# Assigning Patients to Healthcare Centers Using Dispatching Rules

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# Assigning Patients to Healthcare Centers Using Dispatching Rules

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**Abstract**

This study proposes a model for the balanced assignment of patients to healthcare centers in a region. In the suggested model, it is supposed that patients want to go to the nearest center, which causes an imbalance in the workloads of resources between centers. This disproportion is undesirable not only for the centers but also for the patients. Thus, balancing assignments is targeted. This goal is expressed in a model with a multi-objective function. Since balancing is one of the main goals of the sectorization concept, we characterize the model based on it. Unlike studies in the literature, we do sectorization employing dispatching rules. This diminishes the problem's complexity and makes it suitable for solving actual, large, and dynamic problems. We simulated the system using the Rockwell Arena software. We consider the effect of different seasons, days, and hours on the system. The dispatching rule used for sectorization is optimized using the OptQuest software. The numerical results demonstrate that by optimizing the dispatching rule, it is possible to enhance the objective function significantly.

*Keywords:* Patient Assignment; Balancing; Sectorization; Dispatching Rule; Dynamic Problems; Simulation; Optimization

## 1. Introduction

One of the main goals of health systems is to ensure a balanced distribution of workload among healthcare centers. This target is further compounded by the need to account for patients' geographic proximity to their chosen centers, which often leads to trade-offs. This matter is closely related to the concept of sectorization (Teymourifar, 2023). While sectorization has various interpretations in the literature (Liu et al., 2020; Teymourifar et al., 2020a; Teymourifar et al., 2021a,b,c), in our study, it specifically pertains to achieving workload and distance equilibriums within a healthcare system (Zhou et al., 2002). Several authors have made significant contributions to the literature on patient assignments to healthcare centers. Bartenschlager et al. (2022) emphasize the substantial impact of efficient assignment of patients to hospitals during the COVID-19 pandemic on reducing wait times and enhancing service. Fasshauer et al. (2021) assess the challenge of patient assignment during the pandemic. Granja et al. (2014) contribute to optimizing patient admission scheduling using simulation-based methods, resulting in significant reductions in completion times and patient waiting periods. However, none of these studies use dispatching rules (DRs) for this purpose. DRs are employed in production scheduling to assign and/or sequence jobs or tasks to be processed on machines or workstations. They improve production efficiency, reduce lead times, minimize waiting times, and enhance overall production performance.

In the context of the diverse literature, our paper aims to strike a balance between healthcare workload and accessibility through sectorization, leveraging DRs, and simulation, as discussed in the subsequent sections. Our primary focus is evaluating healthcare centers' workloads and patient accessibility to the centers. The proposed model comprises single-objective (SO) functions derived from these indicators, collectively forming the multi-objective (MO) function.

An innovative aspect of our research is the application of DRs for patient allocation to healthcare centres for examinations, which has not previously been explored in the literature. While DRs have traditionally been employed in scheduling problems (Ozturk et al., 2019), their use in patient assignment to healthcare centres represents a novel endeavor. DRs offer numerous advantages, including efficient solutions within polynomial time and adaptability to various problem types (Teymourifar et al., 2020b).

The existing methodologies for addressing sectorization models exhibit wide variation in the literature. Particularly for problems involving integer programming, achieving satisfactory solutions, even for moderately sized instances, poses a formidable challenge (Teymourifar et al., 2021c). Furthermore, real-world problems are dynamic (Bartenschlager et al., 2022; Fasshauer et al., 2021; Granja et al., 2014) and often entail MOs (Doudareva and Carter, 2022; Parashar et al., 2023), which escalates the complexity of sectorization models. In pursuit of a model applicable to real-world scenarios, we employ simulation techniques (Basaglia and Spacone, 2022; Fava et al., 2022; Matthews et al., 2023; Teymourifar, 2019).

Our approach involves a comprehensive analysis of system conditions across different seasons, days of the week, and hours. This approach reduces the sensitivity of results to parameter values and enhances the model's generalizability. Additionally, we fine-tune DRs to yield more optimal solutions. While simulation has been used in the past to tackle sectorization models (Teymourifar, 2023), our unique contribution lies in leveraging this technique to optimize DRs. We rigorously evaluate our results based on both the derived SO and MO functions. Our findings strongly support the suitability of DRs for patient allocation to healthcare centres. Furthermore, we demonstrate the effectiveness of simulation as a valuable tool for designing and optimizing DRs in this context. With this combined approach, we can efficiently solve the problem within a short time frame while producing interpretable solutions.

The remainder of this paper is structured as follows: The second chapter is dedicated to the literature review. Section 3 provides a concise problem description and motivation. In the Experimental Results section, we present and analyse the outcomes of our study. The paper concludes with a discussion of our findings and directions for future research.

## 2. Literature Review

Efficient patient assignment is a critical aspect of healthcare management, impacting various factors such as patient satisfaction, length of stay, and resource utilization (Dehghan-Bonari et al., 2023; Hashemi et al., 2022; Hajipour et al., 2021). There are plenty of studies delving into diverse methods and strategies for patient assignment within healthcare systems, shedding light on their implications and effectiveness. Cildoz et al. (2023) compare acuity-based rotational patient-to-physician assignment (ARPA) with simple rotational patient assignment (SRPA) in an emergency department (ED). The authors find that ARPA is associated with improvements in all operational metrics. Imhoff et al. (2022) explore the effects of batched patient-physician assignment on patient length of stay in the ED. The authors uncover that batch assignments negatively impacted the in-room patient length of stay. Additionally, there are concerns about this approach due to its association with stress and frustration. Rosenow et al. (2022) conducted a retrospective cross-sectional study to investigate the impact of an automated patient assignment system on resident productivity in the ED. The authors report significant increases in patient visits per hour and per shift post-implementation, indicating the potential benefits of automated assignment systems.

Patient assignment systems extend beyond the ED. Hodgson et al. (2020) review the theory behind these systems and highlight the advantages of specific models, including provider-in-triage and rotational patient assignment. These models can enhance patient outcomes, including length of stay and patient satisfaction. Almeida et al. (2019) present a case study focused on the optimal locations for new medical centers, aiming to improve existing infrastructure. The authors develop a web-based system that automates the decision process and offers scientific-based results. This approach provides flexibility in assigning patients to healthcare centers and optimizing resource allocation. Lin et al. (2017) tackle the patient assignment and grouping problem within a home healthcare system in Hong Kong. Using heuristic methods, the authors aim to improve workload balance, minimize delays in patient visits, and enhance operator efficiency. Li et al. (2016) propose a new care delivery scheme for integrated multi-site care networks, focusing on improving access to care. The authors develop methods to optimize physician assignments, balancing the trade-off between patient access and physician work time loss. Patterson et al. (2016) conducted a retrospective medical record review exploring the relationship between patient chief complaints and the time interval between patient rooming and resident physician self-assignment. Chan (2016) investigates how teamwork might reduce moral hazard within healthcare systems. Physicians in the same location had better information about each other, enabling the self-managed system to increase throughput productivity by reducing a "foot-dragging" moral hazard. Song et al. (2015) explore the impact of queue management on patient wait times and length of stay. They reported that a dedicated queuing system significantly decreased the average length of stay and wait times, highlighting the importance of efficient flow management.

These studies emphasize the importance of optimizing patient assignment in healthcare settings. Whether in EDs, home healthcare systems, or ambulatory care units, effective assignment methods can lead to improved patient outcomes and resource utilization. Consequently, healthcare administrators and policymakers must consider these findings when implementing patient assignment strategies to enhance the quality and efficiency of healthcare delivery.

Production scheduling has a comprehensive literature. Ozturk et al. (2019) propose novel DRs for dynamic scheduling problems, utilizing simulation and gene expression programming. Teymourifar et al. (2020b) introduce efficient DRss for complex scheduling challenges, combining gene expression programming and simulation to outperform traditional rules and maintain robustness for similar complexities. Despite the various applications of DRs, they have not been utilized in healthcare management.

## 3. Model Description

This section describes the proposed model. The used notations in the models are summarized in Table 1.

Table 1: Used notations.

| Notation | Description |
|---|---|
| $l$ | Index of seasons (Spring, Summer, Fall, or Winter) |
| $m$ | Index of week parts (weekday or weekend) |
| $n$ | Index of hours |
| $SN$ | Set of hours |
| $pt^{lm}$ | Pattern that represents season $l$ and week part $m$ |
| $\lambda_n^{lm}$ | Arrival rate at hour $n$ in pattern $pt^{lm}$ |
| $ar^{lm}$ | Scale of $\lambda_n^{lm}$ compared to $\lambda_n^{11}$ |
| $i$, $ii$ | Indexes of patients |
| $I^{lm}$ | Number of patients in pattern $pt^{lm}$ |
| $SI^{lm}$ | Set of patients in pattern $pt^{lm}$ |
| $r_i^{lm}$ | Arrival times of patient $i$ in pattern $pt^{lm}$ |
| $(X_i^{lm}, Y_i^{lm})$ | Coordinate of patient $i$ in pattern $pt^{lm}$ |
| $j$, $k$ | Indexes of healthcare centers |
| $J$ | Number of healthcare centers |
| $SJ$ | Set of healthcare centers |
| $(X_j^{ce}, Y_j^{ce})$ | Coordinate of healthcare center $j$ |
| $z_{ij}^{lm}$ | Decision variable about the assigning patient $i$ to healthcare center $j$ in pattern $pt^{lm}$ |
| $d_{ij}$ | Euclidean distance of patient $i$ from healthcare center $j$ |
| $tf_n^{lm}$ | Traffic rate at time interval $n$ in pattern $pt^{lm}$ |
| $tr^{lm}$ | Scale of $tf_n^{lm}$ compared to $tf_n^{11}$ |
| $a_{ijn}^{lm}$ | Accessibility of patient $i$ to healthcare center $j$ in pattern $pt^{lm}$ |
| $w_a^{lm}$ | Weight of accessibility in the rule for pattern $pt^{lm}$ |
| $p_{ij}^{lm}$ | Examination time of patient $i$ in healthcare center $j$ in pattern $pt^{lm}$ |
| $pr^{lm}$ | Scale of $p_{ij}^{lm}$ compared to $p_{ij}^{11}$ |
| $t_j^{b,r_i^{lm}}$ | Busy time of healthcare center $j$ when patient $i$ arrives in pattern $pt^{lm}$ |
| $u_j^{r_i,lm}$ | Workload of healthcare center $j$ when patient $i$ arrives in pattern $pt^{lm}$ |
| $t^b$ | Total busy time of healthcare center $j$ in pattern $pt^{lm}$ |
| $T$ | Total period |
| $u_j^{lm}$ | Workload of healthcare center $j$ in pattern $pt^{lm}$ |
| $\bar{u}^{lm}$ | Average workload of healthcare centers in pattern $pt^{lm}$ |
| $w_u^{lm}$ | Weight of workload in the rule for pattern $pt^{lm}$ |
| $c_j^{lm}$ | Maximum accessibility time to healthcare center $j$ in pattern $pt^{lm}$ |
| $\bar{c}^{lm}$ | Average maximum accessibility time to healthcare centers in pattern $pt^{lm}$ |
| $\bar{c}^{up,lm}$ | Upper limit for maximum accessibility time to healthcare centers in pattern $pt^{lm}$ |
| $o$ | Index of objective function |
| $f_o^{lm}$ | Objective function $o$ in pattern $pt^{lm}$ |
| $f_o^{*,lm}$ | Best (minimum) value found for objective function $o$ in pattern $pt^{lm}$ |
| $f_o^{**,lm}$ | Worst (maximum) value found for objective function $o$ in pattern $pt^{lm}$ |
| $f^{lm}$ | MO function of patients' assignment in pattern $pt^{lm}$ |
| $f^{*,lm}$ | Best (minimum) value found for the MO function in pattern $pt^{lm}$ |
| $f^{*,up,lm}$ | Best (minimum) value found for the MO function in pattern $pt^{lm}$ considering $\bar{c}^{up,lm}$ |

Let us consider a regional healthcare system with a $J$ number of centers, whose set is denoted by $SJ$. It is assumed that patients enter the system according to the Poisson distribution, and the arrival rates vary according to the seasons, week parts, and hours. The pattern that represents arrivals in season $l$ and week part $m$ is shown as $pt^{lm}$. The corresponding number and set of patients are denoted as $I^{lm}$ and $SI^{lm}$, respectively. Week parts are weekdays or weekends. The arrival rate in the time interval $n$ of pattern $pt^{lm}$ is shown as $\lambda_n^{lm}$. Differences between consecutive arrival times, i.e., $r_i^{lm} - r_{ii}^{lm}$, $\forall i \in SI^{lm}$, $\forall l = 1, ..., 4$ are called $\forall m = 1, 2$ inter-arrival times, which are supposed to be according to the Exponential distribution. Mean inter-arrival time in the interval $n$, which is the mean time between consequent arrivals in the interval, is shown as $\frac{1}{\lambda_n^{lm}}$. Patients arrive in the system and choose one of the centers to be examined there. In the time interval $n$ of pattern $pt^{lm}$ accessibility time of patient $i$ to center $j$ is as in Equation 1. $d_{ij}$ and $tf_n^{lm}$ are the Euclidean distance of patient $i$ to center $j$ and the traffic rate at time interval $n$ in pattern $pt^{lm}$, respectively.

$$a_{ijn}^{lm} = d_{ij} \times tf_n^{lm}, \forall i \in SI^{lm},\ \forall j \in SJ,\ \forall n \in SN,\ \forall l = 1, ..., 4,\ \forall m = 1, 2. \quad (1)$$

We define the workload of resources in center $j$ as the ratio of their busy time to total time. In pattern $pt^{lm}$, the workload of resources in center $j$ at the arrival time of patient $i$ is defined as in Equation 2.

$$u_j^{r_i,lm} = \frac{t_j^{b,r_i^{lm}}}{r_i^{lm}}, \forall i \in SI^{lm},\ \forall j \in SJ,\ \forall n \in SN,\ \forall l = 1, ..., 4,\ \forall m = 1, 2. \quad (2)$$

Patients prefer to go to the center with the lowest accessibility times. However, this causes imbalances in the workload of the centers. This may also cause dissatisfaction among the patients. Thus, the tradeoff between patients' accessibility time to centers and the workloads of centers is beneficial for the entire system. In order to achieve this, it is assumed that a central system advises them to choose a center at the time of their arrival. It is presumed that the system is aware of the accessibility of the patients as well as the workloads of the centers. To trade off $a_{ijn}^{lm}$ and $u_j^{r_i,lm}$ in the pattern $pt^{lm}$, a weight is assigned to them, denoted by $w_a^{lm}$ and $w_u^{lm}$, respectively. In fact, $w_a^{lm} \times a_{ijn}^{lm} + w_u^{lm} \times u_j^{r_i,lm}$ is a DR and $w_a^{lm}$ and $w_u^{lm}$ are the weights of DR in the pattern $pt^{lm}$.

$$\begin{gathered} w_a^{lm} \times a_{ijn}^{lm} + w_u^{lm} \times u_j^{r_i,lm} \leq w_a^{lm} \times a_{ikn} + w_u^{lm} \times u_k^{r_i,lm} \\ \forall i \in SI^{lm},\ \forall j \neq k \in SJ,\ \forall n \in SN,\ \forall l = 1, ..., 4,\ \forall m = 1, 2. \end{gathered} \quad (3)$$

In each pattern, each patient must be assigned to only one healthcare center, and at least one patient must be allocated to each healthcare center, which is provided by the Constraints 5 and 6.

$$z_{ij}^{lm} = \begin{cases} 1, & \text{if } \textit{patient } i \textit{ is assigned to healthcare center } j \textit{ in pattern } pt^{lm}. \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

$$\forall i \in SI^{lm}, \forall j \in SJ, \forall l = 1, ..., 4, \forall m = 1, 2.$$

$$\sum_{j \in SJ} z_{ij}^{lm} = 1, \ \forall i \in SI^{lm}, \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{5}$$

$$\sum_{i \in SI^{lm}} z_{ij}^{lm} \geq 1, \ \forall j \in SJ, \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{6}$$

The workload of healthcare center $j$ in pattern $pt^{lm}$ is defined as in Equation 8, where $T$ is the total time, and $t_j^b$ is the busy time of the center during the time.

$$u_j^{lm} = \frac{t_j^b}{T}, \ \forall j \in SJ, \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{7}$$

It is aimed to have a balanced workload between the health centers, which is satisfied by minimizing Equation 8.

$$f_1^{lm} = \sum_{j \in SJ} |u_j^{lm} - \bar{u}^{lm}| \ \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{8}$$

$\bar{u}^{lm}$ in Equation 8 is calculated as in Equation 9.

$$\bar{u}^{lm} = \frac{\sum_{j \in SJ} u_j^{lm}}{J}, \ \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{9}$$

Maximum accessibility time to healthcare center $j$ in pattern $pt^{lm}$ is expressed as in Equation 10, in which $a_{ijn}^{lm}$ is the accessibility of patient $i$ to healthcare center $j$ in pattern $pt^{lm}$.

$$c_j^{lm} = max \ (a_{ijn}^{lm} \times z_{ij}^{lm}), \ \forall i \in SI^{lm}, \ \forall j \in SJ, \ \forall n \in SN, \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{10}$$

To be minimized, the average of maximum accessibility times to healthcare centers in pattern $pt^{lm}$ is defined as in Equation 11.

$$f_2^{lm} = \bar{c}^{lm} = \frac{\sum_{j \in SJ} c_j^{lm}}{J}, \ \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{11}$$

An upper limit is specified for $f_2^{lm}$ as in Constraint 12.

$$f_2^{lm} \leq \bar{c}^{up,lm} \ \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{12}$$

A balanced between the maximum accessibility times to healthcare centers is expected, which is met by minimizing Equation 13.

$$f_3^{lm} = \sum_{j \in SJ} |c_j^{lm} - \bar{c}^{lm}| \quad \forall l = 1, ..., 4, \ \forall m = 1, 2 \tag{13}$$

The best and worst values found for SO function $o$ in pattern $pt^{lm}$ are denoted as $f_o^{*,lm}$ and $f_o^{**,lm}$ $\forall o = 1, 2, 3$, respectively. In this case, if the value of SO function $o$ in pattern $pt^{lm}$ is $f_o^{*,lm}$, then the value of MO function is obtained from Equation 14.

$$f^{lm} = \sum_{o=1}^{3} \frac{f_o^{lm} - f_o^{*,lm}}{f_o^{lm} - f_o^{**,lm}} \quad \forall l = 1, ..., 4, \ \forall m = 1, 2 \tag{14}$$

It is aspired to minimize $f^{lm}$, whose best value is indicated as $f^{*,lm}$. If Constraint 12 is incorporated in the model, $f^{*,up,lm}$ is utilized instead of $f^{*,lm}$.

## 4. Solution Method

In this section, the solution method is described. The primary idea of the method can be summarized as follows: the values of $w_a^{lm}$ and $w_u^{lm}$ have significant effects on the objective functions and should be optimized. The method consists of five stages, as below.

Step 1: The values of $w_a^{lm}$ and $w_u^{lm}$ that provide $f_o^{*,lm}$ or $f_o^{**,lm}$, $\forall o = 1, ..., 3$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$ are found. They are portrayed as the ideal and anti-ideal points of each SO function. These values are acquired just to use in Equation 14 to calculate the MO function.

Step 2: The values of $f_o^{lm}$ are calculated for the case in which $w_a^{lm} = 1$ and $w_u^{lm} = 1$ $\forall o = 1, ..., 3$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$. It is presumed that the DRs are formed using these weights in the current state of the system, i.e., the situation before optimization for all patterns. Using them and $f_o^{*,lm}$ and $f_o^{**,lm}$ in Equation 14, $f^{lm}$ $\forall o = 1, ..., 3$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$ is calculated. It is supposed that these values represent the current state for all patterns.

Step 3: To optimize $f^{lm}$ i.e. to find $f^{*,lm}$, the values of $f_o^{*,lm}$ and $f_o^{**,lm}$ $\forall o = 1, ..., 3$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$ are again used in Equation 14 and a search is done on $w_a^{lm}$ and $w_u^{lm}$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$. This also provide the values of $f_o^{lm}$ that cause to $f^{*,lm}$, $\forall o = 1, ..., 3$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$ in Equation 14.

Step 4: Including Constraint 12 in the model, the values of $w_a^{lm}$ and $w_u^{lm}$ that provide $f^{*,up,lm}$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$ are found.

Step 5: Using the values of $w_a^{lm}$ and $w_u^{lm}$, $f_o^{lm}$ and $f^{lm}$, $\forall o = 1, ..., 3$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$ are calculated including Constraint 12.

At first, the model is simulated in the Rockwell Arena software. Then, operating this model, the stages of the method are implemented in the OptQuest software.

## 5. Experimental Results

In this section, experimental results are presented. Some parts of the data used in this section are from a case study conducted between 2015-2018, in which a regional healthcare system in the Eskişehir province of Turkey was surveyed. More details can be found in reference [19].

The arrival rates of patients are varied. The index $l$ represents the season such that $l = 1, 2, 3, 4$ stand for Spring, Summer, Fall, and Winter, respectively. $m = 1, 2$ symbolize weekday and weekend, respectively. $pt^{lm}$, i.e., the pattern where time is Spring and weekday forms a base, and some parameters in other patterns are proportional to it.

Arrivals of patients into the system are according to the Poisson distribution, and inter-arrival times are according to the Exponential distribution. $\lambda_n^{11} = 850\ \forall n = 1, ..., 8$, $\lambda_n^{11} = 2880\ \forall n = 9, ..., 16$, $\lambda_n^{11} = 460\ \forall n = 17, ..., 24$ of which $\lambda$ and $n$ represents the average inter-arrival time in seconds and the index of hours, respectively. For other patterns, inter-arrival times are gained as in Equation 15, where $ar^{lm}$ is the scale of $\lambda_n^{lm}$ compared to $\lambda_n^{11}$ $\forall n \in SN$, $\forall l = 1, ..., 4$, and $\forall m = 1, 2$. The values of $ar^{lm}$ are given in Table 3. according to various patterns.

$$\lambda_n^{lm} = \lambda_n^{11} \times ar^{lm}, \forall n \in SN,\ \forall l = 1, ..., 4,\ \forall m = 1, 2. \tag{15}$$

Patients' arrival times are generated according to the Normal distribution with a mean of 50 and a standard deviation of 10, which is expressed as $X_i^{lm}$ and $Y_i^{lm} \sim NORM(50,10)$, $\forall i \in SI^{lm}$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$. We assume that there are ten healthcare centers in the area whose coordinates are given in Table 2. They are likewise yielded randomly according to $NORM(50,10)$, which are fixed for all periods.

Table 2. Coordinates of healthcare centers.

| | $j$ =1 | $j$ =2 | $j$ =3 | $j$ =4 | $j$ =5 | $j$ =6 | $j$ =7 | $j$ =8 | $j$ =9 | $j$ =10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $X_j^{ce}$ | 46.75 | 48.56 | 41.29 | 59.62 | 39.95 | 51.47 | 67.19 | 53.24 | 77.56 | 63 |
| $Y_j^{ce}$ | 62.12 | 58.42 | 50.52 | 35.12 | 35.34 | 52.36 | 36.59 | 61.86 | 35.46 | 57.68 |

At hour $n$ of pattern $pt^{11}$ the traffic rates are: $tf_n^{11}$=1.5 $\forall n = 7, 9, 17, 19$, $tf_n^{11}$=2 $\forall n = 8.18$, $tf_n^{11}$=1. For other patterns, traffic rates are got as in Equation 16. The values of $tr^{lm}$ according to different patterns are shown in Table 3.

$$tf_n^{lm} = tf_n^{11} \times tr^{lm}, \forall n \in SN,\ \forall l = 1, ..., 4,\ \forall m = 1, 2. \tag{16}$$

At pattern $pt^{11}$, it is assumed that the examination times are distributed according to the Continuous uniform distribution in the interval [15, 30], in minutes, which is expressed as $p_i^{11} \sim UNIF(15, 30)$, $\forall i \in SI^{11}$,. For other patterns, the examination times are obtained as in Equation 17. The values of $pr^{lm}$ according to different patterns are shown in Table 3.

$$p_{ij}^{lm} = p_i^{lm} = p_i^{11} \times pr^{lm}, \ \forall j \in SJ, \ \forall l = 1, ..., 4, \ \forall m = 1, 2. \tag{17}$$

Table 3. Values of the parameters $ar^{lm}$, $tr^{lm}$ and $pr^{lm}$.

| | $ar^{lm}$ | $tr^{lm}$ | $pr^{lm}$ |
|---|---|---|---|
| $l = 1, m = 1$ | 1 | 1 | 1 |
| $l = 1, m = 2$ | 0.5 | 1 | 1.5 |
| $l = 2, m = 1$ | 1.5 | 1 | 2 |
| $l = 2, m = 2$ | 1.5 | 1 | 3 |
| $l = 3, m = 1$ | 0.5 | 1 | 1 |
| $l = 3, m = 2$ | 0.2 | 1 | 1.5 |
| $l = 4, m = 1$ | 0.2 | 1.5 | 1 |
| $l = 4, m = 2$ | 0.15 | 1.5 | 1.5 |

Accessibilities are calculated as in Equation 1, which considers the Euclidean distance from each center of the patients and the traffic rate at the relevant pattern and time interval. As noted before, at first, the described system is simulated in the Rockwell Arena software using the parameters of $pt^{11}$ and $w_a^{11} = 1$ and $w_u^{11} = 1$. Then the steps of the solution method are implemented in the OptQuest software. The stopping condition of the optimization process is to reach 100 iterations. We utilize a system with an Intel Core i5 processor, 2.4 GHz with 12 GB of RAM, and Rockwell Arena 14. All results are the average of ten replications, each lasting 720 hours, i.e., one month.

Step 1: The values of $w_a^{lm}$ and $w_u^{lm}$ that provide the ideal and anti-ideal points of each SO function per pattern are acquired as in Table 4. As mentioned in Section 4, these values are just used in Equation 14 to calculate the MO function.

Table 4. The results of step 1 in the solution method.

| | $f_o^{**,lm}$ or $f_o^{*,lm}$ | $w_a^{lm}$ | $w_u^{lm}$ | $I^{lm}$ |
|---|---|---|---|---|
| | $f_1^{**,lm}$=1.86 | 1 | 0.01 | |
| | $f_1^{*,lm}$=0.4 | 0.01 | 1 | |
| $l = 1, m = 1$ | $f_2^{**,lm}$=78.88 | 0.09 | 1 | 2997.5 |
| | $f_2^{*,lm}$=66.41 | 0.01 | 0.93 | |
| | $f_3^{**,lm}$=32.1 | 0.01 | 0.99 | |
| | $f_3^{*,lm}$=28.03 | 0.89 | 0.04 | |
| | $f_1^{**,lm}$=2.61 | 1 | 0.01 | |
| | $f_1^{*,lm}$=0.65 | 0.01 | 1 | |
| $l = 1, m = 2$ | $f_2^{**,lm}$=150.54 | 0.94 | 0.04 | 6183.1 |
| | $f_2^{*,lm}$=118.81 | 0.01 | 0.99 | |
| | $f_3^{**,lm}$=54.53 | 0.01 | 0.88 | |
| | $f_3^{*,lm}$=49.08 | 0.94 | 0.04 | |
| | $f_1^{**,lm}$=1.22 | 1 | 0.01 | |
| | $f_1^{*,lm}$=0.54 | 0.01 | 1 | |
| $l = 2, m = 1$ | $f_2^{**,lm}$=164.02 | 0.96 | 0.52 | 1961.4 |
| | $f_1^{*,lm}$=131.38 | 0.01 | 0.99 | |
| | $f_3^{**,lm}$=58.14 | 0.01 | 0.95 | |
| | $f_1^{*,lm}$=54.08 | 0.96 | 0.52 | |
| | $f_1^{**,lm}$=1.22 | 1 | 0.01 | |
| | $f_1^{*,lm}$=0.65 | 0.01 | 1 | |
| $l = 2, m = 2$ | $f_2^{**,lm}$=246.03 | 0.96 | 0.52 | 1961.4 |
| | $f_2^{*,lm}$=202.06 | 0.01 | 0.99 | |
| | $f_3^{**,lm}$=86.76 | 0.01 | 0.99 | |
| | $f_3^{*,lm}$=81.12 | 0.96 | 0.52 | |
| | $f_1^{**,lm}$=2.61 | 1 | 0.01 | |
| | $f_1^{*,lm}$=0.47 | 0.01 | 1 | |
| $l = 3, m = 1$ | $f_2^{**,lm}$=100.36 | 0.94 | 0.04 | 6183.1 |
| | $f_2^{*,lm}$=72.02 | 0.01 | 1 | |
| | $f_3^{**,lm}$=37.25 | 0.01 | 0.99 | |
| | $f_3^{*,lm}$=32.72 | 0.94 | 0.04 | |
| | $f_1^{**,lm}$=1.81 | 1 | 0.01 | |
| | $f_1^{*,lm}$=0.37 | 0.01 | 1 | |
| $l = 3, m = 2$ | $f_2^{**,lm}$=163.89 | 0.96 | 0.52 | 15652.3 |
| | $f_2^{*,lm}$=139.35 | 0.01 | 0.95 | |
| | $f_3^{**,lm}$=57.84 | 0.01 | 0.99 | |
| | $f_3^{*,lm}$=54.35 | 0.96 | 0.52 | |
| | $f_1^{**,lm}$=1.48 | 1 | 0.01 | |
| | $f_1^{*,lm}$=0.16 | 0.01 | 1 | |
| $l = 4, m = 1$ | $f_2^{**,lm}$=110.77 | 0.05 | 0.46 | 15652.3 |
| | $f_2^{*,lm}$=95.37 | 0.01 | 0.71 | |
| | $f_3^{**,lm}$=38.74 | 0.01 | 1 | |
| | $f_3^{*,lm}$=36.12 | 0.5 | 0.79 | |
| | $f_1^{**,lm}$=1.38 | 1 | 0.01 | |
| | $f_1^{*,lm}$=0.17 | 0.01 | 1 | |
| $l = 4, m = 2$ | $f_2^{**,lm}$=174.28 | 0.48 | 0.96 | 20842 |
| | $f_2^{*,lm}$=159.1 | 0.01 | 1 | |
| | $f_3^{**,lm}$=58.64 | 0.01 | 0.88 | |
| | $f_3^{*,lm}$=55.82 | 0.48 | 0.96 | |

The convergence of the OptQuest algorithm to earn $f_1^{*,11}$ in Table 4. is depicted in Figure 1. This optimization procedure is roughly six minutes. More or less, the same value is valid for other runs.

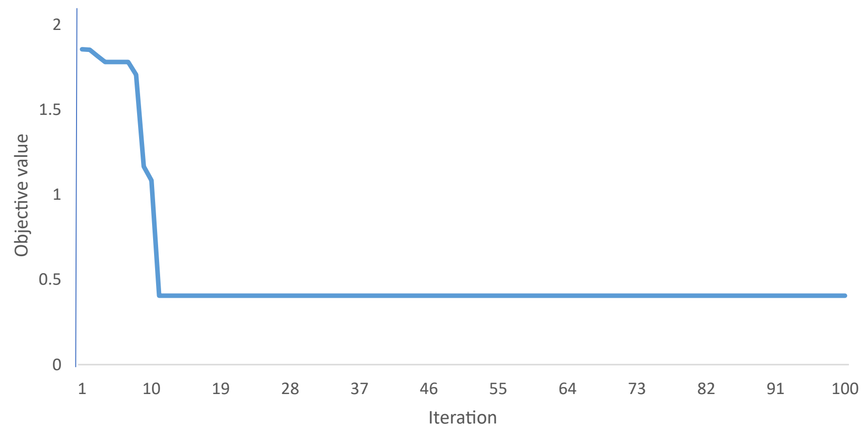


Figure 1: The convergence of the OptQuest algorithm to achieve $f_1^{*,11}$.

If $w_a^{lm} = w_u^{lm} = 1$, using the values of the ideal and anti-ideal points in Table 4. in Equation 14, the values of the MO function in the current state are obtained as in Table 5. Also, in this way, the values of the SO functions in the current state are obtained, as presented in Table 5.

Table 5. Outputs of step 2 in the solution method.

| | $f_1^{lm}$ | $f_2^{lm}$ | $f_3^{lm}$ | $f^{lm}$ |
|---|---|---|---|---|
| $l = 1, m = 1$ | 1.78 | 77.15 | 28.13 | 1.83 |
| $l = 1, m = 2$ | 2.53 | 149.7 | 49.22 | 1.96 |
| $l = 2, m = 1$ | 1.20 | 163.88 | 54.09 | 1.97 |
| $l = 2, m = 2$ | 1.21 | 245.82 | 81.14 | 1.98 |
| $l = 3, m = 1$ | 2.49 | 99.69 | 32.82 | 1.94 |
| $l = 3, m = 2$ | 1.77 | 163.54 | 54.38 | 1.97 |
| $l = 4, m = 1$ | 1.43 | 109.14 | 36.24 | 1.90 |
| $l = 4, m = 2$ | 1.34 | 174.17 | 55.84 | 1.97 |

To optimize the value of the MO function, step 3 of the solution method is applied, whose results are presented in Table 6. During this procedure, the weights of the DR are optimized. The values of the SO functions that provide the optimal MO function are also shown in Table 6.

Table 6. Results of step 3 in the solution method.

| | $w_a^{lm}$ | $w_u^{lm}$ | $f_1^{lm}$ | $f_2^{lm}$ | $f_3^{lm}$ | $f^{*,lm}$ |
|---|---|---|---|---|---|---|
| $l = 1, m = 1$ | 0.01 | 0.87 | 0.52 | 66.82 | 31.43 | 0.95 |
| $l = 1, m = 2$ | 0.01 | 1 | 0.66 | 119.23 | 54.31 | 0.98 |
| $l = 2, m = 1$ | 0.01 | 0.99 | 0.55 | 137.18 | 57.62 | 1.06 |
| $l = 2, m = 2$ | 0.01 | 1 | 0.65 | 204.31 | 86.36 | 0.98 |
| $l = 3, m = 1$ | 0.01 | 1 | 0.47 | 72.03 | 36.95 | 0.93 |
| $l = 3, m = 2$ | 0.01 | 0.99 | 0.37 | 140.55 | 57.65 | 0.99 |
| $l = 4, m = 1$ | 0.01 | 0.95 | 0.17 | 95.92 | 38.21 | 0.84 |
| $l = 4, m = 2$ | 0.01 | 0.96 | 0.18 | 159.28 | 58.22 | 0.87 |

Comparing the values in Table 6 with the values in Table 5, it can be inferred that there is improvement in the objective functions except for the average of maximum accessibility. Hence, to resolve this, as in step 4 of the solution method, Constraint 12 is included to find the optimal value of the MO function. This step correspondingly finds the weights of the related DRS. These results are presented in Table 7.

Table 7. Outputs of step 4 in the solution method.

| | $\bar{c}^{up,lm}$ | $w_a^{lm}$ | $w_u^{lm}$ | $f^{*,up,lm}$ |
|---|---|---|---|---|
| $l = 1, m = 1$ | 28.23 | 0.25 | 1 | 1.73 |
| | 28.44 | 0.14 | 0.99 | 1.49 |
| | 28.64 | 0.16 | 0.99 | 1.48 |
| | 28.84 | 0.07 | 1 | 1.40 |
| $l = 1, m = 2$ | 49.35 | 0.54 | 1 | 1.91 |
| | 49.63 | 0.27 | 0.99 | 1.83 |
| | 49.90 | 0.11 | 0.68 | 1.74 |
| | 50.17 | 0.11 | 0.73 | 1.69 |
| $l = 2, m = 1$ | 54.28 | 0.1 | 0.82 | 1.81 |
| | 54.49 | 0.1 | 0.99 | 1.77 |
| | 54.69 | 0.05 | 1 | 1.54 |
| | 54.89 | 0.05 | 1 | 1.49 |
| $l = 2, m = 2$ | 81.40 | 0.07 | 0.84 | 1.79 |
| | 81.68 | 0.07 | 1 | 1.72 |
| | 81.97 | 0.05 | 1 | 1.66 |
| | 82.25 | 0.03 | 0.94 | 1.42 |
| $l = 3, m = 1$ | 32.95 | 0.42 | 0.91 | 1.86 |
| | 33.17 | 0.27 | 1 | 1.8 |
| | 33.40 | 0.24 | 1 | 1.75 |
| | 33.63 | 0.23 | 1 | 1.74 |
| $l = 3, m = 2$ | 54.52 | 0.30 | 1.00 | 1.92 |
| | 54.70 | 0.23 | 1 | 1.86 |
| | 54.87 | 0.11 | 0.79 | 1.81 |
| | 55.05 | 0.11 | 0.82 | 1.77 |
| $l = 4, m = 1$ | 36.25 | 0.3 | 1 | 1.84 |
| | 36.38 | 0.11 | 0.77 | 1.69 |
| | 36.51 | 0.1 | 0.7 | 1.68 |
| | 36.64 | 0.1 | 0.7 | 1.68 |
| $l = 4, m = 2$ | 55.96 | 0.09 | 0.88 | 1.66 |
| | 56.10 | 0.07 | 0.99 | 1.55 |
| | 56.24 | 0.05 | 0.99 | 1.54 |
| | 56.38 | 0.05 | 0.99 | 1.54 |

We appraise the validation of results as follows: if patients are assigned using DRs with the WDPs in Table 7, similar results should be obtained for each pattern. For this aim, simulations are repeated in OptQuest with the same condition, using only the WDRs in Table 7. The results are given in Table 8 where the gaps are calculated as $\text{Gap}^1 = max(f_3^{lm} - \bar{c}^{up,lm}, 0)$, $\text{Gap}^2 = max(f^{lm} - f^{*,up,lm}, 0)$. $\bar{c}^{up,lm}$ and $f^{*,up,lm}$ are get from Table 7, while $f_3^{lm}$ and $f^{lm}$ are from Table 8.

Table 8. Results of step 5 in the solution method.

| | $f_1^{lm}$ | $f_2^{lm}$ | $f_3^{lm}$ | $f^{lm}$ | Gap[1] | Gap[2] |
|---|---|---|---|---|---|---|
| $l = 1, m = 1$ | 1.58 | 75.76 | 28.35 | 1.64 | 0.12 | 0.0 |
| | 1.42 | 75.37 | 29.39 | 1.75 | 0.95 | 0.26 |
| | 1.46 | 74.67 | 28.49 | 1.50 | 0.0 | 0.02 |
| | 1.16 | 75.7 | 28.76 | 1.44 | 0.0 | 0.04 |
| $l = 1, m = 2$ | 2.47 | 148.48 | 49.33 | 1.91 | 0.0 | 0.0 |
| | 2.35 | 145.06 | 49.64 | 1.80 | 0.02 | 0.0 |
| | 2.2 | 141.92 | 50.06 | 1.70 | 0.16 | 0.0 |
| | 2.17 | 143.06 | 50.31 | 1.77 | 0.14 | 0.8 |
| $l = 2, m = 1$ | 1.1 | 162.11 | 54.3 | 1.82 | 0.02 | 0.01 |
| | 1.07 | 161.59 | 54.34 | 1.77 | 0.0 | 0.0 |
| | 0.95 | 156.46 | 54.74 | 1.53 | 0.05 | 0.0 |
| | 0.95 | 156.46 | 54.74 | 1.53 | 0.00 | 0.04 |
| $l = 2, m = 2$ | 1.1 | 243.16 | 81.44 | 1.66 | 0.04 | 0.0 |
| | 1.08 | 242.09 | 81.54 | 1.74 | 0.0 | 0.02 |
| | 1.03 | 237.62 | 82.18 | 1.66 | 0.21 | 0.0 |
| | 0.94 | 234.91 | 82.09 | 1.43 | 0.0 | 0.01 |
| $l = 3, m = 1$ | 2.38 | 98.18 | 32.97 | 1.87 | 0.02 | 0.01 |
| | 2.23 | 96.69 | 33.18 | 1.79 | 0.01 | 0.0 |
| | 2.19 | 94.6 | 33.37 | 1.74 | 0.0 | 0.0 |
| | 2.18 | 95.38 | 33.54 | 1.80 | 0.0 | 0.06 |
| $l = 3, m = 2$ | 1.68 | 163.76 | 54.42 | 1.92 | 0.0 | 0.0 |
| | 1.64 | 161.43 | 54.64 | 1.86 | 0.0 | 0.0 |
| | 1.56 | 158.5 | 54.98 | 1.78 | 0.11 | 0.0 |
| | 1.54 | 158.5 | 54.98 | 1.77 | 0.0 | 0.0 |
| $l = 4, m = 1$ | 1.31 | 109.8 | 36.23 | 1.85 | 0.0 | 0.01 |
| | 1.09 | 109 | 36.37 | 1.69 | 0.0 | 0.0 |
| | 1.09 | 109 | 36.37 | 1.69 | 0.0 | 0.0 |
| | 1.09 | 109 | 36.37 | 1.69 | 0.0 | 0.0 |
| $l = 4, m = 2$ | 0.97 | 173.74 | 55.93 | 2.23 | 0.0 | 0.57 |
| | 0.81 | 173.31 | 56.09 | 1.56 | 0.0 | 0.01 |
| | 0.67 | 171.34 | 56.52 | 1.47 | 0.28 | 0.0 |
| | 0.67 | 171.34 | 56.52 | 1.47 | 0.14 | 0.0 |

The solution procedure is assumed to be efficient since the gaps are often low. Therefore, when the WDRs in Table 7. are used to form DRs, near-optimal solutions that do not significantly violate Constraint 12 are acquired. The optimization time of each DR in OptQuest is about six minutes for 100 iterations, but dispatching with a DR takes about 3.6 seconds. Therefore, using DRs is also beneficial in terms of computation time. Considering the number of patients in different periods, available in Table 4., it can be concluded that it is straightforward to solve large instances with DRs.

### Managerial Implications

The research in this paper has several practical implications for healthcare managers, which can be summarized as follows:

- It offers insights and methodologies to optimize the assignment of patients to healthcare centers. This helps to achieve a balanced workload in healthcare centers, which ultimately enhances patient care.
- It emphasizes the importance of patient-centered care. Managers can use these insights to ensure that patients have improved access to healthcare facilities, leading to higher patient satisfaction and better outcomes, which can benefit the organization's reputation and success.
- It shows the benefit of implementing DRs in several fields of healthcare management. These rules have the potential to reduce waiting times, enhance efficiency, and improve resource allocation within healthcare facilities.
- It suggests an analytical approach, which involves analyzing system conditions across various factors. This approach reduces sensitivity to parameter values and enhances the generalizability of resource allocation strategies, making them more robust and adaptable to different scenarios.

## 6. Conclusion and Future Works

This study proposes a new approach to assigning patients to healthcare centers. Novelties of the work can be outlined like this: as the first in the literature, the problem is modeled based on the sectorization concept. A dynamic model is described, where patients arrive at the system at different times. Although the variation of the system in diverse time intervals is generally ignored in sectorization problems, this matter is taken into account in this study. The system's status is investigated according to the arrival rates in different seasons, week parts, and hours. It is taken into account that traffic rates and examination times change at different times. Rather than the distance of patients to healthcare centers, the concept of accessibility, which considers traffic rate, is utilized. In this way, different values are allocated to the parameters, and the generalizability of the model is ensured.

Unlike others, this study employs DRs to solve a problem based on the sectorization concept. We use simulation-based optimization to optimize DRs. The validity of the evolved DRs is demonstrated by repeating the simulation model. It is more straightforward to solve large-scale problems with DRs compared to methods like mixed integer programming. Moreover, it is easy to adapt to similar problems. This approach has previously been used mainly for solving scheduling problems, but for the first time in the literature, we use it to assign patients to healthcare centers.

While this study uses DRs to assign patients to simplify the process and facilitate the resolution of challenging real-world cases, it lacks a comparison to alternative methods such as integer programming. This represents a significant limitation of this study. The lack of sensitivity analysis for the parameters used in Section 4 is another limitation of this work. Optimizing DRs needs to lead to statistically significant improvements in results. Not using a statistical experimental design is another shortcoming of this study. Future work will address these gaps.

In this study, both the proposed model and the solution method are applicable to real-life problems. However, it should be noted that the suggested model can only offer a recommendation for patients to select a center. In addition, centers must have an integrated system to implement the model. In this study, it is presumed that the integration exists, but this can be challenging for real systems. Also, this study assumes that healthcare centers are homogeneous. In future studies, it is planned to do sectorization by assigning different and dynamic capacities to healthcare centers.

Recently, there has been a large amount of research dealing with the automated design of DRs using artificial intelligence (AI) (Ozturk et al., 2019). The DRs used in this study are quite simple, and consist of only two features. In feature works, we will include more features to automated design of DRs utilizing AI to be tested on a larger set of problem instances.

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**Supporting Information**

All implemented codes models are accessible via the author's email address.

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**Appendix**

Table of abbreviations

| Abbreviations | Definition |
|---|---|
| ED | Emergency department |
| DR | Dispatching rule |
| MO | Multi-objective |
| NORM | Normal distribution |
| SO | Single-objective |
| UNIF | Continuous uniform distribution |
| WDR | Weights of dispatching rule |