

# **Optimal Physician Scheduling in a Multi-Clinic Network to Improve Patient Accessibility to Outpatient Care**

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## **Abstract**

Cost containment and workforce utilization typically leads to healthcare access regionalization. Little attention has thus been given to patient's spatial accessibility in appointment scheduling. As a result, many outpatients encounter huge travel burden, especially when the service items are routine. We in this research consider a multi-clinic network. In the current practice, outpatient visits are scheduled in large medical centers, which may be far away from the patients' residences. We propose to schedule physicians' weekly visits to local clinics and formulate the optimal physician scheduling decision problem as an integer program. Our aim is to minimize patient travel distance and time. We apply a simulation optimization approach to incorporate spatial uncertainties in follow-up visit requests. We present numerical studies to prove the concept that there is a need for the development of new delivery systems as many routine procedures can be done closer to patients' residences.

## **Keywords**

Integer Programming, Simulation Optimization, Healthcare Appointment Scheduling

## **1. Introduction and Background**

Health care providers are under a great deal of pressure to reduce costs and improve quality of service provided. They set the goal of matching demand with capacity and utilizing resources more efficiently. Given the great emphasis on preventive medicine practice and the short lengths of inpatient hospital stays, outpatient services have become an essential component in health care. Hospitals that cannot make their outpatient services more cost-effective find themselves in financially unviable positions in this fast-growing industry [1].

To achieve cost-effectiveness in outpatient services usually requires making intelligent decisions both at the strategic and operational levels. For comprehensive reviews of the literature, we refer to [2]. The majority of the work focuses on appointment scheduling issues. The rest considers questions pertaining to the size of facilities, equipment and staff, and to resource allocation in multi-clinic networks [3]. In the current practice, these decisions are typically made with the sole consideration of the providers, which sometimes leads to increasing level of patient dissatisfaction [4]. For example, the decisions on hospital location has primarily considered the economies of scale and other benefits, e.g., alleviating the shortage of medical personnel. However, this may result in long-distance outpatient travel, which consequently leads to high level of dissatisfaction and heavy financial burden to patients and their families. More importantly, it may prohibit early disease diagnosis and timely treatment. The inherent fundamental challenge is the undesirable level of access to care among patients.

To reduce long-distance outpatient travels, improvements can also be made both at the strategic and operational levels. Strategically, new clinics are opened to balance the changes in supplies and demands, especially in rural areas and in the areas that are greatly affected by the demographic shifts, e.g., elderly population has continuously migrated to the South and thus new densely populated residential areas are being formed there. Meanwhile, better appointment schedules and resource allocations can be developed for the same objective. Currently, outpatients in a fully-defined catchment area are typically scheduled to major medical facilities in the area. A possible solution is to dynamically provide healthcare services in a more geographically distributed manner. Therefore, we in this paper concern an innovative design of healthcare delivery system at the conceptual level, for which we schedule physicians and patients to the secondary and community-based outpatient clinics to satisfy follow-up consultation

requests in order to reduce the patients' travel distance/time. The mission of the service delivery system we consider is to satisfy all kinds of service requests from patients regardless of provision cost. This ensures that we do not need to consider the costs associated with physician travels. Such service delivery systems can be seen in large multi-clinic care provision networks such as the Veteran Affairs Medical Center networks and those in the Kaiser Permanente Healthcare Organization.

For follow-up visits, physicians divide their available clinic time into appointment slots, which are usually between 15 to 30 minutes long. In addition, providers determine the number of standard slots needed for each category of appointment requests. Routine follow-up visits require a single slot. Providers choose start and end times of their work schedule for each day over a pre-specified period of time (say 1 week) several weeks in advance of that time period. They also provide schedulers with any restrictions on how available slots may be assigned to incoming requests for appointments. In the innovative healthcare delivery system, providers not only choose the times of their work schedule but also the locations. This reflects the emerging concept of retail health services, which conducts certain routine diagnoses in multiple sites but does not attempt to ensure that patients can consult the same physician at each visit.

We in this paper provide proof-of-concept evidence to support the employment of physicians to be scheduled at other clinics than the major medical facility for follow-up visits. We develop a fairly robust but simplistic module that represents the consultation requests from a cohort of patients who reside at geographically diverse locations and associate each request with a time tag. The appointment scheduling decisions are made periodically (say 1 week). Upon the arrivals of the requests in each week, a portion of them, together with physicians, are scheduled to various clinics using an optimal resource allocation problem. Then requests are updated with the addition of newly arrived requests. We generate the new requests via Monte-Carlo simulation.

The remainder of the paper is outlined as follows. In Section 2 we state the problem and formulate it in each decision epoch as an optimal resource allocation problem. In Section 3 we discuss our computational analysis method. In Section 4 we report the results from our numerical studies. Section 5 concludes the paper and point out future research directions.

## 2. Problem Statement and Formulation

Let  $D_s(t)$  be the unsatisfied consultation requests at the beginning of decision epoch  $t = 0, 1, \dots, T$ , in location  $s = 1, 2, \dots, S$ . Let  $A_s(t)$  be the newly arrived consultation requests at epoch  $t$  from location  $s$ . Thus  $D_s(t+1) = D_s(t) + A_s(t)$ . We assume that all consultation requests are identical in terms of resource requirement (**Assumption 1**). Suppose at each decision epoch we are given a set of available physicians and a set of candidate clinic sites. We assume that the capacity level of each physician is identical among all candidate sites and thus the number of patients can be seen by a physician in each epoch is only dependent upon the physician (**Assumption 2**). We also assume that each physician only satisfies consultation requests at one site in one epoch (**Assumption 3**). Finally we assume that each available physician can satisfy any consultation request at any candidate site (**Assumption 4**).

We in this problem schedule each physician at only one clinic in each decision epoch to see a number of patients based on his capacity. Our objective is to minimize the total patient travel distance(time) at each decision epoch. Note that the above problem statement presents a simplification of many real-world settings. We use it as a proof-of-concept model, with which we intend to verify the benefit of scheduling physicians adaptively in a multi-clinic network over the configuration of scheduling all physicians at a central medical facility.

Now we formulate the decision problem in each decision epoch. If we know *a priori* the requests that can be satisfied in a decision epoch, the one-epoch decision problem is thus a static resource allocation problem, in which we want to assign each patient whose request can be satisfied with a physician to one clinic site. Meanwhile, the number of patients that can be assigned to the same site is restricted by the physician's capacity level. Let  $I$  be the set of patients whose requests are satisfied in a given epoch. Let  $J$  and  $K$  be the sets of physicians and candidate clinic sites, respectively. With Assumption 2, we denote  $c_j$  to be the capacity of physician  $j \in J$ . In other words,  $c_j$  is the number of consultation requests that can be satisfied by physician  $j$  in one epoch at any candidate clinic site. With Assumptions 1 and 2,  $I$  can be pre-determined based on the aggregate physician capacity. Details on how to determine  $I$  are included in Section 3. Denote  $\delta_{ik}$  to be the travel distance(time) by a patient  $i \in I$  to a clinic site  $k \in K$ .

For  $j \in J$ ,  $k \in K$ , let decision variables  $x_{jk}$  be 1 if physician  $j$  is scheduled at clinic  $k$ ; 0 otherwise. For  $i \in I$ ,  $j \in J$ ,  $k \in K$ , let decision variable  $y_{ijk}$  be 1 if patient  $i$  is scheduled to see physician  $j$  at clinic site  $k$ ; 0 otherwise. We present the formulation as:

$$\min \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \delta_{ik} y_{ijk} \quad (1)$$

Subject to

$$\sum_{k \in K} \sum_{j \in J} y_{ijk} = 1, \forall i \in I, \quad (2)$$

$$\sum_{i \in I} y_{ijk} \leq c_j x_{jk}, \forall j \in J, k \in K, \quad (3)$$

$$\sum_{k \in K} x_{jk} = 1, \forall j \in J, \quad (4)$$

$$x_{jk}, y_{ijk} \in \mathbf{B}, \forall i \in I, j \in J, k \in K. \quad (5)$$

Constraints (2) ensure that each patient whose consultation request has been satisfied must go to see a physician at a clinic site. Constraints (3) ensure that if physician  $j$  visits site  $k$ , the number of consultation requests that can be satisfied must not exceed the physician's capacity level. With Assumption 3, Constraints (4) ensure that each physician must find a site to visit.

Often times in the current practice, certain consultation requests must be satisfied at the central medical facility or a subset of physicians must stay at the central medical facility due to their limited availability for travel. We call a physician that can travel to secondary and community-based medical facilities a "mobile" physician. We call the rest "stationary" physicians. Let  $J_1$  be the set of mobile physicians and  $J_2$  be the set of stationary physicians. Denote  $J = J_1 \cup J_2$ . Since for any physician  $j \in J_2$ , the site he stations is fixed, we denote the site as  $k(j)$ . With the notation, we present an extension of the Problem (1) – (5) as:

$$\min \sum_{i \in I} \left( \sum_{j \in J_1, k \in K} \delta_{ik} y_{ijk} + \sum_{j \in J_2} \delta_{ik(j)} y_{ijk(j)} \right) \quad (6)$$

Subject to

$$\sum_{k \in K} \sum_{j \in J_1} y_{ijk} + \sum_{j \in J_2} y_{ijk(j)} = 1, \forall i \in I, \quad (7)$$

$$\sum_{i \in I} y_{ijk} \leq c_j x_{jk}, \forall j \in J_1, k \in K, \quad (8)$$

$$\sum_{i \in I} y_{ijk(j)} \leq c_j, \forall j \in J_2, k \in K, \quad (9)$$

$$\sum_{k \in K} x_{jk} = 1, \forall j \in J_1, \quad (10)$$

$$x_{jk}, y_{ijk} \in \mathbf{B}, \forall i \in I, j \in J, k \in K. \quad (11)$$

Constraints (8) and (9) follow Constraints (3) from the previous formulation. Note that Constraints (8) are similar to those in a capacitated facility location problem. These constraints only apply to mobile physicians.

### 3. Analysis Methodology

We in this section present a simulation optimization approach to analyze the physician/patient scheduling procedure over a period of time that contains a number of decision epochs. This approach embeds a Monte-Carlo simulation into optimization to deal with an optimal resource allocation problem under demand uncertainty. There are three parts: 1. consultation request generation; 2. consultation request temporal scheduling; 3. consultation request spatial scheduling and physician scheduling.

In the first part, we randomly generate the number of consultation requests at each patient residential location  $i \in I$  for each decision epoch (1 week). The generations of consultation requests are i.i.d. with respect to patient locations and request times. These i.i.d. multi-dimensional random vectors can be generated at the time or generated from one decision epoch to the other. The output of the first part is  $A_s(t)$ . Note that the two methods stated above are equivalent. This is because in our study, we assume that the generation of randomness at one decision epoch is independent of the scheduling in previous epochs. In the second part, we are given  $D_s(t) = A_s(t) + D_s(t-1)$ . We determine which consultation requests to be satisfied in this particular decision epoch. Here we follow the first-in-first-serve rule. That is, at any patient location, we first schedule those consultation requests that arrive earlier. Among various patient locations, if there are more consultation requests than the remaining capacity, we break the tie randomly. The output of the second part is  $I$ . We also update  $D_s(t)$  by excluding the elements in  $I$ . Now  $D_s(t)$  represents the number of unsatisfied consultation requests at location  $s$  and at the end of epoch  $t$ . In the third part, with the specification of  $I, J, K$ , and  $c_j$ , we solve the optimization problem in (1) -- (5) or (6) – (11).

## 4. Numerical Studies

In this paper, we consider several small-scale problems to illustrate the benefit of “mobilizing” physicians. Therefore, we use Problem (6) – (11) for the optimal resource allocation decision. We believe we can use the model to consider real industrial size problems if our model is populated with real data. We conduct our numerical studies in C and use Cplex to solve all optimal resource allocation problems.

### 4.1 Test Bed

We use the Central Florida Veteran Affairs (VA) healthcare network ([www.visn8.med.va.gov](http://www.visn8.med.va.gov)) as our test bed. Eight central Florida counties (Brevard, Hernando, Hillsborough, Orange, Osceola, Pasco, Polk, and Seminole) are adapted as the test catchment area in this simulation optimization study. Veterans in these eight counties with a total population of 435,442 are served by the James A. Haley Veterans’ Hospital in Tampa, part of the VA sunshine healthcare network (VISN8), and its facilities (see Figure 1). Figure 2 shows the distribution of general population in central Florida.

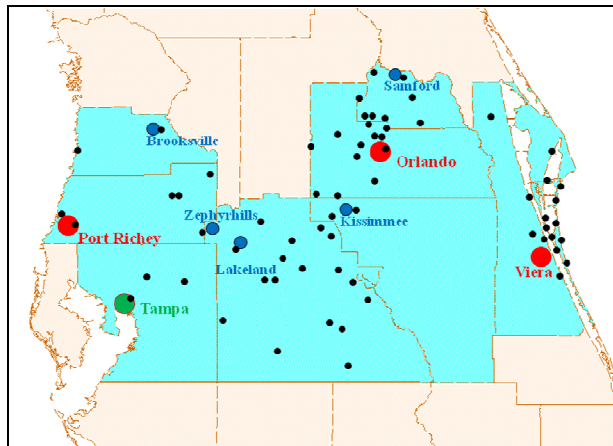


Figure 1. Central Florida VA healthcare Network

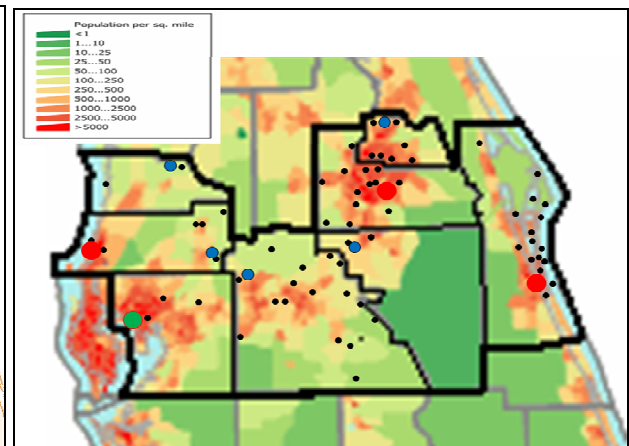


Figure 2. Central Florida population distribution

The Tampa VA is a tertiary care teaching hospital that provides a full range of inpatient and outpatient care, including medicine, surgical, psychiatry, neurology, as well as spinal cord injury service and comprehensive rehabilitation. The Tampa VA is responsible for three major satellite outpatient clinics located in Orlando, Port Richey, and Viera, and five other community based outpatient clinics located in Brooksville, Kissimmee, Lakeland, Sanford, and Zephyrhills. The Tampa VA medical center and its facilities constitute one of the busiest VA networks in the nation. In this study, we focus on veteran outpatients in the network who request cardiology follow-up consultations. These outpatients are eligible for the VA health care medical benefits and are enrolled in the VA health care. In both figures, we use different colors to represent locations of these medical facilities. The central facility in Tampa is indicated by a green dot; three satellite clinics by red dots; and five community based clinics by blue dots. In both figures, we also use small black dots to represent incorporated cities in central Florida.

### 4.2 Data Acquisition

Using the 2005 census data from the National Census Bureau, the general population of every incorporated city and ZIP code in the studied catchment area is obtained. Meanwhile, ZIP codes that are of business use are excluded. As a result, we consider 66 incorporated cities and 195 ZIP codes.

The outpatient travel burden for each patient is measured by the travel distance and travel time taken to see her cardiologist for the scheduled consultation. The travel distance and travel time are obtained via Google Maps. Google Maps allows the creation of driving directions. It gives the user a step-by-step list of how to reach her destination, along with an estimate of the distance between the two locations and the time required. Users may enter an address, intersection, ZIP code, or general area. The name of each incorporated city or each ZIP code is used to mark the starting point of each simulated patient. The address of each VA medical facility is used to mark the destination. The travel distance and time between the two locations are then calculated. The authors do not know exactly how Google Maps designs the driving directions due to Google business proprietary. However, considering the millions of users that resort to Google Maps when inquiring driving directions, it is reasonable to believe that the estimated travel distance and time from Google Maps faithfully reflect the actual patient travel burden.

### 4.3 Experimental Setting

First, we describe the estimation of physician capacity. In Problem (6) – (11), the main parameter we need to estimate is  $c_j$ . We assume that all studied physicians are of the same level of capacity, denoted by  $c$ . To estimate  $c$ , we make the following specifications. One, each decision epoch is one week. Two, in one week, each physician only handles follow-up visits in one session (4 hours). Three, each follow-up visit is scheduled into one single 30-min time slot. Hence, each physician’s capacity is 8, i.e.,  $c = 8$ .

Next we describe the generation of consultation requests that newly arrive at the beginning of each epoch. This generation is dependent upon two parameters: the number of requests and the location of each request. We consider two possibilities in generating the number of requests: 1) the number of requests is of normal distribution with mean being the aggregate physician capacity level and the standard deviation being 0.1 times the mean; 2) the number is of lognormal distribution with the same mean and standard deviation. We consider two possibilities in generating the location of each request: 1) each location (either an incorporated city or a ZIP code) has the same likelihood to become the location of the request; 2) the likelihood is based on the population. Here we assume that the distribution of the general population is identical to that for the population of veterans that need to see cardiologists for routine follow-up visits. Therefore, we consider 4 cases of consultation request generation, summarized in Table 1.

Table 1: Summary of consultation request generation

	Case 1	Case 2	Case 3	Case 4
Quantity of Consultation Request	Normal	Lognormal	Normal	Lognormal
Location of Consultation Request	Uniform	Uniform	Population-based	Population-based

Finally in this section we describe our experimental settings with respect to the physician locations. We consider a system with 5 physicians located in the central medical facility and three satellite facilities (Tampa, Orlando, Port Richey, and Viera). We consider four baseline settings where all 5 physicians are stationary physicians. In each baseline setting, one city has 2 physicians and each of the other three has 1 physician. We consider two innovative settings. We specify 1 of the 5 physicians to be a mobile physician. The first innovative setting is that the mobile physician can visit any of the 9 hospital/clinic sites in the network. The second setting is that the mobile physician can only visit any of the 4 community based centers. It is easy to see that the second innovative setting is a restriction of the first one. The experimental settings are summarized in Table 2. The first two settings correspond to the two innovative settings. The last column indicates whether the mobile physician is allowed to visit the four sites (Tampa, Orlando, Port Richey, Viera) where stationary physicians are located at. We run the simulation for 52 decision epochs (1 year) and with 100 replications. In each decision epoch, we test all 6 settings. For the first two, we solve the optimization problem and record the optimal total travel distance and time. For the next four, we only need to compute the total travel distance and time.

Table 2: Summary of experimental settings

Experimental Setting	Tampa	Orlando	Viera	Port Richey	Mobile	Include/
1	1	1	1	1	1	Yes
2	1	1	1	1	1	No
3	2	1	1	1	0	n/a
4	1	2	1	1	0	n/a
5	1	1	2	1	0	n/a
6	1	1	1	2	0	n/a

### 4.4 Computational Results

With travel distances and times recorded in each decision epoch and for each replication, we calculate the average travel distance and time for a consultation request. Figure 3 shows the comparative results among the 6 settings. From the figure, we can observe that the innovative settings have made improvement over the baseline settings. Setting 2 is shown to be slightly inferior to Setting 1 since we do not allow the mobile physician to visit some of the facilities. Among the baseline settings, Setting 4 is the best. This is due to the fact that there is an extra physician in Orlando, which is closer to the geographic center of the studied area.

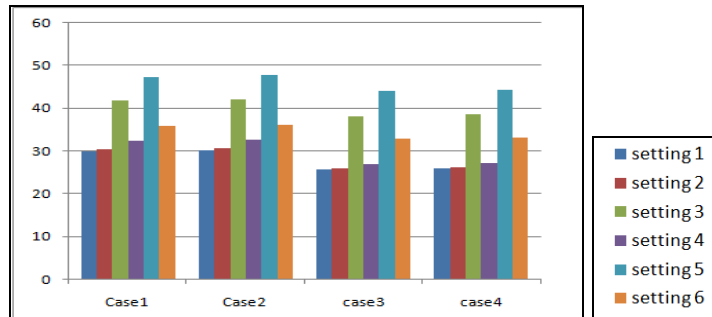


Figure 3: Comparison of average travel distance per consultation request (in miles)

We also calculate the likelihood of each hospital/clinic location being the optimal location so that we schedule the mobile physician to visit. Figure 4 reports these frequency percentage numbers with pie charts with respect to various cases and settings. Figures 4(a) and 4(b) correspond to Setting 1; Figures 4(c) and (d) correspond to Setting 2. Figures (a) and (c) correspond to the case where the requests are generated uniformly over the patient locations (Case 1 in Table 1); Figures (b) and (d) correspond to the case where the requests are population based (Case 3).

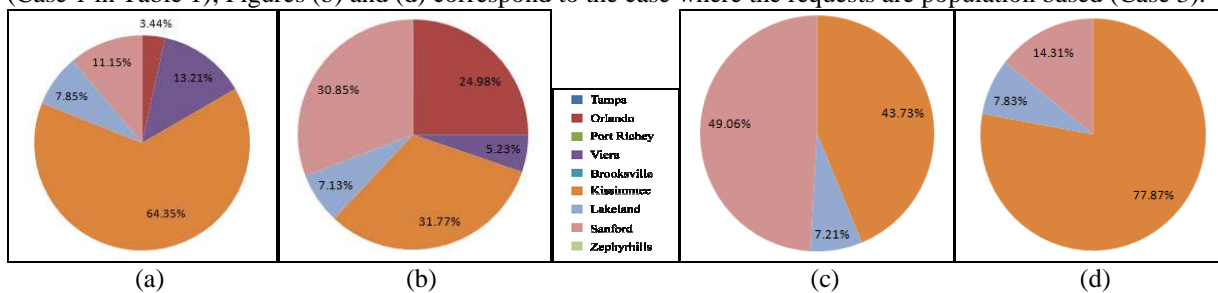


Figure 4: Frequency of a location being the optimal location

Overall across the figures, we observe that Tampa, Port Richey, Zephyrhills, Brooksville are unlikely to be the optimal location. This is because these locations are at the geographic extremes of the area and/or far from most of the patient locations. On the other hand, Kissimmee, closer to the geographic center, is likely to be the location that the mobile physician frequently visits. In (a) and (c), this frequency is much higher relative to other locations, since they correspond to the case where the requests are uniformly generated. When we consider the distribution of the general population in request generation (comparing (a) and (b)), we observe that the frequency of Orlando being the optimal location increases. It is due to the fact that Orlando is a big population center. Meanwhile, the frequency of Sanford increases since it is within the Greater Orlando area.

Due to the limit on the paper length, we cannot report the other experiments we have conducted. Instead, we list them here. One, we have tested various networks with different numbers of physicians. Two, we have considered the case where physicians take vacation each year for a number of weeks. Three, we have run the simulation for a longer period of time. Four, we have considered a classification of patients by various urgency classes. Consequently, we schedule patients' requests based on their urgency classes. Five, we have analyzed a number of hypothetical cases where there is a surge in the population of one patient location. It is often times associated with the new development of a community.

## 5. Conclusions

In this paper, we propose an innovative design of outpatient care delivery in a multi-clinic network. We formulate an optimal physician spatial scheduling problem and provide proof-of-concept evidence to verify the benefit of the proposed design. In our future research, we will test the model with real clinic data, incorporate systems dynamics, and combine the clinic siting and appointment scheduling problems.

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