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ABSTRACT

For the emergency department processes to be improved, it is important to consider various goals and variables which exist in an unpredictable and a highly dynamic environment. Due to such complexities, the decision-making process can be very challenging. Therefore, the application of various techniques and tools to promote the process is crucial. This study introduces a knowledge-based Multi-Objective Optimization method. It was successfully applied to improve and analyze systems within an emergency department in Mecca, using data collected during the Hajj event. Consequently, it presented a multitude of virtually optimized design rules and solutions that had a significant impact on reducing waiting times and length of stay for patients in the emergency department. These solutions were designed to achieve an essential level of improvement and determine the ideal allocation of resources for the main processes. As a result, the overall efficiency and effectiveness of the emergency department were greatly enhanced. Therefore, this methodology provides decision-makers with optimal design configuration tools for healthcare systems and elsewhere, such as process automation and design optimization for production workflow.

Keywords: *healthcare system design configuration, multi objective optimization*

Introduction

Risk assessment and management is the best measure that can be taken to avert catastrophes. The evaluation of action plans for potential risks and the development of strategies that address them can improve the chances of successfully executing and implementing services. However, regardless of how immaculately they are executed, such plans may not work as they can run into unavoidable challenges. For instance, team members can quit or get sick, data may become unavailable, or natural disasters such as hurricanes and tornadoes can derail protocols.

As such, understanding risks that can occur in the Emergency Department (ED) is essential to examining a patient’s workflow journey in the ED. The ED is viewed as an unpredictable place; hence, it is deemed as a high-risk inducing environment. Emergency Department staff experience a variety of situations during their shifts, ranging from patients having upset stomachs and common colds that require simple treatment, to cardiac arrests and trauma that requires complex procedures. Therefore, efficiency, speed, and accuracy during the patient assessment, diagnosis, and treatment are significant because of the unpredictability and heavy workflow in the ED. An ED visit involves a complicated series of interactions, decisions, and activities that make it vital for there to be accurate risk planning and assessment. Therefore, to minimize unexpected human errors and failures, a systematic approach that promotes swift, accurate, and efficient patient treatment and documentation is required.

One responsibility healthcare leader are challenged with is making the best possible decisions to prepare for peak arrival times in the ED. This is crucial to successfully operating hospitals, improving their processes, and reducing the risks that may occur during times of high volume. For example, every year, the Hajj pilgrimage in Saudi Arabia's Holy Capital Mecca draws millions of Muslims from various parts of the world. This important religious event serves as a major celebration within the Islamic faith, leading to a gathering of individuals in Mecca. When making decisions, policymakers typically rely on their knowledge and the available information, recognizing the challenges of ensuring accuracy due to the potential occurrence of accidents during busy period. However, the more one understands that system, the greater the chances are of making more accurate decisions. As such, it is important to gain knowledge concerning system behavior and the effect of preparedness [1]. Traditional methods of managing risks are based on the decision-makers’ experiences as well as trials and errors experienced during the procedure. This approach works at times, but has limitations such as the costs incurred, and it does not ensure accurate results [2].

Hospitals rely on a management system aimed at delivering quality care, efficient resource utilization, and excellent service. However, developing and operating such systems for Emergency Departments (EDs) can be immensely complex. This complexity arises from the extensive range of resources involved in providing care and the varying timeframes in which results are generated [3]. Consequently, EDs around the world encounter difficulties like overcrowding and extended patient waiting times [4]. However, the significance of the emergency department in handling a majority of critical cases within hospitals remains crucial. These factors lead to the utilization of operational research methods to aid decision-makers in improving the overall efficiency of EDs by tackling and managing risks effectively.

Simulation is a commonly used operational research technique with broad applications in the healthcare field [5]. Discrete Event Simulation (DES) lays a crucial role in evaluating complex systems by defining specific points in time and observing the ordered sequence of well-defined events that occur [6]. In the context of designing and improving decision-making processes, Simulation-based Multi-Objective Optimization (SMO) allows decision-makers to potentially obtain optimal or near-optimal solutions for problems involving multiple objectives. In recent years, Discrete Event Simulation has witnessed significant advancements in the healthcare sector. Decision-makers also employ knowledge-based approaches, similar to data mining, to obtain SMO results [7], which increases the value of information gained through SMO. On the other hand, the isolated utilization of these techniques has some challenges. As such, it is advisable to use them in a combined manner in support of design making processes that individually.

This paper aims to use DES and Simulation-based SMO to support decision-makers in the EDs during the Hajj celebration. The focus is on analyzing parametric uncertainty and risk through scenario-based approaches. The study aims to utilize DES and SMO techniques to offer valuable insights into various design options, system limitations, enhanced scenarios, and the best system setups. The ultimate objective is to minimize patient waiting times, establish design standards, and optimize the overall performance of the EDs during the Hajj celebration.

Literature Review

Emergency departments (EDs) hold significant value within hospitals for several reasons. Firstly, they serve a vital role in saving lives by providing immediate and critical medical care. Secondly, EDs have a substantial political impact as they shape the public's perception of healthcare services in comparison to other sectors. Given that individuals worldwide will inevitably require medical services at some point, EDs become a crucial gateway for accessing necessary healthcare. Operational excellence greatly influences the public's perception of the efficiency of healthcare services. Specifically, the flow of patients from the EDs significantly affects the operational conditions in various wards of the hospital. Notably, nearly half of the patients in a hospital originate from the ED, highlighting its substantial impact on overall hospital operations [8]. Thus, the improvement of EDs should be addressed while also ensuring an efficient decision-making process.

Decision-making can prove to be challenging for hospital management, yet decision making in EDs is more sensitive because quality care should be given based on risk of mortality, as well as the count of patients who depart from the ED without receiving any medical treatment [4]. The ones that make the decisions in the ED have major challenges to consider, such as overcrowding, reducing the waiting time for patients, and lacking the right resources that are required by the department. All of these issues occur while trying to maintain high standards of patient care [9]. Due to difficult behaviors experienced by patients, it is often hard to provide them with the care they require. Furthermore, EDs often lack staff and resources as they share with other departments within the hospital [10, 11].

The emergency department functions to treat people in critical or life-threatening situations, which can lead to the neglect of patients with lesser injuries, further increasing the complexities of the ED system. Some scholars have looked into different reasons why EDs are overcrowded and how to end this problem [9, 12, 13]. The primary solutions for addressing the issue involve augmenting resources, such as increasing the number of beds, nurses, and physicians available. Additionally, managing patient overcrowding by redirecting them to alternative wards for treatment is another strategy. Lastly, enhancing resource efficiency through the application of operational research methods is also a key approach to mitigate the problem.

Addressing ED problems does not have a simple, straightforward solution. Regrettably, all available alternatives require making challenging decisions and navigating through uncertain scenarios [9, 14]. In challenging environments like EDs, the ability to make effective decisions relies on essential factors such as knowledge, experience, and information regarding the accomplishments and goals of the current state. These elements play a critical role in enabling decision-makers to navigate difficult situations and make informed choices. The individual knowledge, experience, and preferences of decision-makers are essential components in a typical decision-making process [15], and it's crucial to acknowledge that the effectiveness of this approach is inherently limited by the decision-maker's capabilities. This is a process that seeks to attain better results [2] and is not restricted to clinical practices; it can also be applied to healthcare management [16].

In the health care domain, there is a great execution of services provided and important in the strategies that managers make [17]. First, a traditional approach is characterized by getting information on cause-and-effect interactions. Second, traditionally, it is essential to know and understand the systems that can affect the desired outcomes. Third, decision-makers must employ an evidence-based decision-making approach and collaborate with the surrounding culture. Fourthly, it is essential for them to be integrated into the information-sharing network, and fifthly, when employing decision support tools to aid the decision-making process, these tools must prioritize promoting knowledge accessibility and efficient utilization of that knowledge within the organization [17]. It is crucial to present the conclusion in a presentable manner that can be easily understood and accessed by decision-makers. In the field of decision-making, there has been a notable transition from a preference-based approach to an evidence-based approach for decision-makers [15, 17].

This shift carries significant implications for the decision-making process in the healthcare sector, altering the way decisions are made and evaluated. The manager's profile must be research-oriented and realistic. Moreover, managers should have the ability to make decisions based on both quantitative and qualitative results [16].

Operation Research, is a scientific approach that utilizes OR methods to support decision-making and enhance analysis in organizational problem-solving [18]. In the realm of operations research (OR), several methods have been utilized to aid management decision-making in healthcare. As highlighted by Brailsford, Harper, Patel, and Pitt [5], the most frequently documented cases in the literature involve statistical approaches, followed by simulation, qualitative methods, and mathematical models. These methods play a crucial role in enhancing decision-making processes in the healthcare domain. Simulation is often utilized for evaluating and enhancing planning systems and resource utilization, while statistics tend to focus on finance, regulation, and policy governance. Recent reviews have highlighted the use of OR methods such as simulation, and analytical tools, in addressing the performance of ED [4].

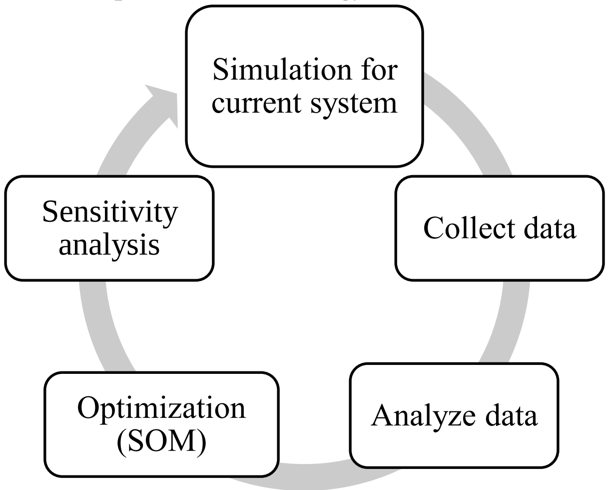
Indeed, the literature contains numerous reports on simulation techniques, particularly the combination of simulation with meta-heuristics, as highlighted in recent studies [4]. Denney [7] contended that simulation holds immense potential as a tool for enhancing the healthcare system. Similarly, Hulshof, Kortbeek, Bouchere, Hans, and Baker [19] discovered relevant literature on the use of operations research (OR). In healthcare planning, particularly at tactical and operational levels, where simulation emerged as a frequently employed method. Further research conducted by Abe, Beamon, Storch, and Angus [20]. Also highlighted simulation, specifically discrete event simulation (DES), as the most extensively studied method among all OR techniques, particularly in analyzing hospital operations, particularly emergency departments. Upon further examination, Saghafian, Austin, and Traub [21] determined that simulation consistently remains the primary tool for analyzing patient flow within an emergency department (ED), while there are several operations research (OR) methods available to analyze the complex behavior of emergency departments (EDs) and support decision-makers, simulation remains the most widely used approach.

The methodology adopted in this research adds a significant contribution to the existing knowledge by combining different methods such as SOM and DES and analysis of the system. This work utilizes data from hospitals in Mecca, Saudi Arabia, specifically focusing on Hajj patients. It represents the first documented effort to optimize the design and enhancement of an emergency department specifically catering to Hajj patients' length of stay (LOS) and time to see/meet a doctor (TTD).

Methodology

This research expands the previous study, where a Discrete Event Simulation model was applied with the OptQuest Optimizer. However, OptQuest is limited to individually changing each parameter (one objective) and running scenarios to search for optimal solutions. In this work, multi-objectives optimization tool used by ModeFRONTIER. This software aims to support decision-making by providing high-quality and proper optimization tools. As shown in Figure 1, The methods were applied as follows: the first step was to learn about the process workflow by gathering data and analyzing it and obtaining knowledge about the ED system behavior. The second step was to apply Multi-Objective Optimization technique to get optimal, or nearly optimal, configurations of the ED system. Additionally, the main effects of factors on responses in the study were evaluated to identify the most significant input variables. Subsequently, Pareto optimal solutions generated that were presented to the emergency department (ED) management for selection based on their preferences. Finally, the study yielded optimal configurations, and rules were applied to decision variables to attain the most favorable outcomes.

Figure 1. *Proposed Methodology*



Model Development

In the ED model development processes, data collection and analysis are done upon understanding what the processes entail. Subsequently, decisions are made on resources to be utilized, processes, and required detail level. Thus, the data collection and analysis phase is considered essential for ensuring accuracy in representing the real emergency department (ED) simulation model. To accomplish this, data was collected over a one-year period specifically for the year 2019. During the analysis, our focus was on the data recorded during the Hajj period, which spanned from 07/01/2019 to 12/31/2019, and encompassed a total of 29,896 patient visits to the ED. The necessary information was extracted from electronic health records. The data collected were the arrival time of the patients, the time each activity started during patient stay, and all physician and nurse activities. For analytical purposes, variations in the number of patients were considered, and were based on every month, day of the week, shift, as well as acuity level. On the other hand, to ensure accuracy, non-reliable data, such as exceptionally high or low individual values, incorrect patient registration, and records without substantial information were excluded. The study was conducted to fill the gap in knowledge where processes lacked information concerning the amount of time taken to get laboratory results, time of minor operations, or time taken by physicians with a patient per meeting. Consequently, prior to implementing the time studies results in the simulation model, they were validated with the ED personnel to ensure their accuracy and reliability.

To provide visual representations of the data analysis, we have included some examples in Figures 2-4. Figure visually represents how the number of patients per month is distributed, indicating a noticeable increase in patient visits between August and November, which corresponds to the period of Hajj. Figure 3 presents the number of patients categorized by their condition and severity levels, ranging from low acuity (C1) to high acuity (C5). The charts show a noticeable surge in the volume of patients visiting the ED, with a significant portion falling into the C3, C4, and C5 categories.

Figure 2. *Patient Arrivals per Month*

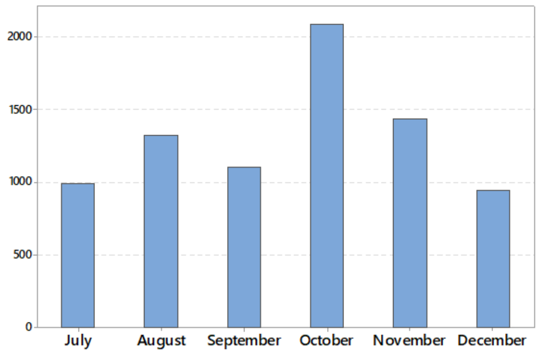


Figure 3. *Patient Arrivals at Area per Conditions and Severity*

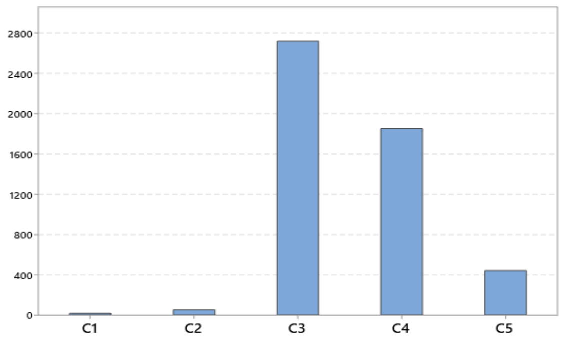


Figure 4 shows number of patient arrivals per shift pattern. The schedule consists of three shifts: the first shift runs from 7:00:00 AM to 3:00:00 PM, the second shift spans from 3:00:00 PM to 11:00:00 PM, and the third shift operates from 11:00:00 PM to 7:00:00 AM. The figures clearly indicate that the daily arrival pattern of patients increases during the evening shift. Figure 5 indicates the patients' arrival patterns per minutes, and it shows patients' pattern, including time to first meeting with the physician or doctor (TTD) and the length of stay (LOS) in ED.

Figure 4. *Patient Arrivals per Shift*

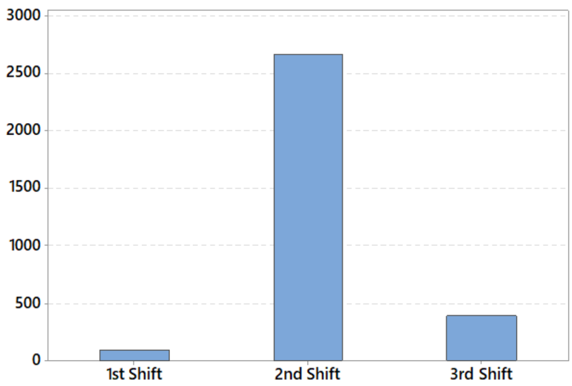
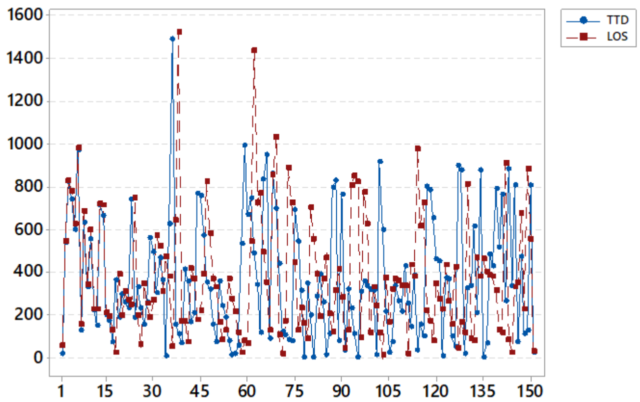


Figure 5. *Patients vs. Length of Stay and Time to See Doctors (Minutes)*



In the data analysis process, the system's resources, activities, and patient group's stochastic behavior, which were a representative of probability, were determined. In the model, the arrival of patients within each hour was randomly distributed. For weekdays, walk-in patients were categorized and assigned different statistical distributions. To classify the patients, various factors were taken into account, including the method of arrival at the ED, time of arrival, weekday, area of specialty, and acuity levels. The values of patients' arrivals were modeled by an application of hourly exponential statistical distributions [22]. To develop the statistical distributions, an estimation approach was adopted, and the minimum, mode, and maximum values were applied. This approach allowed for the creation of various distributions that accurately represented the data. This was done because some historical data were missing. This missing data included triage, physicians and nurses' meeting duration times, x-ray imaging, waiting for laboratory results, and time taken to complete various administrative tasks. The time estimated by the ED personnel for the triage process was used to define a Weibull distribution as the appropriate distribution. Weibull distributions are commonly employed to represent the time required to complete certain tasks. Additionally, they can serve as a useful model when data is not available or limited [22]. In contrast, John Bounded distributions with specific parameter shapes were utilized to fit the remaining processes, some of the factors considered in the study include physician meetings tailored to different categories of patients, the duration of administrative tasks conducted by physicians, response time results for operating rooms (OR), and x-ray results. These distributions were chosen specifically for processes that cannot be adequately approximated using other standard distributions. The use of John Bounded distributions allows for more accurate representation and modeling of these specific processes. Therefore, to effectively build a suitable distribution model for each of the processes, the most optimistic, pessimistic, and likely values were submitted by the ED personnel.

Parameters were introduced according to the historical data and conversations with ED personnel. The study considered several variables to enhance the accuracy of the simulation model. These variables included the service time for patients, which accounted for the varying durations based on factors such as case complexity and treatment requirements. The number and duration of meetings with physicians were also taken into account, recognizing the variability in consultations based on patient conditions and treatment plans. The study utilized a priority-based queue assignment, considering patient type, acuity level, and waiting time to manage the system effectively. Variable patterns of visits to the X-rays department and administrative tasks for physicians were also considered, resulting in a more realistic representation of healthcare dynamics in the simulation model. The goal was to create a comprehensive and accurate model of the healthcare system's functioning.

Results and Discussion

The study utilized the combination of ModeFRONTIER and FlexSim HC software tools. ModeFRONTIER, a multi-objective analysis software, was used for optimization, while FlexSim HC was employed for simulation and analysis. The objective was to find an optimal configuration for the emergency department (ED) that would improve the length of stay and reduce the time required for patients to meet with physicians. By integrating these tools, the study aimed to enhance the ED's performance and patient outcomes. The input variables, which were a result of the impact of the parameters of the experimental phase on the system performance, were selected as variables of the optimization. The parameters included the number of extra beds per department, different extra physicians, and the reduction of the processing time of the two activities: response time from X-ray and minor operations. Table 1 presents the ranges for each of the optimization input parameters.

The study incorporated additional objectives alongside reducing length of stay and time to see the physician in the emergency department (ED) optimization process. These objectives of the study were to optimize resource utilization by minimizing the number of extra beds and physicians required, as well as reducing processing times for operating rooms and response times for X-rays. This aimed to achieve resource-effective solutions and enhance overall efficiency in the healthcare system. These objectives were crucial to ensure practical and balanced solutions that optimize resource utilization while still achieving desired patient outcomes in the ED. Therefore, these additional objectives were added to optimization formulation to consider the effective use of resources.

The optimization parameters considered in the study and their corresponding values are as follows:

1. Emergency extra Beds: The range of values considered for additional emergency beds is from 0 to 5.
2. Specialty area extra Beds: The range of values considered for additional beds in specialty areas is from 0 to 5.
3. Children extra doctors: The range of values considered for additional doctors specializing in children's care is from 1 to 3.
4. Surgery extra doctors: The range of values considered for additional doctors specializing in surgery is from 1 to 3.
5. X-rays & OR doctors: The range of values considered for the number of doctors assigned to X-rays and operating rooms (OR) is from 1 to 3.
6. X-ray time reduction: The values considered for reducing X-ray processing time are 0, 5, 10, and 15 minutes.
7. OR time reduction: The values considered for reducing operating room (OR) processing time are 0, 5, 10, and 15 minutes.

These parameters were explored during the optimization process to find the optimal values that would result in improved performance and efficiency in the emergency department (ED). The optimization algorithm used in the study had the potential to prioritize solutions with high resource usage without considering their effective utilization. To address this, additional objectives were formulated to promote resource efficiency. However, implementing reductions in process time in the real system proved challenging due to the required modifications in working methods, potential need for new technical systems, and the implementation of lean standardization processes. Careful consideration was necessary to ensure practical implementation and to understand the impact of process time reduction on system performance.

The enhancement and sustainability of system productivity can be achieved by continuously improving methods and maintaining day-to-day performance. Reducing resources, such as extra beds and extra physicians, while adding new resources like physicians and hospital beds, can effectively increase system capacity. This approach is straightforward to implement and is particularly useful when the system has clear deficiencies or falls short of target goals. However, it should not be the first option from a productivity standpoint. Other options should be explored before resorting to resource addition, as it may not be the most efficient approach.

Accordingly, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a robust and multi-objective algorithm that was utilized. NSGA-II shows the ability on difficult test problems during simulation results, and Improve the distribution of solutions and enhance convergence closer to the appropriate Pareto optimal front [23].

Figure 6. *3D Scatter Plot of LOS, Alongside the Number of Beds and Process Time Reduction*

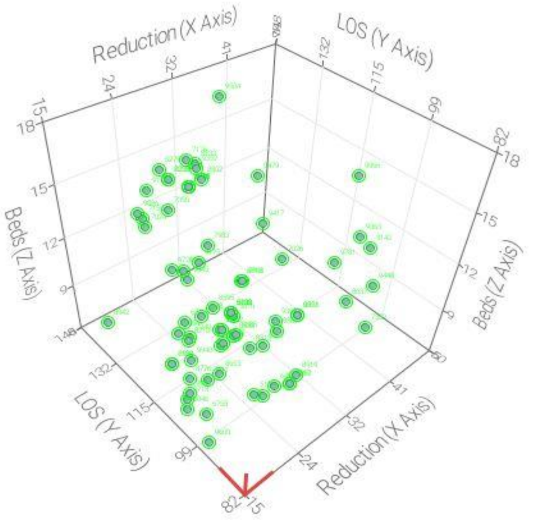
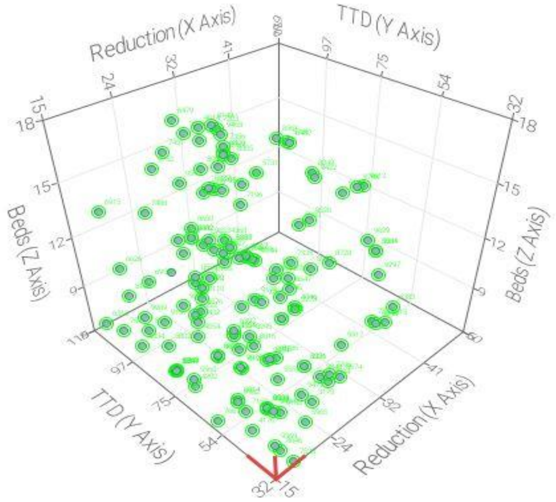


Figure 7. *3D Scatter Plot of TTD, Alongside the Number of Beds and Process Time Reduction*



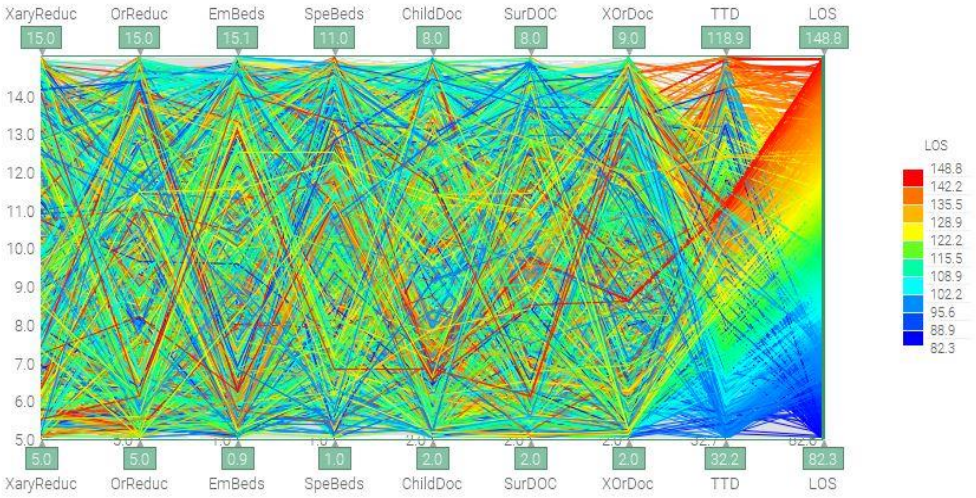
The scatter 3D charts in Figures 6 and 7 show the first results of the optimization. Moreover, possible ED configuration is represented in each point on the charts. In Figure 6, the Y-axis of the graph displays the patients' length of stay (LOS), the Z-axis represents the total number of beds, and the X-axis indicates the overall reduction in process time. This chart illustrates the relationship between LOS, bed availability, and process time reductions. Chart in Figure 7 showcases the correlation between the time to see a doctor (TTD) for patients on the Y-axis, the total number of beds on the Z-axis, and the total amount of process time reductions on the X-axis.

Both charts feature the Pareto front, which denotes the optimal solutions for various combinations of personnel, resources, waiting times, and processing time. It represents the trade-offs between these factors and showcases the most efficient outcomes that cannot be further improved without compromising other aspects. Each point on the Pareto front corresponds to a specific combination and provides its corresponding average values for LOS and TTD of patients.

Figure 8 displays approximately 1,000 possible combinations of the emergency department (ED) based on the given inputs. The chart represents the diverse range of solutions and configurations available for optimizing the ED. The parameters shown in the columns are either in minutes or as the number of resources, providing valuable information for decision-making. This comprehensive representation aids in selecting the most suitable approach to enhance the ED's performance.

To represent the range of values for TTD and LOS, the chart utilizes colors. The diagram below specifically illustrates the range of LOS. The color variations in the chart indicate the different values within the LOS range, allowing for a visual understanding of the possible outcomes associated with the optimization parameters.

Figure 8. *Parallel Coordinates Chart of LOS and TTD (Optimization Results)*



By utilizing a parallel coordinate chart, individuals in positions of decision-making can set upper and lower limits for each variable and effectively explore the range of potential optimal solutions derived from the optimization process. Therefore, by defining minimum and maximum values for each variable or column, healthcare leaders can identify potential solutions pertaining to their areas of interest. However, having access to the entire solution space enables decision-makers to explore more relevant solutions that align with new circumstances. In numerous cases, the initial budget or objectives of a project often experiences modifications over its duration. Consequently, the optimal solution may require adjustments to accommodate various factors, such as the category and quantity of physicians that the clinic successfully recruits. These changes are essential to adapt the project to evolving circumstances and ensure that the solutions remain effective and aligned with the project's goals. By adopting a multi-objective approach, all of these considerations can be effectively incorporated into the final solution, allowing for greater flexibility and adaptability.

Figure 9 depicts an illustrative instance showcasing distinct optimal solutions within predefined boundaries of input parameters. The four optimal solutions encompass various modifications, including a 10-minute reduction in operating room (OR) time and approximately five minutes decrease in X-ray response times. Furthermore, these solutions entail the addition of a maximum of three supplementary X-ray and OR physicians to the emergency department (ED), along with the inclusion of four additional surgery physicians, one extra pediatric physician, two more emergency care beds, and one supplementary bed for the specialty area.

Figure 9. *Optimal Solutions with Delimited Boundaries of Input Parameters*

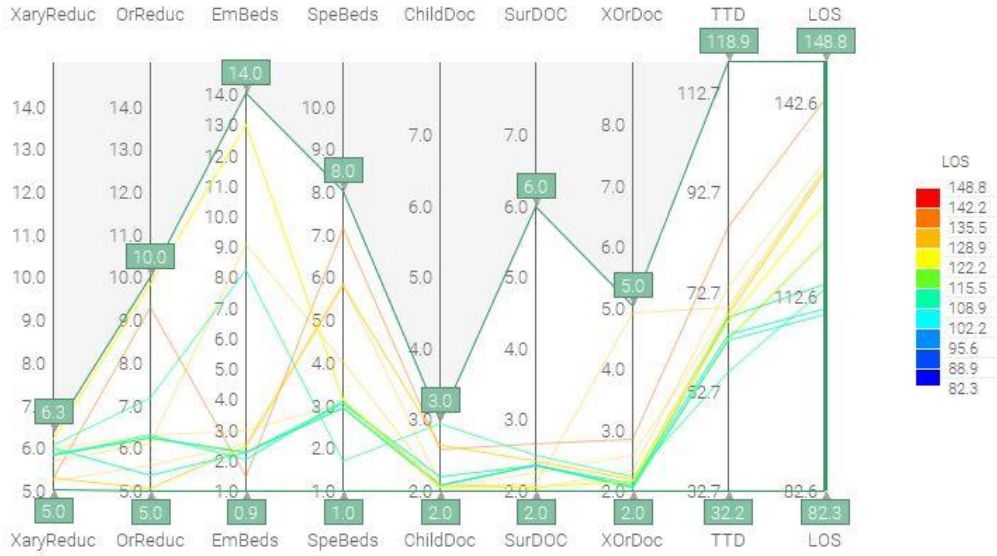


Table 2 displays the outcomes of implementing one of the optimal solutions depicted in Figure 9. The analysis shows a notable improvement in the average length of stay (LOS) with a reduction of around 30% compared to the original model. Additionally, there is a substantial decrease ranging from 35% to 40% in the average time to see a doctor (TTD) when compared to the results obtained from the initial model. These improvements indicate the effectiveness of the adjustments made to the project, resulting in more efficient outcomes for both LOS and TTD. These improvements highlight the effectiveness of the chosen solution in enhancing operational efficiency and patient flow within the healthcare system.

Table 2. *Time to See the Physician and LOS (Optimization Results)*

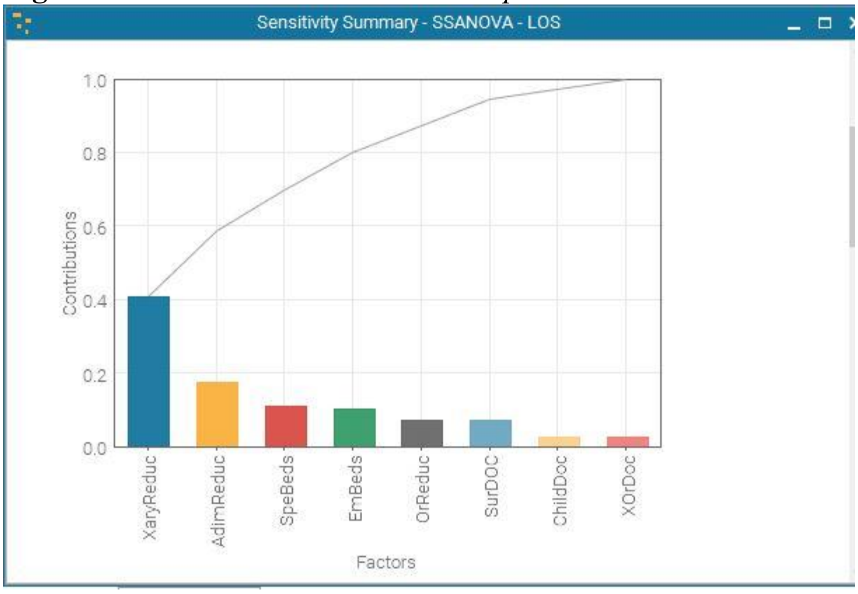
Solutions	**Model (mins)**	**Solutions (mins)**	**Difference**
Total patients LOS_1	133.77	95.08	-38.7
Total patients TTD_1	83.06	53.62	-29.4
Total patients LOS_2	133.77	103.51	-30.3
Total patients TTD_2	83.06	65.23	-17.8
Total patients LOS_3	133.77	113.15	-20.6
Total patients TTD_3	83.06	68.12	-14.9

The considerable enhancement in both LOS and TTD can be observed by examining the preceding table. Adopting this solution or a similar approach that considers the inclusion of extra physicians, beds, and process time reductions, as previously mentioned, would offer the emergency department (ED) a substantial chance to move closer to its objectives. The implementation of these changes holds the potential to significantly enhance the ED's performance and bring it closer to achieving its desired goals. The implementation of such solutions enables the ED to make substantial strides towards improving efficiency and achieving desired outcomes. The optimization reduces the wait time to see a physician by 30 minutes (approximately 60 minutes wait). The average length of stay (LOS) is 50 minutes shorter. The objectives for LOS and TTD have been successfully achieved based on the provided parameters and values. Improved patient care and ED efficiency are evident. The optimal solutions achieved substantial reductions of approximately 50% in the specific objective when compared to a real model. However, for future work, taking into account the input of ED personnel and examining the potential synergies among SMO, lean improvement methodologies, and data mining are crucial aspects to consider.

Sensitivity Analysis

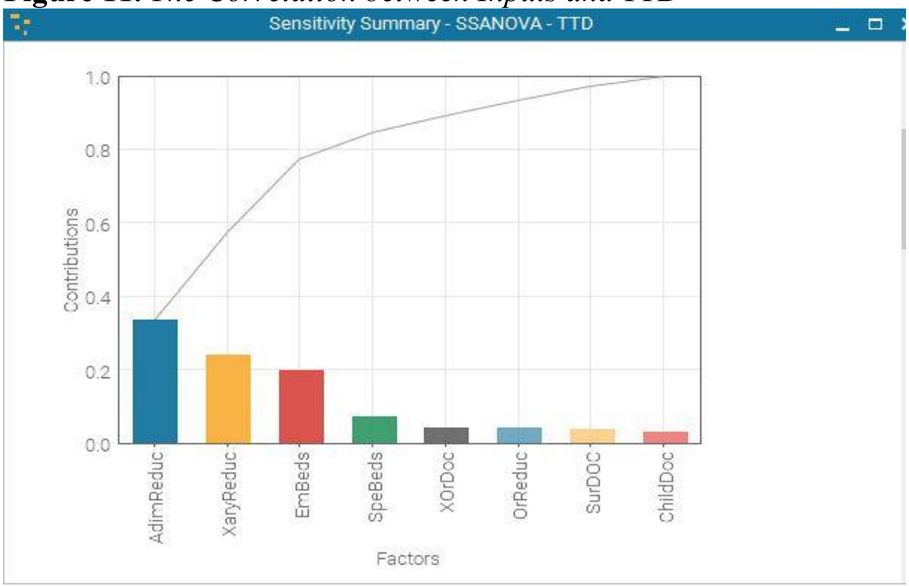
Sensitivity analysis is a method that identifies the most significant input variables by evaluating their main effects on the output responses of a process. Factors, which are the process inputs, have an impact on the responses, also known as dependent variables. The main effect refers to the influence of a single factor on the responses. By conducting sensitivity analysis, it becomes possible to identify influential factors and potentially exclude certain variables from the optimization process. This can lead to a reduction in the computational effort required for optimization by focusing only on the most impactful variables. It can also be implemented to gain a better understanding of the model. To analyze the model and perform sensitivity analysis, the Smoothing Spline ANOVA (SS-ANOVA) proprietary algorithm is employed within the modeFRONTIER tool. This algorithm utilizes a smoothing spline approach to assess the sensitivity of the model and was applied to the same Design of Experiments (DOE) runs. The SS-ANOVA algorithm helps identify the significant factors and their effects on the model responses, enabling a comprehensive understanding of the system behavior and aiding in the decision-making process [24]. The SS-ANOVA results rank the design variables based on their impact on each response, with higher-ranked variables making more significant contributions compared to lower-ranked ones. These results enable the identification of critical continuous variables that significantly influence the responses. Additionally, by considering the uncertainty associated with the defined variables, a normal distribution can be assigned to them as part of an optimization problem. This approach allows for a more comprehensive understanding of the variables' effects and assists in optimizing the system with improved accuracy and reliability. Figures 10 and 11 depict sensitivity analysis plots for the responses of LOS and TTD. These plots display colored bars that represent the sorted relative contributions of the design variables to the corresponding responses. The effects blocks charts display the contribution indices, indicating the relative significance of different terms and the percentage of their contribution to the global variance. Based on the analysis of variable contributions across the two responses, it is evident that the first three continuous design variables, namely XaryReduc, AdimReduc, and EmBed, exhibit the highest levels of association with both LOS and TTD.

Figure 10. *The Correlation between Inputs and LOS*



These variables have a substantial impact on the ED system, suggesting that they play a crucial role in influencing the outcomes of LOS and TTD. It is important to consider and prioritize these variables when optimizing the ED system, as their manipulation can yield significant improvements in both LOS and TTD.

Figure 11. *The Correlation between Inputs and TTD*



Conclusion

This research exemplifies that the combination of SMO and DES can be used to improve the efficiency of EDs as well as healthcare systems at large.

Furthermore, the results indicate the necessity of improving multiple variables simultaneously to achieve substantial system enhancements. The analysis also includes explanations of "what-if" scenarios, encompassing their significance and limitations. Furthermore, this work highlights the advantages of SMO. For instance, these solutions serve as valuable support for decision-making processes, as they present all the optimal trade-off solutions. They offer guidance to managers at emergency departments before implementing changes in the actual system. The present study offers valuable insights into system performance and provides managers with the knowledge needed to guide their efforts in finding improvements. The research has proven that this approach is both time-saving and cost-effective for the ED. It provides a basis for reducing patients' wait times and overall length of stay (LOS), thereby mitigating waiting-time risks. In a particular "what-if" scenario where a 50% reduction in the time required for x-ray and operating room (OR) processes was suggested, notable improvements were observed. The proposed optimization strategy led to a significant reduction of 42.3% in the length of stay (LOS) compared to the current ED system, demonstrating its remarkable effectiveness. Furthermore, another "what-if" scenario was implemented, focusing on reducing the number of physicians exits from the hospital by 50%. In this scenario, half of the physician exits were removed to evaluate its effect on the length of stay (LOS) in the ED. Reducing the number of physicians exits by 50% led to a notable decrease in the overall average length of stay (LOS) within the system. The length of stay (LOS) experienced a reduction of 23.57% compared to the current ED system. This optimization study has successfully identified various combinations for potential improvements in the ED. The objectives of the patients' LOS and TTD reduction was achieved in optimization (30% in the average value of LOS and 35 to 40% reduction in the average value of TTD compared to the original model). Nevertheless, it is important to note that the key to the successful development of this research and the definition of new future collaborative opportunities is primarily due to the continued cooperation of ED management. The future work entails incorporating a comprehensive patient arrival procedure prior to model registration and examining the interaction with lean strategies. Additionally, the utilization of machine learning techniques can enhance patient flow management and resource allocation optimization in the emergency department.

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