Balanced Patient Assignment to Healthcare Centers through Dispatching Rules

Aydin Teymourifar[1,*], Maria A. M. Trindade[2]
[1]Católica Porto Business School, Centro de Estudos em Gestão e Economia, Universidade Católica Portuguesa, Porto, Portugal
[2]SDA Bocconi, School of Management, Milano, Italy
[*]Correspondence: aydinteymurifar@gmail.com

Abstract

In the realm of public health management, ensuring a balanced assignment of patients to healthcare centers is a critical concern. This study introduces a novel approach for this purpose, utilizing dispatching rules. Highlighting the need for an easily applicable approach to regulating patient flow efficiently, the study shows the benefit of utilizing dispatching rules in healthcare management. Innovatively, this research departs from traditional approaches by introducing a multi-objective model grounded in the concept of sectorization. This model, unique in the public health literature, leverages dispatching rules to simplify complex, dynamic patient assignment scenarios. Incorporating various factors, the model is simulated, and the optimization of the dispatching rules is carried out. The study's findings demonstrate that the optimized dispatching rule significantly enhances the model's efficacy in balancing patient assignments across healthcare centers. This improvement is pivotal in addressing the uneven distribution of healthcare resources. This research makes a substantial contribution to the public health literature by offering a novel and practical solution for balancing patient load among healthcare centers. Its successful application in simulated environments suggests a promising pathway for real-world implementations, potentially leading to more efficient healthcare systems and improved patient care outcomes.

Keywords: Patient Assignment; Healthcare Centers; Simulation; Balancing; Dispatching Rules; Sectorization

Highlights

- We suggest an innovative approach to evenly distributing healthcare workloads, aiming for a more equitable allocation of tasks.
- Distinct from previous studies, we underscore the critical role of dispatching rules in balancing patient distribution.
- We demonstrate the tangible advantages of these rules in managing public healthcare as a complex system, emphasizing their importance in enhancing overall healthcare accessibility.

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). The meaning of sectorization varies depending on the context, but generally, it involves dividing a larger area into specific sectors for better management (Porter and Strategy, 1980). In urban planning, it organizes city zones for different uses, promoting structured development (Kaiser et al., 1995). In telecommunications, sectorization leads to an enhancement of a network by partitioning it into multiple sectors (Rappaport, 2002). In environmental management, it allocates areas for sustainable resource and ecosystem preservation (Buchholz, 1998). Each application of sectorization aims to enhance both efficiency and effectiveness within its respective domain.

Furthermore, it is generally desirable for sectors to be balanced and similar according to various criteria, often involving the concept of balancing segments, which is also known as achieving equilibrium between sectors. While multiple interpretations of sectorization exist in the literature (e.g., Liu et al., 2020; Teymourifar et al., 2020a, 2021a, b, c), this study specifically focuses on achieving workload and distance balance within a healthcare system (Zhou et al., 2002). It is crucial to note that in the context of this study, the term 'sectorization' does not pertain to its geographical sense.

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 visitors and 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 centers 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 centers represents a novel endeavor. DRs offer numerous advantages, including efficient solutions within polynomial time and adaptability to various problem types (Teymourifar et al., 2020b; Teymourifar and Trindade, 2024).

The existing methodologies for addressing sectorization models exhibit wide variation in the literature. Particularly for problems involving integer programming (Vahdat et al., 2019), 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; Harper and Mustafee, 2023; 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 better 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 centers. 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.

Based on the above paragraphs, the research question can be refined and articulated as: How can DRs be generated and optimized through comprehensive system analysis across various temporal conditions, such as seasons, days, and hours, to ensure balanced patient assignment across healthcare centers, thereby achieving equitable resource utilization and enhancing access to care?

The paper is structured as follows: The "Literature Review" section offers a comprehensive review of existing works related to our study, laying the foundational context. Following that, the "Description of the Model" section describes our proposed model and the "Solution Method" section explains our chosen approach. In the "Experimental Results" section, we present and analyze the outputs of our study, highlighting key findings. Finally, the paper concludes with a "Conclusions" section where we reflect on our discoveries and suggest avenues 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; Zhang et al., 2023). 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 (Modi et al., 2019).

Production scheduling has a comprehensive literature on the application of DRs. Ozturk et al. (2019) propose novel DRs for dynamic scheduling problems, utilizing simulation and gene expression programming. Teymourifar et al. (2020b) introduce efficient DRs 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. A summary of some promising research directions is as follows:

- **Policy improvement for balanced access to healthcare services:** While studies by Endalamaw et al. (2023) and Khatri et al. (2023) have highlighted the importance of equitable access to healthcare services, there remains a significant gap in the application of DRs for this purpose. These rules, if implemented, could greatly enhance healthcare delivery and the effectiveness of health systems, especially in structuring public health emergency responses for improved health security.

- **Fair healthcare resource allocation:** The works of Dong et al. (2021), Babyar (2018), and Khatri et al. (2023) underscore the critical need for equity in healthcare access and resource allocation. However, the potential of the application of DRs to achieve fair resource distribution and equitable patient assignment has yet to be fully explored. This presents a promising direction for future research on addressing healthcare inequalities, discrimination, and stigma.

- **Service utilization:** The research by Bastani et al. (2021) and Dong et al. (2021) emphasizes the essential aspects of healthcare accessibility and service utilization. Despite this, the application of dispatching rules in this context, especially during challenges such as the COVID-19 pandemic, has not been adequately explored. Implementing these rules could significantly improve access to and utilization of health services, particularly for vulnerable groups like the elderly.

3. Description of the Model

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

Table 1: Used notations.

Notation	Description	Type
l	Index of seasons (Spring, Summer, Fall, or Winter)	Index
m	Index of week parts (weekday or weekend)	Index
n	Index of hours	Index
SN	Set of hours	Set
pt^{lm}	Pattern that represents season l and week part m	Notation
λ_n^{lm}	Arrival rate at hour n in pattern pt^{lm}	Parameter
ar^{lm}	Scale of $\frac{1}{\lambda_n^{lm}}$ compared to $\frac{1}{\lambda_n^{11}}$	Parameter
i, ii	Indexes of patients	Index
I^{lm}	Number of patients in pattern pt^{lm}	Variable
SI^{lm}	Set of patients in pattern pt^{lm}	Set
r_i^{lm}	Arrival times of patient i in pattern pt^{lm}	Variable
(X_i^{lm}, Y_i^{lm})	Coordinate of patient i in pattern pt^{lm}	Parameter
j, k	Indexes of healthcare centers	Index
J	Number of healthcare centers	Parameter
SJ	Set of healthcare centers	Set
(X_j^{ce}, Y_j^{ce})	Coordinate of healthcare center j	Parameter
z_{ij}^{lm}	Decision variable about the assigning patient i to healthcare center j in pattern pt^{lm}	Decision variable
d_{ij}	Euclidean distance of patient i from healthcare center j	Variable
tf_n^{lm}	Traffic rate at time interval n in pattern pt^{lm}	Parameter
tr^{lm}	Scale of tf_n^{lm} compared to tf_n^{11}	Parameter
a_{ijn}^{lm}	Accessibility of patient i to healthcare center j in pattern pt^{lm}	Variable
w_a^{lm}	Weight of accessibility in the rule for pattern pt^{lm}	Parameter
p_{ij}^{lm}	Examination time of patient i in healthcare center j in pattern pt^{lm}	Variable
pr^{lm}	Scale of p_{ij}^{lm} compared to p_{ij}^{11}	Parameter
$t_j^{b,r_i^{lm}}$	Busy time of healthcare center j when patient i arrives in pattern pt^{lm}	Variable
$u_j^{r_i,lm}$	Workload of healthcare center j when patient i arrives in pattern pt^{lm}	Variable
t^b	Total busy time of healthcare center j in pattern pt^{lm}	Variable
T	Total period	Parameter
u_j^{lm}	Workload of healthcare center j in pattern pt^{lm}	Variable
$\bar{u}^{lm}$	Average workload of healthcare centers in pattern pt^{lm}	Variable
w_u^{lm}	Weight of workload in the rule for pattern pt^{lm}	Parameter
c_j^{lm}	Maximum accessibility time to healthcare center j in pattern pt^{lm}	Variable
$\bar{c}^{lm}$	Average maximum accessibility time to healthcare centers in pattern pt^{lm}	Variable
$\bar{c}^{up,lm}$	Upper limit for maximum accessibility time to healthcare centers in pattern pt^{lm}	Parameter
o	Index of objective function	Index
f_o^{lm}	SO function o in pattern pt^{lm}	Objective function
$f_o^{*,lm}$	Best (minimum) value found for objective function o in pattern pt^{lm}	Variable
$f_o^{**,lm}$	Worst (maximum) value found for objective function o in pattern pt^{lm}	Variable
f^{lm}	MO function of patients' assignment in pattern pt^{lm}	Objective function
$f^{*,lm}$	Best (minimum) value found for the MO function in pattern pt^{lm}	Variable
$f^{*,up,lm}$	Best (minimum) value found for the MO function in pattern pt^{lm} considering $\bar{c}^{up,lm}$	Variable

Let us consider a regional healthcare system with J 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 λ_n^{lm}. Differences between consecutive arrival times, i.e., $r_i^{lm} - r_{ii}^{lm}$, $\forall i \in SI^{lm}$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$ are called 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.

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

In various academic and practical contexts, the term 'traffic rate' may carry diverse interpretations. However, within the scope of our study, it is specifically defined as a coefficient that plays a pivotal role in influencing the accessibility of patients to healthcare facilities.

We define the workload of resources in center j as the ratio of their busy time to total time. We define the busy time of a resource as the period when the resource is occupied with work. It's a measure of how long the resource is not idle and is actively contributing to the tasks or operations within the simulation model (Rossetti, 2021). It's important to highlight that the whole facility is considered a single-unified resource. In pattern pt^{lm}, the workload of resources in center j at the arrival time of patient i is defined as in Equation 2.

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

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}.

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

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.

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

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

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

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

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.

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

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

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

A balance 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.

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

The primary goal of the model is to minimize f^{lm}, which is the essential objective function of the model. The best value of this function is denoted as $f^{*,lm}$. If Constraint 12 is incorporated in the model, $f^{*,up,lm}$ is utilized instead of $f^{*,lm}$.

It is important to emphasize that the model described in this study does not fall under the category of integer programming. Rather, it is specifically developed as a formulation intended for simulation modelling.

Figure 1 provides an outline of the model.

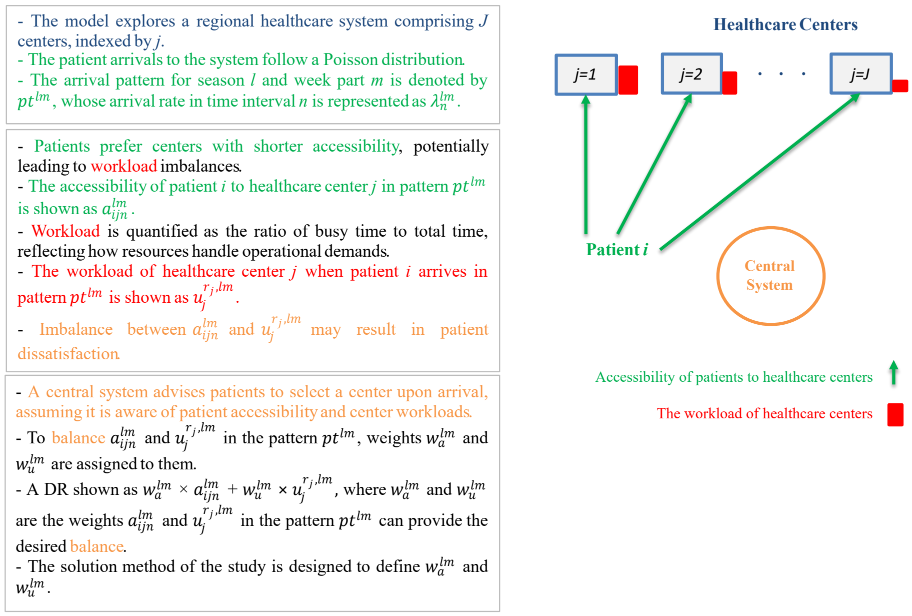

Figure 1: An outline of the model

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 provides the values of f_o^{lm} that lead 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. The technique used is discrete event simulation (DES), which models a system's behavior as a sequence of distinct, ordered events over time. It is especially valuable in disciplines like operations research, computer science, and industrial engineering for studying complex systems, including manufacturing processes, telecommunications networks, and hospital services. This approach supports informed decision-making and performance assessment without disrupting real-world activities (Law et al., 2007). DES differs from other simulation methods, such as Agent-Based Modeling (ABM), by focusing on events that occur at specific times to change the system's state. In contrast, ABM simulates the behaviors and interactions of individual agents, enabling complex system dynamics to emerge from these interactions (Banks et al., 2005; Macal and North, 2010).

Then, operating the simulation model, the stages of the method are implemented in the OptQuest software. A detailed explanation of the models, including their implementation in Rockwell Arena and OptQuest software, and all relevant information can be accessed via the email address of the corresponding author.

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 and 2018, in which a regional healthcare system in the Eskişehir province of Turkey was surveyed. More details can be found in Teymourifar (2019).

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. $\frac{1}{\lambda_n^{11}} = 850$ $\forall n = 1, ..., 8$, $\frac{1}{\lambda_n^{11}} = 2880$ $\forall n = 9, ..., 16$, $\frac{1}{\lambda_n^{11}} = 460$ $\forall n = 17, ..., 24$ of which $\frac{1}{\lambda}$ and n represents the mean inter-arrival time in seconds and the index of hours, respectively. This implies that the busiest time of day is during hours 17 to 24. For other patterns, mean inter-arrival times are gained as in Equation 15, where ar^{lm} is the scale of $\frac{1}{\lambda_n^{lm}}$ compared to $\frac{1}{\lambda_n^{11}}$

$\forall n \in SN$, $\forall l = 1, ..., 4$, $\forall m = 1, 2$. The values of ar^{lm} are given in Table 3. according to various patterns.

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

It's vital to acknowledge that the rates mentioned pertain to mean inter-arrival times throughout the entire studied region rather than being confined to just a single healthcare center.

The model assumes that the centers operate as EDs with round-the-clock (24/7) operations, as opposed to a standard healthcare system with traditional working hours. In general, patient arrivals tend to decrease during the night in most healthcare systems, except in emergency rooms, where this pattern is not seen.

The coordinates of patients 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

Note: As outlined in Table 1, j is the index for healthcare centers, while X_j^{ce} and Y_j^{ce} denote the x-coordinate and y-coordinate of center j, respectively.

Traffic rate significantly influences patients' accessibility to healthcare facilities. At hour n of pattern pt^{11} the traffic rates are: tf_n^{11}=1.5 $n = 7, 9, 17, 19$, tf_n^{11}=2 $n = 8, 18$, and tf_n^{11}=1 for all other hours. For other patterns, traffic rates are got as in Equation 16, which quantifies how traffic rates are influenced by variable factors such as days of the week or seasonal changes relative to tf_n^{11} $\forall n \in SN$ as the reference pattern for traffic rate. The values of tr^{lm} according to different patterns are shown in Table 3.

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

The reason tf_n^{11}, $\forall n \in SN$ is defined as the reference pattern for traffic rates is its demonstrated stability during observations, showing less variability compared to other patterns. Consequently, it provides a reliable standard against which fluctuations in other patterns can be measured. This conclusion and the values presented in Table 3 are based on observations collected between the years 2015 and 2018 (Teymourifar, 2019).

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

Note: As mentioned in Table 1, l, m, ar^{lm}, tr^{lm}, and pr^{lm} demonstrate the indexes of seasons, week parts, the scales of arrival rate compared to the base case, traffic rate compared to the base case, and examination time compared to the base case, respectively.

Table 3 showcases the variations in inter-arrival times, traffic rates, and processing times at different times of the year. For instance, the table reveals that during winter, the mean inter-arrival times are shorter and traffic rates are higher compared to spring. These metrics are derived from a case study (Teymourifar, 2019).

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 10 replications, each lasting 720 hours, i.e., one month. Replication plays an essential role in simulation studies, significantly influencing the reliability and robustness of the results. The reason for defining ten replications is that it can be completed in a relatively short time but it should be noted that similar results are achieved with a higher number of replications. In this context, a comparative analysis of simulation outputs from 10 replications versus 100 replications reveals minimal variance across the evaluated variables. To quantify this matter, the absolute percentage difference for each output is calculated as follows: the absolute value of subtracting the output from the 100 replications from that of the 10 replications, dividing this difference by the output of the 10 replications, and multiplying the result by 100 to convert it to a percentage. This measure reflects the relative change in the outputs as a result of varying the number of replications. Here, 'outputs' refer to the variables utilized in the objective functions of the simulation. Notably, the maximum absolute percentage difference observed is 2.40%, indicating that the simulation outputs maintain substantial stability across different replication counts. The statement regarding completing ten replications in a short time is valid specifically for the system we used, whose features have been detailed in the preceding lines. However, with a more advanced system, it would likely be feasible to perform many more iterations, such as 1000 or more, within a similar time frame. 720 hours are used to represent one month. Other time-related measurements, such as seasons, parts of the week, and specific hours, are defined and managed using distinct parameters, as detailed in Table 1.

The basic parameters of the model, along with their corresponding values and sources, are summarized in Table 4.

Table 4. Values of the parameters

Parameter	Value/Distribution	Source
Number of centers	10	Case study (Teymourifar, 2019)
Coordinates of centers	*NORM*(50,10)	Assumption
Week parts	Weekday or weekend	Standard working calendar
Seasons	Spring, Summer, Fall, Winter	Typical seasons
Mean inter-arrival times in pt^{11}	850 for hours ranging from 1 to 8, 2880 for hours ranging from 9 to 16, 460 for hours ranging from 17 to 24	Case study (Teymourifar, 2019)
Service time in pt^{11}	*UNIF*(15,30)	Case study (Teymourifar, 2019)
Traffic rates in pt^{11}	1.5 for hours ranging from 7,9,17,19 2 for hours ranging from 8,18 1 for all other hours	Case study (Teymourifar, 2019)

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 5.

Table 5. 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	

Note: As stated in Table 1, l, m, $f_o^{**,lm}$, $f_o^{*,lm}$, w_a^{lm}, w_u^{lm}, and I^{lm} signify the indexes of seasons, week parts, the worst (maximum) value found for the SO function o in pattern pt^{lm}, the best (minimum) value found for objective function o in pattern pt^{lm}, the weights of accessibility and workload in the DR for pattern pt^{lm}, and the number of patients in pattern pt^{lm}, respectively.

As described in Step 1 of the solution method, the ideal and anti-ideal points of each SO function per pattern summarized in Table 5 are just used in Equation 14 to calculate the MO function.

The convergence of the OptQuest algorithm to earn $f_1^{*,11}$ in Table 5. is depicted in Figure 2. This optimization procedure is roughly six minutes. More or less, the same value is valid for other runs.

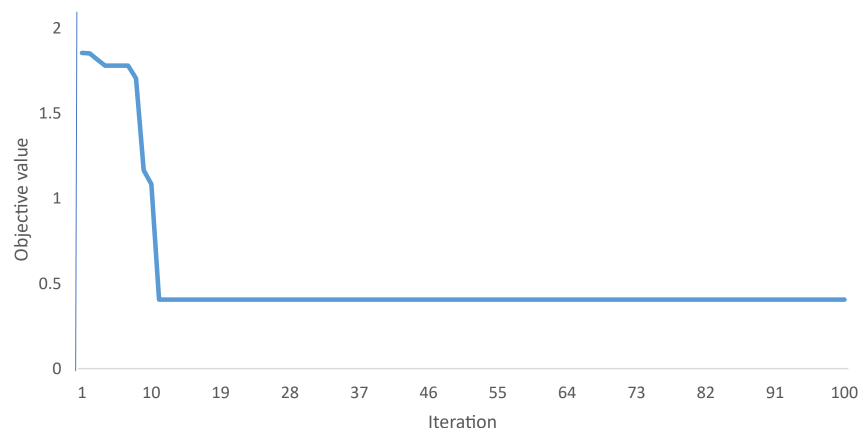

Figure 2: The convergence of the OptQuest algorithm to achieve $f_1^{*,11}$, which represents the best (minimum) value found for the objective function labeled as f_1 under specific conditions indicated by the pattern pt^{11}.

Setting 100 iterations in OptQuest is a parameter choice. However, it is evident from Figure 2 that, after iteration 10, the optimization process has already converged. Convergence is reached when additional iterations fail to yield significant improvements, often indicating that an optimal or near-optimal solution has been found. In this case, despite the initial 100-iteration setting, the substantial lack of progress beyond the 10th iteration suggests that the model has effectively reached its improvement capacity.

If $w_a^{lm} = w_u^{lm} = 1$, using the values of the ideal and anti-ideal points in Table 5. in Equation 14, the values of the MO function in the current state are obtained as in Table 6. Also, in this way, the values of the SO functions in the current state are obtained, as presented in Table 6.

Table 6. 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

Note: As indicated in Table 1, l, m, f_1^{lm}, f_2^{lm}, f_3^{lm}, and f^{lm} represent the index of seasons, the index of week parts, the first, the second, the third objective function for pattern pt^{lm}, and the MO function of patients' assignment in pattern pt^{lm}, respectively.

As a fundamental objective of this study, we aim to optimize the values of objective functions in the current state, which are summarized in Table 6. To optimize the value of the MO function, step 3 of the solution method is applied, whose results are presented in Table 7. 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 7.

Table 7. 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

Note: As stated in Table 1, l, m, w_a^{lm}, w_u^{lm}, f_1^{lm}, f_2^{lm}, f_3^{lm}, and $f^{*,lm}$ signify the index of seasons, the index of week parts, the weight of accessibility in the rule for pattern pt^{lm}, the weight of workload in the rule for pattern pt^{lm}, the first, the second, the third objective function for pattern pt^{lm}, and the best (minimum) value found for the MO function in pattern pt^{lm}, respectively.

The weights of accessibility and workload presented in Table 7 provide the minimum value for the MO function in each pattern. These weights generate the DRs that provide the best solution for each pattern. Comparing the values in Table 7 with the values in Table 6, 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 8.

Table 8. 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

Note: As mentioned in Table 1, l, m, $\bar{c}^{up,lm}$*,* w_a^{lm}*,* w_u^{lm}*, and* $f^{*,up,lm}$ *indicate the index of seasons, the index of week parts, the upper limit for maximum accessibility time to healthcare centers in pattern* pt^{lm}*, the weight of accessibility in the rule for pattern* pt^{lm}*, the weight of workload in the rule for pattern* pt^{lm}*, and the best (minimum) value found for the MO function in pattern* pt^{lm} *considering* $\bar{c}^{up,lm}$*, respectively.*

Table 8 summarizes the weights of accessibility and workload, resulting in the determination of DRs that yield the best solution for each pattern while considering the constraint on the average maximum accessibility times to healthcare centers within each pattern.

We appraise the validation of results as follows: if patients are assigned using DRs with the WDPs in Table 8, 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 8. The results are given in Table 9 where the gaps are calculated as Gap^1=$max(f_3^{lm} - \bar{c}^{up,lm}, 0)$, 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 9. 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

Note: As stated in Table 1, l, m, f_1^{lm}, f_2^{lm}, f_3^{lm}, *and* f^{lm} *indicate the index of seasons, the index of week parts, the first, the second, the third objective function for pattern* pt^{lm}, *and the MO function of patients' assignment in pattern* pt^{lm}, *respectively.*

Discussion on the Efficiency of Solution Method

The solution procedure is assumed to be efficient since the defined gaps are often low. To clarify, we define a 'low' gap as being less than 0.05. However, different thresholds may be appropriate depending on the specific objectives and context of the study. Therefore, when the WDRs in Table 8. 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 5., it can be concluded that it is straightforward to solve large instances with DRs.

Drawing upon the findings from Tables 7, 8, and 9, it can be inferred that the proposed solution method generates DRs, which enhance the values of the MO function for each pattern while adhering to the constraint regarding the average maximum accessibility times to healthcare centers within each pattern.

Overall, it can be concluded that a balanced assignment of patients across healthcare centers is achievable through the generation and implementation of DRs.

Discussion on the Implications of Proposed Methods on Patient Waiting Times

An important metric for healthcare delivery is the consideration of patient waiting time, as it directly impacts patient satisfaction, treatment outcomes, and overall system efficiency. It is crucial to note that workload, which is derived from the resource utilization level, does not directly correspond to patient waiting times. The relationship between waiting time and utilization can be non-linear, meaning that a higher workload does not necessarily translate to proportionally longer waiting times, or conversely. Given this non-linear relationship, it is possible that a patient assignment may lead to scenarios with balanced accessibility and workload values but ultimately experience longer waiting times. Additionally, it is important to recognize that waiting time is primarily associated with patient experiences, while workload pertains to the allocation and utilization of healthcare center resources. While this study does not account for the complex dynamics between resource utilization and patient waiting times, the developed model includes waiting times as an important output of the simulation. So, the model can be easily used to develop DR to decrease waiting times. Consequently, the model can be effectively utilized to develop DRs aimed at reducing waiting times.

Managerial implications

The paper presents significant managerial implications for healthcare administrators. The results confirm that developing and implementing DRs can provide a balanced distribution of patients across healthcare centers. Furthermore, it has been discussed that DRs can be used to reduce patient waiting times. The implementation of DRs is not complex, enabling their application to address real-world challenges in healthcare settings.

The paper highlights the advantages of implementing DRs across diverse healthcare management domains. DRs hold promise for reducing waiting times, boosting efficiency, and optimizing resource allocation within facilities (Ozturk et al., 2019). The approach advocated by the paper, involving the comprehensive analysis of system conditions across multiple factors, reduces sensitivity to parameter values and enhances the generalizability of resource allocation strategies. This makes them more resilient and adaptable to various scenarios, enabling healthcare managers to navigate dynamic environments effectively.

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.

In the literature review section, we highlighted promising research directions. This study addresses these gaps by applying and testing DRs in healthcare settings. Our work demonstrates how DRs can enhance access, allocation, and utilization of healthcare services, ensuring equitable resource distribution. These findings not only fill critical gaps identified in previous research but also provide scalable, evidence-based strategies that can inform future policy-making and contribute to more resilient and equitable health systems.

Considering the points discussed earlier, it is evident that the research question outlined in the Background section has been adequately answered. The practical relevance and alignment of findings with objectives can be succinctly summarized as follows: The model's practical significance stems from its innovative approach to patient assignment, which integrates dynamic factors like traffic rates and varying examination times essential in real-world healthcare settings. The study's results harmonize with its objectives by presenting a more adaptable and realistic solution for patient allocation, addressing the complexities often overlooked in traditional approaches. Simulation emerges as a powerful tool for generating and refining DRs, with significant practical applications in healthcare management. The consistency of DRs across different periods offers a stable framework adaptable to evolving healthcare center demands and patient needs, strategically balancing predictability and adaptability in dynamic environments. While the optimized DRs remain static over time, they are strategically designed to dynamically address varying problems, contributing to a consistent and reliable framework for patient assignment and ultimately reducing complexity and potential errors. The separable nature of the problem structure provides a structured approach to managing multifaceted issues in patient allocation, further enhancing the efficiency of healthcare systems.

Several limitations of this research should be meticulously addressed. For instance, the research supposes that patients select hospitals purely based on accessibility. This assumption is restrictive as it overlooks other crucial factors that significantly influence patient decisions, such as the quality of care, such as the skill of the medical staff, reputation, and the diversity of services provided. Furthermore, factors like patient experience, costs, and personal referrals play a significant role in their decision-making. We suppose the existence of a central system that, being informed about patient accessibility and center workloads, advises patients on their choice of center upon arrival. Furthermore, we assume that in the current system, centers are assigned to patients with equal consideration given to patient accessibility and center workloads. While these assumptions enable a more manageable analysis of the model, they must be carefully examined to comprehensively understand the potential limitations inherent in the study. Another limitation relates to the parameter values used in the model and simulation, which require further analysis in future studies using a statistically robust experimental design.

This study employs DRs to streamline patient assignments, addressing complex real-world scenarios. However, it lacks a comparative analysis with alternative methodologies like integer programming, primarily due to the absence of similar studies in the current literature. This highlights the innovative nature of our approach but also points to a limitation in direct validation. The lack of sensitivity analysis for the used parameters 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 (Ozturk et al., 2019). The DRs used in this study are quite simple and consist of only two features. In future works, we will include more features, such as the total duration of patient stays, to automate the design of DRs utilizing AI to be tested on a larger set of problem instances.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Conflict of interest
The authors declare no conflict of interest (financial or non-financial).

Human and animal rights
The research does not involve any data collected from human participants or experiments with animals.

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Availability of data and materials
All implemented models are available to the public via the following GitHub link.

https://github.com/aydinteymurifar/DR-for-assigning-patients-to-healthcare-centers-

A video detailing the models implemented in Rockwell Arena and OptQuest software is available at the following link for further insight.

https://www.youtube.com/watch?v=IAV1YivwNnc

Additionally, details of the results obtained from the model can be accessed through the corresponding author's email address.

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