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ORIGINAL RESEARCH

An Appointment Planning Algorithm for Reducing Patient Check-In Waiting Times in Multispecialty Outpatient Clinics

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Abstract
Long waiting times are a major reason for patient dissatisfaction in outpatient clinics. Existing research in patient scheduling has established the relationship between the number of providers and patient waiting times. However, no research has explored the problem by considering patient flow through multiple stages with multiple servers. In this paper, a Multispecialty Outpatient Clinic Appointment Planning Algorithm (MOCAPA) is developed. The goal of the planning algorithm is to reduce patient check-in waiting times in multispecialty clinics by exploring the patient interaction with multiple stages in the system (i.e., the clinic front desk and the providers). The paper results show that in a multi-stage outpatient clinic, patient waiting times can be reduced by (1) classifying patients according to their status at the clinic (i.e., *new* vs. *existing*) and (2) balancing the patient type ratio of arrivals per appointment time period.

Keywords Multispecialty clinics · Waiting time · Front desk · Systems operation · Patient flow · Operations management

1 Introduction

Developing healthcare systems capable of meeting patient needs is a very important problem for two major reasons: (1) the rapid increase in healthcare expenditures and (2) the simultaneous growth of demand for healthcare services and patients' expectations of service quality [1]. Excessive appointment waiting time has been identified as a primary source of overall patient dissatisfaction among the general medical patient population [2]. It is important for patients to undergo consultation without the added burden of inefficiencies in the healthcare system [3]. The inefficient

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management of clinic resources (i.e., staff and providers) impacts the overall quality of service provided to patients in outpatient clinics.

Ahmadi-Javid et al. [1] divided the type of decisions made to design and plan for outpatient appointment systems (OASs) into three categories: *strategic*, *tactical*, and *operational*. The *strategic* decisions are long-term decisions made to determine the main structure of an OAS. *Tactical* decisions are medium-term decisions related to how patients are scheduled, or how groups of patients are processed. *Operational* decisions are short-term and are concerned with scheduling individual patients efficiently. Current research in OAS has provided limited attention to *strategic* and *tactical* decisions [1] although both are important aspects to consider when improving the efficiency of outpatient clinics.

In this paper, a methodology is developed to address *strategic* and *tactical* decisions in multispecialty outpatient clinics. A typical multispecialty clinic houses multiple providers with different specialties including surgery, ear nose and throat (ENT), and orthopedics. In multispecialty clinics, providers share one common front desk area. Staff members at the clinic's front desk are responsible for checking-in patients, collecting copays, scheduling appointments by phone and follow-ups, scanning/filing documents, verifying medical records, insurance/id cards, and benefits, distributing faxes, making copies, and checking-out patients. Sharing a common front desk area in a multispecialty clinic results in long waiting times for patients to register and see providers during periods of high demand [4, 5]. Therefore, the total number of stages (i.e., service stops) and the number of resources per stage have a direct impact on the OAS configuration and its outcomes [6, 7]. Multispecialty clinics not only have multiple stages but also multiple resources per stage.

The goal of this paper is to reduce patient waiting times before seeing the provider in multispecialty clinics by exploring the patient interaction with the clinic front desk and the providers. The motivation for this research comes from a real clinic with more than one stage (i.e., front desk and provider stages) with multiple servers in each stage. Given such configuration, at the *strategic* level, the objective of this paper is to study the clinic outcomes when considering different number of resources (i.e., staff and providers) in each stage of the process. At the *tactical* level, the objective of the paper is to determine the number of appointments per day reserved for *new* and *existing* patients such that the patient waiting time to see a provider is minimized. The authors develop a planning algorithm to assist in the appointment scheduling process in outpatient clinics that house multiple providers with different specialties. The algorithm establishes appointment planning protocols for a day based on the clinic resource capacities and providers' schedules. A scheduling protocol will indicate the maximum number of *new* patients that should be scheduled per appointment time period (i.e., 8:00 am and 8:30 am) given the provider's availability for the day (i.e., 5 providers in the office on Mondays from 8:00 am to 12:00 pm). A clinic manager can check the protocols provided by the algorithm and decide on the system configuration that will best meet the clinic's goals. The performance of the protocols generated by the algorithm is tested using an existing discrete-event simulation model of a real multispecialty outpatient clinic [4, 8].

The rest of the paper is organized as follows. In Sect. 2, a review of closely related work is presented. A detailed description of the problem situation is presented in

Sect. 3. Section 4 discusses the methodology followed to develop the decision-making framework. In Sect. 5, a description of the computational experiments and case study is presented. The discussion of the computational results is given in Sect. 6. Finally, Sect. 7 provides concluding remarks and recommendations for the patient service management in multi-specialty outpatient clinics.

2 Literature Review

The literature on patient scheduling in outpatient clinics is extensive. Topics such as minimizing patient waiting times for service have received a lot of attention amongst researchers and practitioners [9–15]. However, few studies apply operations research techniques to study *strategic* and *tactical* level decisions for access policies in outpatient settings. For instance, Swisher et al. [16] use a discrete-event simulation model to study the operation of outpatient clinics and show that results were very sensitive to changes in the clinic environment including the patient mix, scheduling technique, and staffing levels.

Most of the literature on patient scheduling in outpatient clinics can be categorized in two areas: access policy and number of servers considered. In terms of access policy, the literature has established three major types of policies: traditional, open-access, and hybrid. Robinson and Chen [17] compare open access versus traditional scheduling models. Their computational study demonstrates that the open-access policy outperforms the traditional policy in most cases. Gupta and Wang [18] develop a Markov decision process model for the appointment-booking problem in which the patients' choice behavior is modeled explicitly. They demonstrate that an open-access policy performs badly when there is greater variability of same-day demand or higher positive dependence among same-day demands for different physicians. Qu et al. [19] compare a single-period hybrid policy with a two-period hybrid policy assuming the number of appointments is given. The authors develop an optimization model to maximize the expected number of patients scheduled and to minimize the variance of the number of patients scheduled and show that their single-period hybrid policy is not worse than the two-period hybrid policy.

In terms of the number of servers, most of the existing work in OAS restrict the clinic capacity to a single provider (i.e., one doctor) to estimate the number of open-access appointments to match the clinic demand [20] and when multiple providers are considered, they are assumed to be identical [1, 21]. The only exception is the work presented by Srinivas and Ravindran [6], where a stochastic optimization model for a two-stage multi-server clinic is developed to obtain a schedule configuration at the *operational* level. The model minimizes the weighted sum of excessive patient waiting time, resource idle time, resource overtime, and denied appointment requests. In terms of single server papers, Qu et al. [22] develop a closed-form mathematical solution and conclude that the number of open access appointments depends on the number of appointment requests, provider capacity, among others. Kopach et al. [23] use simulation to study a double-booking strategy for patient appointments. Their results show that double-booking allowed for better continuity of care. Muthuraman and Lawley [24] propose a stochastic overbooking model in a hybrid appointment system. The model showed improvement in patient waiting time and revenue.

The amount of resources in outpatient clinics is a key component of the clinic profit. An excessive number of clinic resources will increase the operational cost of the clinic due to underutilization. In contrast, an insufficient number of resources will increase patient waiting times and will cause service delays which decreases the quality of care provided to the patient. Based on the review of previous research, we have identified the following gaps in the literature. First, existing research on outpatient scheduling does not consider strategic (i.e., long term) decisions in determining the main structure of an OAS [6]. For instance, systems interconnectedness is rarely considered when designing OAS even though patients flow through multiple stages in outpatient clinics. Therefore, the guidelines proposed in the literature, which assume single stage systems, do not apply to a multi-stage clinic [25]. Second, most of the existing work of designing schedule configuration restrict models to a single provider (i.e., one doctor) [26, 27] and mathematical models are needed to extend current research to consider multiple providers [28]. To the best of our knowledge, this is the first study to develop a mathematical approach that considers patient multi-stage flow and multiple providers when designing OAS at the *strategic* and *tactical* level.

3 Modeling Framework

In this section, a description of the problem is provided. The dynamics of the appointment system and assumptions to formulate the Multispecialty Outpatient Clinic Appointment Planning Algorithm (MOCAPA) are then introduced.

3.1 Problem Description

Multispecialty outpatient clinics operate with many providers (i.e., typically 5 or more) with different specialties (i.e., surgeon, ENT, orthopedics) while sharing a single front desk. The system configuration increases patient queues at the front desk which impact patient waiting times to see their providers during high service demand periods. Front desk operation in multispecialty clinics is complex. There are multiple activities that are managed by limited resources and lack of planning in terms of resource allocation can cause patient delays. For instance, clinic appointments are managed by the front desk staff. Typically, patients will call the clinic in advance to set-up an appointment with providers. This task is challenging since the staff will manage appointments for multiple physicians with different specialties and schedules. The front desk staff will manage appointments while dealing with patient check-in and check-out processes whose volume varies according to the numbers of providers available to serve patients on a particular day. Upon arrival to the clinic, patients will wait in line to perform their check-in. The front desk staff will request patient documentation (insurance/id cards), scan/copy/fill patient documents, save copies for medical records, collect copay, and ask the patient to fill-out some paperwork. The amount of paperwork needed from the patient depends on whether the patient visits the clinic for the first time or not.

In general, patients are classified into two groups: *new* and *existing* patients. Patients arrive to the system based on their appointment time. The number of patients expected per time period is determined by the number of providers available in the system. For example, if six providers are scheduled to work at the clinic, then 6 patients are expected at the clinic per time period. *New* patients visit the clinic for the first time and are required to complete more paperwork than those patients who are already in the system. *New* patients usually have more questions and require individual attention from the front desk staff. The extra time used to answer questions for *new* patients increases the waiting times of the other patients already in queue waiting to check-in, submit documents, or ask questions. Therefore, clinic managers should consider patients' demands and provider's schedules at the time of allocating resources to the clinic front desk. The problem faced by the clinic managers is to determine the number of *new* patients to schedule per appointment time period given the number of patients expected per appointment time period, the providers' schedule, and the number of staff members performing patient check-in at the clinic's front desk. The goal of the proposed methodology is to reduce patient waiting times by assuring that the waiting time, for all of the scheduled patients, does not exceed a specified threshold.

3.2 Notation and Assumptions

In this section, an abstraction of the operational details is provided. Let F be the set of front desk staff members. Let I represent the set of providers. Let s represent the number of medical specialties in the clinic including orthopedics, ENT, surgery, and audiologists. Let J be the set of patients seeking service at the clinic at the time period t and n be the size of set J. Typically, an appointment with a provider for a *new* patient will last 30 min and appointment for an *existing* patient will last 15 min. Let T be the set of 15-min time slots, indexed t. The assumptions concerning this problem setting are as follows:

1. Front desk staff members can perform all front desk tasks. The differences among staff, in terms of completion of the tasks, are negligible. This assumption is motivated by common observations in the existing system.
2. Patients arrive to the front desk and select the front queue with the shortest line. Patients will stay in the same queue until check-in service is completed. This assumption is also motivated by the observation of the system. Since there is variability in the amount of time it takes for patients to check-in, patients will hesitate to move between queues.
3. No shows and late arrivals are not considered in this research. Patients visiting this clinic are seeking service by a specialist (i.e., surgeons and ENT). These providers are fully booked for extended periods of time and patients show for their appointment on time. Instead of not showing to their appointment, these patients will call beforehand to reschedule.

Additional notation will be defined in Sect. 4. The framework proposed in Sect. 4 provides a new way to design appointment systems in outpatient clinics that not only considers providers' schedules but also how clinic front desk activities impact scheduling decisions.

4 Methodology

The methodology developed in this paper considers a worst-case scenario analysis for planning patient scheduling in multispecialty clinics. The goal of applying this strategy is to make the methodology general, so it can be applied to any multispecialty clinic configuration. The worst-case scenario analysis is used to determine the expected maximum waiting time for a patient at the time of check-in. The research *hypothesis* is that patient waiting time at the check-in can be reduced by limiting the number of *new* patients scheduled at the same appointment period (i.e., 8:00 am) without compromising the target number of patients to be served by the clinic per day. The methodology computes the number of *new* and *existing* patients to schedule per appointment period according to the providers' schedule for the day.

In Sect. 4.1, the worst-case scenario analysis is explained in detail. An integer programming model, named IP1, is also derived. IP1 is used to obtain the maximum expected waiting time (W_{max}) at the front desk before seeing the provider. In Sect. 4.2, a second integer programming model is formulated, named IP2. IP2 finds the best appointment times for *new* and *existing* patients per day. Both models, IP1 and IP2, are used to derive the Multispecialty Outpatient Clinic Appointment Planning Algorithm (MOCAPA) for scheduling patients in multispecialty outpatient clinics. Section 4.3 discusses the Multispecialty Outpatient Clinic Appointment Planning Algorithm (MOCAPA) in detail.

4.1 Worst-Case Scenario Analysis

In this section, a worst-case scenario analysis is presented. The purpose of the analysis is to compute the expected worst-case maximum waiting time to be experienced by a patient during the check-in service and before seeing a provider. The analysis considers the number of providers available during the day $|I|$ at each appointment period and the number of front desk staff members $|F|$ available at each appointment time. For instance, at 8:00 am on a Monday, there are seven providers who can serve patients and there are two staff members in the front desk to take care of the patient check-in. Since there are seven providers, the maximum number of appointments that can be scheduled for 8:00 am is seven. Also, those seven patients, if scheduled, will be arriving for check-in at about the same time of the day and they will be served/checked-in by the two front desk staff members. The question that needs to be answered at this point is, how many of those seven 8:00 am appointments should be assigned to *new* patients? Remember, *new* patients require more check-in time (i.e., service time) at the front desk than *existing* patients. The worst-case scenario analysis, presented next, will answer this question based on the following assumptions: (1) patients will arrive for check-in at about the same time, (2) the order of patient arrivals is not known, (3) the check-in time for *existing* patients is always less than the check-in time for *new* patients, and (4) the check-in times for *existing* patients and *new* patients are deterministic.

The following integer programming model (IP1) is formulated to determine the maximum expected patient waiting time at the front desk before seeing a provider when given a set of patients J of size n and a set of front desk staff members F of size m. The size of n is determined based on the number of providers available at a given appointment period. Table 1 lists the sets, parameters, and decision variables for IP1.

IP1 Model:

$$max\, z : W_{max} \tag{1}$$

subject to:

$$\sum\nolimits_{j\in J} x_{fjh} \leq 1, \quad \forall h \in G, \forall f \in F \tag{2}$$

$$\sum\nolimits_{h\in G f\in F} x_{fjh} = 1, \quad \forall j \in J \tag{3}$$

$$x_{fjh} \leq \sum\nolimits_{\ell\in J} x_{f\ell(h-1)}, \quad \forall j \in J, f \in F, h \in G\backslash\{1\} \tag{4}$$

$$\sum\nolimits_{j\in J} x_{fj1}p_j + \sum\nolimits_{h\in G\backslash\{1\}} \left(\sum\nolimits_{j\in J} (x_{fjh} - \sum\nolimits_{\ell\in J} x_{f\ell,h-1} + 1)p_j\right) \geq W_{max}, \quad \forall f \in F \tag{5}$$

Table 1 Sets, parameters, and decision variables for IP1

Sets	
F	Set of front desk staff members indexed f
J	Set of patients indexed j
G	Set of positions indexed h
Parameters	
n	Number of patients
m	Number of front desk staff members performing patient check-in
p_j	Check-in service time for patient j
W_f	Completion time of all the patients assigned to staff member f
Decision variables	
x_{fjh}	$=1$ if a patient j is in queue position h waiting to be served by front desk staff member f, 0 otherwise
W_{max}	Maximum expected waiting time at the front desk before seeing the provider, $W_{max} = \max_{f\in F} W_f$

$$\sum\nolimits_{j \in J h \in G} x_{fjh} \le \lceil {}^{|J|}/{}_{|F|} \rceil, \quad \forall f \in F \tag{6}$$

$$x_{fjh} \in \{0, 1\} \quad \forall j \in J, f \in F, h \in G \tag{7}$$

Equation (1) is the objective function which maximizes the expected waiting time at the front desk before seeing the provider. Let W_f be the completion time of all the patients assigned to staff member f, which is computed using the left-hand side of Eq. (5). The considered measure of performance is the maximum completion time $W_{max} = \max\limits_{f \in F} W_f$. The model generates the maximum waiting time for the worst-case scenario. Equation (2) states that at most, one patient can be assigned to each front desk staff queue position, while Eq. (3) states that each patient must occupy only one position in one of the one staff queue. Equation (4) guarantees continuous assignments and Eq. (5) establishes that the total waiting time for service for each front desk staff member must be greater than or equal to W_{max}. Equation (6) forces a balanced distribution of patients between the front desk staff. The model assumes that patients arrive to the front desk and select the front desk queue with the shortest line. The model also assumes that $n \ge m$ and that patient sequences in the queue cannot be changed because sequences depend on the patients' order of arrivals.

The following lemma establishes that for a given set of patients waiting to be checked-in, say k, the maximum waiting time in queue W_{max} is found by sequencing patients in the queue in non-increasing order of their expected service time p_j. Therefore, the proposed problem, when $|F| = 1$, is solvable in polynomial time.

Lemma 1. *Let Y_f be the set of patients waiting to be served by staff member f ordered so that*

$$p_{y[1,f]} \ge p_{y[2,f]} \ge p_{y[3,f]} \ge \cdots \ge p_{y[n_f,f]},$$

where n_f is the number of patients in Y_f, then W_f is optimal.

Proof. Let Y_f' be as set Y_f but with the patients in positions $n_f - 1$ and n_f exchanged.

W_f for Y_f is:

$$W_f = p_{y[1,f]} + p_{y[2,f]} + p_{y[3,f]} + \cdots + p_{y[n_f-2,f]} + p_{y[n_f-1,f]}.$$

W_f' for Y_f' is:

$$W_f' = p_{y[1,f]} + p_{y[2,f]} + p_{y[3,f]} + \cdots + p_{y[n_f-2,f]} + p_{y[n_f,f]}.$$

It is supposed, by contradiction, that $W_f < W_f'$, then:

$$p_{y[1,f]} + p_{y[2,f]} + \cdots + p_{y[n_f-2,f]} + p_{y[n_f-1,f]} < p_{y[1,f]} + p_{y[2,f]} + \cdots + p_{y[n_f-2,f]} + p_{y[n_f,f]}.$$

then

$$(p_{y[1,f]} - p_{y[1,f]}) + (p_{y[2,f]} - p_{y[2,f]}) + \cdots + (p_{y[n_f-2,f]} - p_{y[n_f-2,f]}) + p_{y[n_f-1,f]} < p_{y[n_f,f]}.$$

Finally.

$$p_{y[n_f-1,f]} < p_{y[n_f,f]},$$

which cannot be true given.

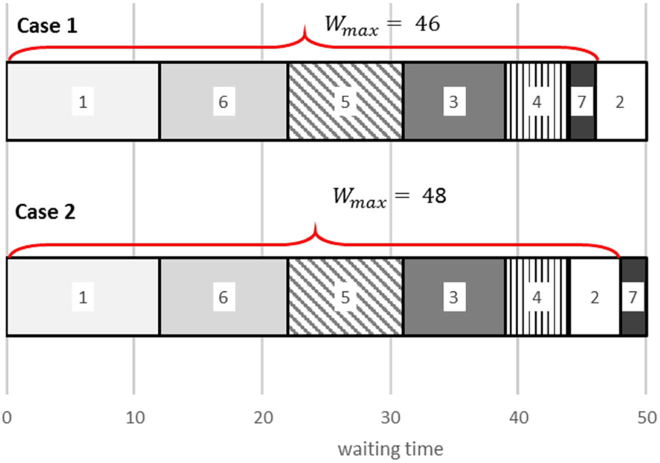
$$p_{y[n_f-1,f]} \geq p_{y[n_f,f]}.$$

It must be concluded that $W_f \geq W_f^{'}$.

An example is used to illustrate the problem where $n = 7$ and $m = 1$. The patient service times at the front desk p_j are listed in Fig. 1. Figure 1 also shows two different sequences of patient arrivals for the same appointment period (i.e., 8:00 am). In case 1, patient arrivals to the front desk occur in the following sequence $Y_1 = \{1, 6, 5, 3, 4, 7, 2\}$. In case 2, patient arrivals to the front desk occur in the following sequence $Y_2 = \{1, 6, 5, 3, 4, 2, 7\}$. Case 2 presents the optimal W_{max} generated through full enumeration. Notice that the only difference between case 1 and case 2 is the position of the last two patients which illustrates the proof for Lemma 1. The maximum waiting time W_{max} experienced by a patient in this example, under the worst-case scenario, is 48 time units.

There is a special case for the described problem when $|F| > 1$. As presented in Lemma 2, an optimal W_{max} solution can be easily found for the case in which all *existing* patients will have the same check-in service times and all *new* patients have the same check-in service time.

Lemma 2. *It is assumed that the time for service for all existing and new patients is constant. It is also assumed that the number of patients waiting for service* $\forall i \leq |J|/|I|$ *which implies that patients will always choose the shorter line for waiting. Let E be*



J	p_j
1	12
2	4
3	8
4	5
5	9
6	10
7	2

Fig. 1 Illustrative example of the problem

the set of existing patients $j \in E$, $E \subseteq J$, *with* $p_j = p_E$ *and let* N *be the set of new patients* $j \in N$, $N \subseteq J$, *with* $p_j = p_N$, *where* $p_N > p_E$. *Let* J_i *be the set of patients waiting to be served by server* i. *An optimal solution is found if* $|N| \geq \frac{|J|}{|I|}$ *and if for any* $i \in I$, *at least* $|J_i| - 1$ *patients are in* N.

Proof. If a set J_i where at least $|J_i| - 1$ patients are in N has exactly f jobs ($f = |J|/|I|$). Then, using Lemma 1, the maximum waiting time for server i is $= \sum_1^{f-1} p_N$. It is obvious that if a second patient $j \in E$ enters server i queue, then set J_i will have only $|J_i| - 2$ patients in N. Then, using Lemma 1, $\lambda' = \sum_1^{f-2} p_N + p_E$. Since $p_N > p_E$, clearly W_{max} is decreased in the new case by $p_N - p_E$.

Although Lemma 2 presents an optimal way to decide how many *new* and *existing* patients to schedule every period, its application is not practical since it is very unlikely that each member of the individual patient groups share the same check-in service times. Therefore, new methods are needed to find a balanced scheduled that will minimize patient waiting times in multi-specialty clinics.

4.2 Finding a "Balanced" Schedule

This section turns to patient and resource scheduling and formulates an integer program (IP2) to find the best appointment times for *new* and *existing* patients given the providers' daily schedules. IP2 uses the solution of IP1 to generate a scheduling protocol for the day. Remember that IP1 provides a W_{max} for each appointment period *given* the *number of providers* and the *expected number of patients per type* to be scheduled. Then, IP1 can be used to determine the number of patients per type that will be scheduled at each appointment time period given a clinic W_{max} benchmark. For instance, given α providers, the solution of IP1 can be stated as follows, from 8:00 am to 12:00 pm, $60\% \times \alpha$ appointments must be reserved for *existing* patients and $40\% \times \alpha$ appointments must be reserved for *new* patients.

Using IP1 solution, IP2 will assign specific time appointment slots to *new* and *existing* patients during the day by solving the model using a "representative" historical patient demand and doctors' availability for each day of the week. The IP2 model produces an optimal calendar schedule for the doctors, i.e., the best appointment time for each doctor to see *new* or *existing* patients according to their availability. For convenience, we list the notation of the IP2 in Table 2.

We now state the model IP2:

IP2 Model:

$$max\ z : \sum_{i \in I} \sum_{k \in K} \sum_{l \in L} w_{ik}^l \tag{8}$$

Subject to:

$$\sum\nolimits_{l \in L} w_{ik}^l \leq h_{ik}, \quad \forall i \in I, \forall k \in K \tag{9}$$

Table 2 Sets, parameters, and decision variables for IP2

Sets	
I	Set of doctors indexed i
K	Set of patient types, indexed k ($k = 1$ *new* patient, $k = 2$ *existing* patient)
T	Set of 15-min time slots, indexed t
L	Set of appointment start times, indexed l
Parameters	
h_{ik}	Number of patients of type k requesting an appointment with doctor i per day
n_t	Number of *new* patients allowed at time period t, computed using IP1
Decision variables	
x^l_{ikt}	$=1$ if time period t is occupied by patient type k seeing doctor i and the appointment started at time period l, otherwise $x^l_{ikt} = 0$
w^l_{ik}	$=1$ if a patient type k has an appointment with doctor i starting at time period l, otherwise $w^l_{ik} = 0$

$$\sum_{i\in I}\sum_{l=t-1}^{t} x^l_{ikt} \le n_t, \quad \forall t \in T, k = 1 \tag{10}$$

$$\sum_{k\in K}\sum_{l=t-1}^{t} x^l_{ikt} \le 1, \quad \forall t \in T, \forall i \in I \tag{11}$$

$$x^l_{ikt} - w^l_{ik} = 0, \quad \forall i \in I, k = 1, \forall t \in T, l = \{t-1, t\} \tag{12}$$

$$x^l_{ikt} - w^l_{ik} = 0, \quad \forall i \in I, k = 2, \forall t \in T, l = t \tag{13}$$

$$x^l_{ikt} \in \{0, 1\} \quad w^l_{ik} \in \{0, 1\}, \forall i \in I, \forall k \in K, \forall l \in L, \forall t \in T \tag{14}$$

The objective function (8) maximizes the number of scheduled appointments for the day. The decision variable x^l_{ikt} is a binary variable that equals 1 if period t is occupied by a patient type k seeing doctor i. Likewise, the decision variable w^l_{ik} equals 1 if a patient type k has an appointment with doctor i starting at time period l. Variables x^l_{ikt} and w^l_{ik} are related through Eqs. (12) and (13) and together they control the patient volume. Equation (9) forces the model to schedule at most h_{ik} patients of type k for each doctor i. Equation (10) checks that at most n_t *new* patients are scheduled per appointment time period. Equation (11) ensures that at most one patient is scheduled for each doctor per time period. Equations (12) and (13) are used to reserve sequential time periods for those appointments requiring more than one 15-min time slot. For instance, some appointments will require two 15-min appointment time periods to be completed. The model makes sure that *new* patients occupy two time periods. Constraint (14) requires each variable to be binary. The IP2 model is NP-Hard and difficult to solve. Although the problem is NP-Hard, it can be solved with Microsoft Excel using the open source OpenSolver (www.opensolver.org) Add-in. In most cases, the solution is found in less than 30 s.

4.3 Multispecialty Outpatient Clinic Appointment Planning Algorithm (MOCAPA)

In this section, an algorithm is derived to plan for clinic appointments in multispecialty clinics by considering not only the availability of the providers but also the interaction of the patients with the front desk staff. The Multispecialty Outpatient Clinic Appointment Planning Algorithm (MOCAPA) uses the integer programming models discussed in Sects. 4.1 and 4.2 to plan for a daily schedule. The goal of the algorithm is to assist in the development of a scheduling protocol that can be used by the front desk staff at the time of setting up appointments with patients. Figure 2 illustrates the framework of the MOCAPA algorithm.

MOCAPA uses IP1 and IP2 to find the number of *new* and *existing* patients to be scheduled to see a provider at the beginning of each appointment period. IP1 is used to compute W_{max} per time period given a set of patients J, a set of providers I, and a set of front desk staff members F. Set J contains a mix of *new* and *existing* patients. W_{max} is then compared against maximum patient waiting time allowed by the clinic per time period $t(\delta_t)$. Parameter δ_t is defined by the clinic manager. If $W_{max} > \delta_t$, the members of set J are updated by decreasing the number of *new* patients by one and increasing the number of *existing* patients by one and IP1 is solved again. The size of set J remains the same. The process continues until the $W_{max} \leq \delta_t$ condition is satisfied. If $W_{max} \leq \delta_t$, then the number of *new* patients allowed at time period $t(n_t)$ is obtained by counting the number of *new* patients in J. After obtaining the n_t values per time period, MOCAPA calls IP2 to find the schedule protocol for the day. The steps of the algorithm are stated as follows:

Step 1 Obtain the number of physicians $|I|$ and the physicians' schedule for the day and the benchmark in terms of the maximum patient waiting time allowed by the clinic per time period t (δ_t).
Step 2 Using $|I|$ and δ_t, find the maximum number of *new* patients that will make $W_{max} \leq \delta_t$ by solving IP1.
Step 3 Develop an appointment scheduling protocol for the day using model IP2.

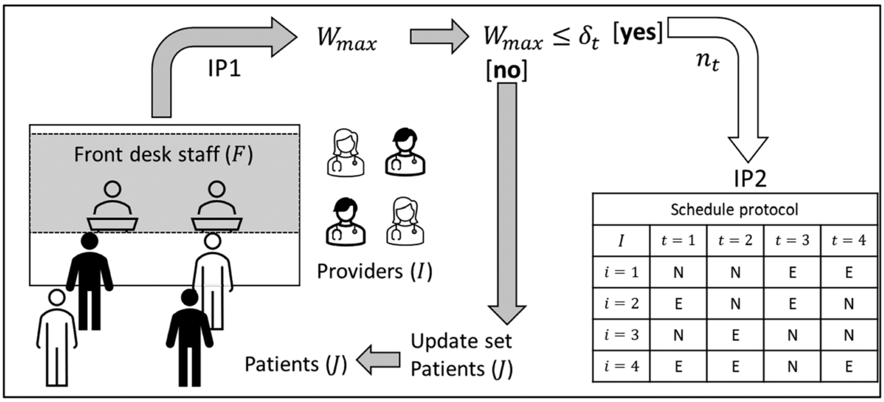


Fig. 2 General description of the MOCAPA algorithm

5 Computational Study

The computational study is based on a multispecialty outpatient clinic located in San Marcos, Texas. The clinic has multiple problems related to patient management. The most important issues facing this clinic include (1) patients unable to set-up appointments and (2) long waiting times to check-in at the clinic. The multispecialty clinic has four front desk staff members and one manager that provides extra help when needed. All the staff members perform multiple tasks, and they rotate their position on different days.

The clinic has seven providers with the following specialties: orthopedics, general surgeons, and ENT. A typical weekly schedule for all the providers is presented on Table 3. Provider's availability determines the amount of appointment slots to be allocated to patients per day. The providers' schedule presented in Table 3 depicts one of the challenges of the front desk operations which is to manage patients for multiple providers with different schedules. For example, on those days where most of the providers are available (i.e., Mondays), a higher volume of patients is expected which creates longer periods of waiting for patients due to front desk crowding.

The performance measures considered in this study focused on patient waiting times. Specifically, the study is interested in limiting the amount of wait experienced by any patient. The primary performance measure considered in this study is the maximum waiting time experienced by any patient before seeing a provider, as explained in Sect. 4. In addition, the following performance measures are considered: average patient waiting time and the average number of patients served per type.

5.1 Experimental Setup

The computational study was run using the discrete-event simulation model developed by Mocarzel et al. [4]. The clinic configuration, used to test the performance of the MOCAPA algorithm, is based on the resources/providers listed in Table 3 and the historical patient demand data for one month, which was provided by the clinic (see Table 4). The clinic serves an average of 73 patients per day. The check-in service times for *new* and *existing* patients were modeled using probability distributions. For *new* patients, the check-in service time was modeled using a uniform distribution with parameters: minimum 8 and maximum 11 min. For *existing* patients, the check-in service time was modeled using a uniform distribution with parameters: minimum 4 and maximum 5 min. Service time distributions were based on a real clinic multispecialty clinic operation in central Texas. The expected number of patients served by doctor per day of the week was computed using the historical data and the results are shown in Table 4. In Table 4, the letters "E" and "N" stands for *existing* and *new* patients, respectively.

The computational study compares the performance of the MOCAPA algorithm with the *clinic current operation* using a simulation model [4]. The protocol followed by the clinic (i.e., current operation strategy) is to schedule patients

Table 3 Weekly schedule for physicians

Name	Specialty	Monday	Tuesday	Wednesday	Thursday	Friday
Doctor 1	Orthopedics	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm		8am–12 pm 1:30 pm–4 pm
Doctor 2	Orthopedics	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1:30 pm–5 pm	
Doctor 3	ENT	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm		8am–12 pm
Doctor 4	Surgeon	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm		9am–11am	
Doctor 5	Surgeon	8am–12 pm, 1 pm–5 pm		8am–12 pm, 1 pm–5 pm	1 pm–5 pm	8am–12 pm
Doctor 6	Surgeon	8am–12 pm, 1 pm–5 pm		8am–12 pm, 1 pm–5 pm	8am–12 pm	8am–12 pm
Doctor 7	Audiologist	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm	8am–12 pm, 1 pm–5 pm	8am–12 pm 1 pm–5 pm

Table 4 Average patient demand per day for each doctor. "E" and "N" stands for *existing* and *new* patients, respectively

Day of the week	Doctor 1		Doctor 2		Doctor 3		Doctor 4		Doctor 5		Doctor 6		Doctor 7	
	E	N	E	N	E	N	E	N	E	N	E	N	E	N
Monday	14	11	10	8	16	9	2	3	5	2	6	5	12	8
Tuesday			12	6	16	10	3	1					8	7
Wednesday	16	12	1	1	17	6			5	0	6	2	11	2
Thursday			20	9			5	1	2	1	3	1	10	4
Friday	7	4			7	8			4	3	1	1	5	0

by assigning the first appointment available. Therefore, under this scenario, set J is defined from the beginning. In addition, the author compares the performance of the MOCAPA algorithm against the *optimal solution* which will be determined using complete enumeration. In the *optimal solution* strategy, every possible combination of *new* and *existing* patients per time period is considered to obtain the best system performance.

A total of twenty simulation replications are used to assess the performance of the MOCAPA algorithm and the complete enumeration. The computational study considers six operational scenarios for the multispecialty outpatient clinic: (1) clinic operates with 5 doctors and 2 staff members are available for check-in at the front desk, (2) clinic operates with 5 doctors and 3 staff members are available for check-in at the front desk, (3) clinic operates with 6 doctors and 2 staff members are available for check-in at the front desk, (4) clinic operates with 6 doctors and 3 staff members are available for check-in at the front desk, (5) clinic operates with 7 doctors and 2 staff members are available for check-in at the front desk, and (6) clinic operates with 7 doctors and 3 staff members are available for check-in at the front desk. The computational results provide the maximum number of *new* patients to schedule per appointment period that satisfy $W_{max} \leq 15$ min. The maximum number of patients arriving per appointment period is equal to the numbers of providers available at the clinic during the day.

6 Results

The computational results are summarized in Tables 5, 6, and 7. These tables list the parameters of the experiments in the first three columns and the performance measurement results in the remaining columns. The performance measures include the maximum number of *new* patients recommended to be schedule per time period, maximum check-in time experienced by a patient waiting to check-in, average waiting time experienced by all patients at the check-in process, the expected number of *existing* patients to be served per day (8-h period), and the expected number of *new* patients to be served per day (8-h period). For each performance measure, the average and confidence interval half-width are provided. Please notice that for Table 5,

Table 5 Computational results for current operation of multispecialty clinic

Solution method	Number of providers available during a day of operation	Number of front desk staff members performing check-in	Maximum check-in wait experienced by a patient	Waiting time experienced by all patients	Number of *existing* patients served per day	Number of *new* patients served per day
Clinic current performance (benchmark)	5	2	18.79 ± 0.99	6.06 ± 0.08	44	36
		3	10.52 ± 0.17	3.06 ± 0.04	44	36
	6	2	21.17 ± 0.41	8.41 ± 0.10	52	44
		3	10.92 ± 0.09	4.21 ± 0.05	52	44
	7	2	26.97 ± 1.05	10.40 ± 0.25	61	53
		3	17.83 ± 1.14	5.63 ± 0.05	61	53

Table 6 Computational results for the MOCAPA algorithm

Solution method	Number of providers available during a day of operation	Number of front desk staff members performing check-in	Maximum number of *new* patients per time period	Maximum check-in wait experienced by a patient	Waiting time experienced by all patients	Number of *existing* patients served per day	Number of *new* patients served per day
MOCAPA algorithm	5	2	3	14.47 ± 0.30	5.06 ± 0.09	48	32
		3	4	10.29 ± 0.19	2.62 ± 0.09	48	32
	6	2	3	14.09 ± 0.19	5.35 ± 0.06	70	26
		3	5	10.90 ± 0.10	3.81 ± 0.09	60	36
	7	2	-	-	-	-	-
		3	6	14.66 ± 0.32	4.78 ± 0.03	70	44

Table 7 Computational results for the optimal solution

Solution method	Number of providers available during a day of operation	Number of front desk staff members performing check-in	Maximum number of *new* patients per time period	Maximum check-in wait experienced by a patient	Waiting time experienced by all patients	Number of *existing* patients served per day	Number of *new* patients served per day
Complete enumeration (optimal solution)	5	2	3	14.47 ± 0.30	5.06 ± 0.09	48	32
		3	4	10.29 ± 0.19	2.62 ± 0.09	48	32
	6	2	3	14.09 ± 0.19	5.35 ± 0.06	70	26
		3	5	10.90 ± 0.10	3.81 ± 0.09	60	36
	7	2	1	15.00 ± 0.23	6.53 ± 0.08	96	16
		3	6	14.66 ± 0.32	4.78 ± 0.03	70	44

the maximum number of *new* patients to be scheduled per time period is not provided since the clinic does not follow this process. The clinic typically schedules most of their patients on the first appointment available.

Table 5 lists the results for the clinic current performance which is the benchmark for the analysis. The table shows that the maximum check-in wait time experienced by any patient, for most cases, is over the clinic required limit of 15 min. The only two cases, where the $W_{max} \leq 15$ min constraint is satisfied, occur when the number of providers equals 5 or 6 and the number of front desk staff members performing check-in is equal to 3.

The results for the MOCAPA algorithm are presented in Table 6. The algorithm uses $\delta_t \leq 15$ min. The MOCAPA algorithm shows a lot of potential in terms of reducing the maximum check–in time experienced by any patient. For five out of the six scenarios, the algorithm was able to find a protocol that will allow the clinic to serve the expected patient demand while keeping the maximum waiting time experienced by the patients under 15 min. However, no feasible solution was found for the experiment where the number of providers equals 7 and the number of front desk staff members equals 2. The MOCAPA algorithm was able to find a solution for most of the experiments in less than 2 min.

Table 7 shows the optimal results found using complete enumeration for the scenarios considered in this computational study. Under this strategy, a solution was found for every experiment. The results of Tables 6 and 7 show that the MOCAPA algorithm found the optimal solution for five of the six scenarios considered in the case study. However, only the total enumeration strategy was able to find a solution for the experiment where 6 providers and 2 front desk check-in staff members were considered. However, even though the solution is optimal, it is not practical because the number of *new* patients allowed to be scheduled per time period is very low which might cause patient preemption. The total enumeration method took about 2 h to find a solution for most of the experiments.

7 Conclusion

In this paper, the author presents a computational study for patient admission planning in multispecialty outpatient clinics that considers the operation of the clinic front desk. A Multispecialty Outpatient Clinic Appointment Planning Algorithm (MOCAPA) is developed to assist in the appointment planning process at the strategic and tactical level in outpatient clinics that house multiple providers with different specialties. The MOCAPA algorithm is the first methodology designed to address *strategic* and *tactical* decisions in multispecialty outpatient clinics. The algorithm addresses patient scheduling while considering the main structure of the OAS and how groups of patients are processed. The algorithm establishes appointment planning protocols for a day based on the clinic resource capacities and providers' schedules. The performance of the protocols generated by the algorithm was tested using an existing discrete-event simulation model of a real multispecialty outpatient clinic.

The MOCAPA algorithm can be implemented in outpatient clinics with multiple stages and with multiple resources in each stage. The algorithm is designed to help clinic managers address long-term *strategic* and *tactical* decisions for OAS. The algorithm is generalizable to any multi-stage clinic with multiple servers per service station as long as the number of patient groups is not greater than two. At the *strategic* level, the algorithm seeks to improve patient waiting times by considering the impact of having a different number of resources (i.e., staff and providers) in each stage of the process. At the *tactical* level, the algorithm determines the number of appointments per day reserved for different patient groups as defined by the clinic managers. The algorithm provides a mathematical-based strategy to reduce patient waiting time before seeing a provider by exploring the patient flow between multiple stages in the system. To implement the algorithm, clinics should access to their historical data in terms of providers schedules and their expected demand. In addition, time studies will be needed at the front desk and providers stages to estimate the processing times for each patient type. The algorithm provides scheduling protocols to allocate appointment to different patient groups that will reduce patient waiting times to see providers.

The results of the computational study show that in an outpatient clinic with multiple providers with different specialties, patient waiting times can be reduced by (1) classifying patient according to their status at the clinic (*new* vs. *existing*) and (2) balancing the patient type ratio of arrivals per appointment time period. The results of this research show that there is a trade-off between the maximum number of *new* patients that can be scheduled per appointment time at the clinic versus the patient waiting time at the front desk. One of the advantages of the MOCAPA algorithm is that it provides optimal solutions for the problem faster than the complete enumeration algorithm. One of the limitations of the MOCAPA algorithm is that the patient mix (i.e., *new* versus *existing* patients) can become unbalanced when trying to develop policies only focusing on reducing patient waiting times. The results show that the number of new patients is significantly smaller for some of the MOPACA algorithm experiments reported in Table 6. The goal of the algorithm is to reduce the patient waiting time. In those experiments where the clinic configuration is unbalanced (i.e., number of providers available > > number of front desk staff members available), the algorithm schedules more existing patients because they take less time to process by the front desk. For instance, when the active number of providers is 6 and the number of front desk staff members is 2 (lower bound), the MOPACA algorithm schedules only 26 new patients which represents a reduction of 18 new patients when compared to the numbers reported by the clinic current operation in Table 5. However, the patient waiting decreases by about 7 min with the MOCAPA algorithm. The results reported in Table 6 should be used as a guideline to operate the clinic and not as a final or unique solution. For instance, a clinic manager can look at the results and make decisions in terms of which system configuration will work best for the expected goals. For example, if 26 *new* patients are not enough, then the manager should plan to increase the number of staff members available for check-in, so the waiting time does not exceed at a specific level.

As part of future work, the author will explore the impact of no-shows and walk-ins when planning patient appointments for multi-specialty clinics. In addition, the authors will formulate the problem such that the patients would be classified into more than two groups when considering service times. For instance, service times can be defined based on the provider specialty. In terms of the algorithm, the authors will study ways to produce schedule protocols with a more balanced mix of patients (i.e., new versus existing). Finally, the author would like to compare the performance of the MOCAPA algorithm against other appointment policies.

Data Availability Raw data were generated at the outpatient clinic. Derived data supporting the findings of this study are available from the corresponding author on request.

Declarations

Conflict of Interest The author declares no competing interests.

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