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MULTI-CRITERIA OPTIMIZATION OF CUSTOMER SERVICE PROCESSES USING COMPUTER SIMULATION

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Purpose: The aim of this paper is to analyze the impact of service time on the efficiency of a service system in the context of the trade-off between minimizing customer waiting time in a queue and maximizing the utilization rate of service stations.
Design/methodology/approach: The study was conducted using discrete-event simulation in the FlexSim environment. A model of a customer service system with three service stations was developed, where customer arrivals were described by an exponential distribution and service times by a triangular distribution. The modal value of the service time was defined as the decision variable. Multi-criteria optimization was applied using the OptQuest module to identify compromise solutions.
Findings: The results revealed relationships between service time, queue length, and workstation utilization. Compromise solutions were identified, allowing for relatively short waiting times while maintaining a high yet stable level of resource utilization. It was found that excessive workstation loading leads to a rapid increase in waiting time and the number of customers abandoning the system.
Research limitations/implications: The main limitation of the study is the use of simplified modeling assumptions, including a homogeneous customer stream and the lack of direct comparison with analytical queueing models. Future research may extend the model by incorporating additional factors such as customer differentiation, service prioritization, or dynamic resource allocation.
Practical implications: The results can support service managers in planning the number of service stations, defining service time standards, and making decisions related to the organization of customer service processes.
Social implications: Improving the efficiency of customer service systems may contribute to enhanced service quality, reduced waiting times, and lower levels of customer frustration, thereby positively affecting overall customer satisfaction.
Originality/value: The value of the paper lies in the application of a simulation-based optimization approach to the analysis of a service system under realistic operating conditions, including variability in service times and customer behavior. The study provides practical insights for service management and a basis for further research in service process optimization.
Keywords: computer simulation, multi-criteria optimization, customer service process, queueing system, FlexSim.
Category of the paper: Research paper.

1. Introduction

The contemporary service sector is characterized by increasing variability in customer demand and the need for rapid response to client needs. Managing customer flow and optimizing service processes have become key elements shaping the quality of provided services and the competitiveness of organizations (Rosak-Szyrocka et al., 2022; Ingaldi, 2020). In many institutions, such as administrative offices, banks, customer service centers, or public agencies, the main challenge lies in balancing the number of employees involved in service delivery with the dynamically changing number of customers entering the system (Krynke, 2021, 2023a).

In such systems, it is particularly important to reach a compromise between reducing customer waiting times and ensuring the rational use of human and infrastructural resources (Krynke, 2023b; Gonçalves et al., 2025). An insufficient number of service stations leads to longer queues, decreased customer satisfaction, and potential reputational losses for the organization (Ingaldi, Ulewicz, 2019). Conversely, an excessive number of service positions results in underutilized personnel and increased operational costs (Putra et al., 2024).

Simulation tools are increasingly used to analyze and optimize service processes. Simulation makes it possible to reproduce the actual course of a process, assess system behavior under different conditions, and evaluate the effects of organizational changes without interfering with the real object (Beaverstock et al., 2017). One of the widely used environments for modeling service processes is FlexSim, which enables model development, performance analysis, and the execution of optimization experiments (Mou, 2024).

The purpose of this study is to develop a model of a service system with three workstations and to analyze the impact of service time parameters on key performance indicators such as queue length, average waiting time, and workstation utilization rate. The conducted research aims to demonstrate how appropriate management of process parameters can improve the efficiency of service systems and enhance service quality (Nawrocki, Zieliński, 2024; Pachura et al., 2024).

2. Simulation as a tool for analysis and improvement of service processes

Service systems are characterized by variability in both the number of customers and service times, which makes their analysis using traditional deterministic methods often insufficient (Kowalik, Klimecka-Tatar, 2018). In such cases, simulation methods are particularly useful, as they allow for modeling the behavior of systems under realistic conditions, incorporating event randomness and interactions between system components (Álvarez Sánchez, Suárez del Villar Labastida, 2022).

Discrete-event simulation (DES) enables the analysis of customer flow through the system, assessment of resource utilization, and identification of process bottlenecks. This allows not only an accurate reproduction of the current system performance but also testing of potential improvement scenarios without interfering with real-world operations (Pawlak, 2025). As a result, both the costs and risks associated with implementing organizational changes can be reduced.

In practice, simulation is particularly valuable in the service sector, where customer waiting time, resource utilization, and the quality of service interactions are the main factors influencing perceived service quality (Ilk, Shang, 2022). Simulation analysis makes it possible to determine how changes in process parameters, such as the number of service stations, service time, or queue discipline, affect system performance and customer satisfaction.

The FlexSim environment provides tools for both building simulation models and conducting comparative and optimization experiments (Daroń, 2022). Its built-in experimentation module allows the analysis of multiple system configurations, while the use of heuristic algorithms in optimization enables the search for solutions that balance customer waiting time with resource utilization levels (Krenczyk et al., 2018; Laguna, 2011).

In the context of service process analysis, optimization does not usually aim to find a single “ideal” solution, but rather to identify compromise solutions that ensure an acceptable level of service time while maintaining reasonable resource utilization (Kaczmar, 2019). This approach is particularly important in service systems where customer arrivals are inherently irregular and difficult to predict.

3. Model description and simulation assumptions

3.1. Model structure

The simulation model was developed in the FlexSim environment and represents a customer service system consisting of three independent service stations. Customers arrive at the system randomly, following a probability distribution of interarrival times, and are directed to a shared waiting area. Subsequently, each customer is assigned to the first available service station.

The model includes the following components:

- Entry area (Source) – generates customers entering the system.
- Waiting area (shared queue) – represents the space where customers wait for service.
- Three service stations (ServiceDesk1, ServiceDesk2, ServiceDesk3) – each characterized by a specific service time, which may differ among the stations.
- Exit (Sink) – represents customers leaving the system after completing their service.

Additionally, to reflect the aspect of customer satisfaction, a constraint on the maximum acceptable waiting time was introduced. If a customer's waiting time before the start of service exceeds 60 minutes, the customer abandons the queue and leaves the system as a dissatisfied customer. The number of such customers is recorded, and its analysis is presented in the results section.

The spatial layout of the model, including the placement of key system components, is shown in Figure 1.

Figure 1. Layout of service stations in the FlexSim environment.

Source: Own study.

The figure illustrates the visual representation of the customer service system. The entry point generates arriving customers, who then move to the waiting area (displayed as a queue). The three service stations are arranged in parallel, allowing for simultaneous processing of multiple requests. After service completion, customers leave the system through the exit element (Sink). The spatial arrangement and flow design were structured to allow intuitive observation and interpretation of system behavior.

Upon entering the system, each customer moves to the common queue shared by all service stations. When one of the stations becomes available, the next customer in line is automatically assigned to the nearest free operator and begins service.

3.2. Customer flow logic in the ProcessFlow environment

The operational logic of the model was implemented in the ProcessFlow module, which allows for a precise representation of the customer's lifecycle within the system. This logic defines the sequence of events occurring from the moment a customer enters the system, through the service process, to either successful completion or withdrawal after exceeding the acceptable waiting time (Figure 2). The input stream generates "customer" entities, which are directed to a shared queue. Each customer is then either served at the first available workstation or, if their waiting time exceeds the predefined threshold, leaves the system as a dissatisfied customer. Customers who successfully complete the service process exit the system as satisfied customers.

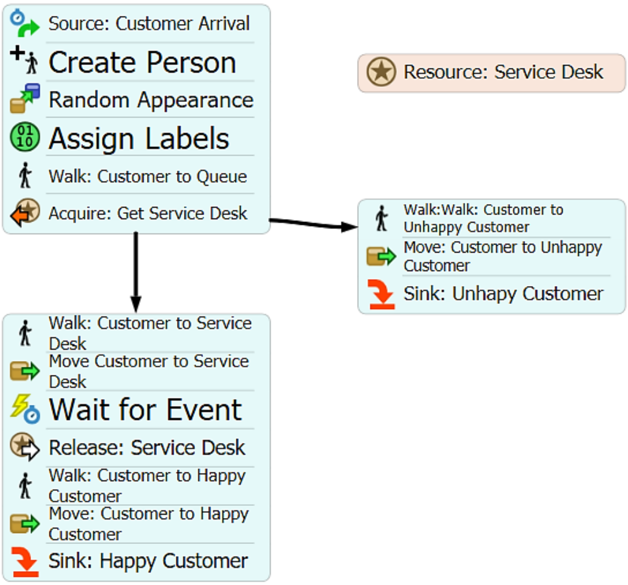

Figure 2. Customer flow diagram in the ProcessFlow module of the FlexSim environment.

Source: Own study.

The ProcessFlow model enables a detailed representation of both the service processes and the decision-making logic governing customer behavior.

Customer arrivals are generated according to an exponential distribution, reflecting the random nature of arrivals in the system:

$$T_{Arrival} = exponential(0.0, 200, getstream(activity)) \tag{1}$$

Upon creation, each customer entity is assigned a timestamp label, which allows for the subsequent calculation of total waiting time. The customer is then directed to the shared queue. When a service station becomes available, the customer proceeds to that workstation for service.

The service time at each station is defined using a triangular distribution, where the modal value serves as the optimization parameter:

$$T_{Service} = Triangular(T_{min}, T_{max}, T_{mode}) \quad (2)$$

where:
T_{min} = 200 s,
T_{max} = 900 s,
T_{mode} = optimization parameter (range: 200-900 seconds).

The modal value T_{mode} takes values within the range of 200 to 900 time units, and its variation directly affects both the utilization level of the service stations and the average customer waiting time in the queue.

The modal value was defined in the model parameter table and linked to the service time of operators within ProcessFlow, enabling direct control by the optimization module.

The simulation was executed over a time horizon corresponding to one operational working day, with the duration of a single model run set to 8 hours. This configuration enables the analysis of system performance under typical operating conditions while ensuring result repeatability and comparability across scenarios with varying modal service times.

3.3. System performance criteria and optimization variables

The evaluation of the service system's performance was based on three primary indicators describing its efficiency and service quality.

The first indicator is the average customer waiting time in the queue. This value reflects the operational effectiveness of the system and serves as a key measure of customer comfort. Longer waiting times increase the risk of negative service perception and the formation of service bottlenecks.

The second performance indicator is the utilization rate of service stations, which determines the level of system resource load and indicates whether available workstations are used effectively. Low utilization suggests underuse of personnel and infrastructure capacity, while excessively high utilization can lead to queue growth and the risk of system overload.

The third evaluation criterion is the number of customers abandoning the service process. In the model, it was assumed that if the waiting time exceeds 60 minutes, the customer leaves the system without receiving service, and is thus classified as a dissatisfied customer. This measure serves as an indirect indicator of customer satisfaction and enables the assessment of how system parameters influence service quality and potential customer loss.

Within the optimization process, a single decision variable was defined, the mode of the triangular distribution representing the service time at each workstation. The modal value, interpreted as the most probable service duration, can take values within a specified range. Its variation directly affects the customer service rate, and consequently, the queue length, resource utilization level, and the number of customers who abandon the queue.

The objective of the optimization procedure is to determine the modal value that ensures a balance between minimizing customer waiting time and the number of dissatisfied customers, while maintaining an appropriate level of workstation utilization. Hence, the analyzed problem is of a multi-objective nature, where the result is not a single optimal solution but a set of Pareto-efficient solutions that guarantee balanced system performance.

4. Results and analysis

In order to determine the impact of the modal value of the service time on the performance of the system, an optimization experiment was carried out using the OptQuest module in the FlexSim environment. The optimizer configuration included 40 feasible solutions, for which successive combinations of input parameters were automatically generated. Each scenario was executed multiple times, with the number of replications ranging from 5 to 10. The replication count was dynamically adjusted depending on how many simulation runs were required to achieve an 80% confidence interval at a 5% significance level.

This approach ensured statistically stable results that could serve as a basis for comparing the analyzed scenarios and assessing the effect of the modal parameter on the average queue waiting time, workstation utilization, and the number of customers who abandoned the service process.

Figure 3 presents the Pareto curve illustrating the relationship between the average waiting time of customers in the queue and the average utilization rate of service workstations. The numbered circles (1-40) correspond to consecutive scenarios generated by the optimizer. The red arrow indicates scenario 25, which was selected for further analysis as it represents a compromise solution, ensuring high but still stable workstation utilization (approx. 89%) combined with a moderate waiting time and a limited number of customer resignations. A detailed analysis of the waiting time distribution for this scenario is presented later in Figure 5.

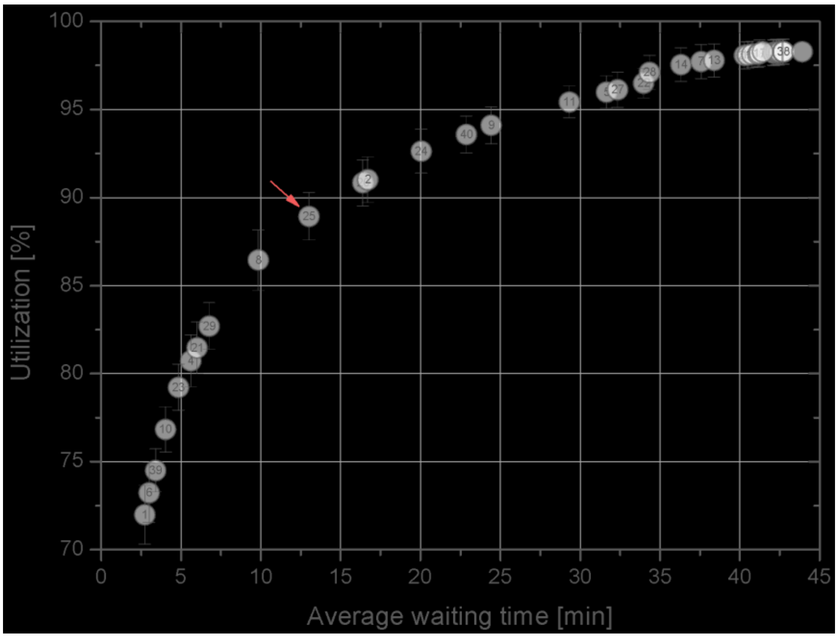

Figure 3. Relationship between average customer waiting time and workstation utilization.

Source: Own study.

The analysis of the chart shows that at low workstation utilization levels (below approximately 70-85%), the average waiting time remains acceptable from both the customer's and the organization's perspective. However, as workstation utilization increases beyond this range, a sharp rise in the average waiting time is observed. This indicates that the system enters an overload region, queues grow faster than the service capacity can handle.

From a practical point of view, this highlights the necessity of maintaining workstation utilization below a certain threshold value. Otherwise, the apparent cost efficiency of higher utilization becomes illusory, leading to reduced service quality and increased customer dissatisfaction.

Figure 4 shows the relationship between the modal value of the service time (as assumed in the triangular distribution) and the customer dissatisfaction ratio, defined as the proportion of customers who abandoned the service process due to exceeding the permissible waiting time:

$$R = \frac{number\ of\ dissatisfied\ customers}{total\ number\ of\ customers} \cdot 100\% \tag{3}$$

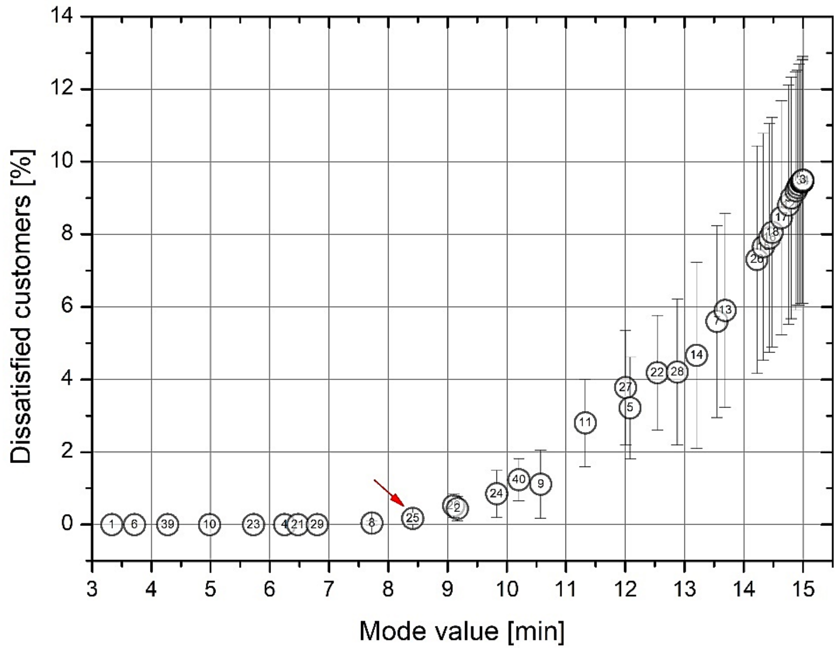

Figure 4. Relationship between the modal value of service time and the customer dissatisfaction rate.
Source: Own study.

As before, the red arrow indicates scenario 25, selected for further analysis due to its compromise nature, combining high workstation utilization (approx. 89%) with relatively short waiting times and a limited number of customer resignations.

The results clearly show that increasing the modal value of the service time leads to a noticeable rise in the dissatisfaction ratio. This outcome is intuitive, the longer the individual service takes, the faster the queue grows, and more customers exceed the threshold waiting time of 60 minutes, after which they abandon the system without being served.

Thus, the modal value of the triangular distribution is a key optimization parameter in the model. However, it cannot be minimized without constraint, excessively low modal values would violate the realistic conditions of the process. Therefore, optimization aims to find such a system operating point that maintains a balance between performance and service quality.

Figure 5 presents a histogram of the distribution of customer waiting times in the queue. The histogram was constructed using data from all ten replications, with the values transformed into probability density form, so that the chart reflects a continuous distribution and allows for interpretation regardless of the number of observations.

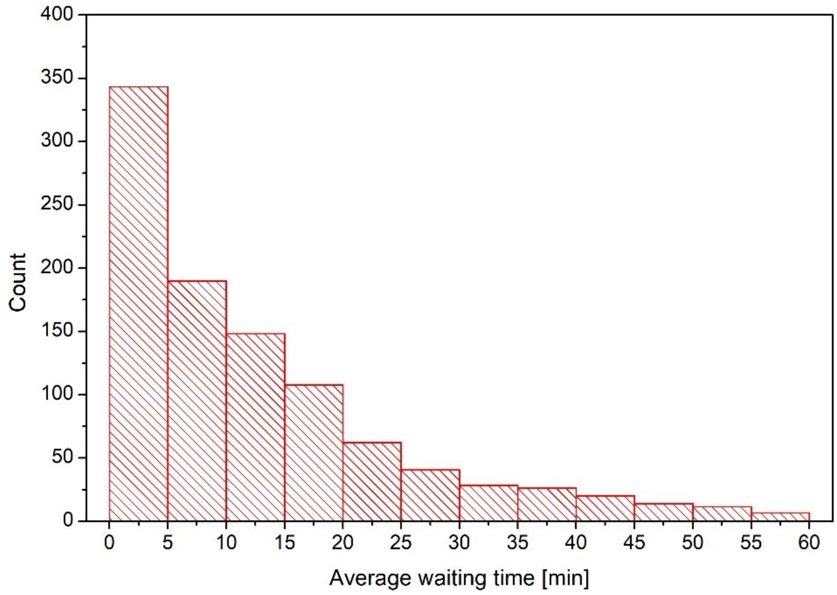

Figure 5. Histogram of customer waiting time distribution (probability density).

Source: Own study.

The histogram indicates a strongly skewed distribution, which is typical of queueing systems operating under conditions of partial load imbalance. Most customers experience waiting times shorter than the average, while a relatively small number of cases are characterized by significantly extended waiting times, resulting in dissatisfaction and resignation from further waiting.

Such system behavior confirms the previous findings regarding the influence of service parameters and workstation load on queue stability. At the same time, this distribution justifies the necessity of using multiple replications and aggregated results, as a single simulation run may not provide a representative outcome.

5. Summary

The conducted research confirmed that computer simulation combined with multi-criteria optimization constitutes an effective tool supporting the improvement of customer service systems. The use of the FlexSim environment enabled the development of a model that accurately reflects the actual course of the service process and allows for the analysis of how variations in time parameters affect key performance indicators of the system.

The application of the OptQuest optimization algorithm made it possible to determine a set of compromise solutions illustrating the relationship between the utilization level of service workstations and the average customer waiting time. The analysis of the Pareto curve revealed that the equilibrium point of the system occurs at a workstation utilization level of approximately 89%, which ensures a relatively short waiting time and a limited number of customer resignations.

The simulation results clearly indicate that excessive workstation loading leads to a sharp increase in the average waiting time and destabilization of the system. This means that striving for maximum resource utilization may produce effects opposite to those intended, resulting in system overload, reduced service quality, and customer loss. Therefore, optimal management of service time requires a compromise between operational efficiency and customer satisfaction.

The analysis of the waiting time distribution (Figure 5) confirmed the characteristic asymmetry typical of queueing systems operating under unstable load conditions. Most customers are served in less than the average time, while a small number of cases with significant delays have a substantial impact on the perceived quality of service.

From a managerial perspective, the obtained results may support decision-making in planning the number of service workstations, determining time standards, and reorganizing processes depending on customer inflow dynamics. The model developed in the FlexSim environment can be further extended to include additional variables such as differentiation of employee competence levels, customer prioritization, or the application of dynamic resource allocation.

In conclusion, it can be stated that the use of simulation and optimization methods enables not only a deeper understanding of the mechanisms governing service system performance but also the development of practical recommendations that support managerial decisions aimed at improving service processes.

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