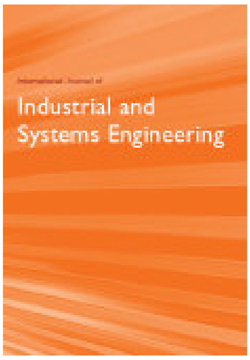

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Simulation-based optimisation: analysis of the emergency department resources under COVID-19 conditions

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Simulation-based optimisation: analysis of the emergency department resources under COVID-19 conditions

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Abstract: The emergency department (ED) is the most important section in every hospital. The ED behaviour is adequately complex, because the ED has several uncertain parameters such as the waiting time of patients or arrival time of patients. To deal with ED complexities, this paper presents a simulation-based optimisation-based meta-model (S-BO-BM-M) to minimise total waiting time of the arriving patients in an emergency department under COVID-19 conditions. A full-factorial design used meta-modelling approach to identify scenarios of systems to estimate an integer nonlinear programming model for the patient waiting time minimisation under COVID-19 conditions. Findings showed that the S-BO-BM-M obtains the new key resources configuration. Simulation-based optimisation meta-modelling approach in this paper is an invaluable contribution to the ED and medical managers for the redesign and evaluates of current situation ED system to reduce waiting time of patients and improve resource distribution in the ED under COVID-19 conditions to improve efficiency.

Keywords: emergency department; simulation-based optimisation; S-BO; meta-model; COVID-19.

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1 Introduction

China introduces a new strain of coronavirus as a causative of a new respiratory disease after several people contracted an unusual pneumonia in December 2019 (Kemp et al., 2020; Shirazi et al., 2020). With the rapid spread of the disease in China and then to other parts of the world, the new coronavirus, scientifically known as severe acute respiratory syndrome corona virus2 (SARS-CoV-2) and the resulting disease called coronavirus disease 2019 (COVID-19), caused great concern and panic among the people of the world (Kumar et al., 2020). The World Health Organization stated that the outbreak of the virus resulted in public health emergencies around the world (Islam et al., 2020; Amin. 2020). Statistics show that the death rate worldwide has increased significantly because of this new virus (Coustasse et al., 2020). Table 1 shows the number of death and infection as of 6.30.2020 in different countries.

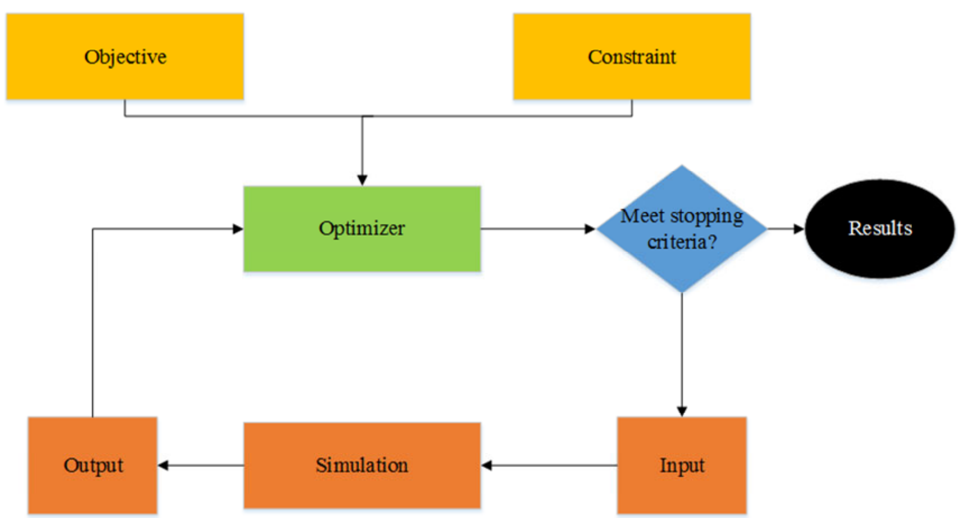
Table 1 Number of death and infection

Country	*Total deaths*	*Total confirmed cases*
China	3,301	82,230
USA	1,243	85,228
Iran	2,378	32,332
Italy	9,136	86,498
Spain	4,858	64,059
France	1,992	32,542
UK	759	14,547
Germany	325	48,582

Source: World Health Organization (2020)

The emergency department (ED) is the most important section in every hospital (Abedi and Abedini, 2017). Recently, the increasing demand for emergency services especially in the face of an unexpected crisis such as COVID-19 has imposed great pressure on the ED of hospitals (Singh and Avikal, 2020). This is due the admission of voluminous number of patients in everyday routine while most of them do not need emergency care. Previous studies show that ED visits has grown up to 20% between years 1995 and 2005 (Nawar et al., 2007). The ED overcrowding problem could cause long queues with long waiting times, which makes patients to leave without treatment and finally leads to great decrease in health outcomes and hospital productivity. In COVID-19 condition, an efficient planning of EDs for all levels of strategic and operational decisions is of great importance, considering the limitation in available resources (Saha et al., 2020). An ED is usually comprised of two main units which are the urgent care unit and cardiopulmonary resuscitation (CPR) (Tasri and Tasri, 2020). In some cases, a rapid assessment section is in the ED that is stationed in parallel with main sections for treatment process improvement. There are also other units in an ED such as observation units which is tasked with symptoms evaluation or the acute care units for chest pain or any other heart problems (Home, 2020). All units must be equipped with necessary medical equipment. Patients within the EDs are referred to different units regarding the type of their disease and also the level of urgency (Wu et al., 2020). For this reason, a pretreatment phase called triage is performed by specialised nurses to determine the type and level of patient's disease and classify them according to their needs. Patients with higher emergency level are prior for treatment and others are supposed to wait in the waiting room (Al-Neyadi et al., 2018). Recently, using the simulation model as a tool for optimisation systems has grown in healthcare units. Simulation-based optimisation (S-BO) applies the simulation model evaluation to optimisation methods; that is, it uses the simulation model to find a system's optimum configuration (Abdolmaleki et al., 2019). The first stage in a S-BO framework includes system analysis and data gathering (Yang and Yang, 2020). The second stage includes choosing and using a suitable optimisation method to finding the most favourable solution (Yousefi et al., 2020). The ED behaviour is complex, because the ED has several uncertain parameters such as the time of arrival of patients, etc. The complexity of an ED structure makes decision making a very challenging process. These decisions play a significant role in ED performance and productivity. The appropriate decision making process requires system analysis with the aim of efficient resource allocation (Babaeinesami and Ghasemi, 2020). However, this analysis is not supposed to be performed in an straightforward way due to uncertainty of system's parameters. Considering system uncertainty in modelling methodology requires utilising stochastic or fuzzy approaches. These approaches are mainly used for modelling variations such as arrival or service rates for patients. To this end, resource planning in all strategic, tactical and operational levels is performed by monitoring different states of ED in order to help managers enhance system performance and pass standard qualifications (Mishra et al., 2018). Simulation is an appropriate tool to deal with the complexities of systems, and an easy way to understand system behaviour (Abolghasemian and Darabi, 2018; Bashir et al., 2020). Since performing simulation models for complex systems such as the ED is quite difficult to deal with via analytical methods, computer simulation is required. In this way, the current situation of the system and processes is imitated to prepare a configuration to evaluate different scenarios in all operations and managerial levels strategies (Chen et al., 2019). Simulation is an appropriate tool to overcome the complexities of systems, and is an easy way to understand system behaviour (Abolghasemian et al., 2020; Ansorena and Valdecantos, 2021). Figure 1 depicts a S-BO process mechanism. Another important component of S-BO-based meta-modelling is meta-model. According to Abolghasemian et al. (2020), a meta-model is a mathematical model approximated by a surrogate model that is used instead of simulation model. In the S-BO problems, the objective function is stochastic with random characteristics and uncertain conditions. Therefore, objectives can be clearly specified when the simulator runs the simulation model with different scenarios to find a setting that fits objectives. Thus, S-BO is an appropriate tool for achieving such goals (Barton, 2009).

Figure 1 S-BO mechanism (see online version for colours)



Source: Yousefi et al. (2020)

There have been extensive studies in the field of simulation application for ED modelling. For example, more information about this modelling type is presented in the study of Paul et al. (2010). Nevertheless, it should be noted that, simulation is not an optimisation method and does not provide optimal decisions. In order to achieve the optimal solutions, S-BO methods are required.

As an example, an integration of simulation and heuristic optimisation methods could be utilised in the field of healthcare systems planning and optimisation (Zeinali et al., 2015). Recent studies have shown that, patients flow could be raised by 28% and an average of 40% decrease in patient waiting time is possible to be achieved by implementing optimal plans suggested by S-BO solutions (Ahmed and Alkhamis, 2009).

Although simulation is not a technique for finding the optimal value of decision variables, but the simulation models and analytical optimisation-based simulations using exact and heuristics methods are used widely in the healthcare system (Ghasemi and Khalili-Damghani, 2020; Samant and Prakash, 2021). Vanbrabanat et al. (2019) studied scientific literature of S-BO on ED. They studied on new management policy to provide ED managers, and increase efficiency in the hospital performance. Also, Yousefi et al. (2020) presented a systematic review to progress made on the subject while showing possible complexities in ED. Bal et al. (2017) proposed a hybrid methodology combined of lean techniques and discrete event simulation (DES) models. The goal of this paper was to improve the efficiency of ED by reducing the overcrowding and patient waiting times. Duguay and Chetouane (2007) developed a DES model of an ED in Canada. The purpose of their research is to minimise the waiting time of patients and to increase total service delivery and system flow. Ahmed and Alkhamis (2009) provided an S-BO for the operational design of ED at a Kuwaiti public hospital. The S-BO model provided by them can reduce waiting time of patients by 40% and increase patient throughput by 20%. Waleed and Arisha (2013) presented a simulation-based decision support system (DSS) framework for medical centre system improvement. Results show that the unblocking of ED flow using bed allocation is more effective than increasing the ED personnel. Kadri et al. (2014) developed a simulation-based DSS to prevent and predict strain situations in an ED in order to increase their management ability of the healthcare system. Also, a DES model was built to evaluate the strain situations, examine the relationship between the strain situations and propose corrective actions. Findings shown the importance of anticipation and management of strain situation in the ED. Zeinali et al. (2015) presented an S-BO in the ED by meta-modelling approach. Results shown the total waiting time of patients is decrease by 48%. Feng et al. (2015) presented a multi-objective (MO) programming by a non-dominated sorting genetic algorithm II (NSGA II) and multi-objective computing budget allocation (MOCBA) medical for key resources configuration in the ED according to patients flow or ED output. Traore et al. (2018) presented a framework for mathematical modelling and simulation model to create a DSS tool for evaluation of medical systems. Daldoul et al. (2018) presented a stochastic model to minimise patient waiting time in an ED. The objective of this study was to optimise the human and material resources required to decrease the average total patient waiting time. Chen and Wang (2016) developed a DES model and proposed a simulated-annealing-based algorithm to find a resources configuration to solve the randomly constrained DES model using optimisation problem. Results demonstrated that proposed algorithm had an increase of 38.28% in the main efficiency compared to the current resources configuration. Aghapour et al. (2019) proposed a MO optimisation for capacity planning and reconfiguration for disaster-resilient health infrastructure and an unplanned capacity planning in disaster. Ordu et al. (2020) proposed a model that linked each and every service and specialty such as out-patient and in-patient services, with the purpose of predicting demand for all the specialties, capturing all the uncertainties of patient flow within a medical centre setting by DES model, and building a linear programming solution to approximate the number of beds and required resources of a healthcare system in England. Results showed a varied view to decision making with a DSS tool for short and long-term policies in order to build a rational and realistic pattern. Pegoraro et al. (2020a) presented a DSS framework for ED decision management using DES model and multiple criteria decision making (MCDM). Pegoraro et al. (2020b) provided a hybrid MCDM method such as DEMATEL and PROMETHEE II to help ED managers design improvement actions and make decisions that reduce overcrowding.

In this paper, a simulation-based optimisation-based meta-model (S-BO-BM-M) is presented to define the optimal combination of the ED key resources under COVID-19 conditions to minimise the arriving patients total waiting time in an ED in the Iranian public hospital subject to resource capacity and budget constraints. Meta-modelling approach in this paper is an invaluable contribution to the ED managers for the redesign and evaluate of current situation ED system to reduce waiting time of patients and improve resource combination. We believe that by control of the ED condition, we can minimise patients waiting times and improve the resources efficiency. According to the literature review mentioned above, aim of paper is propose the discrete event S-BO-BM-M to decrease the waiting time of patients in the ED under COVID-19 conditions. Also, we show how simulation and analytical optimisation are useful method to create the suitable surrogate model of the simulation response.

The remainder of this paper is including of the following sections: in Section 2, we provide methods consist DES model and S-BO. Then, the results and discussion have been presented in Section 3 and Section 4, respectively. Finally in Section 5, the conclusions and the suggestions for future studies are presented.

2 Methods

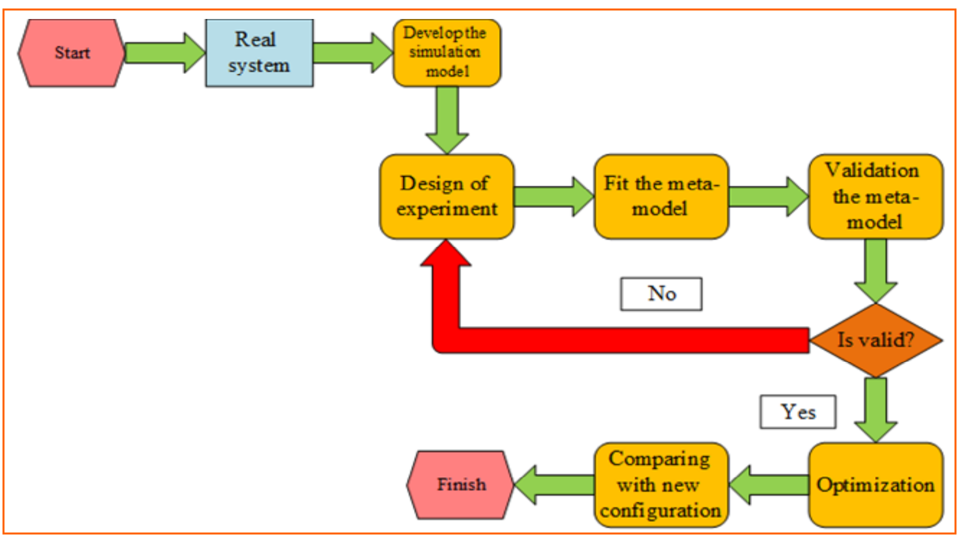
2.1 DES model

The DES model is the best way to improve system output when optimiser is faced with uncertainty in the parameters of the system such as ED's patients arriving rate or patients queue length (Ghasemi et al., 2020; Ghasemi and Khalili-Damghani, 2021). In this study, a DES model for the considered ED was constructed by ARENA® software. The aim of this paper is to define a new combination of the main ED resources that can reduce the waiting time of arriving patients, according to the resources cost and other predetermined constraints during the outbreak of COVID-19. In fact, we want to simulate the patients arriving at the ED to reach the optimum key resources configuration that minimise the objective function, which is the total waiting time of patients. We ran the simulation model for a work month, four days considered for warm-up period and ten replication times. The warm-up period is considered for the simulation model to reach its steady state and remove any bias from the results. Also, to determine the number of simulation replications the average half-width for all replications is computed by trial-and-error method until the average half-width is less than 5% different from the average mean and length of running time of the simulation is smooth.

2.2 Simulation-based optimisation

The simulation model provides an easy way to understand and explain behaviour of the physical system based on a subset of the decision variables (Ghasemi and Babaeinesami, 2020). The output of the simulation model is defined as an objective function. The subset of the input variables are the decision variables that are used as input values to the simulation model to create the response surface, which is the waiting time of patients. Estimation of simulation output has advantages such as explicit form, deterministic response and computational efficiency. The estimation is a model of the simulation which is called a meta-model (AlJaberi et al., 2017). A meta-model is a surrogate model of the simulation model, where subset of the decision variables as input in the simulation model is used to explain the system behaviour. The simulation model of the ED was carried out to gain response variables for various experiments of 2^5 full-factorial design to find settings that meet the objective function of the problem. In this paper, the design of experiment (DOE) is employed to evaluate the decision variables and interaction effect between variables on response surface (which is waiting time of patients of the ED during the outbreak of COVID-19). In the model, a 2^K full-factorial DOE is used to determine nonlinear regression coefficients of k decision variables on ED efficiency.

Figure 2 The S-BO (see online version for colours)



In this paper, a simulation-based analytical optimisation-based meta-model is used to conduct the optimisation of the ED to obtain new key resources configuration and minimise the arriving patients total waiting time in an ED under COVID-19 conditions in an Iranian public hospital with the consideration of resource capacity and budget constraints. The S-BO process is illustrated in Figure 2. According to Barton (2009), an S-BO-BM-M has important steps such as meta-model form, DOE, run the simulation experiment, fit the meta-model, verification of the validation (V&V) of the meta-model and optimise the meta-model.

3 Results

Imam-Ali Hospital is public medical centre that located in the Shar-e-Kord city in Iran. The Imam-Ali Hospital ED is open 24 hours a day. According to data collected from recorded archive, an average of patients is 44,000 in a year. The infectious ward of Imam-Ali Hospital has been assigned for patients with coronavirus. The Imam-Ali Hospital ED has three sub-units, Chest Pain Unit (CPU), for patients with acute chest pain or any other heart problems and Intensive Care Unit (ICU), for patients with major trauma, severe burns, respiratory failure and cardiothoracic surgery and surgery unit, for patients that need surgery. According to the data collected, 40% of patient entries to the ED are in critical condition. Therefore, it is necessary patients receive medical care as soon as possible. Since minimise the total waiting time is vital, we decided to consider this section in our problem of resource planning. The important resources in the ED are receptionists (X_1), nurses (X_2), heart residents (X_3), general surgeons (X_4) and beds (X_5). In its current situation, the ED has three receptionists, four nurses, one heart resident, one general surgeon and eight beds. Patient entry process at the ED is shown in Figure 3. According to the emergency severity index (ESI) standard, arriving patients are divided to five levels, designated from 1 to 5 (e.g., patients with ESI 1 are highest priority and the patients with ESI 5 are lowest priority).

3.1 Developing the nonlinear regression meta-model

The S-BO-based meta-modelling with DOE is developed in this section. First step of creating a meta-model is defining the intervals for considered input variables. Predefined input variables are shown in Table 2.

Table 2 Predefined input variables

Variables	*Description*	*Lower-bound*	*Upper-bound*
X_1	Number of receptionists	2	3
X_2	Number of nurses	2	4
X_3	Number of heart residents	1	7
X_4	Number of general surgeon	1	4
X_5	Number of beds	6	12

The decision variables are X_1, X_2, X_3, X_4, X_5. These variables are used for the evaluation of the results of simulation model with the interval levels of 2, 3, 4 and 7, respectively. Possible combinations of variables are $2 \times 3 \times 7 \times 4 \times 7 = 1{,}176$. It is evident that the run of 1,176 simulation experiments are highly time consuming. Therefore, instead of running all possible combinations, a full factorial design with $2^5 = 32$ combination is employed. The nonlinear regression meta-model considered for estimating the waiting time of patients is shown in equation (1).

$$
\begin{aligned}
y = {} & \beta + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_1 X_3 + \beta_7 X_1 X_4 + \beta_8 X_1 X_5 \\
& + \beta_9 X_2 X_3 + \beta_{10} X_2 X_4 + \beta_{11} X_2 X_5 + \beta_{12} X_3 X_4 + \beta_{13} X_3 X_5 + \beta_{14} X_4 X_5 \\
& + \beta_{15} X_1 X_3 X_4 + \beta_{16} X_1 X_3 X_5 + \beta_{17} X_1 X_4 X_5 + \beta_{18} X_2 X_3 X_4 + \beta_{19} X_2 X_3 X_5 \\
& + \beta_{20} X_2 X_4 X_5 + \beta_{21} X_3 X_4 X_4 + \beta_{22} X_1 X_3 X_4 X_5 + \varepsilon
\end{aligned} \tag{1}
$$

Equation (1) is a meta-regression model with five factor interaction between decision variables. In equation (1), y is the waiting time of the patients, β is intercept coefficients, β_1–β_5, are main effect coefficients, β_6–β_{14}, are two-ways interactions coefficients, β_{16}–β_{21}, are three-ways interactions coefficients, β_{22}, is four-way interaction coefficient and ε is error term. The results of the DOE are shown in Table 3. After running the simulation model, response surface results for the 2^5 full-factorial DOE were gathered and the nonlinear regression meta-model were estimated. Analysis of variance and estimated coefficient effects are presented in Table 4. F-value of the model is 5.4. F-value implies that the model parameters are quite significant. Because, there is only 0.064% probable that F-value this large occurs due to noise. Therefore, P-value less than 0.05 show the model parameters are significant.

Figure 3 Patient entry flow (see online version for colours)

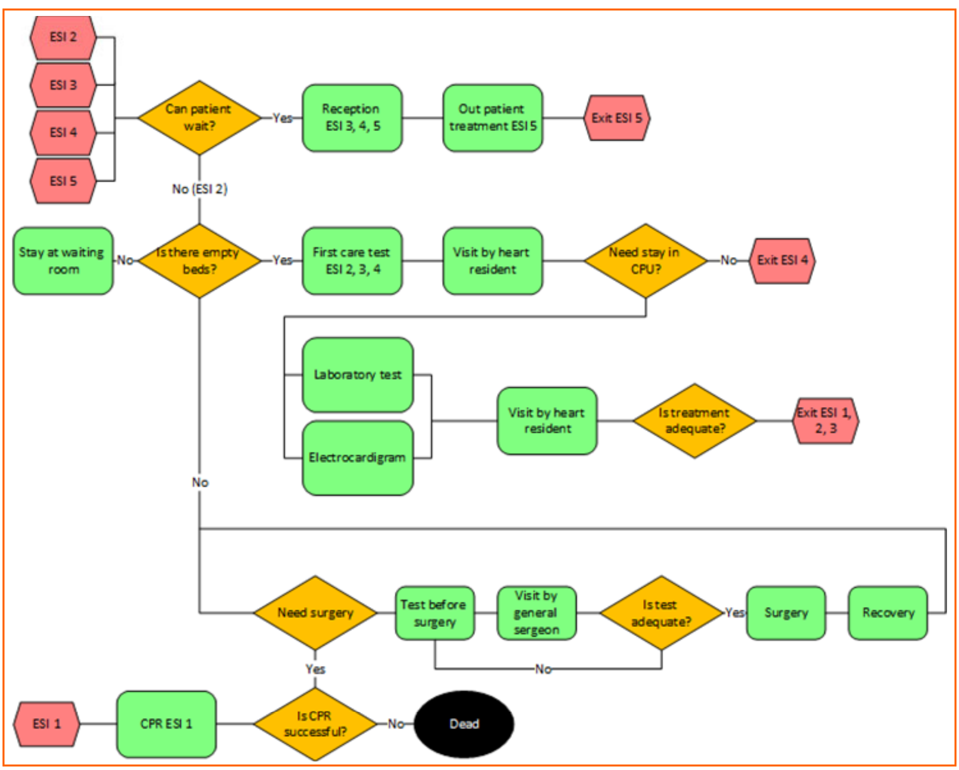


Table 3 The results of DOE

Runs	*Variables*					*Response*
	Receptionist	*Nurses*	*Heart residents*	*General surgeons*	*Beds*	*Waiting time of patients*
1	3	4	7	4	12	93.49
2	2	4	1	4	12	101.71
3	2	2	1	4	6	107.74
4	3	4	1	4	6	94.73
5	2	2	7	4	12	110.81
6	3	4	1	1	6	103.18
7	2	2	7	1	12	101.27
8	2	4	1	1	12	97.42
9	3	2	1	4	12	104.50
10	2	2	1	4	12	104.57
11	3	2	1	1	12	103.99
12	2	4	7	1	6	98.57
13	2	4	1	1	6	103.99
14	3	2	7	1	12	92.22
15	2	4	7	4	6	93.22
16	2	4	7	1	12	96.42
17	2	2	7	1	6	96.84
18	3	2	1	1	6	101.61
19	3	2	7	1	6	97.52
20	2	4	7	4	12	107.94
21	2	4	1	4	6	99.77
22	3	4	1	1	12	92.95
23	3	4	7	1	6	96.66
24	2	2	7	4	6	107.37
25	3	2	7	4	6	108.45
26	3	4	7	1	12	98.41
27	3	2	1	4	6	98.52
28	2	2	1	1	6	99.16
29	3	4	1	4	12	108.33
30	3	2	7	4	12	97.49
31	3	4	7	4	6	94.52
32	2	2	1	1	12	110.38

In this case, only (X_1, X_2, X_3, X_4), ($X_1X_3X_5$), ($X_2X_3X_4$), ($X_2X_3X_5$), ($X_2X_4X_5$), ($X_1X_3X_4X_5$) are significant model parameters. Because, *P-value* > 0.1 shows the model parameters are not significant. However, since X_5 is the decision variable, we consciously considered it in the model, even if it is not significant. In Table 4, last column shows the status of variables and all of the insignificant factor *P-value* > 0.05 is shown as eliminated.

Adeq-precision, measures the ratio of signal to noise. A ratio > 4 is adequate for us. Our model ratio is 7.835 which show that it is a desirable model. Therefore, this model can be used to navigate the design space.

Table 4 Analysis variance

Source	*Sum of squares*	*F-value*	*Prob. > F (P-value)*	*Coefficients*	*Status*
Intercept	2.11	5.41	0.0064	+6.442	Significant
Receptionist X_1	0.19	10.78	0.0095	+0.884	Significant
Nurses X_2	0.28	15.75	0.0033	+0.563	Significant
Heart residents X_3	0.13	7.29	0.0244	+0.367	Significant
General surgeons X_4	0.13	7.35	0.0239	+1.569	Significant
Beds X_5	0.033	1.84	0.2084	+0.499	Insignificant
X_1X_3	0.024	1.36	0.2730	–0.142	Eliminated
X_1X_4	0.016	0.91	0.3648	–0.494	Eliminated
X_1X_5	0.064	3.60	0.0903	–0.113	Eliminated
X_2X_3	0.002	0.12	0.7404	–0.026	Eliminated
X_2X_4	0.068	3.83	0.0822	–0.163	Eliminated
X_2X_5	0.0007	0.044	0.8384	–0.081	Eliminated
X_3X_4	0.063	3.54	0.0924	–0.186	Eliminated
X_3X_5	0.009	0.53	0.4847	–0.062	Eliminated
X_4X_5	0.072	4.05	0.0750	–0.191	Eliminated
$X_1X_3X_4$	0.028	1.58	0.2404	+0.103	Eliminated
$X_1X_3X_5$	0.14	8.15	0.0189	+0.017	Significant
$X_1X_4X_5$	0.005	0.29	0.6032	+0.057	Eliminated
$X_2X_3X_4$	0.16	8.85	0.0156	–0.015	Significant
$X_2X_3X_5$	0.13	7.16	0.0254	+0.007	Significant
$X_2X_4X_5$	0.30	17.13	0.0025	+0.021	Significant
$X_3X_4X_5$	0.018	1.03	0.3360	+0.031	Eliminated
$X_1X_3X_4X_5$	0.24	13.78	0.0048	–0.013	Significant

According to the analysis, the meta-model (in terms of actual factors) can be employed to build prediction functions about the response to consider intervals of each variable. The estimated meta-model is shown in equation (2):

$$\begin{aligned} y' = \sqrt{y} &= 6.442 + 0.844X_1 + 0.563X_2 + 0.367X_3 + 1.569X_4 + 0.499X_5 \\ &+0.017X_1X_2X_4 + 0.015X_2X_3X_4 + 0.007X_2X_3X_5 + 0.021X_2X_4X_5 \\ &-0.013X_1X_3X_4X_5 \end{aligned} \tag{2}$$

In equation (2), $\sqrt{y}$ is transformation function of y. In equation (2), the main factors of X_1, X_2, X_3, X_4 are significant, and X_5 is insignificant, but we purposely decided to use it in the final model because we want to obtain optimum value of main factor finally. All two-factor interactions are insignificant because *p-value* is greater than 0.005, that was eliminated in the model. Three-factor interactions ($X_1X_2X_4$), ($X_2X_3X_4$), ($X_2X_3X_5$), ($X_2X_4X_5$)

are significant. Finally, the four-factor interactions between ($X_1X_3X_4X_5$) are significant. Other kinds of interactions such as five-factor interactions are summarised in Table 4, because they are insignificant.

Figure 4 The normal plot of residuals (see online version for colours)

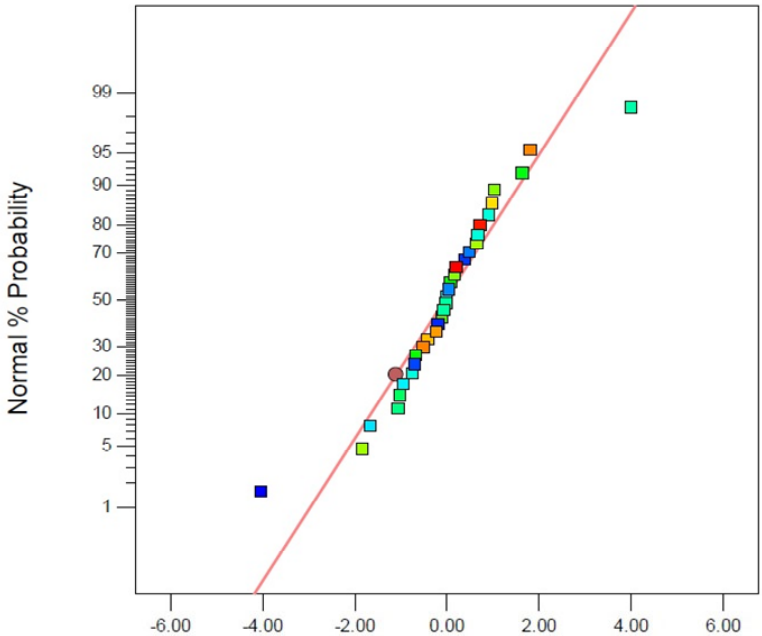
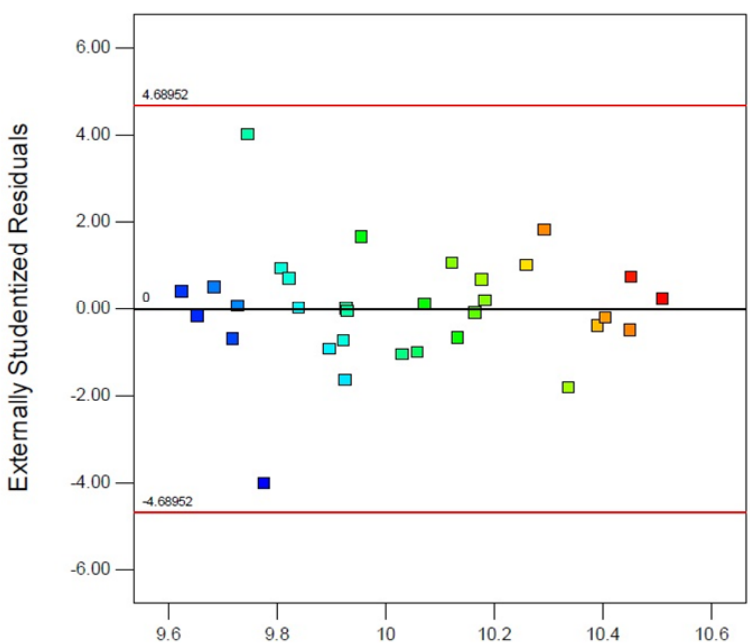


Figure 5 Residuals vs. predicted diagram (see online version for colours)



The important remaining step is the validation of the estimated model. Validation shows that the system model is satisfactory. To this end, the 'normal plot of residuals' and 'residuals vs. predicted' are used that are shown in Figure 4 and Figure 5. According to Figure 4, there is no insignificant deviation. Also, in Figure 5, no out-of-layer predictions are observed. Therefore, the model can be considered quite valid.

4 Discussion

Counter graphs of 'waiting time of patients' between nurses vs. heart resident, nurses vs. general surgeon and receptionist vs. heart resident are represented in Figure 6, Figure 7 and Figure 8, respectively. When number of nurses and number of heart resident are in high level (Figure 6), number of nurses is in high level but the number of general surgeons is in the moderate level (Figure 7) or both the receptionist and heart resident are in high level (Figure 8), the minimum waiting time of patients occur in the ED. Such an analysis gives us a rough idea of the situation. Meanwhile, we want to know the determined number of the resources to minimise the waiting time of patients. For this purpose, mathematical programming is widely used to optimise the problem.

Figure 6 Counter graphs between nurses and heart resident (see online version for colours)

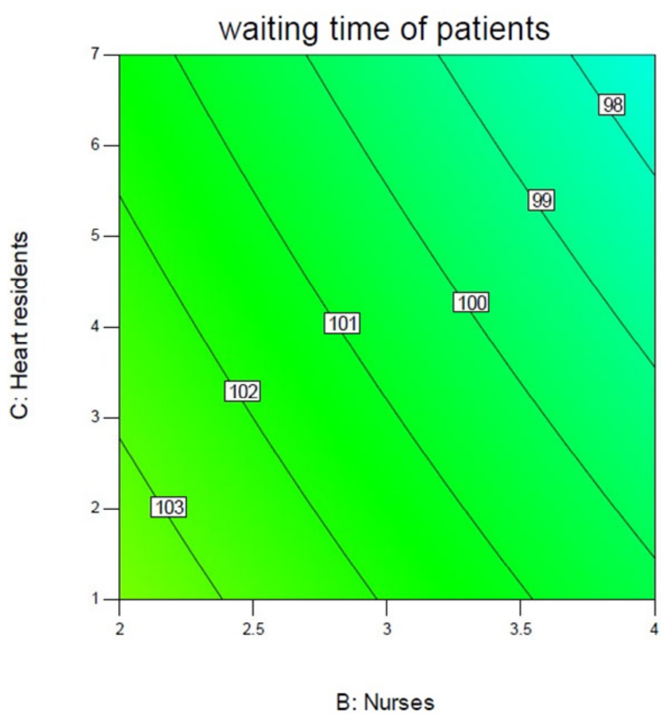


Figure 7 Counter graphs between nurses and general surgeons (see online version for colours)

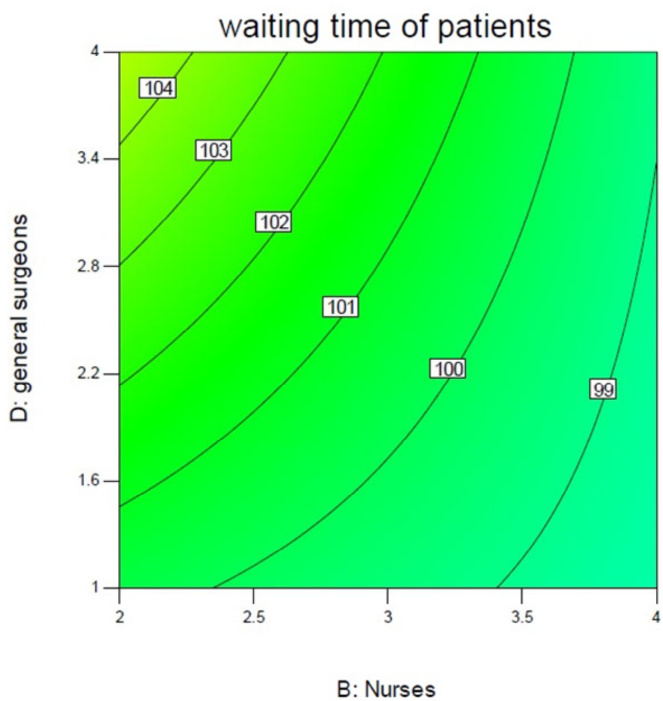
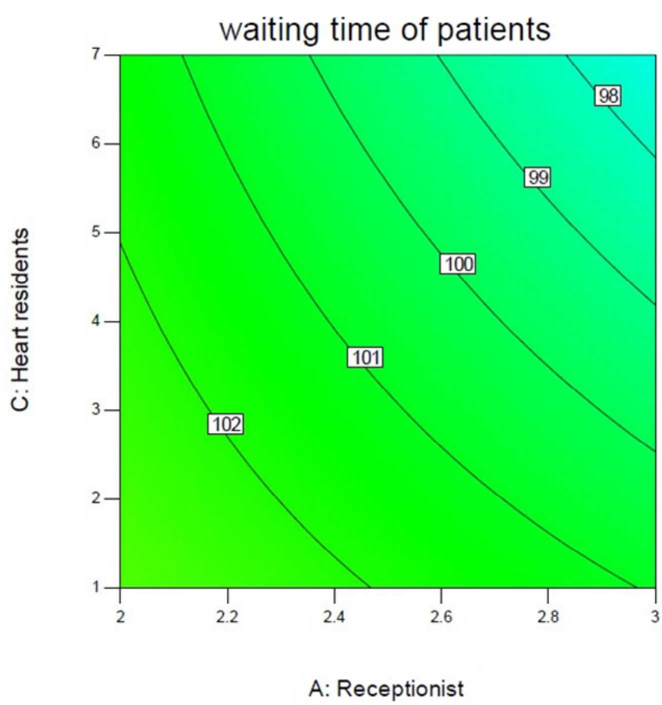


Figure 8 Counter graphs between receptionist and heart resident (see online version for colours)



4.1 Mathematical programming

The mathematical programming for minimising the waiting time of patient subject to budget to determine the number of key resources under COVID-19 conditions are given as follow:

$$\begin{aligned} y' = \sqrt{y} &= 6.442 + 0.844X_1 + 0.563X_2 + 0.367X_3 + 1.569X_4 + 0.499X_5 \\ &+0.017X_1X_2X_4 + 0.015X_2X_3X_4 + 0.007X_2X_3X_5 + 0.021X_2X_4X_5 \\ &-0.013X_1X_3X_4X_5 \end{aligned} \quad (3)$$

subject to:

$$\sum_{i=1}^{5} C_i X_i \leq B \qquad \forall i = 1, \ldots, 5 \quad (4)$$

$$L_i \leq X_i \leq U_i \qquad \forall i = 1, \ldots, 5 \quad (5)$$

$$\sum_{i=1}^{5} X_i = 23 \qquad \forall i = 1, \ldots, 5 \quad (6)$$

$$X_i \in integer \qquad \forall i = 1, \ldots, 5 \quad (7)$$

where y' is objective function, (X_1, X_2, X_3, X_4, X_5) is the number of the receptionists, nurses, heart residents, general surgeon and beds. Equation (4) represents the monthly salaries should not exceed the budget. Equation (5) represents the upper and lower bound of the decision variables. Equation (6) imposes that the sum of the number of resources equal 23. Finally, equation (7) ensures that the problem is integer. The nonlinear regression model has been solved by LINGO® and the optimal condition obtain. The optimal combination is (3, 2, 7, 4 and 7). By replacing the new resources configuration in our simulation model, determined the best total costs of 25.2. Table 5 shows a comparison between optimal combination and current combination in this ED. According to the results, one reception be cut back, two nurses be cut back, two heart residents and general surgeons be added and two beds cut back in the ED. These changes cause reduce by 5% in budget and 44% improvement in the waiting time of patients.

Table 5 Comparison between current and optimal condition

Condition	X_1	X_2	X_3	X_4	X_5	*Budget*	*Waiting time of patients (min)*
Current	2	4	5	2	9	26.6	9
Optimal	3	2	7	4	7	25.2	5

5 Conclusions

ED is one of the saturation sections in the hospitals during COVID-19 pandemic. The management of patient’s flow, especially the total waiting time of arriving patients in the ED under COVID-19 conditions is the most important issue. For this purpose, this paper, applies a S-BO-based meta-modelling to a real case problem in an ED in Iran.

Meta-modelling approach in this paper is an invaluable contribution to the ED and medical managers for the redesign and evaluates of current situation ED system to reduce waiting time of patients and improve resource combination under COVID-19 conditions to improve efficiency.

This methodology can be used as a DSS tool for the evaluation of the ED performance by changing the ED key resources configuration. This method could be used for decision making in all management levels such as operational, tactical and strategic. Therefore, a DES model is developed using ARENA® software for investigating detailed waiting time of patients and for evaluating new resources configuration. We used a meta-modelling approach to develop an integer nonlinear programming model. The model is used to obtain the number of key resources. The key resources considered are: the number of receptionist, number of nurses, number of heart resident, number of general surgeon and number of beds. Simulation and optimisation is used both to evaluate the ED performance and to minimise waiting time of patients. Our approximate model causes reduce by 5% in budget (e.g., decrease of the total costs from 26.6 to 25.2) and 44% decrease in the waiting time of patients (e.g., decrease of the waiting time of patients from 540 sec to 300 sec). For future research, the authors suggest to extend this methodology to other sections of hospital and uses the other meta-models and compare their results together. As there was no systematic database for some parts of budget elements, the medical expert's estimations and healthcare officers were asked to help. Also, considering a periodic meta-model according to different work shifts in the ED is an attractive idea for developing the context.

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