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ORIGINAL ARTICLE

An efficient integrated simulation–Taguchi approach for sales rate evaluation of a petrol station

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Abstract This study proposed an incorporated simulation–Taguchi model to optimize a petrol station sales rate. In addition, it provided a regression model to forecast the sales rate. Initially, Witness 2014 simulation software© was used to simulate the operating system of a petrol station. Next, the obtained simulation results were used as the input for Taguchi method to optimize the process. Taguchi L_4 standard orthogonal array was taken to optimize the petrol station parameters including the number of pumps, number of cashiers and customers' interarrival times (IATs) to obtain a better sales rate. Three noise factors such as petrol station location, different cashiers and different dispensers considered as potential factors affecting the response. Based on Taguchi methodology, number of pumps and IAT were identified as highly contributing factors on the sales rate. The remaining factor (number of cashier) similarly influences the response, but the effect is not very significant. Therefore, the importance sequence of the sales rate parameter is IATs $>$ number of pumps $>$ number of cashiers. The regression equation was formulated to maximize the sales rate (Liter) and then verified by the confirmation runs.

Keywords Simulation · Sales rate · ANOVA test · Taguchi · Petrol station · Service industry

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1 Introduction

Service industries have acknowledged the effect of customer satisfaction on their competitive advantage [1–4]. Service level has a direct influence on customer satisfaction. Therefore, improving and optimizing the service level increase the efficiency of companies in competitive markets [5]. In this regard, numerous tools have been presented to apply qualitative principles or consider interrelationships between decision elements to satisfy the customers' necessities [6, 7].

Petrol stations are categorized as the service industries which deal with people's daily life. In this industry, fuel quality, service speed and price can be translated as the major components of competitive advantage. Since the price and quality have attained significant attention in majority of the businesses, rapid service and subsequently the length of queues are the most significant factors affecting the customer satisfaction and consequently the profits [8]. Service companies work in dynamic environments. Therefore, their performance should be evaluated using dynamic approaches. Simulation modeling is considered as a valuable tool for all researchers, practitioners and managers to investigate dynamic systems [9–11]. Furthermore, as simulation modeling can be incorporated with other approaches [56, 64], its integration with Design Of Experiments (DOE) is a very interesting research area [12–16].

Among the various techniques in DOE, Taguchi method could be used to determine the influence of process factors on the output response using minimum number of experiment. Taguchi design can be utilized to evaluate a process by considering the incontrollable (noise) parameters [57, 58]. In addition, by utilizing a simulation model, Taguchi leads to a model which is capable to assess the influence of significant factors on system output. Hence, providing an integrated simulation–Taguchi approach for the aim of simulating the sales rate of petrol stations is valuable since (1) critical decision making is a severe issue in numerous service businesses, (2) these business must be precisely examined regarding their performance and (3) applying proper tools to improve the operations is useful to save the time and money [17, 18]. In spite of the enormous applications of simulation in service-related companies [19–23], few efforts have been done to integrate it with Taguchi analysis. As far as we know, no combination has been done on a petrol stations' sale system. This research offers a worthy contribution on incorporation of simulation and Taguchi to gain an expectable model to improve the sale system of a petrol station. It presents a novel and significant knowledge for applying simulation and suggesting diverse alternatives to the Taguchi model.

2 Literature review

Different areas of operation management including production, services, defense, construction and health care have used simulation to analyze their performance [24–27, 61–63]. The suitability and implication of simulation methods can cover the complications of operating systems [28].

Managers are simultaneously concerned about their income and customer satisfaction [15]. Formation of a typical queue structure includes the structure of the line, arrival and service-related actions, discipline of the queue and demand group [29]. Present researches in this area emphasis on improving the satisfaction of customers. The least queue length and waiting time are two important subjects that provide a significant role in increasing the quality of service. Therefore, both the enterprise's revenue and customer satisfaction must be deliberated to offer an optimum service. Consequently, different circumstances must be evaluated to achieve the best potential situation that can satisfy both customers and companies' desires [30].

From the strategies practiced to increase the quality of service and accordingly satisfaction of the customers in this area, Cornillier et al. [31] proposed a precise procedure for the replenishment problem of petrol station. In another related study, a petrol station was simulated by Moazzami et al. [11] and examined its performance using different scenarios.

As a systematic and statistical method, DOE aims to control the relationship among significant factors of process and their output result. Otherwise, it is practiced to determine the interaction and cause and effect of factors wherever in other techniques not addressing. Investigation of DOE outcomes is important to accomplish the inputs of process and optimize its output [32–34, 59].

Many studies have integrated Taguchi DOE with simulation. Dooley and Mahmoodi [35] introduced experimental designs that are beneficial to investigate robustness in simulation studies. Mayer and Benjamin [36] developed the techniques and concepts presented by Taguchi and adapted them for simulation-based design. Abdul-Nour [37] provided a simulation-based Taguchi study on variability of just-in-time production system. Chen et al. [38] suggested a computer simulation experiments for a manufacturing problem. DOE supports an adaptive and sequential method for experimentation. On the other hand, Taguchi uses one big experiment to investigate the main effects and some significant interactions. Taguchi approach uses linear graphs to allocate numerous process factors and their interactions in numerous orthogonal array columns [39, 60].

Simulation-based Taguchi method has been used in many research areas. Tsai [40] used this incorporation to explain managerial issues in joined systems of manufacturing. Shang et al. [41] determined the correct level of delayed differentiation using the simulation-based Taguchi method. Shukla et al. [42] used this approach to supply chain network optimization. A combination of simulation-based DOE was practiced by Hussain and Saber [43] to quantitatively assess the influence of diverse reasons of the bullwhip effects. Gijo and Scaria [44] applied a simulation-based Taguchi approach to design a motor in a great electrical company. Based on Subulan and Cakmakci [45], experimental design is a functional technique for process improvement and product development. Seeking other potential areas, the suggested method of Azadeh et al. [46] is beneficial to recognize the preferred strategy of maintenance management. As an example of service industry, Baril et al. [47] integrated Discrete Event Simulation (DES) and DOE to allocate nurses and consulting rooms to each orthopedist. The considered constraints were four appointment arrangement instructions and three flows of patients. In a very recent study, Abd Khalid et al. [48] used Taguchi approach to decrease the minimum quantity of simulation experiments.

Preceding studies of this area demonstrate that the outcomes of simulation can be used for further investigation of DOE. In this research, a simulation-based Taguchi approach was proposed to simulate and investigate the sale system of a petrol station. To the best of our knowledge, this is an initial effort to investigate the sale system of a petrol station using a combined simulation–Taguchi approach. To fill this gap, this research proposed a combined simulation–Taguchi approach to examine and improve the sale system of a petrol station to help managers to proficiently manage their operations.

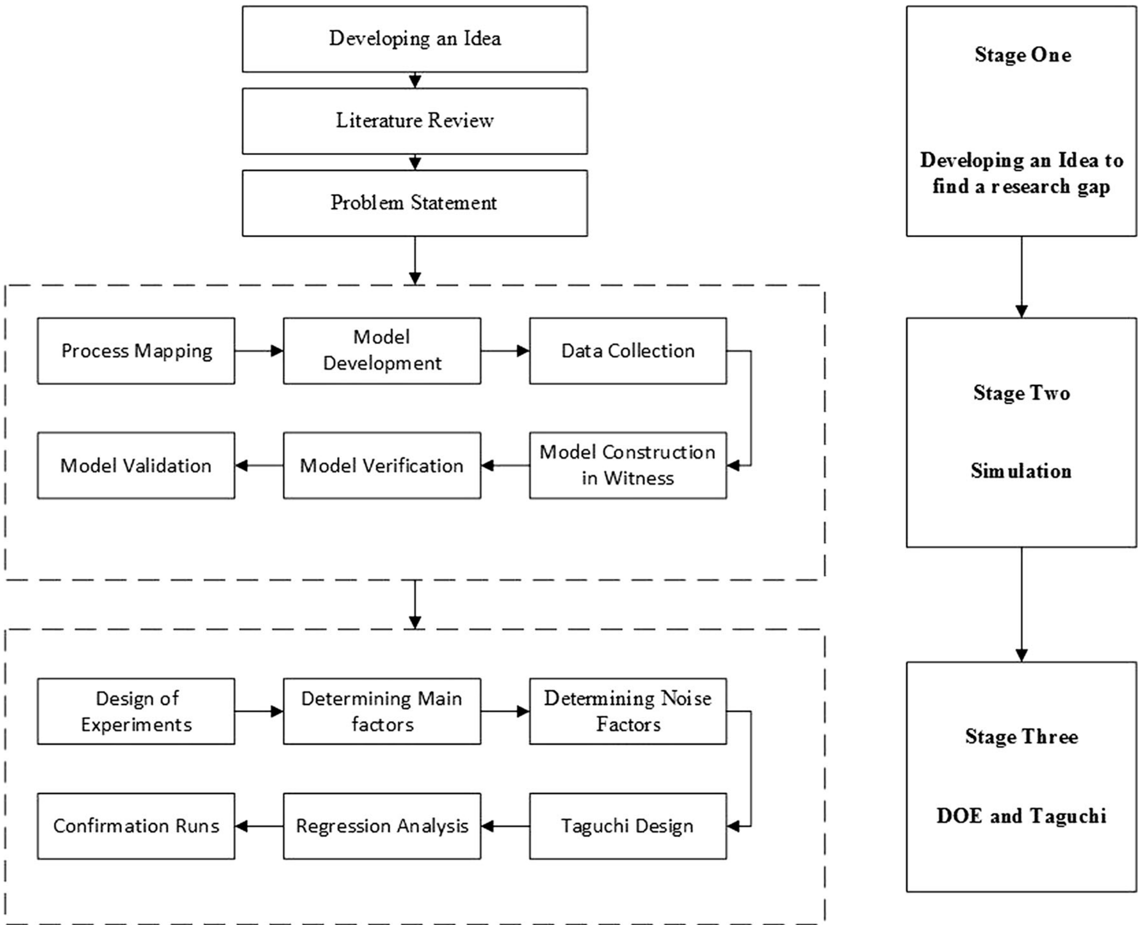

Fig. 1 Procedure of study

Different steps of this study are illuminated in next stage. A schematic diagram of these steps is shown in Fig. 1. It demonstrates how the Taguchi approaches can be integrated with simulation modeling to investigate a petrol station sales rate. A detailed explanation of each step is discussed as follows:

1. Developing an idea, the literature review and problem statement.
2. Process mapping to provide a schematic view of the model.
3. Model development, data collection and model construction in Witness © to finalize the simulation model. Detailed explanation of each section is discussed in relevant sections.
4. Model verification and validation have been conducted in a separate section.
5. A series of main factors should be determined to perform a DOE. Here, IATs, number of pump and number of cashier, are considered as the main factors of the DOE. In addition, three noise factors of location, different cashier's performance and different dispensers are considered as noise factors.
6. Last step is to determine a proper Taguchi design. The Taguchi model was constructed, and its outputs were applied to provide a regression model for sales rate prediction. Finally, some confirmation runs confirmed the originated results.

3 Case study

A petrol station located in Malaysia has been used as the case study of this research. It has two core platforms with four fuel dispensers on each side. Two nozzles are available in each dispenser and provide two types of petrol (Petrol with octane 95 and 97). Customers can buy their requirements from a supermarket which is located at the back of petrol station counter. Two cashiers work in payment counter. Typically, one of the cashiers assists customers for their payments if they only make the process of refueling. The second cashier makes the shopping activities in addition to fuel payments. The payment process can be done with cash or credit card. In addition, the fuel price is

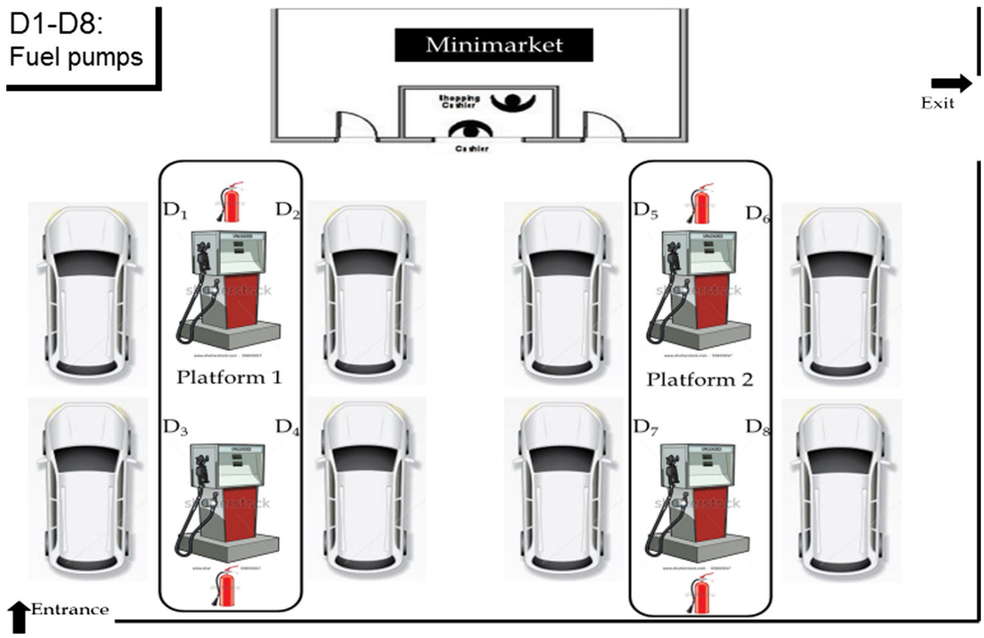

Fig. 2 Petrol station layout

different based on the Octane number (type 95 or 97 Octane).

3.1 Layout of petrol station (process mapping)

The petrol station layout is presented in Fig. 2. This scheme is applied to plot the entire process of model. The operation flow and entire process are shown in Fig. 3.

4 Model development

This section discusses the different steps of model development. It includes the description of processes, model assumption, data collection and model construction. These subsections are then followed by model verification and validation.

4.1 Description of processes

Cars reach to the station and can select among eight available (D_1–D_8) pumps. This choice is affected by system unoccupied pumps. In case of no available pump, their choice would be affected by the shortest line (queue) and space to the cashiers. Payment process includes paying money regarding the chosen fuel type (petrol Octane 95 or 97). As soon as receiving the payment by cashier, the nozzle will be refilled precisely as per the paid value (Petrol with octane 97 is more expensive). Refilling course initiates as the drivers goes to the chosen pump and get the paid nozzle. Subsequently, the drivers top up the tank equivalent to the payment value. Finally, drivers put the nozzle back and leave the system once the refueling process ended.

4.2 Model assumption

Subsequent rules are seen in the modeling process:

- Each client has four alternatives to choose; types of petrol (95 or 97) and payment method (credit card or cash).
- Once a driver came into the system, he/she will not leave it.
- Shopping is considered in the model.
- Changing of the queue lines is not possible (no jockeying in the model).
- Fluctuations of the petrol rates were neglected.

4.3 Data collection

Stop-watch method was employed for gathering the required data. A statistical distribution was fitted once the sufficient sets of related data were gathered. The IAT is the gap among the first entry of a customer and the following. The entries (cars) were tracked to observe their fuel type and differentiate their categories, checking their shopping and also payment method to be considered in the model. As mentioned before, two cashiers are available in the system. The related data of each cashier were collected to be applied in the simulation model. The next sets of data were refilling time. It is defined as the period of taking the nozzle, refilling process and placing to its initial location. The pumps' cycle time is a reliant factor of refilling

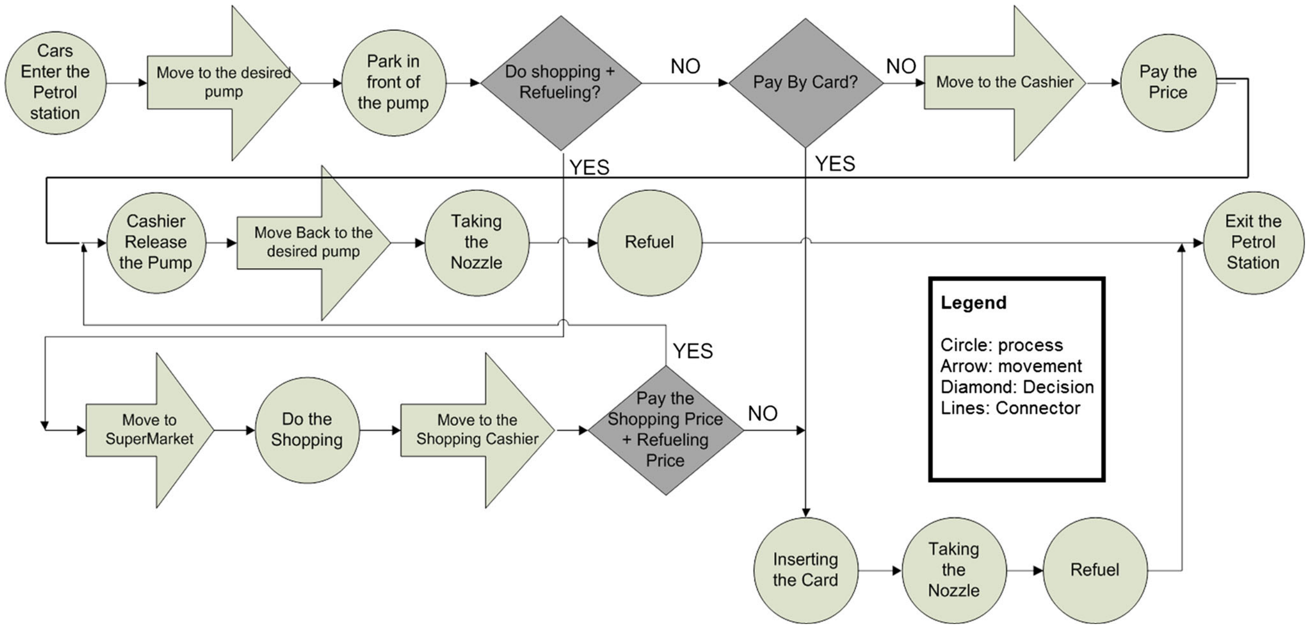

Fig. 3 Process mapping diagram

Table 1 Statistical distributions of gathered data

Collected data	Sample size	Fitted distribution by Easyfit ©
95 Cash + shop (IAT)	178	Neg.exp (5)
95 Cash (IAT)	200	Neg.exp (3.5)
95 Card + shop (IAT)	146	Neg.exp (36.5)
95 Card (IAT)	76	Neg.exp (45)
97 Cash + shop (IAT)	89	Neg.exp (38.39)
97 Cash (IAT)	150	Neg.exp (25.22)
97 Card + shop (IAT)	40	Neg.exp (155.25)
97 Card (IAT)	56	Neg.exp (130.28)
Cashier 1 (process)	200	N (0.6757,0.0985)
Cashier 2 (process)	200	Normal (1.1684,0.1)

amount. In other words, it is separate from the whole time required to leave the system. Consequently, the fuel usage data were gathered accordingly. The sales quantity (for each type of fuel and based on liter) was gathered to be employed in verification of the model (see Sect. 5).

4.4 Model construction

EASYFIT© (version 5.5) was applied to plot the appropriate statistical distribution. It can be applied as a separate software or with Microsoft Excel. The gathered information of every component of the model was analyzed by EASYFIT© to fit proper statistical distributions. Anderson–Darling, Kolmogorov–Smirnov and Chi-Square tests were concurrently deployed to fit the appropriate statistical distributions. Subsequently, the model elements and related connections were designed in Witness simulation software. Process mapping was applied to make the arrangement of the process, orders of activities and the components. Five replicates were considered in model simulation. In addition, the length of replications was set to 1440 (min) which is equivalent to 24 h. Best probability distributions of each component are presented in Table 1. The scheme of the model is shown in Fig. 4.

5 Verification of the model

Verification checks the precision of simulation model. It checks the model representation with the real case study. Subsequent to the construction of the model, its representation was visually investigated, to be comparable and

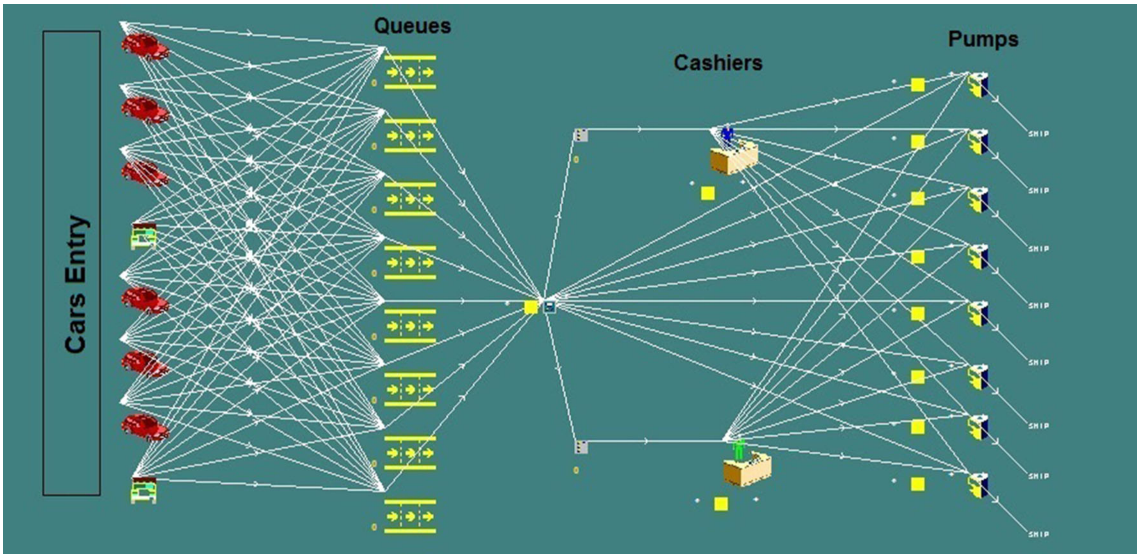

Fig. 4 Schematic diagram of the model

Table 2 Model verification results

No.	Station name	% Busy	Replication time (min)	Utilized time (min)	Mean (min)	No. of operations (manually)	No. of operations (witness report)	Difference (%)
1	P1	7.71	1440	111.024	1.356	72	70	2.780
2	P2	9.21	1440	132.624	1.356	98	108	9.440
3	P3	8.03	1440	115.632	1.356	85	89	4.706
4	P4	8.75	1440	126.000	1.356	93	87	6.451
5	P5	13.29	1440	191.376	1.356	141	147	3.990
6	P6	11.42	1440	164.448	1.356	121	120	1.060
7	P7	8.33	1440	119.952	1.356	88	89	1.130
8	P8	7.46	1440	107.424	1.356	79	82	3.797
Average difference (%)								4.17

parallel to the condition of real case [49]. Overall quantity of operations was chosen for model verification and rationality. Based on Table 2, the variation percentage is <5 % (the satisfactory level) which is appropriate [55].

6 Model validation

Validation concerns with building of the accurate model. A valid model is an accurate drawing of the real case [50]. It is classically achieved by model calibration. This process should be repeated till the correctness of model is satisfied. The compulsory quantity of replications was determined by Eq. (1) suggested by Ahmed [51] before to the validation of model. The replications quantity to gain an appropriate accurateness is four replicates or more.

$$N(m) = \left(\frac{S(m)t_{m-1,\left(1-\left(\frac{\alpha}{2}\right)\right)}}{\bar{X}(m)\varepsilon}\right)^2 \tag{1}$$

In which, $N(m)$ is the simulation runs quantity to attain the preferred accuracy level; $\bar{X}(m)$ is the mean approximation of a preliminary quantity of runs m; $S(m)$ is the standard deviation approximation of m quantity of runs; α is confidence level; ε is the permissible percentage error; and $t_{m-1,\left(1-\left(\frac{\alpha}{2}\right)\right)}$ is critical value of the two-tailed t-distribution at a significance level, by $m-1$ freedom degrees. The $X(m)$ and $S(m)$ values are presented in Table 3.

Validation of the model was conducted after finding the compulsory replicates of simulation runs. The results of five simulation replicates were compared to

Table 3 Model Replications

	Replicate					$X(m)$	$S(m)$
	1	2	3	4	5		
Actual daily sales rate (L)	10,261	10,933	10,971	11,074	11,118	10,871.4	349.34

Table 4 Validation of the model

Replicates	Actual daily sales rate (L)	Simulated daily sales rate (L)	Variation
1	10,261	10,261.1	0.00097
2	10,933	11,679.8	6.83000
3	10,971	11,017.8	0.42266
4	11,074	11,661.8	5.30793
5	11,118	10,776.4	3.07249
Average variation			3.12681

Table 5 Controllable and noise process factors and levels

No.	Type	Main factors	Level (1)	Level (2)
1	Controllable	IAT-A (time)	See Table 6	See Table 6
2		No. of cashiers-B (number)	1	3
3		No. of fuel dispensers-C (number)	6	10
4	Incontrollable (noise)	Location-D	Suburb	City center
5		Different cashiers-E	Cashier 1	Cashier 2
6		Different dispensers-F	Dispenser 1	Dispenser 2

daily sales rate. Validation data are shown in Table 4. As it is clear, average percentage of variation for five simulation replicates is 3.12681 (<5 %) which is acceptable [55].

7 Taguchi method

The simulation results were applied for further investigation by Taguchi technique. Taguchi method is a robust design technique and has produced a great and exceptional quality enhancement discipline which differs from traditional method. It can fulfill the problem solving requirements and process design optimization projects in the service industries. Taguchi recommends Signal-to-Noise ratio (S/N) as the objective function of matrix experiments. The S/N ratio is used to measure the quality characteristics and is also used to evaluate the parameters which are sufficiently significant through the ANOVA test [52, 53]. Taguchi objective function is classified into three categories of smaller the better, larger the better and nominal the best. Here, larger the better technique was deployed to evaluate the process parameters in order to predict a model for sales rate. The three process parameters which influence the sales rate are number of pumps, number of cashiers and interarrival times (IATs). In addition, location of petrol station, different cashier and different dispenser have been considered as incontrollable (noise) factors.

The noise factors were considered to improve the accuracy of predicted model. The location of petrol station regarding the population can make different IATs of customers which affect the response, and different cashiers with distinct performance could be influential in payment process time. Finally, different pressure of dispenser could affect the refueling time. The time-related parameters were collected by stop-watch data collection method. The investigated response was sales rate (based on Liter). Therefore, the best design for an experiment with three controllable factors in two levels is L_4 orthogonal array. The number of pump and number of cashier in real model is 8 and 2, correspondingly. Here, the range of all factors was set as upper −20 % for level (1) and lower +20 % for level (2) as shown in Table 5. The factors and their corresponding values are listed in Table 5. Since the nature of IATs is different from other factors, each element should be considered separately in simulation model. So, the low and high levels of IATs are considered as statistical distribution as listed in Table 6. The sales rate for each element per runs is calculated, and sum of them has been used as total sales rate for each run.

Table 6 High and low levels of IATs

Model input element	Level (1)	Level (2)
Fuel type 95 (cash) + shopping	4	6
Fuel type 95 (cash)	2.8	4.2
Fuel type 95 (card) + shopping	29.2	43.8
Fuel type 95 (card)	36	54
Fuel type 97 (cash) + shopping	30.7	46.1
Fuel type 97 (cash)	20.2	30.3
Fuel type 97 (card) + shopping	124.2	186.3
Fuel type 97 (card)	104.2	156.3

The final design of L_4 orthogonal array is depicted in Table 7.

8 Results and discussion

Minitab 16 Software© has been used for the purpose of data analysis. The results were transformed in signal-to-noise (S/N) ratio in Taguchi method. The mean and (S/N) ratio for each parameter have been computed to evaluate the effect of parameters on sales rate. Table 8 shows the L_4 Taguchi design analysis using main effect parameters for the mean and S/N ratio. As mentioned before, the larger the better types of (S/N) ratio was selected to optimize the sales rate which is defined as;

$$\mathrm{SN}_l = -10\log_{10}\left(\frac{1}{m}\sum_{j=1}^{m}\frac{1}{y_{ij}^2}\right) \tag{2}$$

where m is the number of observations and y_{ij} is the value of sales rate loss for the ith observation.

The response table for the mean and signal-to-noise ratio indicates that the IATs is the top influential parameter on the sales rate, while number of cashiers and number of pumps are the second and third, respectively. The IATs significantly affect the queue length of system. Therefore, the interaction between IATs and other two parameters must be considered to optimize the response without overloading the queue length of station.

In our previous work, Galankashi et al. [54], a traditional DOE was used to optimize the performance of the simulated petrol station. At that point, a full factorial design including three factors with two (high and low) levels (2^3, 3FI) was deployed to discover the significant influence of factors on queue length and sales rate. The number of pump, number of cashier and IATs were examined as main factors of the design where the noise factors were neglected. Design Expert version 9 software© was applied to progress the factorial design and investigate the gathered data. The ANOVA to obtain the percentage contribution of each factor is listed in Table 9. Figure 5 illustrates the contribution percentage of parameters on sales rate without considering the noise parameters.

The results indicate that the most significant factor is IATs with roughly 63 % contribution. In addition, number

Table 7 L_4 orthogonal array design layout

Run	Inner array controllable factors			Outer noise array					
				Location-D	1	1	2	2	
				Different cashier-E	1	2	1	2	
				Different dispenser-F	1	2	2	1	
	IATs-A	No. cashier-B	No. pump-C		R_1	R_2	R_3	R_4	Mean
1	1	1	1		11,049.1	11,472.4	12,131.7	11,990.2	11,660.85
2	1	2	2		11,505.0	11,954.5	12,587.6	12,254.6	12,075.43
3	2	1	2		8679.1	9024.8	9487.6	9102.8	9073.575
4	2	2	1		8452.4	8832.6	9211.3	9043.9	8885.05

Table 8 L_4 Taguchi design analysis for controllable factors and factors' ranking

Factors	S/N analysis				Mean analysis				Optimum setting
	1	2	Effect (delta)	Rank	1	2	Effect (delta)	Rank	
Design: Taguchi orthogonal array design L_4 (2**3)									
A-IATs	81.49	79.06	2.42	1	11,868	8979	2889	1	1
B-no. cashier	80.25	80.31	0.06	3	10,367	10,480	113	3	2
C-no. pump	80.15	80.40	0.24	2	10,273	10,575	302	2	2

Table 9 ANOVA table (partial sum of squares) for response surface (response: sales rate)

Source	Sum of squares	*df*	Mean square	*F* value	*p* value	Status	Contribution percentage
Model	112,267,315.9	3	37,422,438.64	82.27552017	<0.0001	Significant	
A-no. pump	1,939,055.773	1	1,939,055.773	4.263132712	0.0455		1.4859
B-no. cashier	28,804,362.11	1	28,804,362.11	63.32815182	<0.0001		22.074
C-IATs	81,523,898.04	1	81,523,898.04	179.235276	<0.0001		62.475
Curvature	28,386.49355	1	28,386.49355	0.062409442	0.8040	Not significant	
Error	18,193,717.19	40	454,842.9298				13.942
Cor total	130,489,419.6	44					

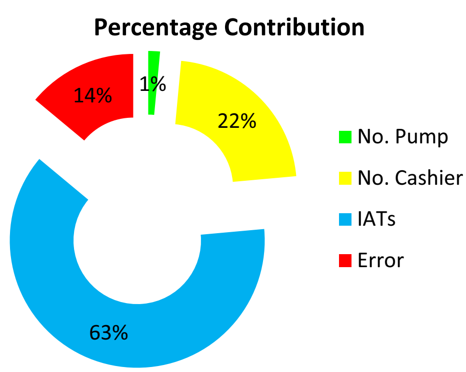

Fig. 5 Plot of percentage of contribution (sales rate)

of cashiers and number of pumps with 22 and 1 % are other influential factors on sales rate, respectively. The 13.942 % of error has a significant influence on output which needs to be considered in order to analyze and optimize the process parameters.

The main effect plots for the mean and S/N ratio are depicted in Fig. 6a, b. The plots demonstrate that the most optimal combination of investigated levels to maximize the sales rate is obtainable when the IATs-A is in level 1 (mean the arrival times of customer is faster), number of cashier-B is 3 and number of pump is 10. Table 10 presents the optimum setting for parameters based on main effects plot of means and S/N ratios. Figure 7 illustrates the interaction plot for sales rate.

Table 10 Optimum settings of parameters

No.	Factor	Level	Actual value
1	Interarrival times (IATs)-A	1	See Table 6
2	No. of cashier-B	2	3
3	No. of pump-C	2	10

8.1 Regression analysis

The regression analysis is used to predict the value. It is commonly used to find out which of the independent variable are related to the dependent variable. The Minitab

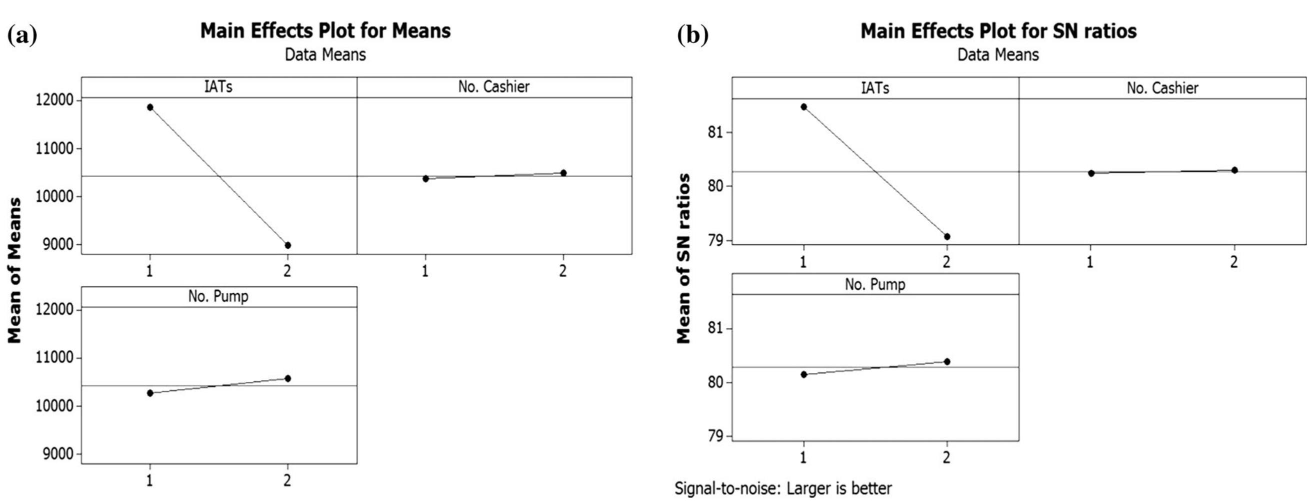

Fig. 6 Main effect plot for **a** mean and **b** S/N ratio

Fig. 7 Interaction plot—data means for sales rate

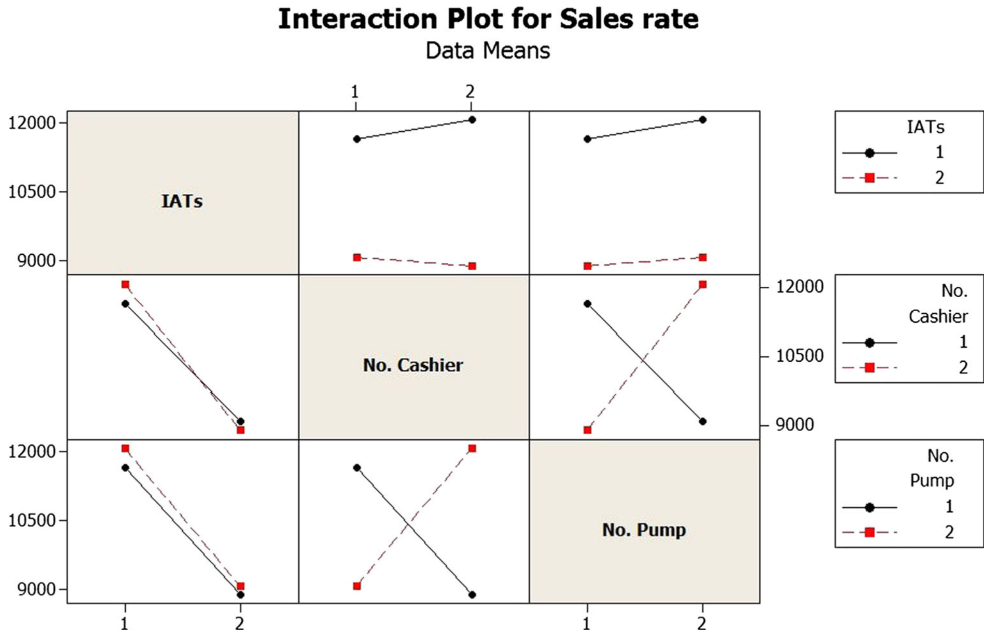

Table 11 S/N ratio response for controllable factors

Factor	Level 1	Level 2
A	**81.47**	79.05
B	80.23	**80.29**
C	80.14	**80.38**

The highlighted values are selected as the optimum level of each factor

software regression analysis tab was used to explore the equation. In this case, the regression equation is expressed by means of all controllable factors such as IATs, number of cashiers and number of pumps in addition to noise factors.

$$\hat{Z} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \tag{3}$$

$$\text{Sales rate} = 14135 - 2889\,\text{IATs} + 113\,\text{no. cashier} + 302\,\text{no. pump}. \tag{4}$$

8.2 Confirmation runs

Once the investigation of the experiment is achieved, it should be confirmed that the calculations are correct enough. This process is called as confirmation runs. The understanding and results of an experiment might comprise a best setting to satisfy the objectives of the experiment. Even if the best result is achieved, the conformation runs should be conducted to ensure that nothing has changed and that the response values are adjacent to their forecasted values. Therefore, the prediction of the optimized sales rate is achievable through Eqs. (5) and (6) refer to the optimum levels of parameter based on S/N ratio. Table 11 demonstrates the S/N ratio response for the controllable factors in two levels. The highlighted values are selected as the optimum level of each factor.

$$\overline{\overline{Z}} = \frac{\left(\sum_{i=1}^{6} \text{SN}_{\ i}\right)}{6} = 80.26 \tag{5}$$

$$\hat{Z} = \overline{\overline{Z}} + \sum_{1}^{3}\left(X_{\mathrm{f}} - \overline{\overline{Z}}\right) \tag{6}$$

where, $\overline{\overline{Z}}$ is the average of the total S/N ratio results and X_{f} is the optimum level of each factor.

$$\hat{Z} = \overline{\overline{Z}} + \left(\text{A1} - \overline{\overline{Z}}\right) + \left(\text{B2} - \overline{\overline{Z}}\right) + \left(\text{C2} - \overline{\overline{Z}}\right) \tag{7}$$

The $\hat{Z}$ is equal to 81.62. Five more runs (based on the optimum setting of parameters) have been designed to verify the predicted model. Table 12 shows the confirmation experiments and the related response.

An error of 1.26 % (<5 %) revealed that the S/N ratio attained from new confirmation runs is not meaningfully different from the predicted S/N, which is desirable. The new experiments indicate important progress in terms of S/N with a difference of 1.36 among the predicted S/N ratio and the average of S/N ratio (Z). Consequently, it can be determined that the optimum setting proposed in Table 10 expresses the most significant levels of the design parameters that yield a robust and insensitive design for sales rate. The achieved result using Taguchi's technique was comparatively consistent with the outcome of classical DOE technique.

Table 12 Confirmation experiment

Run	Optimum levels of factors						
	IATs-A_1		No. cashier-B_2		No. pump-C_2		Response (sales rate)
	Level	Actual	Level	Actual	Level	Actual	
1	1	See Table 6	2	3	2	10	12,923.4
2	1	See Table 6	2	3	2	10	12,845.7
3	1	See Table 6	2	3	2	10	13,012.4
4	1	See Table 6	2	3	2	10	12,982.3
5	1	See Table 6	2	3	2	10	13,062.7
Mean response							12,965.3
Actual S/N ratio							82.62
Predicted S/N $(\hat{Z})$							81.62
(%) S/N error							1.26 %

9 Conclusion and recommendation

In this study, a simulation-based Taguchi method was proposed to analyze the performance of a petrol station. Specifically, this research developed an integrated simulation–Taguchi approach to study and improve the sales rate of a petrol station. In addition, it provided a regression model to forecast the sales rate. The proposed methodology of this research suggests a valuable contribution for managers of service industry as it is very hard to investigate the performance of dynamic operating systems. With regard to obtained results, the design is robust to the second and third factors which are number of cashiers and number of dispensers. Changes in response are highly affected when the level of factor-A (IATs) changes, the sensitivity of response to the IATs, meaning that location can be an important factor when analyzing the petrol station behavior. Crowded locations have more customer and consequently it provides more sale rate. According to the simulated system, the optimum setting for influential parameters is when IATs are in level 1, number of cashiers are 3 and number of pumps are 10. The predicted regression model can be used for different scenarios based on constraints. The high dependency of response to time-related parameters demonstrates that the profit level can be increased through an efficient combination between parameters and constraints. Although this research was an initial effort to investigate a petrol station sale system using an integrated simulation–Taguchi model, there are some limitations which can be considered in future studies. The results of this study can be checked by other simulation packages. Therefore, as a future direction, other simulation softwares can be applied to do the process of this study and check the similarity of results. In addition, the framework and methodology of this research can be applied to other service industries to investigate their performance.

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