Simulation Modeling for Evaluation of the Patients' Queue System Performance at Emergency Department

Arman Bahari (✉ arman_bahari@eng.usb.ac.ir)

University of Sistan and Baluchestan

Farzaneh Asadi

Islamic Azad University Branch of Lahijan

Behnoosh Moody

University of Sistan and Baluchestan

Research Article

Keywords: Healthcare management, Emergency department, Meta-modeling, Simulation-based-optimization, factorial design

Posted Date: June 3rd, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-517784/v1>

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Simulation modeling for Evaluation of the Patients' Queue system Performance at Emergency Department

Arman Bahari ^{1*}, Farzaneh Asadi ², Behnoosh Moody³

¹ Ph.D. in Industrial engineering, Assistant Professor, Faculty of Industry and Mining, University of Sistan and Baluchestan, Zahedan, Iran

² Ph.D. student of Industrial Engineering, School of engineering, Islamic Azad University Branch of Lahijan, Lahijan, Iran

³M.Sc. in IT Management, University of Sistan and Baluchestan, Zahedan, Iran

* **Corresponding Author:** Arman Bahari

Abstract

Background: The aim of this article is to develop a metamodel using a simulation-based approach to analyze the performance of the Patients' Queue system of the emergency department.

Methods: In this study, the variables affecting on resource efficiency were identified and analyzed using inferential statistics and then one-way ANOVA to estimate the effects of effective factors. Furthermore, the ED performance was simulated using Visual Paradigm software. Then, the results obtained from the implementation of the simulation model were considered as the input of the experimental design.

Results: The findings indicate that the non-linear regression model could predict the length of the queue. Also, this model, according to acceptable parameters, can be used to predict the dependent variable.

Conclusion: Therefore, the minimum value of queue length based on the developed model is obtained when the minimum length of the queue is obtained when the number of ED secretaries is at a high level and the number of paramedics and nurses is at a low level.

Trial registration:

Keywords: Healthcare management, Emergency department, Meta-modeling, Simulation-based-optimization, factorial design

Paper type - Original Article

1- Background

Hospitals are considered as one of the key units in the health care system which play an important role in providing health care and therapeutic services. Normally, 50-80% of public health budgets are spent on hospitals. The decisions related to emergency department resources is always regarded as an important activity due to the vital impact of the emergency department on the health of individuals in the community which has a significant impact on the performance of the department (1). The emergency department is of great importance as the heart of the hospital and is considered as one of the first points of contact for patients in the health care system. This department has an important and sensitive place in the health care system due to the need for fast, effective quality care and its numerous and complex processes. Its proper management and organization of processes today is considered as one of the most important priorities of the Ministry of Health. Therefore, planning to find the strengths and weaknesses of improving the quality of emergency department through reviewing and analyzing its performance are considered as the important and valuable issues. Each wrong decision has irreparable consequences for the quality of services provided to patients. Therefore, the decision-maker should properly analyze the hospital system and resources, and then allocate them effectively. Such analysis is not easy in a system like the emergency department as the behavior of such an environment is random and the behavior of this system is time-dependent i.e. major changes in patient admission and service rates are observed over time. The process of using the emergency department as the main point of entry into the hospitals increased in recent years due to the significant growth of demand for various reasons such as population growth, leading to dissatisfaction among the clients (2-5).

However, people's dissatisfaction with the hospital service despite their high capacities and costs and the increasing demand for health and treatment forced the related managers to reduce costs

and increase efficiency and productivity by optimally allocating resources. Therefore, customer satisfaction is considered as one of the main and acceptable advantages in the service sectors (6-9).

In addition, the enactment of state laws in countries, especially in Iran, based on the 2025 vision plan and the declaration of the second phase of the revolution in Iran, which is becoming a model country in the region, requires the health system to supply high-quality services to patients in the shortest possible time. Therefore, the combined service providers and scarce resources in the field of health in different parts of these centers to determine the desired performance criteria under certain conditions and restrictions are considered as an important issue which is considered by researchers in the field of optimal management of health centers to improve the current situation (10).

The simulation model, mathematical programming, and statistics are considered as the most important instruments for managers to analyze the system. Researchers and specialists use these instruments to dynamically analyze the system without interrupting the system operation (11-13). Further, integrating real-world simulation models with designing experiment models is considered as a major challenge for a large number of professionals, researchers, and managers (14-18). The experiment design is used as a valuable set of mathematical techniques to statistically model and systematically analyze a problem with the desired response to optimize variables. This statistical technique is used to predict the model and evaluate the acceptable effects of queue system factors when integrated with the simulation (19).

A simulation-based experiment design model is beneficial for evaluating the performance of the emergency department queue system because making decisions at high levels of management in the service sectors is first considered as a serious challenge. Second, the performance of

department services is affected by time, cost, and personnel constraints. Third, using various optimization process tools interrupts system operations (20-22).

The experiment design is considered as a mathematical, statistical, and systematic technique used to determine the relationship between the effects of factorial process and their output, i.e. it is used to identify the causality and distinguish between parameters which are impossible to determine. It is necessary to analyze the results of experiment design on the input management to optimize output. Cheng and Kleinen (2000) implemented an optimization model for experiment design. This model was implemented to solve the problem of deviation in refracting the manufacturing system process (23). Tsai (2002) evaluated and optimized the operation of the production system in steel plant in Taiwan through experiment design and simulation. He found that this approach can simultaneously evaluate and optimize the operational status in the multifunction systems (24). Ken and Hugh (2011) implemented a regression model with experiment design and simulation for manufacturing systems of Latin Hypercube Sampling (LHS) samples (McKay et al., 2000), uniform design (Feng et al., 2000), and Maximum Entropy Sampling (MES) (Sherry Wein, 1987) (25). In addition, Lee et al. (2015) developed a simulation and statistical modeling-based experiment design model to predict product delivery time to the customer, including several workstations, device failures, batch processing, etc. which can measure the exact queue time. Further, this method was implemented in semiconductor manufacturing systems and the total queue time was evaluated based on a set of designed data according to six basic performance criteria of manufacturing time (14). Daktova et al. (2019) simulated the queue system in the post office to optimize the costs. The queue system model was based on event-customer and customer service termination. In the simulation system, the minimum number of service counters was

determined according to the conditions of the system, leading to saving and optimizing the system (26).

Based on the literature review, it is necessary to apply an integrated experiment design and simulation approach for analyzing the queue system on patient services. Therefore, experiment design and simulation-based integrated model for analyzing and optimizing the emergency department queue system was introduced by considering different scenarios to help managers evaluate the organization efficiency which mainly aimed to analyze the performance of the queue system to optimize the best combination of emergency department resources to reduce the queue length of the patient's admission. Therefore, a new idea was introduced by computer simulation to survey different scenarios and experiment design was introduced as the input of the simulation model.

2- Method

The present descriptive and analytical study was conducted in the first six months in 2017. The variables affecting the empowerment of resource efficiency in a complex system and explaining their degree of impact were identified. The statistical population included the number of paramedics, nurses, cardiologists, general practitioners, secretaries and the number of hospital beds in Modares General Hospital in Tehran. The effective indicators were determined to formulate the basics, definitions and theoretical concepts through library resources and research literature consisting of the time of patients' admission (queue time), the number of patients referred to the emergency department (queue length), the number of patients discharged from the emergency department, the number of patients referred to a cardiologist and general practitioner, the staff costs in the emergency department and the number of patients required for cardiopulmonary

resuscitation. The measured variables were assessed by a number of experts and scholars who were familiar with the research topic. Finally, the required time data were collected for four periods and each period for 1 week from 4 am-12 pm by the chronometer.

To validate the model, the absolute relative error value in different parts of the emergency department was calculated. The accuracy and validity of the simulated model can be predicted if this value is less than 5% (confidence interval). The results of ANOVA validation statistical tests and estimating the p-value criterion in Table 1, which was collected for quasi-model of the regression response level with different effects, indicated that the quasi-model with three different effects is selected as a candidate model as highlighted. Therefore, these types of patients need to receive services when they enter the emergency department. In addition, this department is considered in the process-based simulation due to the importance of resource planning to reduce the queue in the intensive-care unit. These key variables are identified through theoretical resources in the health literature (27).

Table 1. Regression meta-model selection results (experimental design from software output (Design Expert 10))

Regression meta-model	P-value	Model status
Two interactions	0/0788	Not significant
Three interactions	0/0483	Significant
Four interactions	0/298	Not significant
Five interactions	0/312	Is not significant

* The significant level of 05/0 > p

Statistical inferences and F-test were performed for validating the model and analyzing the data. Here, we used Design Expert (10) software to software to perform experimental design to find interactions of the main factors in the acceptance level of 0.95. In addition, p-values and factor coefficients were estimated in the meta-model. Only those factors with a p-value <0.05 were accepted.

a simulation model was created by using Visual Paradigm to analyze ED system. Visual Paradigm software is an enterprise management and software development tool which offers all the features required to design enterprise architecture, project management, enterprise process management, software development and team collaboration (15). The main inputs required to create the model, which are determined by the hospital managers according to the budget, included amount of patients allocated for each part of the process, the amount of the costs allocated to the resources, and the number of patients needed to repeat the simulation. In this model, the process begins when a patient arrives through the Hospital and ends when a patient is discharged from the Hospital or died.

The triage system in the ED assigns each patient and emergency severity index (ESI) which is based on the urgency in which the patients are evaluated by the nurse and categorized from levels 1 (most urgent) to 5 (least urgent). During April to October in 2017, according to the archived files, the percentage of ESI Level 1 patients, who were the most urgent and usually were brought with an ambulance, account for 2%. These patients were sent immediately to the CPR (Cardio Pulmonary Resuscitation) where they could be resuscitated. If CPR action is successful, the patient is transferred to CPU (Cardio Pulmonary Unit) for further treatment. The ESI 2 patients go through the community health worker who assesses their acuity. Then, they pass the reception and directly go to CPU. About 20% of the patients in ED are of ESI 2. ESI 3, 4, and 5 should go through the receptionist who collects the patient's personal information and locates their files. After the reception, ESI 3 and 4 patients go to the CPU to receive treatment and ESI 5 patients leave ED after being visited by a general physician. This department receives an average of 52000 patients a year, which is about 145 patients daily.

The ED in this study consists of one community health worker, two receptionists, three nurses, one cardiologist, and seven beds (5). In Table 2, Predetermined Parameter for each variable which were determined by managerial consideration are illustrated. About 40% of patients of this ED have heart problems and they should receive their services as soon as possible (27). Therefore, these types of patients need to receive medical treatment as soon as they enter the ward. Also, since resource planning (in order to reduce the queue) in the intensive care unit is also important, this sector is also considered in process simulation. The key resources in the ED included community health workers (CHW) (x_1), receptionists (x_2), nurses (x_3), cardiologists (x_4), and beds (x_5). These key variables are identified through theoretical resources in the health literature (27). Figure 1, illustrates the simulation flow of the patients in the form of process simulation in Visual Paradigm International Ltd 12.0¹(28).

Table 2. The defined management parameters for key variables

Decision Variables	L_i	U_i	Monthly Costs (\$)
Community Health Workers(X_1)	1	2	27000
Receptionist (X_2)	1	3	22500
Nurse (X_3)	1	6	36000
Cardiologist (X_4)	1	3	31500
Bed(X_5)	5	10	90000
* L_i : The minimum accepted amount of resources			
* U_i : The maximum accepted amount of resources			

¹ www.visual-paradigm.com/

Figure1. Patient simulated flow in the ED

3- Findings

First, it is necessary to ensure the accuracy of the model. Therefore, the amount of deviation in the simulation and actual values of the system was calculated by generating simulated data and extracting the patients' archive data. Table 3 indicates the mean deviation of five simulation iterations for patient admission time as 1.136% (less than 5% of the allowable error). Therefore, the validity of the simulation model is acceptable.

Table 3. Validation results of the simulation model

Deviation	Real time of daily patient admission (seconds)	Simulation time of patient admission (seconds)	Iterations
-----------	--	--	------------

0/000	954	954	1
3/730	947	200	2
0/040	999	952	3
1/410	1003	415	4
0/500	1010	668	5
The average deviation (percent)			
1/136			

The results obtained from the simulation model were used for analyzing the experiment design which was used to build the model, analyze and optimize the performance of the emergency department. A complete factorial design with two levels (top and bottom) was used to determine the effects of queue length and patient admission parameters for the key factors in this department. Table 3 indicates the paramedics, emergency secretary, nurse, cardiologist and hospital bed along with their levels. The queue response level variable was measured after each experiment. Each experiment was repeated five times to verify the validity of the collected data and the mean replications were considered as the response level variable for the queue length. 2⁵-32 experiments were designed and implemented in the simulation model based on a complete factorial design for 5 influential variables. The Design Expert 10 Software was used to develop a complete factorial design plan and collect the statistical data. Table 4 indicates the complete factorial design and the length of the queue measured in each experiment as the response variable.

Table 4. 2^k design of experiments

Experiment Number	Variables					Waiting line (Number)
	Community Health Worker	Receptionist	Nurse	Cardiologist	Beds	
1	1	3	1	3	5	1
2	1	1	6	3	5	10
3	2	3	6	1	5	6
4	1	3	6	1	10	5
5	1	1	1	3	10	3
6	2	1	6	1	5	7
7	2	1	1	3	10	8
8	1	3	1	1	5	1
9	2	1	6	3	10	2
10	1	1	6	3	10	9
11	2	1	1	3	5	2
12	1	3	6	1	5	8

13	2	3	1	3	5	4
14	2	1	1	1	5	2
15	1	1	6	1	10	9
16	2	1	1	1	10	9
17	1	1	1	1	5	2
18	3	3	6	3	10	8
19	2	3	6	3	5	4
20	2	3	1	1	5	1
21	1	3	1	3	10	8
22	1	1	1	1	10	3
23	1	1	1	3	5	5
24	1	3	6	3	5	1
25	2	3	6	1	10	10
26	2	3	1	3	10	8
27	1	3	1	1	10	5
28	1	3	6	3	10	2
29	2	1	6	3	5	5
30	2	3	1	1	10	1
31	1	1	6	1	5	2
32	2	1	6	1	10	2

Only acceptable effects were identified in the model based on the auto-select feature of Design Expert Software. Then, the statistical analysis was performed for each effect. Table 5 indicates the results of the statistical analysis of the emergency department queue length. Since $Prob > F$ is less than 0.05 according to the results of one-way analysis of variance, the estimated model is acceptable for the queue length, i.e. only the effect of paramedic variable (X_1) is acceptable among the main effects, unlike the other ones. However, since the objective was to determine the optimal value of these variables, which is considered as a decision variable, other main effects were deliberately considered in the final model. The two-way effects X_2X_4 , X_3X_5 , the three-way effects $X_2X_3X_5$ and the four-way effects $X_1X_2X_4X_5$ are acceptable and the other effects are not acceptable for the model. Therefore, removing unacceptable effects can improve the model. R^2 is 0.8235, indicating that 82.35% of the model explains all the variability of the response data around the mean. Generally, the consistency of the design space with the estimated model can be found according to the results of the statistical analysis.

Table 5. Results of the statistical analysis of Models

Resource	sum of squares	Estimation of coefficients	F value	P* Value
----------	----------------	----------------------------	---------	----------

Model	203/53	4/78	5/19	0/0008**
X₁	52/53	1/128	12/05	0/0022**
X₂	5/28	-0/41	1/2	0/2830
X₃	1/53	0/22	0/35	0/5590
X₄	0/28	0/094	0/064	0/8020
X₅	9/03	0/53	2/07	0/1640
X₂X₄	28/26	0/91	6/03	0/0225**
X₃X₅	47/53	1/22	10/90	0/0030**
X₂X₃X₅	22/78	-0/84	5/22	0/0320**
X₁X₂X₄X₅	38/28	-1/09	7/78	0/0070**
R² = 82/35 %				
Std. DV. = 2/09 CV = 43/68				
PRESS = 252/98				

* Statistical test: F distribution

** The significant level of 05/0> p

In addition, there is a nonlinear relationship among the queue length factors. Therefore, the multiple regression equation for the experiment design was adjusted, and the R^2 and PRESS statistics were reported to be optimal. Equation (1) shows the estimated acceptable factors along with the sentences and their coefficients.

$$y = 4.78 + 1.38X_1 - 0.41X_2 + 0.22X_3 + 0.094X_4 + 0.53X_5 + 0.91X_2X_4 + 1.22X_3X_5 - 0.84X_2X_3X_5 - 1.09X_1X_2X_4X_5 \quad (1)$$

Figure 2 displays the normal probability of residuals for the response level of the queue length. Accordingly, the residuals are generally located around the right line, indicating a normal distribution error. Figure 3 shows the predictive points of the residuals. Accordingly, the data do not follow any specific pattern. Figure 4 shows the dependent variable of the estimated model, in which the optimal value of the queue length is 3~875.2 when the secretary factor is at its highest level. As the optimal resource values are replaced by the current conditions in the current system, the system costs decrease from 4140 thousand Rials to 1980 thousand Rials. In addition, the patients' waiting time reduces from 4 hours and 42 minutes (282 minutes) to 2 hours and 22 minutes (142 minutes) in 1 workday.

Design-Expert® Software
queue length

Color points by value of
queue length:

Figure 2. The normal probability of residuals

Design-Expert® Software
queue length

Color points by value of
queue length:

Figure 3. predictive points of the residuals

Figure 4. Cube display of queue length

4- Discussion

Five main variables including the number of paramedics, emergency secretary, nurses, cardiologist and number of hospital beds were identified and the simulation and experiment design-based framework were presented and implemented to analyze the queue system in the emergency department of Modares Hospital in Tehran. Studying the available literature indicated that various solving methods are used to solve planning and management problems in the field of health which are the quasi-model-based method, data envelopment analysis, metaheuristic method and mathematical programming. For example, Zinali et al. (2015) studied the planning of effective resources in the emergency department of a hospital in Iran using the quasi-model-based method, which could reduce the average waiting time of patients well (27). Similarly, Bahari and Asadi (2020) could obtain the optimal distribution of effective resources to reduce patients' waiting times in this department through the quasi-model framework among the effective resources of the emergency department in a public hospital in Iran (28). In addition, Al- Rafi'i et al., (2014) used

the data envelopment analysis in the emergency department of a public hospital in Jordan to determine the best distribution of nurses, increase their effective use and reduce the patients' waiting time (29). Further, Ahmed and Al-Khamis (2009) introduced a meta-heuristic method as a decision-making support tool for optimal resource allocation at a public hospital in Kuwait, resulting in improving the patients' waiting time (30).

One of the strengths of the present study is the researchers' efforts to analyze the emergency department using powerful simulation and experiment design instruments after identifying the factors influencing the waiting queue. Since simulation and statistical analysis are considered as the most important instruments which help managers analyze the system, creating integration between simulation and performing statistical analysis is always considered as a major challenge for the managers. The experiment design can evaluate the effective factors in a system well through performing related statistical analyses. Therefore, a simulation-based experiment design model can be useful for achieving the goal of evaluating the system performance such as a queue system in the emergency department. However, no matter how powerful the simulation instrument is, it is not considered as an optimization instrument to determine the exact amount of variables, and the approximate value of the variables is specified only with the experiment design tools.

5- Conclusion

The performance analysis of the emergency department queue system was conducted through simulation and experiment design. According to the proposed framework, the current system operations, layouts, and other constraints are unchangeable due to the integration between the simulation and experiment design. The proposed approach was used to determine the effect of the number of paramedics, secretaries, nurses, cardiologists and hospital beds on the waiting queue of

those referred to the emergency department and accelerating the process of serving patients following reducing the queue length. Therefore, the simulation model of the emergency department was first developed and then the obtained data were used as an input in the experiment design. It was found that the factors affecting the queue length were identified and determined through the acceptable factors of the nonlinear regression model for the queue length. This nonlinear regression model can be used with good accuracy to predict the dependent variable (queue). The regression model is valid and reliable since the amount of obtained p is trivial. The reason why the validity of the regression model is high is that the deviation in the simulation values and the real system is low. According to the developed model, the lowest queue length is obtained when the number of emergency secretary factors is at the top level and paramedics and nurses is at their lowest level (Figure 4), leading to a reduction in the costs and time of providing services to patients. Considering what mentioned above and that the emergency department and its related costs play a vital role in patients and the system operating costs, the results of this optimization approach can be provided to hospital managers to redesign and control the admission process to increase productivity until the patient is discharged from the emergency department.

It is worth noting that the effect of uncontrollable variables such as human error is overlooked in simulating and developing the mathematical model. Therefore, it is recommended that this framework be used when there are uncontrollable variables as the main idea for future research. In addition, the mathematical problem be developed through applying managerial constraints such as cost to determine the exact value of all variables.

7- Acknowledgement

The authors would like to thank all of the individuals involved in data collection, field monitoring, and data analysis for this study. The authors also thank the managers and staff of Tehran's Modarres Emergency Department for their participation in this study and for gathering the necessary information, for survey feedback, and for overall help with the study.

6- Declarations

Ethics approval and consent to participate

The ethical committee board of Tehran's Modarres Emergency Department has approved the proposal of this research. We asked for the informants' and respondents' informed consent after explaining the research. The necessity for obtaining informed consent was waived by the ethical committee board of Tehran's Modarres Emergency Department, due to the complete anonymity of the study data. Therefore, study data was in no way traceable to individuals.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analyzed during the current study available from the corresponding author (A.B) on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

None.

Authors' contributions

Concept and design: AB, FA. Acquisition, analysis or interpretation of data: AB, FA, BM. Drafting of the manuscript: AB, FA, BM. Critical revision of the manuscript: AB, FA, BM. Administrative, technical or material support: AB, FA, BM. Supervision: AB, FA, BM. All authors read and approved the final version.

7- References

- 1) Abbott D, Marinov MV. An event-based simulation model to evaluate the design of a rail interchange yard, which provides service to high speed and conventional railways. *Simul Model Pract Theory* 2015; 52: 15-39. doi: 10.1016/j.simpat.2014.12.003.
- 2) Ajdari A, Mahlooji H. An adaptive exploration-exploitation algorithm for constructing metamodels in random simulation using a novel sequential experimental design. *Communications in Statistics - Simulation and Computation* 2014; 43(5): 974-68. doi: 10.1080/03610918.2012.720743.
- 3) Amiri M, Mohtashami A. Buffer allocation in unreliable production lines based on design of experiments, simulation and genetic algorithm. *Int J Adv Manuf Technol* 2012; 62(1): 371-83. doi: 10.1007/s00170-011-3802-8.
- 4) Antony J. *Design of Experiments for Engineers and Scientists*. 2nd ed. Elsevier; 2014.
- 5) Wu DD, Olson DL. A System Dynamics Modeling of Contagion Effects in Accounts Risk Management. *Systems Research and Behavioral Science* 2014; 31(4): 502-11. doi: 10.1002/sres.2291.
- 6) Chetouane F, Barker K, Viacaba Oropeza AS. Sensitivity analysis for simulation-based decision making: Application to a hospital emergency service design. *Simulation Modelling Practice and Theory* 2012; 20: 99-111. doi: 10.1016/j.simpat.2011.09.003.
- 7) Denman NG, McGree JM, Eccleston JA, Duffull SB. Design of experiments for bivariate binary responses modelled by Copula functions. *Computational Statistics & Data Analysis* 2011; 55(4): 1509-20. doi: <https://doi.org/10.1016/j.csda.2010.07.025>.
- 8) Nawar EW, Niska RW, Xu J. National Hospital Ambulatory Medical Care Survey: 2005 emergency department summary. *Adv Data* 2007; (386): 1-32. PMID: 17703794.
- 9) Erkan BY, Heragu SS, Krishnamurthy A, Malmberg CJ. Simulation based experimental design to identify factors affecting performance of AVS/RS. *Computers & Industrial Engineering* 2010; 58(1): 175-85. doi: 10.1016/j.cie.2009.10.004.
- 10) Zilm F, Crane J, Roche KT. New directions in emergency service operations and planning. *J Ambulatory Care Manage* 2010; 33(4): 296-306.
- 11) Rahiminezhad Galankashi M, Fallahiarezoudar E, Moazzami A, Yusof NM, Helmi SA. Performance evaluation of a petrol Station queuing system: A simulation-based design of experiments study. *Advances in Engineering Software* 2016; 92: 15-26. doi: <http://dx.doi.org/10.1016/j.advengsoft.2015.10.004>.
- 12) Jahangirian M, Naseer A, Stergioulas L, Young T, Eldabi T, Brailsford S, et al. Simulation in health-care: lessons from other sectors. *Oper Res Int J* 2012; 12(1): 45-55. doi: 10.1007/s12351-010-0089-8.

- 13) Koiritzin MA, Newton F, Wu B. A graph theoretic approach to simulation and classification. *Computational Statistics and Data Analysis* 2014; 70: 281-94. doi: <http://dx.doi.org/10.1016/j.csda.2013.09.026>.
- 14) Li M, Yang F, Wan H, Fowler JW. Simulation-based experimental design and statistical modeling for lead time quotation. *J Manuf Syst* 2015; 37(1): 362-74. doi: <http://dx.doi.org/10.1016/j.jmsy.2014.07.012>.
- 15) Lopez-Fidalgo J, Rivas-Lopez MJ. Optimal experimental design for partial likelihood information. *Computational Statistics and Data Analysis* 2014; 71: 859-67. doi: 10.1016/j.csda.2012.10.009.
- 16) Mende M, Thompson SA, Coenen Ch. It's all relative: how customer-perceived competitive advantage influences referral intentions. *Mark Lett* 2015; 26: 661-78. doi: 10.1007/s11002-014-9318-x.
- 17) Moazzami A, Rahiminezhad Galankashi M, Khademi A. Simulation, Modelling and Analysis of a Petrol Station. *International Review on Modelling and Simulations (I. RE.MO.S.)* 2013; 6(1): 246-53.
- 18) Molina-Azorin JF, Tari JJ, Pereria-Moliner J, Lopez-Gamero MD, Pertuspa-Ortega EM. The effect of quality and environmental management on competitive advantage: A mixed methods study in the hotel industry. *Tourism Management* 2015; 50: 41-54. doi: <http://dx.doi.org/10.1016/j.tourman.2015.01.008>.
- 19) Hoot NR, Aronsky D. Systematic review of emergency department crowding: causes, effects, and solutions. *Ann Emerg Med* 2008; 52(2): 126-36. doi: 10.1016/j.annemergmed.2008.03.014.
- 20) Pinto LR, Silva PMS, Young TP. A generic method to develop simulation models for ambulance systems. *Simulation Modelling Practice and Theory* 2015; 51: 170-83. doi: <http://dx.doi.org/10.1016/j.simpat.2014.12.001>.
- 21) Rogers HP, Strutton D, Doddridge BF. Measuring Customer Satisfaction with Logistics Services: An Investigation of the Motor Carrier Industry. *Proceedings of the 1997 Academy of Marketing Science (AMS) Annual Conference*; Springer, Cham; 2014. doi: https://doi.org/10.1007/978-3-319-13141-2_39.
- 22) Trzeciak S, Rivers EP. Emergency department overcrowding in the United States: an emerging threat to patient safety and public health. *Emerg Med J* 2003; 20: 402-5.
- 23) Cheng RC, Kleijnen JPC, Melas VB. Optimal design of experiments with simulation models of nearly saturated queues. *Journal of Statistical Planning and Inference* 2000; 85(1 and 2): 19-26. doi: 10.1016/S0378-3758(99)00061-0.
- 24) Tsai ChS. Evaluation and optimization of integrated manufacturing system operations using Taguch's experiment design in computer simulation. *Computers & Industrial Engineering* 2002; 43(3): 591-604.
- 25) Can B, Heavey C. Comparison of experimental design for simulation-based symbolic regression of manufacturing systems. *Computers & Industrial Engineering* 2011; 61(3): 447-62. doi: <https://doi.org/10.1016/j.cie.2011.03.012>.
- 26) Ďutková, Silvia, Achimský, Karol, Hošťáková, Dominika, (2019) Simulation of Queuing System of Post Office, *Transportation Research Procedia*, Volume 40, Pages 1037-1044, <https://doi.org/10.1016/j.trpro.2019.07.145>
- 27) Zeinali F, Mahootchi M, Sepehri MM. Resource Planning in the Emergency Department: A Simulation-Based Metamodeling approach. *Simulat. Modell Pract Theory* 2015; 53(2): 123-38. doi: <https://doi.org/10.1016/j.simpat.2015.02.002>.
- 28) Bahari A, Asadi F. A Simulation Optimization Approach for Resource Allocation in an Emergency Department Healthcare Unit. *Global Heart*. 2020; 15(1): 14. DOI: <https://doi.org/10.5334/gh.528>
- 29) RH, Li MH, Shurrah M. Applying simulation and DEA to improve performance of emergency department in a Jordanian hospital. *Simulation Modelling Practice and Theory* 2014; 41: 59-72. doi: <https://doi.org/10.1016/j.simpat.2013.11.010>
- 30) Ahmed MA, Alkhamis TM. Simulation optimization for an emergency department healthcare unit in Kuwait. *European Journal of Operational Research* 2009; 198(3): 936-42. doi: <https://doi.org/10.1016/j.ejor.2008.10.025>

Figures

Figure 1

Patient simulated flow in the ED

Figure 2

The normal probability of residuals

Design-Expert® Software
queue length

Color points by value of
queue length:

Figure 3

predictive points of the residuals

Design-Expert® Software
Factor Coding Actual
queue length

X1 = A: A
X2 = B: B
X3 = C: C

Actual Factors
D: D = 2
E: E = 7.5

Figure 4

Cube display of queue length