USING A FUZZY EXPERT SYSTEM FOR SERVICE QUALITY IMPROVEMENT. THE CASE OF A CAR WASH STATION

Marius PÎSLARU

Gheorghe Asachi Technical University of Iași 67 Profesor Dimitrie Mangeron, Iasi, Romania mpislaru@tuiasi.ro

Ramona-Diana LEON

National University of Political Studies and Public Administration 30A Expozitiei, 012104 Bucharest, Romania ramona.leon@facultateademanagement.ro

Adrian VÎLCU

Gheorghe Asachi Technical University of Iași 67 Profesor Dimitrie Mangeron, Iasi, Romania avilcu@tuiasi.ro

Abstract. The paper aims to present how could an expert system, based on fuzzy logic, be used for the service quality improvement of a car wash point station. A single-case study is approach and four linguistic variables are taken into consideration, namely: (i) the average waiting time (mean delay); (ii) the ratio factor (of traffic intensity) in the car wash station; (iii) the number of stands; and (iv)the number of employees per shift. Further, the Gaussian membership functions are selected for the fuzzy sets and 27 rules are established. Data are processes using MATLAB Fuzzy Logic Toolbox. The results prove that the number of stands and the number of employees per shift directly influence the average waiting time and as such, have a major impact on the perceived service quality. Although, the case under discussion is a simple one, it facilitates a heuristic approach of the business environment and it proves that the adoption of these computational techniques may foster service quality improvement.

Keywords: fuzzy logic; expert system; service quality improvement.

Introduction

The "waiting lines" (queuing lines) is one of the most important areas in operations management (Debo, Parlour, & Rajan, 2012; Kremer & Debo, 2015), and it represents a number of customers waiting to be served (at the store house, ticket bank, traffic light, washing cars etc.). In most situations, customers accept that they have to wait for the service to be delivered but they are not willing to wait for too long. Further, various studies have demonstrated that long queues influence customer satisfaction (Borges, Herter, & Chebat, 2015), perceived value of the service (Debo et al., 2012; Koo & Fishbach, 2010; Kremer & Debo, 2015) and customer loyalty (Bielen & Demoulin, 2007). This basically have their roots in service quality which incorporates a relational and operational dimension; the former focuses on understanding customers' desires (Payne & Frow, 2005) while the latter concentrates on the activities that need to be perform in order to ensure service efficiency (Stank, Goldsby, & Vickery, 1999; van Riel, Semeijn, Ribbink, & Bomert-Peters, 2012).

Although the relationship between queue length and service quality is emphasized by several scholars (Alonso, Barreda, dell'Olio, & Ibeas, 2018; van Riel et al., 2012), its direction is debatable. Thus, Kremer and Debo (2015) and Debo et al. (2012) state that an increased queue length can signalize a high quality service while De Vries, Roy, and De Koster (2018) argue that there is a negative relationship between the waiting time and service quality. The former concentrate on product sales while the latter focus on restaurants. Thus, the perspective is different do to the fact that when it comes to products, a long queue is directly associated with a high level of quality; if the product has a high quality, more customers want it. The situation is different when it comes to services; a long queue is usually considered to be a signal that the company does not have the capacity to satisfy customers' demand in a timely manner.

Chowdhury, 2013, p.475)			
Advantages	Disadvantages		
 It provides models that are capable of determining arrival pattern of customers or the most appropriate number of service stations. It is helpful in creating a balance between the two opportunity costs, namely: optimization of waiting costs and service costs. It provides better understanding of waiting lines in order to foster the development of an adequate service with a tolerable waiting time. It offers information regarding setting up workstations, requirement of manpower and number of customers. 	 Uncertainty is present in almost all queuing situations and it arises due to the fact that: (i) we may not know the form of the theoretical probability distribution which applies; (ii) we may not know the parameters of the process even when the particular distribution is known; (iii) we could know the probability distribution of the outcomes and not the distribution of the actual outcomes. The distributions are usually assumed in queuing models. In multi-channel queuing, the departure from one queue often forms the arrival of another; this makes the analysis more difficult. Most of the real life queuing problems are too complex to be solved using queuing theory technique. The waiting space may be limited. The arrival rate is state dependent since long queues have a negative impact on customers' satisfaction. The working period usually has peak periods and slack periods; during these, the arrival rate is highly different from the overall average. Queue discipline may not be first come, first serve. 		

Table 1. The advantages and disadvantages of the queuing theory (Brown, 2012;Chowdhury, 2013, p.475)

Within this framework, the theory of waiting line (queuing theory) is developed. Thus, it involves studying the behavior of customers and of those who provide the services (El-Naggar, 2010; Oyatoye et al., 2011; Render, Stair, & Balakrishnan, 2006; Rodríguez Jáuregui, et al., 2017) and it provides various quantitative and qualitative models that can help managers understand and make the best decisions. Nevertheless, it has several advantages and disadvantages (Table 1).

For a given number of service lines, waiting systems can be characterized by: (i) percentage of time, or probability, for which the customer is served; (ii) the likelihood of having a certain number of clients in the system; (iii) the average number of units (customers) in the system; (iv) average time spent by each client in the system (waiting time plus service time); (v) the average number of units (customers) in the waiting line; (vi) the environment spent by each client on the waiting line; and (vii) percentage of time, or the likelihood of a new customer arriving to have to wait for the service to be delivered (Render, Stair & Hanna, 2006; Rodríguez Jáuregui et al., 2017). Based on these information, the managers will be able to improve the quality of their services.

Against this background, the current article aims to present how could an expert system, based on fuzzy logic, be used for the service quality improvement of a car wash point station. Thus, the paper is structured as follows: Section 2 brings forward the characteristics of a general queuing system while Section 3 emphasizes the case study particularities. A fuzzy system is designed for the service quality improvement of a car wash point station and the results prove that the number of stands and the number of employees per shift directly influence the average waiting time and as such, have a major impact on the perceived service quality. Further, the article closes by drawing several conclusions and emphasizing the theoretical and practical implications of the research findings.

Simulation of queuing systems

All models represent simulations of real-world phenomena. From a general perspective, decisional simulations are a way of exploring, in a safe and controlled environment, what may happen if a certain situation occurs (Leon, 2016); it is somehow similar with the process labeled by Thorndike as "trial and error learning", only this time variables and models are involved instead of human actions and the process takes place in a hypothetic environment and not in a real one. From a more restrictive perspective, decisional simulation is a method of studying systems' behavior through experiments (Leon, 2016). It refers to a specific class of dynamic models that require the detailed observation over time of the random sizes that interfere in one complex system.

Simulating a waiting lines system is an example of discrete simulation. Generally, the waiting phenomena can appear in any situation that has the following characteristics: (i) there is a significant number of applicants for certain services; (ii) it is not known when the service will be requested; (iii) there are a number of service stations performing the requested service; (iv) the serving time is not known for certain; and (v) there are uncertainties regarding customer behavior after arrival in the system service (Derbala, 2005).

The Service System is characterized by: (i) the number of waiting lines; (ii) the number of servers; (iii) the servers, arrival and service patterns; and (iv) the service priority rules (Zheng, Lin, Chen, & Xu, 2018).

Our approach is a single-line, multiple-server system, has better performance in terms of waiting times than the same system with a line for each server (Figure 1). The Number of Servers System (S1,...,Sm) serving capacity is a function of the number of service facilities and server proficiency. In this model the terms server and channel are

equivalent. It is assumed that a server or channel can serve one customer at a time (Baldwin, Davis IV, Midkiff, & Kobza, 2003).



Figure 1. Components of a queuing system

The properties of our specific waiting line models are (Chase, Aquilano, & Jacobs, 1998): **Layout**: multichannel.

Service phase: single.

Source population: infinite.

Arrival pattern: Poisson distribution: the arrival process is random and we assume it is a Poisson distribution.

Queue: FCFS (First Come First Served). This rule states that customers in line are served on the basis of their chronological arrival.

Service pattern: Exponential distribution. Other important factor is time the car (unit) spends with the server once the service has started, named **service rate** as the capacity of the server (the number of units per period time). A good approximation of the service rate can be given by exponential distribution.

Permissible queue length: unlimited.

Because a quantitative analysis involves information about the modeling system and complex probabilistic modeling techniques, a qualitative analysis is needed to identify the correlations between the various system parameters and their prediction. Thus, using a fuzzy model is natural.

Fuzzy logic control systems are a solution commonly used for automated control applications of processes with uncertain or variable parameters in wide limits, including physiological processes. Design fuzzy regulators is primarily based on empirical experience, however recent analytical design methods, through neuro-fuzzy techniques allow obtaining satisfactory, or even good, solution solutions, avoiding it accurate mathematical modeling of the process. Using these methods for a decision process is an ambitious study subject to the characteristics of these processes, but at the same time it is a modern one, both through description design methods, and by using them in a management field in full development (Mendel, 2017).

From a managerial point of view, the control of service features and maintenance services can only be achieved by controlling the process that provides the service. Measurement and control of process results are essential to achieving and maintaining the required service quality. When a service quality system is established, the customer represents the point of convergence of all the expected actions (Paraschivescu, 2006).

The decision-making process involves complex and usually undefined parameters with a high degree of uncertainty due to the fact that the conditions of the problem are not properly perceived. Any dynamics of the system cannot be described by the use of traditional mathematics due to the inherent complexity and ambiguity. That's why it's more convenient to use fuzzy logic for this approach. Fuzzy logic is a scientific tool that allows modeling of systems without detailed mathematical calculations using both qualitative and quantitative data. Estimates or calculations are made by words, while knowledge is represented by the IF-THEN linguistic rules (Phillis & Kouikoglou, 2009).

In order to design and illustrate the fuzzy expert system, the problem of improving the quality of a car wash point station is considered. An expert system is designated to replace the human expert from a certain field and it is made from the following components: knowledge basis, inference engine and user interface.

Fuzzy expert systems are capable of solving problems with uncertainty elements, the reasoning developed by them is based on fuzzy logic. Unlike classical logic, in which only two values of truth are used, fuzzy logic allows all predicates to admit truth values in the interval [0,1], providing a more accurate representation of the real world (Zadeh, 1994).

The uncertainties regarding system's variables and parameters are expressed through membership functions. The rules that reflect causal constraints are expressed in the form of a collection of instructions of type IF - THEN. These can be provided by human experts or can be extracted from the numerical data obtained through measurement, and they describe the operation of the system that should be modeled (Kwang, 2005).

The main idea is that, based on fuzzy logic approach, it can monitor certain parameters of a process, the parameters that essentially determine the quality of the executed service to the account that can be quantified. Knowledge-based society is a reality, and continuing education is one of the most effective solutions to remain competitive. Therefore, ensuring a quality management of the services based on computational technologies is a threshold to be overcome.

Service quality improvement - case study

In order to illustrate the design of fuzzy system for service quality improvement a car wash point station will be considered. The way of doing business in a car wash point station is quite simple. A client brings his dirty car in order to be cleaned up. If a car wash stand is available, the client takes it inside the stand. If the stand is unavailable, the client has to wait until it becomes available. The goal is to advice the manager of the station on how to adopt a decision in order for the client to be satisfied.

The first step in designing an expert system is problem specification It should determine the input and output variables of the system, as well as the ranges in which these fall in. For the considered case, there are four linguistic variables: (i) average waiting time (mean delay) *t*; (ii) ratio factor (of traffic intensity) in the car wash station *r*; (iii) number of stands *s*; and (iv) number of employees per shift *e*.

The client's average waiting time t is the most important performance criterion of the station. The mean delay should not exceed the limits which the clients consider as being acceptable.

The ratio factor of the service centre r represents the ratio between the client arrival rate λ , and the departure rate μ . The magnitudes of λ and μ indicate the rate of waiting clients. Apparently, the ratio factor is proportional to the number of stands *s*.

The number of stands, *s*, and the initial number of employees per shift, *e*, directly influence the client's average waiting time and as such, has a major impact on the car wash station's performance. By increasing *s* and *e*, we obtain smaller values of the average waiting time, but at the same time will increase the costs implied by opening stands and increasing the number of employees per shift.

In the considered model are three input variables - t, r and s, and an output variable – e. In other words, the car wash centre's manager wants to determine the number of employees per shift which are necessary for keeping the average waiting time within an acceptable range.

The ranges of the linguistic variables are specified in Table 2 along with normalised values of parameters *t*, *r* and *s* contained in the interval [0,1]. It can be noticed that for the mean delay parameter *t*, only three linguistic variables are considered – *Very Short, Short and Average* because values like *High and Very High* are simply not practical. A manager cannot allow letting a client wait longer than the average time.

Linguistic variable	Linguistic value	Notation	Normalized limits
0			
Average waiting	Very Short	VS	[0, 0.25]
time (<i>t</i>)	Short	S	[0.2,0.6]
	Average	А	[0.5,0.8]
Number of	Low	L	[0, 0.4]
stands	Average	А	[0.4,0.7]
(S)	High	Н	[0.6,1]
Ratio factor	Low	L	[0, 0.5]
(<i>r</i>)	Average	А	[0.4, 0.75]
	High	Н	[0.7, 1]
Number of	Very Low	VS	[0, 0.25]
employees per	Low	L	[0, 0.3]
shift	Rather Low	RL	[0.25, 0.45]
(<i>e</i>)	Average	А	[0.35, 0.75]
	Rather High	RH	[0.55, 0.75]
	High	Н	[0.7, 1]
	Very High	VH	[0.8, 1]

Table 2. Linguistic variables and their ranges

Fuzzy sets can have a variety of forms depending on the nature of the case in question. For our case we choose Gaussian membership functions for adequate representation of the expert's knowledge and at the same time, significantly simplifies the computation process. In Figure 2 are presented the fuzzy sets for all linguistic variables used in the

possible. 0.1 0.8 3.4 Owner 11 0.4 ... 0.1 ÷. 0.3 0.4 11.4 11.4 10.1 0.2 14 0.3 0.4 0.8 0.0 10.1 Los Average High Rather High High Very-High Rotherst ine 1 ma Austano 2.8 10:8 timbers 0.6 0.6 Technel of 0.4 Degree (0.4 0.2 0.2 0.2 0.4 0.6 0.8 0.2 0.4 0.6 0.0 Accesto

fuzzy system. One of the key points refers to maintaining sufficient overlap in some adjacent neighboring sets, such that the fuzzy system has a response as linear as possible.

Figure 2. The fuzzy sets for all linguistic variables used in the fuzzy system

Furthermore, the fuzzy rules must be obtained. In order to accomplish this requirement, an expert acknowledgement is required using the fuzzy linguistic variables previously defined. The necessary knowledge can also be collected from books, databases, and diagrams or based on observations.

There are three input and one output variables in our example (Figure 3). It is often convenient to represent fuzzy rules in a matrix form. Figure 3 presents the graphical representation of the three input parameters and of the only one output.



Figure 3. The interface for representing the input and output data of the system

A detailed analysis of the operations at the car wash point and based on an expert opinion determined us to obtain 27 rules that represent the complex relationships between all the variables used in the expert system as can be seen in the Figure 4.

 P (Mean-dulay in Very-short) and (Ratio-factor is Low) and (Barriser of stands is Low) thin (Barriser of employees is Very-low) (1)
2. # (Mean-delay is Short) and (Ratio-factor is Low) and (Ramber of stands is Low) then (Number-of-employees is Very-low) (1)
3. # (Mean-delay is Average) and (Ratio-factor is Low) and (Number-of-stands is Low) then (Number-of-employees is Very-low) (1)
4. # (Mean-delay is Very-short) and (Ratio-factor is Low) and (Number of stands is Average) then (Number of employees is Very-low) (1)
5. # (Mean-delay is Short) and (Ratio-factor is Low) and (Number-of-stands is Average) then (Number-of-employees is Very-low) (1)
(Mean-delay is Average) and (Ratio-factor is Low) and (Number of stands is Average) then (Number of employees is Very-low) (1)
 # (Mean-delay is Very-short) and (Ratio-factor is Low) and (Number-of-stands is High) then (Number-of-employees is Low) (1)
 # (Mean-delay is Short) and (Ratio-factor is Low) and (Namber-of-stands is High) then (Namber-of-employees is Low) (1)
 # (Mean-delay is Average) and (Ratio-factor is Low) and (Namber-of-stands is High) then (Rumber-of-employees is Very-low) (1)
10. If (Mean-delay is Very-short) and (Ratio-factor is Average) and (Number-d-stands is Low) then (Number-d-employees is Low) (1)
 If (Mean-delay is Short) and (Ratio-factor is Average) and (Number of stands is Low) then (Number-of-employees is Very-low) (1) If (Mean-delay is Average) and (Ratio-factor is Average) and (Number-of-atands is Low) then (Number-of-employees is Very-low) (1)
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14 if (Mean-delay is Short) and (Ratio-factor is Average) and Number of stands is Average) then (Number of employee is (2w) (1)
15 If (Mean-delay is Average) and (Ralio-factor is Average) and (Ramber of stands is Average) then (Number of employees is Very-kne) (1)
16. If (Mean-delay is Very-short) and (Ratio-Tactor is Average) and (Namber-of-stands is High) then (Namber-of-employees is Average) (1)
17. If (Mean-delay is Short) and (Ratio-factor is Average) and (Number-of-stands is High) then (Number-of-employees is Low) (1)
18. If (Mean-delay is Average) and (Ratio-factor is Average) and (Number-of-stands is High) then (Number-of-employees is Very-low) (1)
19. If (Mean-delay is Very-short) and (Ratio-factor is High) and (Number-of-stands is Low) then (Number-of-employees is Very-High) (1)
 # (Mean-delay is Short) and (Rato-factor is High) and (Number-of-stands is Low) then (Number-of-employees is High) (1)
 If (Mean-delay is Average) and (Ratio-factor is High) and (Number-of-stands is Low) then (Number-of-employees is Average) (1)
 If (Mean-delay is Very-short) and (Ratio-factor is High) and (Number-of-stands is Average) then (Number-of-employees is Average) (1)
 If (Mean-delay is Short) and (Ratio-factor is High) and (Number-of-stands is Average) then (Number-of-employees is Average) (1)
24. If (Mean-delay is Average) and (Ratio-factor is High) and (Number-of-stands is Average) then (Number-of-employees is Low) (1)
25. If (Mean-delay is Very-short) and (Ratio-factor is High) and (Number-of-stands is High) then (Number-of-employees is Rather High) (1)
25 If (Mean-delay is Short) and (Ratio-factor is High) and (Number-of-stands is High) then (Number-of-employees is Average) (1)
27. If (Mean-delay is Average) and (Ratio-factor is High) and (Number-of-stands is High) then (Number-of-employees is Rather Low) (1)
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Figure 4. The rule base which define the fuzzy system

Once defined the fuzzy sets and fuzzy rules their codification is necessary, this way actually constructing the expert system. In order to do this, we used MATLAB Fuzzy Logic Toolbox from MathWorks (Fuzzy Logic Toolbox User's Guide 2018) because such an instrument offers a complete environment for building and testing an expert system. MATLAB Fuzzy Logic Toolbox has five integrated graphical editors: the editor for the fuzzy inference system, the rules editor, the editor for membership functions, the fuzzy inference viewer and the 3D viewer of output data.



Figure 5. Evaluation and representation of the rules

The last and most laborious task is that of evaluating and tuning the system. Once the rules are introduced in the system, the Rule Viewer module can be viewed, which shows

what happens with the system in the moment when the values of the input data are scrolled. Depending on the interest, we can see the optimal solution in Figure 5.

Fuzzy Logic Toolbox is capable to generate 3D surfaces that help us analyze the performance of the system. These surfaces can be represented as well by varying whichever two of the input parameters, the other one remaining constant, as it can be clearly observed from Figure 6.

Even in this situation, the expert may not be satisfied with the system's performance; in this case, additional membership functions can be added, for example for the universe of discourse of the number of stands *s* parameter. As a result, the number of rules must be modified, in the sense of its increase, in order to give a better accuracy of the system, and then the output data must be compared with the ones previously obtained. Broadly speaking, the tuning of a fuzzy expert system is a greater consumer of time than fuzzy sets determination or rules construction (Pîslaru, Schreiner, & Trandabăț, 2010).



Figure 6. 3D images of the output variable

Discussion and conclusions

In the paper it is presented in a synthetic way, the results of the approach and procedures for the quality assurance process at a car wash station. The paper supports the computational techniques represented by an expert system using fuzzy logic as a starting point in the elaboration of quality assurance procedures. Computational techniques are considered a step forward in service quality assurance. Using computational techniques is another way to manage a business. Even though the proposed case study brings to the reader a lot of information about fuzzy logic, it has been tried to address them in a "friendly" manner, so understanding the problem would not raise great difficulties.

The novelty that the research is represented by the fuzzy expert system of quality assurance process which is characterized by a very high degree of complexity, case in which the adoption of such computational techniques proves its efficiency. Thus, the work contributes to quality improvement of service management using fuzzy technique which in economic terms translates in time and money savings.

The case under discussion is a simple one, but the real processes (production, services, etc.) are characterized by a very high degree of complexity, in which case the adoption of such computational techniques proves the efficiency it eventually translates into time and money savings. The present period is characterized by profound scientific and technological transformations. The volume of information doubles every 20 years, and technologies are replaced after only four years. Knowledge-based society is a reality, and continuing education is one of the most effective solutions to remain competitive.

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