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An intelligent algorithm for optimization of resource allocation problem by considering human error in an emergency department

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Abstract

Human error is a significant and ever-growing problem in the healthcare sector. In this study, resource allocation problem is considered along with human errors to optimize utilization of resources in an emergency department. The algorithm is composed of simulation, artificial neural network (ANN), design of experiment (DOE) and fuzzy data envelopment analysis (FDEA). It is a multi-response optimization approach to optimize human error, cost, wait time, and patient safety, and productivity. Skill, rule, and knowledge (SRK) based approach is used to model human error. Simulation is applied to determine the relationship between human resource utilization and human error and also to model SRK behavior. ANN is utilized to predict response variables. FDEA is used to identify the optimum scenario. This is the first study that considers human errors along with resource allocation in the emergency department (ED). Second, it is equipped with verification and validation at each phase. Third, it is a practical approach for emergency departments (EDs).

Keywords: Human error, resource allocation, skill, rule, knowledge-based approach, multi-response optimization, discrete-event simulation

1- Introduction

The healthcare sector has become a very complex system in the last decade due to the growth in patient referral(Plsek and Greenhalgh, 2001).The other main reasons for this complexity are the emergence of various departments and a variety of services to patients (Carayon, 2016).It is important to note that healthcare sector couldn't deal with this complexity and it led to the human errors' growth(Berwick, 2003).Some researchers have evaluated and compared different industries due to safety and error, and finally determined healthcare sector as an unsafe industry (Amalberti et al., 2005).Carthey et al. (2001)studiedthe human error rate and finally stated that about ten percent of patients who visit healthcare sector face human errors in their treatment process. Increasing the number of patient referral to healthcare sector puts more pressure on the system and its resources. Workload growth leads to exhaustion of resources (fatigue), reduction of human resources' concentration, and finally more human errors (Montgomery, 2007).Error classification frameworks and approaches are widely used in the last decade and many sources of human errors are determined in the healthcare sector. Although various frameworks and approaches are presented to this day, Skill, Rule, and Knowledge

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(SRK) based behavior which is presented by (Rasmussen, 1982) is one of the most applicable concepts. SRK based behavior classifies human errors in an organization into three main groups as follows:

- Skill-based errors: This type of error occurs when the operator is not at an acceptable level of conscious. The skill-based error is classified into two groups of error including lapses and slips. Lapse occurs when the operator forgets some part of an activity while slip occurs when the operator performs a part of an activity in a wrong way. Both types of skill-based errors are done unintentionally. The sources of this type of error can be fatigue and lack of concentration.
- Rule-based error: This type of error occurs when the operator employs a wrong rule or instruction in performing a right activity or right rule or instruction in a wrong activity.
- Knowledge-based error: This type of error occurs when the operator faces an activity which is not meant to happen and the operator has not been trained for it. In this situation, he has to apply his knowledge for performing the activity. If any error happens in this situation, it should be classified as a knowledge-based error.

Later, many researchers have studied SRK based behavior and improved its application and algorithm. Reason (1997) presented a new algorithm based on SRK behavior for error classification. Since researchers faced some problems in employing the presented algorithm, Saurin et al. (2008) presented an improved algorithm for error classification based on SRK based behavior.

Various sources of human errors are determined in healthcare sector. One of the most important and mentioned sources of human errors in the healthcare sector is workload which leads to concentration and ability reduction. When the workload increases in a system, the resources have to work harder and without any rest. In ED this problem is much more important and complicated. The patient arrival rate into EDs is stochastic and most of the time their health status is critical (or after a while, their health status may become critical) and they need a fast examination (Lynn and Kellermann, 1991). It is possible to evaluate and measure workload in an ED using utilization. Utilization is an index which takes values between 0 and 1. Utilization equal to 1 means that the resource has been busy all the time and didn't have any time for rest and in other words show the high workload in a system. Utilization is significant in resource allocation and is considered as one of the objectives that should be maximized in most of the studies. It is important to consider human factors when optimizing a system that is composed of human resources. It is possible to consider utilization as a key to connect conventional resource allocation problem with optimizing human errors in a system.

1-1- Human error in healthcare

Many researchers have studied human error identification and classification in the last decade. van der Sijs et al. (2010) used SRK based behavior and simulation environment to study the correctness of drug safety alert handling and errors. Moody (2012) employed lean principles and human factors in an ED. They used SRK based behavior for error classification. Vaughn-Cooke et al. (2015) studied error classification among diabetes patients and identified two main categories including skill-based errors and intentional violations. At the end, they presented risk mitigation strategies for safety improvement. Fernandez and Gillis-Ring (2003) reviewed the literature and presented strategies for preventing human errors in the healthcare sector. Azadeh et al. (2016) used improved SRK based behavior and discrete-event simulation for human error classification and optimization in an emergency department (ED).

1-2- Simulation in healthcare

Many researchers have studied resource allocation in ED in the last decade. Amaral and Costa (2014) presented an approach based on multi-criteria decision analysis for resource allocation in an ED in Brazil. They used PROMETHE II method for analyzing the collected data. The results showed 70% reduction in waiting time of patients. Azadeh et al. (2013) used discrete-event simulation and data envelopment analysis to improve the quality of care in medical centers. Al-Refaie et al. (2014) presented a simulation-based approach to optimizing the performance of an ED in a Jordanian hospital. The presented approach evaluated possible scenarios and finally, the best scenario determined using data envelopment analysis (DEA). Abo-Hamad and Arisha (2013) presented a simulation-based framework to determine the most efficient level of resources in order to optimize the objectives such as cost, patients' waiting time and costs of human resources. Rau et al. (2013) used discrete event simulation as

an effective tool for strategic capacity planning for an outpatient therapy clinic. They showed that average waiting time for new patients decreased if they were given priority over returning patients. There are several tools to evaluate, improve, and optimize processes in industrial and service units. Discrete event simulation (DES) is known as an applicable tool for evaluation and optimization of complex systems in which mathematical modeling is not applicable(Nasiri et al., 2017). Using simulation in the healthcare sector is not new. It is been about four decades that researchers especially non-academic healthcare practitioners use simulation as a decision support technique (Gaba, 2007).

In this study, an integrated algorithm for optimizing resource allocation and human errors is presented. The purpose of this study is to present an integrated algorithm for optimizing resource allocation with respect to a human error in an ED. This is the first study that considers human error and safety along with resource allocation, simultaneously. The presented algorithm is composed of multi-response optimization, SRK based behavior. The contributions of the current study comparing previous studies are as follow:

- This is the first study that considers skill, rule, and knowledge based errors in resource allocation problem in healthcare sector.
- The relation between utilization and human errors' rate of occurrence is quantified using least square error regression models.
- The proposed multi-objective problem considers traditional objectives such as cost and time along with patient safety.
- The proposed algorithm is capable of dealing with hybrid uncertainty. Simulation modeling deals with stochastic parameters, while fuzzy based methods are used to deal with uncertainty in decision making.

2- Methodology

This study presents an integrated algorithm for optimizing resource allocation and human errors. First, the historical data regarding human errors are collected per day for 6 months from the case under study. Then, using improved error classification algorithm presented by (Saurin et al., 2008) each error type is classified. In the next step, the relation between resource responsible for the error and its utilization is determined. This relation is the key to connect this phase to the next phase which is simulation-based optimization. The flowchart of the presented algorithm in this study is presented in figure 1.
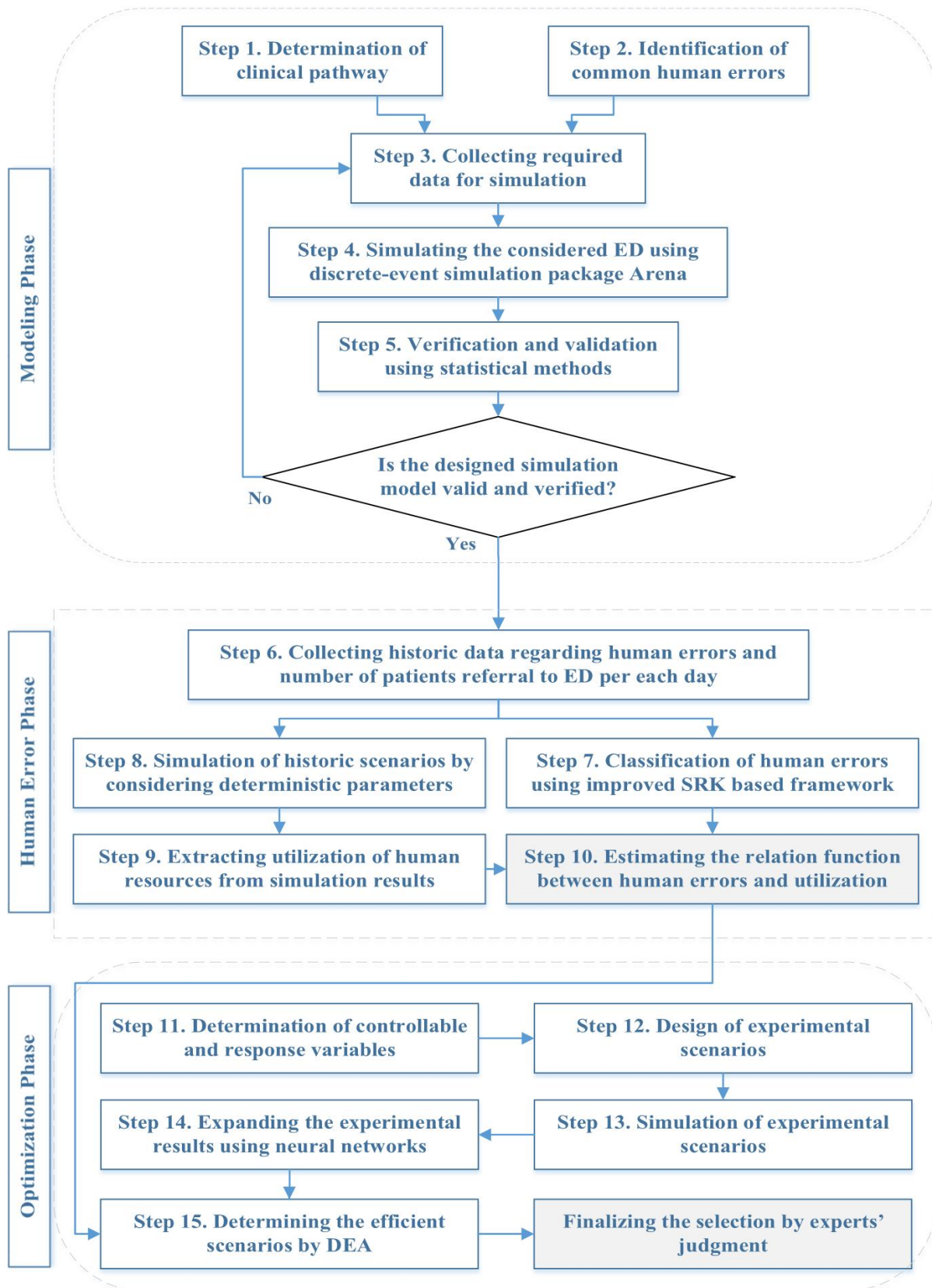
Fig 1. Flowchart of the presented algorithm

The steps of the presented algorithm are explained as follows:

2-1- Modeling phase

Step 1. Clinical pathway: In order to model a system, first, all the interactions, entities and processes in the system should be determined. Since the purpose of this study is to optimize an emergency department, the details of such a system should be determined. In the healthcare sector, patients are the most important entity which circulates through the system to get health services. The clinical pathway of each healthcare sector is defined based on many reasons and is specific. In order to determine the clinical pathway of the considered system, interviews with experts of the system should be performed.

Step 2. Identification of common human errors: In order to identify common human errors, interviews with experts and directors of the considered emergency department should be performed. Most of the emergency departments have the records of human errors in their information system.

Step 3. Collecting required data: Since the presented algorithm is simulation based, collecting required and validate data is a significant step. The required data are collected using the data records from ED information system such as time between the arrival of patients and the rest of data are estimated using experts' judgment such as required time for visiting fast patients.

Step 4. Modeling: ED is a complex system and in order to consider the problem as close as possible to real-world condition, discrete-event simulation (DES) is used instead of mathematical modeling. After determining the clinical pathway of considered ED and collecting required data for modeling, it is possible to simulate the department using a DES package.

Step 5. Verification and validation of simulation model: After simulating the considered ED, it is important to make sure that simulated model is representing the considered case with an acceptable level of error. In order to verify the simulated model experts' judgment is used. For validating the model, three performance variables for the model such as "mean wait time of patients in triage" are considered. The obtained results of the simulation model for performance variables are compared to real data collected from the case using 2 sample t-test.

2-2- Human error phase

Now in order to connect resource allocation problem with human errors reduction, the relation function between human resource utilization and rate of human errors should be determined. In this way, it is possible to consider the rate of human errors occurring as one of the response variables. The next phase is dedicated to this matter.

Step 6. Historical data collection: In order to determine the relation function between human resource utilization and rate of human errors' occurrence, historical data regarding a number of patients' referral to considered ED and human errors' reports are collected per day for six months.

Step 7. Human error classification: Many researchers have presented human error classification frameworks so far. SRK based behavior presented by Rasmussen (1990) is one the most known and accepted frameworks in this regard. In the presented algorithm, improved SRK behavior presented by (Saurin et al., 2008) is considered for classifying human errors. Considering the human error classification algorithm, it is possible to determine each historical data regarding human errors in considered ED. Since each type of human error has a different source of occurrence, in order to act effectively, the type of each error should be identified and then it is possible to make preventive and improvements plans. That's the reason for classifying human errors before estimating the relation function with human resource utilization.

Steps 8 and 9. Historical scenarios' simulation: After determining the number of human errors' occurrence for each day, it is possible to use simulation base model to evaluate each day by considering the number of patients referred to ED and number of human errors per each day as deterministic variables. After simulating all historical periods (100 days), the utilization of human errors responsible for errors are determined and extracted from simulation results.

Step 10. Relation function estimation: In order to evaluate the relation function between utilization of human resources responsible for errors with rate of human errors' occurrence, least squares estimation approach is employed for linear, quadratic and cubic regression. The variables considered for estimation are the utilization of human resource responsible for errors and rate of occurrence for each error type.

2-3- Optimization phase

Now the relation function between each type of human errors and resource utilization is determined and it is possible to evaluate the ED at different resource levels by considering human errors. The optimization phase is dedicated to resource allocation optimization by considering human factors.

Step 11.Controllable and response variables: In a simulation optimization approach, the meaningful changes are made to controllable variables in order to find the optimal values of response variables which are the objectives of the model. Controllable variables are representing the human resources and equipment for allocation. Controllable and response variables are determined based on the objectives of the study, budget and resource limitations and experts' judgment.

Step 12.Design of experiment (DOE): After determining controllable variables and their upper bounds and lower bounds, it is possible to use DOE to develop experimental scenarios. DOE is used when the number of all possible scenarios is high and it is time and cost consuming, and also when the optimization process may need to be repeated due to the erratic nature of the case. To do this, Taguchi is used in the presented algorithm as a known and acceptable method to design experimental scenarios.

Step 13.Simulation of experimental scenarios: In order to evaluate the experimental scenarios, the simulation-based model with stochastic variables is considered. Since the simulation base model is validated and verified, it is possible to change the inputs of the model and evaluate other situations for the case. Therefore, experimental scenarios are simulated and response variables of the model are extracted.

Since it is possible that optimal solution is not among experimental ones and only the experimental possible solutions are evaluated, experimental results should be expanded to the whole possible solutions. In the presented algorithm, ANN is used to expand the experimental results.

Step 14.Experimental scenarios' expansion: Now in order to expand the results of experimental scenarios into whole possible combinations of controllable factors, an estimation tool is needed. There are many estimation tools such as regression models and ANN that try to find some patterns in data at hand and then by using founded patterns, it is possible to estimate new scenarios' response variables. In presented algorithm multi-layer perceptron (MLP) is considered for prediction.

In the presented algorithm, ANN is used for estimation of all possible scenarios while experimental scenarios' data will be used for training and testing. The different structures should be examined to find the best estimation network for the problem at hand. Various structures are run and when the structure with a final error less than 0.1 is found the search is complete.

After finding the best estimation network, it is possible to estimate response variables for all possible scenarios. Since estimation networks are prone to errors (e.g., over fitting), each structure is run for ten times with random data sets (70% training data, 30% for test and validation and random DMUs for each data set in each run). After running each structure each time, two errors' components including training error and test error is extracted. The mean absolute percentage error (MAPE) for each structure is calculated by the following equations, Equations 1 to 3.

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\text{Actual Value}_i - \text{Set Point Value}_i}{\text{Actual Value}_i}\right| (N: \text{the number of rows}) \tag{1}$$

$$\text{Error}_n = \sqrt{(\text{Train. MAPE})_n * (\text{Test. MAPE})_n} \tag{2}$$

$$\overline{\text{MAPE}} = \frac{\sum_{n=1}^{10}\text{Error}_n}{10} \tag{3}$$

Equation 1 is used for calculating errors regarding training and test data. Since in estimation functions, overfitting is possible, and it cannot be diagnosed using a training errors indicator, errors related to testing data for calculating the final error of each run is considered. A geometric mean is used for calculating the related error of each run of each structure using equation 2. Besides considering test error in the final error indicator, random data sets in each run for each structure is used. Since each structure is run for ten times, equation 3is used for calculating the final mean error of each neural network structure. Finally, ANN-MLP and RBF different structures are evaluated, the search is done when a structure presents the $\overline{\text{MAPE}}$ less than 0.1 which is considered as the best estimation network

for the problem. After determining the best structure, it is used to estimate the non-experimented scenarios results.

The input variables of ANN, are controllable variables, which are a number of considered resources for allocation. The output variables of the model are response variables including mean weighted wait time of patients in the ED, mean wait time of patients in triage, mean utilization of nurses, a mean wait time of patients for bed, redundancy score, and cost. It is notable that outputs estimation is done by an ANN structure separately for each output.

Step 15.Determining the efficient scenario: The efficiency scores of all possible scenarios are calculated using fuzzy data envelopment analysis (FDEA). The scenario with the highest efficiency score is identified as the optimal scenario. Since it is possible to have more than one efficient DMU, DEA models considered in this study are full ranking models and are able to present values more than 1 which helps us to rank the scenarios easily.

3- Experiment

This study is employed in an actual ED in Tehran, Iran. The considered ED is located in the middle of Tehran, and one of the most crowded regions of capital and serves more than 30000 patients a year. The department is consisting of two main parts including "General" and "Critical" section. "Critical" section is composed of CPR and ICU units, which serves critical stage patients. About 95% of patients are served in "General" section while others are a critical stage and are referred to "Critical" section. The key resources considered in the department are Triage Nurse, Nurse, Physician, Beds, CPR units, and Oxygen capsule.

The department has two triage nurses, three physicians, four nurses, twenty beds, a CPR unit and three sets of oxygen capsules currently. The clinical pathway of considered ED is presented in Figure ۲. The patients' referral to the ED is classified into two clusters including "self-referral" and "ambulance delivery". After entering the ED, patients are monitored by triage nurses and the stage of patients is determined. There are four stages of the patients' illness severity including "fast", "sub-acute", "acute", and "critical (or CPR)" patients. Then each patient is sent to other divisions based on the patient's stage.

3-1- Human error

Human errors are rising in healthcare sector due to the congestion of patients and lack of experienced and well-trained staff. Common human errors of the considered department are also identified and presented in table 2. The information system of considered ED has archived the reports regarding stated human errors in the system.

Table 2. Common human errors in the considered ED

| Human Error	Error Explanation	Source of Error
Unsafe Transportation	This error occurs in patients transportation among sections of ED such as Radiography and usually cause physical injuries	The fatigue of nurse responsible for transportation and crowded ED are possible reasons. The old and wrong structure of building and routes is also a reason.
Venipuncture Error	This error causes the patients dissatisfaction and physical damage.	The lack of concentration due to fatigue and work pressure along with lack of experience and training are possible reasons.
Wrong Sampling	The treatment process lasts longer and leads to patient's dissatisfaction.	The lack of concentration due to fatigue and work pressure along with lack of experience and training are possible reasons.
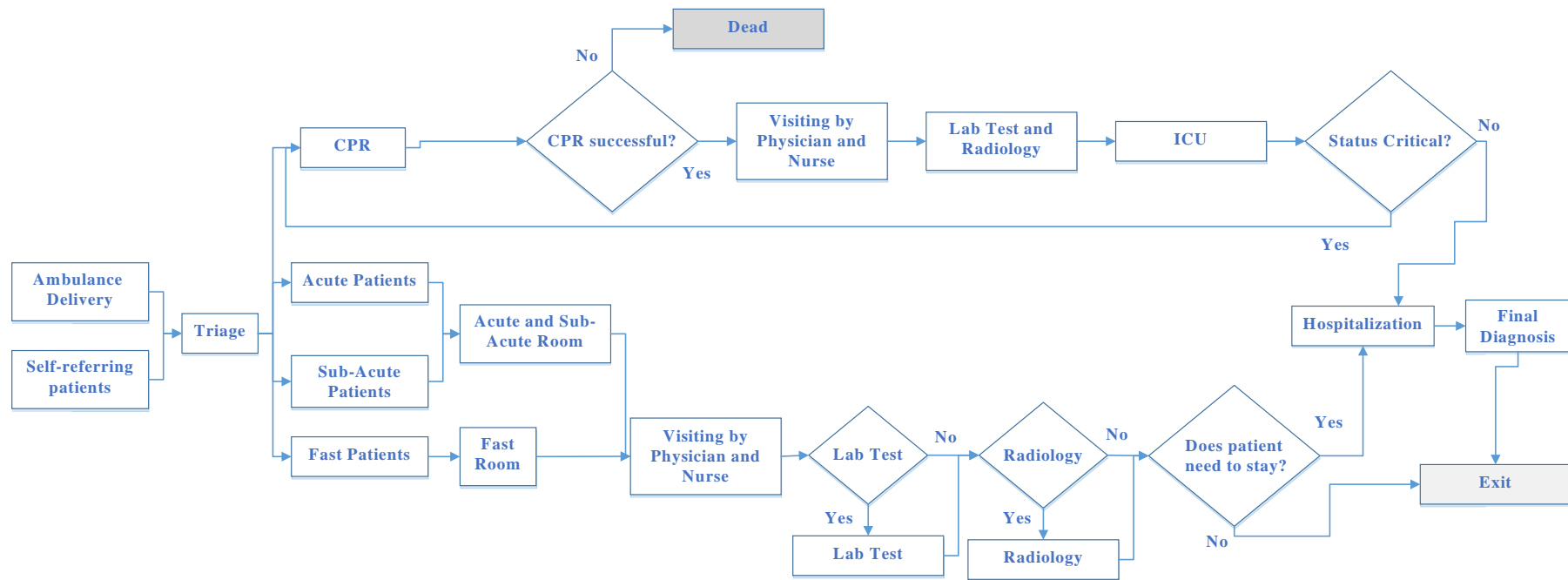
Fig 2. Clinical pathway of considered ED

3-2- Modeling

For modeling the problem based on the determined clinical pathway, discrete-event simulation package, Arena v.14 is used. Figure ٣ presents the designed model for the considered ED. The simulation package Arena is a modular discrete event simulation based package which has been used by many researchers in past decade(Nasiri et al., 2017).

The simulation model is designed based on the clinical pathway of considered department presented in figure ٣ and is explained as follows.

In this model, patients are known as entities. They enter the network via a Create module. Then, the severity of their illness is assigned to them through a Decide module and four Assign modules as attributes. Patients have to wait for nurses and doctors in the triage station, in which their severity stage is determined. After evaluation of patients' condition, they are transmitted to a fast, acute, sub-acute, and CPR rooms depending on the severity of their illness. During the transfer of patients to these rooms, there may be a transportation error. In this case, the patient's transportation time will be increased with a certain probability. Also, during this unsafe transportation, the illness severity of the patients may be increased with a certain probability. After transferring patients to rooms, the necessary services (e.g., Venipuncture, examination, etc.) are provided to patients via a Process module in which the action of seize-delay-release shows reserving and assigning required staff for a specific duration and release them after receiving services.

Then, if necessary, patients will undergo radiographic imaging and blood sampling. There can be possible errors during the process of venipuncture and sampling. The venipuncture errors can increase the time needed to conduct venipuncture and sampling errors which result in re-sampling. In the end, after taking due actions to stabilize patients' situation, if there is any need for further care, s/he will be transferred to hospitalization units, otherwise, s/he will be dismissed.

As mentioned earlier, three types of human errors are considered in the simulation model, including transportation, venipuncture and sampling errors. In order to show the occurrence of these errors, seven sub-models are designed (sub-models A-G), where sub-model A is used for transportation errors. Sub-models B-D are related to the venipuncture error and sub-models E-G are related to the sampling error.

In order to better understand how errors occur in the network, transportation error is explained in details as follows.

In sub-model A, only one entity is generated and enters the network at a specified time (shown in the table in the form of Bold). When this entity reaches "Assign13" module, an arbitrary variable (i.e., TP) will get a value of 2, which represents the occurrence of a transportation error in the network. Then, the entity waits in "Delay1" module as many as TBOTE until the next transportation error occurs.

By defining a condition (i.e. TP≤1) in a Decide module, the patient is directed to the "Assign1" module. Thereby, his/her transport time will be changed to a certain value (shown in the table in the form of Bold). Also, when an entity reaches "Assign1" module, the TP value is subtracted one unit. In this case, due to the defined condition (i.e. TP≤1) in the Decide module, the entities will be directed to the "Assign2" module and the transportation time will be restored. It should be noted that the initial value of variable TP is considered one.
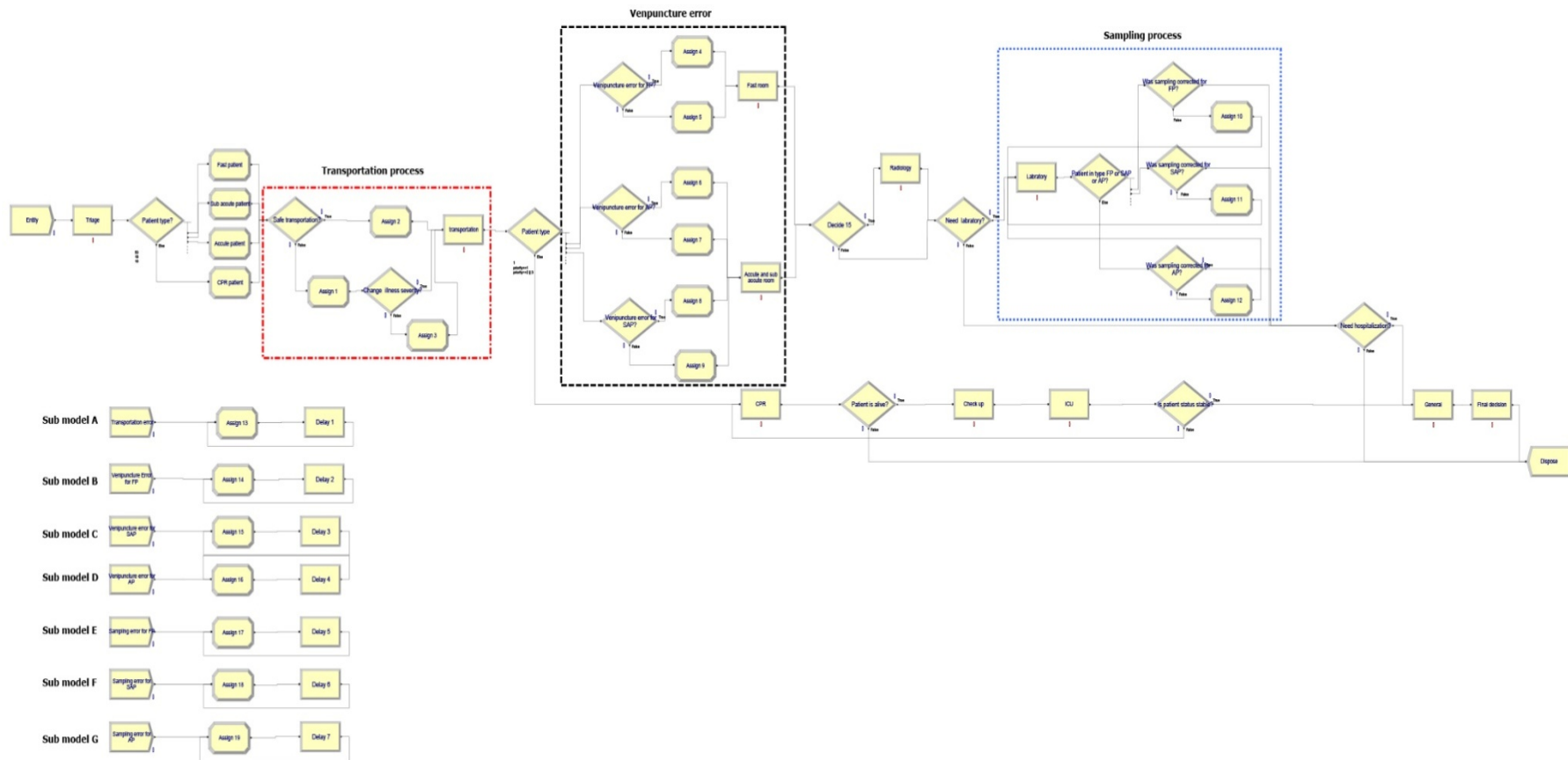
Fig 3. The simulation model of considered ED in Arena v.14

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3-3- Artificial Neural Networks (ANNs)

ANN is a processing algorithm inspired by biological nervous systems, such as the brain. ANNs are applied when there are no functional forms and there is a need for data-based algorithms. ANNs are great substitutes for regression models and other statistical analysis and techniques (Singh et al., 2003).

Among various artificial neural networks, ANN-MLP is a well-known method for estimation in engineering problems. MLP networks consist of an input layer, one or more hidden layers and an output layer. Each layer is composed of a number of particles called neurons working with each other for solving specific problems. In ANN-MLP, outputs are calculated using a linear combination of neurons in hidden layers, while each one is a function based on the weighted sum of inputs as follows (Equation 4):

$$y = f(x, \theta) + e \tag{4}$$

Where e is the error component, x is the vector of explanatory variables, and $\hat{y} = f(x, h)$ is the unknown function for prediction based on available data. The ANN-MLP network is as follows (Equation 5):

$$\hat{y} = F(v_0 + \sum_{j=1}^{m} H\left(\lambda_j + \sum_{i=1}^{n} x_i w_{ij}\right) v_j) \tag{5}$$

Where $\hat{y}$ the estimation value (i.e., output), F is the output layer function, H is hidden layer function, n is the number of inputs, m is number of hidden units, x is the input vector ($i = 1, ..., n$), θ is the weights vector, v_0 is the output bias, λ_j is the hidden units biases ($j = 1, ..., m$), w_{ij} is the weight from input unit i to hidden unit j, and v_j is the weight from hidden unit j to output. Some features (e.g., the number of hidden layers, training function, transfer function of hidden layers and number of neurons in hidden layers) can affect the performance of the created network. Thus, in order to find the best structure, trial and error method are used(Azadeh et al., 2017).

3-4- Data Envelopment Analysis (DEA)

DEA is used to evaluate the relative effectiveness of a group of decision-making units (DMUs), while there are several inputs and outputs for each DMU. The efficiency computed in this problem is the ratio of the weighted sum of outputs to the weighted sum of inputs. So for maximizing the DMUs' efficiency, inputs should be minimized while the outputs are fixed (input-oriented model) or outputs should be maximized while the inputs are fixed (output-oriented model). In this study four conventional DEA models including BCC input-oriented, BCC output-oriented, CCR input-oriented, and CCR output-oriented are considered. The input and output variables of each DEA model are presented in table 3.

Table 3. Input and output variables of DEA models

Input Variables	Output Variables
Number of Triage Nurses	Mean weighted wait time of patients
Number of Physicians	Mean wait time for patients in Triage
Number of Nurses	Frequency of skill-based Error
Number of Beds	Mean wait time for bed
Number of CPR units	Redundancy Score
Number of oxygen capsules	Cost

It is notable that the "frequency of skill-based error" is calculated based on the nurse utilizations which are estimated using ANN. Redundancy score is determined for each scenario based on the experts' judgment. Since the department refused to share the information regarding human resources expenses and costs, a relative set of values based on experts' judgment is considered.

There are *n (n=810)* DMUs and each of them has *m (m=6)* inputs and *s (s=6)* outputs, the efficiency of the *j*th DMU will be computed by mathematical programming model as follows:

$$Max\ \theta = \sum_{i=1}^{s} u_i \left(\alpha y_{jq}^m + (1-\alpha) y_{jq}^l, \alpha y_{jq}^m + (1-\alpha) y_{jq}^u \right)$$

$$s.t.$$

$$\sum_{j=1}^{m} v_j \left(\alpha x_{jq}^m + (1-\alpha) x_{jq}^l, \alpha x_{jq}^m + (1-\alpha) x_{jq}^u \right) = 1$$

$$\sum_{i=1}^{s} u_i \left(\alpha y_{jk}^m + (1-\alpha) y_{jk}^l, \alpha y_{jk}^m + (1-\alpha) y_{jk}^u \right)$$

$$- \sum_{j=1}^{m} v_j \left(\alpha x_{jk}^m + (1-\alpha) x_{jk}^l, \alpha x_{jk}^m + (1-\alpha) x_{jk}^u \right) \le 0, \quad k = 1,...,n$$

$$u_i, v_j \ge 0, \ j = 1,...,m, \quad i = 1,...,s.$$

(8)

The proposed model is developed based on α-cuts method. It considers input and output variables as triangular fuzzy numbers. Since simulation results are stochastic, the minimum values obtained for each variable are considered as minimum values of fuzzy numbers. The mean values are considered as the center of the fuzzy numbers, finally maximum value of the variable is considered as the maximum value of fuzzy numbers. For controllable variables, fuzzy numbers are considered equal due to deterministic nature.

4- Computational results
The obtained numerical results are presented as follows:

4-1- Collecting required data for simulation
Required data for simulation are collected from the considered ED and are presented in table 4.

Table 4. Distribution function of processes

Process	Explanation	Distribution Function (minutes)
Patients Arrival	Time between arrivals of patients	Exponential(10)
Initial Examination (Triage)	The time of initial examination	Tria(1, 2, 3.5)
Transportation Time	The required time for transporting patients to the rooms based on the patients' stage	Tria(1.5, 2, 3)
CPR	The required time for performing CPR	Tria(40, 60, 110)
Acute and Sub-Acute Room	The required time for nurse	Tria(3, 4, 5)
	The required time for both physician and nurse	Tria(5, 6.5, 8)
Fast Room	The required time for nurse	Tria(2, 4, 5)
	The required time for both physician and nurse	Tria(2, 4, 5)
Blood Test (Laboratory)	Preparing the results of blood test	Tria(140, 220, 310)
Final Diagnosis	The process time for critical patients	Tria(4, 6, 8)
	The process time for acute patients	Tria(3, 4, 5)
	The process time for sub-acute patients	Tria(2, 3, 4)
Repeated Venipuncture (Error)	The time between occurring repeated venipuncture error in acute	Exponential(450)
	The time between occurring repeated venipuncture error in sub-acute room	Exponential(1280)
	The time between occurring repeated venipuncture error in fast room	Exponential(2250)
Consequence of Repeated Venipuncture Error	The process in acute and sub-acute room for acute patients	Tria(3.5, 5, 6.5)

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Table 4. Distribution function of processes

Process	Explanation	Distribution Function (minutes)
	The process in acute and sub-acute room for sub-acute patients	Tria(3, 3.5, 5.5)
	The process in fast room for fast patients	Tria(3, 4, 5.5)
Sampling Error	The time between occurring sampling error in acute room	(7200*Beta) a = 0.46, b = 1.5
	The time between occurring sampling error in sub-acute room	(7200*Beta) a = 0.296, b = 1.11
	The time between occurring sampling error in fast room	(17300*Beta) a = 0.348, b = 1.99
Repeated Sampling	The required time of process	Tria(230, 310, 350)
Transportation Events(Error)	The time between occurring unsafe transportation error	Exponential(1750)
Consequence of Transportation Error	The required time for transferring patients is increased	Triangular(3, 4, 5)

4-2- Verification and validation of simulation model

The simulation verification and validation results are presented in table 5.

Table 5. Verification and validation results for simulation model

Performance Variable	Real Data	Simulation Results	t-test Results
Mean wait time in Triage	Sample Size = 30 Sample Mean = 5.04 Standard Deviation = 0.6282	۴٫۵۴۰۵	p-value = 0.097 Confidence Level = 0.95
Mean wait time for bed	Sample Size = 30 Sample Mean = 31.5 Sample Standard Deviation = 6.0034	28.5673	P-value = 0.112 Confidence Level = 0.95
Mean wait time of fast patients for examination in fast room	Sample Size = 30 Sample Mean = 16.3 Sample Standard Deviation = 3.582	17.4832	P-value = 0.172 Confidence Level = 0.95

4-3-Historical data collection

The historical data regarding human errors' occurrence in considered ED including wrong sampling, repeated venipuncture, and unsafe transportation are collected from the case under study.

4-4- Human error classification

After collecting historic data regarding human errors, SRK based behavior is employed for error classification. The results of human error classification are presented in table 6.

Table 6. The results of human error classification

Human Error	Error Type	Source of Error	Error Frequency Percentage
Unsafe Transportation	Skill-Based	Crowd and work pressure which cause resource fatigue and loss of focus	%۵۵
	Rule-Based	Lack of attention to patients' transportation procedures	%۲۱
	Knowledge-Based	Insufficiency and inability of the human resource + lack of experience	%۲۴
Repeated Venipuncture	Skill-Based	Crowd and work pressure which cause resource fatigue and loss of focus along with lack of training	%۴۴
	Rule-Based	Lack of attention to venipuncture procedures	%۱۰
	Knowledge-Based	Insufficiency and inability of the human resource + lack of experience	%۳۲
	No Error	The human resource is not responsible for the error	%۱۴
Wrong Sampling	Skill-Based	Crowd and work pressure which cause resource fatigue and loss of focus	%۵۹
	Rule-Based	Lack of attention to sampling procedures	%۱۷
	Knowledge-Based	Insufficiency and inability of the human resource + lack of experience	%۲۴

4-5- Historical scenarios' simulation

After collecting the number of patients' referral to the considered ED for historic data and classifying related human errors, it is possible to simulate each day using simulation model and extract the utilization of human resources responsible for errors. The related results for historic data are presented in appendix 1.

4-6- Relation function estimation

Now it is possible to determine a relation function between resource utilization and rate of each human error type using least square estimation. The results of the correlation coefficient between each type of error and resource utilization are presented in table ۷.

Table 7. Correlation between each type of human error and resource utilization

Human Error	Correlation Coefficient	Confidence Level
Skill-Based	**0.888**	**%۹۵**
Rule-Based	-0.220	%۹۵
Knowledge-Based	0.133	%۹۵

As shown in table 7, only skill-based error has a direct relation with the utilization of human resource responsible for error (Nurse). After evaluating linear, quadratic and cubic regression estimation, it determined that cubic regression has the best performance in estimation as it is shown in figure 4. The result for cubic regression estimation is presented in figure 5.
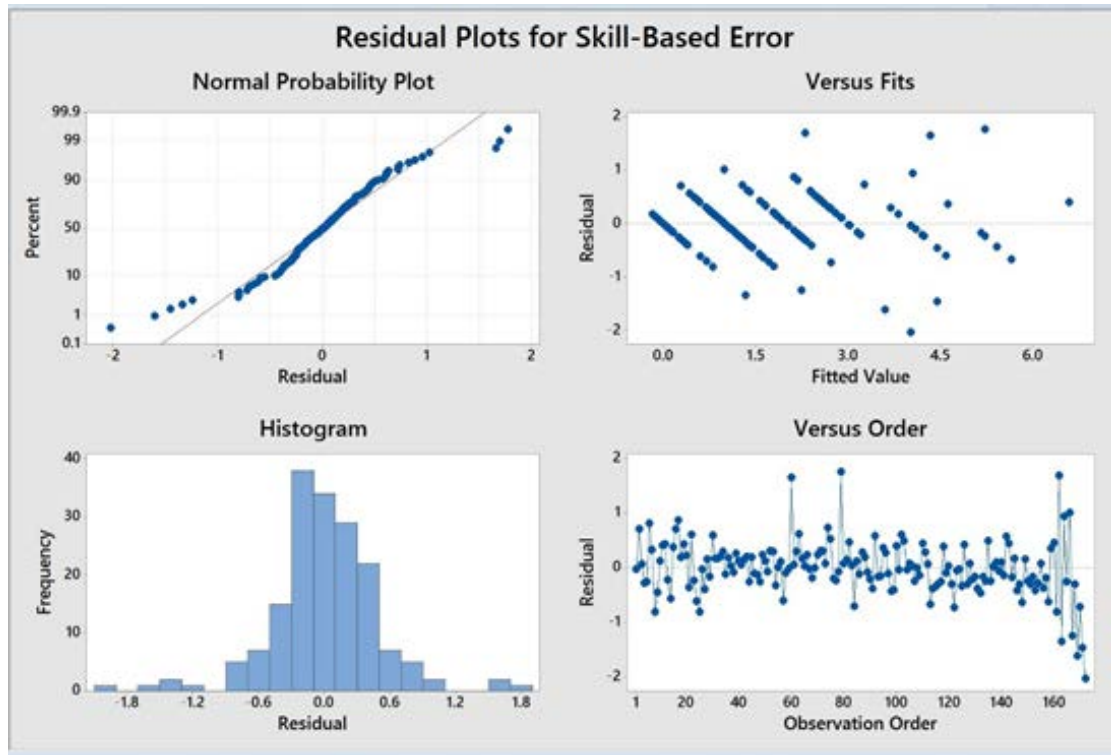
Fig 4. The performance of cubic regression for relation function estimation of skill-based error
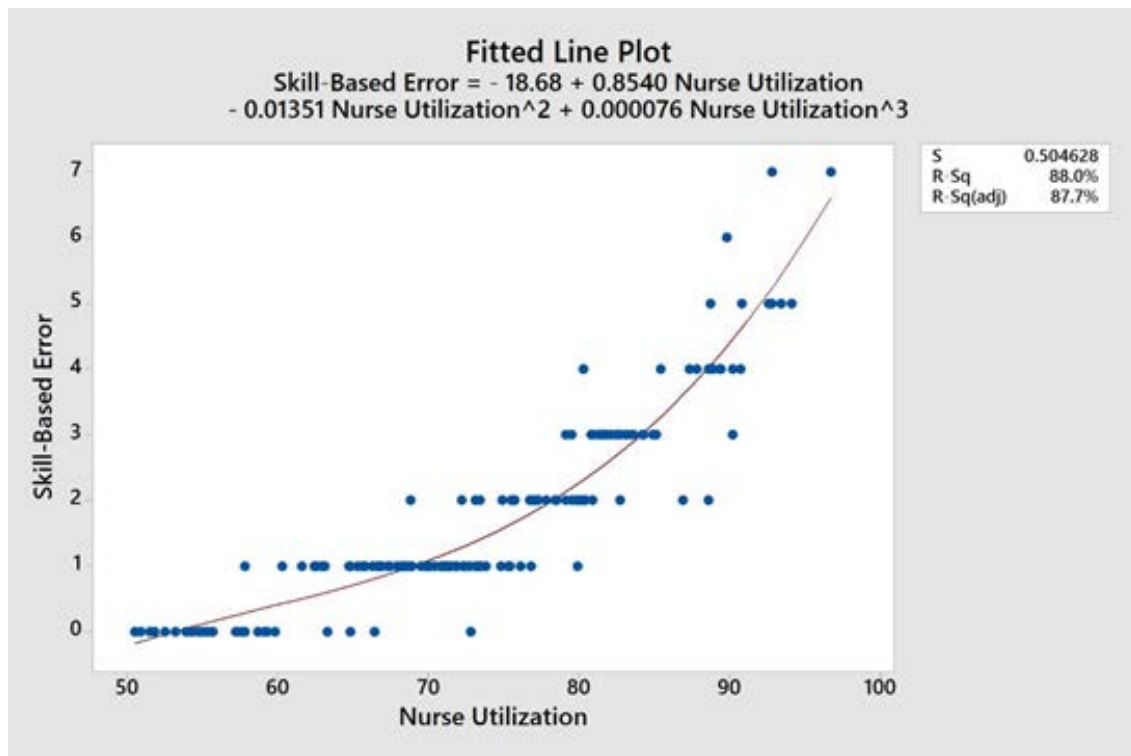

Fig 5. Result of cubic regression for relation function estimation of skill-based error

Finally, the relation function between nurse utilization and skill-based error is presented in equation 12.

$$S = -18.68 + (0.8540 * U) - (0.01351 * U^2) + (0.000076 * U^3) \tag{12}$$

4-7- Controllable and response variables

Since the main goal of this study is to optimize resource allocation in healthcare, controllable variables are considered based on resources and equipment. Controllable variables of this study are presented in table 8.

Table 8. Controllable variables of the study

Controllable Variables	Lower Bound	Upper Bound
Number of Triage Nurses(X_1)	١	٣
Number of Physicians(X_2)	2	4
Number of Nurses (X_3)	٣	5
Number of Beds(Y_1)	٢١	٢٥
Number of CPR units(Y_2)	١	٢
Number of oxygen capsules (Y_3)	٣	5

4-8- Design of experiments

After determining controllable variables of the study, it is possible to develop experimental scenarios using the design of experiments. Experimental scenarios of this study are presented in table 9.

Table 9. Experimental scenarios developed by Taguchi DOE

Scenario	Replication	Triage Nurse	Physician	Nurse	Bed	CPR	Oxygen capsule
1	1	1	2	3	21	1	3
2	2	1	2	3	21	1	3
3	3	1	2	3	21	1	3
4	4	1	2	3	21	1	3
5	5	1	2	3	21	1	3
6	1	3	4	5	21	1	5
7	2	3	4	5	21	1	5
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
179	4	1	4	3	25	2	4
180	5	1	4	3	25	2	4

4-9- Simulation of experimental scenarios

After developing experimental scenarios using the design of experiments, it is time to evaluate each scenario's performance. Therefore, each scenario is run using simulation model and response variables are obtained from the results. Experimental results obtained from simulation are presented in table 10.

Table 10. Response variables of experimental scenarios

Scenario	Mean weighted wait time of patients	Mean wait time for patients in Triage	Nurse Utilization	Mean wait time for Bed	Redundancy Score	Cost
1	0.48878	0.12233	0.92511	0.48734	0.52632	178.5
2	0.41116	0.10238	0.95455	0.54363	0.52632	178.5
3	0.49512	0.11938	0.96041	0.57893	0.52632	178.5
4	0.42356	0.09473	0.90473	0.50478	0.52632	178.5
5	0.55929	0.14724	0.92526	0.49865	0.52632	178.5
6	0.03433	0.00635	0.75484	0.56282	0.94737	193.5
7	0.03052	0.00427	0.78436	0.60238	0.94737	193.5
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
179	0.06453	0.17655	0.91480	0.01684	0.73684	301
180	0.07143	0.14679	0.93974	0.01858	0.73684	301

4-10- Experimental scenarios' expansion

In order to expand experimental results to the whole possible scenarios, ANN-MLP is been considered. First, the best structure of ANN should be determined. Parameter tuning results for each output using ANN-MLP is presented in tables 11.

Table 11. Optimal artificial neural network structures for output estimation

Estimation Network	Output 1	Output 2	Output 3	Output 4	Output 5	Output 6
Mean Absolute Error	0.0912	0.0896	0.0831	0.0769	0.0994	0.0901
Structure	MLP –12th structure	MLP – 8th structure	MLP – 3th structure	MLP- 7th structure	MLP – 8th structure	MLP – 12th structure

Finally, response variables of all possible scenarios are estimated using optimal ANN structures determined in table 11and are presented in table 12.

Table 12. Response variables of all possible scenarios

Scenario	Mean weighted wait time of patients	Mean wait time for patients in Triage	Frequency of skill-based Error	Mean wait time for bed	Redundancy Score	Cost
1	0.083204039	0.06241201	3.734654584	0.482562800	0.789473684	286
2	0.085995326	0.098590681	3.947802804	0.361487992	0.684210526	287.5
3	0.096704514	0.043142716	4.383490096	0.052352458	0.736842105	294
4	0.043886979	0.003107543	1.056535765	0.448396541	0.947368421	296
5	0.041315589	0.006029096	1.613332521	0.522501551	0.947368421	293
6	0.055730016	0.04996295	2.199508690	0.351751293	0.736842105	193.5
7	0.561875696	0.007679562	0.699579469	0.448987034	0.736842105	182.5
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
806	0.566786899	0.122053497	1.316094807	0.136963216	0.736842105	287
807	0.065593522	0.006766870	2.366414305	0.060382783	0.894736842	201.5
808	0.472130612	0.006815953	3.343298863	0.560742363	0.736842105	281.5
809	0.080160969	0.007021427	0.749469553	0.156705080	0.947368421	294.5
810	0.093708727	0.054557812	4.380229296	0.016415600	0.789473684	297.5

4-11- Determining the efficient scenario

In order to determine the optimal scenario among all possible scenarios, FDEA is used. FDEA calculates an efficiency score for each scenario considering the controllable and response variables. The obtained results for optimal scenarios are presented in table 13.

Table 13. Most efficient scenarios among all possible scenarios

Rank	Scenario Number	Triage Nurse	Physician	Nurse	Bed	CPR	Oxygen Capsule	Mean weighted wait time of patients	Mean wait time for patients in Triage	Frequency of skill-based Error	Mean wait time for bed	Redundancy Score	Cost
1	507	3	4	5	22	1	3	0.035038	0.003058	0.720896	0.283646	0.842105	195.5
2	327	3	4	5	24	1	3	0.037098	0.004265	0.85305·	0.044381	0.842105	201.5
3	314	3	4	5	25	1	3	0.035409	0.003709	1.190421	0.016233	0.842105	204.5
4	93	3	4	5	21	1	3	0.036636	0.003484	0.911279	0.514104	0.842105	192.5
5	303	2	4	5	25	1	4	0.040248	0.031538	0.784326	0.010913	0.842105	204
6	81	3	4	5	25	1	4	0.038710	0.005067	1.501912	0.009207	0.894736	205
7	32	3	4	5	24	1	4	0.042610	0.004782	1.133768	0.055915	0.894736	202
8	501	3	4	5	23	1	4	0.038517	0.007032	0.600736	0.141904	0.894736	199
9	701	3	4	5	22	1	4	0.047888	0.003337	1.2576··	0.317495	0.894736	196
10	742	3	4	5	25	1	5	0.046212	0.003411	1.612639	0.011512	0.947368	205.5

After confirming results by the experts of considered ED, based on the estimated values for response variables and controllable values of these efficient scenarios, scenario number 2 is determined as the best scenario.

In order to evaluate the improvements, the determined optimal scenario is compared with the current situation of the considered ED and related results are presented in table 14.

Table 14. Comparison between optimal scenario and current situation of the ED

Scenario	Triage Nurse	Physician	Nurse	Bed	CPR	Oxygen Capsule	Mean weighted wait time of patients	Mean wait time for patients in Triage	Frequency of skill-based Error	Mean wait time for bed	Redundancy Score	Cost
Optimal Scenario 327	3	4	5	24	1	3	0.0370	0.0042	0.853	0.0443	0.842	201.5
Current Situation ٤٧٤	2	3	4	21	1	3	0.0752	0.0613	3.486	0.5173	0.684	185.5
Improvements and Performance Changes							-50.7%	-93.1%	-75.5%	-85.2%	23%	8.6 %

5- Conclusion

The purpose of this study was to present an integrated algorithm toward optimizing resource allocation by considering human errors in an emergency department. An actual ED in Tehran, Iran was considered as the case under study. Since work pressure is known as a significant source of human error, it is important to present an integrated algorithm toward balancing the utilization of resources in order to reduce human errors. In this regard first, required data for modeling the case under study was collected from the case. Then, the simulation model was validated and verified by collecting real data regarding three performance variables and comparing them to simulation results using t-test. Then historic data regarding human errors in the considered ED along with a number of patient referral per day were collected from the ED's database. In the next step, human errors' historic data evaluated using improved error classification SRK based behavior presented by (Saurin et al., 2008). After obtaining each type of error frequency per day, each day was simulated using simulation base model and with considering a number of patients' referral to the case. Then the utilization of nurses (human resource responsible for the identified errors) extracted from the results. After that by employing Spearman

correlation coefficient between nurses' utilization and frequency of each type of error was calculated. The results indicated that utilization of human resources responsible for errors and skill-based error's frequency are correlated (p-value = 0.888). In order to determine the relation function between nurses' utilization and skill-based error's frequency, least squares method was employed. Since utilization is the main index in optimizing resource allocation, after obtaining the relation function between utilization of nurses and human errors, it is possible to integrate both concepts and optimize them both. In this regard, controllable variables were determined based on the human resources and key equipment of considered ED. Then thedesign of experiments was used to develop experimental scenarios. After that, each experimental scenario was simulated and response variables of the study, which represents the objectives of the study, were obtained. In order to expand the experimental results to the whole possible scenarios, ANN-MLP is employed. First, best structures of ANN are determined for each response estimation. Then all possible scenarios' response variables were estimated. In order to find the optimal scenario, FDEA was used in this study. The efficiency scores of all possible scenarios calculated and efficient scenarios determined. Final results indicated that by adding one more triage nurse, one more physician, one more nurse and four more beds to the department, mean weighted wait time of patients will be reduced by 50.7%, mean wait time for patients in triage will be reduced by 93.1%, frequency of skill-based error will be reduced by 75.5%, mean wait time for bed will be reduced by 85.2%, and redundancy score will be increased by 23%. Although this improvement increases the resource costs of the considered ED by 8.6%.

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Appendix 1. Mean utilization of nurses for historic data

March	Utilization (%)	April	Utilization (%)	May	Utilization (%)	June	Utilization (%)	July	Utilization (%)	August	Utilization (%)
1	78.4	1	55.7	1	53.2	1	83.1	1	57.8	1	80.9
2	72.2	2	73.4	2	89.8	2	69.9	2	71.9	2	80.2
3	77.8	3	66.7	3	68.3	3	89.3	3	96.7	4	75.4
4	80.1	4	50.5	4	64.8	4	73.1	4	70.1	5	77.1
6	71.9	5	76.7	5	73.1	5	80.9	5	68.5	6	92.8
7	79.5	6	87.3	6	66.6	6	55.7	6	72.3	7	72.4
8	75.7	7	54.9	7	52.5	7	70.8	7	82.7	9	70.9
9	66.4	8	76.9	8	65.7	8	90.8	8	69.5	10	73.5
10	73.8	9	68.6	9	88.6	9	82.7	9	84.2	11	57.6
11	77.3	10	54.3	10	79.5	10	54.7	10	58.7	12	67.9
12	62.9	11	65.3	11	68.9	11	93.4	11	74.9	13	59.3
14	81.8	12	83.5	12	65.7	12	59.8	12	72.4	14	71.1
15	71.5	13	68.2	13	82.5	14	63.1	13	67.9	15	75.3
16	74.8	14	66.9	14	64.7	16	78.5	14	85.1	16	75.5
17	82.1	15	76.7	15	51.8	17	80.8	15	84.9	18	81.7
18	57.8	16	57.2	17	85.4	19	81.5	16	73.2	19	76.8
19	79.1	17	66.3	18	81.3	20	84.3	17	90.2	20	80.3
20	76.8	18	88.9	19	71.3	21	67.9	18	55.6	21	72.8
21	62.6	19	79.1	20	79.8	22	68.6	19	71.8	22	88.7
22	65.8	20	57.3	21	54.2	23	89.4	20	61.6	23	71.9
23	59.1	21	65.6	22	92.8	24	68.9	21	79.9	24	68.8
24	80.8	22	67.3	23	67.9	25	55.2	22	68.7	25	79.9
25	79.8	23	69.8	24	50.9	26	62.4	23	83.6	26	72.3
26	63.3	24	64.7	25	81.6	27	82.6	24	53.9	27	86.9
27	76.8	25	87.3	26	68.4	28	77.8	25	51.5	28	76.1
28	78.4	26	80.4	27	64.8	29	94.1	26	55.3	29	90.2
29	73.3	27	68.8	28	67.3	30	73.2	27	60.3	30	88.6
30	66.8	28	67.4	29	70.4	31	72.7	28	62.4	-	-
-	-	29	90.7	30	82.6	-	-	29	92.6	-	-
-	-	30	70.1	-	-	-	-	30	87.8	-	-