Consultation sequencing of a hospital with multiple service points using genetic programming

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Abstract. Two types of outpatients, that is, scheduled patients and walk-ins, arrive at a hospital. The hospital has multiple service points, that is, one consultation room and several examination rooms. Each patient goes to the consultation room first, and some of them visit other service points before consulting the physician again. The arrival of walk-ins, the duration of each service, and the visiting route of service points are uncertain. The objective function consists of three terms with appropriate weights to combine them; the average waiting time for the first consultation of a scheduled patient, that of a walk-in, and the average total waiting time of a patient requesting the second consultation. The problem of sequencing patients waiting for consultation is focused, assuming that other service points adopt FCFS. To alleviate the stress of waiting, up to a pre-fixed number of waiting patients are displayed to indicate the consultation sequence. The consultation sequence is decided by a dispatching rule, and the rule is generated by genetic programming (GP). The simulation experiments indicate that the rules produced by GP can be reduced to simple fixed ordered rules. It also indicates that the increase of the maximum display length deteriorates the objective function value.

Keywords: sequencing, hospital, simulation, genetic programming

1. INTRODUCTION

Minimizing the staying time of outpatients in hospitals may be the benefit of all patients and hospitals. Hospitals are eager to minimize the waiting time of patients to reduce the physical and mental suffering of patients, and to utilize the limited space of the hospitals effectively. Staying longer in a hospital may increase the risk of many kinds of infectious diseases for patients. Therefore, the minimization of the waiting time of patients is a reasonable objective. With the advance of medical technology, patients are often requested to visit several service points such as taking blood samples, conducting a urine test, X-ray examination, and an ultrasound scanning, before or after consulting their physicians, especially in medium and large scale hospitals. The visiting route of service points depends on the condition of each patient, and its service time is also stochastic. Several service points are a single server mode because of expensive equipment and/or a limited number of clinical experts in handling equipment. In addition, the arrival of patients is not deterministic, even if the major part of the outpatients arrive at the hospital with an appointment.

In the present study, the problem of minimizing the waiting time of patients in a hospital is considered. If each service point is considered as a machine, and each patient is a job, then the problem can be considered as a job shop scheduling problem under the dynamic arrival of jobs and the objective is to minimize the average waiting time. Needless to say, it is practically impossible to obtain the optimal solution because of the stochastic nature of the problem, in addition to the complex flow of jobs. From the practical viewpoint, simple procedures are attractive, even if the performance of the procedures does not produce near-optimal solutions. One important difference between patients and jobs is the existence of emotion in patients. It is important to minimize the occurrence of a situation that a patient feels unfairness while waiting for the service. One typical example is a case that a patient who has just arrived is called first even if there are waiting patients. Nevertheless, the problem is not solved by applying a simple FCFS (first-come, first-served) discipline, because there are multiple types of patients in general. In the present study, two types of patients, that is, scheduled patients and walk-ins are considered. A scheduled patient tends to arrive at the hospital near his or her scheduled time, and if he or she arrived earlier than his or her scheduled time, and the current time is later than the scheduled time, it is generally recognized that he or she has priority over walk-ins. However, it is also important to give priority to walk-ins, or patients requesting the second consultation to realize the reasonable allocation of waiting times among patients. Morikawa et al. (2013) discuss the situation that a physician pays attention to the waiting time of both scheduled patients and walk-ins. In minimizing the waiting time of patients, finding a balanced allocation of waiting times among different types of patients, by using a simple procedure if it is possible, is a challenging research issue. The present study attempts to find a dispatching rule for selecting the next patient in front of the consultation room by the aid of genetic programming (GP). Simulation experiments indicate that at the end of the GP procedure that generates and then investigates numerous rules, simple dispatching rules are judged as effective for minimizing the weighted sum of waiting times under the investigated environment.

2. BRIEF LITERATURE REVIEW

The problem considered in the present study can be connected to appointment scheduling in terms of the minimization of waiting time of outpatients. In appointment scheduling, the conflicting objectives of minimizing the waiting time of patients, minimizing the total idle time of the physician, and minimizing the overtime are often involved in the problem. Related studies are classified and reviewed by Cayirli and Veral (2003), and Gupta and Denton (2008). The allocation of appointment times for appointment requests is the primal issue of the appointment scheduling, and there are two types of rules to generate appointment times; individual appointment rules and block appointment rules (Ho and Lau, 1992). The former rules can assign any appointment time for each patient, while the latter rules adopt the starting time of a block, assuming that the session is divided into several blocks in advance and each block can accept multiple patients. The present study assumes that the session is divided into several blocks, and scheduled patients arrive at the hospital based on their appointment time.

Many recent research papers consider the appointment scheduling under advanced-access environment. Under this environment, patients can make an appointment on the morning of the day (Murray and Berwick, 2003; Murray and Tantau, 2000). As the arrival of appointment requests is uncertain, thus preparing capacity for stochastic demand, and allocating each arriving appointment request to one of open slots or assigning an appointment time for each request is a hard task. No-shows and cancellations are also sources of under-utilization of resources, and thus overbooking is adopted as a countermeasure against these phenomena. Accepting walk-ins can be considered as a passive method to improve the utilization of resources. A limited list of recent papers that discuss these issues and propose solution models include Cayirli and Yang (2014), Chen and Robinson (2014), Morikawa et al. (2015), Peng et al. (2014), Robinson and Chen (2010), and Truong (2015).

In appointment scheduling, it is generally assumed that each patient requests a single type of service, and leaves the hospital after receiving the requested service. However, Kopach et al. (2007) analyze the patient flow, and include the following four service points in their simulation study; check-in, physician consult, nurse consult, and check-out. Koizumi et al. (2005) also discuss the patient flow, but they focus on the flow among multiple hospitals and facilities, not within a hospital.

The present study assumes that a patient may visit several service points before leaving the hospital. In addition, there may be several candidate routes for them. The service time at each service point is generally uncertain. In addition, several walk-ins may arrive at the hospital. The problem situation can be considered as a stochastic job shop scheduling problem with dynamic arrival of jobs, and these problem are studied by, for example, Gholami and Zandieh (2009), Gu et al. (2009), and Tavakkoli-Moghaddam et al. (2005). Probably, the most realistic scheduling method in such complicated scheduling environment is the use of dispatching rules. When a machine finishes the process of a job, then one of the waiting jobs in front of the machine is selected by using an appropriate dispatching rule. Many rules have been proposed in the literature, but some researchers apply the genetic programming (GP) in generating dispatching rules; see, for example, Dimopoulos and Zalzala (2001), Nguyen et al. (2013), and Tay and Ho (2008). Within the limited knowledge of the authors, there are no dispatching rules that are expected to produce near-optimal schedule under two types of patients and multiple visiting routes. Therefore, GP is adopted in the present study with necessary modifications to reflect the condition of a hypothetical hospital described next.

3. ASSUMPTIONS AND PERFORMANCE MEASURES

3.1 Assumptions

The morning session of a hospital which has m distinctive service points, $\Theta_1, \dots, \Theta_m$, is considered. Each service point has one service provider to accept at most one patient at a time. Let Θ_1 be the consultation room operated by a physician. The other service points provide medical test or treatments. The hospital opens the reception desk at time t_s, and closes it at time t_e. All service providers start their service at time t_c, where $t_c \geq t_s$. The session is closed if all patients have received all the necessary services.

In every morning session, the hospital accepts exactly n_s scheduled patients and also accepts n_w walk-ins on average. The scheduled time of a patient is the time for the first consultation, assuming that all scheduled patients go to the consultation room first. To accept n_s scheduled patients, the hospital prepares n_s appointment times in advance and use these times in every session. The arrival time of scheduled patients is not deterministic but expected to arrive at around his or her scheduled time. No-shows and cancellations of scheduled patients can never happen. Walk-ins arrive at the hospital within the interval $[t_s, t_e]$ randomly, and go to the consultation room first.

Although some patients leave the hospital after the first consultation, other patients must visit other service points, and they visit the consultation room again before leaving the hospital. The route of service points of a patient is decided at the end of the first consultation. However, the number of candidate routes is known, and the frequency of the selection of each candidate route is available from the historical record. The distribution of service times of scheduled patients and walk-ins in each service point is also available.

The results of the test conducted in service point j become available with a delay of τ_j after the completion of the service, assuming that such a delay is negligible in several service points. One example of non-trivial delay may exist in testing blood samples. Even if $\tau_j > 0$, the status of the patient and the service provider becomes free at the end of the service, and thus the patient goes to the next service point, and the service provider starts the service for the next patient. Nevertheless, the second consultation requests all of the results of tests. Therefore, each patient requesting his or her second consultation will be treated as a waiting patient, only when all test results become available.

All service points except the consultation room, do not assign any appointment time to patients. Therefore, from the viewpoint of fairness, each service point adopts the FCFS discipline. On the other hand, there is a complicated situation in front of the consultation room. Three types of patients may be waiting when congested, that is, scheduled patients, walk-ins, and patients requesting the second consultation. To alleviate the stress of waiting under such a complicated situation, the hospital displays the consultation sequence for waiting patients up to a pre-fixed number of patients. The physician always calls the patient at the head of consultation sequence displayed. The sequence is displayed at the earliest beginning time of the first consultation, that is, t_c, and the sequence will be updated when a new patient arrives or the physician calls the patient at the head of the sequence. Once it is displayed, the sequence is treated as frozen, and no one can cut into the sequence. The sequence contains patients waiting in front of the consultation room. In other words, no planned or expected patients to be arrived soon are included in the sequence. If a patient can find his or her position in the sequence, the starting time of his or her service can be estimated if all patients follow the displayed sequence. To make the system responsive to the waiting condition, however, the maximum length of the sequence is specified.

3.2 Performance Measures

In the present study, two types of patients are considered and each scheduled patient has an appointment time for his or her first consultation. In addition to the arrival of walk-ins, both scheduled patients and walk-ins may visit the consultation room again to receive his or her second consultation. Under such a complicated condition, constructing the rational objective function is not a simple task. One reasonable objective is to reduce the waiting time until the first consultation, as many patients may feel somewhat comfortable by consulting his or her physician. Needless to say, it is also important to reduce the total waiting time in the hospital, and to pay attention to the difference of patient types, that is, scheduled patients or walk-ins in the first consultation. Based on this discussion, the present study adopts the following objective function f to be minimized.

$$f = \alpha \bar{W}_{1,s} + \beta \bar{W}_{1,w} + \gamma \bar{W}_2, \tag{1}$$

where the sum of three non-negative weight parameters α, β, and γ becomes one. The three terms on the right hand side represent the average waiting time for the first consultation of a scheduled patient, the average waiting time for the first consultation of a walk-in, and the average waiting time of a patient after the first consultation, respectively. The last term does not pay attention to the type of patients, and excludes the patients who have received his or her first consultation and then left the hospital immediately.

The waiting time of a scheduled patient i for his or her first consultation, $W_{1,s,i}$, is given by Equation (2), where s_i represents the start time of the first consultation, a_i represents the scheduled time of i, and r_i represents the arrival time of i. The operator $[\ \ ]^+$ indicates that negative values are treated as zero. Equation (2) means that if a scheduled patient can consult the physician earlier than the scheduled time, the waiting time of him or her is treated as zero.

$$W_{1,s,i} = [s_i - \max\{a_i, r_i\}]^+. \tag{2}$$

The waiting time of walk-in j for his or her first consultation, $W_{1,w,j}$, is defined by Equation (3). If a walk-in j arrives at the hospital earlier than t_c, the time duration until t_c is excluded in the waiting time assuming that all patients are fully aware that the waiting is unavoidable until t_c.

$$W_{1,w,j} = s_j - \max\{r_j, t_c\}. \tag{3}$$

The waiting time after the first consultation is simply given by the difference between the arrival time at a service point, and the start time of the service at that point. By adding all waiting times until the start of the second consultation, the total waiting time of a patient is obtained. The objective function (1) uses three average values by dividing the total waiting times by the total number of corresponding patients.

An additional explanation may be necessary in defining the waiting time after the first consultation, if $\tau_j > 0$ in service point j. As it is assumed that all results are prerequisites in the second consultation, it is impossible to realize zero waiting time even if a patient goes to the consultation room immediately after visiting j. Nevertheless, in calculating the waiting time, the existence of inevitable delay is ignored to simplify the calculation of waiting times. Inclusion of the inevitable delay in waiting time will motivate the adoption of new equipment and/or new technologies to reduce the waiting time of the patients.

4. SCHEDULING METHODS

4.1 Genetic Programming

As explained in the previous section, it is assumed that the consultation room displays the consultation sequence, while other service points adopt FCFS discipline. Therefore, two decision terms exist; the maximum length of the consultation sequence displayed, and the generation mechanism of the sequence. In concrete terms, the latter indicates the method of selecting one waiting patient to be added to the tail of displayed sequence.

Because of the stochastic arrival of patients, and the existence of three types of patients in terms of the objective function, it may be impossible to generate rules or procedures that select the most suitable patient to be added at the end of the displayed sequence in all possible situations. Note that the visiting route of each patient is decided at the end of the first consultation.

To tackle this difficulty, the present study adopts a genetic programming (GP) approach that generates rules dynamically reflecting the performance of the current set of rules. In the present study, each rule is represented by a binary tree as shown in Figure 1. The tree represents the following equation: $(2-1)+(3 \times 4)$. There are two types of nodes in a tree: Nodes with two direct child nodes, and nodes without direct child nodes. The former nodes are called *operator* nodes, while the latter nodes are *terminal* nodes. By giving related values for each patient, such as the arrival time, waiting time, or the expected service time, via these terminals, the rule gives a combined value to be used for selecting the most preferable patient among waiting patients. The present study assumes that a smaller value is preferable in the selection.

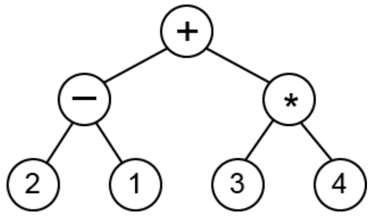

Figure 1: A binary tree representing $(2-1)+(3 \times 4)$

A simplified procedure of GP can be written as follows:

Step 1 (Creation of the first generation): Create N binary trees by selecting operators and terminals randomly from the sets of candidates prepared in advance.

Step 2 (Evaluation of each tree): Obtain the objective function value of each tree, and then calculate the fitness of each rule.

Step 3-1 (Creation of the next generation: Duplicate best rules): In non-increasing order of fitness, select a pre-fixed number of trees and copy these rules to the next generation.

Step 3-2 (Creation of the next generation: Genetic operations): The roulette wheel selection is adopted. This means that a tree giving a higher fitness value has a higher probability in the selection. Select one or two trees, and apply one of the following genetic operations; reproduction, crossover, and mutation. Figure 2 shows an example of crossover and mutation operations.

Step 3-3 (Creation of N trees for the next generation): Apply Step 3-2 until the number of distinct trees generated reaches N. Use these trees as the next generation.

Step 4 (Termination): Stop the procedure if the number of iterations of Steps 2 and 3 reaches a pre-specified maximum value, G.

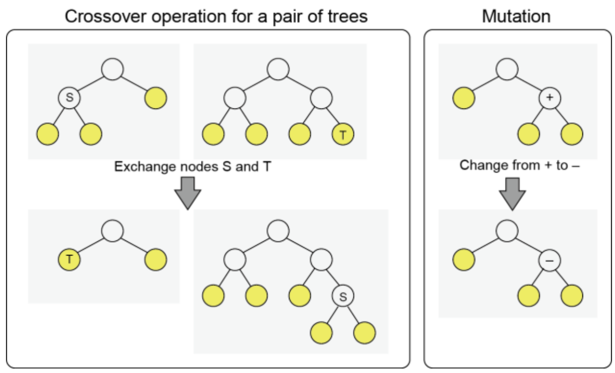

Figure 2: Example of crossover and mutation operations

4.2 Operators and Terminals

Table 1 shows the selected 13 operators based on previous studies and preliminary experiments. The first argument of the operator corresponds to the left child node in the tree, and the second one corresponds to the right child node. Some functions can be realized by using these operators. For example, $|x| = \max\{-x, x\}$, and the negation of a binary variable y is realized by $|y-1|$.

From the investigation of available information on patients waiting in front of the consultation room, eight terminals were selected as shown in Table 2. When these terminals are included in a tree, each terminal returns the corresponding value of the candidate patient at the moment of calling. Some terminals may need additional explanations. The terminal ST returns 0 for the first candidate patient in a session, and if the sequence is empty, return the requested value based on the last consultation. The candidate position in the consultation sequence, P, is equal to 1 if the sequence is empty. In addition to eight terminals shown in Table 2, four constant values, that is, 0, 1, α, and β, were also included as terminals.

For the patients requesting the second round of consultation, there is no need to pay attention to the type of patients, that is, scheduled patients or walk-ins. Therefore, it is possible to prepare three queues as shown in Figure 3. Let x, y, and z be the queue for scheduled patients, walk-ins, and patients requesting the second round of consultation, respectively. The number of patients in queue x, y, and z, is represented by n_x, n_y, and n_z, respectively. In queues y and z, patients are ordered based on their arrival time at the queue. On the other hand, queue x is managed to order patients in non-decreasing scheduled times. Within the same scheduled time, arrival time is used to break a tie. Patients requesting the second round of consultation are included in queue z after all of his or her test results become available.

Table 1: The meaning of operators

Symbol	Meaning of operator (a, b)
+	a + b
–	a – b
*	a * b
/	a / b (if b = 0, then return a)
max	max{a, b}
min	min{a, b}
eq	if a = b, then return 1; else return 0
le	if a ≤ b, then return 1; else return 0
ge	if a ≥ b, then return 1; else return 0
lt	if a < b, then return 1; else return 0
gt	if a > b, then return 1; else return 0
and	if a ≠ 0 and b ≠ 0, then return 1; else return 0
or	if a ≠ 0 or b ≠ 0, then return 1; else return 0

Table 2: The meaning of terminals

Symbol	Meaning
TY	Type of patient: Scheduled patient = 0; walk-in = 1; patient waiting for the second round consultation = 2.
WB	Total waiting time until arriving at the waiting room.
WH	Waiting time in front of the consultation room.
ST	If the same type of patient is at the tail of the displayed sequence, then 1; otherwise 0.
AT	The average consultation time.
AR	The arrival time at the waiting room for consultation.
TW	The number of the same type of patients waiting and not included in the consultation sequence.
P	The candidate position in the consultation sequence.

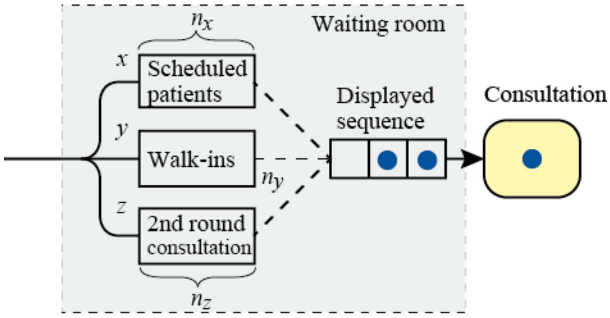

Figure 3: Three queues of patients in the waiting room

When selecting a patient to be inserted into the tail of the displayed sequence, there are at most three candidates, each from queues x, y, and z. If, for example, there are no patients in queues y and z, then the patient at the head of queue x is selected. If there are at least two candidates, the dispatching rule is applied to each patient, and the one with the smaller value is selected. To break a tie, a secondary priority is given as follows: x is the highest, while z is the lowest.

The maximum display length, L, is expected to affect the objective function value. If $L = 1$, which is the minimum value under the condition of displaying the consultation sequence, then it is possible to select the most preferable patient from queues for the next by considering the latest conditions of patients waiting. For example, if the scheduled time of the patient at the head of queue x is sufficiently ahead of the current time, it may be profitable to select a patient from queues y or z. Such a careful selection becomes difficult for the increased value of L. However, from the viewpoint of patients, a larger value of L is generally preferable because each patient can estimate his or her start time of consultation. Therefore, we should pay attention to the tradeoff when deciding the maximum display length. The effect of the maximum display length, L, on the objective function value is investigated by simulation experiments.

5. SIMULATION EXPERIMENTS

5.1 Conditions

There are one consultation room Θ_1 and two medical test rooms, Θ_2 and Θ_3. The consultation time of a patient is assumed to follow an exponential distribution, and the mean consultation time is shown in Table 3. Under the condition that the service time at a test room is assumed to follow a normal distribution, $N(20, 3^2)$ and $N(3, 0.5^2)$ are used for Θ_2 and Θ_3, respectively. The results of the test in Θ_2 becomes available at the end of the service, while the results of test in Θ_3 become available 30 minutes later. At the end of the first consultation, the visiting route of each patient is determined based on the probability shown in Table 4.

The reception desk opens at 8:00, closes at 11:00, and the earliest start time of all services is 9:00 am. The inter-arrival time of walk-ins is 20 minutes, and the following 20 scheduled times are prepared for accepting scheduled patients: 9:00, 9:00, 9:00, 9:00, 9:00, 9:30, 9:30, 9:30, 9:30, 10:00, 10:00, 10:00, 10:30, 10:30, 10:30, 11:00, 11:00, 11:00, 11:30, 11:30. A scheduled patient arrives at the hospital t minutes earlier than his or her scheduled time, where t follows a normal distribution $N(10, 5^2)$. The current time is represented by the minutes from the midnight. For example, 9:00 am is 540 (min), and the noon is 720 (min).

Table 3: The average consultation time (min)

	First round	Second round
Scheduled patient	5.0	3.0
Walk-in	6.0	3.0

Table 4: Visiting routes and their selection probability

Route	Probability	
	Scheduled	Walk-in
$\Theta_1 \rightarrow \Theta_3 \rightarrow \Theta_2 \rightarrow \Theta_1$	0.3	0.4
$\Theta_1 \rightarrow \Theta_3 \rightarrow \Theta_1$	0.3	0.3
$\Theta_1 \rightarrow \Theta_2 \rightarrow \Theta_1$	0.3	0.25
Θ_1	0.1	0.05

To minimize the effect of randomness involved in the target environment, the data of all patients to be arrived at the hospital over 4,000 sessions were generated in advance and used in every generation of GP. The data include the visiting route of each patient with the exact service time in each service point. Therefore, if the same dispatching rule is activated in two sessions, the same objective function will be obtained.

In applying GP, the following parameter values were adopted; $N = 100$, $G = 20$, $\rho = 0.01$, $\sigma = 0.59$, and $\tau = 0.4$, where ρ, σ, and τ represent the probability of reproduction, crossover, and mutation, respectively. Four cases were generated by changing the weight of parameters (α, β, γ) in the objective function as follows: Case I (0.4, 0.4, 0.2), Case II (0.4, 0.2, 0.4), Case III (0.2, 0.2, 0.6), and Case IV (0.6, 0.1, 0.3).

5.2 Alternative Dispatching Rules

In addition to FCFS rule, which always selects the patient arrived earliest among three queues, several alternative dispatching rules are prepared to highlight the performance of the obtained rules by GP.

5.2.1 Estimated objective function value-based rule

Based on the status shown in Figure 3, the effect of selecting the patient at the head of each queue on the objective function value is calculated roughly. Only patients in queues x, y, and z are considered and the additional average waiting time is estimated when the patient at the head of each queue is selected. Let the average consultation time of a patient in queue i be p_i, and f_i be the objective function value if the patient at the head of queue i is selected. For all other patients the minimum waiting time is added under the average consultation time.

For patients in queue x, the average waiting time of n_x patients can be expressed as $f_{xx} = n_x(n_x - 1)p_x/(2n_x)$. All patients in queue y must wait the completion of the first patient from x, thus the minimum average waiting time of patients in y can be written as $f_{xy} = p_x + n_y(n_y - 1)p_y/(2n_y)$. Similar development produces the following equation: $f_{xz} = p_x + n_z(n_z - 1)p_z/(2n_z)$. By using weights for these terms, the estimated objective function value can be written as $f_x = \alpha f_{xx} + \beta f_{xy} + \gamma f_{xz}$. A similar calculation gives f_y, and f_z. By deleting the same terms, it is possible to represent the objective function values as follows: $f_x = (\beta + \gamma)p_x$, $f_y = (\alpha + \gamma)p_y$, $f_z = (\alpha + \beta)p_z$. The rule based on this estimated value is named EST in the experiments.

5.2.2 Fixed Ordered Rules

Figure 3 indicates that at most three patients should be compared when selecting the next patient. As each queue has the same type of patient, and each queue corresponds to a term of the objective function defined by Equation (1), it is a reasonable idea to give a fixed order of priority among these three queues. The factorial of 3 produces six orders such as $x \to y \to z$, and $y \to x \to z$. The expression $x \to y \to z$ means, for example, the patient in queue x is always selected. If queue x is empty then the patient in y is selected. If both x and y are empty, then the patient in queue z is selected.

5.3 Results and Discussion

The combination of four cases and three levels of the display length brings 12 conditions. Because of the page limitation, only four rules generated by GP under $L = 1$ are shown below:

Case I: *(−(WB, AT), TY)
Case II: max (AT, * (AT, + (ST, eq (WH, TY))))
Case III: −(β, TY)
Case IV: eq (TY, le (+ (/ (0, gt (AR, −(TY, TY))), −(ST, WH)), TY))

Even though the output of GP sometimes contained complicated terms such as the last rule shown above, a closer examination of these rules revealed that, in general, most of them can be transformed into fixed ordered rules based on the average consultation time and other related values. The above four rules can be rewritten as follows:

Case I: $y \to x \to z$, if WB $\geq$ 3, otherwise $y \to z \to x$.
Case II: $z \to x \to y$.
Case III: $z \to y \to x$.
Case IV: $x \to z \to y$, assuming that ST – WH $\leq$ TY.

The objective function values by simulating 100,000 sessions using 9 different rules are summarized in Table 5. At first, the effect of the maximum display length is examined. The objective function value given by GP indicates that increasing the display length deteriorated the objective function value, which is a reasonable behavior. On the other hand, FCFS was insensitive to the value of display length in all cases. Some rules indicated an opposite behavior. For example, in Case I, rule $z \to x \to y$ shows that the worst value was given under $L = 1$. Such an unexpected behavior was produced in inferior rules in each case.

In terms of the minimization of the objective function, the proposed GP realized the minimum value in all cases. Table 5 also indicates that one of the fixed order rules produced the minimum value in all cases. More specifically, $y \to x \to z$ in Case I, $z \to x \to y$ in Case II, $z \to y \to x$ in Case III, and $x \to z \to y$ in Case IV. This correspondence is already indicated in the above examination.

As the maximum number of candidates in the selection is three, and each queue is maintained separately, thus it is rational that one of the fixed ordered rules performed well. The rule EST, which includes the rough estimation of the objective function value indicated one of the best rules in Cases II and IV, but indicated inferior performance in other cases.

Table 5: The objective function value produced by each rule under three levels of maximum display length

Case	Rule	Maximum Display Length		
		1	3	6
Case I	GP	41.2	42.3	43.6
$\alpha = 0.4$	FCFS	45.5	45.5	45.4
$\beta = 0.4$	EST	58.0	54.6	50.7
$\gamma = 0.2$	$x \to y \to z$	50.6	48.9	47.4
	$x \to z \to y$	58.6	55.2	51.1
	$y \to x \to z$	41.2	42.3	43.7
	$y \to z \to x$	41.5	42.5	43.7
	$z \to x \to y$	58.1	54.7	50.7
	$z \to y \to x$	42.3	43.3	44.2
Case II	GP	53.7	54.7	56.1
$\alpha = 0.4$	FCFS	58.6	58.6	58.6
$\beta = 0.2$	EST	53.8	54.8	56.1
$\gamma = 0.4$	$x \to y \to z$	63.0	61.8	60.4
	$x \to z \to y$	55.9	56.5	57.5
	$y \to x \to z$	62.7	61.9	60.7
	$y \to z \to x$	54.6	55.6	56.9
	$z \to x \to y$	53.8	54.7	56.1
	$z \to y \to x$	54.0	55.2	56.3
Case III	GP	58.2	61.4	65.7
$\alpha = 0.2$	FCFS	72.2	72.3	72.2
$\beta = 0.2$	EST	66.3	67.4	69.0
$\gamma = 0.6$	$x \to y \to z$	85.5	82.7	78.7
	$x \to z \to y$	71.4	72.1	72.7
	$y \to x \to z$	79.9	78.8	76.7
	$y \to z \to x$	59.1	62.4	66.5
	$z \to x \to y$	66.3	67.5	69.0
	$z \to y \to x$	58.1	61.5	65.6
Case IV	GP	39.0	41.6	45.4
$\alpha = 0.6$	FCFS	51.4	51.3	51.3
$\beta = 0.1$	EST	39.1	41.6	45.4
$\gamma = 0.3$	$x \to y \to z$	46.4	47.4	49.0
	$x \to z \to y$	39.2	41.6	45.5
	$y \to x \to z$	56.0	54.6	53.3
	$y \to z \to x$	56.6	55.4	53.7
	$z \to x \to y$	39.3	42.0	45.9
	$z \to y \to x$	55.9	54.7	53.0

6. CONCLUSION

The consultation sequencing problem of a hospital has been investigated in the present study. In the simulated environment, the hospital has three service points, and each patient goes to the consultation room first. After that, some of them visit other one or two service points and return to the consultation room again. Two types of patients are involved, that is, scheduled patients and walk-ins. To minimize the weighted sum of the average waiting times, the best dispatching rule is explored by GP. The simulation results indicate that the rules produced by GP often correspond to simple fixed ordered rules. The rules produced by GP support an intuitive idea of prioritizing the queues based on their weight. However, if two queues have the same weight, their priorities should be decided carefully. Otherwise, the inappropriate ordering of them may deteriorate the objective function value greatly.

The present study assumes that the scheduled times are given in advance. Under the complex flow of patients and the stochastic arrival of walk-ins, the decision of scheduled times for minimizing the waiting times is an important research issue. Increasing the number of service points, and examining other service disciplines in each service point are also involved in the remaining research issues.

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REFERENCES

Cayirli, T., Veral, E. (2003) Outpatient scheduling in health care: a review of literature. *Production and Operations Management*, **12**, 519–549.

Cayirli, T., Yang, K.K., 2014. A universal appointment rule with patient classification for service times, no-shows, and walk-ins. *Service Science*, **6**, 274–295.

Chen, R.R., Robinson, L.W. (2014) Sequencing and scheduling appointments with potential call-in patients. *Production and Operations Management*, **23**, 1522–1538.

Dimopoulos, C., Zalzala, A. M. S. (2001) Investigating the use of genetic programming for a classic one-machine scheduling problem. *Advances in Engineering Software*, **32**, 489–198.

Gholami, M., Zandieh, M. (2009) Integrating simulation and genetic algorithm to schedule a dynamic flexible job shop. *Journal of intelligent Manufacturing*, **20**, 481–498.

Gu, J., Gu, X., Gu. M. (2009) A novel parallel quantum genetic algorithm for stochastic job shop scheduling. *Journal of Mathematical Analysis and Applications*, **355**, 63–81.

Gupta, D., Denton, B. (2008) Appointment scheduling in health care: challenges and opportunities. *IIE Transactions*, **40**, 800–819.

Ho, C.-J., Lau, H.-S. (1992) Minimizing total cost in scheduling outpatient appointments. *Management Science*, **38**, 1750–1764.

Koizumi, N., Kuno, E., Smith, T. E. (2005) Modeling patient flows using a queuing network with blocking. *Health Care Management Science*, **8**, 49–60.

Kopach, R., DeLaurentis, P.-C., Lawley, M., Muthuraman, K., Ozsen, L., Rardin, R., Wan, H., Intrevado, P., Qu, Xiuli, Willis, D. (2007) Effects of clinical characteristics on successful open access scheduling. *Health Care Management Science*, **10**, 111–124.

Lin, J., Muthuraman, K., Lawley, M. (2011) Optimal and approximate algorithms for sequential clinical scheduling with no-shows. *IIE Transactions on Healthcare Systems Engineering*, **1**, 20–36.

Morikawa, K., Takahashi, K., Hirotani, D. (2013) Outpatient sequencing with consideration of the average waiting times. *Journal of Japan Industrial Management Association*, **64**, 119–127 (in Japanese).

Morikawa, K., Takahashi, T., Hirotani, D. (2015) Performance evaluation of candidate appointment schedules using clearing functions. *Journal of Intelligent Manufacturing*, Online First, DOI 10.1007/s10845-015-1134-5.

Murray, M., Berwick, D.M. (2003) Advanced access: reducing waiting and delays in primary care. *Journal of the American Medical Association*, **289**, 1035–1040.

Murray, M., Tantau, C. (2000) Same-day appointments: exploding the access paradigm. *Family Practice Management*, **7**, 45–50.

Nguyen, S., Zhang, M., Johnston, M., Tan, K. C. (2013) Learning iterative dispatching rules for job shop scheduling with genetic programming. *International Journal of Advanced Manufacturing Technology*, **67**, 85–100.

Peng, Y., Qu, X., Shi, J. (2014) A hybrid simulation and genetic algorithm approach to determine the optimal scheduling templates for open access clinics admitting walk-in patients. *Computers & Industrial Engineering*, **72**, 282–296.

Robinson, L.W., Chen, R.R. (2010) A comparison of traditional and open-access policies for appointment scheduling. *Manufacturing & Service Operations Management*, **12**, 330–346.

Tavakkoli-Moghaddam, R., Jolai, F., Vaziri, F., Ahmed, P.K., Azaron, A. (2005) A hybrid method for solving stochastic job shop scheduling problems. *Applied Mathematics and Computation*, **170**, 185–206.

Tay, J. C., Ho, N. B. (2008) Evolving dispatching rules using genetic programming for solving multi-objective flexible job-shop problems. *Computers & Industrial Engineering*, **54**, 453–473.

Truong, V.-A. (2015) Optimal advance scheduling. *Management Science*, **61**, 1584–1597.