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(Research Paper)

Integrating Simulation Modeling and Network Data Envelopment Analysis for Healthcare Supply Chain Management

Masoomeh Zeinalnezhad [1]
Department of Industrial Engineering, Faculty of Engineering, West Tehran branch, Islamic Azad University, Tehran, Iran, zeinalnezhad.m@wtiau.ac.ir
Somaieh Alavi
Department of Industrial Engineering, Faculty of Engineering, Shahid Ashrafi Esfahani University, Isfahan, Iran, somaieh.alavi1361@gmail.com
Nassibeh Janatyan
Quality Management Research Group, Management Institute, University of Isfahan, Isfahan, Iran, n.janatyan@gmail.com
Parviz Ghafariasl
Department of Industrial and Manufacturing Systems Engineering. Kansas State University, Manhattan, KS, 66506, USA, parvizghafari@ksu.edu

Abstract

Purpose: Nowadays, in healthcare management, performance evaluation of hospital emergency departments (EDs) has received increased attention because of epidemic diseases. Few studies have combined simulation with Data Envelopment Analysis (DEA) for performance evaluation. However, they often fail to account for relative dependencies across the system structure. Most focus on internal ED processes and neglect external relationships. Network Data Envelopment Analysis (NDEA) can measure the relative efficiency of organizational units by capturing the interplay among multiple inputs and

[1] Corresponding author, Orcid: 0000-0001-6767-1157 2423-6950 / © University of Isfahan
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outputs. This paper develops a hybrid model that integrates discrete-event simulation with NDEA for evaluation and improvement of a hospital ED.

Design/methodology/approach: The emergency department of Tehran Imam Khomeini Hospital provided data on different patient groups over 60 days, covering about 7,000 individuals. The main processes of a two-level supply chain were designed and modeled. Simulation using Arena software evaluated supply chain performance in terms of costs and patient flow time.

Findings: Based on simulation results for the current system, ten improvement scenarios were designed and simulated. Running experiments with different configurations allowed analysis of those scenarios and provided valuable information to ED management for re-engineering processes. The results of the improvement scenarios and of the current system were treated as 11 separate decision-making units (DMUs) in the NDEA model. The analysis identified the best models in terms of overall productivity, efficiency, and effectiveness of the supply chain.

Practical implications: This study indicates that dedicating MRI and CT scan devices for emergency department (ED) use can substantially reduce patient waiting times and overall patient flow times. This improvement stems from addressing diagnostic imaging, a key bottleneck in ED operations. The findings offer practical recommendations for optimizing resource allocation and streamlining processes within emergency departments. By targeting specific improvements, such as enhanced imaging availability, EDs can boost efficiency and patient care.

Originality/value: This research proposes an innovative integrative approach for performance evaluation combining Discrete-Event Simulation (DES) and Network Data Envelopment Analysis (NDEA). The proposed approach provides new insights into healthcare system optimization.

Keywords: Productivity, Performance evaluation, Discrete-event Simulation, NDEA, Healthcare

1. Introduction

Healthcare supply chain management refers to the integrated management of material flow, monetary flow, and distribution of human resources across all activities to provide optimal services at the right time to patients as the final clients (Kim & Kim, 2019). Because of their high significance and sensitivity, hospital emergencies are critical. This study aims to evaluate the performance of a multi-level supply chain by integrating discrete-event simulation and network data envelopment analysis (NDEA). Several researchers have contributed to this field. Zhang et al. (2022) employed neural networks to evaluate emergency logistics capability for public health emergencies. Vaishnavi and Suresh (2020) used fuzzy logic to improve health organizations. Applying the Analytic Network Process, Ala *et al.* (2024) developed a performance evaluation of integrated emergency supply chains. Göleç and Karadeniz (2020) presented a fuzzy model to measure healthcare supply chain performance using competency-based operation evaluation. Discrete-event simulation has

often been used to reduce waiting time in queues and patients' flow time in the system (Dosi *et al*., 2023). Vogelmann *et al.* (2023) argued that discrete-event simulation is a valuable tool for effective management of health supply chains. In prior work, few studies have evaluated health supply chain performance using discrete-event simulation (Abideen & Mohamad, 2021); those that do mostly focus on internal emergency processes such as bed placement, scheduling, or routing. This paper develops a hybrid model that integrates discrete-event simulation modeling with NDEA for performance evaluation and improvement of a hospital ED. The objectives of this research are as follows:

i) Design a conceptual model for the emergency department processes

ii) Simulating the emergency processes and development of the model

iii)Using NDEA models to select the most efficient

First, the current situation at the operational level is simulated, and then different scenarios are designed to investigate possible optimizations. Finally, to determine the best scenario in terms of overall supply chain productivity, NDEA will be employed. The article is organized as follows: first, a background and brief literature review are provided. Then, the research methodology is explained, including how the simulation model is developed and its relationship with data envelopment analysis. Finally, the results are discussed and conclusions are drawn.

2. Literature review

2.1 Health supply chain performance evaluation

Health supply chain performance evaluation plays a critical role in strengthening healthcare systems, particularly within the public sector (Longaray *et al*., 2023). Numerous studies have emphasized the importance of assessing key indicators such as operational efficiency, material management effectiveness, and financial performance in public healthcare organizations. These evaluations are vital for identifying improvement areas and streamlining processes to ensure optimal patient service delivery (Bayrak & Göncü, 2023). For example, an assessment of tracer drugs across primary healthcare units revealed challenges in inventory management, LMIS reporting, and storage practices (Wang *et al*., 2023). Such issues adversely affected the overall quality of healthcare delivery, underscoring the need to address supply chain inefficiencies in healthcare settings. In response to the unprecedented challenges of the COVID-19 pandemic, attention increased on evaluating vaccine supply chain performance using tools like DEA (Mishra et al., 2024). This approach highlighted the complex link between sustainable competitive advantage and effective supply chain management in healthcare, emphasizing the need for strategic decision-making and

resource optimization. Additionally, the pandemic's disruptive effects led hospitals to reassess supply chain practices using methods such as the balanced scorecard or discrete-event simulation (Chorfi, 2024).

Drei and Angulo-Meza (2025) presented a literature survey on the integration of Data Envelopment Analysis (DEA) with Lean Manufacturing and Lean Healthcare, highlighting key topics and identifying gaps that suggest avenues for future research, particularly in the healthcare sector. Andam *et al.* (2024) designed a model for healthcare services supply chain performance evaluation using a neuromorphic multiple-attribute decision-making technique. Seifi *et al*. (2025) examined the evaluation and prioritization of artificial intelligence–integrated blockchain factors in the healthcare supply chain using F-AHP and F-DEMATEL. The findings suggest that integrating AI and blockchain in healthcare can lead to significant improvements in managing healthcare systems.

2.2 Discrete-event simulation for management of the health supply chain

The health sector's demands have increased over the years, and its related organizations have become larger, more complex, and more costly. The inherent uncertainty of these issues complicates decision-making. Discrete-event simulation (DES) has been used to address this problem (Vogelmann *et al.* 2023). DES is recognized as an effective management tool for health supply chains, as supported by numerous studies. These studies demonstrate the successful application of DES in modeling blood collection centers, enabling researchers to explore various configurations and evaluate scheduling strategies (Doneda *et al.*, 2021). Moreover, the use of DES techniques in healthcare settings shows promise, although some implementation challenges remain. DES has also proven particularly useful for simulating demand patterns during disruptive events such as the COVID-19 pandemic, allowing timely testing of production augmentation policies to bolster supply chain resilience while controlling costs. In summary, the broad capabilities of DES offer a robust approach to optimizing operations, supporting informed decision-making, and enhancing the overall performance of health supply chains (Bahrami & Shokouhyar, 2022). Thus, DES emerges as an indispensable tool in healthcare logistics management, playing a pivotal role in improving efficiency and effectiveness in supply chain operations (Akpan, *et al.*, 2024).

2.3 NDEA for performance evaluation of a multi-level supply chain

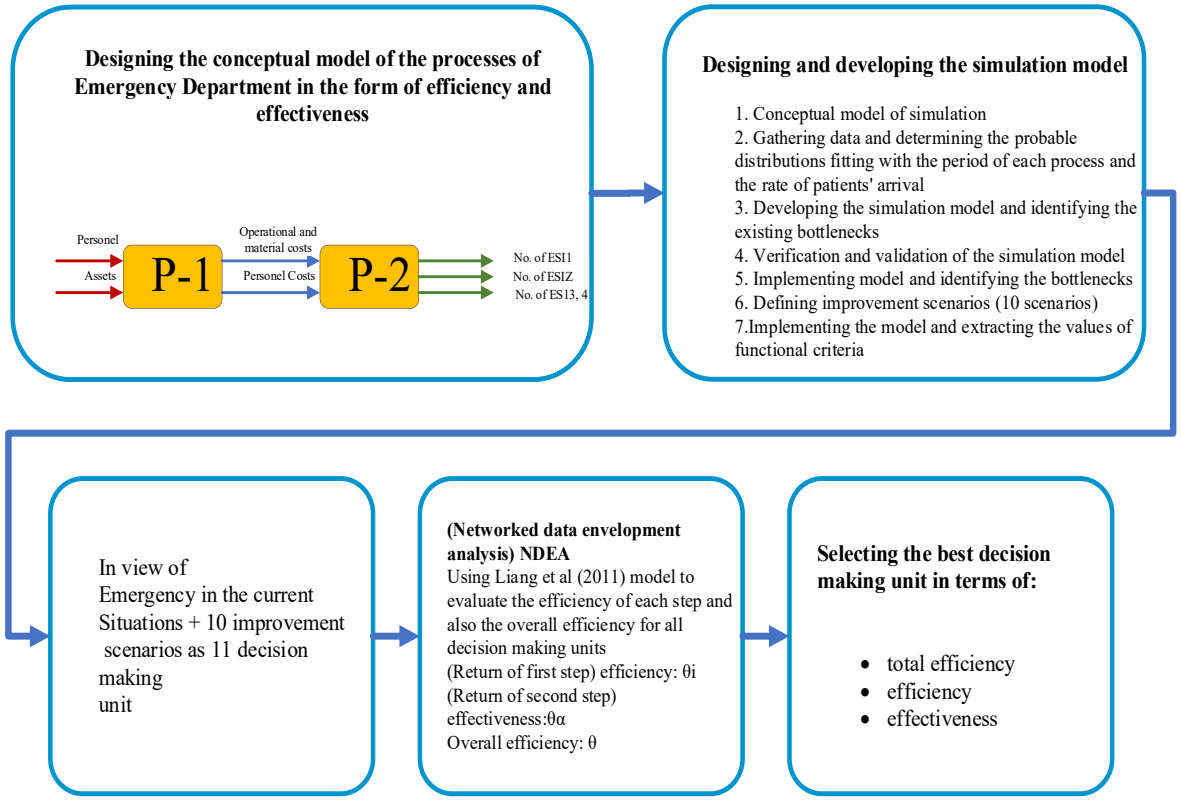
DEA is an essential tool for assessing the effectiveness of healthcare supply chains (HSCs) (Jomthanachai *et al.*, 2021). Numerous studies emphasize the value of advanced methodologies—such as DEA, deep learning, and artificial intelligence—for improving HSC performance and forecasting their sustainability. Applying DEA in HSCs allows categorization of stakeholders, including manufacturers, distributors, and retailers, to optimize supply chain efficiency and bolster managerial performance in the healthcare sector. Moreover, innovative NDEA models, like NDEA-R, mark a notable advance over traditional DEA approaches by addressing challenges related to ratio data and internal network structures (Gerami *et al.*, 2023). Consequently, these models help produce more accurate efficiency scores for decision-making units within healthcare supply chains.

NDEA is a highly valuable instrument for evaluating the effectiveness of health supply chains operating at multiple levels (Azadi *et al.*, 2023; Lotfi *et al.*, 2023). As a method, NDEA enables a thorough examination of decision-making units (DMUs) within intricate systems, accounting for internal divisions and interactions to furnish impartial efficiency ratings for all components. By employing a maximin strategy at two tiers, NDEA optimizes the minimum efficiencies of divisions and DMUs, thereby augmenting the discriminatory capability of conventional DEA models and effectively addressing complexities arising from incomplete and imprecise data common in realistic supply chain scenarios (Pourbabagol, 2023). This approach not only assesses the performance of individual constituents but also provides valuable insights into the overall efficiency of the entire supply chain network, empowering better decision-making regarding partner selection, order distribution, and continuous improvement initiatives within contemporary cooperative supply chains (Alavi & Abootalebi, 2021). Afonso *et al.* (2025) used fuzzy trapezoidal numbers within a network framework. They collected data from Portuguese public hospitals, including 18 variables related to efficiency, quality, and access, and applied a slack-based fuzzy network-DEA model capable of handling undesirable outputs. Because of significant operational and environmental differences between hospitals in Portugal, a subsampling frontier approach based on exogenous variables was used.

3. Methodology

3.1 Research steps

In Figure 1, the research methodology, comprising five main steps, is presented. The first step is to design a conceptual model for emergency department processes, given that the objective of the current study is to measure efficiency and effectiveness and ultimately evaluate performance.



Fi. 1. Research methodology

In this study, feedback from hospital administrators and healthcare experts was directly incorporated into the conceptual design of emergency department processes. Specifically, in the initial stage of the research methodology, the conceptual model was developed through interviews and surveys with 10 hospital managers and university professors. Their input enabled the precise identification of two core processes within the emergency services supply chain and served as the foundation for simulation model development. This engagement with key stakeholders shows that practical and experiential insights were integrated into the model's structure, thereby enhancing the accuracy, validity, and applicability of the study's outcomes.

In the second step, a simulation of the emergency processes and development of the model in Arena 14 software was conducted. Arena simulation software offers several advantages, including enhanced visibility into complex systems, faster model development, and the ability to explore "what-if" scenarios without disrupting real-world operations. It also

facilitates easier validation and debugging of models, making it a powerful tool for decision-making and process improvement (Meresa *et al.*, 2025). The process includes seven general steps, through which the values needed for the 11 DMUs — the current situation and the 10 proposed improvement scenarios — are obtained (third step).

As the emergency services supply chain has been considered a two-step process, using traditional DEA models to select the most efficient unit is not suitable. Therefore, in the fourth step, NDEA is developed for decision-making regarding effectiveness and overall efficiency.

3.2 Ethical consideration

In healthcare research, particularly studies involving patient data, as in the case of emergency department simulations, maintaining ethical standards is critical. The study collected data from approximately 7,000 patients over 60 days, including sensitive information such as triage outcomes, waiting times, and treatment pathways. Although the document does not detail the ethical procedures followed, the following considerations should be emphasized:

i) Informed Consent and Anonymity: Any data collection involving patients must ensure informed consent, with participants being aware of the purpose, scope, and use of the data. Given the retrospective nature of hospital data, all personal identifiers must be removed or robustly pseudonymized to maintain anonymity.

ii) Data Protection and Confidentiality: Patient data must be handled in compliance with applicable privacy laws and institutional policies (e.g., HIPAA or GDPR equivalents, depending on jurisdiction). Secure storage, restricted access, audit trails, and encryption of data are standard practices to protect confidentiality.

iii) Ethical Approval: The study should be reviewed and approved by an Institutional Review Board (IRB) or ethics committee to ensure that the rights and well-being of patients are safeguarded during data usage, with documentation of the approval and any waivers recorded.

iv) Use of Data in Simulation Models: While simulations provide a valuable tool for healthcare optimization, the data feeding these models must be ethically sourced. Simulated scenarios should be validated and interpreted cautiously so that policy recommendations do not unintentionally harm patient care or exacerbate disparities.

By addressing these ethical principles, healthcare simulation and performance evaluation can responsibly improve patient outcomes and system efficiency without compromising patient privacy or trust.

3.3 Statistical analysis

In this study, Discrete-Event Simulation (DES) will be used to evaluate the performance of processes within the emergency department. To represent different process times, probability distributions such as normal, uniform, and exponential will be applied. These distributions will realistically simulate durations for activities like waiting, physician consultations, and the use of medical equipment. For example, times for triage, physician visits, and other treatment stages will be modeled with appropriate distributions to capture random variation in healthcare processes. To ensure validity and reproducibility, simulated patient flow times will be compared with observed flow times from the emergency department. This comparison will use confidence intervals to assess the alignment and accuracy of the simulation model. Specifically, average flow times for different patient groups (ESI1, ESI2, ESI3, and ESI5) in the real system and in the simulation will be compared, and confidence intervals for these times will be calculated to verify close agreement. Additionally, cross-validation will be employed to further assess the model's accuracy by comparing simulation results with real-world data for each patient group, supporting the transparency and reproducibility of the findings.

Finally, to evaluate the efficiency and performance of the simulation results, an NDEA model will be applied. This model will assess the simulation outcomes across multiple scenarios and determine the efficiency of each scenario based on inputs (such as personnel, equipment, and costs) and outputs (such as waiting times and patient flow).

4. Analysis and results

4.1 Simulation model development

The case study of this article is the emergency department of Imam Khomeini Hospital. In the current system, the emergency department of Imam Khomeini Hospital consists of:

i) Triage: in this section, it is determined whether a patient is in urgent condition or in normal condition.

ii) Cardio Pulmonary Resuscitation (CPR): if a patient is in urgent condition, they are sent to this section for resuscitation.

iii) Emergency Department 1: includes 22 beds and is allocated to patients of ESI 1 and ESI 2. In every working shift, 5 physicians and 5 nurses provide services to the patients.

iv) Emergency Department 2: includes 18 beds and is allocated to patients of ESI 3 and ESI 4. In every shift, 5 physicians and 5 nurses provide services to the patients.

v) Fast Track Department and Financial Department: this section is dedicated to patients of ESI 5 type.

The classification of patients referred to the emergency room is based on the prioritization of patients based on their disease conditions which as observed in Figure 2.

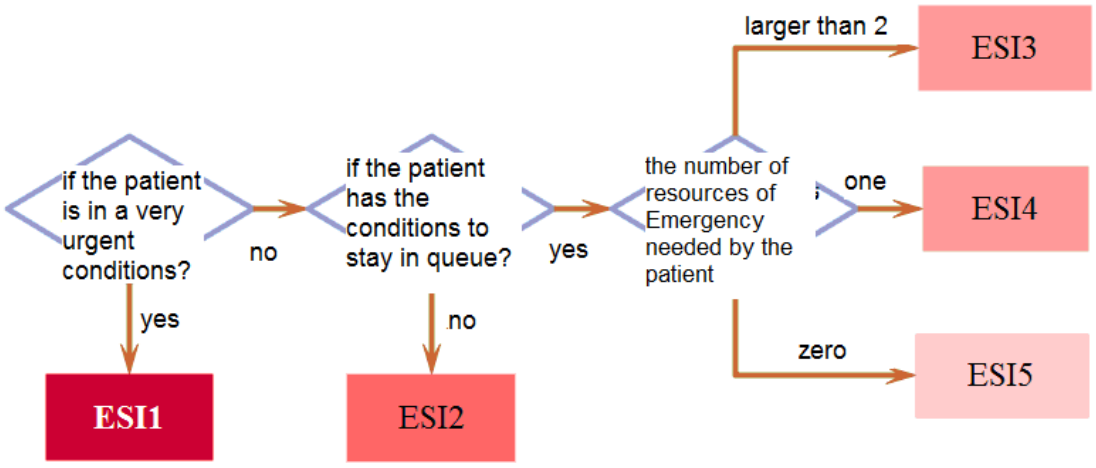


Fig. 2. The determination of the emergency state index of patients

As observed in Figure 2, after the patient arrives at the emergency department (whether by ambulance or self-referral), they are sent to triage. There, their condition is classified according to ESI level. If the condition is critical (ESI-1), the patient is sent to cardiopulmonary resuscitation (CPR) and, if they survive resuscitation, returned to the emergency department. Patients classified as ESI-2 are sent to Emergency 1. Patients with ESI-3 or ESI-4 are sent to Emergency 2. ESI-5 patients are directed to the clinic.

Patients sent to Emergency 1 and Emergency 2 are first seen by a physician. After examination, if additional care is needed (including radiology, orthopedics, laboratory tests, CT scan, MRI, or minor surgery), they are referred to the appropriate service and then returned to the corresponding emergency area until the physician provides a final assessment. If the patient's condition permits and hospitalization is not required, they are discharged; otherwise, they are admitted to a hospital ward.

4.2 Data collection and the probability distributions

In this step, data were gathered from different groups of patients over a 60-day period, totaling about 7,000 patients. The required information includes: time of the triage process; time of nurse involvement in the first step after the patient's arrival to the emergency department; time of the physician's first visit; time to perform additional examinations (including radiology, orthopedics, laboratory, CT scan, MRI, and outpatient procedures); time of nurse involvement in the second step; time of the physician's second visit; time of discharge procedures; time of resuscitation services (only for ESI-1 patients); and, for ESI-1 patients, time of triage section, time of reception procedures, time at the cash desk, and time

of the doctor's visit. Also, the proportions of ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients among all patients are 5.1%, 14.7%, 30.41%, 0. (should be 49.7% for ESI-5?), and 49.7%, respectively. The probability distributions of the emergency processes were calculated using Arena Input Analyzer, as shown in Table 1.

Table 1. Probability distribution of the input data

Process	ESI 1 (CPR)	ESI 2	ESI 3,4	ESI 5
Resuscitation section	Norm (38.3, 3. 69)			
Nurse in step 1	Tria (1.5, 5, 7.5)	Tria (1.5, 5, 7.5)	Uniform (1.5, 5, 7.5)	
Nurse in step 2	20+Exp (15.9)	Tria (2.5, 40, 58.5)	Tria (20.5, 42, 57.5)	
Doctor in step 1	6.5+Exp (4.37)	6.5+Exp (4.37)	7.5+Exp (4.21)	
Doctor in step 2	Norm (9.45, 2.55)	Norm (9.71, 2.61)	Tria (4.5, 10, 14.5)	
Laboratory	Norm (142, 36.3)	Tria (64, 127, 229)	Tria (63, 128, 230)	
M.R. I	Tria (31.5, 45, 58.5)	Tria (33.5, 42,60.5)	34.5+Exp (10.9)	
CT scan	Norm (43.8, 5.61)	32.5+ Expo (12)	Tria (31.5, 41.2, 59.5)	
Radiology	Uniform (4.5, 20.5)	Uniform (4.5, 20.5)	Uniform (4.5, 20.5)	
Orthopedics	Tria (14.5, 20, 40.5)	Tria (14.5, 20, 40.5)	Tria (14.5, 20, 40.5)	
Outpatient surgery	11.5+Exp (15.1)	11.5+Exp (15.1)	11.5+Exp (15.1)	
Release	Uniform (30, 120)	Uniform (30, 120)	Uniform (30, 120)	
Reception				Uniform (2.4)
Cash desk	Uniform (1,2)	Uniform (1,2)	Uniform (1,2)	Uniform (1,2)
Doctor fast track				4.5+Exp (4.72)

The average rate of patients' arrival was obtained for the under-study period for various hours of day and night according to Figure 3.

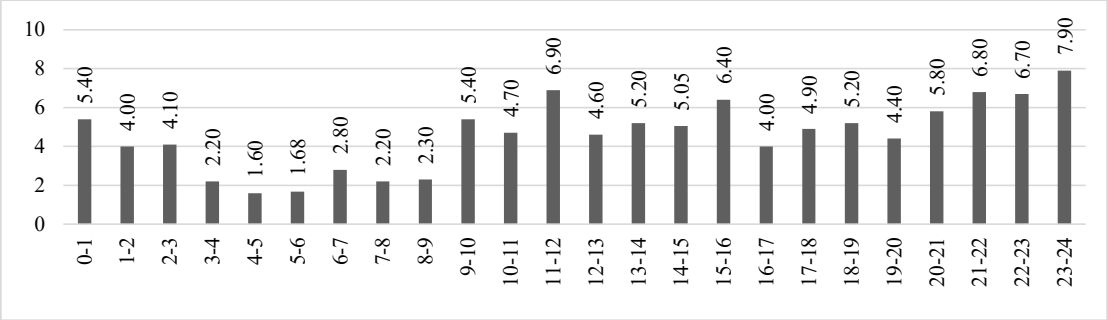


Fig. 3. Patients' arrival rate within 24 hours

4.3 Results of the simulation model

The simulation model was run using Arena 14 software. In Figure 4, the various parts of the model are presented. In the following, the logic of the model will be explained briefly in every section.

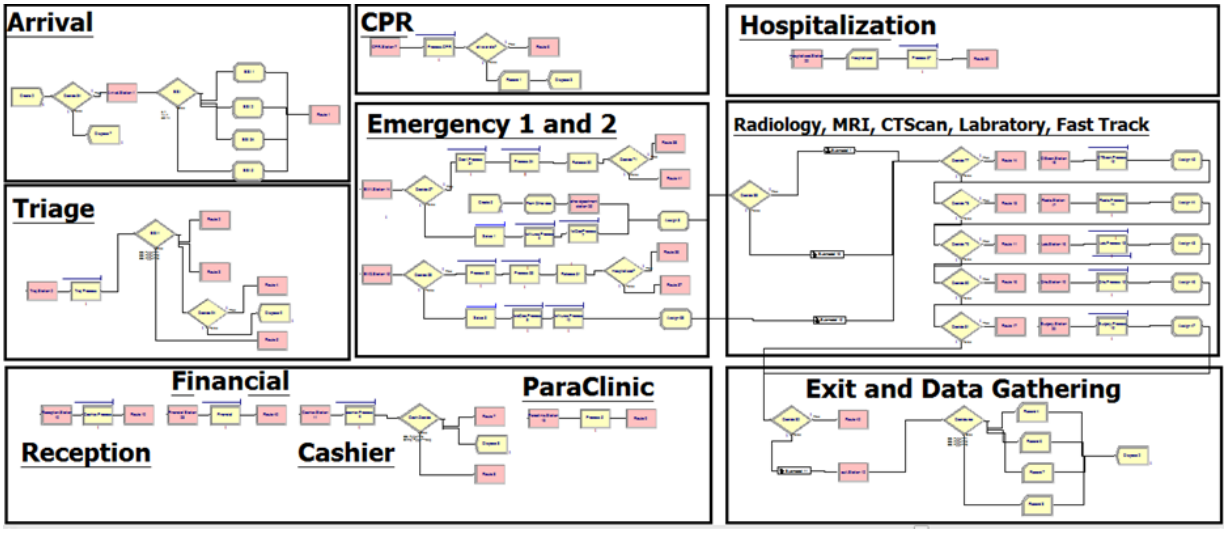


Fig. 4. The simulation model (current system)

In Patients' entering section, the Create Module was used to classify patients based on the schedule of the arrival rate in the system (Figure 4). Then, using a Decide Module and based on the ratio obtained for each of the ESI1 to ESI5 patients, they were distinguished from each other and, using the Assign Module, the type and probability distributions of the duration of performing the process in different steps were allocated as Attributes to the patients. In the triage section, after spending the triage process time, based on the disease type and using a Decide Module plus Route and Station Modules, patients were sent to the related section. Also, some patients left the emergency department after triage due to crowding; this was implemented using a Decide Module and an exit. In the CPR section (Cardio Pulmonary Resuscitation), ESI1 patients spent the resuscitation process time and were then divided into two outcomes using a Decide Module: patients who survived were sent to Emergency 1, and those who died were removed from the system. In the outpatients section, ESI5 patients, after spending the time for admission and at the cash desk in a queue, were seen by a doctor and then left the system. The Financial operational section includes reception, cash desk, and financial operations for releasing ESI5 patients.

ESI1 and ESI2 patients were transferred to Emergency 1, and ESI3 and ESI4 patients were transferred to Emergency 2 after triage. In this section, the nurse performed the initial assessment and measures; if needed, the patient was transferred to the more-examinations section. After completing those examinations, the patient returned to the corresponding ED to be seen by a doctor and receive secondary measures. After the secondary measures, the patient was either sent to the discharge area or to the hospitalization area for further care.

The more-examinations section includes laboratory, radiology, MRI, CT scan, orthopedics, and outpatient surgery. A patient could be sent to one or more of these services depending on their condition. To model this section, an important point is that the ED patient

would not leave their bed until it was their turn in the more-examinations section. This was implemented by using a Release Module after seizing the required resource. The logic for the more-examinations section was designed so that when a patient needed it, the system constantly checked whether a bed was available. When a bed became available, the patient was admitted based on priority to the required service(s) and then returned to the associated ED to be rechecked by a doctor.

4.4 Verification and validation

Figure 5 illustrates the model animation, showcasing a busy moment where every bed in Emergency Department 2 is occupied, alongside 15 of the 22 beds in Emergency Department 1 being filled. Furthermore, the sections for CT scans, radiology, and orthopedics are entirely occupied. Such circumstances generally arise during the late hours of the day, reflecting the actual functioning of the system.

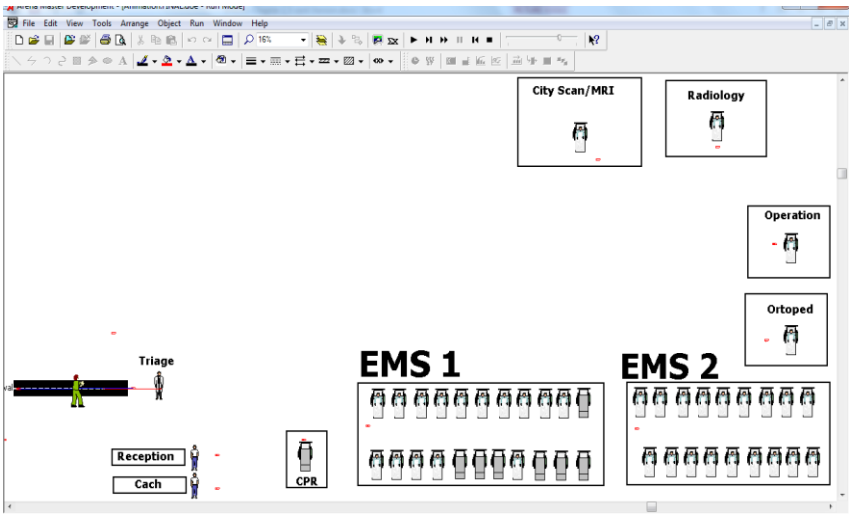


Fig. 5. An image of the model animation in Arena 14 software

In the context of model validation, a comparison was made between the flow times of patients in both real and simulated systems. The waiting times for each patient group seeking admission to emergency department beds were analyzed, demonstrating that the model has been validated appropriately. More specifically, the flow times of patients were assessed within the confidence intervals produced by Arena software, and the findings indicate that the simulated data aligns closely with actual observations from the real world. The outcomes are detailed in Table 2.

Table 2. The average patients' flow time in the system (real and simulation data)

Type of patient	Average patients' flow time in the system based on the real data	Average patients' flow time in the system based on the simulation model	Half Width	Lower limit	Upper limit
ESI 1	9.95	10.30	0.78	9.52	11.08
ESI 2	14.65	13.54	1.22	12.33	14.75
ESI3, 4	12.38	11.70	0.90	10.80	12.60
ESI5	0.69	0.71	0.01	0.70	0.72

Figure 6 presents a comparison of the average waiting times between the actual system and the simulated model. It shows that the real patient waiting times are encompassed within the confidence intervals, thereby validating the consistency of the simulated model with the actual system.

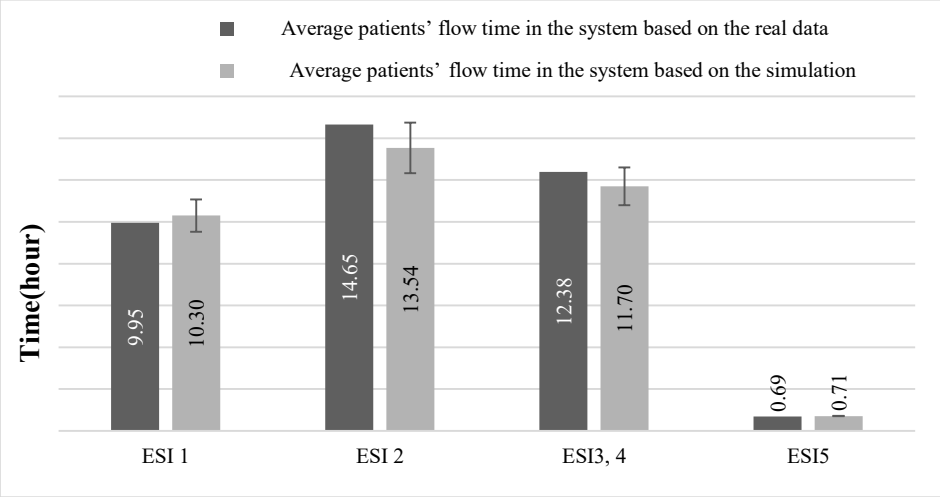


Fig. 6. Comparison of the simulation results versus the real ones

To enhance the reliability and generalizability of the simulation model, a cross-validation technique was utilized. In this approach, the average patient flow times within the simulated system were compared against real-world data for each ESI group. The actual values consistently fell within the established confidence intervals, thereby affirming the statistical correspondence between the simulated and real data. This validation not only substantiates the model's precision in mirroring essential operational features of the emergency department but also bolsters its credibility as a resource for assessing improvement scenarios. The congruence between the simulated and observed data guarantees that the simulation outcomes are both realistic and actionable.

4.5 Bottlenecks' identification

The model's implementation was structured such that the number of repetitions was set to 15. This specific count of repetitions resulted in a reduction of the output results' variability in the simulation model to below 5%. The warm-up period for the model was established at 48 hours. The duration for patient admissions was determined to be 60 days, with the model's termination condition being that once the admission period concludes, all patients who had entered the model prior to this time would complete their processes and exit the system, thereby concluding the model's operation.

The simulation model was executed, and the waiting times for patients in the queue were analyzed to pinpoint bottlenecks. The MRI and CT scan departments exhibited the longest

queues, indicating they are the most congested and costly areas of the hospital. On average, over 80% of hospitalized patients and more than 85% of emergency department patients require imaging services from one or both of these sections. Table 3 illustrates the waiting durations for patients in the queue. For ESI2 patients, the waiting time in the MRI and CT scan queue is approximately 10 hours, while for ESI3 patients, this duration is similarly lengthy, averaging around 6 hours (refer to Table 3).

Table 3. Patients waiting time in MRI and CT scan queue (hour)

Type of patient	Average patients' flow time in the system according to the simulation model	Total queue waiting time	Waiting time in the CT scan queue	Waiting time in the MRI queue
ESI 1	10.30	5.12	0.54	0.42
ESI 2	13.54	8.6	6.89	1.32
ESI3, 4	11.70	7.9	6.24	0.95
ESI5	0.71	0.25		

4.6 Development of the improvement scenarios

Upon identifying the current bottlenecks within a system, the subsequent step involves the introduction of improvement scenarios. These scenarios are crafted with the objective of enhancing the performance metrics of the system under examination. Below, several scenarios are proposed for the enhancement of the hospital emergency department. As indicated in the overall framework of the study, these scenarios are taken into account in the subsequent analysis and within the networked data envelopment analysis model, functioning as a new decision-making unit until their efficiency and effectiveness are evaluated against one another. The role of the simulation model is to facilitate the calculation of the model's conditions, as well as the variables and parameters necessary for the networked data envelopment analysis model, following the implementation of the proposed changes. The scenarios under consideration include:

1. Prioritizing ESI2 patients in the MRI and CT scan sections over ESI3 and ESI4 patients, as well as those referred from other sections to the imaging department (it is important to note that ESI1 group patients in the current model, which reflects the existing situation, receive the highest priority).
2. Prioritizing all patients within the emergency department over those from other departments in the MRI and CT scan sections.
3. Introducing an MRI device specifically for the emergency department, with an estimated cost of 20 billion Rials.
4. Introducing an MRI device to enhance service quality for all patients.
5. Introducing a CT scan device specifically for the emergency department, with an estimated value of 100 billion Rials.
6. Introducing a CT scan device to improve service quality for all patients.

7. Introducing two CT scan devices specifically for the emergency department.
8. Introducing two CT scan devices to enhance service quality for all patients.
9. Introducing both a CT scan device and an MRI device specifically for the emergency department.
10. Introducing both a CT scan device and an MRI device to improve service quality for all patients.

The performance criteria of a system refer to the variables utilized to evaluate its performance. In this study, the performance criteria for each scenario are computed using the developed simulation model. Subsequently, these variables serve as inputs for the mathematical model of data envelopment analysis, which is employed to ascertain the relative capabilities of the scenarios through a two-step process tailored for the emergency department. The performance criteria encompass the total number of personnel, including doctors, nurses, technicians, and support staff; the aggregate value of all equipment, such as beds, consumables, and existing devices ranging from CT scans and MRIs to surgical room apparatus; the general and administrative expenses of the emergency department; staff-related costs; patient waiting times in queues; patient flow times within the emergency department; and the number of patients categorized into ESI1, ESI2, ESI3, and ESI4 groups.

4.7 Interaction between simulation and NDEA

In this research, the Discrete-Event Simulation (DES) model is integrated with NDEA to assess the performance of the emergency department within the hospital.

The connection between DES and NDEA is as follows:

- DES (Discrete-Event Simulation): This model replicates various processes in the emergency department, including patient admissions, waiting times in queues, durations of treatment, and the utilization of resources such as beds and medical equipment. These simulations are performed using Arena software, which aids in pinpointing bottlenecks and deficiencies within the system.
- NDEA (Network Data Envelopment Analysis): Following the simulation of various scenarios, the outcomes are fed into the NDEA model. This model assesses the efficiency and productivity of each scenario by examining the resources utilized (including staff and equipment) and the resulting outputs (such as waiting times in queues and treatment durations for patients).

DES functions as a mechanism to simulate the actual processes occurring in the emergency department along with various potential improvement scenarios. Subsequently,

NDEA evaluates the results of these simulations to determine the efficiency of each scenario and to identify optimal strategies for enhancing system performance.

In conclusion, DES provides a simulation of the operational intricacies of the system. At the same time, NDEA leverages this information to assess the efficiency of each scenario, thereby facilitating the identification of the most effective modifications and enhancements within the hospital's emergency department system.

4.8 Mathematical model of NDEA

As previously noted, this research employs the model developed by Liang *et al.* (2006). The model and the interrelationship among the variables are illustrated in Figure 7 and represented in Equation 1.

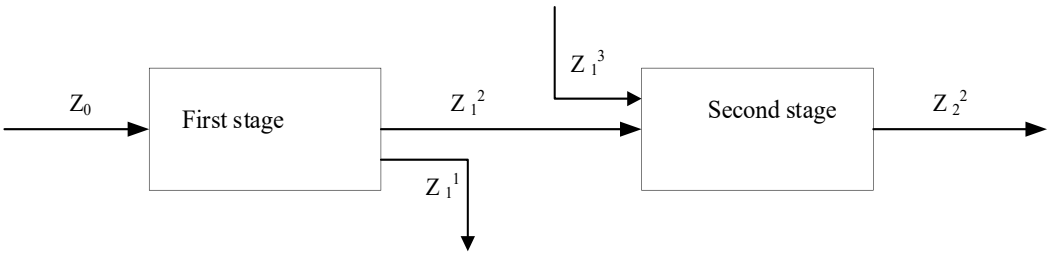


Fig. 7. Networked data envelopment analysis

In Equation (1), the initial constraint stipulates that the aggregate inputs of the first stage, in conjunction with the total of the intermediate inputs for step p and the total inputs for step p, must equal one. The subsequent constraint illustrates that the total outputs from the first step must be less than the cumulative outputs of that same step.

$$\max \sum_{p=1}^{p} \left(\sum_{r=1}^{R_p} U_{pr} Z_{pr}^{0\,1} + \sum_{k=1}^{S_p} \eta_{pk}\ Z_{p\,k}^{0\,2} \right) \tag{1}$$

S.t.

$$\left\{ \sum_{i=1}^{i0} v_{0i}\ z_{i\,0}^{0} + \sum_{p=2}^{p} \left(\sum_{k=1}^{S_p=1} \eta_{p-1\,k} Z_{p-1\,k}^{0\,2} + \sum_{i=1}^{I_p} v_{p-1\,i} z_{p-1\,i}^{0\,3} \right) \right\} = 1$$

$$\left\{ \sum_{i=1}^{i0} v_{0i}\ z_{i\,0}^{0} + \sum_{p=2}^{p} \left(\sum_{k=1}^{S_p=1} \eta_{p-1\,k} Z_{p-1\,k}^{0\,2} + \sum_{i=1}^{I_p} v_{p-1\,i} z_{p-1\,i}^{0\,3} \right) \right\} = 1$$

$$\left(\sum_{r=1}^{R_1} U_{1\,r}\ Z_{1\,r}^{j\,1} + \sum_{k=1}^{S_1} \eta_{1\,k}\ Z_{1\,k}^{j\,2} \right) \leq \sum_{i=1}^{I_0} V_{0\,i}\ Z_{0\,i}^{j}\ \ \forall j$$

$$\left(\sum_{r=1}^{R_p} U_{p\,r}\ Z_{p\,r}^{j\,1} + \sum_{k=1}^{S_p} \eta_{p\,k} Z_{p\,k}^{j\,2} \right) \leq \left(\sum_{k=1}^{S_{p-1}} \eta_{p-1\,k}\ Z_{p-1\,k}^{j\,2} + \sum_{i=1}^{I_p} V_{p-1\,i}\ Z_{p-1\,i}^{j\,3} \right)$$

The third limitation indicates that the total of the input variables at step p, combined with the total of the intermediate variables at the same step, must not exceed the total of the intermediate variables plus the total of the input variables (which are introduced externally during the same step) at step p -1.

$Z_{p\,r}^{j\,1}$: rth element of $(r = 1, \dots, R_p)$ of the output vector for the jth decision-making unit that moves from step p but does not go to the next step $(p + 1)$.

$Z_{p\,k}^{j\,2}$: kth element of (k= $1, \dots, S_p$) of the output vector for the jth decision-making unit that moves from step p and goes to the next step $(p + 1)$ as a part of the input.

$Z_{p\,i}^{j\,3}$: rth element of $(k = 1, \dots, I_p)$ of the output vector for the jth decision-making unit in the step $(p + 1)$ that is entered as input at the beginning of this step.

$U_{p\,r}$: the output coefficient of the part that arises from step p.

$\eta_{p\,k}$: the output coefficient of the part $Z_{p\,k}^{j\,2}$that is entered into the next step as input.

$\nu_{p\,i}$: the output coefficient of parts that are entered in step (p+1) as input.

Also, the efficiency of each step can be calculated using the formula presented in the Equation 2:

$$\theta_p = \left(\sum_{r=1}^{R_p} U_{pr}\, Z_{p\,r}^{j\,1} + \sum_{k=1}^{S_p} \eta_{pk}\, Z_{p\,k}^{j\,2}\right) \Big/ \left(\sum_{k=1}^{S_p=1} \eta_{p-1\,k}\, Z_{p-1\,k}^{j\,2} + \sum_{i=1}^{I_p} \nu_{p-1\,i}\, Z_{p-1\,i}^{j\,3}\right) \tag{2}$$

Also, the weight of each step in the whole process chain using the formula presented in Equation 3 can be observed.

$$w_1 = \sum_{i=1}^{I_0} \upsilon_{0i}\, z_{i\,0}^{0} \Big/ \left\{\sum_{i=1}^{I_0} \upsilon_{0i}\, z_{i\,0}^{j} + \sum_{p=2}^{p} \left(\begin{matrix}\sum_{k=1}^{S_{p-1}} \eta_{p-1\,k} Z_{p-1\,k}^{i2} \\ + \sum_{i=1}^{I_p} \upsilon_{p-1\,i} z_{p-1\,i}^{i3}\end{matrix}\right)\right\} \tag{3}$$

w_p

$$= \left(\sum_{k=1}^{S_{p-1}} \eta_{p-1\,k} Z_{p-1\,k}^{j2} + \sum_{i=1}^{I_p} \upsilon_{p-1\,i} z_{p-1\,i}^{j3}\right) \Big/ \left\{\sum_{i=1}^{I_0} \upsilon_{0i}\, z_{i\,0}^{j} + \sum_{p=2}^{p} \left(\begin{matrix}\sum_{k=1}^{S_{p-1}} \eta_{p-1\,k} Z_{p-1\,k}^{i2} \\ + \sum_{i=1}^{I_p} \upsilon_{p-1\,i} z_{p-1\,i}^{i3}\end{matrix}\right)\right\}.$$

Moreover, in equation 4 the final return of the process using the following formula can be calculated:

$$\theta = \sum_{p=1}^{p}\left(\sum_{r=1}^{R_p} U_{p\,r}\, Z_{p\,r}^{j\,1} + \sum_{k=1}^{S_p} \eta_{p\,k} Z_{p\,k}^{j\,2}\right) \Bigg/ \left\{\sum_{i=1}^{I_0} \upsilon_{0i}\, z_{i\,0}^{j} + \sum_{p=2}^{p}\left(\sum_{k=1}^{S_{p-1}} \eta_{p-1\,k} Z_{p-1\,k}^{i2} + \sum_{i=1}^{I_p} \upsilon_{p-1\,i} z_{p-1\,i}^{i3}\right)\right\} \quad (4)$$

Here, the supply chain network considered for the research problem should be adjusted to the suggested model of Liang *et al.* (2006). The inputs to the first step are shown by $z_0^j Z_0^j$, and because we consider the two variables of staff and fixed assets as inputs of the first section, here $z_{i\,0}^{j}\, Z_{0\,1}^{j}$ represents the number of employees and $z_{i\,2}^{j}$the total value of the assets that are available to the emergency department; J presents the decision maker or the emergency department number. Of course, here there are not several emergency departments. However, an emergency has been examined in different scenarios, and it is assumed that each scenario is a decision-maker unit. Considering that there are 10 scenarios, and considering the current situation as a decision-maker unit, there are 11 values for j.

The two variables of "general and administrative costs" and "personnel costs" that, as shown in Figure 2, are removed from step 1 and entered into step 2. Z_1^2 variables that are defined in the form of general and administrative costs$Z_{0\,1}^{j\,1}$ and personnel cost $Z_{0\,1}^{j\,2}$. Finally, the final output of the emergency model is that the number of ESI1, ESI 2, and ESI 3,4 patients is defined as $Z_{2\,1}^{j\,2}$, $Z_{2\,2}^{j\,1}$, and $Z_{2\,3}^{j\,1}$.

The results of the simulation are shown in Table 4.

Table 4. Results of the simulation model

	Number of staff	Value of total assets	General & administrative cost		Staff costs	Patients 'Flow time (hours)				Waiting time (hours)				Number of patients left the emergency department			
	People		Billion Rials			ESI 1	ESI 2	ESI 3,4	ESI 5	ESI 1	ESI 2	ESI ,4	ESI 5	ESI 1	ESI 2	ESI 3,4	ESI 5
	$z_{0\,1}^{j}$	$z_{0\,2}^{j}$	$z_{1\,1}^{j\,1}$	$z_{1\,1}^{j\,2}$	-	-	-	-	-	-	-	-	$z_{2\,1}^{j\,1}$	$z_{2\,2}^{j\,1}$	$z_{2\,3}^{j\,1}$	-	
Current situation	150	60	2.5	1.5	10.3	13.54	11.7	0.71	5.12	8.6	7.9	0.25	140	106	123	2028	
Scenario 1	150	60	2.5	1.5	10.4	13.08	9.21	0.71	5.18	6.5	6.9	0.25	134	112	156	2028	
Scenario 2	150	60	2.5	1.5	10.4	12.63	9.01	0.68	5.19	6.39	6.78	0.23	138	114	160	2118	
Scenario 3	155	62	2.7	1.53	10.4	11.22	8.6	0.72	5.15	5.43	5.32	0.23	138	128	167	2000	
Scenario 4	155	62	2.7	1.53	10.4	12	8.92	0.72	5.16	5.59	6	0.25	138	120	161	2000	
Scenario 5	155	70	2.8	1.55	8.63	10.11	8.02	0.71	4.65	5.05	5.32	0.22	167	142	180	2028	
Scenario 6	155	70	2.8	1.55	9.8	10.55	8.6	0.71	4.9	5.42	5.81	0.23	147	136	167	2028	
Scenario 7	160	80	3.1	1.6	7.8	9.92	8.12	0.71	4.63	5.21	5.72	0.24	185	145	177	2028	
Scenario 8	160	80	3.1	1.6	9.1	10.01	8.15	0.71	5.23	5.45	5.92	0.26	158	144	177	2028	
Scenario 9	160	72	3	1.58	9.9	9.98	8	0.71	5.01	6.9	6.36	0.23	145	144	180	2028	
Scenario10	160	72	3	1.58	10.2	10.9	9.06	0.71	5.14	7.24	**7.05**	0.23	141	132	159	2028	

In this research, ten scenarios were created to enhance emergency performance with the aim of decreasing the queue waiting time for emergency patients as well as minimizing the flow time of patients within the emergency department. The scenarios focus on modifying three key factors that influence both the flow time of patients in the emergency department and the queue waiting time for emergency patients. These factors include prioritizing emergency patients over those from other hospital departments when utilizing MRI and CT scanners, increasing the number of CT devices from one to two, and raising the number of MRI devices from one to two.

The findings indicate that the most effective scenario for reducing the queue waiting time for patients in the emergency department is the addition of two CT scan devices specifically allocated for emergency use (scenario 7). Furthermore, the optimal scenario for decreasing the queue waiting time for patients in the queue involves the addition of either one or two CT scanners or an MRI device (scenarios 4 to 8). However, a thorough examination of the scenarios reveals that the addition of a CT scan or MRI device will only yield significant benefits if it is dedicated to the emergency department. In other words, if the newly added MRI or CT scan device is also accessible to patients from other departments (due to high demand in those areas), this increase will not substantially enhance the flow time of patients in the emergency department.

It is important to note that the incorporation of an MRI or CT scan device will lead to a decrease in the waiting time for patients in the queue, as well as a reduction in the length of their stay in the emergency department. This is due to the enhancement of these two performance metrics across all scenarios. However, as previously stated, when the objective is to minimize waiting times and streamline patient flow in the emergency department for these specific cases, the distribution of MRI or CT scanners to all patients within the hospital would not be an advisable course of action.

4.9 Discussion

The necessary values for the mathematical parameters were derived from the application of the simulation model across various scenarios, as illustrated in Table 5.

The final ranking of each decision-maker unit (scenarios) is calculated in terms of the efficiency of each step separately ($p = 1, p = 2$) and the total efficiency of the chain. The results of the model are observable in Table 6.

Table 5. Values of the input parameters

	Number of staff	Value of total assets	General & administrative costs	Staff costs	Number of patients left the Emergency			
	People	Billion Rials	Billion Rials	Billion Rials	ESI 1	ESI 2	ESI3, 4	ESI5
DMU	z_{01}^{j}	z_{02}^{j}	z_{11}^{j1}	z_{11}^{j2}	z_{21}^{j1}	z_{22}^{j1}	z_{23}^{j1}	
Current situation	150	60	2.5	1.5	140	106	123	400
Scenario 1	150	60	2.5	1.5	134	112	156	410
Scenario 2	150	60	2.5	1.5	138	114	160	402
Scenario 3	155	62	2.7	1.53	138	128	167	411
Scenario 4	155	62	2.7	1.53	138	120	161	398
Scenario 5	155	70	2.8	1.55	167	142	180	406
Scenario 6	155	70	2.8	1.55	147	136	167	408
Scenario 7	160	80	3.1	1.6	185	145	177	400
Scenario 8	160	80	3.1	1.6	158	144	177	401
Scenario 9	160	72	3	1.58	145	144	180	405
Scenario 10	160	72	3	1.58	141	132	159	409

As illustrated in Table 6, the emergency department will yield the highest overall return in scenario 5.

In this scenario, the goal was to incorporate a CT scan device specifically for patients in the emergency department. Given that one of the longest wait times for patients in the emergency department occurs in the CT scan area, this consideration was among the primary factors addressed in the scenario design. Furthermore, the emergency department in scenario 3 is projected to achieve the second-highest overall return. The aim in this scenario was to introduce an MRI device tailored for emergency patients. Additionally, the emergency department in scenario 7 has secured the third position regarding overall return. The objective in this scenario was to install two CT scanners and assign them to the emergency department.

In summary, the scenarios that achieved the highest rankings in terms of overall returns indicate that the most effective strategy for minimizing emergency wait times in the hospital involves the addition of CT scanners and MRI devices.

Table 6. The results of the mathematical model

	Decision-making unit	Final return	Final ranking	Return of the first step of the process	Weight of the first step of the process	Return of the second step of the process	Weight of the second step of the process
	i	θ	-	θ_1	w_1	θ_2	w_2
Current situation	1	0.9378	4	0.7120	0.76159	0.6533	0.23841
Scenario 1	2	0.8356	8	0.5897	0.56252	1	0.43748
Scenario 2	3	0.8297	9	1	0.49289	0.8732	0.50711
Scenario 3	4	0.9775	2	0.7644	0.73222	0.9709	0.26778
Scenario 4	5	0.9233	6	0.5547	0.66038	0.7572	0.33962
Scenario 5	6	1	1	1	0.9251	0.1	0.0749
Scenario 6	7	0.8206	10	1	0.41687	0.598	0.58313
Scenario 7	8	0.9711	3	0.6564	0.78712	0.9794	0.21288
Scenario 8	9	0.9322	5	0.5519	0.58037	1	0.41963
Scenario 9	10	0.864	7	1	0.68473	0.9903	0.31527
Scenario 10	11	0.7613	11	0.6008	0.48552	0.6487	0.51448

The results of the NDEA offer a thorough insight into the comparative efficiency of various improvement scenarios within the realm of healthcare supply chain management, particularly in the emergency department of a hospital. By conceptualizing the supply chain as a two-stage process, the NDEA methodology not only elucidates the overall performance of each scenario but also assesses the efficiency of individual stages, thereby capturing the internal dependencies that are frequently overlooked in conventional DEA models. The analysis emphasizes scenarios that incorporate the addition of dedicated CT and MRI devices for the emergency department—most notably Scenario 6—which significantly improve system efficiency by decreasing patient waiting times and flow times, both of which are vital metrics in emergency care. These results highlight the necessity of strategic resource allocation in high-demand sectors, thereby facilitating data-driven decision-making in healthcare operations. Consequently, NDEA emerges as a robust instrument for managers to pinpoint bottlenecks, prioritize investments, and execute strategies that enhance the overall effectiveness and responsiveness of the healthcare supply chain. To improve the accessibility and clarity of the findings, a summary, Table 7, has been included to synthesize the key outcomes from both simulation results and NDEA analysis, allowing for more straightforward comparisons across scenarios.

Table 7. Summary of key findings from simulation and NDEA analysis

Scenario	Intervention	Avg. queue waiting Time (Hrs)	Avg. patients' Flow Time (Hrs)	Efficiency score	Final ranking
Current	-	8.6	13.54	0.9378	4
Scenario 5	Add CT (Dedicated to ED)	5.05	10.11	1.0000	1
Scenario 3	Add MRI (Dedicated to ED)	5.43	11.22	0.9775	2
Scenario 7	Add 2 CTs (Dedicated to ED)	5.21	9.92	0.9711	3
Scenario 1	Priority for ESI2 in Imaging	6.5	13.08	0.8356	8
Scenario 10	Add CT & MRI (General use)	7.24	10.9	0.8640	7

4.10 Research contribution

In this section, the results of the present study are examined and deliberated upon in connection with the research objectives and the current literature regarding healthcare supply chain management and the assessment of healthcare system performance. This research has introduced a novel integrative method for performance evaluation that incorporates DES and NDEA. The suggested method offers fresh perspectives on optimizing healthcare systems.

i) Innovative methodological approach

This research represents a pioneering effort to merge the DES model with NDEA for the assessment of healthcare system performance, with a specific focus on hospital emergency departments. This synthesis empowers researchers and hospital administrators to more

precisely model and evaluate intricate healthcare processes, ultimately facilitating enhanced resource optimization and cost reduction outcomes.

ii) Practical and policy impacts

The results indicate that employing simulation to model various scenarios can markedly enhance patient waiting times, patient flow times, and resource utilization (including medical equipment and staff). Notably, the introduction of dedicated CT and MRI machines in emergency departments leads to a significant decrease in both patient waiting and flow times. These findings can provide a solid basis for informed decision-making regarding resource distribution and process enhancements within hospitals.

iii)Connection to existing research

Prior investigations have largely concentrated on utilizing DES or DEA to refine internal hospital operations and assess healthcare system performance. This study broadens the current understanding by integrating these two methodologies, thereby addressing both internal and external dependencies within the healthcare supply chain through NDEA. This novel approach facilitates more thorough performance evaluations and the formulation of improvement scenarios grounded in more precise and comprehensive data.

iv)Offering novel perspectives

This research emphasizes the critical need for the dedicated allocation of CT and MRI equipment to emergency departments. Such allocation not only minimizes patient wait times and flow durations but also markedly improves the quality of service. The results of this study furnish practical recommendations for hospital administrators and policymakers regarding the most efficient methods for resource allocation and enhancements in patient care. Additionally, the research proposes potential strategies for the analysis and optimization of healthcare supply chains in various contexts and institutions.

v) Contribution to the enhancement of healthcare policy and data-informed decision-making

The integrated model that merges DES with NDEA acts as a robust instrument for assessing healthcare policies and facilitating data-informed decision-making. This study illustrates that by pinpointing bottlenecks and effectively prioritizing resources, it is possible to formulate more efficient healthcare policies. During crises, such as pandemics or unexpected spikes in demand, this model can aid managers and policymakers in making better-informed choices.

4.11 Comparison of the results with previous studies

In this research, a hybrid model that integrates Discrete Event Simulation with NDEA was created to assess and enhance the performance of supply chains within hospital emergency departments. The findings of this research indicated that enhancements across various

scenarios, particularly the incorporation of diagnostic imaging technologies such as MRI and CT scans, significantly influenced the reduction of patient waiting times and the flow times of patients in the emergency department.

Prior investigations, including those conducted by Ayaz and Ismail (2022) and Saleem and Khan (2023), have underscored the application of simulation in medical education and the optimization of hospital operations, typically concentrating on the discrete-event simulation of healthcare systems and scenarios. Nevertheless, only a limited number of studies have utilized NDEA to offer a more thorough assessment of supply chains in intricate settings like emergency departments.

In contrast to earlier research, this study presents a distinctive advantage by merging simulation with NDEA to simulate and evaluate improvement scenarios, thereby facilitating the analysis of internal complexities and network interactions among units. Previous studies, such as those by Decker *et al.* (2021) and Miller *et al*., (2021), primarily concentrated on enhancing internal processes and prioritizing hospital equipment, without taking into account the networked and multi-step evaluation of overall efficiency.

The results of this research distinctly highlight the necessity of distributing resources, including MRI and CT machines, to emergency departments. This aligns with previous studies, such as the one conducted by Saleem and Khan (2023), which examined the enhancement of supply chain efficiency during crises. The dedicated allocation of these devices to the emergency department in this research clearly indicates that concentrating resources in high-demand sectors leads to notable enhancements in patient flow times and a decrease in waiting durations.

In summary, this study, when compared to earlier research, introduces an innovative framework for assessing and enhancing hospital supply chains, particularly within emergency department contexts. This methodology is especially beneficial during emergencies and crises, providing practical solutions for the advancement of healthcare systems.

5. Conclusions

In this study, the assessment of supply chain performance was conducted by integrating two methodologies: discrete-event simulation and networked data envelopment analysis. The outcomes derived from the model indicate that scenarios 5, 3, and 7 are recognized as the top three scenarios regarding the overall efficiency of the supply chain. The model developed in this research can be applied to evaluate the performance of other comparable supply chains. Specifically, in cases where a series of processes exists, one can initially simulate that scenario and establish various decision-making units by formulating improvement scenarios.

Subsequently, by analyzing the results, modifications can be implemented that may yield the most effective outcomes for the entire supply chain. By employing this approach, we simultaneously leverage the simulation capabilities to address the dynamic characteristics of a system at a granular level while also utilizing the ability to examine the process of managing the multi-step nature of the supply chain. Moreover, this research significantly contributes to the domain of healthcare operations by illustrating how a hybrid DES-NDEA framework can inform evidence-based resource allocation and policy-making in emergency departments. The identification of diagnostic imaging as a critical bottleneck, along with the measurable advantages of incorporating dedicated CT and MRI units, offers actionable insights for hospital administrators aiming to enhance patient throughput and service quality. The incorporation of expert feedback into the model development process further enhances the practical significance of the study. In summary, the research presents a scalable and flexible methodology that connects operational modeling with efficiency analysis, thereby facilitating data-driven decision-making in intricate healthcare settings.

5.1 Research limitations and future research suggestions

This study offers significant insights into enhancing emergency department performance through the use of simulation and Network Data Envelopment Analysis (NDEA); however, it is not devoid of limitations. The analysis relied on data from a single hospital, which may restrict the applicability of the findings to other healthcare institutions or systems. Furthermore, the research concentrated solely on quantitative performance metrics, including patient flow time, queue waiting time, and operational costs, neglecting qualitative aspects such as patient satisfaction, staff experience, and clinical quality. The simulation model presupposed a relatively stable environment, failing to account for disruptions like pandemics or unexpected demand surges. Additionally, elements such as budget limitations, feasibility of implementation, and availability of resources were not explicitly incorporated into the model. In light of these constraints, future investigations could consider the incorporation of uncertainty and dynamic demand modeling to improve realism. Including qualitative indicators in the efficiency assessment would also yield a more holistic understanding of system performance. Comparative analyses across various departments or hospitals, along with hybrid models that merge NDEA with multi-criteria decision-making or optimization algorithms, may provide deeper and more widely applicable insights. Lastly, performing sensitivity analyses could assist in pinpointing the most influential variables for enhancing healthcare supply chain efficiency and facilitating more informed managerial decisions.

5.2 Suggestions to integrate with other performance evaluation frameworks

The hybrid model that integrates Discrete-Event Simulation (DES) with Network Data Envelopment Analysis (NDEA) presents a comprehensive framework for assessing efficiency and operational performance within the healthcare sector. This model can be seamlessly combined with various performance evaluation methodologies to yield more in-depth insights:

i) Balanced Scorecard (BSC): The hybrid model enhances BSC by providing quantitative operational metrics (such as patient flow times and resource utilization) to the "Internal Processes" and "Customer Perspective" dimensions, thereby improving strategic decision-making.

ii) Lean Six Sigma: Outputs from the simulation that pinpoint process bottlenecks can directly support Lean Six Sigma initiatives, while NDEA scores can be utilized to evaluate the effectiveness of interventions designed to minimize waste and variability.

iii) Multi-Criteria Decision Making (MCDM): This model can be integrated with MCDM techniques (for instance, AHP and TOPSIS) to incorporate qualitative factors such as patient satisfaction, staff welfare, or clinical outcomes in conjunction with efficiency metrics derived from NDEA.

iv) Machine Learning Forecasting Models: The simulation aspect generates structured data that can be employed to train predictive models for demand forecasting, while NDEA assists in confirming the sustainability of the forecasts made.

5.3 Practical implications

The hybrid model that integrates DES with NDEA offers significant insights for healthcare administrators who seek to enhance the performance of emergency departments. The findings of this research indicate that implementing specific modifications, such as the introduction of dedicated MRI and CT scan equipment for emergency department operations, can lead to a notable decrease in waiting times and patient flow durations. These results provide practical recommendations for the allocation of resources and the optimization of processes within emergency departments, underscoring the necessity of focused enhancements to tackle critical bottlenecks, particularly in diagnostic imaging. The model established in this research can be utilized across various healthcare supply chains, allowing managers to evaluate different improvement scenarios, assess resource efficiency, and make informed decisions that improve patient throughput and the quality of services.

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