World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Review Article)

Check for updates

Service center in electricity distribution sector with variable peak electricity time: A two-stage queuing model approach with nested simulation

Mohammadmahdi Ghasemloo [1], Abolfazl Nateghi [2] and Hadi Gholami Zanjani [3,*]

[1] *Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran.*
[2] *Department of Electrical Engineering, Kharazmi University, Tehran, Iran.*
[3] *Department of Industrial Engineering, University of Science and Culture, Tehran, Iran.*

World Journal of Advanced Research and Reviews, 2024, 24(01), 1433–1446

Publication history: Received on 17 July 2024; revised on 24 August 2024; accepted on 27 August 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.24.1.2597

Abstract

Customer service is essential for any business, significantly impacting customer satisfaction, brand reputation, and reducing associated costs. In the electricity industry, this importance is heightened due to the critical nature of electricity in daily life and growing usage rate of new technologies. Effective customer service in electric distribution companies involves handling a wide range of inquiries, from billing issues to technical support, requiring both remote and on-site assistance. The variability in customer calls, influenced by factors such as peak electricity hours, and different service and customer types, presents unique challenges in designing efficient service centers. This research develops a tailored model for the service center operations of a power distribution company, focusing on optimal staffing levels within budget constraints. A two-stage queuing model is proposed to address the needs of residential and non-residential customers. The study employs nested simulation techniques to account for variability in customer arrival times and peak hours. Key performance indicators (KPIs) are used to evaluate the effectiveness of staffing policies, considering both quantitative and qualitative costs. The study integrates stochastic optimization and ranking and selection methods to identify the best staffing configurations. The findings offer actionable insights for improving customer service efficiency and operational effectiveness in electricity customer service centers.

Keywords: Optimization; Nested simulation; Electricity distribution company; Service center; Variable peak electricity time

1. Introduction

Customer service is a critical component of any successful business, as it directly impacts customer satisfaction, loyalty, and overall brand reputation. Efficient customer service ensures that customers feel valued and heard, fostering a positive relationship Invalid source specified.. It involves promptly addressing customer inquiries, resolving issues efficiently, and providing knowledgeable assistance, which collectively enhance the customer experience Invalid source specified..

While customer service objectives in electricity distribution companies are inherently different from those in other sectors, such as business companies, and the importance of effectively managing customer relations remains critical due to the essential nature of electricity in modern life Invalid source specified., it has gained few attention in the literature on how to design an effective customer support center for an electricity distribution company Invalid source specified.

* Corresponding author: Hadi Gholami Zanjani

Online-resolvable issues such as questions related to renewable energies (e.g., using solar panels), billing inquiries, connect and disconnect requests, and service delays, as well as issues requiring onsite assistance, such as power outages due to line problems, are expected to be handled by the customer service center. The costs incurred by customer dissatisfaction in these service centers can be significant, potentially leading to substantial expenses for customers. Additionally, the variability of customer calls throughout the day is influenced by factors such as peak electricity hours. Customers generally fall into two distinct groups: residential and non-residential. Given the complexity of power distribution services, both residential and non-residential customers are likely to encounter issues that prompt them to seek assistance. These inquiries typically fall into distinct categories, each requiring tailored solutions.

Studying these service centers involves using queuing systems to manage resources and customers. Traditional methods fall short in capturing the complexities where incorporating stochastic simulation techniques into queuing systems provides the tools needed to effectively analyze objectives within the service center and select the optimal staffing configurationInvalid source specified.. We employ a two-stage queuing model to address the specific needs of residential and non- residential customers, a practical approach supported by literature that emphasizes tailored service strategies. Upon constructing the proper queueing model, our focus shifts to formulating the objective function and constraints, which can be categorized as either deterministic or stochastic. Deterministic constraints are effectively managed through integer programming techniques. Subsequently, stochastic simulation emerges as a robust strategy to tackle the stochastic elements inherent in the problem. Our research utilizes nested simulation techniques to handle different layers of uncertainty, conducting outer simulations to generate scenarios and inner simulations to assess performance Invalid source specified.. Ultimately, a procedure for comparing the outcomes, specifically the screen-to-the-best (STTB) algorithm in our case, serves to distinguish favorable outcomes among candidates. In this work we develop a model and further a framework for service center operations of a power distribution company, addressing both remote and on-site issues. The model aims to determine the optimal staffing levels, taking into account predefined budget constraints and operator costs. We simulate feasible scenarios to evaluate KPIs for each scenario, using a ranking and selection technique to identify the best-performing systemsInvalid source specified.. By articulating these key components, our paper lays the groundwork for optimizing staffing levels in the Electricity Customer Service Center (ECSCs), by considering a multi-skill, multi-stage queueing system with impatient customers contributing to the enhancement of customer serviceefficiency and operational effectiveness in this vital sector.

2. Problem Definition

In this section, we begin by explaining the underlying logic of our model and the rationale behind the inclusion of each feature. Subsequently, we address the scenario of fixed peak times and employ a stochastic model to account for variability in customer arrival rates. This approach involves the use of simulation techniques to effectively manage uncertainty and determine optimal staffing solutions. Moreover, we introduce an added layer of complexity by considering two distinct sources of variability, the other one being the variable peak electricity times. To capture the intricate dynamics and interactions impacting service levels, we employ nested simulation methods.

2.1. Model Logic

The ECSC offers a diverse range of service, primarily categorized for residential and non-residential customers Invalid source specified.. This segmentation facilitates targeted assistance, ensuring that callers are routed to operators with specialized expertise to address their specific concerns effectively. In an electricity provider service center, the Non-residential Service Team (NST) is specialized in servicing non-residential customers. Non-residential customers, such as businesses and industrialfacilities, often have more intricate electrical infrastructure and higher power demands, necessitating operators with specific expertise and experience to manage these needs effectively. These operators are trained to handle the technical complexities and ensure minimal disruption to critical operations. As a result, when there are no non-residential customers in the queue, these operators can still provide service to residential customers. Conversely, the Residential Service Team (RST), who primarily serve residential customers, may not possess the specialized training or experience required to address more complex and larger-scale issues presented by non-residential customers. Residential electrical systems are generally simpler, and allowing residential-focused operators to serve non-residential customers could lead to potential errors and inadequate handling of the non- residential customers' needs, thereby compromising service quality and cost Invalid source specified.. NST and RST form the first stage of the service center. There is a possibility that some customers may leave the queue due to prolonged waiting times and some customers might need on-site assistance due to the severity of their problem; this will remain unknown until an operator from RST or NST detects it. Those needing further on-site assistance will be directed to the Technical support team(TST). More waiting times for non-residential customers induces significant costs due to economic losses from downtime. Non-residential customers heavily depend on continuous power for their operations, so any interruption leads to halted production and missed business opportunities Invalid source specified.. Hence, the economic losses are high for non-residential customers due to their dependency on continuous power for operations and the high value of lost productivity ; therefore in the technical queue the priority is with the nonresidential customers and due to the importance of issues, it is assumed that no one abandons the technical queue.

Handling variable peak electricity hours and its impact on the rate of calls is the unique challenge of this sector. During peak hours, the call rate for the service center of an electric distribution company tends to increase significantly, as customers experience more frequent issues and inquiries related to power usage and reliability. The peak electricity time is assumed to be variable, making it challenging to determine the exact rush hours and their duration. However, we assume knowledge of the distribution of both the length and timing of rush hours.

The service center operates in three shifts and staffing levels during each shift could be different. The call rate throughout the day, the percentage of residential and non-residential customers, and the percentage of customers seeking technical assistance vary at different times of the day. For instance, calls related to general inquiries, such as bill payments or submitting move-in or move-out requests, are more frequent during the daytime, while the percentage of customers seeking technical assistance is higher at night. During rush hours, the percentage of nonresidential customers as well as those seeking technical assistance increases. However, the length, start, and end times of the peak hours vary from day to day. Consequently, we need to perform nested simulations to account for this variability Invalid source specified..

2.2. Fixed Peak Electricity Time

In the deterministic model of the ECSC, we consider three units within the service center: the RST as the first unit, the NST as the second unit, and the TST as the third unit.

We have 9 decision variables in our problem, being the number of operators in RST, NST, and TST, in the first, second and third shift. Asssuming $c = (c_1, c_2, c_3)$ to be the cost of hiring one operator for each unit, we find the feasible staffing levels based on the deterministic cost constraint, X_{det}, as below

$$X_{det} = \{(X_1, X_2, X_3) : X_1'c + X_2'c + X_3'c \le C_{max}\}$$

Where X_1, X_2, and X_3 represent the three-dimensional vectors corresponding to the staffing levels of the first, second, and third shifts, respectively. The transposes of these vectors are denoted by X_1', X_2', and X_3'. Note that other deterministic constraints such as minimum cost and minimum or maximum number of staff in each section can be applied in this stage.

We consider two sets of KPIs in our problem that induce different kinds of cost: quantitative and qualitative. Quantitative costs are those that can be measured in monetary terms including costs associated with operational disruptions faced by non-residential customers seeking technical assistance. These disruptions can prevent them from continuing all or part of their operations, leading to financial losses. Operators are paid based on a fixed number of work hours, but they cannot end their shift while customers are still waiting or being serviced. Therefore, operators in the first and second shifts must continue serving the last customer, even if their shift ends. Similarly, third-shift operators must serve all waiting customers until none remain. This situation leads to overtime work, which is compensated for separately and varies depending on the duration of the overtime worked.

Qualitative costs are mostly associated with customer and operator satisfaction, which, while not directly measurable in monetary terms, can significantly impact overall service quality and employee morale. These costs include the mean utilization of operators, the number of customers who abandon the queue, the average waiting times of residential customers in both initial and technical service queues, and the average waiting times of those non-residential customers that don't seek technical assistance in the initial service queue.

One set of costs can be included in the objective function, while the other set can be included as constraints. Incorporating quantitative costs in the objective function and qualitative costs as constraints allows for a balanced optimization approach. This strategy ensures that financial goals, such as minimizing costs, are directly targeted while still upholding critical qualitative aspects like customer and operator satisfaction. By setting qualitative factors as constraints, we can guarantee that service quality and employee well-being are not compromised for cost efficiency. This dual focus helps maintain a high standard of service and operational integrity, ultimately benefiting both the company and its customers. Conversely, placing qualitative costs in the objective function and quantitative costs as constraints would shift the focus towards optimizing service quality and customer satisfaction while treating financial considerations as boundary conditions. However, this approach might lead to solutions that are less cost-effective, as the model would prioritize achieving high service standards potentially at any cost and make it impractical in real-world scenarios where budgetary constraints are critical.

Table 1 The notations of the problem

Notation	Description
W_i	Service time for Customer i in initial queues
T_i	Service time for Customer i in technical queues
Y_i	Waiting time of Customer i in initial queue
Z_i	Waiting time of Customer i in technical queue
a_i	1 if Customer i has abandoned the queue, and 0 otherwise
t_i	1 if Customer i needs technical service, and 0 otherwise
r_i	1 if Customer i is residential, and 0 otherwise
O_j	Overwork time of Operator j
δ_{1j}	1 if Operator j is in NST, and 0 otherwise
δ_{2j}	1 if Operator j is in RST, and 0 otherwise
δ_{3j}	1 if Operator j is in TST, and 0 otherwise

In the ECSC we have M operators in total, and we serve N customers during a working day whose arrivals are treated as random variables. This reflects the inherent uncertainty and variability in customer arrivals, making it necessary to formulate the problem as a stochastic optimization problem. The objective function aims to minimize the expected total quantitative cost associated with operating the service center. This includes the expectation of costs imposed by nonresidential customers who seek technical assistance multiplied by w_1, and the overwork times of operators across three types—NST, RST, and TST—each weighted by constants w_2, w_3, and w_4, respectively and the constraints are related to qualitative costs.

$$argmin_{x\in X_{det}} E\left[w_1\sum_{i=1}^{N}(W_i+T_i+Y_i+Z_i)(1-a_i)t_ir_i+w_2\sum_{j=1}^{M}O_j\delta_{1j}+w_3\sum_{j=1}^{M}O_j\delta_{2j}+w_4\sum_{j=1}^{M}O_j\delta_{3j}\right]$$

$$P\left[\frac{1}{\sum_{i=1}^{N}r_i-\sum_{i=1}^{N}a_ir_i}\sum_{i=1}^{N}(Y_i)(1-a_i)r_i<b_1\right]>\gamma_1$$

$$P\left[\frac{1}{\sum_{i=1}^{N}r_i\,t_i-\sum_{i=1}^{N}a_ir_i\,t_i}\sum_{i=1}^{N}(Z_i)(1-a_i)r_i<b_2\right]>\gamma_2$$

$$P\left[\frac{1}{\sum_{i=1}^{N}(1-r_i)-\sum_{i=1}^{N}(a_i+t_i)(1-r_i)}\sum_{i=1}^{N}(Y_i)(1-a_i)(1-r_i)(1-t_i)<b_3\right]>\gamma_3$$

$$P\left[\frac{1}{N}\sum_{i=1}^{N}a_i<b_4\right]>\gamma_4$$

$$P\left[\frac{1}{\sum_{j=1}^{M}\delta_{1j}}\sum_{j=1}^{M}u_j\delta_{1j}<b_5\right]>\gamma_5$$

$$P\left[\frac{1}{\sum_{j=1}^{M}\delta_{2j}}\sum_{j=1}^{M}u_j\delta_{2j} < b_6\right] > \gamma_6$$

$$P\left[\frac{1}{\sum_{j=1}^{M}\delta_{3j}}\sum_{j=1}^{M}u_j\delta_{3j} < b_7\right] > \gamma_7$$

For the sake of readability, we will denote the objective function as $f\ (x)$ and the functions appearing in the constraints as $g_h(x)$, where $h\ =\ 1, 2, \ldots, 7$. This notation simplifies the representation of the model and allows for clearer reference to the components of the optimization problem.

To solve the problem, we conduct L replications at each staffing level, $x \in X_{det}$, and approximate $E[f\ (x)]$ with $E\left[\hat{f}(x)\right]$, and $P[g_h(x) < b_h]$ with $P[\hat{g}_h(x) < b_h]$ calculated as follows:

$$E\left[\hat{f}(x)\right] = \frac{1}{L}\sum_{l=1}^{L} f_l(x)$$

$$P[\hat{g}_h(x) < b_h] = \frac{1}{L}\sum_{l=1}^{L} I\left(g_{h,l}(x) < b_h\right)$$

Where $f_l(x)$ and $g_{h,l}(x)$ denote the output of the lth replication and I denotes the indicator function.

2.3. Variable Peak Time

Now we can consider the case where the peak electricity times, and consequently, the rush hours for the service center, are variable and follow a joint distribution, $Q(S, E)$. Using the law of total expectation we will have:

$$E\left[\hat{f}(x)\right] = E_{S,E}\left[E\left[\hat{f}_x \middle| S, E\right]\right]$$

$$P[\hat{g}_h(x) < b_h] = E_{S,E}\left[P[\hat{g}_h(x) < b_h | S, E]\right]$$

By iterating over multiple scenarios in the outer simulation and performing simulations in the inner layer, nested simulation helps in obtaining a comprehensive understanding of the system's performance across a range of potential conditions. This methodology is effective in capturing and analyzing variability and uncertainty in complex systems. To implement this approach, we will conduct nested simulation, a technique used to analyze complex systems with multiple levels of uncertainty. It involves running an "outer simulation" to generate scenarios based on the first source of variability, followed by an "inner simulation" within each scenario to account for the second source of variability. This approach allows for a detailed exploration of system performance under various conditions. The outer simulation involves sampling start and end times $(s_1, e_1), (s_2, e_2), \ldots, (s_L, e_L)$ from the joint distribution $Q(S, E)$. Each pair (s_l, e_l) represents a distinct scenario derived from the outer simulation. Subsequently, the inner simulation for each sampled pair (s_l, e_l) entails simulating the system K times to compute specific performance metrics. In the inner simulation, we compute

$$E\left[\ \hat{f}(x)\ |\ S = s_l, E = e_l\ \right] = \frac{1}{K}\sum_{k=1}^{K} f_{lk}(x)$$

$$P[\ \hat{g}_h(x) < b_h\ |\ S = s_l, E = e_l\ ] = \frac{1}{K}\sum_{k=1}^{K} I\left(g_{h,lk}(x) < b_h\right)$$

Then, compute the overall expectation using both the outputs of inner and outer simulation replications. We will have

$$E[\hat{f}(x)] = \frac{1}{L}\sum_{l=1}^{L}\left(\frac{1}{K}\sum_{k=1}^{K} f_{lk}(x)\right)$$

$$E[\hat{g}_h(x) < b_h] = \frac{1}{L}\sum_{l=1}^{L}\left(\frac{1}{K}\sum_{k=1}^{K} I\big(g_{h,lk}(x) < b_h\big)\right)$$

The set of staffing configurations that satisfy the constraints based on the simulation outputs, X_{cons} is then derived

$$X_{cons} = \{x: x \in X_{det}, P[\hat{g}_h(x) < b_h] > \gamma_h \text{ for } h \in \{1,2,\dots,7\}$$

2.4. Finding The Set of Best Systems Using STTB

Now that we have identified feasible staffing levels that meet both deterministic and stochastic constraints, we determine the optimal staffing levels using ranking and selection procedures. ranking and selection procedures are systematic methodologies that assist decision makers in choosing the best alternatives from a pool of options, especially when direct observation of their performance is impractical or costly. Among the various ranking and selection procedures, we opt for STTB method due to its computational efficiency and conservativeness. Computational efficiency is crucial because our framework is designed for ECSC, regardless of size, and does not assume specific computational resources. The conservativeness of the algorithm is important because selecting the staffing level is, most of the time, a one-time decision and incorrect choices can be highly costly in terms of both money and time. In the STTB procedure, systems undergo pairwise comparisons, with each system being evaluated against all others. Based on these comparisons, decisions are made regarding the elimination or retention of each system. Systems found consistently inferior to others are eliminated, while those that remain after this process constitute the subset that is retained for further consideration. When X_{cons} is obtained, for each staffing level we compute the pair $(\hat{\mu}_{f(x)}, \hat{\sigma}^2_{f(x)})$ as the mean and variance of the outer simulation outputs. Then we perform STTB on X_{stoch} to get the subset of the best systems with $1 - \alpha$ confidence level as described in algorithm 1.

Algorithm 1 STTB [13]

1: Input: X_{cons}, α, L

2: $X_{final} \leftarrow X_{cons}$

3: for $x \in X_{\text{final}}$ do

4: for $x' \in X_{final} \setminus \{x\}$ do

5: if $\hat{\mu}_{f(x')} + \delta < \hat{\mu}_{f(x)} - t_{\beta,d}\sqrt{\frac{\hat{\sigma}^2_{f(x)}}{L} + \frac{\hat{\sigma}^2_{f(x')}}{L}}$ then

6: $X_{final} = X_{final} \setminus \{x\}$ and break

7: end if

8: end for

9: end for

10: return X_{final}

Where $\beta = (1-\alpha)^{\frac{1}{|X_{cons}|-1}}$ and $d = n - 1$, and $t_{\beta,d}$ indicates the β quantile of a t-distribution with d degrees of freedom, and δ could be set to zero.

2.5. Proposed Algorithm

The algorithm starts by taking several input parameters: C_{max}, which represents the maximum allowable total cost for staffing; c, a vector detailing the cost associated with each type of operator; γ, the set of probability thresholds for constraints; L, the number of outer simulation replications and K as the number of inner simulation replications; and α, the significance level used for STTB. Next, the deterministic feasible set of staffing levels is calculated using Equation 1. The algorithm then conducts the nested simulation for each staffing configuration. Following this, the algorithm evaluates whether the constraints are satisfied in X_{cons}, and finally, selects the best subset of staffing levels by applying Algorithm 1, resulting in X_{final}. This final set is then returned as the output of the algorithm. An additional round of optimization could be performed on the staffing levels in X_{final} focusing on identifying the configuration with the lowest cost or the one that maximizes the expected value of the objective function.

Algorithm 2 ECSC staffing configuration

1: Inputs: $C_{max}, c, \gamma, L, K, \alpha, b$

2: $X_{stoch} \leftarrow \{\}$.

3: Obtain X_{det}.

4: for $x \in X_{det}$ do

5: Run nested simulation L and K times, respectively.

6: end for

7: Obtain X_{cons}.

8: Obtain X_{final} using Algorithm 1.

9: return X_{final}.

3. Computational results

In the numerical experiment section, we have designed the simulation model and selected the parameters to closely reflect real-world scenarios. Our model aims to accurately represent these real-world assumptions, and we carefully choose the values accordingly. The call center operates for 18 hours daily, from 6 a.m. to midnight. A similar simulation model has been utilized in [17]. The start and end of the peak time follow truncated normal distributions, specifically $N\ (720, 5, 700, 740)$ and $N\ (840, 10, 820, 860)$, meaning that the mean start and end times for rush hour are 6 p.m. and 8 p.m., respectively. During normal hours, the customer call rate is 120 calls per hour, increasing to 200 calls per hour during peak times.

The percentage of customers requiring technical assistance is 5%, with 5% being nonresidential customers. During rush hour, these percentages increase to 10% and 8%, respectively. Additionally, 15% of customers decide to leave the queue if they service does not start in a customer-specific time. The service time for residential customers averages 2 minutes and follows an exponential distribution. For nonresidential customers in the initial queue, the service time follows an exponential distribution with a mean of 5 minutes. Technical service for residential customers averages 30 minutes, while for nonresidential customers, it averages 60 minutes, both following exponential distributions. Impatient customers leave the queue after a random time that follows a uniform distribution between 3 and 5 minutes.

The service center faces certain constraints that limit its staffing choices. Each section must have at least one operator per shift, with a maximum of four operators in NST or RST and six operators in TST per shift. The costs for hiring an operator in NST, RST, and TST are 2, 1, and 4 units, respectively, with the budget allowed to vary between 73 and 79. This results in 2032 feasible staffing levels. The staffing levels can be represented as 9-dimensional tuples.

Next, we will determine the set X_{cons} using the constraints. We set the thresholds for constraints to [50, 50, 45, 0.1, 0.8, 0.8, 0.5] and the confidence levels to [0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9]. By conducting the nested simulation algorithm with 40 macro and 40 micro replications and evaluating all 2032 feasible staffing levels, we identify 20 staffing configurations that satisfy the constraints. The coefficients in the objective function are 3,2,1, and 2, respectively. The staffing configurations along with their mean and variance are presented in Table 2. STTB suggests 11 staffing configurations that satisfy the constraints and are non-dominated in terms of the objectives, as illustrated in Table 1. Among these configurations, we select the one with the lowest cost, which corresponds to the 9-dimensional tuple $(1, 3, 5, 3, 2, 5, 2, 1, 4)$. This concludes the process of selecting an optimal staffing level for the service center. To further analyze the framework, we can observe how the optimal staffing configuration changes when we modify the parameters of the problem. This analysis is particularly beneficial for parameters that are vulnerable to change, as it allows us to assess the robustness of our analysis with respect to those variations.

Table 2 Mean and standard deviation of the objective function for staffing configurations within $\boldsymbol{X_{stoch}}$, denoted as $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\sigma}}$, respectively.

Staffing Levels	$\hat{\mu}$	$\hat{\sigma}$
(1, 3, 5, 3, 2, 5, 2, 1, 4)	2915.92	338.43
(1, 3, 5, 3, 2, 5, 2, 2, 4)	2518.08	284.15
(1, 3, 5, 3, 3, 5, 1, 1, 5)	2761.62	310.01
(1, 3, 5, 3, 3, 5, 1, 2, 4)	2920.98	379.55
(2, 2, 4, 3, 3, 5, 1, 1, 5)	2702.96	267.45
(2, 2, 5, 3, 3, 5, 1, 1, 4)	2903.58	275.14
(2, 2, 5, 3, 3, 5, 1, 1, 5)	2864.38	338.84
(2, 3, 5, 2, 2, 5, 1, 1, 5)	2918.75	393.70
(2, 3, 5, 2, 2, 5, 2, 1, 4)	2971.48	354.86
(2, 3, 5, 3, 3, 4, 1, 1, 5)	2835.31	264.01
(3, 1, 5, 2, 3, 5, 1, 1, 5)	2722.05	334.11
(3, 1, 5, 2, 3, 5, 1, 2, 4)	2842.75	333.46
(3, 1, 5, 3, 3, 4, 1, 1, 5)	2932.06	406.65
(3, 1, 5, 3, 3, 5, 1, 1, 4)	2843.84	187.58
(3, 2, 5, 2, 2, 5, 1, 2, 4)	2842.15	286.59
(3, 2, 5, 3, 3, 4, 1, 1, 5)	2949.66	377.32
(3, 2, 5, 3, 3, 5, 1, 1, 4)	3004.16	361.95
(3, 3, 4, 3, 3, 5, 1, 1, 5)	2840.57	272.12
(3, 3, 5, 2, 2, 5, 1, 1, 4)	2848.16	278.69
(3, 3, 5, 2, 2, 5, 1, 2, 4)	2952.06	432.21

We chose the threshold for NST utilization and tracked the optimal staffing configuration, as shown in Table 3. The results indicate that while the change in the optimal staffing configuration is not significant, there are slight adjustments. Specifically, as the threshold increases, the number of NST operators also tends to increase.

Table 3 Threshold for nonresidential utilization and the corresponding optimal staffing configuration ($\boldsymbol{b_5}$ in Equation 7)

b_5	**Optimal Staffing Configuration**
0.6	(1, 3, 5, 3, 3, 5, 1, 2, 4)
0.65	(1, 3, 5, 3, 3, 5, 1, 2, 4)
0.7	(1, 3, 5, 3, 3, 5, 1, 2, 4)
0.75	(1, 3, 5, 3, 2, 5, 2, 1, 4)
0.8	(1, 3, 5, 3, 2, 5, 2, 1, 4)
0.85	(2, 2, 4, 3, 2, 5, 3, 2, 4)
0.9	(2, 2, 4, 3, 2, 5, 3, 2, 4)

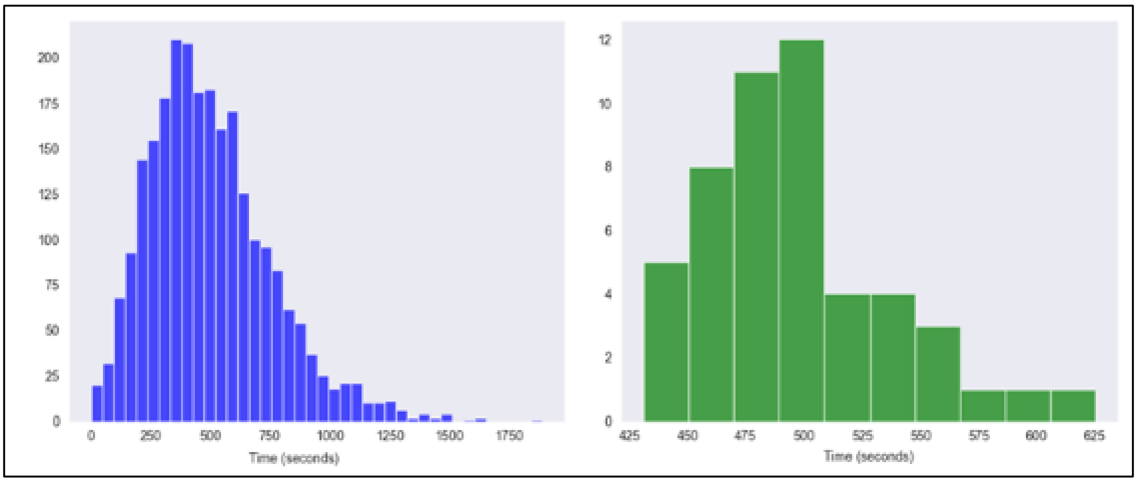
In Table 4, we have adjusted the threshold for customer churn. We observe that as the threshold decreases, the staffing levels change, leading to an increase in the number of operators assigned to the initial queues during the first two shifts.

Table 4 Optimal staffing configurations corresponding to various thresholds of customer churn ($\boldsymbol{b_4}$ in Equation 6)

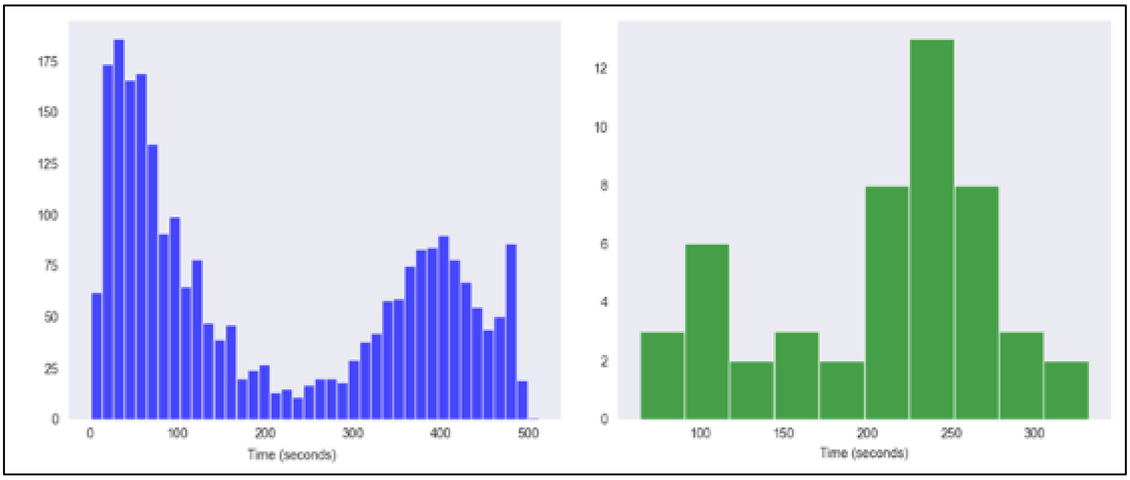
b_4	**Optimal Staffing Configuration**
0.15	(1, 2, 5, 2, 3, 5, 2, 3, 4)
0.13	(1, 2, 5, 2, 3, 5, 2, 3, 4)
0.11	(1, 3, 5, 3, 2, 5, 2, 1, 4)
0.1	(1, 3, 5, 3, 2, 5, 2, 1, 4)
0.09	(2, 3, 5, 3, 3, 4, 1, 1, 5)
0.07	(2, 3, 5, 3, 3, 4, 1, 1, 5)

One can now examine the output distributions of the selected staffing configuration to analyze its characteristics, particularly its variability. We present two histograms for each performance metric included in the objective function or constraints. The first histogram displays the pooled data from all macro and micro replications, providing an overview of the system's behavior. The second histogram shows the mean of the micro replications for each macro replication, highlighting the variability introduced by the fluctuations in peak hours.

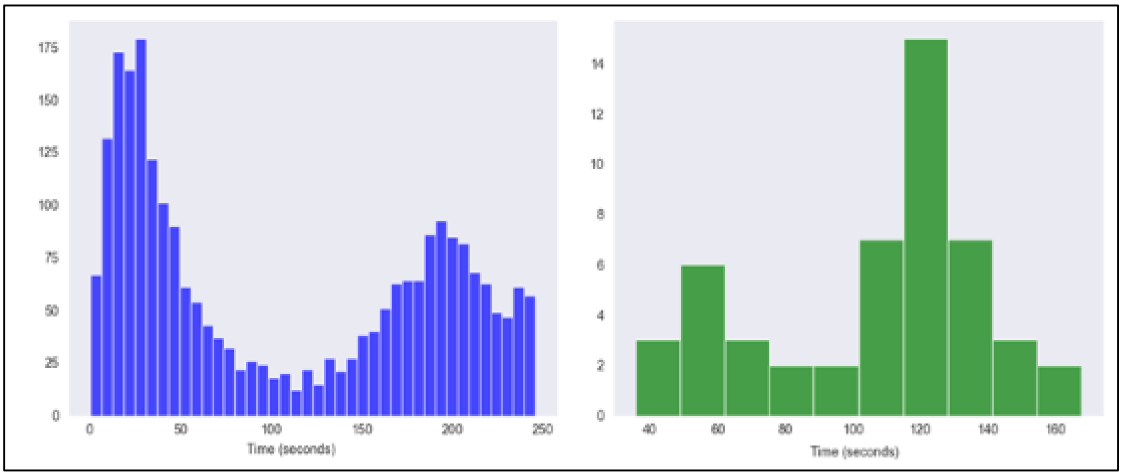
In terms of NST overwork, we observe a bimodal distribution in the overall data, which complicates the identification of the optimal staffing configuration. The histogram of the means also shows bimodality, but the probability of the second mode is higher compared to the pooled data. By carefully examining these histograms, we can assess variability both overall and in the means of the micro replications. If a decision maker finds the variance too high, a budget increase could be proposed to unlock better staffing configurations and achieve improved performance metrics.



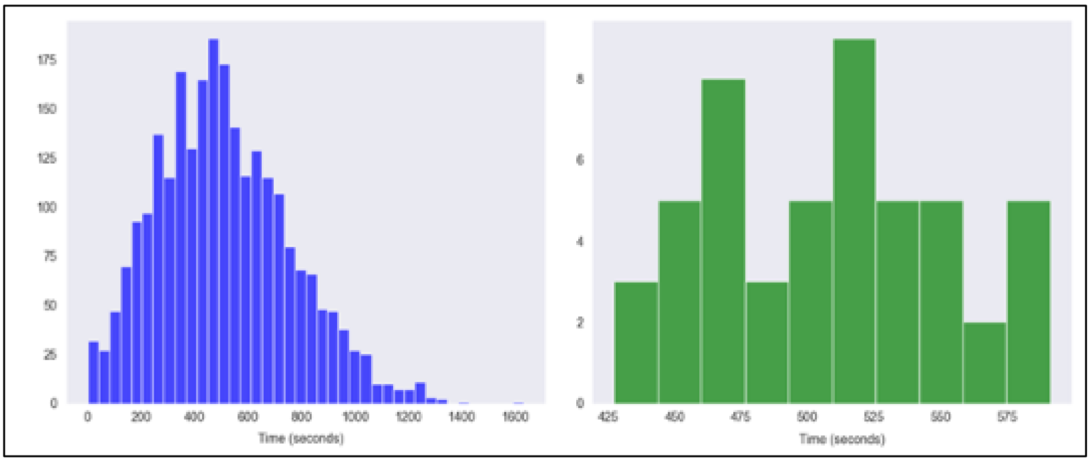
e: total waiting times of nonresidential customers seeking technical assistance



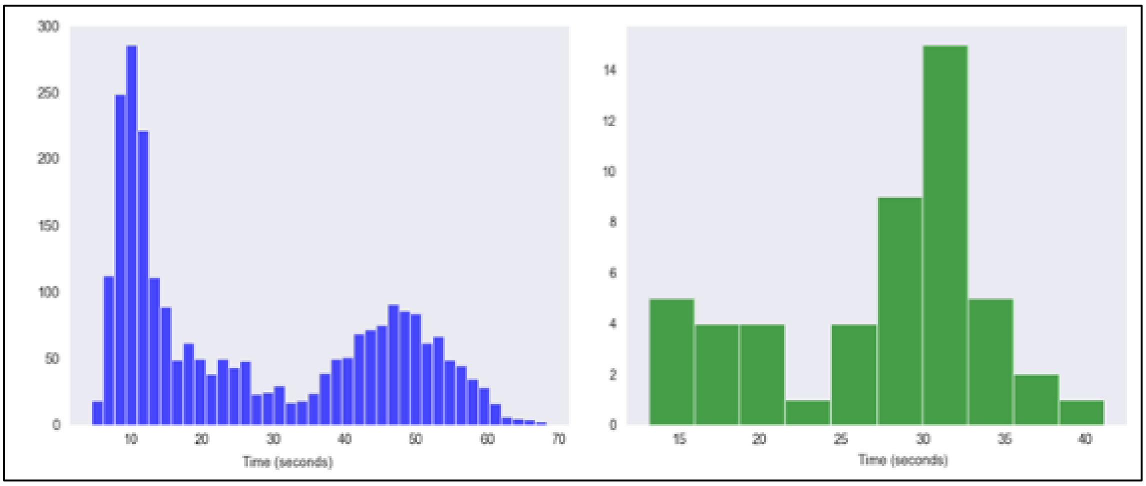
f: NST overwork



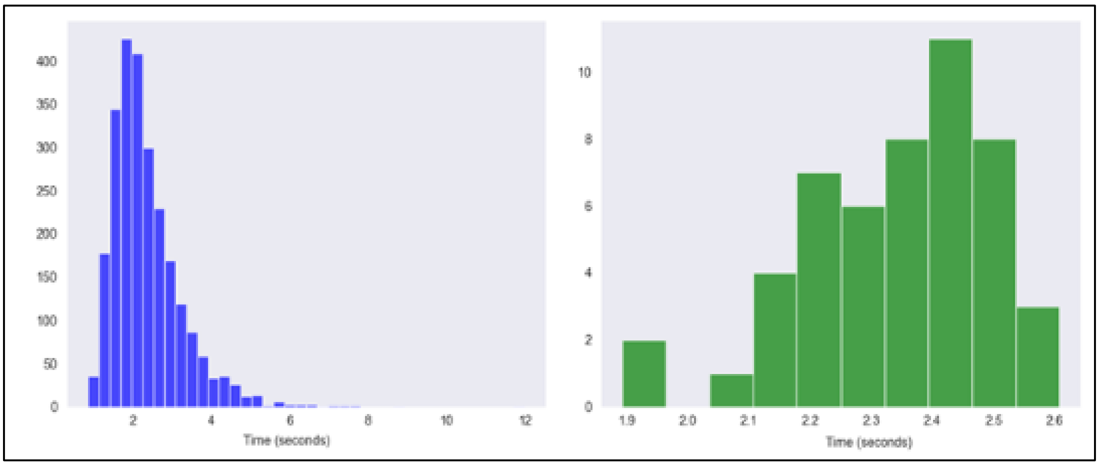
g: RST overwork



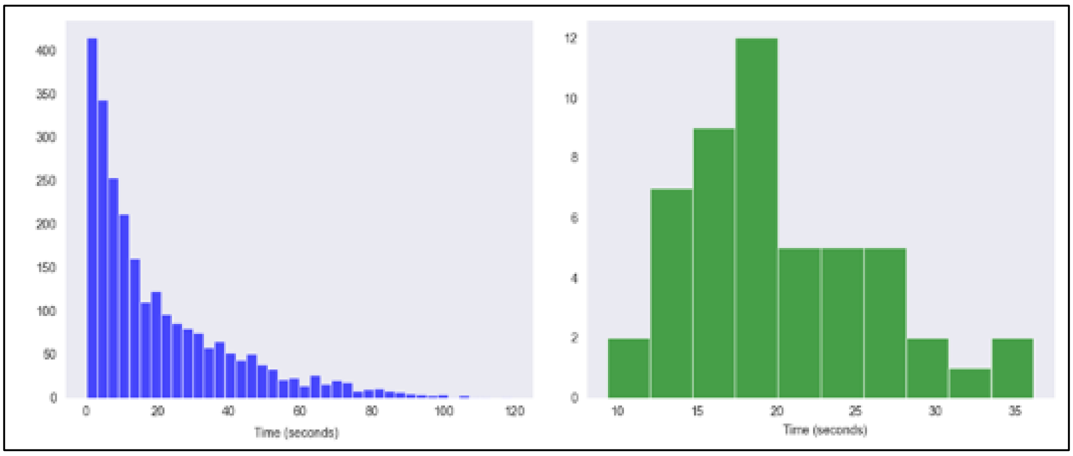
h: TST overwork



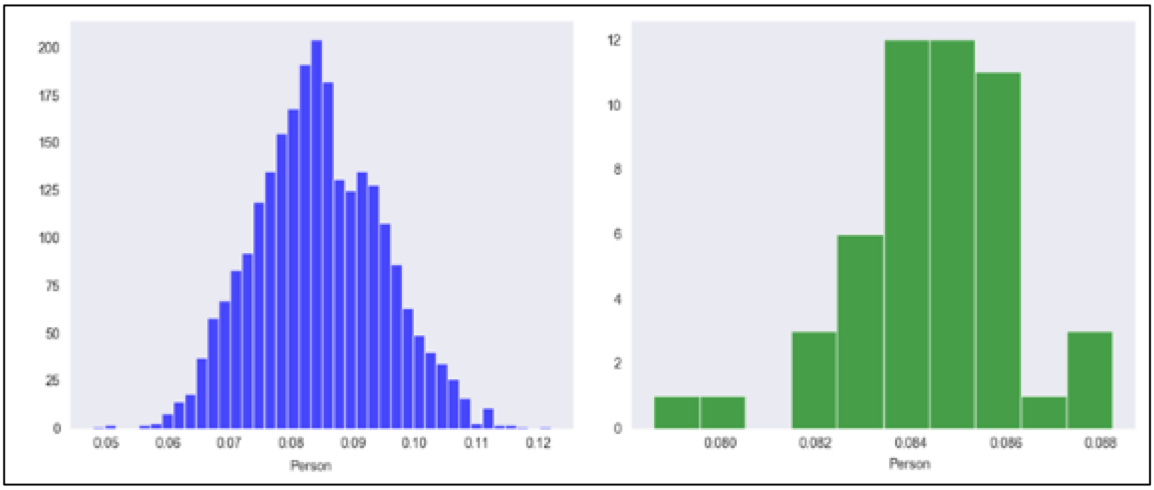
i: mean waiting of residential customers in the initial queue



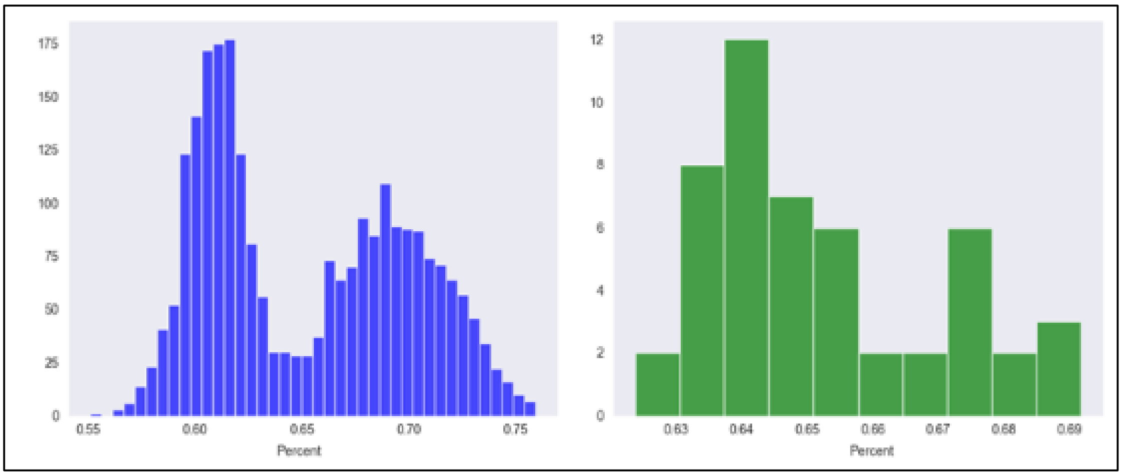
j: mean waiting time of non-residential customers not seeking technical assistance in the initial queue



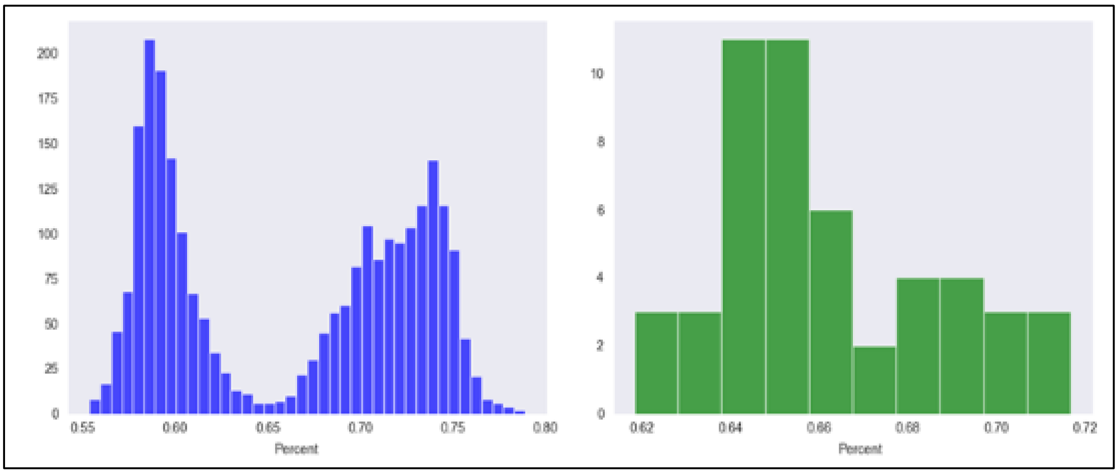
k: mean waiting time of residential customers in the technical queue



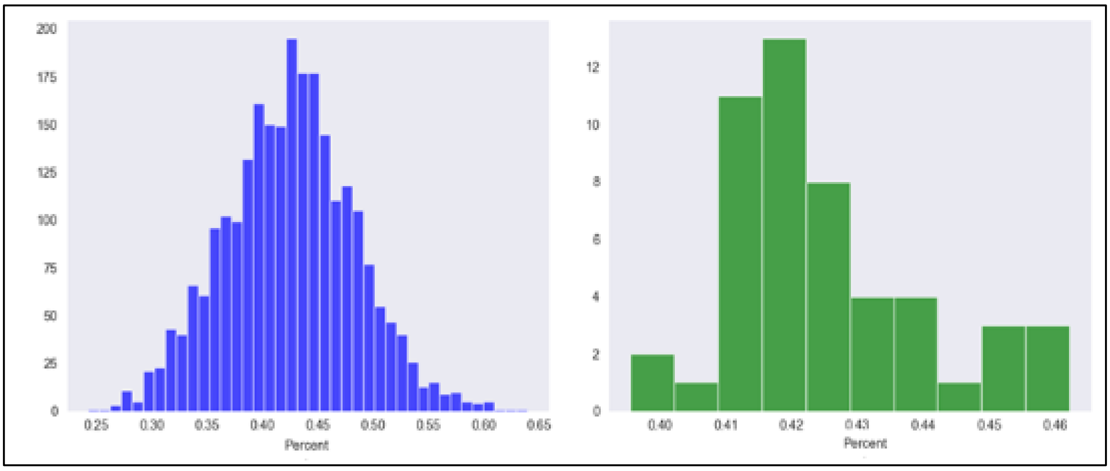
l: customer churn



m: NST utilization



n: RST utilization



o: TST utilization

Figure 1 Histograms of KPIs (plots a-k) pertaining to the optimal staffing configuration are presented, with the left histogram illustrating the aggregated data, while the right histogram depicts the mean derived from micro-replications within each macro-replication

4. Conclusion

In this study, we have developed a [1]nd analyzed a tailored model for the service center operations of a power distribution company, focusing on the optimization of staffing levels under budget constraints. Our research addressed the complexities inherent in customer service within the electric industry, where variability in customer demand, especially during peak electricity hours, and the distinct needs of residential and non-residential customers pose significant challenges. By employing a two-stage queuing model and integrating nested simulation techniques, we accounted for the stochastic nature of customer arrivals and the variability of peak hours. This approach allowed us to evaluate KPIs and identify the best staffing configurations using a combination of stochastic optimization and ranking and selection methods. The histograms of the performance metrics revealed important insights into the overall system behavior and the variability introduced by different operational conditions.

The findings of this research provide actionable insights for improving the efficiency and effectiveness of customer service operations in electricity distribution companies. The proposed model and methodologies can guide decision-makers in implementing optimal staffing strategies that balance operational costs with customer satisfaction. Furthermore, by understanding the variability and uncertainty in service demands, companies can make informed decisions on budget allocation to enhance service quality and meet customer expectations more effectively.

This work advances the broader field of service center optimization by providing a versatile framework that can be tailored and implemented across industries where variability in customer service is a significant challenge. Future research endeavors could expand this model by integrating more dynamic elements of customer service operations, such as real-time staffing adjustments informed by predictive analytics, the adoption of emerging technologies in service management, and the inclusion of load curves during peak demand periods.

Compliance with ethical standards

Acknowledgments

The authors would like to thank all those who contributed to this research, whether directly or indirectly, through support, feedback, or guidance.

Disclosure of conflict of interest

All authors have no conflict of interests to declare

References

[1] Vadavadagi DP. A study on impact of customer satisfaction on brand loyalty. International Journal For Multidisciplinary Research. 2022;4(4).

[2] Pérez A, Rodríguez del Bosque I. Corporate social responsibility and customer loyalty: exploring the role of identification, satisfaction, and type of company. Journal of Services Marketing. 2015;29(1):15-25.

[3] Tontini G, Söilen KS, Zanchett R. Nonlinear antecedents of customer satisfaction and loyalty in third-party logistics services (3PL). Asia Pacific Journal of Marketing and Logistics. 2017;29(5):1116-1135.

[4] Hartmann P, Apaolaza Ibáñez V. Managing customer loyalty in liberalized residential energy markets: The impact of energy branding. Energy Policy. 2007;35(4):2661-2672.

[5] Novixoxo JD, Pomegbe WWK, Dogbe CSK. Market orientation, service quality, and customer satisfaction in public utility companies. European Journal of Business and Management. 2018;10(30):37-46.

[6] Chodzaza GE, Gombachika HS. Service quality, customer satisfaction, and loyalty among industrial customers of a public electricity utility in Malawi. International Journal of Energy Sector Management. 2013;7(2):269-282.

[7] Kurtkoti AS. Customer satisfaction of power distribution companies. Jindal Journal of Business Research. 2014;3(1-2):58-62.

[8] Avramidis AN, L'Ecuyer P. Modeling and simulation of call centers. Proceedings of the Winter Simulation Conference. 2005;9.

[9] Koole G, Li S, Ding S. Call center data analysis and model validation. arXiv preprint arXiv:2402.19209. 2024.

[10] Li P, Feng R. Nested Monte Carlo simulation in financial reporting: A review and a new hybrid approach. Scandinavian Actuarial Journal. 2021;2021(9):744-778.

[11] Nelson BL, Swann J, Goldsman D, Song W. Simple procedures for selecting the best-simulated system when the number of alternatives is large. Operations Research. 2001;49(6):950-963.

[12] Boesel J, Nelson BL, Kim S-H. Using ranking and selection to "clean up" after simulation optimization. Operations Research. 2003;51(5):814-825.

[13] Santos Neto AS, Reis MRC, Coimbra AP, Soares JCV, Calixto WP. Measure of customer satisfaction in the residential electricity distribution service using structural equation modeling. Energies. 2022;15(3):746.

[14] Stock A, Davidson RA, Kendra J, Martins VN, Ewing B, Nozick LK, Starbird K, Leon-Corwin M. Household impacts of interruption to electric power and water services. Natural Hazards. 2023;115(3):2279-2306.

[15] Küfeoğlu S. Economic impacts of electric power outages and evaluation of customer interruption costs. Aalto University. 2015.

[16] Nti IK, Teimeh M, Nyarko-Boateng O, Adekoya AF. Electricity load forecasting: A systematic review. Journal of Electrical Systems and Information Technology. 2020;7(1):13.

[17] M. Ghasemloo and D. J. Eckman, Agglomerative Clustering of Simulation Output Distributions Using Regularized Wasserstein Distance, arXiv preprint arXiv:2407.12100, 2024.