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Simulation-Based Decision Support for Call Centre Staffing Optimisation: A Case Study from the Palestinian Telecom Sector

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ABSTRACT

This research introduces a decision support model based on simulation, designed to enhance staffing strategies and elevate operational performance within a technical support call centre operated by a prominent Palestinian internet service provider. Call centres frequently encounter challenges arising from fluctuating customer demand, often resulting in extended waiting times and elevated abandonment rates, which adversely affect customer satisfaction. To mitigate these issues, a discrete event simulation was developed through the ProModel© platform, integrating statistically fitted probability distributions for call arrival patterns, call handling durations, and customer abandonment tendencies. Following validation, the simulation was utilised to assess various staffing alternatives, with particular focus on reallocating personnel across different shifts. The findings revealed that moving a single agent from the morning shift (8:00 AM to 4:00 PM) to the high-demand afternoon shift (4:00 PM to 12:00 AM) yielded significant enhancements in key performance indicators. This adjustment resulted in a 15% reduction in average customer waiting times and a 27% decrease in call abandonment rates, achieved without increasing the overall staffing level. The study underscores the practical utility of simulation modelling as an evidence-based approach to resource allocation in service-oriented environments. The adopted methodology aligns with established standards in call centre simulation and presents a transferable framework suitable for similar applications within emerging economies.

1. Introduction

Call centres have become an integral component of contemporary business operations, offering essential customer service and sales support across a range of industries [2]. With the continuous rise in call volumes, organisations encounter increasing difficulty in effectively managing these critical points of customer interaction. Simulation has gained recognition as a robust analytical approach for enhancing call centre efficiency [14]. This study presents a discrete event simulation model specifically designed to improve the operational effectiveness of the technical support unit at a leading internet service provider (ISP) in Palestine.

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The operation of call centres is characterised by intricate queuing behaviour, encompassing fluctuating arrival rates and variable service durations [5]. Traditional analytical techniques, such as those based on Erlang models, often fall short in capturing the dynamic and stochastic nature of real-world operations. In contrast, simulation offers a more adaptable framework that accommodates detailed system behaviour and facilitates the exploration of alternative scenarios. A review of relevant literature indicates that simulation consistently provides greater accuracy in forecasting critical performance indicators, such as service levels, when compared to conventional Erlang-based estimates. Empirical studies further illustrate how simulation supports staffing optimisation, the evaluation of trade-offs, and complements decision-making frameworks.

The current research replicates the inbound call process of the ISP's support department, aiming to minimise both customer abandonment and waiting durations. Historical data were employed to estimate call inter-arrival times and service duration distributions, while abandonment patterns were derived through on-site observations. The simulation incorporates the deployment of cross-trained agents during high-demand periods using ProModel software. Findings suggest that reallocating one agent from the early shift to the peak afternoon shift reduces average wait times by 15% and call abandonment rates by 27%. This study provides contributions of both practical and scholarly value. For the ISP, it delivers actionable insights grounded in empirical analysis to enhance customer service quality. From an academic perspective, it demonstrates the effective integration of simulation techniques within call centre performance evaluation, particularly in addressing challenges such as abandonment and enabling statistical validation of output data. The research offers a transferable approach for applying industrial engineering methodologies to optimise service operations within Palestinian call centres and potentially similar contexts elsewhere.

1.1 Problem Statement and Research Questions

The ISP's technical support call centre is currently facing increasing customer waiting times and elevated call abandonment levels, both of which are contributing to diminished customer satisfaction. These operational challenges necessitate performance enhancements to align with international service quality standards. Accordingly, the call centre must improve its key performance indicators (KPIs) through the refinement of staffing strategies. This research is guided by several core inquiries:

- In what ways can simulation modelling be utilised to identify the underlying causes of current KPI shortfalls and assess potential improvements?
- What specific staffing adjustments, such as reallocating personnel across shifts, can improve service levels and reduce abandonment during periods of high demand?
- How can the study embody established best practices in simulation for call centres, particularly regarding distribution fitting, model validation, and statistical analysis of outputs?
- To what degree can the adopted methodology and resulting insights be applied to broader optimisation efforts within call centres throughout Palestine?

To address these questions, the study constructs a discrete event simulation targeting the technical support operations of the ISP. The approach includes estimating relevant input distributions, coding the simulation model using ProModel© software, and analysing a range of staffing configurations. The findings will yield evidence-based guidance aimed at enhancing KPIs and elevating customer satisfaction. This investigation not only provides actionable strategies for the company but also offers a replicable framework for employing industrial engineering methodologies in the improvement of call centre performance. Moreover, it highlights the effectiveness of simulation as a practical tool for advancing service system outcomes.

1.2 Company Background

The ISP operates as a leading provider of internet services and supplementary value-added solutions, having rapidly established itself as one of the largest firms in Palestine. It delivers services across both the West Bank and the Gaza Strip through an extensive infrastructure, which includes a proprietary international fibre optic link. The company's strategic vision centres on reshaping the Palestinian internet sector by prioritising customer requirements and offering innovative, high-quality service solutions. Notable achievements include the introduction of advanced broadband speed tiers, the establishment of data connectivity between the West Bank and Gaza, and tailored service packages for corporate clients. Delivering outstanding customer service remains a core objective for the organisation, complementing its technical capabilities. The company places strong emphasis on fulfilling customer expectations at every point of engagement. The call centre plays a pivotal role in realising this commitment, with dedicated personnel assigned to specialised units handling queries related to technical support, billing, sales, and general services. As the customer base continues to grow, the resulting surge in incoming calls has created challenges in maintaining prompt responses and minimising abandonment rates. This study specifically targets the technical support division of the call centre, which is currently experiencing increased delays and higher rates of call abandonment, thereby affecting overall customer satisfaction. Improving performance under these conditions necessitates a more effective allocation of staffing resources during periods of peak demand. Simulation modelling provides a valuable mechanism for systematically evaluating and comparing alternative staffing configurations to support these operational enhancements.

1.3 The Company Standards

The existing service benchmark permits a maximum waiting period of three minutes. Nonetheless, in alignment with the study's objectives, revised KPIs were established to better reflect international performance standards. The primary KPI addresses customer wait time, which has been redefined to a target of 40 seconds. Analytical findings indicated that nearly 80% of callers experience wait times exceeding this threshold, thus supporting its selection as a reasonable average benchmark. The second KPI pertains to the rate of call abandonment, which has been set at 15% and formally endorsed by the organisation, as depicted in Figure 1.

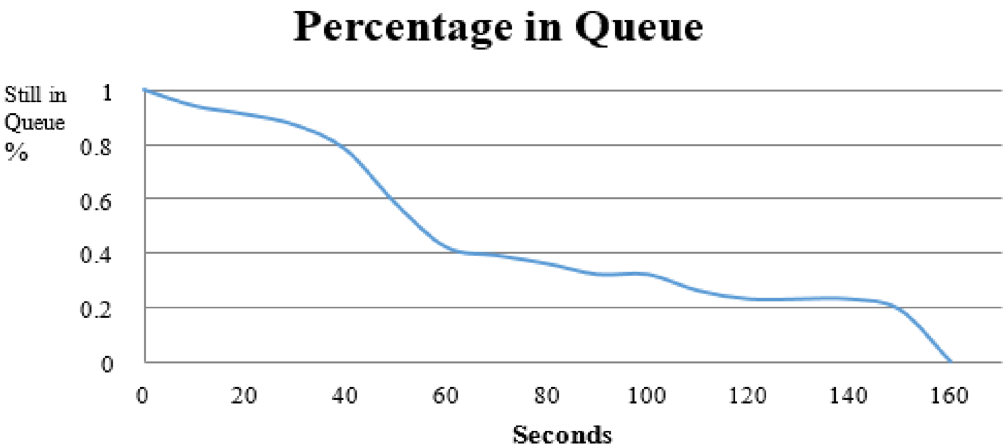

Fig.1: Percentage in Queue at the Technical Department

2. Literature Review

Simulation modelling has increasingly emerged as a critical instrument for conducting data-driven evaluations and enhancing the operational performance of call centres [6]. Since the early 1990s, both academic research and real-world implementation of simulation within this domain have witnessed substantial growth [1]. This literature review highlights the significance and evolving best practices of simulation modelling in call centre environments, with a particular focus on advancements achieved over the past five years. Initial investigations into call centre operations revealed notable deficiencies in conventional analytical tools, such as the Erlang C model, when applied to the complexities of actual call centre systems. Klungle [13] identified several unrealistic assumptions inherent in Erlang-based formulas that were incompatible with empirical call data. Similarly, Bapat and Pruitte [4] contended that simulation offered a more adaptive and comprehensive analytical framework compared to static workforce management systems. Scholars demonstrated that simulation-based capacity projections exhibited over 70% higher accuracy relative to those produced by Erlang C methods.

Contemporary studies have continued to validate these earlier conclusions. Scholars provided mathematical evidence that Erlang C tends to overestimate service levels, particularly when modelling customer abandonment. Numerous case studies have illustrated how simulation has been effectively employed to inform staffing, scheduling, and call routing strategies. Mehrotra and Fama [16] utilised ProModel software to enhance cross-training practices within a collections call centre. Scholars integrated simulation with optimisation algorithms to design near-optimal staff scheduling. Wang et al. [19] incorporated ProModel into a broader framework aimed at optimising workforce allocation in call centres.

Research by scholars surveyed existing workforce management approaches and recommended greater utilisation of simulation techniques. Aksin et al. (2007) remarked that call centres offer a fertile ground for advancements in data acquisition, statistical techniques, and modelling frameworks. Further scholarly attention has been directed at addressing methodological limitations in simulation practice. Garnett et al. [8] introduced probability distributions for accurately representing customer abandonment patterns. Gotway and Young [9] detailed procedures for estimating simulation inputs using aggregated operational data. Mandelbaum et al. [15] proposed refined models of arrival processes to better capture time-dependent fluctuations in demand. In a related domain, Jiang and Huang [10] applied simulation to streamline healthcare facility performance.

Thiongane et al. [18] designed a highly flexible discrete event simulation model adaptable to various call centre structures and operational logics. Kadioglu and Alatas [11] employed machine learning methods to improve call volume forecasting and associated simulations. Khatib et al. [12] demonstrated the scalability of simulation models through integration with cloud computing for large-scale call centres. Additionally, Assaf [3] applied discrete event simulation within the context of social network analysis in the telecommunications sector. The body of academic work reviewed here offers substantial evidence supporting the effectiveness of simulation in call centre management, while also reflecting continuous methodological innovation. Recent progress in analytics, algorithm design, and technological integration has further enhanced simulation's applicability. This study contributes to the field by presenting a new case study built on contemporary best practices in simulation for operational improvement.

3. Methodology

This study employs discrete event simulation to represent the inbound call processes within the technical support division of the call centre. This approach was selected in view of its comparative advantages over analytical and optimisation techniques, particularly when dealing with complex service systems such as call centres. The inherent stochastic variation and time-dependent nature of call volumes and service durations pose significant challenges to traditional mathematical models, which rely on assumptions seldom satisfied in practical environments. For instance, Klungle [13] highlighted the limitations of Erlang C formulations, which depend on exponential service time and Poisson arrival assumptions, both of which rarely align with empirical call centre data. Furthermore, Erlang-based models presume homogeneous servers, infinite queuing capacity, and a single class of incoming calls [4].

These assumptions restrict the capacity of analytical models to capture critical operational features such as non-exponential service time distributions, customer abandonment, call retries, skill-based routing, and intraday variability. Similarly, optimisation methods, including integer programming or heuristic techniques, necessitate the simplification of constraints, objectives, and inter-variable relationships. Discrete event simulation, by contrast, offers a highly adaptable framework that accommodates these complexities. It operates by modelling a system as a chronological sequence of discrete activities. Random events are generated through probabilistic sampling from specified statistical distributions, thereby representing the uncertainty inherent in customer arrivals and call handling durations.

The simulated process flow can be configured to incorporate behavioural details such as abandonment based on wait thresholds, real-time call routing to available agents, and temporary queuing blocks during high-traffic periods. This level of modelling detail allows for realistic system representation without excessive complexity, provided that appropriate assumptions are adopted. An additional advantage of simulation lies in its capacity to test alternative operational strategies by adjusting input parameters and system logic. Modifying staffing levels, routing procedures, or other operational components enables the quantification of performance trade-offs. These data-driven assessments support managerial decisions prior to the implementation of real-world changes [18]. This investigation simulated the inbound call flow of the ISP's technical support centre using ProModel software. ProModel was chosen due to its intuitive interface, built-in queuing structures, and robust capabilities for modelling complex service operations. Compared to alternatives such as Arena, Simul8, or AnyLogic, ProModel provides a practical balance between modelling flexibility and user accessibility for medium-scale systems. Its visual modelling environment expedited logic development and debugging, while its integrated statistical tools enabled effective validation and experimental design. Previous applications of ProModel in similar settings, as seen in the studies by [16; 19], support its appropriateness for this research.

Call arrival distributions were derived by dividing observed call volume data into eleven time intervals using statistical clustering, given the time-dependent nature of call frequencies. Within each interval, lognormal distributions were fitted to handling times. Abandonment patterns were modelled using data collected through direct observation, with the methodology guided by [8] for estimating customer patience distributions. The simulation was validated by comparing its output with historical values for service level and abandonment rate. Upon validation, the base model was adjusted to test the impact of introducing cross-trained personnel during peak demand periods identified in initial simulations. The model's flexibility enabled systematic adjustment of agent allocation across different shifts to identify an optimal staffing strategy. These experiments provided quantifiable insight into the impact on service level, abandonment rates, and other KPIs relevant to current operational conditions.

4. Modelling Methodology and Results

This study utilised discrete event simulation to represent the operational dynamics of the technical support call centre and to assess the effects of refined staffing strategies. The modelling approach was informed by both scholarly methodologies and established industry practices. The process comprised several essential stages, including the examination of input data, formulation of modelling assumptions, fitting of appropriate statistical distributions, verification and validation of the simulation model, execution of experimental scenarios, and the statistical evaluation of simulation outcomes.

4.1 Input Data

In this investigation, the operational infrastructure of the call centre includes an Automatic Call Distributor (ACD) system with a capacity to manage up to 50 trunk lines, thereby facilitating the efficient routing and handling of incoming calls. The workforce consists of 33 agents working in rotational shifts to maintain uninterrupted customer service throughout the day. It should be noted, however, that the analysis does not incorporate the possibility of unplanned shift cancellations, which may affect both staffing availability and overall operational performance. The current allocation of agents is structured as follows: 14 agents are assigned to the morning shift (8:00 AM to 4:00 PM), 17 to the afternoon shift (4:00 PM to 12:00 AM), and 2 to the overnight shift (12:00 AM to 8:00 AM), ensuring comprehensive coverage across the 24-hour cycle.

Table 1
Sample Call Centre Data Sheet

Hour	Answered Calls	Not Answered Calls	Average Duration	Average Holding Time (AHT)
0	13	1	209	33
1	7	0	162	18
2	2	0	159	9
3	0	1	0	0
4	0	0	0	0
5	0	1	0	0
6	0	1	0	0
7	8	0	86	24
8	9	0	538	10
9	12	0	372	5
10	23	0	270	4
11	37	1	298	7
12	31	5	307	16
13	61	0	227	12
14	83	3	212	15
15	80	4	256	24
16	42	1	216	13
17	63	19	329	77
18	69	16	270	75
19	56	20	367	108
20	54	32	504	157
21	66	22	459	117
22	70	13	312	67
23	42	7	368	45

The operational processes within a call centre naturally produce large volumes of data that can offer critical insights into performance improvement opportunities. However, capturing and storing data at the level of individual call transactions requires considerable database resources and leads to increased storage costs. To address this constraint, many call centres implement data aggregation strategies, whereby individual records are summarised into averaged metrics across fixed intervals. In the case under study, the call centre aggregates data into 60-minute intervals, a method which supports the identification of temporal performance patterns. As an example, Table 1 presents a snapshot of the data collection methodology used within the call centre. This structured approach to data summarisation facilitates the extraction of performance indicators, thereby informing evidence-based decision-making and supporting the design of effective strategies aimed at enhancing overall call centre efficiency.

4.2 Analysis of Inter-Arrival Time Patterns

Prior to estimating the inter-arrival rate of incoming calls, a detailed assessment was carried out to explore potential fluctuations in call frequency across various hours of the day. This initial analysis utilised SPSS version 21 to identify any significant temporal patterns. The objective was to determine whether the volume of incoming calls varies meaningfully across defined time segments within a 24-hour period. To evaluate this, the following hypotheses were established:

Hypothesis H0: The temporal distribution of arrivals does not yield significant variations.

In other words, this hypothesis suggests there is no notable difference in call frequency across different time intervals. This null hypothesis is tested against the alternative:

H1: The temporal distribution of arrivals yields significant variations for at least one-time interval.

Table 2
Results of the Student Newman Keuls Test (SNK)

Hour	N	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5	Subset 6	Subset 7	Subset 8	Subset 9	Subset 10	Subset 11
4.00	31	0.8387										
3.00	31	2.1613										
5.00	31	2.3871										
6.00	31	3.2903										
2.00	31	4.9677										
7.00	31	8.0645										
8.00	31	12.0323										
1.00	31	12.0323										
9.00	31	12.0968										
0.00	31	12.0968										
10.0031		23.2903	23.2903									
11.0031		30.0323	30.0323									
12.0031			34.7419	34.7419								
23.0031				41.3871	41.3871							
13.0031					46.0323	46.0323	46.0323					
15.0031						51.5161	51.5161	51.5161				
14.0031							52.8387	52.8387	52.8387			
16.0031								58.4839	58.4839	58.4839		
22.0031									60.7097	60.7097		
18.0031										63.5806	63.5806	63.5806
17.0031											68.6774	68.6774
19.0031												73.4194
21.0031												73.4194
20.0031												76.2903
Sig.												81.2581

The null hypothesis, H0, was tested at a 5% significance level to ensure a rigorous statistical evaluation. The findings provided strong evidence of significant differences in call arrival rates across various time intervals. A One-Way Analysis of Variance (ANOVA) was conducted, utilising the Student-Newman-Keuls (SNK) post hoc test through SPSS software. Based on this analysis, the 24-hour operational cycle was segmented into 11 distinct groups, as depicted in Figure 2, according to the observed patterns in call arrivals. This refined categorisation facilitated the identification of detailed temporal fluctuations in call traffic, reinforcing the rationale for further analysis. Most of the hourly intervals did not satisfy the performance benchmarks, particularly aligning with the highest call volumes observed during peak demand hours. These were concentrated within group 11, covering the time span from 5:00 PM to 11:00 PM, as indicated in Table 2.

To estimate the inter-arrival rate, the total number of calls recorded during this peak period—14,115 calls over the course of a month—was used. This yielded an average rate of 1.27 calls per minute for interval 5. As a result, the corresponding mean inter-arrival time was calculated at approximately 47.44 seconds, following an exponential distribution. Abandonment times were determined through direct on-site observation, in line with the methodological guidelines set forth by Garnett et al. [8]. The average abandonment time was established at 63 seconds, as shown in Table 2, and this value was applied to generate an exponential distribution to represent customer abandonment behaviour.

4.3 Analysis of Inter-Arrival Time Patterns

The available dataset comprises hourly averages for service times, rather than detailed call-by-call records. To evaluate whether service durations differ significantly throughout the day, a statistical assessment was performed using Minitab version 16. The ANOVA method, followed by Tukey's post hoc test, was applied. The results indicated that the hours relevant to this study—from 5:00 PM to 11:00 PM—belonged to the same statistical group, referred to as group A. The null hypothesis, H0, posits that there is no meaningful effect of call hours on service times, implying no disparity in service times based on hours. This hypothesis was tested with a rejection probability of 5%. However, the ANOVA results demonstrated a significant variation in service durations across different hourly intervals. The grouping information produced through the Tukey method is summarised in Table 3.

Table 3
Results of the Tukey Test for AHT

C2	N	Mean	Grouping
23	31	374.42	A
22	31	369.23	A B
21	31	360.68	A B C
20	31	351.16	A B C D
19	31	330.39	A B C D E
18	31	316.68	A B C D E F
17	31	311.71	A B C D E F
15	31	298.74	A B C D E F
11	31	297.29	A B C D E F
16	31	292.87	A B C D E F
14	31	283.42	B C D E F
13	30	279.57	C D E F
9	31	276.32	C D E F
12	31	272.77	D E F
10	31	269.74	D E F
6	31	265.26	D E F
3	31	253.71	E F G
1	31	239.32	F G
2	31	167.42	G H
7	30	120.1	H I
5	31	116.94	H I

Following an evaluation of several candidate distributions, as presented in Table 4, the normal distribution was identified as the most appropriate fit for the dataset. This conclusion is based on the corresponding p-value exceeding the 5% significance threshold, suggesting that the null hypothesis—that the observed data originate from a normally distributed population—cannot be rejected.

Table 4
Goodness-of-Fit Test for 5 P.M. to 11 P.M.

Distribution	AD	P	LRT P
Normal	0.687	0.072	
Box-Cox Transformation	0.502	0.205	
Lognormal	1.504	<0.005	
3-Parameter Lognormal	0.398	*	0.000
Exponential	82.911	<0.003	
2-Parameter Exponential	56.189	<0.010	0.000
Weibull	2.129	<0.010	
3-Parameter Weibull	1.048	<0.005	0.000
Smallest Extreme Value	8.838	<0.010	
Largest Extreme Value	2.818	<0.010	
Gamma	0.711	0.067	
3-Parameter Gamma	0.411	*	0.087
Logistic	0.263	>0.250	
Log-Logistic	0.697	0.041	
3-Parameter Log-Logistic	0.178	*	0.011
Johnson Transformation	0.17	0.933	

4.4 Model Assumptions

To ensure the model remained manageable while still reflecting key operational dynamics, the following assumptions were adopted:

- Call arrival rates and service durations are assumed to remain constant within each hourly interval
- Customers who abandon the queue do not attempt to reconnect at a later time
- It is assumed that trunk line capacity is unlimited, and therefore no call blocking occurs
- Customer abandonment behaviour is modelled using an exponential distribution derived from average patience time

These assumptions reflect a balance between model simplicity and methodological precedence established in previous studies [7]. Incoming calls are directed into the call centre queue, where they await assignment to an available agent. In instances where all agents are occupied, callers remain in the queue and may either choose to wait or abandon the call. Calls that are abandoned are excluded from further processing, while those that remain in the queue are attended to once an agent becomes available. The implementation of this logic is executed using the ProModel programming language, informed by documentation and guidance from ProModel Corporation.

To ensure the reliability of the simulation outcomes, the model is executed across multiple replications, and performance indicators are derived from the average across these simulation runs. When multiple replications are applied, ProModel generates a half-width value representing a 95% confidence interval for the output metrics. The number of required simulation runs is determined by the level of precision sought for the primary performance metric, which, in this case, is the total number of attempted calls. After each simulation run, the overall half-width associated with this metric is evaluated. A target half-width of 10 was established to meet the specified confidence level. Consequently, the number of replications required to satisfy this condition was determined to be 17. The ProModel output results concerning attempted calls are summarised in Table 5.

Table 5
Results of the Attempted Calls from ProModel

Name	Replication	Scheduled Time (MIN)	Capacity	Total Entries
Attempted Calls	Avg	360	9999999	458.53
Attempted Calls	Std. Dev.	0	0	19.3
Attempted Calls	95% C.I Low	360	9999999	448.6
Attempted Calls	95% C.I High	360	9999999	468.45

4.5 Verification, Validation and Experimentation

The conceptual framework was implemented using ProModel simulation software. Verification of the model was achieved through animated process observation and iterative debugging. For validation purposes, the model's output—specifically, service level and abandonment rate—was compared against historical averages using t-tests, as illustrated in Table 6 to Table 8. Experimental scenarios were constructed to assess the impact of assigning an additional cross-trained agent to the 5:00 PM to 11:00 PM shift. The revised staffing arrangement resulted in a reduction of the average customer wait time from 50.1 seconds to 42.7 seconds, while the abandonment rate decreased from 17.6% to 12.9%. Follow-up t-tests confirmed that these improvements were statistically significant.

In addition, the results of an independent samples t-test, presented in Table 6, examined the number of attempted calls under two different conditions. Condition 1 included 31 observations, with a mean of 447 attempted calls, whereas condition 2 comprised 17 observations and yielded a higher mean of 458.5. Despite the apparent difference in means, the statistical test indicated that the variation was not significant. The computed t-value was -0.47, with 46 degrees of freedom, and the corresponding p-value was 0.639. This clearly exceeds the conventional alpha threshold of 0.05, indicating that the observed difference between groups lacks statistical significance. Moreover, the 95% confidence interval for the mean difference, ranging from -62.7 to 38.9, includes zero, implying that the difference is likely due to random variation. Therefore, it can be concluded that the staffing adjustment did not produce a statistically significant change in the number of attempted calls between the two experimental conditions.

Table 6
SPSS T-Test Results for the Attempted Calls

Difference (mu1 - mu2)	-11.9
95% CI for Difference	(-62.7, 38.9)
T-Value	-0.47
P-Value	0.639
Degrees of Freedom (DF)	46
Pooled Std. Dev	83.6352

Table 7 presents the results of the independent samples t-test comparing the mean hold times under two staffing configurations, C1 and C3. For configuration C1, with 31 observations, the average hold time was 46.7 seconds, while configuration C3, comprising 17 observations, recorded a mean hold time of 50.11 seconds. The difference in mean hold times is minimal, and the t-test indicated that this difference is not statistically significant. The estimated mean difference was -3.41 seconds, with a 95% confidence interval ranging from -14.74 to 7.91, which includes zero. The t-value was -0.61 with 46 degrees of freedom, and the associated p-value was 0.547, exceeding the conventional 0.05 threshold for statistical significance. Consequently, the variation observed in average hold time between these two staffing scenarios is likely attributable to random variation rather than an operational effect. Therefore, the staffing adjustment evaluated in this comparison did not yield a statistically significant change in average customer hold time.

Table 7
SPSS T-Test Results for the Average Hold Time

Difference (mu C1 - mu C3)	-3.41
95% CI for Difference	(-14.74, 7.91)
T-Value	-0.61
P-Value	0.547
Degrees of Freedom (DF)	46
Pooled Std. Dev	18.6437

The independent samples t-test results, as presented in Table 8, evaluate the abandonment rates associated with two different call centre configurations, C1 and C2. The analysis reveals a substantial and statistically significant disparity between the two scenarios. Configuration C1, comprising 31 observations, recorded an average abandonment rate of 54.9, whereas configuration C2, based on 17 observations, exhibited a markedly higher average rate of 176.4. The estimated mean difference between the two configurations was -121.5, with a 95% confidence interval ranging from -142.0 to -100.9, which does not encompass zero. The computed t-value was -11.90, and the associated p-value was 0.000 ($p < 0.001$), strongly indicating that the difference is statistically significant. These findings confirm that the abandonment rate in configuration C2 is significantly greater than in configuration C1. Given the considerable magnitude of the difference and the highly significant p-value, it is evident that the staffing or operational modifications implemented in C1 were considerably more effective in reducing abandonment rates compared to those applied in C2. Moreover, the late afternoon shift generally consists of an average of 12 blended agents responsible for both inbound and outbound call handling, in addition to two agents assigned exclusively to outbound calls. This configuration is illustrated in Figure 2.

Table 8
SPSS T-Test for the Abandon Rate

Difference (mu C1 - mu C2)	-121.5
95% CI for Difference	(-142.0, -100.9)
T-Value	-11.9
P-Value	0
Degrees of Freedom (DF)	46
Pooled Std. Dev	33.8224

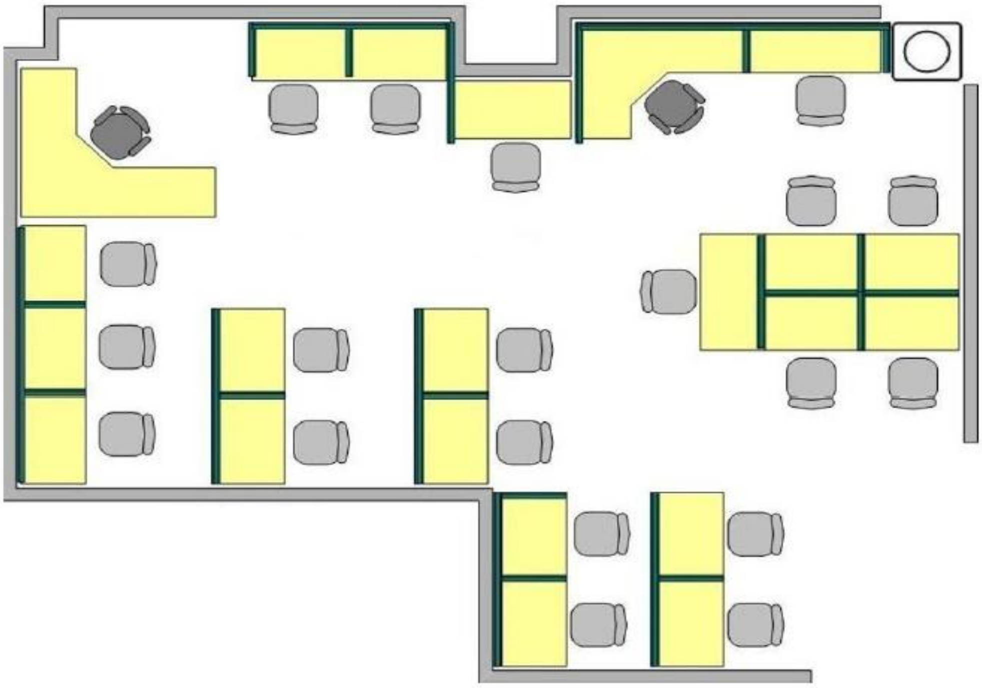

Fig.2: The Layout for the Technical Support Department

4.6 Results and Insights

The validated simulation model offered evidence-based insights into the operational challenges of the call centre and enabled the quantification of potential solutions. A principal observation was that inadequate staffing during the early shift contributed to increased delays and call abandonment, as queues accumulated during that period (Figure 3).

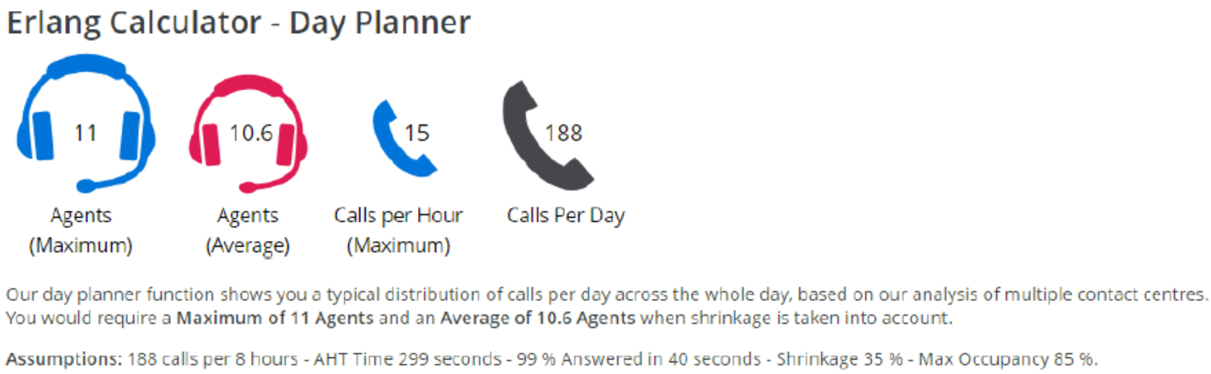

Fig.3: Results Regarding the Number of Staff Required

Reallocating one surplus agent from the 8:00 AM to 4:00 PM shift to the afternoon shift yielded improvements in key performance indicators ranging from 15% to 27%, as reflected in Table 9 and Table 10. Table 9 presents the results of ProModel simulations based on the current staffing structure. Two primary performance metrics were examined: average customer hold time and the number of call abandonments. Across simulation replications, the average hold time was recorded at 50.11 seconds, while the actual observed value stood at 51.76 seconds. This indicates that, on average, customers wait nearly a full minute before being connected to an agent, falling short of widely accepted service level benchmarks. The simulation also revealed an average of 77.71 call abandonments, in contrast to the current observed figure of 176.41 abandonments. This high level of unserved calls underscores the extent to which customers are terminating their calls before receiving assistance. Both performance metrics exhibited considerable variability; maximum hold times reached approximately 279.41 seconds, and abandonment levels peaked at 176.41 calls. These findings highlight severe inefficiencies under the existing staffing arrangement and serve as a baseline for evaluating the effectiveness of improved staffing configurations in subsequent scenarios.

Table 9
Current Situation Results from ProModel

Name	Total Changes	Avg Time Per Change (SEC)	Minimum Value	Maximum Value	Current Value	Avg Value
Hold Time	280.53	76.69	0	279.41	51.76	50.11
Abandonments	176.41	122.56	0	176.41	176.41	77.71

Table 10 presents the simulation results for the final, optimised staffing configuration within ProModel, highlighting the primary outcome measures of average hold time and abandonment rate reported throughout this analysis. Under the revised arrangement, the average hold time was reduced to 42.66 seconds, with the most recent simulation run showing a further improvement to 20.00 seconds. This represents a substantial decrease from the values observed under the current configuration, as depicted in Table 10, indicating enhanced call handling efficiency. Similarly, the average number of abandonments fell to 59.75, down from the previously recorded figure of 129.35, and significantly lower than the baseline value of 176.41. These results signify a meaningful performance enhancement, amounting to an approximate 15% reduction in hold time and a 27% decrease in call abandonment rate. This clearly demonstrates that the reallocation of staff contributed positively to managing customer calls more effectively during peak hours. Overall, the optimised staffing arrangement led to a marked improvement in service level, supporting the conclusion that simulation offers a practical and effective decision-support approach for staffing optimisation in call centre operations.

Table 10
Final Solution Results from ProModel

Name	Total Changes	Avg Time Per Change (SEC)	Minimum Value	Maximum Value	Current Value	Avg Value
Hold Time	326.18	66.13	0	275	20	42.66
Abandonments	129.35	167.74	0	129.35	129.35	59.75

The findings demonstrate that the newly optimised staffing policies yielded substantially improved outcomes relative to the existing configuration, with the enhancements supported by statistical validation as illustrated in Table 11 and Table 12.

Table 11
Results from the SPSS Paired T-Test for the Avg Hold Time

Condition	N	Mean	Std. Dev	SE Mean
Avg Hold Time (orig. sit)	17	50.11	9.36	2.27
Avg Hold Time (improve)	17	42.66	7.54	1.83
Difference	17	7.45	8.69	2.11
95% CI for Mean Difference	(2.98, 11.92)			
T-Value	3.53			
P-Value	0.003			

The presence of statistical significance confirms that the observed improvements are not attributable to random variation but rather reflect a genuine performance advantage of the optimised policies over the current approach.

Table 12
Results from the Paired T-Test for the Abandonment

Condition	N	Mean	Std, Dev	SE Mean
Abandonments (orig. situa)	17	176.41	14.25	3.46
Abandonments (Improve)	17	129.35	15.24	3.7
Difference	17	47.06	13.81	3.35
95% CI for Mean Difference	(39.96, 54.16)			
T-Value	14.05			
P-Value	0			

5. Discussion

The simulation outcomes are consistent with major findings in the existing body of research on call centre operations, reaffirming the practical utility of simulation as a quantitative decision-support tool. The optimised staffing strategies led to notable enhancements in service levels and reductions in abandonment rates, particularly during periods of peak demand. Numerous case studies in the literature have highlighted similar benefits achieved through simulation-based approaches. A common conclusion across these studies is that inefficiencies in resource allocation are a significant factor contributing to underperformance in call centres. For instance, Mehrotra and Fama [16] demonstrated that delays could be mitigated by optimising cross-training, thereby improving capacity flexibility. In parallel, this study showed that reassigning one agent from the early shift effectively alleviated congestion during the late afternoon.

Wang et al. [19] integrated ProModel simulation into a staffing optimisation framework and reported a 22% enhancement in service level. The 15% improvement achieved in this study supports the argument that aligning staffing with demand produces measurable benefits. Likewise, previous studies combined simulation with optimisation techniques and recorded a 29% increase in service performance compared to baseline schedules. The 27% decrease in abandonment observed in the current research also corresponds with earlier findings. Takakuwa and Okada [17] used simulation to refine scheduling, which led to a reduction in abandonment from 9% to 5%. Similarly, Thiongane et al. [18] attained a 26% decline in abandonment rates through rule-based scheduling informed by simulation analysis.

Empirical studies consistently show that validated and well-calibrated simulation models can reveal significant opportunities to enhance traditional or informal staffing policies. Simulation supports quantitative experimentation, allowing researchers to analyse system behaviour under proposed operational changes. Given the inherent complexity of call centres—including unpredictable demand, temporal fluctuations, and varying customer behaviour—analytical methods alone are often insufficient. Simulation offers a robust and adaptable framework that can incorporate these complexities while maintaining computational efficiency and structural clarity compared to traditional queuing models. This study contributes an additional case example illustrating the effectiveness and flexibility of simulation in improving call centre performance. The model developed here provides a foundational structure the company can utilise for ongoing operational refinement. Both the methodology and outcomes presented confirm simulation's role as a vital component of evidence-based call centre planning and design.

Moreover, the validated simulation model acts as a practical instrument for call centre managers, enabling real-time decision-making and proactive shift scheduling. By examining various staffing configurations in advance, managers are better equipped to anticipate the impact of reallocating agents across shifts in response to projected call volumes. This allows for informed decisions without exposing operations to the uncertainty of live experimentation. For example, identifying periods of reduced morning activity and redeploying agents to higher-demand evening hours can elevate service quality without increasing labour expenditure. The model also facilitates the exploration of hypothetical scenarios, enhancing the centre's ability to prepare for increased demand, staffing shortages, or external disruptions such as adverse weather conditions.

6. Conclusion

This study developed a discrete event simulation model aimed at evaluating and enhancing the operational performance of the company's technical support call centre. Historical data were statistically analysed to generate probability distributions for call arrivals, service durations, and abandonment patterns. The conceptual model was constructed and implemented in ProModel software and validated through comparisons with actual performance metrics. Experimental scenarios tested the inclusion of cross-trained personnel during peak demand periods, as initially identified through preliminary simulation iterations. Findings revealed that reallocating a single surplus agent from the morning shift (8:00 AM to 4:00 PM) to the afternoon shift (4:00 PM to 12:00 AM) resulted in a 15% reduction in average wait time and a 27% decrease in abandonment rates. This optimised staffing strategy allowed the organisation to better utilise its existing workforce to address peak-time congestion, eliminating the need for additional recruitment.

The validated simulation model functions as a data-driven decision-support tool designed to enhance customer service outcomes in response to growing call volumes. The research offers an applied case study within the Palestinian service industry context, adhering to established academic protocols and industry-recognised simulation practices. It provides a replicable framework for the company's future operational improvements and encourages broader adoption of simulation-based optimisation within the local industrial sector. Despite the model's value, it is important to recognise its reliance on several simplifying assumptions, such as the presumption of infinite queue capacity, the exclusion of call retries, and a fixed hourly arrival pattern that may not fully capture the variability present in real-world operations. These limitations should be taken into account when interpreting the findings or applying the model to other service environments. Nevertheless, the overall approach and methodology possess sufficient flexibility to be adapted for use in other sectors or regions with similar operational structures, making this simulation model a versatile tool for service process improvement.

7. Recommendations

Based on the analysis and results presented in this study, several recommendations are put forward. Primarily, it is advised that the optimised staffing arrangement be implemented by reallocating one agent from the 8:00 AM to 4:00 PM shift to the 4:00 PM to 12:00 AM shift. Additionally, it is recommended to extend the scope of the simulation model to encompass other departments and shift schedules, thereby enhancing overall resource allocation efficiency. Incorporating demand forecasting and 'what-if' scenario analysis into workforce planning could also improve responsiveness to changing operational conditions. These steps would support the sustained application of simulation techniques for strategic capacity planning as the call centre continues to expand. Furthermore, it is proposed that similar operational systems rigorously adopt simulation methodologies to assess the impact of new technologies, call routing strategies, and service delivery models, thereby promoting simulation-based optimisation as a managerial standard within the broader Palestinian industrial landscape. Future research should consider applying discrete event simulation in other call centres to evaluate the broader applicability and robustness of the methodology across different operational contexts. Such investigations could benefit from integrating uncertainty quantification techniques, such as Monte Carlo simulation, to better account for stochastic fluctuations in call volume. Another important direction would involve the development of integrated arrival models through the combination of forecasting methods and simulation frameworks. Additionally, future studies should explore the application of optimisation algorithms in conjunction with simulation, as well as the use of advanced techniques in machine learning and data mining to improve the quality and reliability of model inputs derived from call centre datasets.

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