015) compared the performance of the online and offline approaches and found that the offline approach had a better performance in terms of reducing patient waiting time as well as staff idle time.

At the tactical decision level, Klassen and Yoogalingam (2009) showed that the best pattern of appointment lengths was a plateau-dome structure. The structure breaks one day's schedule into three sections. In the first section (e.g. morning), the appointment lengths increase over time. The appointment lengths of the middle section (e.g. afternoon) have the same, creating a plateau. The appointment lengths of the last section decrease until the end of the day. Their study found that this pattern results in the least waste of capacity. As opposed to these time-dependent appointment lengths, Nguyen, Iyer Sivakumar, and Graves (2015) proposed a network flow model to determine the optimal allocated capacity based on different groups. In their study, two patient groups with different appointment lengths were considered; they were patients on their first visit and return visits. In Zhou et al.'s work (Zhou et al. 2019), they generalised the idea of different appointment lengths and considered uncertainties in patients' lengths of stay. They raised a point that when managing for maximising hospital revenue, it is important to allocate resources to multiple types of patients and uphold service equity.

At the operation decision level, there are two main streams of studies. One focuses on allocating clients (patients) to services and the other on determining the appointment time. Most studies on allocating patients assumed that all services are identical. For example, Zheng et al.'s study (Zheng et al. 2015) proposed an overbooking scheduling model. Their goal is to maximise the expected profit by optimising the number of overbooked patients in multiple-provider clinics. Other studies took some factors to differential services. Balasubramanian et al. (2014) developed a model that factorised the importance of continuous care. Their study showed that significantly higher revenue was earned when a primary-care provider saw one of his/her own patients compared to when the continuity of care was broken. In determining the appointment time, Chakraborty, Muthuraman, and Lawley (2013) found that compared with a slot scheduling method (slot time is predetermined), scheduling patients at any time in the consultation session can be more efficient; however, it is less attractive in practice because the resulting appointment time has no particular pattern, which means difficulty for patients to follow. As an alternative way to determine the appointment time, Liu and Geng (2020) proposed an ordinal optimisation strategy. Instead of directly controlling the appointment time, their approach was to determine the sequence, in which a list of patients

should be scheduled. Their goal was to utilise the limited medical resources efficiently while ensuring the quality of service for clients.

Although each study in the above focuses on a specific decision level, an outpatient scheduling approach usually covers two or three of the decision levels above. For example, for a study that focuses on appointment time optimisation (at the operation decision level), their scheduling approach used either a pre-scheduled or open-access policy (at the strategic decision level) (Yafei et al. 2019). From the literature above, three remarks are made. The first is that offline scheduling becomes more popular as scheduling systems are more accessible to patients via mobile phones. The second is that most studies only consider waiting time inside health care units. The third is that most of the studies above have only a single optimisation objective.

When considering multiple objectives, e.g. maximising revenue and resource utilisation, the existing work often adds up those objectives with different weights. This type of optimisation is useful as a tool which should provide decision-makers with insights into the nature of the problem, but usually cannot provide a set of alternative solutions that trade different objectives against each other (Savic 2002). On the contrary, in a multi-objective optimisation problem with conflicting objectives, there is no single optimal solution. The interaction among different objectives gives rise to a set of compromised solutions. Investigating scheduling problems with multi-objectives captures more semantics of appointment booking and scheduling in practice (Castro and Petrovic 2012). Therefore, our study is to address the scheduling problem using an offline scheduling strategy with multi-objectives.

2.2 The existing method for hospital scheduling problems

A typical hospital scheduling problem has the following characteristics: 1) schedule a given number of patients, 2) each appointment may take a different amount of time, and 3) each appointment has to meet certain resource constraints. To maximise resource utilisation, an optimal schedule needs to be found. This is an NP-hard problem (Yeh and Lin 2007) as the number of possible schedules grows exponentially if one attempts to exhaust all solutions. That is why researchers use Evolutionary Computation (EC) approaches and other approaches. EC is fundamental for evolutionary algorithms which include Genetic Algorithms (GA) (Kramer 2017; Mitchell 1998), Genetic Programming (GP) (Kennedy and Eberhart 1995), Evolution Programming (EP) (Back 1996), etc.

When applying an EC method such as GA, candidate solutions need to be encoded as an array of bits, called chromosomes. In the hospital scheduling problem, chromosomes can be either represented by a list of appointment times or a list of appointment indexes. Both encoding methods may cause violations of constraints after the crossover and mutation step. For example, when using a list of appointment times as a chromosome, time & space conflicts among appointments may happen due to the randomised nature of GA. Chromosomes with the violations need to be either discarded (Sulis et al. 2020) which causes a considerable waste of computation resources and reduces the algorithm's efficiency, or considered as a penalty when evaluating chromosomes (İnanç and Eren Şenarar 2020; Kaveh et al. 2020; Lin and Chou 2020). The latter way may result in impractical results.

To avoid such constraint violations, many researchers (Roland et al. 2010; Vali-Siar, Gholami, and Ramezani 2018; Zhao, Chien, and Gen 2018; Hamid et al. 2020; Xin and Chen 2021) took a repair approach. The approach resolved violations of constraints by modifying new candidate solutions based on given rules. For example, when using a list of appointment indexes as a chromosome. The crossover step often causes duplicate indexes in one chromosome. The repair step replaces the duplicate indexes with other ones from the previous generation of chromosomes. This made the new chromosomes very similar to the previous ones and diminished the benefits of the crossover step. Besides, this additional modification causes the results hard to converge (Vali-Siar, Gholami, and Ramezani 2018; Zhao, Chien, and Gen 2018). Alternatively, Rivera et al. (2020) used a group of fixed-length containers to encode a chromosome. Each container had one or more appointments. At the crossover and mutation step, chromosome modification only happened at the container level. In this way, time conflict will be avoided. However, as the container length was fixed while the appointment length was not, there are gaps between appointments. Those gaps were considered a time waste, and they reduced resource usage.

In short, when applying traditional encoding methods on scheduling problems, violation of constraints happens in candidate solutions after mutation and crossover steps. To overcome this problem, researchers either used a repair step to fix the solutions, or added gap time in schedules to avoid the violation. The repair step is a waste of computational resources, and the gap time is a waste of healthcare resources. Our new encoding method, DEE, can naturally avoid the violation of constraints. DEE does not require any repair step or gap in schedules, and therefore does not cause any waste of resources. This method can be adapted for any EC algorithm which uses mutation or crossover steps in scheduling problems.

3 Scheduling optimization algorithm

3.1 Optimisation problem

The optimisation problem has two objectives: (1) to minimise the patient waiting time, and (2) to minimise the patient travel time. Further, the following assumptions are applied:

- (1) There are limited health care units in a region, which could offer similar services but are in different locations.
- (2) Patients and health care professionals are punctual.
- (3) The lengths of appointments vary among patients and are determined when patients request services.
- (4) Patients do not know the appointment time or the health care location when they request a health care service. Instead, they will be notified of the time and the location with the length of time (θ) prior to their departure time.

3.2 Mathematical model

A common scheduling method utilises a first-come-first-serve strategy that schedules patients sequentially. Our scheduling algorithm optimises a group of patients to achieve a better overall result in a scheduling system as opposed to the common strategy. We consider the following two scenarios: the pre-scheduled scenario and the open-access scenario. In the first scenario, the scheduling of a group of patients within a pre-defined period of time is taken, where patients are not individually differentiated. After that, the schedule is kept unchanged. In the second scenario, patients are individually scheduled upon their requests being received.

Denote all patients' appointments in the system as $P = \{p_1, p_2, p_3, \dots, p_n\}$ where n is the number of appointments. The time when patients request their appointments is defined as $R = \{r_1, r_2, r_3, \dots, r_n\}$. Patients' preferred appointment times are denoted as $Y^r = \{y_1^r, y_2^r, y_3^r, \dots, y_n^r\}$, and the duration of appointments is denoted as $A = \{a_1, a_2, a_3, \dots, a_n\}$. Patients are given their initial scheduled appointment time as $Y^o = \{y_1^o, y_2^o, y_3^o, \dots, y_n^o\}$ using the first-come-first-serve scheduling method. Their optimised appointment time by the system is denoted as $Y^s = \{y_1^s, y_2^s, y_3^s, \dots, y_n^s\}$. Then, we have:

$$R \leq Y^r \leq Y^o \& R \leq Y^r \leq Y^s \quad (1)$$

Under the pre-scheduled scenario, the re-arrangeable patient appointments P_x is:

$$P_x = \{p_i | p_i \in P, s_j \geq y_i^0 \geq s_{j-1}\} (1 \leq i \leq n) \quad (2)$$

where y_i^0 is the time at which patient p_i departs; s_j is the predefined time point to run the algorithm; s_{j-1} is the previous time point. For example, if the system groups all the patients within 24 hrs and schedule time together, then s_{j-1} can be 8 pm on day 1, and s_j be 8 pm on day 2.

Under the open-access scenario, the re-arrangeable patient appointments P_x is:

$$P_x = \{p_i | p_i \in P, y_i^0 \geq s'_j + \delta_{ik} + \theta\} (1 \leq i \leq n) \quad (3)$$

where s'_j is the time point when a patient requests an appointment, $s'_j \in R$; δ_{ik} is the time required for patient p_i to travel to the health care unit k ($1 \leq k$); θ is a predefined length of time, prior to patients' departure time, it determines when the system confirms patients' appointments; m is the total number of health care units in the region/system.

There are two objective functions:

$$OB - 1 : \text{Min} \sum_{i=1}^{|P_x|} \{y_i^s - y_i^r\} (1 \leq i \leq |P_x|)$$

$$OB - 2 : \text{Min} \sum_{i=1}^{|P_x|} \delta_{ik} (1 \leq i \leq |P_x|)$$

where $|P_x|$ is the number of re-arrangeable appointments. $OB-1$ is to minimise the total waiting time. The $OB-2$ is to minimise the total travel time.

The constraint of this problem is that there is no conflict in the scheduled time. It can be written as:

$$p_i, p_j \in P_x, i \neq j, \\ \text{if } k_i = k_j, \text{ then}$$

Table 1. Indices and parameters in the mathematical model.

Symbol	Explanation
i, j	appointment index
P	total patient appointments
n	number of total patient appointments
R	the time when patients request their appointments
A	appointment durations
y^r	patients preferred appointment time
y^o	initially scheduled appointment time
y^s	optimized appointment time
P_x	a subset of re-arrangeable appointments
s	time point to run the algorithm
δ	length of time required for patients to travel to a health care unit
θ	length of time, prior to patients' departure time, it determines when the system confirms patients' appointments
m	number of health care units
d	health care professional assigned to an appointment

$$[y_i - (y_j + a_j)] \times [(y_i + a_i) - y_j] \geq 0 \quad (4)$$

where k is the health care unit where a patient has an appointment. This constraint ensures that no overlap among appointments in the same healthcare unit. This creates a trade-off between appointment time and choice of health care units.

Here, we give the formal definition of the optimisation problem:

$$\text{OB} - 1 : \text{Min} \sum_{i=1}^h \{y_i - r_i\} (1 \leq i \leq h)$$

$$\text{OB} - 2 : \text{Min} \sum_{i=1}^h \delta_{ik} (1 \leq i \leq h)$$

s.t

$p_i, p_j \in P_x, i \neq j,$
if $s_i = s_j$, then

$$[y_i - (y_j + a_j)] \times [(y_i + a_i) - y_j] \geq 0 \quad (5)$$

All notations used above are summarised in [Table 1](#) below.

3.3 Algorithm

To solve the above multi-objective optimisation problem, NSGA-II (Kalyanmoy et al. 2002) was used in this study. NSGA-II is a well-known genetic algorithm, which is capable of fast sorting and elite searching for multi-objective solutions. Thus, it is ideal for our problem. To implement the genetic algorithm, a new encoding method, DEE, is proposed, in conjunction with the Discrete Event Simulation (DES) (Jun, Jacobson, and Swisher 1999) to calculate the objectives' value of each chromosome. DES has the benefit of mimicking a scheduling process, while NSGA-II is effective in solution searching. Based on this understanding, we combined them based on the theory of engineering hybridisation (Zhang, Ouyang, and Sun 2010) and proposed a hybrid method called DEE-NSGA-II here. Its workflow is illustrated in [Figure 2](#).

The optimisation workflow of the DEE-NSGA-II follows a typical NSGA-II procedure. The method starts with a set of chromosomes that are generated using DEE. Each

chromosome presents a candidate solution to the problem. The algorithm takes the population of chromosomes as parents and reproduces new chromosomes (i.e. offspring in a GA). The reproduction exchanges partial information between two chromosomes, called crossover, and makes minor changes, called mutation. Then, a subset of elite parents & offspring chromosomes is selected to reproduce the next generation of offspring. This process repeats for a given number of generations. Populations from newer generations are expected to perform better than ones from earlier generations as they are offspring from elite chromosomes. To identify those elites, NSGA-II uses fast nondominated sorting and crowding distance sorting to achieve a superior sorting speed and keep diversity among candidate chromosomes. More details on how each step in the NSGA-II can be found in (Kalyanmoy et al. 2002). It is worth noting that applying the NSGA-II algorithm to the problem is not the main contribution of this work. There are many other multi-objective optimisation algorithms that may be suitable for solving the problem. The NSGA-II is picked in this study to demonstrate the effectiveness of DEE, as explained below.

With the scheduling order (chromosome), the DES was used to evaluate the objective functions, step 2 in Figure 2. Details of this step are shown in Figure 3. For each appointment in the scheduling order, a group of health care units with the shortest waiting time available is identified. From this group, the health care unit with the shortest travel time is chosen. The process goes through all the appointments following the order. By summing up the waiting time and travel time of each appointment, the total patients' waiting time and travel time are calculated, which are the values of OB1 & OB2.

In applying NSGA-II or other multi-objective optimisation algorithms, the most challenging part is the representation of candidate solutions (encoding methods). The candidate solution in a GA is typically encoded as a string consisting of N integer numbers (called chromosomes). Conventional encoding methods often require a repair step to resolve constraint violations from chromosomes. This additional step causes GA hard to converge. To overcome this inefficiency problem, we developed a new encoding method, DEE, which uses a scheduling order as a chromosome. Figure 4 shows an example of a scheduling order.

In this example, the scheduling order of 4 appointments a, b, c, d in a queue is determined. The length of the chromosome is the number of appointments. Each digit in the chromosome represents the order in the current appointment queue. For example, the first number '3' means the third appointment in the current queue a, b, c, d. So appointment c will be scheduled first and after that is removed from the appointment queue. The second number '3' means the 3rd appointment in the current appointment queue a, b, d. Therefore, appointment d is scheduled next and then removed from the queue. Similarly, the third number '1' means the 1st appointment in the current appointment queue a, b, which is appointment a. The fourth number '1' means appointment b, which is the 1st appointment in the remaining appointment b. One might notice that the last number in the representation will always be '1' as there is only one appointment in the queue. In summary, the chromosome in Figure 4 represents an appointment scheduling order as (c, d, a, b), and it only decides the order of appointments to be scheduled rather than the appointment time or location. This order will then be processed by the DES to guarantee the constraints in the optimisation problem will not be violated.

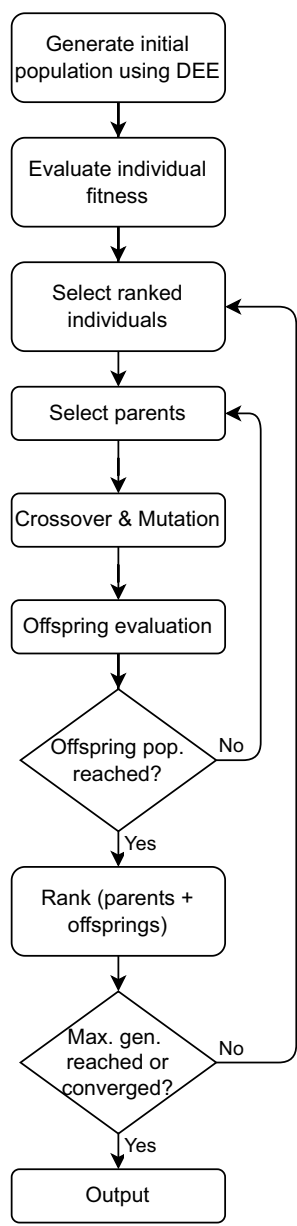


Figure 2. The optimization workflow of the DEE-NSGA-II.

4 Experiment

4.1 Experiment data and setting

In this section, we report two case studies to demonstrate how the proposed method works in a patient scheduling problem. In both cases, we used synthetic patient data to simulate realistic situations. The synthetic data was randomly generated to follow rules in Table 2.

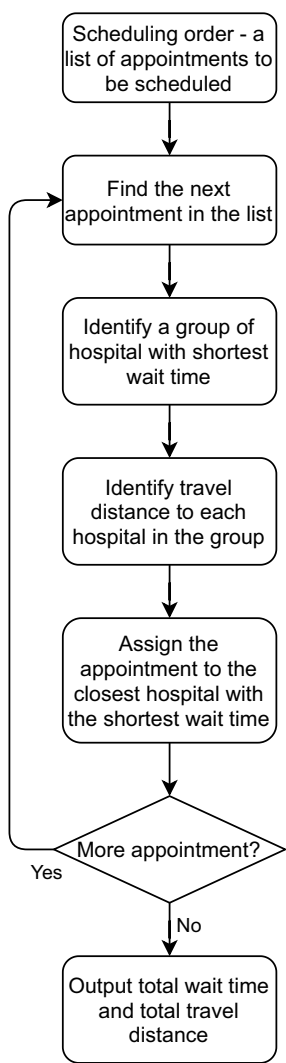


Figure 3. A flowchart of how the DES evaluates individual chromosomes.

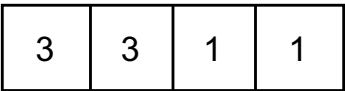


Figure 4. An example of DEE encoded chromosomes representing four appointments to be scheduled.

The proposed method is written in Python 3.6. The NSGA-II module is adopted from pymoo (Blank and Deb 2020) and the DES module is developed by ourselves. pymoo is a python package for multi-objective optimisation algorithms and is developed under the supervision of the original developer of the NSGA-II algorithm (Kalyanmoy et al. 2002).

Table 2. Parameters used in generating synthetic patient appointment data.

Parameters	Value used in generating synthetic data
Number of all appointments (n)	12~24, varies in each experiment.
Time of request appointments (R)	6~12 hrs, varies in each experiment.
Appointment length (A)	0.25~4 hrs, round up to the nearest quarter.
Patient travel time length (δ)	0~1 hr
number of health care units (m)	3
number of health care professionals (q)	3

Table 3 contains a list of parameters used in the proposed DEE-NSGA-II method. The population size and the mutation probability are determined by the number of all appointments (n). The algorithm stops when there is no improvement (objective value changes < 0.0025) for g_s continuous generations or the maximum generation (g_{max}) is reached. The Crossover & Mutation Distribution Index are the control parameters which are inversely proportional to the amount of perturbation in Crossover & Mutation. The smaller the value, the larger the perturbation and vice versa. A smaller value, thus, improves the resilience to premature convergence at the cost of a highly focused search. The default value of 10.0.

- Local Desktop: Processor, Intel Core i5-7600K, Quad-Core, 3.8 GHz, Max Turbo @4.20 GHz. 16 GB RAM.
- Cloud Server (Compute Canada): Processor, Intel Xeon Platinum 8168, 32 Core 2.70 GHz, Max Turbo @3.70 GHz. 64 GB RAM.

4.2 Case studies

Two cases with simulation data were used in this study. The first is the pre-scheduled scenario, which schedules patients in advance of their appointment days, so all requests are optimised at the same time. The second is the open-access scheduling scenario, which schedules patients on the same day that they request an appointment. Compared to the open-access scheduling scenario, the pre-scheduled scenario has more appointments to be arranged and only runs once. It could take considerably fewer computational resources. However, it requires appointments to be made in advance and no changes to appointments can be made after the schedule is made. The open-access scheduling

Table 3. List of parameters in the DEE-NSGA-II method/model and their values in this study.

Parameters	Values used in the experiments
Population size	$2 \times n$
Crossover rate	1
Crossover type	Simulated Binary Crossover
Crossover distribution index	3
Mutation probability	$1/n$
Mutation type	Polynomial Mutation
Mutation distribution index	3
Max. generation (g_{max})	200
Termination criterion (g_s)	20

Two sets of hardware are used for the experiment. The cloud server is used for optimising cases under the open-access scheduling scenario, and the local desktop is for optimising the pre-scheduled scenario.

scenario, on the other hand, optimises all appointments every time a new appointment is added or modified.

In the first case study, we compare DEE-NSGA-II to a baseline scheduling method and a GA using a conventional encoding method (GACE) that is adapted from literature (Vali-Siar, Gholami, and Ramezani 2018; Zhao, Chien, and Gen 2018) using pre-scheduled scenarios. In terms of the total appointments (represented as patient numbers in Figure 5 & 6, we used four different ones (12, 14, 18, 24). Under each number, 6 sets of synthetic appointment data were generated by following the rules in Table 2. Figure 5 shows the results for total waiting time, and Figure 6 shows the results for total travel time.

The baseline scheduling method schedules patients on a first-come-first-serve basis strategy. Note that the same strategy was used in the DES to calculate optimisation objectives. Details of this strategy were explained in Figure 3. The GACE schedules patients using the NSGA-II algorithm with an encoding method which represents a chromosome by a list of appointment indexes. Such an encoding method requires a repair step as explained in Section 2.2.

Figure 5 shows the total waiting time of all patients in each group when under the pre-scheduled scenario. We see that results from DEE-NSGA-II and GACE are clearly better than the baseline. For example, when the patient number is 12, the total waiting time of the baseline method is 25.05 hours, while DEE-NSGA-II takes 13.0 hours and GACE takes 12.5 hours. That means 48.1% and 49.9% waiting time saving from DEE-NSGA-II and GACE, respectively. While the waiting time saved is noticeable across all cases, it is worth noting that the rate of saving declines as the patient number grows. When the patient number increases to 18, the waiting time savings are 28.0% from DEE-NSGA-II and 26.2% from GACE.

Figure 6 shows the total travel time of all patients in each group when under the prescheduled scenario. The effectiveness of both DEE-NSGA-II and GACE on travel time

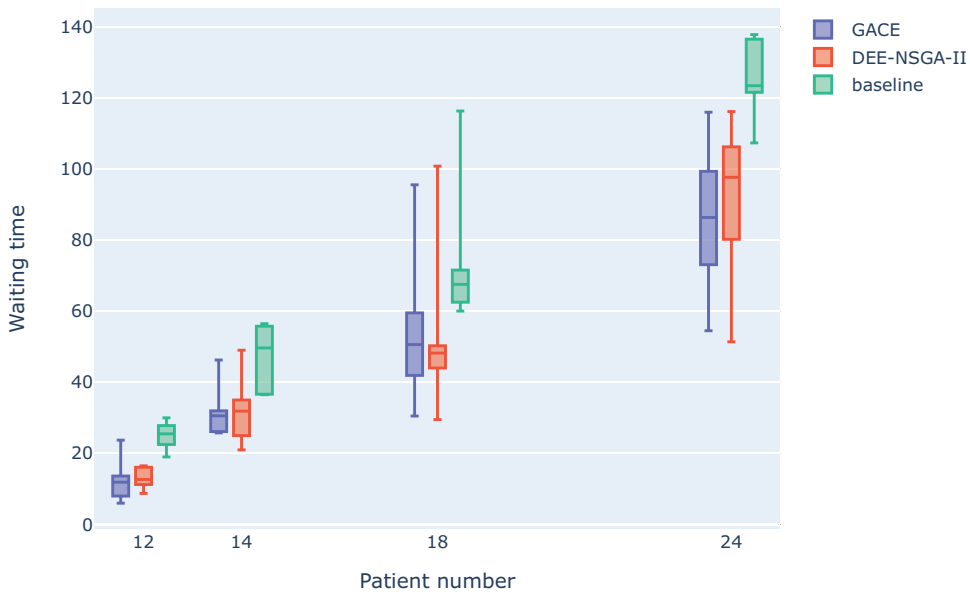


Figure 5. Total waiting time when pre-scheduling different sizes of patient groups.

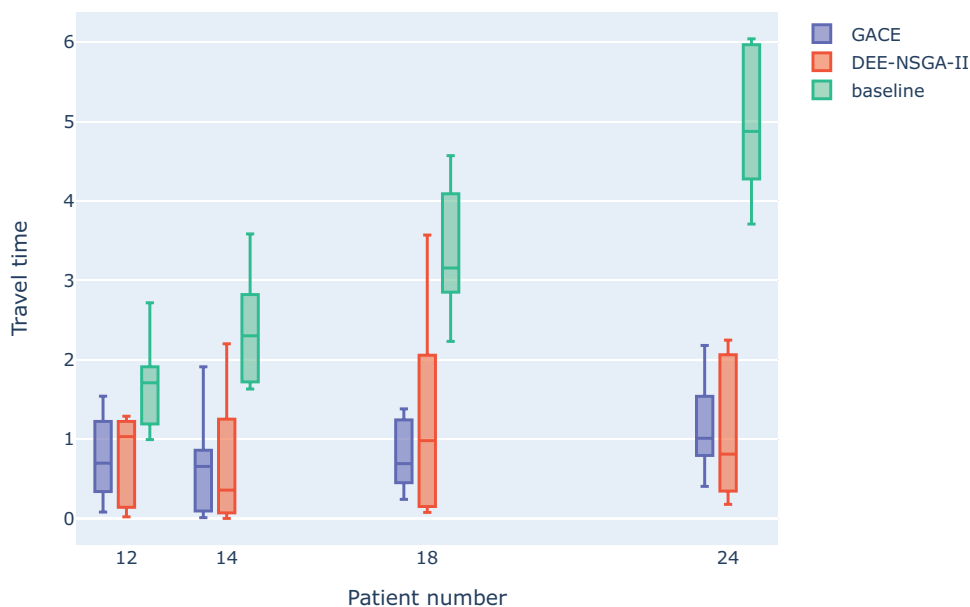


Figure 6. Total travel time when pre-scheduling different sizes of patient groups.

reduction has been demonstrated. In the baseline method, total travel time increase as more patients are scheduled. In contrast, both DEE-NSGA-II and GACE can keep the total travel time low in all cases. The total travel time from DEE-NSGA-II and GACE ranges from 0.7 to 1.0 hours, while the baseline travel time increases from 1.7 hours to 5.0 hours. Compared to the baseline method, the DEE-NSGA-II and GACE reduced 53.7% & 55.3% of travel time respectively when the patient number is 12. When the patient number is 24, the travel time saving is 78.3% from DEE-NSGA-II and 76.7% from GACE.

Figure 7 shows the number of GA optimisation iterations (generations) for DEENSGA-II and GACE to converge when the patient number is 12. The termination criteria in this study are either reaching the max generation (200) or there is no significant change (<0.0025) in objective value in the last 20 generations. On average, GACE takes 130 generations to converge. On the other hand, DEE-NSGA-II requires 108 generations, 17.0% less than GACE. This result supports our claim that our new encoding method DEE has a better convergence rate compared to conventional encoding methods.

In the second case study, we illustrate the open-access scheduling scenario by comparing DEE-NSGA-II to the baseline method. 10 sets of synthetic patient data were used (25 patients). Figure 8 shows the results for total patient waiting time from baseline and the optimisation algorithm using the open-access scheduling. The results from 10 sets of data show an average of 58.2% waiting time savings. Figure 9 shows the results for total patient travel time from baseline and the optimisation algorithm using the open-access scheduling. The results from 6 sets of data show an average of 89.3% travel time reduction.

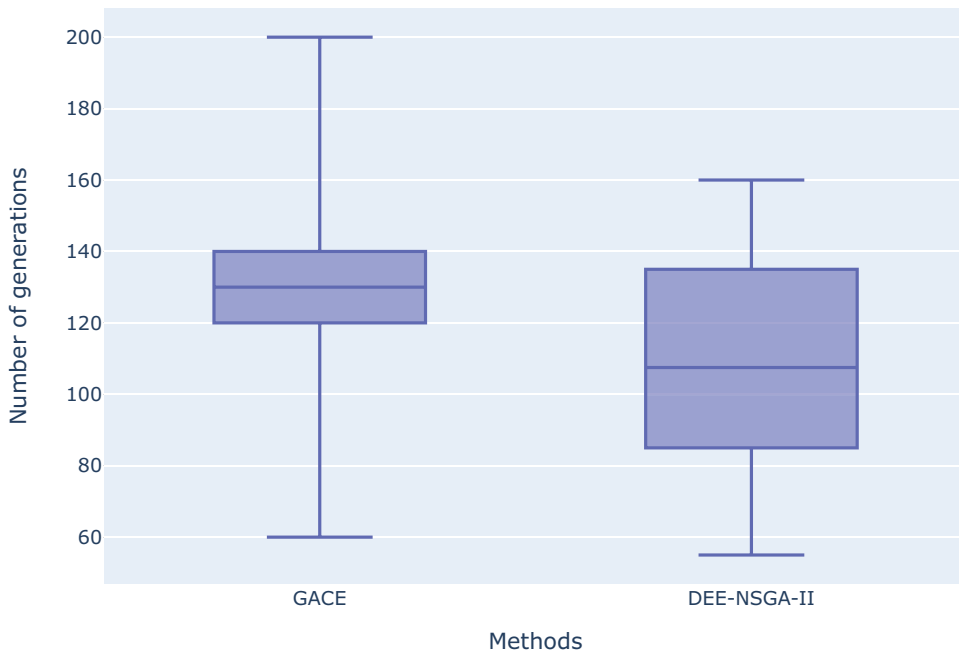


Figure 7. Number of generations for DEE-NSGA-II and GACE to converge.

4.3 Results and discussion

From the above case studies, we found that DEE-NSGA-II is effective for both prescheduling and open-access scheduling. In the first case study, the effectiveness of both DEE-NSGA-II and GACE has been demonstrated. Both algorithms can save 26% to 49% of the total waiting time. When achieving very similar results, DEE-NSGA-II requires 17% fewer iterations to converge than GACE. This result illustrates the benefits of our novel encoding method, DEE. In the second case study, DEE-NSGA-II saved 58.2% waiting time and 89.3% travel time compared to the baseline method. Further, the total waiting time from DEE-NSGA-II is more consistent among 10 sets of test data. The standard deviation of the waiting time from DEE-NSGA-II is 2.1 hours while one from the baseline method is 6.6 hours.

Compared to the waiting time improvement from DEE-NSGA-II, the travel time was reduced more significantly as the patient number grows. We believe that this is partially due to there being only three health care units in the case studies. This makes travel time optimisations simpler than waiting time optimisations. The significant travel time reduction also justifies the importance of optimising travel time in addition to waiting time.

When comparing results from the pre-scheduling and the open-access scheduling, we found that DEE-NSGA-II is suitable for both cases and achieves noticeable time reductions. For example, it achieves 26.8% shorter waiting time and 78.3% shorter travel time when patient number = 24 in pre-scheduling cases. In comparison, it reduces 58.2% the waiting time and 89.3% the travel time in open-access cases. DEE-NSGA-II shows better results in the open-access cases. This advantage may be appreciated as open-access scheduling

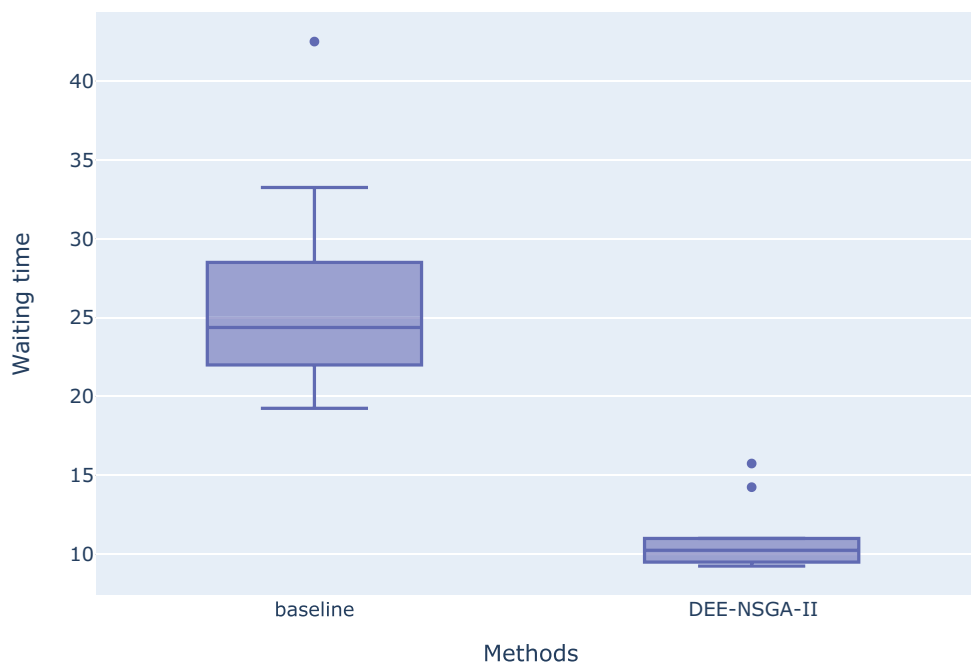


Figure 8. Total patient waiting time from baseline and DEE-NSGA-II methods using open-access scheduling. The results show an average of 58.2% waiting time savings.

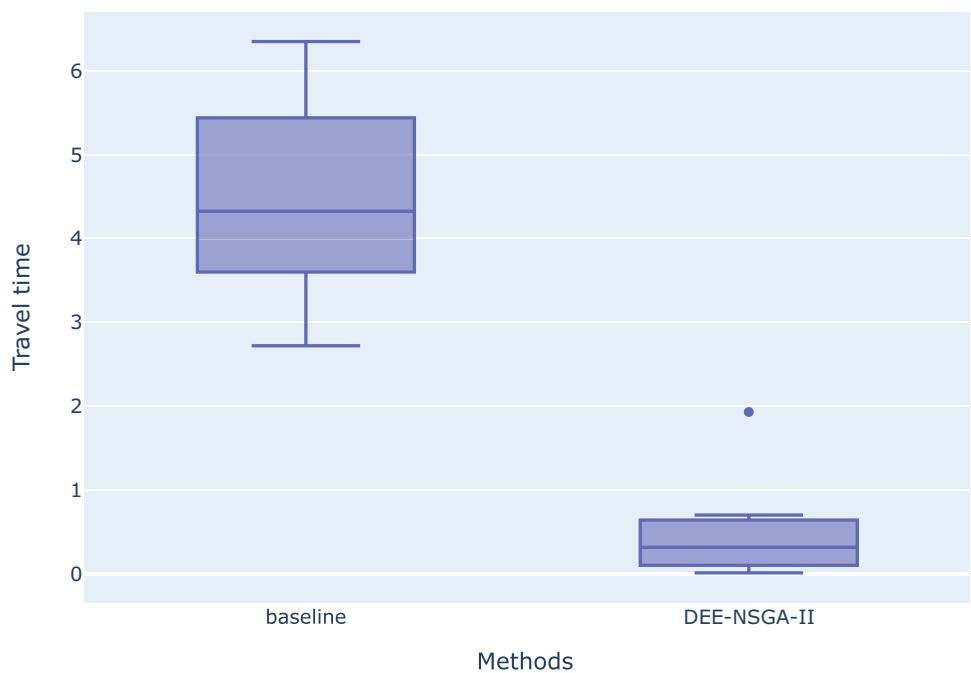


Figure 9. Total patient travel time from baseline and DEE-NSGA-II methods using open-access scheduling. The results show an average of 89.3% travel time reduction.

was found to be more useful in practice. Some reports show that online scheduling has a positive effect on reducing patients' no-show rates (Dobson, Hasija, and Pinker 2011).

5 Conclusion

Outpatient waiting time is a source of dissatisfaction with health care quality, lost productivity for individual patients, as well as increased risk of the deteriorated condition of patients. In addition, long travel time decreases the chance for patients to receive quality health care. To deal with both waiting time and travel time, we defined the problem as an optimisation problem and proposed an optimisation model. To solve the model, we proposed a novel encoding method for DEE-NSGA-II. The DEE-NSGA-II algorithm schedules patients to a health unit based on their locations and desired time. It minimises patients' waiting time outside health care units, and their travel time to the units. To illustrate its performance, two case studies were conducted. The results showed that the algorithm is effective for the pre-scheduling scenario and the open-access scenario. Both waiting time and travel time were significantly reduced compared to a traditional first-come-first-service scheduling system. The results also showed the advantage of the novel encoding method when compared to the conventional encoding methods.

The contributions of this study are highlighted as follows. First, this study investigated a new problem which is to reduce travel time of patients in addition to waiting time. Travel time optimisation was often omitted in existing studies, despite its impact on health care accessibility. To solve these two conflicting objectives, a mathematical model is formulated and implemented in two case studies. The results from the case studies showed its promising benefits in reducing travel time significantly. In addition, different from the existing work which combines multiple objectives into one, our method can be applied to more realistic problems and identify a wider range of alternatives to be selected by decision-makers. Second, a new encoding method, DEE, is developed to represent a candidate solution in GA. It avoids the violation of constraints when generating new candidate solutions, and its application is demonstrated through DEE-NSGA-II. DEE can be useful for solving other types of patient scheduling problems with different objectives, e.g. optimising patient surgical waiting time while considering patients' mental status, risk of disease deterioration, etc. Furthermore, it can also be used in a category of single objective and multiple objectives GA such as BRKGA (Gonçalves and Resende 2011), R-NSGA-III (Vesikar, Deb, and Blank 2018), MOEA/D (Zhang and Hui 2007), and so on. Potentially, the encoding method can be adapted to other evolutionary algorithms, which perform genetic operations on candidate solutions. Examples include Swarm Optimisation Algorithms (Cuevas, Fausto, and González 2020), Evolution Strategy (Knowles and Corne 2000), and Differential Evolution (Price 2013).

There are a few limitations of this study that could be addressed in the future. First, a more sophisticated case study with complex settings could be conducted. The scheduling method should consider patients' & health care professionals' delays, patients' priorities due to their symptoms & deteriorations, hospital preferences, and their changes of locations. It is worth mentioning that the foregoing factors can be generally called human factors, and consideration of the human factors as well as social and cultural factors in operation management has raised great attention recently (Yu et al. 2021; Ogbeyemi et al. 2021). Second, the efficiency of the algorithm has not been investigated. In this study, we have

noticed that the genetic algorithm is computationally expensive. We will investigate the algorithm, especially its efficiency, in the future for a more efficient algorithm. Third, we will also study the robustness and resilience of our scheduling method, as these two properties have been recognised as very important, see the literature (Raj et al. 2014; Han, Liu, and Zhang 2016; Wang et al. 2018). An integrated approach to healthcare system reconfiguration and resource planning and scheduling may need to be taken by following the general framework for integration (Zhang, Wang, and Lin 2019). Lastly, the implementation of the scheduling method has not been discussed. Future studies will investigate how to incorporate our multi-objective scheduling method into an existing patient scheduling system.

Note

1. A general definition to the concept of online scheduling may be directed to (Han et al. 2015).

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The work was supported by the Natural Sciences and Engineering Research Council of Canada [ALLRP 555161-20].

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