Performance Evaluation and Statistical Data Analysis of a Call Center for the Deaf Community

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Abstract—**In this study, we address the performance evaluation of a multi-model call center. We provide an in-depth statistical data analysis to understand the dynamics of waiting times, service times and arrivals. Afterwards, we present our methodology on how to better size and schedule the agents in order to maintain a better service quality, namely more efficient utilization of resources and shorter waiting times.**

I. Introduction

IVèS-Elioz is a platform that offers telephone and physical accessibility services dedicated to deaf and hearing-impaired people. It provides innovative and custom communication services to companies and collectivities wishing to facilitate their exchanges with deaf or hearing-impaired people. They offer 3 communication modes: Sign Language, Cued Speech and Speech to text transcription with trained, qualified relay agents.

The most common criticism for call centers is insufficient service quality which can be summarized as high waiting times with respect to low utilization of agents. Better management of resources, specifically the sizing and scheduling of agents to answer calls within a given service quality, is needed. Operational service quality in call centers is generally defined based on waiting times of customers [1]. IVèS-Elioz has a target to reduce the percentage of customers waiting for more than a threshold T (non-disclosed for confidentiality reason) to 9% level. Another performance criterion is the utilization rate of the agents. The main purpose of IVèS-Elioz is to create a balanced regime between these two contradictory performance criteria.

To achieve this, IVèS-Elioz first needs to understand the dynamics of its current system. The purpose of this paper is to provide a structured performance evaluation of IVèS-Elioz through an in-depth statistical analysis based on the historical data, and present an adaptable path for future studies in order to better size and schedule its agents.

The rest of the paper is organized as follows. In Section II, IVèS-Elioz' call center system is described. In Section III, the statistical data analysis is presented. The general characteristics of incoming calls are discussed in Section III-A. Service times, waiting times and arrival patterns of customers are examined and discussed in Section III-B, Section III-C and Section III-D, respectively. The data analysis part is followed by Section IV, where we discuss our prospective methodology on determining the staffing requirements and scheduling the agents. Section V concludes with final remarks and further extensions.

II. The Description of IVèS-Elioz Call Center

IVèS-Elioz call-center is composed of homogeneous multi-level agents and multi-class incoming calls with different priorities. The call center is operating between 8:30 am to 5:30 pm from Monday to Friday each week. Interpreters (agents) are divided into 3 levels in terms of their scheduled workloads. Level 1 agents are taking charge of all incoming calls, assigned on a time slot of 2 hours maximum. The same interpreter can make a 2-hour shift in the morning and a 2-hour shift in the afternoon. Level 2 agents are taking charge of calls when Level 1 agents are busy. They can make longer shifts of 3 hours which the cumulative service time should not exceed 2 hours. Level 3 agents are acting as supervisors, in charge of calls if Level 1 and Level 2 agents are all busy. Therefore, the workload of Level 3 agents is generally low, except during peak hours. They can make all-day-long shifts.

There are four types of customer profiles and the order of priority among them is as follows: Offer 1, Offer 2, Offer 3 and Offer 4. It is important to distinguish customer profiles because their behaviors can be different. The "Offer 2" type customers are divided as "Offer 2-a" and "Offer 2-b". The quality of service must be higher for the "Offer 2-a" than "Offer 2-b". The handling of a call in the queue is according to an FCFS (First Come First Served) protocol, but with a priority based on customer profiles.

III. Statistical Data Analysis

A. Raw Data Analysis

The statistical analysis is conducted by using the IVèS-Elioz' 2018 summer raw data which involves calls between 01/06/2018 and 31/08/2018. The data set, which was anonymized according to GDPR, consists of 15,798 metadata records created from calls to IVèS-Elioz over that period. Table I presents the features contained in this specific data set.

In this study, only Sign Language (LSF) method is involved in order to validate and refine the need and the approach on a limited scope and therefore more easily apprehensible. Additionally, when SIP codes are checked, it can be observed that some of the calls are interrupted for various reasons. In order to perform the analysis, unsuccessful calls are ignored.

TABLE I
THE FEATURES CONTAINED IN THE DATA SET

Feature (anonymized in italic)	Description
cdrid	The unique identifier of each call
callId	The unique identifier of each event
callingNumber	The calling phone number
calledNumber	The called phone number
terminateCause	The SIP code of the call
serviceMark	The type of the call
presentationTime	Arrival time of the call
sessionStartTime	Handling time of the call by an agent
sessionEndTime	End time of the call
conversationStartTime	Start time of the relay
conversationEndTime	End time of the relay
uid	The user account on which the call is received
customerId	The identifier of the customer
profileId	The type of the customer profile
waitingRealSeconds	The waiting time of the customer
sessionRealSeconds	The service time of the call
conversationRealSeconds	The total relay time
queueName	The name of the queue which the call is taken
topic	The topic of the call which is chosen by the caller
peripherique	The terminal used by the caller
uidAgent	The identifier of the agent who took charge of the call

Calls with an SIP code of 200 were considered as successful calls.

When filtering the raw data and creating graphs, open-source Python libraries were used for scientific computing and data manipulation such as SciPy, NumPy, Pandas and Matplotlib [2]–[5] .

After mapping each of the SIP codes, more than 80% of the calls are considered as successful. When non-LSF modalities and unsuccessful calls are excluded, a total of 9361 calls are examined in the statistical data analysis. The daily numbers of incoming customers for all days are shown in Fig. 1. Arrivals are not stationary through weeks and there is a downtrend towards August, arrivals are decreasing in that time.

It is clear from Fig. 1 and Fig. 2 that Tuesdays and Thursdays are the busiest days of all summer. This observation is crucial while considering the arrival patterns of the customers.

As mentioned in Section II, there are five types of customers. Given in Table II, Offer 2-b type customers have an overwhelming number with more than 80% of incoming calls. For this reason, Offer 2-b type customers directly affect the general trend.

Customer types can behave differently, as will be discussed later in Section III-B and Section III-C. In Fig. 3, the weekly arrival distribution for each type of customer is presented. The arrival rate of the Offer 2-b type of customers fluctuates considerably over the weeks. Their rate decreases drastically towards August. As Offer 2-b type customers represent the majority of the arrivals (80%), this decrease drastically affects the general trend. Another striking point is that Offer 3 type

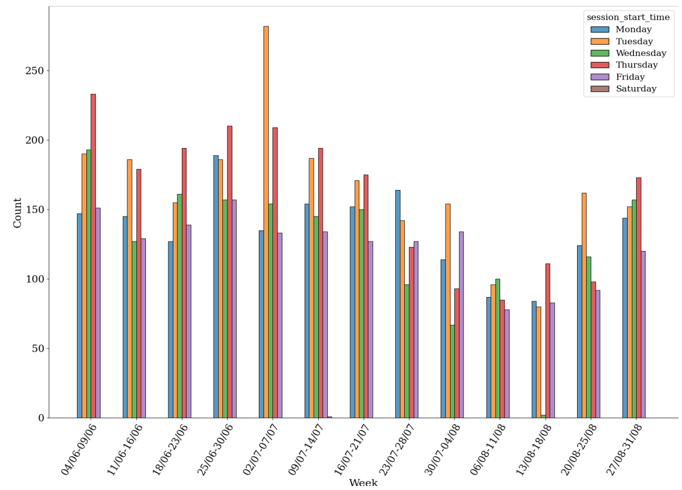

Fig. 1. Daily Number of Incoming Customers

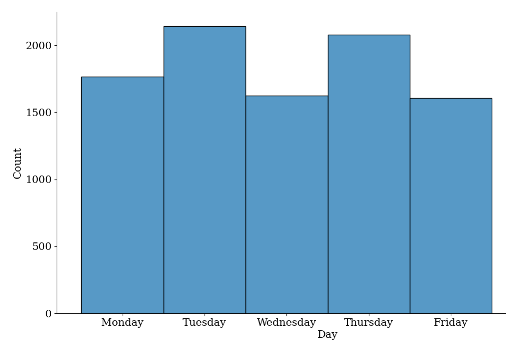

Fig. 2. Frequency of Incoming Customers per Day

TABLE II
NUMBER OF INCOMING CUSTOMERS PER OFFER TYPE

Offer Type	Frequency
Offer 1	824
Offer 2-a	201
Offer 2-b	7537
Offer 3	419
Offer 4	380

customers never arrive after the 7th week. The arrivals of the other types per week seem stationary over the weeks. There are usually two peaks during a day, one just before noon and one right after noon, as shown in Fig. 4. It has been observed that this behavior may change per day in some customer types. As can be seen in Fig. 5, the arrivals of Offer 2-b type customers peak at the same time every day. However, the arrivals of Offer 1 type customers peak before noon on Thursdays, while they peak in the afternoon on the other days, which is presented in Fig. 6.

B. Service Time Analysis

In this section, we first analyze how service times change with respect to customer types. Then, service times are tested

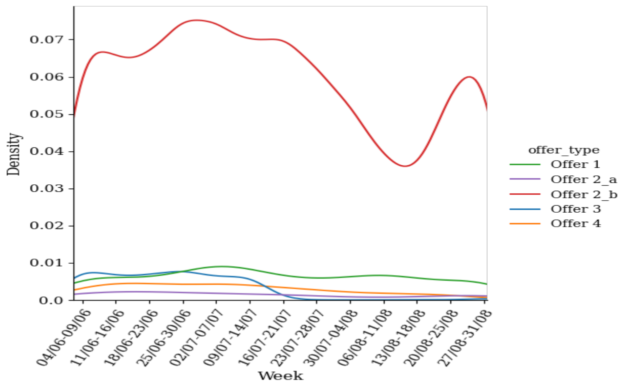

Fig. 3. Distribution of Offer Types per Week

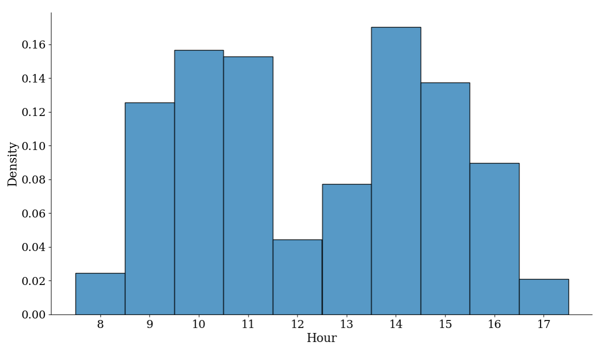

Fig. 4. Distribution of Customers per Hour

whether they differ in the days of the week. Finally, we determine which theoretical distribution best reflects the service time data for each customer type.

1) Service Time Analysis for Each Customer Type: While visualizing the service times in a single plot, Letter-Value plots are used instead of boxplots in order to overcome the problem of an inaccurate representation of outliers in boxplots [6]. Figure 7 presents the Letter-Value plot of service times per offer type. It can be observed that service times vary among offer types. This may be due to the fact that IVèS-Elioz provides different services for different types of customers. For example, Offer 2-a customers seem to have faster service compared to the others. It has to be noted that there might be as well some misleading results. For example, although Offer 1 is the most

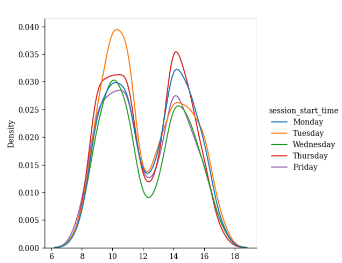

Fig. 5. Offer 2-b Hourly Arrivals for Each Day

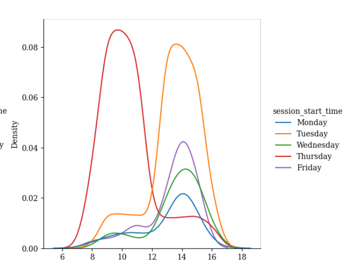

Fig. 6. Offer 1 Hourly Arrivals for Each Day

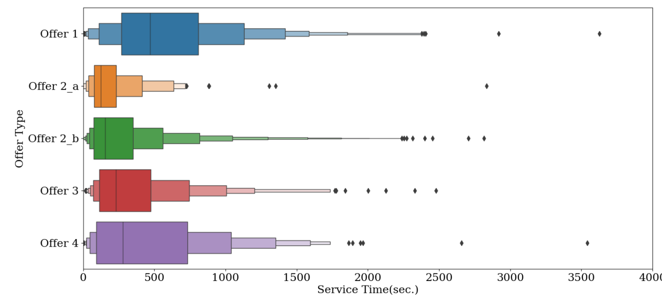

Fig. 7. Letter-Value Plot for Service Times per Offer Type

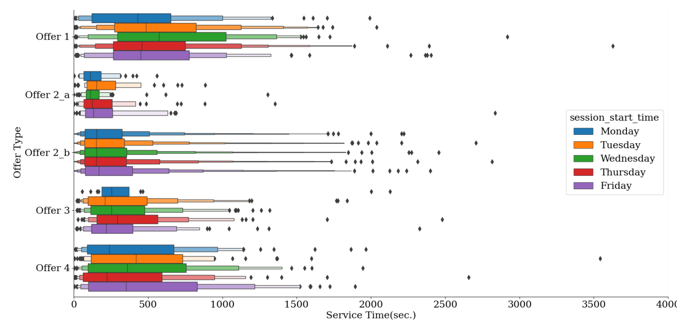

Fig. 8. Letter-Value Plot for Service Times per Day for each Offer Type

prioritized group of customers, their service time seems to be longer than the others (its median is the highest). It could be a biased due to the seasonality of the data set. This issue should be further analyzed with a larger data set.

TABLE III
MEAN SERVICE TIMES PER OFFER TYPE

Offer Type	Mean Service Time(sec.)
Offer 1	600.77
Offer 2-a	223.58
Offer 2-b	281.31
Offer 3	359.72
Offer 4	464.36

2) Service Time Analysis for the Days of the Week: It is important to observe whether there is a significant difference between the days of the week. As will be demonstrated later in this section, service times generally fit well the lognormal distribution. For this reason, two nonparametric tests were conducted to statistically examine whether there is a significant difference between the days of the week. The Kruskal-Wallis and Mood's median tests are useful tests for comparing more than two independent and distribution-free samples [7], [8]. These two tests were conducted for each customer type. P values are big enough to conclude that there is not a significant difference between the days of the week for each offer type. Fig. 8 shows the Letter-Value plot comparing the days of the week in terms of service time. Fig. 9 and Fig. 10 show non-parametric test results for Offer 2-b as an example.

Days	N	Median	Mean Rank	Z-Value
Friday	1424	171,0	3907,5	2,68
Monday	1548	155,5	3729,2	-0,80
Thursday	1588	152,0	3761,6	-0,14
Tuesday	1655	153,0	3732,3	-0,77
Wednesday	1321	155,0	3718,3	-0,92
Overall	7536		3768,5	

Test

Null hypothesis	H_0: All medians are equal
Alternative hypothesis	H_1: At least one median is different

Method	DF	H-Value	P-Value
Not adjusted for ties	4	7,50	0,112
Adjusted for ties	4	7,50	0,112

Fig. 9. Kruskal-Wallis Test Results for Offer 2-b

Days	Median	N <= Overall Median	N > Overall Median	Q3 – Q1	95% Median CI
Friday	171,0	675	749	319,50	(156,532; 181,468)
Monday	155,5	779	769	252,75	(143; 166)
Thursday	152,0	812	776	280,00	(140,460; 166)
Tuesday	153,0	837	818	270,00	(142; 164)
Wednesday	155,0	666	655	284,00	(142; 169)
Overall	156,0				

Test

Null hypothesis	H_0: The population medians are all equal
Alternative hypothesis	H_1: The population medians are not all equal

DF	Chi-Square	P-Value
4	5,04	0,284

Fig. 10. Mood's Median Test Results for Offer 2-b

3) Distribution Fit for Service Times: By using Python package of 'distfit' and R package of 'fitditrplus', service times are fitted to the theoretical distributions [9]. The parameters of the fitted distributions, their AIC and BIC values, goodness of fit test results (Kolmogorov-Smirnov, Anderson-Darling, Cramér–von Mises) obtained and compared. As mentioned earlier, Offer 2-b is the major offer type and Fig. 11 shows the histogram for service time frequencies and visualization of distribution fitting. Even though, the shape of the histogram for service times frequencies show that Lognormal distribution is a good fit, statistical test results indicate that there is not a good fit. This result is not unusual for large data sets.

In order to find a general pattern and get rid of the noise in the data, we separate the data by days, hours or peak hours when necessary and repeat the statistical test on separate data sets. Table IV summarizes the best-fitted distributions for service times of each customer type and their Kolmogorov-Smirnov P-values. We can conclude that the Lognormal distribution is a good fit for Offer 2-b and Offer 3 customers. On the other hand, Weibull distribution is found as the best fit distribution for Offer 1 and Offer 4 customers.

C. Waiting Time Analysis

Waiting time analysis is crucial for the performance evaluation of the current system in IVèS-Elioz. As mentioned earlier, IVèS-Elioz aims to reduce the percentage of customers waiting for more than a threshold T to 9%. For this purpose, the waiting times of the customers are analyzed and it is discussed how much the waiting time of the customers should be reduced to reach the target level. Fig. 12 presents the Letter-Value plot of customer waiting times per offer type.Table V shows the percentage of customers who directly entered the system (zero waiting time), who waited for less than T in the queue and who

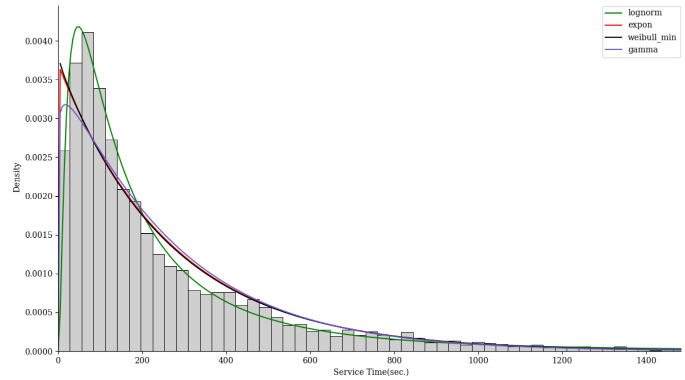

Fig. 11. Histogram for Service Time Frequencies for Offer 2-b

TABLE IV
STATISTICAL SUMMARY OF DISTRIBUTION FITTING OF SERVICE TIMES

Offer Type	Group	# of Calls	Rate/sec.	Fitted Distribution	K-S P-Value
Offer 1	All Calls	822	0.00168	Weibull(1.189 , 628.818)	0.007
Offer 1	Mondays	67	0.00201	Weibull(1.024 , 504.116)	0.302
Offer 1	Tuesdays	259	0.00167	Weibull(1.265 , 642.125)	0.501
Offer 1	Wednesdays	97	0.00144	Weibull(1.218 , 734.171)	0.400
Offer 1	Thursdays	287	0.00171	Weibull(1.184 , 619.771)	0.085
Offer 1	Fridays	112	0.00172	Weibull(1.159 , 609.948)	0.524
Offer 2-a	All Calls	201	0.00459	Lognormal(233.502 , 339.137)	0.070
Offer 2-b	All Calls	7537	0.00369	Lognormal(288.266 , 437.931)	0.001
Offer 2-b	Mondays	1535	0.00394	Lognormal(270.776 , 396.296)	0.548
Offer 2-b	Tuesdays	1637	0.00379	Lognormal(276.029 , 404.175)	0.168
Offer 2-b	Wednesdays	1295	0.00371	Lognormal(291.402 , 464.150)	0.285
Offer 2-b	Thursdays	1566	0.00365	Lognormal(287.235 , 431.299)	0.025
Offer 2-b	Fridays	1397	0.00337	Lognormal(321.591 , 511.126)	0.219
Offer 3	All Calls	419	0.00278	Lognormal(372.824 , 479.429)	0.370
Offer 4	All Calls	380	0.00215	Weibull(0.905 , 443.667)	0.179

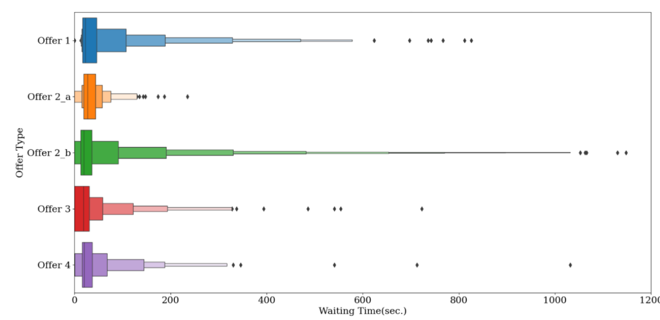

Fig. 12. Letter-Value Plot for Waiting Times per Offer Type

waited for more than T in the queue. It also summarizes the average waiting time of customers per offer type. According to the target level, the performance of the call center is not at the desired level, especially for Offer 1 type of customers. The percentage of customers who waited more than T is slightly more than 20% which should be definitely improved. The other types of offers could not achieve 9% target level neither.

In order to show the relation between average waiting times and the percentage of customers waiting more than T, the data set is divided into groups in terms of offer types and weeks. The data set comprises weekly average waiting times of five offer types, thus we have 65 data points. In Fig. 13 we present a scatter plot of this relationship. The red line represents the desired 9% level and points below this line are acceptable. There is almost a linear relationship between

TABLE V
WAITING TIME PERCENTAGES OF CUSTOMERS PER OFFER TYPE

Offer Type	% of Directly Enters	% of Waiting Time $\leq$ T	% of Waiting Time $> T$	Avg. Waiting Time(sec.)
Offer 1	0.76%	79.03%	20.20%	58.48
Offer 2-a	9.38%	78.13%	12.50%	35.99
Offer 2-b	22.13%	60.99%	16.88%	51.07
Offer 3	27.68%	60.14%	12.17%	36.73
Offer 4	12.73%	73.21%	14.06%	46.41

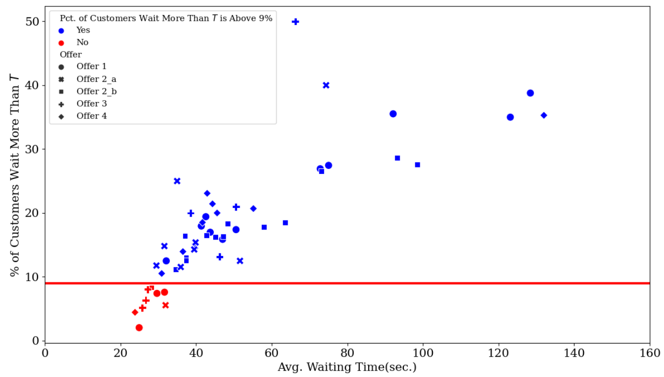

Fig. 13. Relationship Between Weekly Avg. Waiting Times of Each Offer Type and Percentage of Customers Waiting Time $> T$

these two variables. The important thing we observe from this relationship is if the average waiting time can be reduced to around 30 seconds, the target level will most likely be achieved. To increase the number of data points, we also find daily average waiting times of five offer types and conclude that the relationship stays the same.

D. Arrival Process

In Section III-A, by examining the raw data the general arrival characteristics of customers is presented. In this section, the distribution of customers' arrivals is discussed, taking into account those findings in Section III-A. Tuesdays and Thursdays are the busiest days as shown in Fig. 2, hence these days are classified as busy days. Other working days of the week are classified as non-busy days. There are two peaks during the day, one just before noon and one right after noon, as shown previously in Fig. 4. Thus, working hours of a day are divided into two: peak hours (09:00-11:30 – 14:00-16:00) and off-peak hours. For each customer type, the arrival data of the customers is fitted to the theoretical distributions for the day and hour combinations which are divided according to their workloads. Table VI shows the summary of arrival patterns of different type of customers for busy and non-busy days, also for peak and non-peak hours in both type of days. It also presents the best-fitted distributions along with their chi-square P-values. Note that, for Offer 3 and Offer 4 types of customers, days are not differentiated as busy and non-busy because these customers have different behaviors throughout the week. Additionally, only the first 6 weeks are taken into account for Offer 3 type of customers, as we observe almost no arrivals after the 7th week.

TABLE VI
STATISTICAL SUMMARY OF DISTRIBUTION FITTING OF ARRIVAL PROCESSES

Offer Type	Group	Avg. Calls/Hr.	Fitted Dist.	Chi-Sq. P-Value
Offer 2-b	Busy Days - Peak Hours	18.7920	Neg. Bin. (6; 0,24201)	0.162
Offer 2-b	Busy Days - Off-Peak Hours	6.1538	Neg. Bin. (2; 0,24528)	0.814
Offer 2-b	Non Busy Days - Peak Hours	16.0310	Neg. Bin. (6; 0,27235)	0.42
Offer 2-b	Non Busy Days - Off-Peak Hours	5.4718	Neg. Bin. (2; 0,26767)	0.813
Offer 1	Busy Days - Peak Hours	1.9000	Geometric (0,34483)	0.008
Offer 1	Busy Days - Off-Peak Hours	1.1538	Geometric (0,46429)	0.095
Offer 1	Non Busy Days - Peak Hours	1.0513	Geometric (0,4875)	0.385
Offer 1	Non Busy Days - Off-Peak Hours	0.3282	Geometric (0,7529)	<0,001
Offer 2-a	Busy Days - Peak Hours	0.4923	Geometric (0,6701)	0.018
Offer 2-a	Busy Days - Off-Peak Hours	0.2000	Geometric (0,8333)	0.01
Offer 2-a	Non Busy Days - Peak Hours	0.3538	Geometric (0,7386)	0.058
Offer 2-a	Non Busy Days - Off-Peak Hours	0.1897	Geometric (0,8405)	0.001
Offer 3	All Days - Peak Hours	2.0270	Geometric (0,3304)	<0,001
Offer 3	All Days - Off-Peak Hours	0.6067	Geometric (0,6224)	<0,001
Offer 4	All Days - Peak Hours	0.9750	Geometric (0,50633)	0.661
Offer 4	All Days - Off-Peak Hours	0.4640	Geometric (0,68306)	0.005

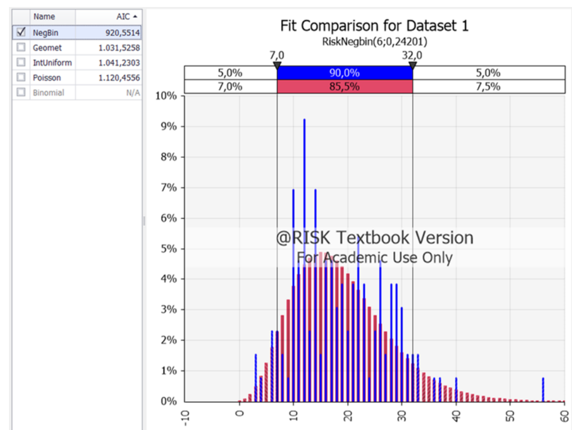

Fig. 14. Histogram for Hourly Arrival Frequencies for Offer 2-b – Busy Days Peak Hours

To set an example of our analysis, Fig. 14 presents the hourly arrival frequencies for Offer 2-b on busy days and peak hours. Negative-Binomial distribution is chosen as the best fitted distribution to the arrival data.

IV. FUTURE WORK

In order to achieve the IVèS-Elioz' service quality goal, it is necessary to determine the staffing level requirements. IVèS-Elioz call-center is composed of homogeneous multi-level servers and multi-class incoming calls with different priorities. Thus, it is a complex system. There is an extensive and growing literature on handling complex call centers. Due to the uncertainty governing the call center environment (customer and server behaviors), the literature has typically addressed problems in call centers using stochastic models; in particular queueing models. [1], [10]–[17].

After reviewing the recent queuing literature on call centers, the most appropriate queueing model, that captures sufficiently well the dynamics of IVèS-Elioz call center, is the model of Jouini and Roubos [15]. The authors studied multiple classes of customers with a non-preemptive priority and abandonment where they consider FCFS queueing discipline. Using the outcomes of our statistical data analysis, their model can be integrated into IVèS-Elioz's system. Considering that they use a Markovian queueing model like most of the studies in the literature, Poisson arrivals and exponential service times should be assumed using the parameters in Section III-B and Section III-D. Even though the exponential distribution is not suitable for modeling service times according to statistical tests conducted in Section III-B, it seems like a good fit in terms of shape as can be seen in Fig. 11. Additionally, common service times can be assumed as they proposed. We will validate the proposed queueing model by crosschecking the existing and the model-based staffing levels and the corresponding performance criteria. After the model is validated, we will determine the staffing requirements that ensure the target service quality described in Section III-C.

Given the staffing level requirements, the remaining problem is to schedule the agents. When the overall staffing process in call centers is examined, we observe that the first step is generally to estimate the customer load. Then, the minimal number of agents required during each time period over the planning horizon is determined; which we want to handle via a queueing model. The next step is selecting staff shifts that cover the requirements which is defined as shift scheduling problem, and allocating employees to the shifts which is defined as rostering problem. It is seen that these problems have been studied extensively and generally handled separately in the literature [18]–[24].

Unlike the models proposed in the literature, there are no fixed shifts in IVèS-Elioz system. Agents can start their shifts at any working hours. As mentioned earlier, there are multiple levels of agents that differ only in their workload. Since these situations make our system unique, we want to present a combined shift scheduling and rostering model that simultaneously determines the shifts and the agent assignments, thus the periods that each agent is working to ensure the staffing level requirements.

V. Conclusion

In this study, we address the statistical analysis and performance evaluation of IVèS-Elioz call center for deaf and hearing impaired people. We first define the operational hierarchy of the call center and the characteristics of its customers. Then, key indicators such as service times, waiting times and arrival patterns of the customers are analyzed using IVèS-Elioz summer 2018 raw data. We acknowledge the fact that current data used in this preliminary work is not big enough and fail to capture the long-term system behaviour. We expect to have a larger data set in the future. Thus, we can validate the statistical analysis and conduct a sensitivity analysis on the seasonality of the data. As a continuation of this study, we aim to build our future models, discussed in Section IV, in light of the statistical results we will obtain from this expanded and more consistent data set.

Acknowledgment

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