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Article

Optimization of French Hospital Department Activities Using an Efficient Discrete Event Simulation Model

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Abstract: A mismatch between patient demand and emergency departments (EDs)' capacity to deliver care often leads to poor patient flow and overcrowding, and therefore an increase in waiting. This paper presents a mid-term decision support system dealing with scheduling and allocation of resources in the ED of the Hospital Center of Troyes, France. An efficient performance evaluation tool based on discrete event simulation (DES) is developed. Through a what-if scenario strategy, 145 scenarios were simulated that allowed us to create a new benchmark that does not exist in the literature. To rank and select the best alternatives, the VIKOR multicriteria analysis method and the entropy method were used. With the objective of minimizing the waiting time and inpatient stay under an additional resource cost constraint, this work has helped to quantify and analyze the impacts related to the structural and organizational reorganization of the ED.

Keywords: emergency department; wait times; discrete event simulation; resource allocation; VIKOR method



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1. Introduction

1.1. Problem Statement

Managing patient flow in the ED is one of the most important and difficult issues for hospital management [1–3]. The main problems facing emergency services are congestion and increasing demand for the activities of EDs, which obviously impacts the optimal use of resources that guarantee the quality of care. Hence, the limitation of human and material resources.

The conjunction of these problems is the cause of the appearance of situations of crisis within an emergency service. These lead to the dissatisfaction of patients who are obliged to wait for a long time, and who sometimes decide to leave without seeing the doctor. Faced with this situation, it is essential for ED managers to anticipate and manage this situation.

In this context, healthcare engineering is increasingly being developed in order to improve ED productivity and to propose different improvement strategies that may reduce ED crowding.

This paper focuses on the optimization of the activities of an ED to improve the quality of services offered to patients. Therefore, as a main contribution of this paper, a decision-making tool for healthcare management is introduced. Both waiting time and inpatient stay are to be optimized under additional resources cost constraint.

An analytical approach based on simulation and optimization is proposed to solve this problem. We first developed an efficient performance-evaluation tool based on DES. Then, we addressed resource optimization. To this aim, we used a what-if scenario strategy and a VIKOR multi-criteria analysis method to select the best scenarios. A large experimental study based on 145 scenarios was carried out. This allowed us to create a new benchmark that does not exist in the literature.

The remainder of this paper is organized as follows: Section 2 presents related works concerning EDs. Section 3 presents the performance evaluation model. In Section 4, the simulation-based optimization approach proposed for solving healthcare resource allocation is presented. Experimental results are discussed. Finally, Sections 5 and 6 present the conclusion and give a few future research directions.

1.2. An Efficient Simulation-Based Optimization Approach

Managing healthcare systems to reduce overcrowding with acceptable costs is a global concern for hospital managers. In this context, the aim of this study is to present a mid-term decision support system dealing with scheduling and allocation of resources in the ED of the Hospital Center of Troyes, France (Figure 1). The main objective is to minimize patient waiting time and inpatient stays under an additional resource cost constraint. To achieve this, an efficient DES model was first built with the details of the complex flow processing, the resources such as emergency physicians and nurses, and medical examination rooms with capacity of the resources. After its verification and validation, the simulation model was used to explore how ED structures and processes impact the system behavior with “what-if” scenario analysis. A new benchmark was created and 145 scenarios were designated including human resources adjustment, material resources modification, and a process adjustment strategy.

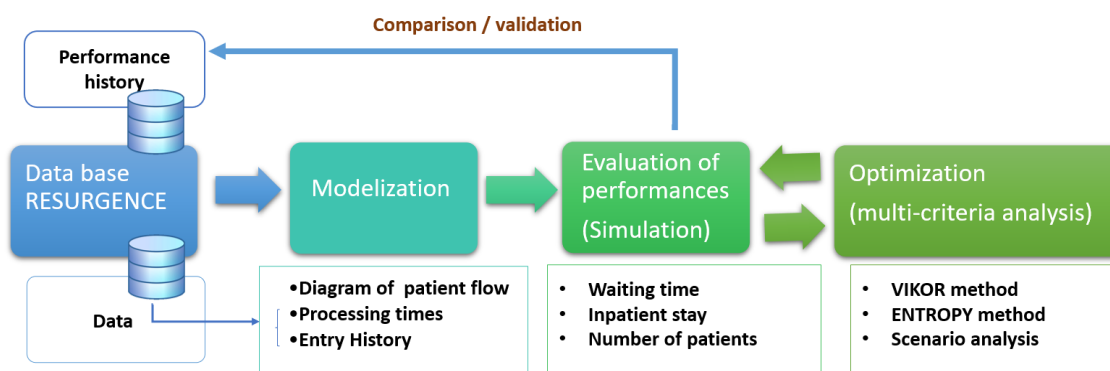


Figure 1. Simulation-based optimization approach.

Following this, to help the decision maker (DM) reach the best decision, we used the VIKOR method ([4,5]) to rank and select from a set of scenarios and determine compromise solutions for a problem with conflicting criteria. As they have an impact on the assignment decision, the entropy method [6] was used to determine the weights of criteria. To the best of our knowledge, integrating the VIKOR method with the entropy method to improve the ED performance has never been done.

2. Literature Review

During the last decades, EDs have faced different problems that affect their performance, such as overcrowding, insufficient staffing, long waiting times, and long inpatient stays. In addition, cost pressures on hospitals and budget constraints have forced them to provide high-quality service at an ever reduced cost.

In this context, the human and material resource planning of the healthcare system is widely reported in the literature, and different methods and approaches have been introduced, such as mathematical, linear programming, heuristics, or simulation models for the desired optimization [7–12].

2.1. Mathematical Methods in Healthcare

El-Rifai et al. [13] presented a stochastic mixed-integer linear programming solved by an average approximation approach to optimize physician and nurse organization in the ED of the Hospital Center of Lille, France. The authors aimed to minimize the patient

waiting time under the uncertainty of the number of patient arrivals and their service. Then, a discrete-event simulation model was used to evaluate the resulting personnel schedules.

In [7], Feng et al. presented a multi-objective simulation optimization algorithm that integrates a non-dominated sorting genetic algorithm II (NSGA II) and multi-objective computing budget allocation (MOCBA) in order to determine the optimal medical resource allocation solution that minimizes the patient LOS and the total medical wasted cost.

Recently, Achmad et al. [8] proposed an improvement on ant colony optimization with semi-random initialization for the nurse rostering problem. To avoid violation of the hard constraint, the authors applied semi random initialization and ant colony optimization to minimize the violation of soft constraint.

2.2. Simulation Methods in Healthcare

DES has become an effective decision-making tool, increasingly accepted by decision makers as a viable tool for improving operations and reducing costs. According to a recent study by Brailsford [9], the use of computer simulation has increased in recent years. Hence, it is more widely used in the health sector.

An important feature of simulation experiments is that users can choose different system parameters to improve and optimize the performance of their systems. Hence, once a model representing the current situation of the care system is built (baseline model), what-if scenarios can be run on the DES model to test alternatives reflecting new policies and interventions. The later provides the DM with accurate information about the expected performance and evidence regarding the most promising changes to put in place [14].

Many research studies have been concerned more with addressing different alternatives either to optimize the service level of EDs using the available resources or to study the impact of different expansion alternatives to reduce overcrowding with acceptable costs. Various research on capacity planning of human resources and equipment, beds and rooms, and substituting and modifying the processes and procedures of ED has been conducted [5,10,15–19].

For instance, in [15], the authors proposed 18 schedule plans to be simulated for ED staff and identified an option that allow reducing the average inpatient stay by 14.5 min. They demonstrated that when implementing this option, the long waiting times would be reduced and physician utilization would be increased. Bedoya-Valencia and Kirac [18] realized through the simulation of different scenarios that restructuring of resource capacities in the ED will reduce the average inpatient patients by 14%, average patients' time to be seen by a physician or physician assistant by 16%, and leveled resource utilization by between 70% and 80%.

2.3. Multi-Criteria Analysis Methods in Healthcare

In making a comprehensive decision, the decision maker should take into account a combination of mentioned scenarios and criteria that sometimes conflict. In this situation, multi-criteria decision making (MCDM) methods are useful to help the manager to find the best decision. In [20], the authors carried out a literature review on the applications of these methods in healthcare, performed a comparison between these methods, and applied them to a hypothetical case study. Some of these methods were applied to structure decision-making in healthcare areas such as the AHP method [21]. AHP can be used also as a weighting method and its results can be used as an input for another MCDM method [5]. TOPSIS [22], ELECTRE [23], PROMETHEE [24], and PROMETHEE II [25] are widely used in healthcare areas. According to Zheng et al. [26], there are no better or worse techniques, but for some decision problems, there is always a method that is more appropriate than others.

One of the commonly used MCDM methods is the VIKOR method. This method focuses on ranking and selecting alternatives and determining the solution or compromise that is the closest to the ideal by analyzing different scopes and weights of the criteria. In [27], the authors provided a review on the applications of the VIKOR method in several

application areas. Thus, the number of papers related to VIKOR method increased from a single article in 2004 to 180 articles in 2015. However, only 2.84% of these papers used the VIKOR technique in healthcare fields.

Along with the successful deployment of VIKOR method for solving complex decision-making problems, other variants of it, such as comprehensive VIKOR, fuzzy VIKOR, regret theory-based VIKOR, modified VIKOR, and interval VIKOR methods, have come into the picture depending on the type of decision problem and requirements of the concerned DM. They have been applied in different decision-making scenarios and have typical characteristics and mathematical formulations. However, a comparative analysis of the VIKOR method and its variants ([4]) showed that for any decision problem, the original VIKOR is the best method for a solution without unnecessarily complicating the related mathematical computations.

This state of the art allows us to see that the resource allocation problem in healthcare systems is still a topical issue. Modeling and simulation methods has been mostly used to understand the functioning of the complex ED system and to predict its reactions to the various changes it faces.

This study allows analysis of the complex trade-off between resources allocation and cost minimization when optimizing healthcare systems.

The main contributions of this paper can be summarized as follows:

- To develop a decision making tool for healthcare management based on an efficient simulation–optimization approach;
- To develop an efficient DES model for performance evaluation;
- To carry out a large experimental study through the test of 145 scenario, hence creating a new benchmark that does not exist in the literature;
- To analyze the complex trade-off between resource allocation and cost minimization when optimizing healthcare systems. The VIKOR multi-criteria analysis method and the entropy method are used to this aim.

3. Discrete Event Simulation Model

This research was conducted in the ED at the Troyes city Hospital Center, which provides treatment services 24 h a day and receives an average of 62,000 patients per year. All the historical performance and input data were gathered from the ED's information system, as well as from surveying experts in this field.

We collected the summary attendance to emergencies (Résumé de Passage aux Urgences: RPU) of every patient from 2016 to 2019. The data collected represent 252,438 records in total. The RPU is a standardized collection of data for each emergency attendance used by all the French EDs to summarize their activity. The RPU contains 20 information fields that describe the passage of the patient in the ED.

3.1. System Description

The ED center consists of two main circuits. First there is a short circuit whose estimated duration of care after medical contact is less than 1 h. In this circuit, pediatric, gynecological, and psychiatric patients are supported. They are mostly autonomous patients who do not need major paramedical care. Second, there is a long circuit receiving patients whose estimated duration of care after medical contact is more than 3 h. Patients arriving at the ED follow a process depicted in Figure 2. The process begins when a patient arrives at the ED entrance door and ends when a patient is discharged from the ED or transferred to the hospital inpatient units.

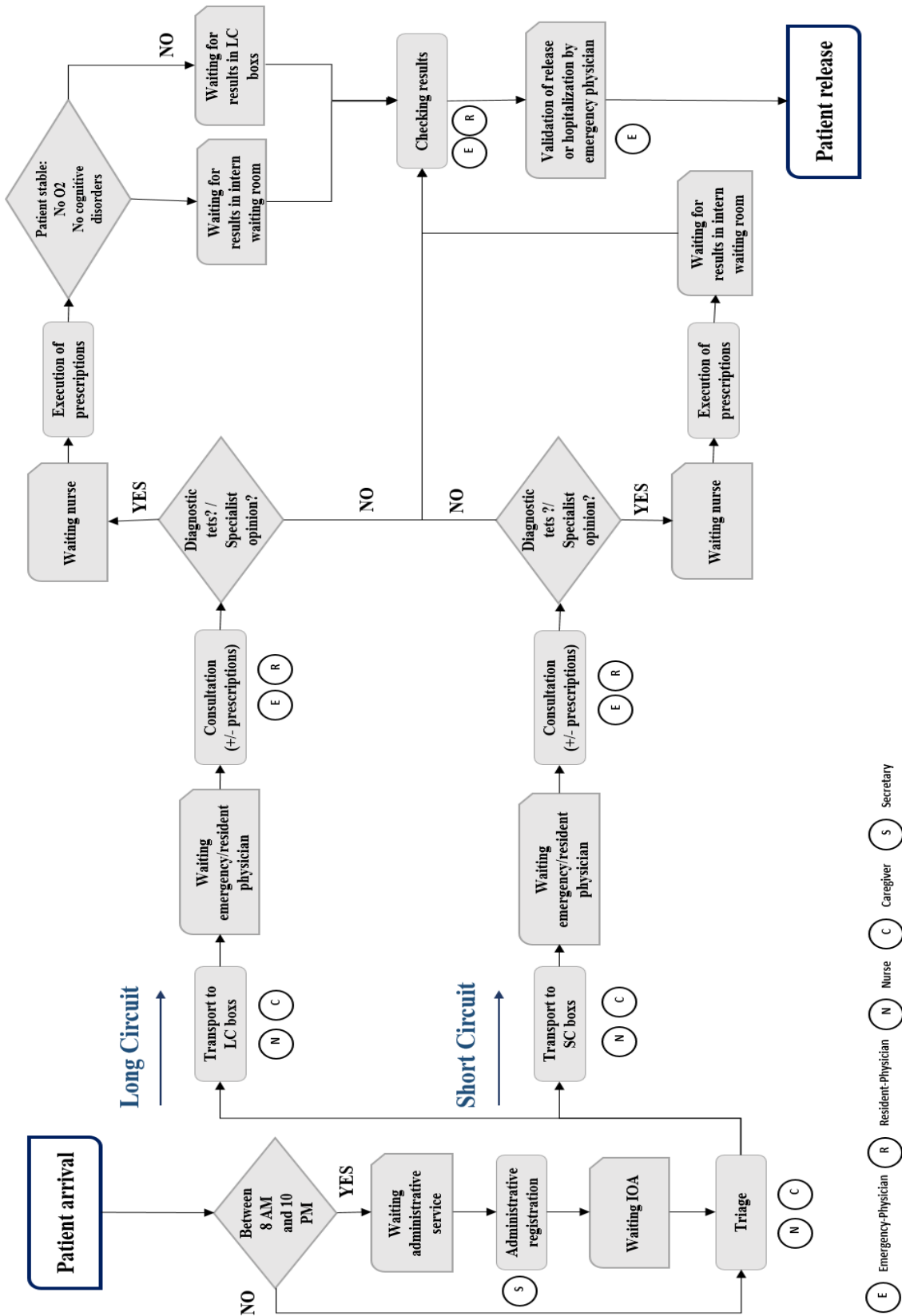


Figure 2. Diagram of patient flow in ED service.

Triage service, assured by the triage nurse or “IOA” (infirmière organisatrice d’accueil), is the patient’s first medical contact with ED staff. The triage system identifies (1) the

condition of patients and (2) the pathway each patient state will go through (short or long circuit). Then, the IOA assesses the patient's clinical status and assigns a recommended maximum waiting time based on the severity of his or her condition. As denoted in [28], this step of the process plays a critical role in determining how quickly patients must be seen and how to route them to the appropriate resources throughout the process.

Based on the patient's condition and symptoms, there are eight levels of patient acuity in the ED of the Hospital Center of Troyes. This classification [29], called EP (abbreviation of *état patient* in french), helps ED staff to have a better understanding of their patient flow.

When a patient arrives at the ED between 8 a.m. and 10 p.m., they are first registered at the reception by the receptionist; then, they are triaged by the triage nurse in a dedicated room (medical examination room) at the ED entrance. Patients who arrive between 10 p.m. and 8 a.m. will be directly examined and triaged by the triage nurse, who also does the administrative registration.

Emergency patients follow a particular rule regarding their flow in the ED. In fact, the patient's medical condition has a direct impact on their priority of passage in the ED: a patient with a more serious state is more important than a patient with a relatively less serious pathology. Nevertheless, based on medical severity, a patient with a stable state may wait for a long time because of the permanent presence of patients with a more severe state. Therefore, the priority of passage is a compromise between the severity of the patients and their arrival time. Once an appropriate room (medical examination room) becomes free and the patient is assigned to a bed, a patient's inpatient stay starts. At that moment, the patient's waiting time will be recorded (AWT = entrance time to the room – arrival time in the ED).

The consultation begins when the right emergency physician becomes available. The emergency physician makes a first assessment and decides if the patient needs further tests to confirm or refine his diagnosis. If not, the patient is discharged to go home. In the case where tests are requested, the patient can wait for the test results in his or her room or can be transferred, if possible, to an internal waiting room (sitting or on a stretcher) to release the room for other patients.

3.2. Data Collection and Processing

Based on the previously confirmed patient flow diagram (Figure 2), our simulation model was modeled by a DES system using the Arena simulation tool. The system requires three kinds of inputs: arrival rates of patients, the frequency of each pathway, and the processing times of services.

- **Service times distribution:** The input analyzer of Arena software is used to generate the distributions of service times. The statistical distributions of service times are displayed in Table 1.

Table 1. Synthesis of the processing time distribution.

Operation	Time (minutes)
Administrative registration	TRIANG (0.5, 1.5, 2)
Triage	From 8 a.m. to 10 p.m.: NORMAL (5, 2) From 10 p.m to 8 a.m.: NORMAL (10, 2)
Transportation time	Short circuit: UNIFORM (5, 10) Long circuit: UNIFORM (5, 15)
Consultation (short circuit)	UNIFORM (3, 10)
Consultation (long circuit)	UNIFORM (5, 20)
Radiology	TRIANG (5, 15, 25)
Scanner	TRIANG (15, 20, 25)
Echography	TRIANG (10, 15, 30)
Specialist advice	UNIFORM (60, 240)
Final Exam (short circuit)	NORMAL (5, 3)
Final Exam (long circuit)	TRIANG (5, 10, 15)

• **Patient arrival distribution:** The nature of ED arrivals is strongly correlated with the hour of the day, as it is impacted by human behavior. In fact, we can see on the graph in Figure 3 that the hourly rate of patient arrivals (number of arrivals per hour/total) in the ED follows a repetitive pattern from one day to another. We notice that it is low during the late night period (from 12 p.m. to 6 a.m.) and increases during the day (from 8 a.m. to 10 p.m.), with peak at 10 a.m., 2 p.m., and 6 p.m. For our purposes, we generated a parametric distribution dependent on the number of daily arrivals for each time slot in the day.

Let T_i be the random variable that models the inter-arrival time, t_h the average arrival rate observed for the hour h of the day, and Y_j the number of daily arrivals for the day j . Following the procedure introduced in the previous section, we find that the distribution that models the time of arrival of patients is the exponential distribution of the average $Y_j \times t_h$, i.e., $T_i \sim \text{Exp}(\frac{1}{Y_j \times t_h})$.

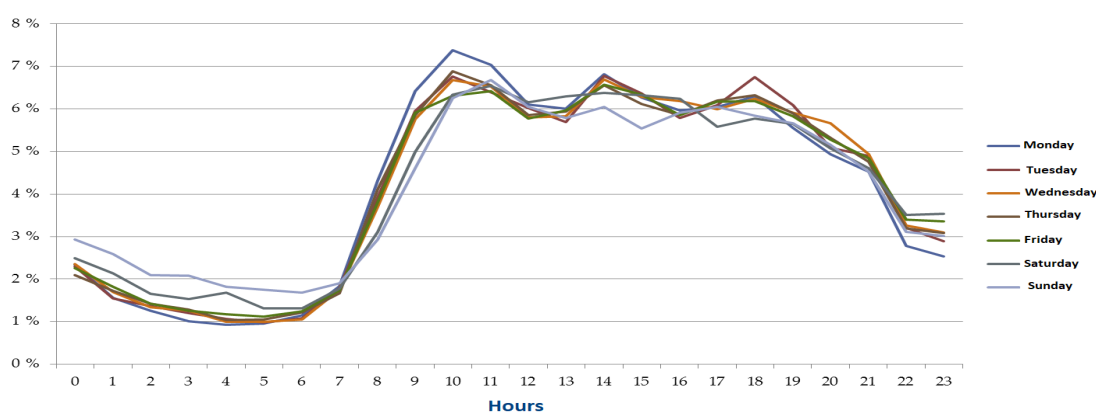


Figure 3. Patient arrival rate in the ED of the Hospital Center of Troyes per day of the week and per hour.

• **Queue priority:** In our case study, the priority of patients for a given department is subject to two conditions: the time of arrival T_{arr} and the patient's state EP . We will model our queues with an additional attribute $P_{FdA} = \frac{EP}{T_{arr}}$ that will be assigned to a patient and will serve as a priority indicator in queues [30]. The higher the P_{FdA} index is, the higher the patient's priority over others.

3.3. Model Validation

The verification and validation of the simulation model are steps that allow us to evaluate its robustness and check its ability to replicate real-world observed data before its use for the optimization process. To this end, and after detailed reviews, we checked with hospital management teams that the simulation model reflected reality with a high level of accuracy. Then, we referred to three indicators of simulated performances to compare their agreement with the actual observations: Total patient arrival, Average waiting time (AWT) and Average inpatient stay (AS).

Figure 4 compares the results of total patient arrival based on the category of EP from the model and real-world data. The comparison results show a gap of 3.2% to 6%. Tables 2 and 3 compare the results of real and simulated data of total arrival, AWT, and AS based on EP category in short and long circuits. The results show that simulated and real-world arrival data are similar for all types of patients. Moreover, the results of the AWT and the AS in Tables 2 and 3 show that there is little gap between the real-world and simulated data. This confirmed the model as validated, reliable, and apt to support experiments.

In the next section, we focus on the use of our simulation mode as an effective and efficient tool to answer and analyze “what if” questions about ED scenarios with financial implications. Then, to make a comprehensive decision, the combination of these scenarios

should be taken into consideration. Hence, we will present the VIKOR method to rank and select the best scenario.

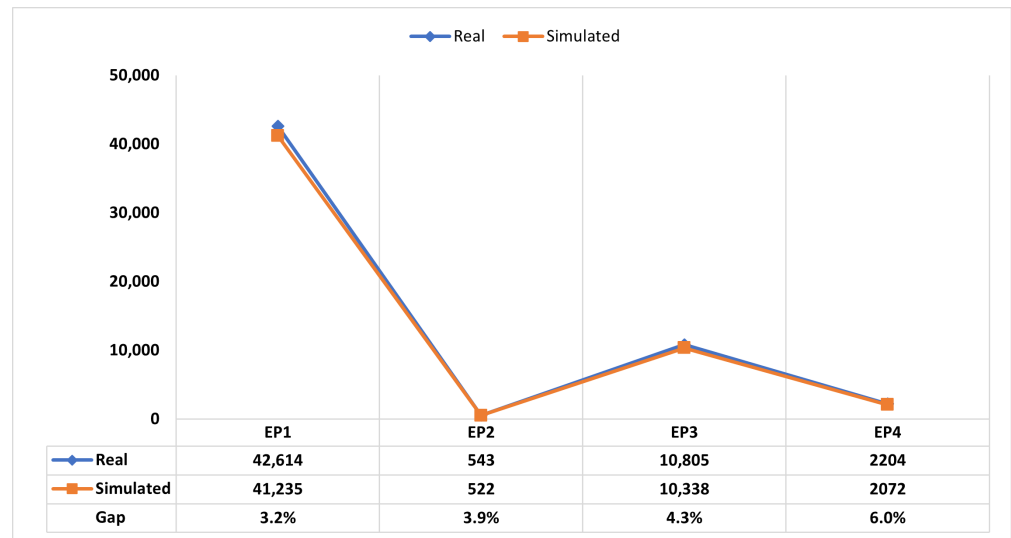


Figure 4. Comparison between real and simulated patient arrival.

Table 2. Comparison of performance based on EP category—short circuit.

Short Circuit							
Total Arrival		Average Waiting Time (min)			Average Inpatient Stay (min)		
EP Real	EP Simulated	Real	Simulated	Gap	Real	Simulated	Gap
EP1 (31,540)	EP1 (31,000)	69	75	-6 (8%)	88	84	4 (5%)
EP2 (222)	EP2 (177)	92	64	28 (30%)	137	143	-6 (4%)
EP3 (3851)	EP3 (3711)	56	59	-3 (5%)	175	173	2 (1%)
EP4 (369)	EP4 (363)	56	60	-4 (7%)	195	177	18 (9%)

Table 3. Comparison of performance based on EP category—long circuit.

Long Circuit							
Total Arrival		Average Waiting Time (min)			Average Inpatient Stay (min)		
EP Real	EP Simulated	Real	Simulated	Gap	Real	Simulated	Gap
EP1 (11,074)	EP1 (10,681)	85	81	4 (5%)	311	316	-5 (2%)
EP2 (321)	EP2 (330)	70	77	-7 (10%)	395	394	1 (0%)
EP3 (6954)	EP3 (6721)	81	71	10 (12%)	417	412	5 (1%)
EP4 (1835)	EP4 (1800)	70	71	-1 (1%)	397	403	-6 (2%)

4. Resource Optimization

In this study, we propose a decision support system for the efficient management of the ED based on the coupling of optimization and simulation. After embedding patient

flow process logic in the model, different scenarios were proposed to evaluate their impact on the ED performances. The objective was to maximize the reduction in waiting time and inpatient stay and to minimize the cost of adding an additional resource. To verify the relevance of these scenarios, we used our DES model as a performance evaluator. Then, to analyze and compare the scenarios, we used the VIKOR multicriteria decision support method.

4.1. Methodology

Four steps are considered in this study to improve the ED's performance indicators:

- Criteria selection
- Weight criteria selection
- Designing simulation scenarios
- Ranking scenarios: VIKOR Method

For all scenario, the efficient simulation model was configured to run for 365 days, plus 2 days for a warm-up period, and each scenario involved five replications. The analysis output was used to evaluate the impact of each scenario on the ED performances.

4.2. Criteria Selection

The aim of this study is to provide quantifiable measures for the effects of scenario operational strategies. From the hospital's point of view, there are three performance criteria that should be mentioned in decision making, which are:

- a. Average waiting time (AWT): defined as the time between patient arrival time at the ED and the first consultation by the emergency physician;
- b. Average inpatient stay (AS): defined as the time between the first medical ex am (consultation) and the patient's discharge time from the ED;
- c. Cost: defined as the cost related to the addition of medical or paramedical staff. The cost units for the staff are monthly and were established from the hospital index grid.

4.3. Weight Criteria Selection

In order to rank alternatives, classical MCDM methods require the calculation of alternative rating and criteria weights that rely on its importance and DM preferences/judgments. In this study, an objective entropy method was applied [6]. Based on this method, the weight of each criterion was calculated for the scenarios to be tested for the short and long circuit; their values are as follows:

- Short circuit: AWT (0.55), AS (0.23), cost (0.22);
- Long circuit: AWT (0.58), AS (0.31), cost (0.11).

4.4. Designing Simulation Scenarios

For investigating the problem, a new benchmark was created through 145 scenarios that were proposed for different strategies and based on specific motivating questions of the ED manager. Figure 5 shows the categorization of scenarios tested in this study.

We started first with the evaluation of the actual staffing level and its corresponding measures of performances. This analysis is considered as the base case scenario that will be used for comparison against the other proposed scenarios.

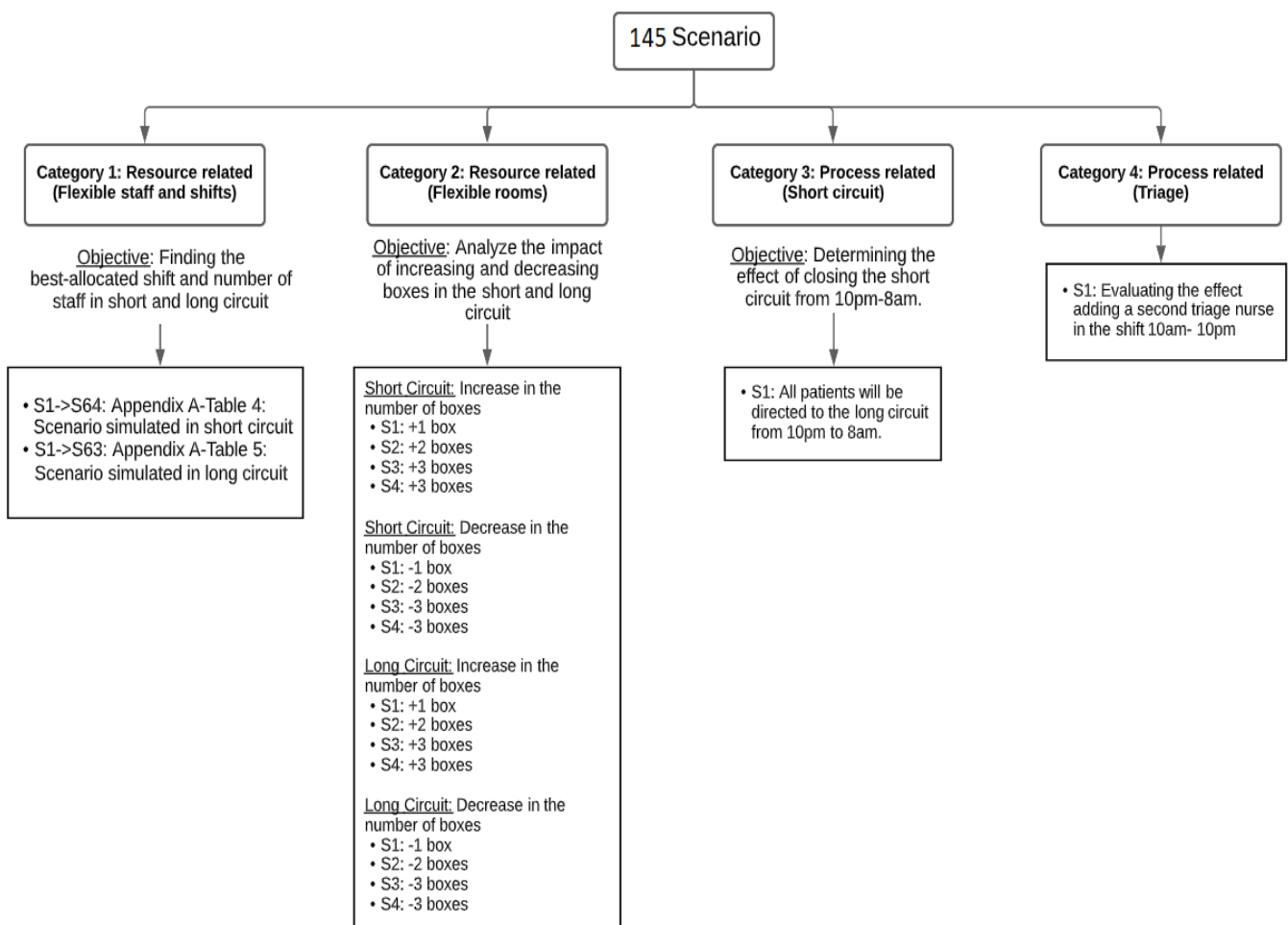


Figure 5. Categorization of simulation scenarios.

- **Category 1: Resource-related (flexible staff and shifts)**

The objective is to find the best-allocations of shifts and number of staff in the short and long circuits. In this category, human resource adjustment take into account the schedule and the number of ED staff in the short and long circuits. ED performances can be improved by changing the capacity level of human resources in different shifts. Two time constraints were imposed for the addition of human resources; we cannot add an emergency physician or a resident physician in the shift from 8 a.m.–12 p.m., or a nurse or a caregiver in the shift from 6 a.m.–11 p.m. The cost of adding human resources is considered. For the decrease in the staff number, we test only the impact of removing personal over 24 h.

To allow DM to select the most efficient solution, we make a sensitivity analysis on the shift patterns and analyze their impact on the AWT and AS. For example, if we test the impact of adding a nurse during a 12 h time slot, we test the first shift pattern from 6 a.m. to 12 a.m., then from 7 a.m. to 13 p.m., from 8 a.m. to 14 p.m., etc. The decision matrix and the scenarios proposed for the short and long circuits are presented in Tables A1 and A2.

- **Category 2: Resource-related (flexible rooms)**

Additional resources can be adopted as a direct solution to improve the ED's performance. In order to analyze the impact of modification of the capacity of the ED's resources, 16 scenarios were tested. Thus, only the number of rooms was modified. The objective is to evaluate the ED's performances by increasing or decreasing by maximum number of rooms equal to 4, the limit of rooms not to be exceeded in light of the current structure.

- **Category 3: Process-related (short circuit)**

Process-related strategy is a concept serving to accelerate the ED process. The objective of the scenario proposed in this category is to determine the effect of closing the short circuit from 10 p.m.–8 a.m. All patients will be redirected to the long circuit during this shift.

- **Category 4: Process-related (triage)**

The objective of this scenario is to determine the effect of adding a second triage nurse from 10 a.m. to 10 p.m.

4.5. Ranking Scenarios: VIKOR Method

We use the VIKOR method to rank alternatives based on the criteria [4,5]. The working steps of are as follows:

Step 1: Normalize the decision matrix. Hence, the application of the VIKOR method starts with the development of the decision matrix, which shows the performance of the alternatives with respect to various criteria.

A decision matrix $F = (f_{ij})_{m \times n}$ with m alternatives and n criteria is constructed as follows:

$$F = \begin{pmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{pmatrix};$$

Step 2: From the given normalized decision matrix, determine the best $f_{(ij)_{max}}$ and the worst $f_{(ij)_{min}}$ values of all the criteria;

Step 3: Calculate utility measure S_i and regret measure R_i :

$$S_i = \sum_{j=1}^n W_j \left[\frac{(f_{ij})_{max} - f_{ij}}{(f_{ij})_{max} - (f_{ij})_{min}} \right] \quad \text{for beneficial attributes,}$$

$$S_i = \sum_{j=1}^n W_j \left[\frac{f_{ij} - (f_{ij})_{min}}{(f_{ij})_{max} - (f_{ij})_{min}} \right] \quad \text{for non-beneficial attributes,}$$

$$R_i = \text{maximum of } \left\{ W_j \left[\frac{(f_{ij})_{max} - f_{ij}}{(f_{ij})_{max} - (f_{ij})_{min}} \right] \right\} \quad \text{for beneficial attributes,}$$

$$R_i = \text{maximum of } \left\{ W_j \left[\frac{f_{ij} - (f_{ij})_{max}}{(f_{ij})_{max} - (f_{ij})_{min}} \right] \right\} \quad \text{for non-beneficial attributes,}$$

where W_j is the weight of the j^{th} criterion,

Step 4: Computing the VIKOR values (Q):

$$Q_i = v \frac{S_i - S_{i-min}}{S_{i-max} - S_{i-min}} + (1 - v) \frac{R_i - R_{i-min}}{R_{i-max} - R_{i-min}}$$

where v is the weight of the strategy of ‘the majority of attributes’ (or ‘the maximum group utility’). Its value lies between 0 and 1. The authors in [4,5] indicate that usually a value of v as 0.5 is preferred and that the compromise can be selected with ‘voting by majority’ ($v > 0.5$), with ‘consensus’ ($v = 0.5$) or with ‘veto’ ($v < 0.5$).

Without loss of generality, it takes the value 0.5, where $S_{i-max} = \text{Max } S_i$, $S_{i-min} = \text{Min } S_i$, $R_{i-max} = \text{Max } R_i$, and $R_{i-min} = \text{Min } R_i$;

Step 5: Rank in ascending order the alternatives according to the values of S , R , and Q . Once ranked, a' is considered to be the compromise solution (with minimum Q value) only if the following two conditions are satisfied:

- Condition 1 : Acceptable advantage $Q(a'') - Q(a') \geq DQ$ where a'' is the second best alternative in the ranking list by Q and $DQ = \frac{1}{N-1}$;
- Condition 2 : Acceptable stability in decision making. Alternative a' must also be the best ranked by S or/and R .

If one of these conditions is not satisfied, a set of compromise solutions is then proposed as follows:

- Alternatives a' and a'' if only Condition 2 is not satisfied, or
- Alternatives a', a'', \dots, a^N if Condition 1 is not satisfied and a^N is determined by the relation $Q(a^N) - Q(a') < DQ$ for maximum N .

4.6. Simulation–Optimization Results

For investigation of ED, we first developed an efficient simulation model that accurately reflects the operational model. Then, AWT and AS performances were analyzed through the proposed scenario.

- Result analysis of human resource adjustment scenario: Category 1

In Category 1, the objective was to explore scenarios of the actual ED resource schedule and test their impact on the weighted AWT, AS, and costs associated with the resource to be added. As demonstrated in Figures 6 and 7, 117 alternative staffing levels were generated through the addition or combination of shifts for both the short and long circuits. Thus, the VIKOR method was applied. For each scenario, we recovered the simulated performances (AWT, AS, and cost) in order to construct the decision matrix (Appendix A, Tables A1 and A2). The rows represent the scenarios and the columns represent criteria. The time unit is the minute and the cost unit is Euro. This matrix and the weight of each criterion are used as an input to the VIKOR method. Figures 6 and 7 present the final ranking of these scenarios.

According to the VIKOR method ranking, Scenario 6 is the best alternative to apply in the short circuit. A nurse and a caregiver must be added to the current staff with a cost of EUR 4200 in monthly salary. By doing so, the weighted AWT and AS are reduced by 26 min and 10 min, respectively, when compared with the base case.

For the long circuit, the best solution was Scenario 63, where an emergency physician, a caregiver, and a nurse must be added to the staff in the 10 a.m.–10 p.m. shift. This will reduce the AWT and AS by 10 min and 3 min, respectively.

Depending on the scenarios tested and the simulation results obtained, we note that in all cases, adding resources in the long circuit slightly reduces the performances in comparison to the basic model. This will be necessary to test by changing the premises, as the limit may be architectural. In the short circuit, adding an emergency physician or intern physician did not positively impact the costs and slightly reduced the AWT and AS. Thus, we notice that the resource that has the greatest impact on improving the optimized ED performances is the nurse, since it always brings the greatest gain in performances.

- Result analysis of room adjustment scenario: Category 2

In Category 2, we aim to analyze the impact of increasing and decreasing the number of rooms in the short and long circuits. Four rooms are the maximum that can be added in both circuits. The results of this strategy are follows:

- Short circuit: Increase in the number of rooms: The number of rooms was increased from the current state of 13 rooms to 14, 15, 16, and 17 rooms. However, the biggest reduction in ED performances came from adding the third room (i.e., a total of 16 rooms), which reduced ED AWT and AS by an average of 5 min.
- Short circuit: Decrease in the number of rooms: Removing 3 rooms had no impact on short circuit performances. After removing the fourth room, the waiting time increased by an average of 3 min.
- Long circuit: Increase in the number of rooms: The number of rooms was increased from the current state of 14 rooms to 15, 16, 17, and 18 rooms. However, the biggest increase in ED performance came from adding the first room (i.e., a total of 15 rooms), which reduced ED AWT and AS by an average of 5 min.
- Long circuit: Decrease in the number of rooms: Closing the first room resulted in waiting time increasing by an average of 5 min.

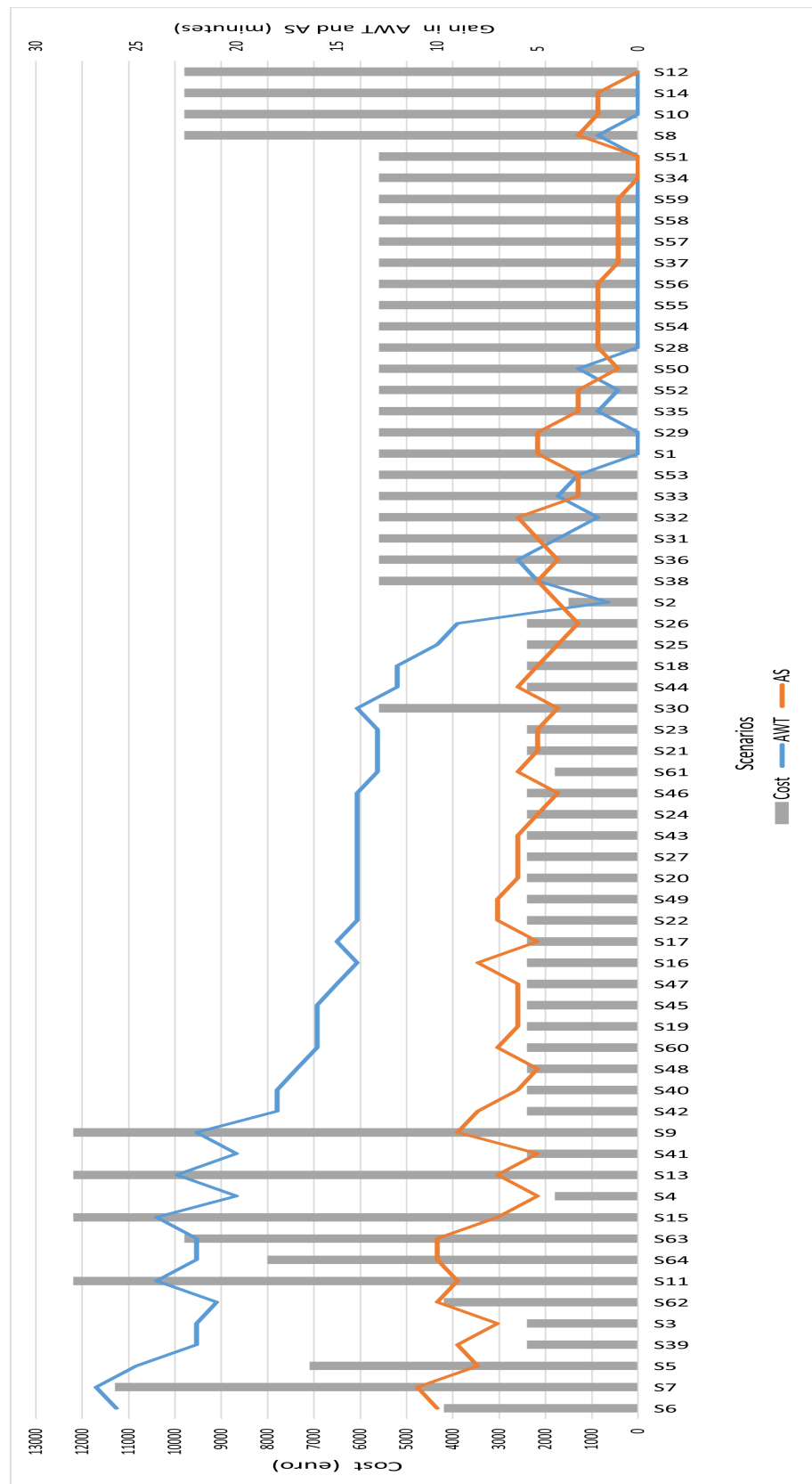


Figure 6. Result of the classification of the scenarios for Category 1 (resource-related—flexible staff and shifts, short circuit).

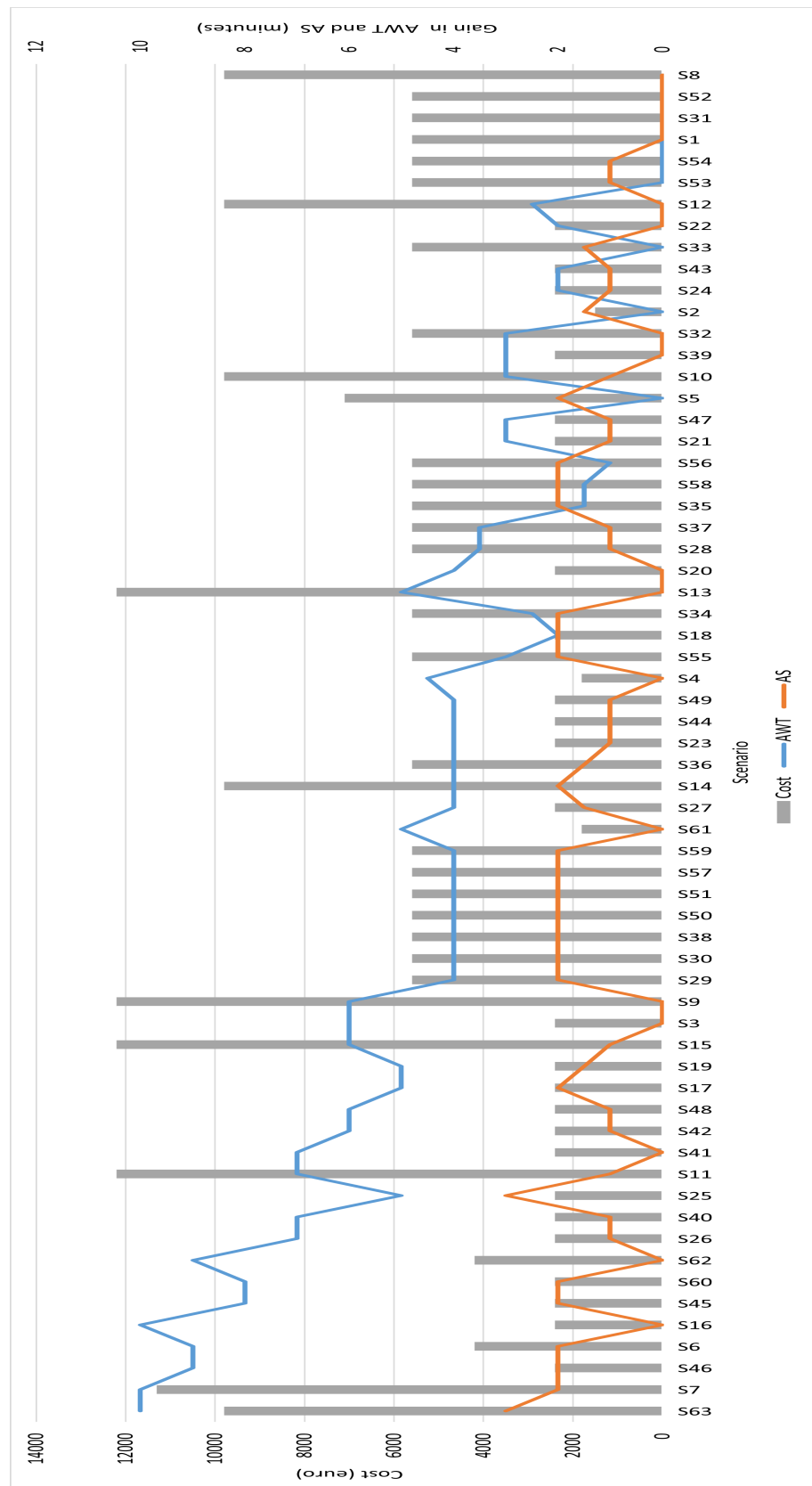


Figure 7. Result of the classification of the scenarios for Category 1 (resource-related—flexible staff and shifts, long circuit).

In Category 2, the results proved that there was no significant difference between the base case and both cases when other rooms are opened or closed in the short or long circuit, as measured by the AWT and AS.

- **Result analysis of scenarios related to eliminating the short circuit: Category 3**

Eliminating the short circuit during the shift from 10 p.m. to 10 a.m. will reduce waiting time by an average of 5 min in the short circuit and 25 min in the long circuit. However, this modification has almost no impact on the AS.

- **Result analysis of scenarios related to the addition of an additional triage nurse: Category 4**

Adding a second triage nurse during the shift from 10 p.m. to 10 a.m. will reduce the waiting time by an average of 5 min and the inpatient stay time by an average of 2 min in both the long and short circuits.

5. Discussion

The objective of this study was to explore the characteristics of various improvement strategies and to determine the best strategies that reduce patients' waiting time and inpatient stay in the Hospital Center of Troyes. Different scenarios have been proposed such as human resources adjustment, material resources modification, and process adjustment strategy.

We used the simulation model to evaluate alternative choices for decision makers through "what-if" scenarios, allowing them to understand each scenario's impact before making changes in practice.

To appropriately adjust human resources schedules, various scenarios were designed for the long and short circuits by taking into account conflicting criteria. These criteria were: AWT, AS, and cost. The entropy method was applied to calculate the weight of each criterion. The VIKOR method was used to rank the scenarios. It is worth noting that we were unable to compare our approach to existing approaches, as the input data and the considered indicators are different. We therefore opted for a comparison between the different scenarios of the study.

In the short circuit, Scenario 6 was the best scenario in the ranking list, where a nurse and a caregiver must be added and present 24 h in the ED. Implementing this scenario would reduce acute patients' overall AWT and AS by approximately 26 min and 10 min, respectively, and it requires the addition of a nurse and a caregiver to the staff with a monthly cost of EUR 4200. For the long circuit, Scenario 63 was the best and would reduce the AWR and the AS by 10 min and 3 min, respectively, by adding an emergency physician, a caregiver, and a nurse in the 10 a.m.–10 p.m. shift.

One more insight from the scenario analysis was the fact that hiring or reducing the number of rooms in the ED does not substantially affect the measures of performance.

As it was shown to be adaptable to all categories of patient flows and ED structures, the simulation model we developed for our case study can be extended and used in similar EDs.

Managerial insights: In this study, we tackled a real-world problem that has not been tackled previously in the literature arising in the Hospital Center of Troyes. The managers of the hospital face an increasing demand for medical services and significant challenges to deliver high-quality and timely patient care while maintaining reduced costs.

Using the proposed work, it is possible to study different investments in human and material resources that could be added to the emergency department in order to improve its performance. To this end, first, a simulation model was created to simulate the emergency department. Second, several scenarios, created with the hospital's managers, were then evaluated according to three criteria: the average waiting time, the average inpatient stay, and the investment cost (related to the added resources). The managers' goals were to investigate how the emergency department can be improved for patients while maintaining the costs.

The studied scenarios have shown some unexpected outcomes for the managers. Though the intuitive response was to add doctors to the emergency department, scenarios in which nurses and caregivers were added yielded the best performance. Moreover, we studied scenarios in which resources can be removed for certain shifts while keeping the same performance.

This work is a showcase of the usefulness of simulation-based optimization approaches. They allow managers to simulate complex systems and optimize resource usage and inherent performance indicators.

6. Conclusions

This paper addresses the performance of the ED of the Hospital Center of Troyes. This ED faces serious problems and challenges such as congestion and an increase in AWT and AS, which result in patient and ED staff dissatisfaction. The entropy and VIKOR methods were utilized in this paper in order to improve the ED's performance. A conceptual model that introduces patient flow in the ED was used to construct and simulate current practices at the Hospital Center of Troyes through a discrete event simulation model that was created and developed on Arena simulation software. In our simulation model, patient arrival was considered to be non-homogeneous in terms of time of day and day of the week. The model was validated with a gap of less than 6% between simulated and observed performances within the confidence interval range of 95%.

Perspectives: One of the post-care phases in the ED is to find a place for patients to be hospitalized, but this case is not modeled, as it requires the modeling of external units in the ED. The integration of these units into the simulation model will improve the performance of the model and will allow the optimization of the overall flow of patients in the hospital. For the optimization part, the developed method does not make it possible to increase the number of resources available in the department and is only interested in the reorganization of available resources. In view of improving the model, we can develop a meta-heuristic that allows both the dimensioning and the planning of human resources in the ED, and the method will have two objectives to be minimized: the number of staff (or maximizing the occupancy rate of resources) and the AWT and AS for patients.

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Appendix A

E-Phy: emergency physician; I-Phy: internal physician.

Table A1. Proposed scenarios of Category 1 and their decision matrices (short circuit).

Scenario	Additional Staff				Performance			Shift Pattern
	E-Phy	I-Phy	Nurse	Caregiver	AWT	AS	Cost	
S1	1				0	-5	5600	24 h
S2		1			-1.5	-4	1500	24 h
S3			1		-22	-7	2400	24 h
S4				1	-20	-5	1800	24 h
S5	1	1			-25	-8	7100	24 h
S6			1	1	-26	-10	4200	24 h
S7	1	1	1	1	-27	-11	11,300	24 h
S8	1				-2	-3	9800	9 h-12 h
S9	1		1		-22	-9	12,200	E-Phy: 9 h-12 h C: available 24 h
S10	1				0	-2	9800	12 h-15 h
S11	1		1		-24	-9	12,200	E-Phy: 12 h-15 h C: available 24 h
S12	1				0	0	9800	15 h-18 h
S13	1		1		-23	-7	12,200	E-Phy: 15 h-18 h C: available 24 h
S14	1				0	-2	9800	18 h-21 h
S15	1		1		-24	-7	12,200	E-Phy: 18 h-21 h C: available 24 h
S16			1		-14	-8	2400	6 h-12 h
S17			1		-15	-5	2400	7 h-13 h
S18			1		-12	-5	2400	8 h-14 h
S19			1		-16	-6	2400	9 h-15 h
S20			1		-14	-6	2400	10 h-16 h
S21			1		-13	-5	2400	11 h-17 h
S22			1		-14	-7	2400	12 h-18 h
S23			1		-13	-5	2400	13 h-19 h
S24			1		-14	-5	2400	14 h-20 h
S25			1		-10	-4	2400	15 h-21 h
S26			1		-9	-3	2400	16 h-22 h
S27			1		-14	-6	2400	17 h-23
S28	1				0	-2	5600	8 h-14 h
S29	1				0	-5	5600	9 h-15 h
S30	1				-14	-4	5600	10 h-16 h
S31	1				-4	-5	5600	11 h-17 h
S32	1				-2	-6	5600	12 h-18 h
S33	1				-4	-3	5600	13 h-19 h
S34	1				0	0	5600	14 h-20 h
S35	1				-2	-3	5600	15 h-21 h
S36	1				-6	-4	5600	16 h-22 h
S37	1				0	-1	5600	17 h-23
S38	1				-5	-5	5600	18 h-24 h
S39			1		-22	-9	2400	6 h-13 h
S40			1		-18	-6	2400	7 h-14 h
S41			1		-20	-5	2400	8 h-15 h
S42			1		-18	-8	2400	9 h-16 h

Table A1. Cont.

Scenario	Additional Staff				Performance			Shift Pattern
	E-Phy	I-Phy	Nurse	Caregiver	AWT	AS	Cost	
S43			1		-14	-6	2400	10 h–17 h
S44			1		-12	-6	2400	11 h–18 h
S45			1		-16	-6	2400	12 h–19 h
S46			1		-14	-4	2400	13 h–20 h
S47			1		-15	-6	2400	14 h–21 h
S48			1		-17	-5	2400	15 h–22 h
S49			1		-14	-7	2400	16 h–23 h
S50	1				-3	-1	5600	8 h–15 h
S51	1				0	0	5600	9 h–16 h
S52	1				-1	-3	5600	10 h–17 h
S53	1				-3	-3	5600	11 h–18 h
S54	1				0	-2	5600	12 h–19 h
S55	1				0	-2	5600	13 h–20 h
S56	1				0	-2	5600	14 h–21 h
S57	1				0	-1	5600	15 h–22 h
S58	1				0	-1	5600	16 h–23 h
S59	1				0	-1	5600	17 h–24 h
S60			1		-16	-7	2400	10 h–22 h
S61				1	-13	-6	1800	10 h–22 h
S62			1	1	-21	-10	4200	10 h–22 h
S63	1		1	1	-22	-10	9800	10 h–22 h
S64	1		1		-22	-10	8000	10 h–22 h

Appendix B

Table A2. Proposed scenarios of Category 1 and their decision matrices (long circuit).

Scenario	Additional Staff				Performance			Shift Pattern
	E-Phy	I-Phy	Nurse	Caregiver	AWT	AS	Cost	
S1	1				0	0	5600	24 h
S2		1			0	-1.5	1500	24 h
S3			1		-6	0	2400	24 h
S4				1	-4.5	0	1800	24 h
S5	1	1			0	-2	7100	24 h
S6			1	1	-9	-2	4200	24 h
S7	1	1	1	1	-10	-2	11,300	24 h
S8	1				0	0	9800	9 h–12 h
S9	1		1		-6	0	12,200	E-Phy: 9 h–12 h C: available 24 h
S10	1				-3	-1	9800	12 h–15 h
S11	1		1		-7	-1	12,200	E-Phy: 12 h–15 h C: available 24 h)
S12	1				-2.5	0	9800	15 h–18 h
S13	1		1		-5	0	12,200	E-Phy: 15 h–18 h C: available 24 h
S14	1				-4	-2	9800	18 h–21 h
S15	1		1		-6	-1	12,200	E-Phy: 18 h–221 h C: available 24 h

Table A2. Cont.

Scenario	Additional Staff				Performance			Shift Pattern
	E-Phy	I-Phy	Nurse	Caregiver	AWT	AS	Cost	
S16			1		-10	0	2400	6 h–12 h
S17			1		-5	-2	2400	7 h–13 h
S18			1		-2	-2	2400	8 h–14 h
S19			1		-5	-1.5	2400	9 h–15 h
S20			1		-4	0	2400	10 h–16 h
S21			1		-3	-1	2400	11 h–17 h
S22			1		-2	0	2400	12 h–18 h
S23			1		-4	-1	2400	13 h–19 h
S24			1		-2	-1	2400	14 h–20 h
S25			1		-5	-3	2400	15 h–21 h
S26			1		-7	-1	2400	16 h–22 h
S27			1		-4	-1.5	2400	17 h–23 h
S28	1				-3.5	-1	5600	8 h–14 h
S29	1				-4	-2	5600	9 h–15 h
S30	1				-4	-2	5600	10 h–16 h
S31	1				0	0	5600	11 h–17 h
S32	1				-3	0	5600	12 h–18 h
S33	1				0	-1.5	5600	13 h–19 h
S34	1				-2.5	-2	5600	14 h–20 h
S35	1				-1.5	-2	5600	15 h–21 h
S36	1				-4	-1.5	5600	16 h–22 h
S37	1				-3.5	-1	5600	17 h–23 h
S38	1				-4	-2	5600	18 h–24 h
S39			1		-3	0	2400	6 h–13 h
S40			1		-7	-1	2400	7 h–14 h
S41			1		-7	0	2400	8 h–15 h
S42			1		-6	-1	2400	9 h–16 h
S43			1		-2	-1	2400	10 h–17 h
S44			1		-4	-1	2400	11 h–18 h
S45			1		-8	-2	2400	12 h–19 h
S46			1		-9	-2	2400	13 h–20 h
S47			1		-3	-1	2400	14 h–21 h
S48			1		-6	-1	2400	15 h–22 h
S49			1		-4	-1	2400	16 h–23 h
S50	1				-4	-2	5600	8 h–15 h
S51	1				-4	-2	5600	9 h–16 h
S52	1				0	0	5600	10 h–17 h
S53	1				0	-1	5600	11 h–18 h
S54	1				0	-1	5600	12 h–19 h
S55	1				-3	-2	5600	13 h–20 h
S56	1				-1	-2	5600	14 h–21 h
S57	1				-4	-2	5600	15 h–22 h

Table A2. Cont.

Scenario	Additional Staff				Performance			Shift Pattern
	E-Phy	I-Phy	Nurse	Caregiver	AWT	AS	Cost	
S58	1				−1.5	−2	5600	16 h–23 h
S59	1				−4	−2	5600	17 h–24 h
S60			1		−8	−2	2400	10 h–22 h
S61				1	−5	0	1800	10 h–22 h
S62			1	1	−9	0	4200	10 h–22 h
S63	1		1	1	−10	−3	9800	10 h–22 h

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