Safety Science 66 (2014) 61–74

Contents lists available at ScienceDirect

Safety Science

journal homepage: www.elsevier.com/locate/ssci

Multi-response simulation optimization approach for the performance optimization of an Alarm Monitoring Center

Barış Şimşek [a], Yusuf Tansel İç [b,*]

[a] Department of Chemical Engineering, Faculty of Engineering, Ankara University, 06100 Tandoğan, Ankara, Turkey
[b] Department of Industrial Engineering, Faculty of Engineering, Baskent University, 06810 Baglica, Etimesgut, Ankara, Turkey

ARTICLE INFO

Article history:
Received 1 February 2013
Received in revised form 16 December 2013
Accepted 3 February 2014
Available online 3 March 2014

Keywords:
Simulation–optimization
Multi-response Taguchi optimization
Taguchi method
TOPSIS
Alarm Monitoring Center

ABSTRACT

This study offers a multi-response simulation–optimization approach to optimize an Alarm Monitoring Center's performance. In this paper, the multi-response simulation–optimization application is firstly addressed in the Alarm Monitoring Center. Five performance criteria affect the performance of Alarm Monitoring Center and five factors, each of which has three control levels, are identified. The data belonging to the performance criteria, which are determined, are obtained with the help of the running scenarios combining with the factor levels using Taguchi design. Then, signals to the noise (*S*/*N*) ratios are calculated for these which are obtained from the performance data. A decision matrix is generated with *S*/*N* ratios; the TOPSIS method is used to transfer the multi-response problems into the single-response problems. The system improvement rate is also determined by finding the levels of factors to optimize the system using Taguchi's single response optimization methodology.

1. Introduction

The need for reaching relevant authorities, especially in the security problems, has recently increased in parallel with the developments in the information and computer technologies. Since 2001, the safety and security issues have gained major importance all around the world, creating one of the fastest growing industry sectors. The state in Turkey is not different (Ilgaz, 2007). Among the European countries, Turkey ranks second after Poland in the size of its private security guards. Although Turkey has been dealing with socio-economic issues for last decades, the increases in safety threats have made the security a prime concern for citizens. The security sector in Turkey especially consists of physical security services whereas in economically developed countries, the security sector is more weighted toward the methods of electronic security. Therefore, it can be expected that as the Turkish economy develops, a change toward the methods of electronic security will occur (Ilgaz, 2007).

"Alarm Monitoring Center" (AMC) is a newly developing concept in Turkey. The alert systems, which are established in houses and workplaces, send information to related alert monitoring center nearby any alert situations, and provide the intervention of police or fire department or health care departments for various alert types (robbery, fire, etc.). Alert monitoring centers provide service for 7 days 24 h. The receptors of these systems transfer incoming alerts to computer screens which sort by importance of alert. Every communication detail of the alert place is automatically provided to operator. The alert monitoring center performs certain procedures and processes, which was determined before.

House and workplace alert systems are typically composed of fire and robbery alert systems. The main purpose of robbery alert systems is to sense the passage of any persons in the time intervals which are determined. In practice, these systems accept every entry in the time intervals, which are determined, as robbery and send information to the alert monitoring center. Many different sensors are being used in buildings in order to sense unwanted entries and to send these senses to the desired centers as electrical signals. Robbery sense sensors or perimeter and interior detector devices can generally be classified; ultrasonic movement detectors, passive infrared detectors (PIR), sound detectors, light sensors, capacitance sense detectors and acoustic glass break detectors (Eren, 2006).

The fire monitoring systems are the electronic notification alert systems, which sense the fire incidences in the region by sensors. These are generally used as building fire systems: ionization, optical smoke type of fire detectors, fixed temperature, temperature rising speed detectors, linear temperature rising detectors, heat type detectors, flame detectors, sound alert/horns, sound – flash alert horns, analog addresses, and conventional fire notification alert panels (Eren, 2006). Heat and smoke detectors are the most widely used fire detection devices. Heat detectors are designed to

* Corresponding author. Tel.: +90 312 2466666/1316.
E-mail address: ytansel@baskent.edu.tr (Y.T. İç).

http://dx.doi.org/10.1016/j.ssci.2014.02.001
0925-7535/

detect a rapid increment of heat in the area of the detector (CSAA, 2011). Smoke detectors could detect the presence of smoke in an area (CSAA, 2011). There are two well-known types of smoke detectors, ionization and photoelectric. Ion detectors detect a flaming fire faster; however a photo electric detector detects a smoldering fire quicker in most situations (CSAA, 2011). Carbon Monoxide (CO) or gas detection equipments are used for detection of the specific gas or vapor to be encountered (CSAA, 2011). Sensors are linked to a control unit via low-voltage wiring or a narrowband radio frequency signal which is used to interact with a response device (Elfahaksany et al., 2011).

The procedure of data collection in an AMC is illustrated in Fig. 1. The robbery alert system senses the unwanted entries to the building and, as desired, notifies the alert monitoring center about the situation. Detectors are connected to system panels, and sirens and flashers are connected to the alarms.

In any alert situations, the control panel makes the alarm equipments active due to the coming signals. Then, if the system is connected to any alert monitoring centers, the control panel notifies the central security station about the alert/failure state of system. The detectors, which provide this information, are movement detectors, glass break detectors to sense the glass breaks in first floor, seismic detectors and magnetic contacts in windows/doors. The fire alert system is sensitive to any smoke, any chemical gas, nonlinear rising of area temperature and light radiation. If the data of detectors, which are used, exceeds the certain level in security zones, these data are sent to the central control unit through the control panel by different communication methods. Then, the fire cooling systems are being activated. The computer–phone integration system is a system which forwards the coming call to operator and at the same time, provides the clients information to the operator screen. Alert zone and alert type are transferred to the alert monitoring center telephone central. At the same time, the information of conference between client and operator is reflected to the screen. So, the client conference times and alerts types are recorded to the database.

In previous researches, the performance analysis of Alarm Monitoring Centers (AMC) has not been studied. An AMC system can provide a variety of functions such as customer service, contact centers service, and technical support (Rothrock, 2011; Ma et al., 2011). AMC is similarly considered as "Call Centers" for queuing system which consists of customers (callers), servers (telephone agents), and queues. The incoming calls are classified as true or false. This is a former process of filtering without noticing to the relevant departments. True ones are forwarded to related institutions.

In this study, an AMC performance is improved. This study is the first in the literature to carry out the performance improvement of AMC with the simulation–optimization. First of all, the performance criteria of system as well as factors and their levels that affect these performance criteria are identified for performance optimization of AMC. The data belonging to performance criteria, which are determined, are obtained with the help of running scenarios combining with the factor levels using Taguchi design. Then, signal to noise (S/N) ratios are calculated for these obtained performance data. After a decision matrix is generated with S/N ratio, TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) is used to transfer the multi-response problems

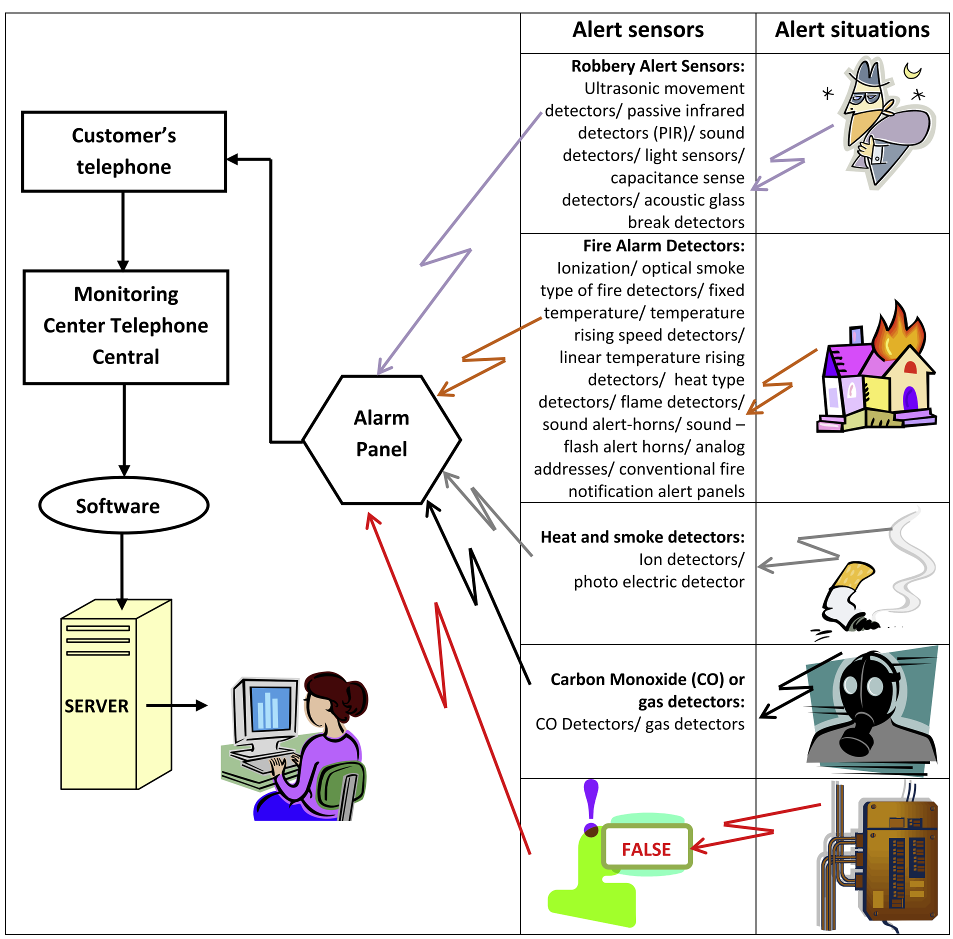


Fig. 1. Data collection procedure.

into the single-response problems. As a result, the best factor levels are identified according to Taguchi method principles for one-response problem (Simsek et al., 2013).

The remainder of this paper about the performance optimization of AMC is organized as follows: a literature survey is provided in Section 2. System is defined and then the performance analysis of the existing system is presented in Section 3. The details of the proposed methodology and the empirical results are discussed in Section 4. The conclusions are presented in Section 5.

2. Literature review and conceptual background

2.1. Simulation–optimization

Simulation is a useful tool for modeling and analyzing the performance of dynamic and complex system. Simulation can also be used for some purposes such as the prediction of the performance of system in the conditions which are proposed and according to specified criteria, the comparison of the proposed system designs or policies and in order to determine which factors are effective on the performance of system (Wainer, 2009). In a simulation study, the data which are collected from the real system is used to estimate the input parameter which is required to run the model of system (Law, 2007).

In last decade, the computer simulation has been a more important tool for studying, understanding and controlling complex systems. The complexity and uncertainty of the nature of complex systems require complex solution tools or hybrid approaches including knowledge management, mathematical modeling, simulation, decision support systems, etc. (Guo et al., 2003; Bagdasaryan, 2011; Wang et al., 2011; Alexander and Kelly, 2013).

The simulation model does not provide a method for the optimization. To solve a simulation–optimization problem, the response surface methodology (RSM), meta-model applications and meta-heuristic methods are proposed in the literature (Yang and Chou, 2005; Kuo et al., 2008). The RSM simulation–optimization approach presents a statistical summary of simulation results. It provides some graphical illustrations and extrapolations from the simulated system conditions, and also, has the potential to offer assistance in the optimization (Yang and Chou, 2005; Kuo et al., 2008). Also, other abstract model called meta-model is used to replace the simulation model. Meta models provide an application to the statistical summarization of simulation results, allowing interpolation from the currently simulated system conditions to reduce the requirements of the run time. Meta-models are also taking a role as the objective function in the optimization process considering system boundaries (Dengiz and Akbay, 2000; Dengiz, 2009; Kleijnen, 1979; Kleijnen and Sargent, 2000; Kumar and Sridharan, 2010). On the other hand, meta-heuristics (such as particle swarm optimization, genetic algorithms, simulated annealing, ant colony optimization, tabu-search, or scatter search) can be used as an incorporated local search algorithm associated with the simulation software for a simulation–optimization problem (Yang and Chou, 2005; Pasandideh and Niaki, 2006; Syberfeldt et al., 2009; Kuo and Yang, 2011). Although there are various studies in the literature that address single-response simulation–optimization problems, most of the industrial real case simulation–optimization problems include the multi-response characteristics (Yang and Chou, 2005). Some of the approaches were proposed in the literature for the solution of the multi-response simulation–optimization problem (Myers and Carter, 1973; Azadivar and Lee, 1988; Castillo and Montgomery, 1993; Khuri, 1996; Fan and Castillo, 1999; Park et al., 2001; Yang and Tseng, 2002; Angün et al., 2003; Pasandideh and Niaki, 2006; Rosen et al., 2007; Oddoye et al., 2009; Um et al., 2009; Syberfeldt et al., 2009; Kuo and Yang, 2011; Azadeh et al., 2011; Yazgan et al., 2011; Subulan and Çakmakçi, 2012).

Multi Attribute Decision Making (MADM) methods, especially TOPSIS (technique for order preference by similarity to ideal solution) (Yang and Chou, 2005), GRA (Grey Relational Analysis) (Kuo et al., 2008; Chiang and Hsieh, 2009), DEA (Data Envelopment Analysis) (Liao, 2004), and AHP (Analytic Hierarchy Process (Liao and Kao, 2010; Azadeh et al., 2011) incorporated to Taguchi methods to solve the multi response simulation–optimization problems. For example, Yang and Chou (2005) proposed to TOPSIS based Taguchi optimization to solve the multi-response simulation–optimization problem. They illustrated a real case study from an integrated-circuit packaging company. Also, Kuo et al. (2008) used GRA-based Taguchi optimization to solve the Yang and Chou's (2005) problem. On the other hand, Azadeh et al. (2011) presented a decision support system based on Fuzzy Analytical Hierarchy Process (Fuzzy AHP), TOPSIS, and the computer simulation to find the most efficient number of operators in a cellular manufacturing system. The Fuzzy AHP method was used to find the importance weight of the criteria. Also, the TOPSIS method was used to rank alternative scenarios (Azadeh et al., 2011).

2.2. AMC domain

The AMCs of today now plays a vital role in the chain of security protecting homes and businesses alike. There is no study in the literature to performance improvement of an AMC (Web of Science, 2013). The present research explores the possibility of a hybrid Taguchi method and TOPSIS approach to solve a multi response simulation–optimization problem with the discrete factors in the AMC domain. The goal of this study is to provide a systematic AMC modeling framework to analyze the performance of system as well as gross-level toward the improvement of an AMC service system design. We believe that the simulation–optimization approaches, which only involve in the single response, shed little light on the evaluation of overall service performance for particular AMC. In order to manage AMCs effectively with the proper performance, managers should know the optimal level of the quality characteristics of their system.

2.3. Research contributions

While the queue-centered analytic models are still popular, several factors such as rapid change operations, cheaper and faster computing, and complex call traffic have recently increased the demand for the analysis of even more complex AMC through the simulation. Although there are some research approaches of operation which deal with the call center problems based on the optimization such as mathematical and stochastic programming models, they still focus on only single response (Atlason et al., 2004; Artalejo et al., 2007; Jouini et al., 2009; Cezik and Ecuyer, 2008; Robbins and Harrison, 2010; Roubos and Jouini, 2013; Valle et al., 2012). Also, the previous call center simulation studies are only focused on the specific quantity measures such as average talk time, calls per hours, and average speed of answer at the gross-level. The simulation model is a successful tool in solving the performance analysis problems of stochastic call center and allows analyzing of the likely behavior of an AMC system under the selected conditions. However, it does not provide a method for the optimization. The performance optimization of the AMCs is very important for the optimal setting of control factors. A macro research level such as "improving the way in which the link between efficiency and quality of service is modeled" is significant for future AMC operations research. The present study predicts the system performances for any combinations of levels of the controllable factors (quality characteristics) by using the main effects of the control factors according to the principles of a Taguchi's robust design method.

Although there is a significant body of literature in the call center domain that addresses the single-response optimization problems, the practical problems often embody many characteristics of a multi-response optimization problem in AMC domain. For example, one such practical problem is to minimize the average number of customer waiting in queue while simultaneously maximizing the average system utilization. So, this makes the problem more complex to solve. In order to tackle the difficulties of multi-response optimization, we propose a combined TOPSIS-based Taguchi approach. This study is focused on solving a multi-response simulation–optimization problem with discrete variables using a TOPSIS-based Taguchi optimization, which has not been considered in the traditional queue-centered analytic models.

3. Proposed multi-response simulation–optimization methodology

There are 5 flow steps in the performance optimization of AMC. This flow diagram is given in Fig. 2. The TOPSIS procedure is used to integrate all the determined performance values of the system into a single value that can then be used as the single performance in the simulation–optimization problems (Simsek et al., 2013).

The current AMC system is simulated in this study. The performance values are obtained with the results of simulation model. SIMAN, Slam and SIMSCRIPT are the simulation languages of major event sequence. Over the years, these languages have started to become more process oriented. These three languages bring into the use of high level languages such as FORTRAN and C in models. This facility is an important feature that should be in terms of the realization complex systems. SIMAN simulation language is a general purpose simulation language which is developed for modeling discrete, continuous or discrete–continuous systems (Pegden et al., 1995). In this study, SIMAN simulation language is used to modeling of the AMC.

A large number of simulation experiments have to be examined when the number of system parameters increases. To solve this problem, the Taguchi method presents special orthogonal arrays to examine the entire system parameter space with only a small number of the simulation experiments (Kuo et al., 2008). Therefore, the first step of the proposed methodology of simulation–optimization is to determine an appropriate orthogonal array in which every row illustrates a simulation scenario. The simulation runs are then executed by following the experimental structure of the selected orthogonal array (Kuo et al., 2008). The proposed TOPSIS-based Taguchi method includes the idea of a multi-response robust design principles to solve the multi-response simulation–optimization problem. The robust design procures an effective method for obtaining the optimal composition of design variables such that the product is efficient and has a high level of performance, and also is robust to noise factors (Yang and Chou, 2005; Kuo et al., 2008; Simsek et al., 2013). The noise factors are defined as uncontrollable factors. The signal-to-noise ratio (S/N ratio, η) is a useful metric to find significant factors by evaluating minimum variance (Kuo et al., 2008). S/N ratios can be used for measuring a system performance. The "smaller is better" response is suitable for the seven performance measures determined for AMC. S/N ratio for the smaller is better is given by equation:

$$\eta_{ij} = -10\log_{10}\left[\frac{1}{n}\sum_{k=1}^{n} y_{ijk}^2\right] \quad (1)$$

where y_{ijk} be the simulation result for the response j of scenario i, in the k th replication; n is the total number of replications (Kuo et al., 2008). The multiple-response problem has been converted to the single-response problem with following steps using TOPSIS methodology (Yurdakul and Ic, 2003; Yurdakul and Ic, 2005; Yang and Chou, 2005; Yurdakul and Ic, 2009).

3.1. TOPSIS methodology

TOPSIS has been developed by Hwang and Yoon (1981) for solving the MADM problems. It is based on the idea that an alternative, which is chosen, should have the farthest distance from the negative ideal solution and on the other side, the shortest distance from the positive ideal solution (Jafarian and Vahdat, 2012; Mahdavi et al., 2008; Grassi et al., 2009). In our study, TOPSIS method is selected for five main reasons (Zeleny, 1982; García-Cascales and

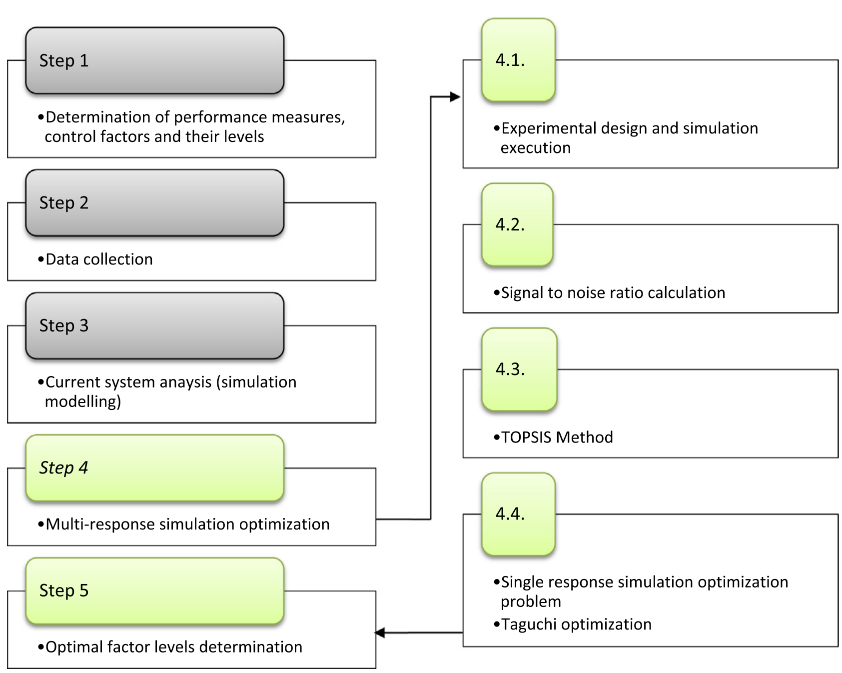


Fig. 2. Proposed performance optimization framework.

Lamata, 2012; Shih et al., 2007): (i) TOPSIS procedure is rational and understandable. (ii) The computation process is depicted in a simple mathematical form. (iii) The importance weights can be obtained by the direct assignation. (iv) A simple computation process can be easily programmed into a spreadsheet. (v) TOPSIS procedure is not affected by any extra parameter (e.g., ξ is GRA method and v in VIKOR method) as it happens in case of other MADM methods (Chakraborty, 2011). For this reason, the TOPSIS method is highly stable for the decision making studies. The TOPSIS procedure consists of the following steps:

i. *Determination of decision matrix.*

In the TOPSIS method application, characteristic values of alternatives at attributes are inputs and placed in the matrix form as shown in Eq. (2).

$$D = \begin{bmatrix} \eta_{11} & \eta_{12} & \cdots & \eta_{1n} \\ \eta_{21} & \eta_{22} & \cdots & \eta_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \eta_{m1} & \eta_{m2} & \cdots & \eta_{mn} \end{bmatrix} \tag{2}$$

where, η_{ij} is S/N ratio and, $i = 1,2,\ldots,$ number of scenarios (m), $j = 1,2,\ldots,$ number of responses (n)).

ii. *Calculate normalized ratings by the vector normalization.*

$$r_{ij} = \frac{\eta_{ij}}{\sqrt{\sum_{i=1}^{m} \eta_{ij}^2}} \qquad i = 1,\ldots,m \text{ and } j = 1,\ldots,n \tag{3}$$

iii. *Calculate weighted normalized rating.*

The weighted normalized value v_{ij} is calculated by Eq. (4).

$$v_{ij} = w_j r_{ij} \qquad i = 1,\ldots,m \qquad j = 1,\ldots,n \tag{4}$$

These weights can be obtained by the direct assignation.

iv. *Identify positive ideal and negative ideal solutions.*

The positive ideal value set A^* and the negative ideal value set A^- are determined as follows:

$$A^* = \left\{ (\max_i v_{ij} \mid j \in J), (\min_i v_{ij} \mid j \in J') \right\} \tag{5}$$

$$A^- = \left\{ (\min_i v_{ij} \mid j \in J), (\max_i v_{ij} \mid j \in J' \right\} \tag{6}$$

where J is associated with the benefit criteria, and J' is associated with the cost criteria.

The A^* and A^- are defined in terms of the weighted normalized values, as shown in Eqs. (5) and (6):

v. *Calculation of separation measures.*

The separation between scenarios can be measured by the n-dimensional Euclidean distance. The separation of each scenario from the positive ideal solution, A^*, and the negative ideal solution, A^- is then given by Eqs. (7) and (8) respectively:

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2} \tag{7}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{8}$$

vi. *Calculation of relative closeness to the ideal solution.*

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*}; \qquad i = 1,\ldots,m \tag{9}$$

4. The performance improvement of an Alarm Monitoring Center

4.1. Determination of the performance measures

A discrete system is one for which the state variables instantaneously change at the separated point of time (Law, 2007). The simulated AMC has two-serviced queue system. A queue system is an example of discrete system, since state variables (e.g., the number of customer in the AMC system) change only when a customer arrives or when a customer finishes being served and system. The state variables of the system must be monitored for estimating the performance criteria in the discrete event simulation model using the time advancement technique with the closest event to the time.

The performance analysis of AMC is focused on the quantity measures to specify the service quality within an individual service activity of AMC operations. The measure of a "telephone service factor" is used as a core factor (Ma et al., 2011). So, we have been determined five controllable service grade oriented factors for AMC. The factor levels have determined by the expert's opinion by taking into consideration of the characteristics of the current system. Seven performance measures (R1–R7) are also determined for the equilibrium state of the system. R1, R2 and R3 are present the percentage of the average service times according to the type of job. R4 and R5 are present in the average number of customers waiting in the queues. These measures give an idea about how much customer satisfaction is provided. Finally R6 and R7 provide information about the rates of service utilization according to the type of job. The measures of performance and their weights are assigned by the consensus of the two managers who are responsible of AMC (Table 1).

4.2. Determination of factors and their levels

In this section, five factors, each of which has three control levels affecting to the performance criteria, are determined. The first and second factors are probability of Type-1 job type and probability of Type-3 job type login system respectively. The third and fourth factors are the average service delay time of first and second service. The last factor is the probability of false job logout system. These factors are symbolized A, B, C, D, E respectively and their levels are illustrated in Fig. 3.

4.3. Simulation model establishment of current system

Analysis of system performance are contained these sections such as the definition of problem, the determination of input probability distribution, modeling system with SIMAN simulation language and validation of model.

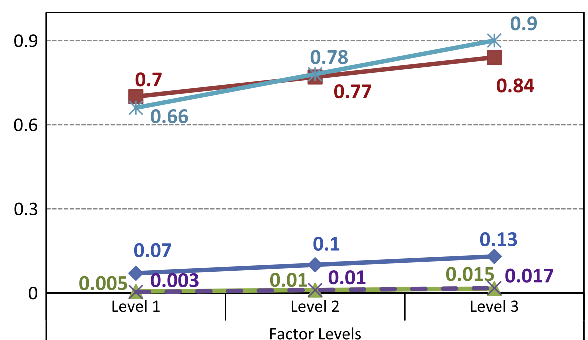
4.3.1. System identification

The service system is working 24 h and 7 days. Loss of service before or after the shift is being ignored. There are not any interruptions in daytime (like lunch, etc.). There are 3 types of entries in the system; Type-1 (fire – 0.10 possibility), Type-2 (robbery – 0.20 possibility) and Type-3 (wrong – 0.70 possibility). The simulation model has two serial services, which of each has a queue. There is some priority scheduling in this research. Three types of priority according to job type were determined for "Queue-1" and "Queue-2". In the queues, Job Type-1 is more privileged than Job Type-2. Also, Job Type-2 is more privileged than Job Type-3. There are two different work stations (phones), each of which

Table 1
Determination of the performance measures and their weights.

Symbol	Performance measure	Description	Assigned performance measure's weights	Normalized weight
R1	Average time in system of Type-1 job (h)[b]	The average time that spent for the type of fire work in the system	2	0.051
R2	Average time in system of Type-2 job (h)	The average time that spent for the type of robbery work in the system	2	0.051
R3	Average time in system of Type-3 job (h)	The average time that spent for the type of wrong work in the system	9	0.231
R4	Average number of customer waiting in phone 1 queue[a]	The average number of callers waits to meet with first operator in the first line	5	0.128
R5	Average number of customer waiting in phone 2 queue	The average number of callers waits to meet with second operator in the second line	5	0.128
R6	Service 1 utilization rate[c]	The percentage of time that first operator talking on the phone with customers	8	0.205
R7	Service 2 utilization rate	The percentage of time that second operator talking on the phone with customers	8	0.205
Total			39	1.0

[a] Queue is a line that the caller waits to meet with operator.
[b] Job is the call type was transmitted to the operator by the customer.
[c] Service is an operator speaking on the phone with customers.



	Level 1	Level 2	Level 3
A: The probability of Type-1 job login system	0.07	0.1	0.13
B: The probability of Type-3 job login system	0.7	0.77	0.84
C: Average service 1 delay time (hour)	0.005	0.01	0.015
D: Average service 2 delay time (hour)	0.003	0.01	0.017
E: The probability of fault job logout system	0.66	0.78	0.9

Fig. 3. Factor levels.

has a queue in the system; "Service 1" and "Service 2". 90% Of probability of wrong or empty work, 10% of probability true work gone from the "Service-2". The alert notifications, which come, wait for getting process from "Phone-1". The client, who completes these service processes, joins the queue to speak to the "Service 2". Calls are being classified here as true or wrong alerts. Wrong ones are removed from the system. But true ones are forwarded to related institutions. Time between arrivals is coming from the exponential distribution with 0.14 h average. Average "Service 1" time has normal distribution between (0.0020, 0.0062, 0.0099) hours, and the average service time has between (0.0014, 0.0060, 0.098) hours. With these assumptions, the 30 days simulation of system can be made.

4.3.2. Determine input probability distribution

Simulation, which is performed, is needed to determine the probability distribution of input. Simulation uses random values from these distributions. Some special distributions have special statistical values (Law, 2007). These statistics are acquired from data and compared to the point statistics of theoretical distribution. A compliant distribution should be determined for data after the collection of data. A pre-analysis is performed for the data set. First of all, statistics of various samples are calculated due to data. If the sample width is smaller for the sample average, it can be ignored. The main purpose of pre-analysis is to determine whether a model is compliant for data or not. With this purpose, many diagrams are developed. Some of them are general (for example histogram), and some of them are special for some special models. After the examinations about time interval between arrivals, the exponential distribution is accepted as candidate model of data modeling in this study. After the determination of suitable distribution for data, the parameter values should be determined for the usage of this distribution. There are many ways to specify the form of an estimator for a particular parameter (β) of selected exponential distribution, and many alternative ways to evaluate the quality of an estimator. In this study, we used "maximum-likelihood estimator-MLE" since the basis for MLEs is most easily understood in the discrete case (Law, 2007). The parameters of exponential distri-

Table 2
χ^2 Test results for the time interval between arrivals.

Intervals	Observed values	Intervals	Expected value $n * [F(Y_u) - F(Y_l)]$	Adjacent intervals (k)	Observed values	Expected value	χ^2 Test statistics	$\chi^2_{3;0.95}(\chi^2_{k-m-1,1-\alpha})$
1	28	0.016–0.136	**32.12**[b]	1	28	32.12	3.24[a]	7.81
2	18	0.136–0.256	23.54	2	18	23.54		
3	9	0.256–0.376	7.71	3	9	7.71		
4	4	0.376–0.496	6.19	4	13	16.75		
5	6	0.496–0.616	6.336					
6	1	0.616–0.736	1.056					
7	1	0.736–0.856	1.049					
8	1	0.856–0.976	1.062					
Total	68							

[a] Null hypothesis H_0 = the X_i's are interdependent and identically distributed random variables with distribution function F. Since 3.24 < 7.81, null hypothesis would not reject.
[b] **68 ∗ [F(0.136) − F(0.016)] = 32.12.**

Table 3
χ^2 Test results for the average service time 1.

Intervals	Observed values	Intervals	Expected value $n * [F(Y_u) - F(Y_l)]$	Adjacent intervals (k)	Observed values	Expected value	χ^2 Test statistics	$\chi^2_{3;0.95}(\chi^2_{k-m-1,1-\alpha})$
1	28	0.0016–0.0136	33.01	1	28	33.01	2.309[a]	5.99
2	18	0.0136–0.0256	20.22	2	18	20.22		
3	9	0.0256–0.0376	10.32	3	9	10.32		
4	4	0.0376–0.0496	5.430	4	13	13.890		
5	6	0.0496–0.0616	5.075					
6	1	0.0616–0.0736	0.871					
7	1	0.0736–0.0856	1.582					
8	1	0.0856–0.0976	0.932					
Total	68							

[a] Null hypothesis H_0 = the X_i's are interdependent and identically distributed random variables with distribution function F. Since 2.309 < 5.99, null hypothesis would not reject.

bution model for AMC application are estimated by most possibility method and calculated as β = 0.14 (see Fig. A1).

On the other hand, for the average time of "Service 1" and "Service 2" data, normal distribution model is accepted as the candidate model for the modeling data. For average time of "Service 1", a and b parameters of normal distribution (Law, 2007) is calculated as 0.0020 and 0.0099 by the moment method. For the average time of "Service 2", a and b parameters of normal distribution is calculated as 0.0014 and 0.0098 by the moment method (see Figs. A2 and A3).

4.3.3. Verification of the model

The final step in the process of modeling is to verify the selected model. This step includes the goodness of fit tests. The goodness of fit tests is statistical techniques that provide to test model hypothesis (Walpole et al., 2007). χ^2 (Chi-square) goodness of fit test is carried out in 95% confidence level. The appropriate distribution with Chi-square goodness of fit tests determined as follows. The time interval between arrivals is distributed with 0.14 h mean exponential distribution (Table 2), average "Service 1" delay time is distributed with (0.0020 and 0.0099) hours mean uniform distribution (Table 3), average "Service 2" delay time is distributed with (0.0014 and 0.0098) hours mean uniform distribution (Table 4).

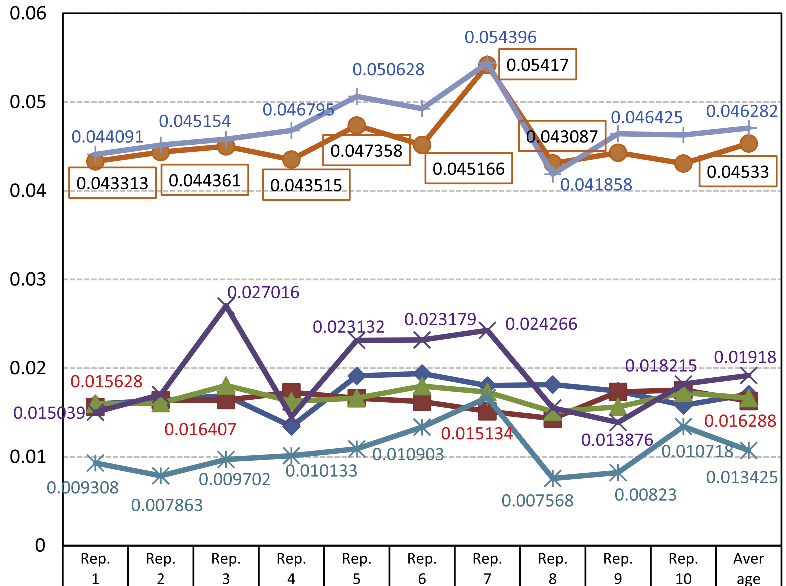
4.3.4. Modeling of the system with SIMAN

The simulation model of the AMC is coded by SIMAN which has been validated and is used for the empirical illustrations. The study horizon was 30 days (720 h). These data came from a real case study. Incoming calls (call time, call type, etc.) are saved on the computer with the systems such as the automatic number identification (ANI) and the computer telephony integration (CTI). The calling time of an incoming call is instantly transferred to the com-

Table 4
χ^2 Test results for the average service time 2.

Intervals	Observed values	Intervals	Expected value $n * [F(Y_u) - F(Y_l)]$	Adjacent intervals (k)	Observed values	Expected value	χ^2 Test statistics	$\chi^2_{3;0.95}(\chi^2_{k-m-1,1-\alpha})$
1	28	0.0016–0.0136	31.43	1	28	31.43	1.818[a]	5.99
2	18	0.0136–0.0256	19.54	2	18	19.54		
3	9	0.0256–0.0376	11.87	3	9	11.87		
4	4	0.0376–0.0496	5.129	4	13	15.996		
5	6	0.0496–0.0616	7.879					
6	1	0.0616–0.0736	0.634					
7	1	0.0736–0.0856	0.547					
8	1	0.0856–0.0976	1.814					
Total	68							

[a] Null hypothesis H_0 = the X_i's are interdependent and identically distributed random variables with distribution function F. Since 1.818 < 5.99, null hypothesis would not reject.



	Rep. 1	Rep. 2	Rep. 3	Rep. 4	Rep. 5	Rep. 6	Rep. 7	Rep. 8	Rep. 9	Rep. 10	Average
Average time in system of Type-1 job(h)	0.01596	0.01639	0.01691	0.01344	0.01912	0.01939	0.01803	0.01815	0.01742	0.01581	0.01706
Average time in system of Type-2 job(h)	0.01563	0.01641	0.0164	0.01728	0.01662	0.01623	0.01513	0.01432	0.01733	0.01754	0.01629
Average time in system of Type-3 job(h)	0.01601	0.01606	0.01805	0.01627	0.01663	0.01797	0.0173	0.0151	0.01564	0.01724	0.01663
Average number of customer waiting in phone1 queue	0.01504	0.01701	0.02702	0.01454	0.02313	0.02318	0.02427	0.01551	0.01388	0.01822	0.01918
Average number of customer waiting in phone2 queue	0.00931	0.00786	0.0097	0.01013	0.0109	0.01335	0.0167	0.00757	0.00823	0.01343	0.01072
Service 1 utilization rate	0.04331	0.04436	0.045	0.04352	0.04736	0.04517	0.05417	0.04309	0.04428	0.04307	0.04533
Service 2 utilization rate	0.04409	0.04515	0.04582	0.0468	0.05063	0.04926	0.0544	0.04186	0.04643	0.04628	0.04707

Fig. 4. Seven responses and their performance values in current systems.

Table 5
L_{27} experimental results.

Exp. no.	Taguchi design L_{27}					S/N ratios						
	A	B	C	D	E	R1	R2	R3	R4	R5	R6	R7
1	1	1	1	1	1	46.3553	47.5350	47.3145	51.4373	65.3682	34.9294	39.8870
2	1	1	1	1	2	46.7335	46.8665	46.8531	51.6439	65.4005	34.8057	39.0102
3	1	1	1	1	3	47.5185	46.4442	47.3205	51.0506	67.5557	34.1842	38.6877
4	1	2	2	2	1	37.6506	36.4101	37.6321	37.6004	40.5903	29.0406	28.9403
5	1	2	2	2	2	37.9575	36.7302	37.7734	39.9153	39.6077	29.3760	29.1311
6	1	2	2	2	3	38.4898	37.4185	37.5662	37.3779	40.3682	28.9830	28.8138
7	1	3	3	3	1	32.6109	29.7538	32.1492	29.1234	29.2534	26.0154	25.0487
8	1	3	3	3	2	30.8657	30.1456	31.7599	29.0830	29.2989	26.0347	25.1365
9	1	3	3	3	3	32.8227	31.6565	32.0228	30.8484	28.1447	25.0224	24.6187
10	2	1	2	3	1	32.8642	33.1236	32.0868	37.6307	24.7298	28.8311	24.4863
11	2	1	2	3	2	32.8722	33.0745	32.1972	37.6149	24.6594	28.8362	24.5442
12	2	1	2	3	3	33.1468	32.8745	31.6818	36.7559	23.6231	28.6873	24.2567
13	2	2	3	1	1	34.8402	35.4156	37.7492	28.2278	71.7676	25.1174	38.7476
14	2	2	3	1	2	36.7392	38.6177	38.6921	30.1177	63.4655	24.7696	39.5787
15	2	2	3	1	3	34.1673	35.4515	37.2087	27.0951	70.9950	24.7261	38.7808
16	2	3	1	2	1	40.1578	40.6772	40.0794	49.3500	38.1379	34.2664	28.6505
17	2	3	1	2	2	39.8835	40.0619	39.8203	48.2908	36.9365	34.0931	28.5407
18	2	3	1	2	3	40.5006	40.8603	40.1879	49.6614	40.0724	35.0489	29.7080
19	3	1	3	2	1	33.5859	33.6329	33.9968	28.0205	45.8146	25.2574	29.6881
20	3	1	3	2	2	34.8402	34.9960	34.5836	28.7644	29.2539	25.1983	29.2539
21	3	1	3	2	3	34.8359	33.7569	34.0360	26.8260	45.1675	24.7268	29.3968
22	3	2	1	3	1	33.6050	35.4819	35.2130	58.2942	29.6126	35.8129	25.3227
23	3	2	1	3	2	35.0902	34.0479	33.6601	52.0516	24.3232	34.5753	24.1529
24	3	2	1	3	3	35.9819	34.1085	34.0685	53.2349	24.9786	35.0141	24.5211
25	3	3	2	1	1	41.4198	43.0325	41.6425	38.9986	67.0523	28.7525	39.0998
26	3	3	2	1	2	40.8192	40.6537	40.8574	36.2304	65.9859	28.1438	38.7266
27	3	3	2	1	3	42.6448	41.1271	41.1668	41.0690	63.5436	30.1088	38.9924

puter screen. In this study, the customers have sought to AMC 69 times in 24 h. The time (68 pieces) interval probability distributions between the saved calls were determined by the following steps. The determination of steps that are in the distribution of collection of data input possibility, determination of the distribution family, estimation of parameters and goodness of fit test. The speaking durations (service time) of operators with the customers are automatically transferred to the computer screen again. The distribution families of speaking durations of operators with the customers were determined by similar methods again. With the probability distributions time (68 pieces) interval between the calling times of the incoming calls within 24 h, the distribution family of periods of conversation of operators with customers has been defined, and the model of the existing system has been formed with SIMAN. Ten replications generated from the simulation model where obtained from real observations of the alarm

Table 6
TOPSIS values using vector normalization.

Exp. no.	Taguchi design (L_{27})					Weighted normalized decision matrix							S_i^*	S_i^-	C_i^*
	A	B	C	D	E										
1	**1**	1	1	1	1	0.024	0.041	0.064	0.016	0.079	0.015	0.008	0.008	0.058	**0.878**
2	**1**	1	1	1	2	0.024	0.040	0.064	0.016	0.080	0.015	0.008	0.008	0.058	**0.878**
3	**1**	1	1	1	3	0.024	0.040	0.064	0.016	0.082	0.015	0.008	0.006	0.061	**0.914**
4	**1**	2	2	2	1	0.019	0.031	0.051	0.012	0.049	0.012	0.006	0.042	0.023	**0.357**
5	**1**	2	2	2	2	0.019	0.031	0.051	0.013	0.048	0.013	0.006	0.043	0.023	**0.346**
6	**1**	2	2	2	3	0.020	0.032	0.051	0.012	0.049	0.012	0.006	0.042	0.024	**0.357**
7	**1**	3	3	3	1	0.017	0.025	0.044	0.009	0.036	0.011	0.005	0.059	0.007	**0.106**
8	**1**	3	3	3	2	0.016	0.026	0.043	0.009	0.036	0.011	0.005	0.059	0.007	**0.105**
9	**1**	3	3	3	3	0.017	0.027	0.044	0.010	0.034	0.011	0.005	0.060	0.006	**0.091**
10	2	1	2	3	1	0.017	0.028	0.044	0.012	0.030	0.012	0.005	0.063	0.005	0.075
11	2	1	2	3	2	0.017	0.028	0.044	0.012	0.030	0.012	0.005	0.063	0.005	0.075
12	2	1	2	3	3	0.017	0.028	0.043	0.012	0.029	0.012	0.005	0.064	0.005	0.067
13	2	2	3	1	1	0.018	0.030	0.051	0.009	0.087	0.011	0.008	0.021	0.059	0.741
14	2	2	3	1	2	0.019	0.033	0.053	0.010	0.077	0.011	0.008	0.021	0.050	0.707
15	2	2	3	1	3	0.017	0.030	0.051	0.009	0.086	0.011	0.008	0.022	0.058	0.731
16	2	3	1	2	1	0.021	0.035	0.055	0.016	0.046	0.015	0.006	0.043	0.025	0.368
17	2	3	1	2	2	0.020	0.034	0.054	0.015	0.045	0.015	0.006	0.044	0.023	0.345
18	2	3	1	2	3	0.021	0.035	0.055	0.016	0.049	0.015	0.006	0.040	0.027	0.399
19	3	1	3	2	1	0.017	0.029	0.046	0.009	0.056	0.011	0.006	0.040	0.027	0.404
20	3	1	3	2	2	0.018	0.030	0.047	0.009	0.036	0.011	0.006	0.057	0.009	0.142
21	3	1	3	2	3	0.018	0.029	0.046	0.008	0.055	0.011	0.006	0.041	0.027	0.395
22	3	2	1	3	1	0.017	0.030	0.048	0.018	0.036	0.015	0.005	0.055	0.015	0.213
23	3	2	1	3	2	0.018	0.029	0.046	0.016	0.030	0.015	0.005	0.062	0.010	0.143
24	3	2	1	3	3	0.018	0.029	0.046	0.017	0.030	0.015	0.005	0.061	0.011	0.153
25	3	3	2	1	1	0.021	0.037	0.057	0.012	0.082	0.012	0.008	0.013	0.056	0.815
26	3	3	2	1	2	0.021	0.035	0.056	0.011	0.080	0.012	0.008	0.015	0.054	0.781
27	3	3	2	1	3	0.022	0.035	0.056	0.013	0.077	0.013	0.008	0.016	0.052	0.769

m_{A1} = 1/9 (0.878 + 0.878 + 0.914 + 0.357 + 0.346 + 0.357 + 0.106 + 0.105 + 0.091) = 0.448.

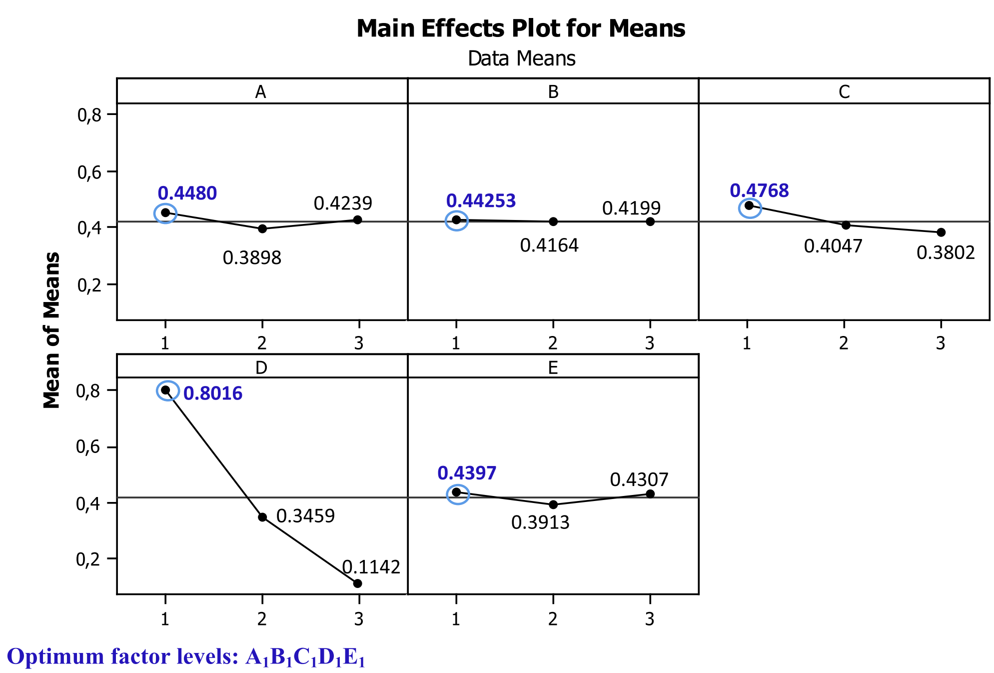


Fig. 5. Means plots for factor effects using vector normalization.

monitoring system. The average seven responses were calculated and are given in Fig. 4.

According to the job type [Type-1 (fire), Type-2 (robbery) and Type-3 (false)], the average time in system is respectively calculated; 0.01706 h, 0.01629 h and 0.01663 h. The average number of customer waiting in "Service 1" (phone 1) and "Service 2" (phone 2) are respectively calculated as 0.01918 and 0.01072. "Service 1" and "Service 2" average utilization rate, in other words traffic densities, are also respectively calculated as 0.04533 and 0.04707.

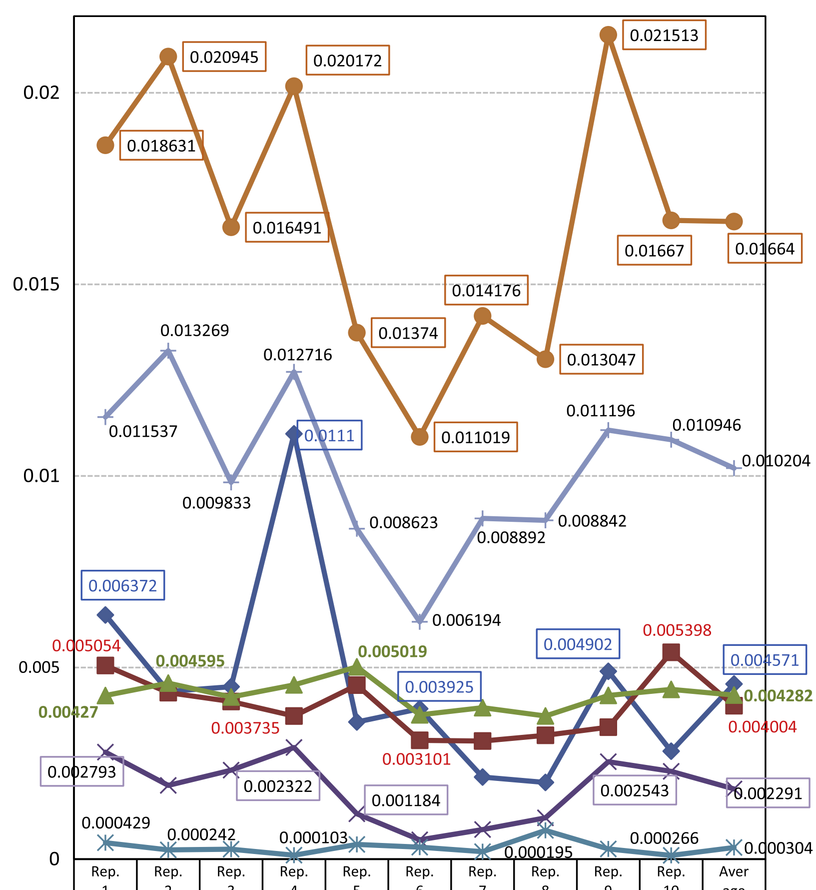
4.4. Simulation–optimization

In this study, a Taguchi orthogonal array (L_{27}) is selected to collect the simulation results (Phadke, 1989). In Table 5, columns 1–5 are represented the five control factors and their levels. For each experimental scenario, there are 10 replications to collect the proper simulation response variance data. The study took ten replications for each factor assignment to estimate the impact of noise factors. The experiments were carried out in a randomized order for each replication. The seven responses are; the average time in system of Type-1 job (R1), the average time in system of Type-2 job (R2), the average time in system of Type-3 job (R3), the average number of customer waiting in phone 1 queue (R4), the average number of customer waiting in phone 2 queue (R5), the service 1 utilization rate (R6), and the service 2 utilization rate (R7).

The simulation model provided the seven performance measures simultaneously to represent the multi-response simulation–optimization problem. S/N ratios are calculated from Eq. (1) for each response. The experimental design and S/N ratios for simulation results are shown in Table 5.

To convert multi-response simulation–optimization problem to single response problem TOPSIS method is used (Simsek et al., 2013). In Table 5 columns 7–13 is illustrated to 'decision matrix' for the first step of the TOPSIS methodology. The normalized decision matrix and then the weighted normalized decision matrix are obtained by using Eqs. (3) and (4) respectively (Table 6). The positive ideal solution (A^*) and negative ideal solutions (A^-) could be found by Eqs. (5) and (6). Eqs. (7) and (8) is used to determine the separation measures (Simsek et al., 2013). Finally, Eq. (9) is used to calculate of the similarity to ideal solution for each scenario, (C_i^*).The final results are summarized in Table 6.

By using the robust design principles, the average responses (TOPSIS ranking scores) by factor levels can be determined. According to the robust design principles, by using the additive property,



	Rep. 1	Rep. 2	Rep. 3	Rep. 4	Rep. 5	Rep. 6	Rep. 7	Rep. 8	Rep. 9	Rep. 10	Average
Average time in system of Type-1 job(h)	0.00637	0.00438	0.0045	0.0111	0.00358	0.00393	0.00214	0.002	0.0049	0.00282	0.00457
Average time in system of Type-2 job(h)	0.00505	0.00435	0.00411	0.00374	0.00454	0.0031	0.00308	0.00323	0.00344	0.0054	0.004
Average time in system of Type-3 job(h)	0.00427	0.0046	0.00423	0.00455	0.00502	0.00377	0.00395	0.00374	0.00427	0.00443	0.00428
Average number of customer waiting in phone1 queue	0.00279	0.00192	0.00232	0.00291	0.00118	0.0005	0.00077	0.00108	0.00254	0.00229	0.00183
Average number of customer waiting in phone2 queue	0.00043	0.00024	0.00026	0.0001	0.00038	0.00031	0.0002	0.00075	0.00027	9.8E-05	0.0003
Service1 utilization rate	0.01863	0.02095	0.01649	0.02017	0.01374	0.01102	0.01418	0.01305	0.02151	0.01667	0.01664
Service2 utilization rate	0.01154	0.01327	0.00983	0.01272	0.00862	0.00619	0.00889	0.00884	0.0112	0.01095	0.0102

Fig. 6. Simulation results for optimal parameter setting condition.

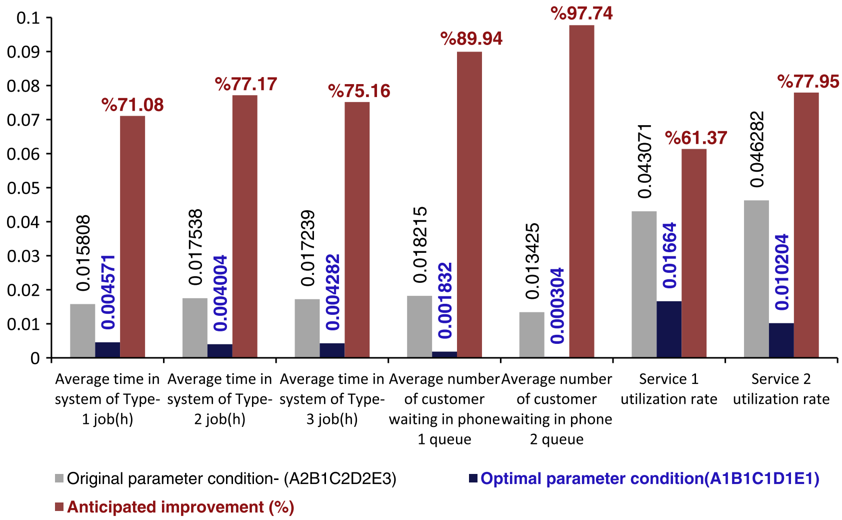


Fig. 7. Anticipated improvement in optimal parameter condition.

the average responses by factor levels can be solved (Yang and Chou, 2005). For example, the determination of the optimal factor setting for A at level 1 (m_{A1}) from Table 6 is shown as Eq. (10):

$$\begin{aligned} m_{A1} &= 1/9(C_1^* + C_2^* + C_3^* + C_4^* + C_5^* + C_6^* + C_7^* + C_8^* + C_9^*) \\ &= 1/9(0.878 + 0.878 + 0.914 + 0.357 + 0.346 + 0.357 \\ &\quad + 0.106 + 0.105 + 0.091) = 0.448 \end{aligned} \tag{10}$$

Eq. (10) is the average value of the effects shown in factor A column and level 1 rows from the L_{27} (see Table 6) orthogonal array. The same procedure is then applied to all other factor levels. The resulting factor effects are showed in Fig. 5. Their associated factor effect plots are shown as Fig. 5. The final optimal parameter design of A_1 B_1 C_1 D_1 E_1 can be determined by using the TOPSIS ranking scores (Fig. 5).

4.5. Comparison with the original process parameter setting

In order to predict the anticipated improvement under the selected optimum conditions in the parameter design stage, ten additional simulation runs were made by the optimal parameter settings for seven responses (Fig. 6). Then, the results obtained from these simulation runs were compared with the values obtained from the original parameter setting simulation results of AMC. Fig. 7 shows these results.

Fig. 7 reveals the significant anticipated improvement in the optimal parameter condition (TOPSIS-based Taguchi method's result), providing the average time in system of Type-1 job as being 0.004571, which is smaller than 0.015808 in the original parameter condition. Similarly, with the anticipated improvement in the optimal parameter condition, the average number of customer waiting in phone 2 queue is 0.000304, which is smaller than 0.013425 in the original parameter condition. So, the average time in system of Type-1 job decreases 71.08% and the average number of customer waiting in phone 2 queue decreases 97.74%. As a result, the proposed TOPSIS-based Taguchi method outperformed original parameter condition's results for the average time in system of Type-1 job (71.08%), the average time in system of Type-2 job (77.17%), the average time in system of Type-3 job (75.16%), the average number of customer waiting in phone 1 queue (89.94%), the average number of customer waiting in phone 2 queue (97.74%), the service 1 utilization rate (61.37%), and the service 2 utilization rate (77.95%) (Fig. 7). The improvements were quite significant. In general, the comparative results demonstrated that the proposed method is effective in solving the Alarm Monitoring Center optimization problem.

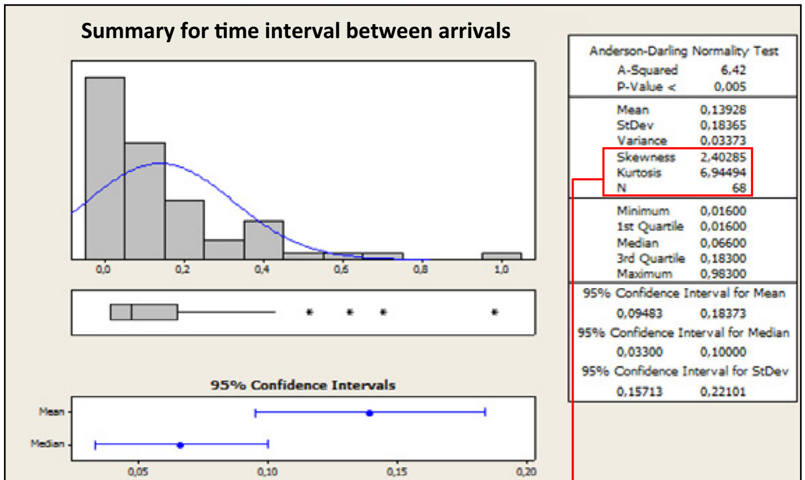
5. Conclusions

This paper proposed a TOPSIS-based Taguchi method to solve the multi-response simulation–optimization problem in an Alarm Monitoring Center. This study demonstrates how the simulation modeling and the TOPSIS-based Taguchi approach can be used to design and performance optimization of an Alarm Monitoring Center. The use of a TOPSIS-based Taguchi experimental design provides an effective way to convert the multi-response simulation–optimization problem into the single-response problem. The study illustrated the effectiveness of the proposed method. Fig. 7 is illustrated that the difference in the performance between the optimal conditions and the current conditions is significant. It should also be noted that, in practice, many organizations struggle to improve the performance of system to the competitive advantage such evaluations.

TOPSIS based Taguchi application has been proposed to effectively solve (see Fig. 7) the AMC performance optimization problem with the multiple performance measures. TOPSIS based Taguchi method provides an effective way to convert multi-response simulation–optimization problem into the single-response problem. The TOPSIS method provides the global performance scores (C_i^*) for all responses. Thus, according to the Taguchi's robust design principles, the average responses by factor levels are easily determined. Moreover, S/N ratios and Taguchi's basic orthogonal arrays are two main advantages of the Taguchi method. The performance optimization process becomes more reliable when the S/N ratio is used, especially when various different responses can be treated as a dynamic characteristic. Using the S/N ratio is also useful way to obtain robust system design by evaluating minimum variance (Simsek et al., 2013). Taguchi advocated the S/N ratio as a single indicator that jointly and simultaneously considers the average value and standard deviation of test results to determine the relative importance of the factors under study (Chang et al., 2011). Also, an L_{27} orthogonal array is used to reduce the experiment time and the simulation costs. In the Taguchi's L_{27} $(3 ** 5)$[1] design (orthogonal array), only 27 simulation experiment scenario are required. If the full factorial design were used, it would have least 5^3 = 125 simulation runs.

The TOPSIS based Taguchi application is very simple and easy to perform compared to the other multi-response simulation–optimization methodologies i.e., RSM, the meta-model applications and

[1] $(3 ** 5)$ means 5 factors with 3 levels each.

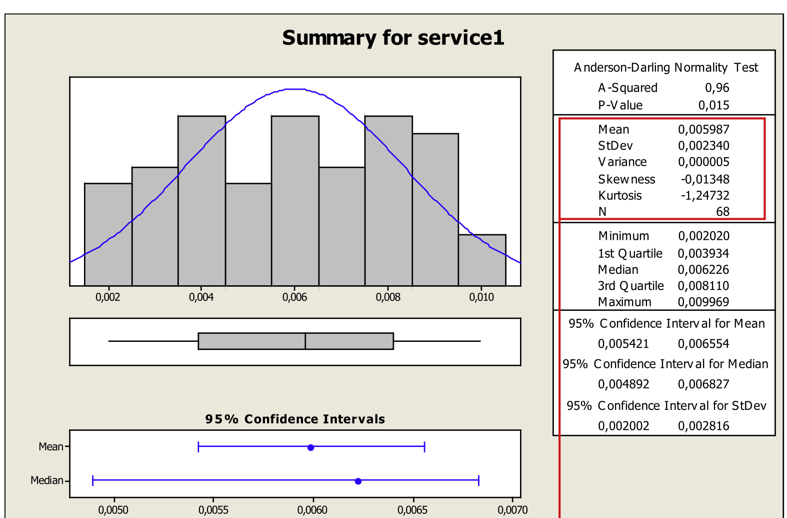


Estimation of β parameter:

$$\hat{\beta} = \frac{\sum_{i=1}^{n} x_i}{n} = \frac{9.47104}{68} = 0.14$$

Distribution Type	Skewness	Kurtosis
Normal	0	3
Uniform	2	1,8
Exponention	2	[6,9]
Laplace	0	3
Rayleigh Dağılım	0,6	0,2

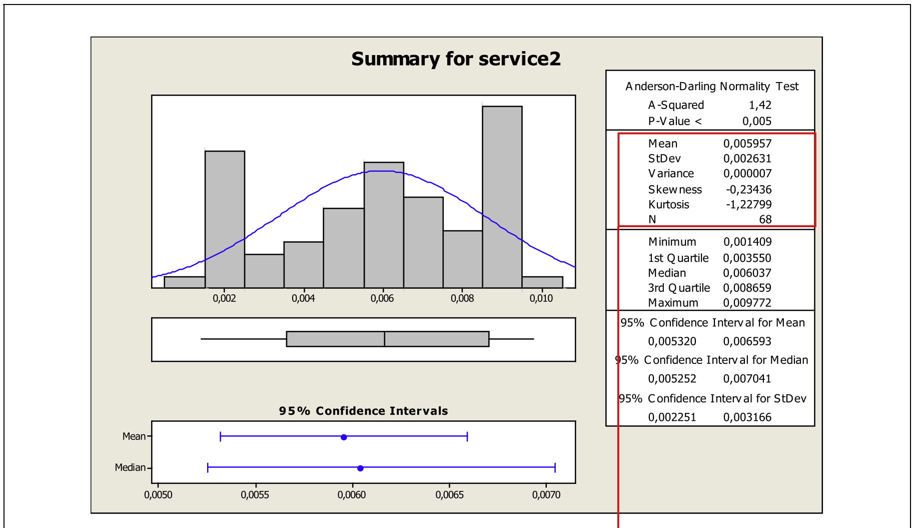
Fig. A1. Histogram for the time interval between arrivals.



$$f(x) = \frac{1}{b-a}, a < x < b; \quad E(x) = \frac{a+b}{2} = 0.0060; \quad \mathrm{var}(x) = \frac{1}{12}(b-a)^2 = 0.000005; \quad a = 0.002 \quad b = 0.0099$$

Fig. A2. Histogram and parameter estimation for the service 1.

the meta-heuristic methods (Simsek et al., 2013). These methodologies are known to increasingly become difficult for the practitioners as the number of variables of the evaluation increase. Two main problems, namely large simulation time and simulation cost requirements for experiments and complex mathematical and statistical calculations resulting from RSM, the meta-model applications and the meta-heuristic methods, will be encountered in practice (Simsek et al., 2013).



$$f(x) = \frac{1}{b-a}, a < x < b; \quad E(x) = \frac{a+b}{2} = 0.006; \quad \mathrm{var}(x) = \frac{1}{12}(b-a)^2 = 0.000007; \quad \begin{matrix} a = 0.0014 \\ b = 0.0098 \end{matrix}$$

Fig. A3. Histogram and parameter estimation for the service 2.

Study outcomes were shared with the AMC institution and studies have been initiated to increase the system performance. The proposed methodology can easily be extended to other service industry's applications. The proposed method presents a new option for solving multi-response simulation–optimization problems in service industry.

Appendix A.

See Figs. A1–A3.

References

Alexander, R., Kelly, T., 2013. Supporting systems of systems hazard analysis using multi-agent simulation. Safety Sci. 51, 302–318.

Angün, E., Gurkan, G., Hertog, D., Kleijnen, J.P.C., 2003. Response surface methodology with stochastic constraints for expensive simulation. In: Working Paper-Tilburg University, Netherlands. Available at: <http://www.tilburguniversity.nl/faculties/few/im/staff/kleijnen>.

Artalejo, J.R., Economou, A., Gómez-Corral, A., 2007. Applications of maximum queue lengths to call center management. Comput. Oper. Res. 34, 983–996.

Atlason, J., Epelman, M.A., Henderson, S.G., 2004. Call center staffing with simulation and cutting plane methods. Ann. Oper. Res. 127, 333–358.

Azadeh, A., Nazari-Shirkouhi, N., Hatami-Shirkouhi, L., 2011. A unique fuzzy multi - criteria decision making: computer simulation approach for productive operators' assignment in cellular manufacturing systems with uncertainty and vagueness. Int. J. Adv. Manuf. Technol. 56, 329–343.

Azadivar, F., Lee, Y.H., 1988. Optimization of discrete variable stochastic systems by computer simulation. Math. Comput. Simul. 40, 331–345.

Bagdasaryan, A., 2011. Discrete dynamic simulation models and technique for complex control systems. Simul. Model Pract. Theory 19, 1061–1087.

Castillo, E., Montgomery, D.C., 1993. A nonlinear programming solution to the dual response problem. J. Qual. Technol. 25, 199–204.

Central Station Alarm Association (CSAA), 2011. A Practical Guide to Fire Alarm Systems, third ed. Vienna.

Cezik, M.T., Ecuyer, P.L., 2008. Staffing multiskill call centers via linear programming and simulation. Manage. Sci. 54 (2), 310–323.

Chakraborty, S., 2011. Applications of the MOORA method for decision making in manufacturing environment. Int. J. Adv. Manuf. Technol. 54, 1155–1166.

Chang, C.Y., Huang, R., Lee, P.C., Weng, T.L., 2011. Application of a weighted Grey–Taguchi method for optimizing recycled aggregate concrete mixtures. Cem. Concr. Compos. 33, 1038–1049.

Chiang, Y.-M., Hsieh, H.-H., 2009. The use of the Taguchi method with grey relational analysis to optimize the thin-film sputtering process with multiple quality characteristic in color filter manufacturing. Comput. Ind. Eng. 56 (2009), 648–661.

Dengiz, B., 2009. Redesign of PCB production line with simulation and Taguchi design. In: Proceedings of the 2009 Winter Simulation Conference, pp. 2197–2204.

Dengiz, B., Akbay, K.S., 2000. Computer simulation of a PCB production line: meta-modeling approach. Int. J. Prod. Econ. 63, 195–205.

Elfahaksany, A., Hernandez, J., Garcia, J.C., Reyes, M., Martell, F., 2011. Design and development of a house-mobile security system. Engineering 3, 1213–1224.

Eren, M., 2006. Computer Controlled Building Security Systems. Master of Science Thesis, Marmara University, Institute of Science and Technology, Istanbul, Turkey.

Fan, S.K.S., Castillo, E., 1999. Calculation of an optimal region of operation for dual response systems fitted from experimental data. J. Oper. Res. Soc. 50, 826–836.

García-Cascales, M.S., Lamata, M.T., 2012. On rank reversal and TOPSIS method. Math. Comput. Model. 56 (5–6), 123–132.

Grassi, A., Gamberini, R., Mora, C., Rimini, B., 2009. A fuzzy multi-attribute model for risk evaluation in workplaces. Safety Sci. 47, 707–716.

Guo, Y., Chen, L., Wang, S., Zhou, J., 2003. A new simulation optimisation system for the parameters of a machine cell simulation model. Int. J. Adv. Manuf. Technol. 21, 620–626.

Hwang, C.L., Yoon, K., 1981. Multiple Attributes Decision Making Methods and Applications. Springer, Berlin.

Ilgaz, P., 2007. Turkish Safety & Security Equipment & Services Market. US Commercial Services, US Department of Commerce, USA.

Jafarian, M., Vahdat, S.E., 2012. A fuzzy multi-attribute approach to select the welding process at high pressure vessel manufacturing. J. Manuf. Process. 14 (3), 250–256.

Jouini, O., Dallery, Y., Aksin, Z., 2009. Queueing models for full-flexible multi-class call centers with real-time anticipated delays. Int. J. Prod. Econ. 120, 389–399.

Khuri, A.I., 1996. Multi-response surface methodology. In: Ghosh, S., Rao, C.R. (Eds.), Handbook of Statistics, vol. 13. Elsevier, Amsterdam.

Kleijnen, J.P.C., 1979. Regression meta-models for generalizing simulation results. IEEE Trans. Syst. Man Cybernet. SMC9 2, 93–96.

Kleijnen, J.P.C., Sargent, R.G., 2000. A methodology for fitting and validating meta-models in simulation. Eur. J. Oper. Res. 120, 14–29.

Kumar, S.N., Sridharan, R., 2010. Simulation-based meta-models for the analysis of scheduling decisions in a flexible manufacturing system operating in a tool-sharing environment. Int. J. Adv. Manuf. Technol. 51, 341–355.

Kuo, R.J., Yang, C.Y., 2011. Simulation optimization using particle swarm optimization algorithm with application to assembly line design. Appl. Soft Comput. 11, 605–613.

Kuo, Y., Yang, T., Huang, G.W., 2008. The use of a grey-based Taguchi method for optimizing multi-response simulation problems. Eng. Optimiz. 40 (6), 517–528.

Law, A., 2007. Simulation Modelling and Analysis, fourth ed. McGraw-Hill, USA.

Liao, H.-C., 2004. A data envelopment analysis method for optimizing multi-response problem with censored data in the Taguchi method. Comput. Ind. Eng. 46, 817–835.

Liao, C.-N., Kao, H.-P., 2010. Supplier selection model using Taguchi loss function, analytical hierarchy process and multi-choice goal programming. Comput. Ind. Eng. 58, 571–577.

Ma, J., Kim, N., Rothrock, L., 2011. Performance assessment in an interactive call center workforce simulation. Simul. Model Pract. Theory 19, 227–238.

Mahdavi, I., Mahdavi-Amiri, N., Heidarzade, A., Nourifar, R., 2008. Designing a model of fuzzy TOPSIS in multiple criteria decision making. Appl. Math. Comput. 206, 607–617.

Myers, R.H., Carter, W.H., 1973. Response surface techniques for dual response systems. Technometrics 15, 301–317.

Oddoye, J.P., Jones, D.F., Tamiz, M., Schmidt, P., 2009. Combining simulation and goal programming for healthcare planning in a medical assessment unit. Eur. J. Oper. Res. 193, 250–261.
Park, T., Lee, H., Heeseok, L., 2001. FMS design model with multiple objectives using compromise programming. Int. J. Prod. Res. 39 (15), 3513–3528.
Pasandideh, S.H.R., Niaki, S.T.A., 2006. Multi-response simulation optimization using genetic algorithm within desirability function framework. Appl. Math. Comput. 175, 366–382.
Pegden, C.D., Shannon, R.E., Sadowski, R.P., 1995. Introduction to Simulation Using SIMAN. second ed.. McGraw-Hill, USA.
Phadke, M.S., 1989. Quality Engineering Using Robust Design. Prentice-Hall, Englewood Cliffs, NJ.
Robbins, T.R., Harrison, T.P., 2010. A stochastic programming model for scheduling call centers with global service level agreements. Eur. J. Oper. Res. 207, 1608–1619.
Rosen, S.L., Harmonosky, C.M., Traband, T.M., 2007. A simulation optimization method that considers uncertainty and multiple performance measures. Eur. J. Oper. Res. 181, 315–330.
Rothrock, L., 2011. Performance measurement and evaluation in human-in-the-loop simulations. Human-in-the-Loop Simul. Meth. Pract.. http://dx.doi.org/10.1007/978-0-85729-883-6_2.
Roubos, A., Jouini, O., 2013. Call centers with hyperexponential patience modeling. Int. J. Prod. Econ. 141, 307–315.
Shih, H.-S., Shyur, H.-J., Stanley, L.E., 2007. An extension of TOPSIS for group decision making. Math. Comput. Model. 45 (7–8), 801–813.
Simsek, B., Ic, Y.T., Simsek, E.H., 2013. A TOPSIS-based Taguchi optimization to determine optimal mixture proportions of the high strength self-compacting concrete. Chemometr. Intell. Lab. Syst. 125 (2013), 18–32.
Subulan, K., Çakmakçı, M.A., 2012. A feasibility study using simulation-based optimization and Taguchi experimental design method for material handling—transfer system in the automobile industry. Int. J. Adv. Manuf. Technol. 59 (5–8), 433–443.
Syberfeldt, A., Ng, A., John, I.J., Moore, P., 2009. Multi-objective evolutionary simulation–optimisation of a real-world manufacturing problem. Robot. Cim.-Int. Manuf. 25, 926–931.
Um, I., Cheon, H., Lee, H., 2009. The simulation design and analysis of a flexible manufacturing system with automated guided vehicle system. J. Manuf. Syst. 28, 115–122.
Valle, M.A., Varas, S., Ruz, G.A., 2012. Job performance prediction in a call center using a naive Bayes classifier. Expert Syst. Appl. 39, 9939–9945.
Wainer, A.G., 2009. Discrete-Event Modeling and Simulation: A Practitioner's Approach (Computational Analysis, Synthesis, and Design of Dynamic Systems). CRC Press, USA.
Walpole, E.R., Myers, H., Myers, L.S., Ye, K., 2007. Probability & Statistics for Engineers & Scientists, eighth ed. Pearson Prentice Hall, Upper Saddle River, New Jersey.
Wang, J., Chang, Q., Xiao, G., Wang, N., Li, S., 2011. Data driven production modeling and simulation of complex automobile general assembly plant. Comput. Ind. 62, 765–775.
Web of Science, 2013. Web of Knowledge, Thomson Reuters. <http://www.webofknowledge.com>.
Yang, T., Chou, P., 2005. Solving a multi-response simulation–optimization problem with discrete variables using a multiple-attribute decision-making method. Math. Comput. Simul. 68 (1), 9–21.
Yang, T., Tseng, L., 2002. Solving a multiple objective simulation model using a hybrid response surface method and lexicographical goal programming approach – a case study on IC ink marking machines. J. Oper. Res. Soc. 53, 211–221.
Yazgan, H.R., Beypinar, I., Boran, S., Ocak, C., 2011. A new algorithm and multi-response Taguchi method to solve line balancing problem in an automotive industry. Int. J. Adv. Manuf. Technol. 57 (1–4), 379–392.
Yurdakul, M., Ic, Y.T., 2003. An illustrative study aimed to measure and rank performance of Turkish automotive companies using TOPSIS. J. Fac. Eng. Arch. Gazi Univ. 18 (1), 1–18.
Yurdakul, M., Ic, Y.T., 2005. Development of a performance measurement model for manufacturing companies using the AHP and TOPSIS approaches. Int. J. Prod. Res. 43 (21), 4609–4641.
Yurdakul, M., Ic, Y.T., 2009. Application of correlation test to criteria selection for multi criteria decision making (MCDM) models. Int. J. Adv. Manuf. Technol. 40 (3–4), 403–412.
Zeleny, M., 1982. Multiple Criteria Decision Making. Mc Graw-Hill, New York.