Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

CALL CENTER AGENT SCHEDULING EVALUATION USING DISCRETE-EVENT SIMULATION: A DECISION-SUPPORT TOOL

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ABSTRACT

Call center agent scheduling is the process of assigning agents to their respective shifts throughout a day in which information regarding the volume and arrival profile of calls is unknown. The construction of such a schedule will have a direct impact on the quality of service and the finances of this call center. Of great importance is knowing when and how to assess this agent schedule despite the uncertainties of how the day will actually unfold. The answers to these questions and their contribution to maintaining a certain level of performance are explored. Through discrete-event simulation, we were able to simulate different agent schedules of a call center for the disabled community, anonymized as the abbreviation ANGUS. Our results indicate the capability of evaluating schedules based on the simulation's predicted outcomes. With such insight, it is indeed possible to meet the performance criteria objectives developed by ANGUS.

1 INTRODUCTION

Call centers are facilities established to assist in the process of delivering interactive services through telecommunication channels. Within these establishments are agents who are responsible for placing and receiving calls. Statista Business Intelligence. (2019) presents a previously performed statistical report in which call center agents were found to constitute over 1.8% of the employed citizens within the U.S. in 2019. Due to the significant added value these centers contribute to the business world, the previously mentioned report also indicated an expected growth in the global call center market of almost 50% up until 2027. Researchers in the domains of forecasting, queuing theory, capacity planning and agent scheduling have thus found these facilities to be an interesting area of study.

During a typical day in an inbound call center, an undetermined volume of incoming calls is received by the available agents. In addition to the unknown volume of incoming calls, the call center does not possess information regarding the inter-arrival profile of these calls. With this lack of information, we realize the importance of constructing well-thought-out agent schedules. These schedules are formulated with the objective of maximizing two typical performance criteria: the quality of service (QoS) and the average agent utilization rate (AUR). Gans et al. (2003) views the notion of service quality from three different angles: agent accessibility, service effectiveness and customer interaction. It is the first notion which interests us, ensuring that customer waiting times do not exceed a certain threshold before being answered. Agent utilization, also denoted as agent occupancy, is represented by the ratio of actual agent working hours to the total duration of an agent's shift. This ratio would then give us an assessment of the financial state of the call center. Large call centers that perform properly constructed and optimized agent scheduling for hundreds of agents may provide services to thousands of customers per hour, all the while maintaining average agent utilization rates of 90%-95%, as shown in Gans et al. (2003). Such an AUR can have a dramatic effect on the finances of the call center, as agent salaries constitute 60%-70% of the total costs of these facilities. Different call centers can sometimes provide the same services as one another and must thus compete over customers seeking these services. This competition leads to an increased emphasis on the process of reducing customer waiting times. Ensuring a high QoS would thus reduce the possibility of these customers switching over to competing companies.

The study carried out in this paper revolves around ANGUS, a call center platform. This call center offers remotely accessible services dedicated to disabled individuals. These services are meant to facilitate the everyday lives of these people, whether they wish to communicate with their fellow coworkers or perform administrative tasks. As with any call center, ANGUS aims to improve its customers' QoS and enhance its financial capabilities. ANGUS differs from other typical call centers in regards to the type of customers served, the agents' level of skills and their constricted shift durations. As the services provided by ANGUS include ensuring the communication between deaf or hard of hearing people and some emergency public services, the goal of minimizing customer waiting times and therefore optimizing the QoS is further emphasized. While agents in typical call centers are not necessarily required to be qualified in a certain skill, ANGUS recruits highly skilled interpreters to be able to efficiently carry out the role of real-time translation. Having such qualifications has a direct effect on the salaries which these interpreters receive, which then highlights the significance of having an optimized AUR. Due to the fact that the translation process is heavily mind consuming, ANGUS agents have a limit of 2 hours on their shifts in order to ensure the smooth operation of the call center and a better customer satisfaction. Such a limit would not exist on agents working elsewhere. Multiple studies have been carried out with the purpose of constructing an optimized agent schedule which would improve a call center's performance criteria, some of which will be cited later on in this article.

In light of the uncertainties regarding the volume and arrival profile of calls, it is difficult to assess the performance of a schedule without the aid of process modeling and simulation approaches. It is through these simulations that we are able to evaluate the performance criteria of interest. These evaluations can then be used in either a pre-planning or a post-planning phase. A pre-planning phase would permit us to validate the effectiveness of a proposed schedule before implementing it in the real-life call center. A post-planning phase would allow an experienced user to improve this schedule through certain manipulations. Such manipulations can be made intelligently through our simulation model's visual representations.

This study is structured as follows: Section 2 introduces a literature review of some of the research work performed on both the inputs of simulation models and the models themselves. Section 3 details the services provided by ANGUS as well as the added value the simulation has to offer. Section 4 highlights the model's inputs, outputs and development methodology. Section 5 provides an experimental examples to test our model on. The results of these examples are then displayed and analyzed in section 6. Finally, section 7 concludes by wrapping up this article's discussion and presenting possible future contributions in continuation of this work.

2 LITERATURE REVIEW

Gans et al. (2003) gives an in-depth review of call centers and the research prospects revolving around them. When it comes to assessing the state of a call center, Mehrotra and Fama (2003) differentiate between three important aspects: customer satisfaction, financial costs and employee satisfaction. In order to quantify these aspects, Avramidis and L'Ecuyer (2005) present us with performance metrics which include the quality of service and the agent utilization rate. Aksin et al. (2007) presents a multi-disciplinary perspective on operations management research in modern call centers.

Mehrotra and Fama (2003) also provide insight into the key inputs required for constructing a simulation model. These inputs include: call routing logic, call forecasts, service time forecasts, agent schedules and abandonment rules. Avramidis and L'Ecuyer (2005) show how the lack of high-quality and detailed data could create an obstacle to constructing a well-functioning simulation model. As these models prove to be sensitive to uncertainties in the arrival process, many articles regarding call volume forecasting can be found in the literature. Mabert (1985) and Andrews and Cunningham (1995) present us with some statistical models for predicting the number of incoming calls. Gans et al. (2015) presents a multiplicative univariate forecasting model to meet long-run average quality of service objectives. Aldor-Noiman et al. (2009), however, presents a univariate mixed-effect forecasting model which attempts to balance the workload per agent with the quality of service objective. Ibrahim et al. (2016) offers an assessment of the out-of-sample prediction accuracy for different models to arrive at the "best" method to be adopted.

Despite the Erlang C model being a widely used traffic modeling formula, as shown in Chromy et al. (2011), Robbins et al. (2010) question how well the model fits real call centers. Such a study aims at improving queuing models that properly shape the study case's behavior. These models would then provide more accurate staffing requirements which can then be inserted into our simulations. One of the older simulation works is that done by Tanir and Booth (1999), in which the construction, execution and analysis of a call center in Canada was carried out. Some more recent instances in which simulation models were utilized include Petitdemange et al. (2020), in which a data-driven simulation approach was adopted for enhancing the performance of emergency call centers. A whole collection of simulation applications can be found in Mandelbaum (2006).

Other studies concentrated on the process of constructing an optimized agent schedule in a multi-skill call center, as done by Avramidis et al. (2010). Chiu et al. (2009) developed a constraint-based particle swarm optimization method for scheduling. Atlason et al. (2008), however, utilized a robust non-traditional method that performs well over a range of different problems. It is precisely these schedules on which we wish to test our simulation models. These simulations would then help us evaluate the performance of these schedules.

It is clear that the road towards improving our simulation models does not only consist of properly modeling the call center's dynamics into our virtual environment, but also of investing time in improving the form and quality of the inputs we insert into these models. This article provides the possibility of evaluating call center agent schedules based on performance criteria estimations through predictive simulation.

3 ANGUS SYSTEM DESCRIPTION

Customers of ANGUS have 6 offer types to choose from, based on their needs and contract requirements. Calls of each offer type are placed within a separate dedicated FIFO (First-In-First-Out) queue, as shown in Figure 1. In addition to the FIFO priority system, there is an overall priority rule which prioritizes certain calls over others. The overall priority rule for call forwarding is in decreasing order of priority starting from offer #1 down to offer #6. Having implemented the call forwarding priority rules, calls are then transferred to agents belonging to one of three levels. Level 1 agents are considered regular employees, whereas level 2 agents serve as additional resources. Level 3 agents, however, act as supervisors for both level 1 and 2 agents. Calls of any type are first handled by level 1 agents. When none are available, level 2 agents then also receive calls. If both level 1 and 2 agents are completely occupied, level 3 agents would then assist in answering incoming calls.

All three levels of agents are also characterized by different shift durations. Agent scheduling is therefore of crucial importance in order to properly assign these agents to their respective shifts. However, even if an optimized schedule were to be drawn up, insight on the performance criteria of our call center is still lacking. Only through a well-modeled simulation which properly shapes the dynamics of ANGUS can we evaluate our schedules prior to their implementation. In terms of performance criteria goals, ANGUS aims for a quality of service (QoS) of 90% for calls of waiting times less than 1 minute, and a maximized average agent occupation rate (AUR). Such metrics would ensure customer satisfaction and assist in improving the company's financial state. Indeed, an optimized schedule with a proper estimation of the number of required agents during a certain day could overturn poor results in the case of improper assignment of

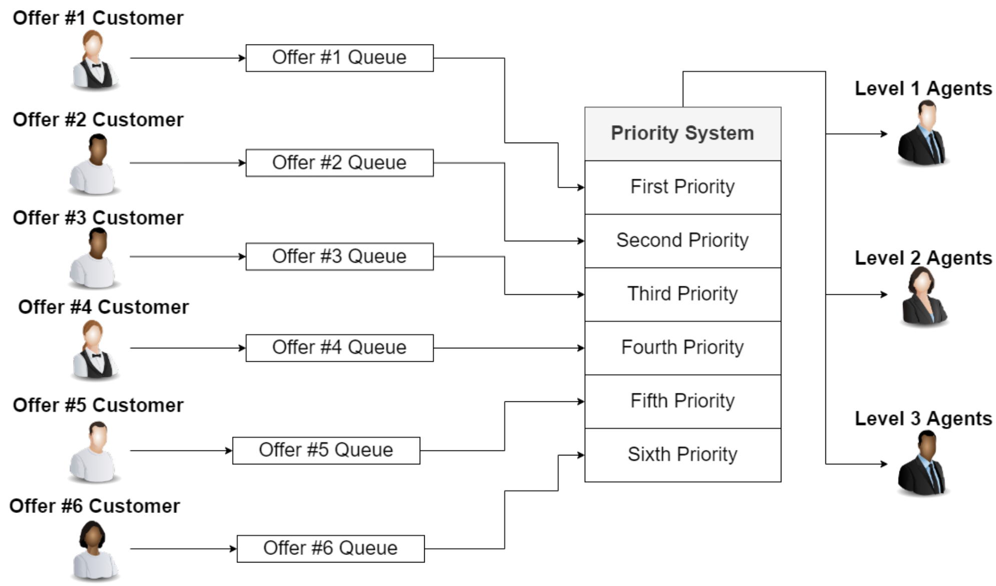


Figure 1: ANGUS services diagram.

these agents to their respective shifts. Exploring the historical data of ANGUS, we managed to capture an event that further emphasizes this possibility of improvement. The performance criteria of two particular days, day #1 and day #2, are shown in Table 1. Day #1 shows almost twice the number of incoming calls as day #2. Despite day #2 having a greater amount of total agent labor hours than day #1, there is a slight drop in the QoS as well as a significant decrease in the AUR.

Table 1: ANGUS performance comparison over two particular days.

Criteria	Day #1	Day #2
Number of incoming calls	700	369
Agent labor hours	63.5	66
$QoS_{1minute}$	98%	94%
AUR	71%	51%

The reason behind such a finding in day #2 can be traced back to misplaced agent resources throughout the day. After reviewing the historical data regarding the arrival profile of calls and the number of assigned agents per shift, the following occurrences were observed. Shifts in which a high volume of calls was received had an understaffed agent pool, resulting in a reduced quality of service. Shifts in which a low volume of calls was received had an overstaffed agent pool, resulting in a reduced agent utilization rate. In order to avoid running into such unwanted performance criteria, our simulation model would assist us in evaluating these criteria and thus performing the necessary changes required prior to the day being planned. This model would also provide insight into how a day would unfold based on a set of initial conditions. Such insight could thus serve as a decision-support tool during the actual planned day. It should be noted that this comparison of days #1 and #2 was carried out for the purpose of highlighting the problem statement which this study aims to resolve. As such, the simulation section 5 of this study has no relation to either of the previously mentioned days.

4 METHODOLOGY

In this section, we explain the functionality of the services provided by ANGUS to its customers and present the model we constructed to simulate agent schedules on a working day. This model will be used to simulate different schedules and discern the differences they show us in terms of performance criteria. Based on the simulation model's outputs, we are able to properly evaluate simulated schedules. Schedules which are found to be performant would be then relayed onto the ANGUS supervisors to carry out the suggested planning. On the other hand, schedules which are found to be poorly planned would be subjected to an adjustment procedure carried out by the planning supervisors to perform the necessary changes.

4.1 Model Inputs

The inputs inserted into our simulation model were derived from a statistical analysis of ANGUS's 24-hour historical data of a typical working day in the past. This statistical analysis was carried out using the powerful programming language Python. These inputs are presented as follows:

1. **Service Times:** Upon careful inspection of the historical data provided by ANGUS, we were able to derive a histogram of the call service times for each possible offer type. The histogram of offer #1 was then used to generate a service time test dataset which was then compared to the original data provided by ANGUS. This comparison validated the use of the suggested service time histogram. We plot offer #1's service time probability in Figure 2a.

2. **Agent Recovery Time:** According to ANGUS's work environment policies, an agent is allowed a certain period of time to recover after a call has been taken. This recovery period is dependent on how long the call lasted. The longer the call lasts, the longer the agent has to recover.

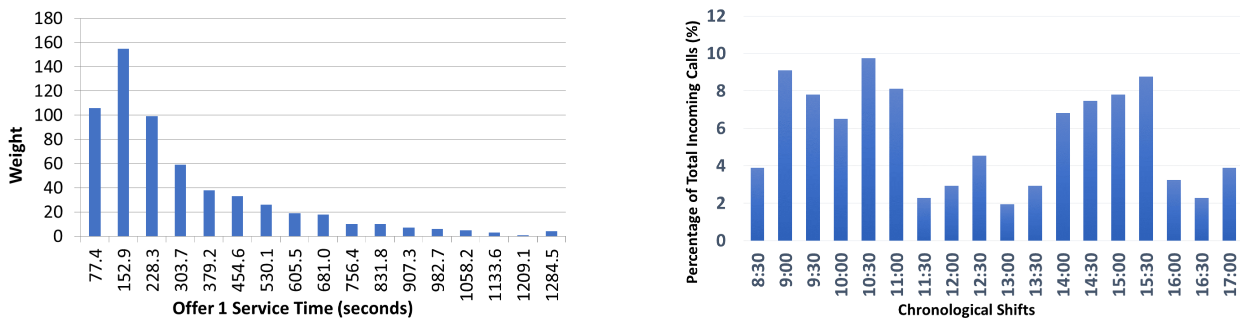
3. **Arrival Profile:** Further analyzing the data, we were able to estimate the number of customers calling throughout the working hours of a typical day, as shown in Figure 2b. Two peaks in the volume of incoming calls can be seen during the day: one in the morning and another in the afternoon.

4. **Offer Type Occurrence Probability:** By tracking the offer type of every incoming call with the data we were given, we derive the probability of a call belonging to one of six offer types, as shown in Figure 3. These probabilities are then presented as additional input to our simulation model.

5. **Agent Schedule:** In order to simulate the available agents throughout the day, we require a schedule depicting those who are present and able to receive calls and those who are not. Further information regarding the schedules adopted throughout our simulations can be found in the scenario section 5 later on in this paper.

4.2 Model Development

With the purpose of evaluating the performance criteria of ANGUS, our simulation model was developed to replicate their services over a 24-hour horizon in a virtual environment. Witness Horizon is our simulation software of choice due to its flexibility and interoperability with other software. An Excel file was coupled with our Witness model in order to provide a graphical user interface for both inputting data and visualizing simulation results. Figure 4 provides a clear overview of how the simulation flows from start to end. Once the simulated day starts, our model receives the volume of incoming calls for each shift of the day. However, the inter-arrival times of these calls within the same shift are randomized. After a call has been generated, the offer type it belongs to is chosen based on the previously mentioned probability input shown in Figure 3. The call is then inserted into its respective queue. Then, depending on priority, calls are



(a) (b)

Figure 2: Service time weighted occurrence (a) and Incoming call arrival profile (b).

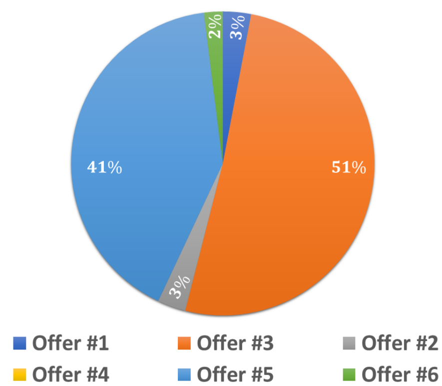


Figure 3: Offer type occurrence probability.

directed towards available agents. If no agent is immediately available, the call then waits within its queue until an agent becomes available. After being received by an agent, the call offer type depicts its duration based on the service time histogram input. Once the simulation clock time reaches 17:30, indicating that the working hours of the day have been simulated, the simulation is terminated.

4.3 Model Validation

In order to validate that our model correctly shapes the dynamics of the ANGUS call center, a comparison between the simulation-based results and actual real-life data was carried out. A typical working day with data-based inputs was simulated in our virtual environment, and the following metrics were recorded: the quality of service (QoS) and the average utilization rate (AUR). These metrics were then compared to those measured on the actual test day as shown in Table 2. This comparison provided positive feedback, as our model's results were within a $\pm$ 5% confidence range.

Table 2: Simulation model validation results.

Source	$QoS_{1minute}$	AUR
ANGUS historical data	77.9%	41.1%
Simulation model results	80%	41%

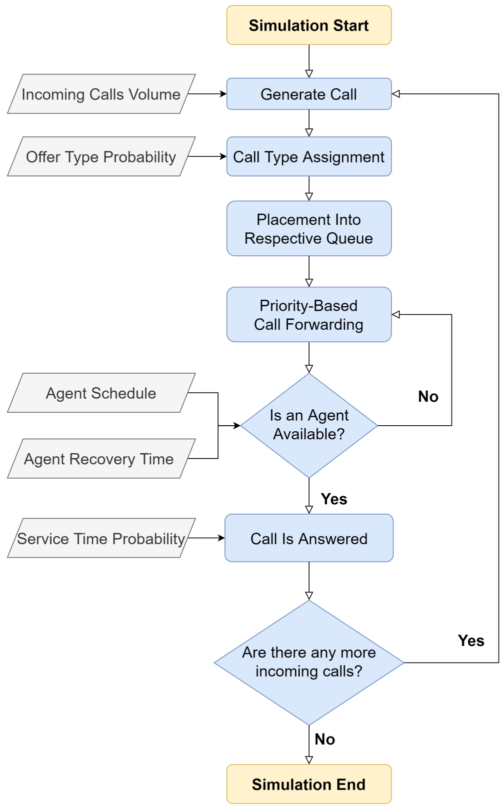


Figure 4: Simulation flow chart.

4.4 Model Outputs

As the simulation runs, our model keeps track of the in-queue call waiting times before being answered by an agent or abandoning the queue. Based on these waiting times, we are able to calculate the QoS criterion using the formula of equation (1). Longer waiting times contribute to a decrease in the QoS.

We are also able to record the service times carried out by the agents and compare them to these agents' shift duration. Using the formula of equation (2), we are able to calculate our second performance criterion, the AUR. The higher the cumulative service time-to-shift duration ratio is, the higher the AUR.

Due to the coupling of the Witness model with an Excel file, we are able to derive some helpful visualizations. These include the allocated agent resources within each shift and the average utilization rate variation throughout the working hours of the day. Such information allows us to identify the root cause of low QoS and AUR criteria.

$$QoS_x = \frac{\text{number of calls with waiting times} < x}{\text{total number of calls}} \times 100 \tag{1}$$

$$AUR = \frac{\sum \text{agent service duration}}{\sum \text{agent shift duration}} \times 100 \tag{2}$$

5 SIMULATED SCENARIOS

In this section, we launch our simulation model using the previously mentioned inputs. We first describe the scenarios we plan to simulate. We then proceed to present the results obtained through our simulations. These results are then analyzed and converted into useful information regarding the evaluation of our schedule. For the purpose of evaluating agent schedules, three scenarios having different schedules were simulated. Green filled, blue filled and orange filled time slots represent the planification of level 1, level 2 and level 3 agents' shifts respectively throughout the working hours of the simulated day. These scenarios are presented as follows:

1. **Scenario #1:** The first scenario is characterized by the empirically drawn schedule shown in Figure 5. Based on the knowledge of the incoming volume of calls throughout the days of the year, it was noticed that 2 significant peaks of incoming calls take place during a certain period of the morning and another period of the afternoon. ANGUS planning supervisors therefore constructed this schedule in such a way that agent shifts would heavily cover those 2 peak periods of the day.

2. **Scenario #2:** The second scenario is characterized by the optimized schedule shown in Figure 6. Pehlivan et al. (2021) found that the most fitting queuing model which would best estimate ANGUS's staffing requirements was that of Jouini and Roubos (2014). This queueing model was therefore used to identify how many agents would be required throughout the time slots of the day being simulated in order to maintain customer waiting times below a certain threshold. A Mixed-Integer Linear Programming (MILP) optimization algorithm which properly models ANGUS's agent scheduling constraints was then used to schedule the agents' shifts based on the queueing model's suggested staffing requirements. The objective function assigned to the MILP algorithm was to minimize agent over-staffing.

3. **Scenario #3:** The third scenario is characterized by the adjusted optimized schedule shown in Figure 7. This schedule represents an adjusted version of the optimized schedule of scenario #2. Using the analysis carried out in the Results section 6 later on in this paper, we were able to adjust the planning of agent schedules throughout the simulated day to improve the obtained performance criteria. The red rightwards arrows indicate the changes made on scenario #2's schedule based on the previously mentioned analysis.

The comparison of the first two scenarios would indicate the ability of our model to properly assess schedules and assist us in indicating which one would yield better results. The comparison of the second and third scenarios would then highlight our capability of further adjusting existing schedules based on our simulation's findings.

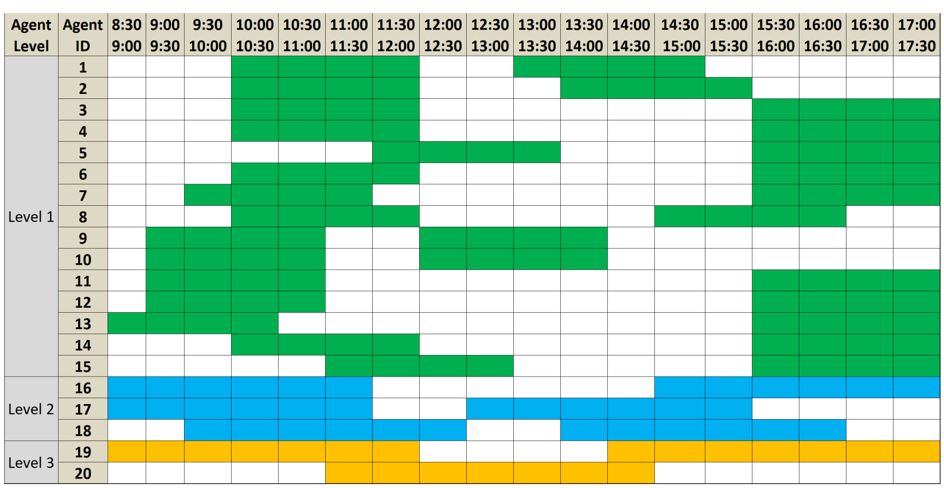


Figure 5: Empirically drawn schedule.

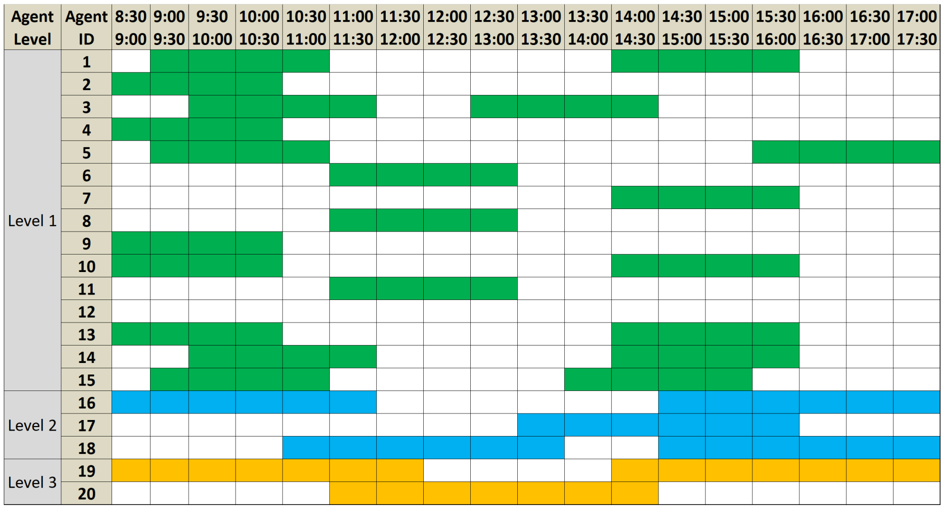


Figure 6: Optimized schedule.

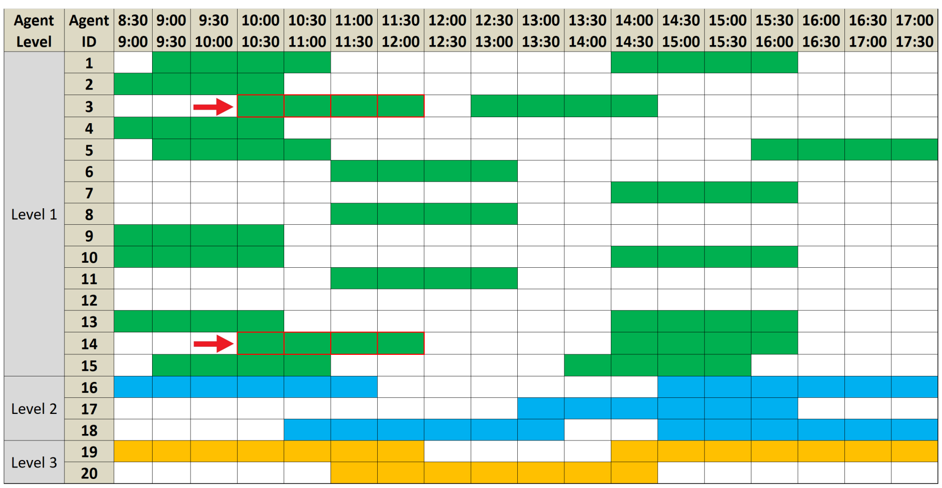


Figure 7: Adjusted optimized schedule.

6 RESULTS

In order to build confidence in our obtained results, 100 simulation replications were launched for each scenario. After simulating the first two scenarios, we are able to extract the average values of the replications' performance criteria results. As shown in Table 3, a clear improvement can be seen in scenario #2 with respect to scenario #1. Higher QoS and AUR indicate reduced customer waiting times and higher agent occupancy respectively. As expected, the optimized schedule was proven to be more efficient than the empirically drawn one. In order to further exploit our simulation model outputs, we must pinpoint the root cause of any low readings in our performance criteria. Hence, a third scenario representing an improved version of the second scenario was carried out. We started off by plotting the average agent utilization rate variation over the course of the entire scenario #2 work day as shown in Figure 8.

It was then possible to classify shifts into one of three types: understaffed, overstaffed or adequately staffed. Understaffed shifts indicate a deficit in the number of agents with respect to the number of received calls, which results in a decrease in the QoS. Overstaffed shifts, however, indicate an excess in the number of agents, which results in the decrease in the AUR. Adequately staffed shifts indicate a sufficient number of assigned agents to meet ANGUS's performance criteria objectives. Based on Figure 8, we realize that

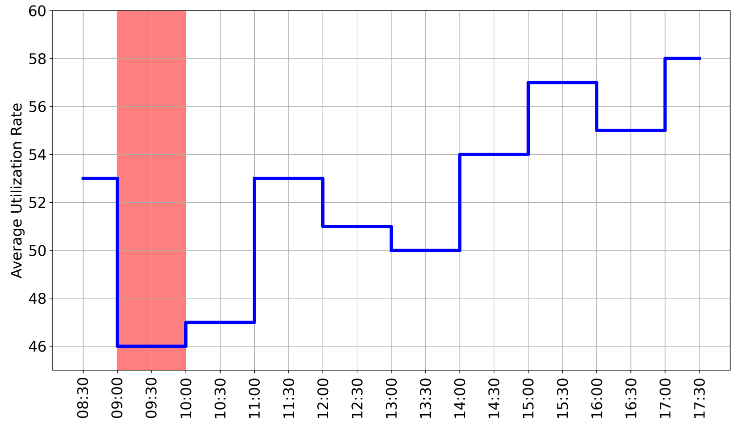


Figure 8: Scenario #2 AUR variation.

the most significant decrease in the AUR occurs within the 9:00 - 10:00 time window, which can then be classified as an overstaffed period. Upon reviewing the agents assigned during this period, we decide to delay the morning shifts of agents 3 and 14 by 30 minutes, so that they now begin those shifts at 10:00 rather than 9:30. These schedule manipulations were carried out in the hopes of improving both the AUR and QoS. Our decision was based on a simple observation rather than a scientific procedure, as no framework is present to dictate which shifts are to be altered, added or removed. After simulating this new schedule, we can see how the performance criteria and total agent labor hours evolved in Table 3.

Table 3: Performance criteria results of different scenarios.

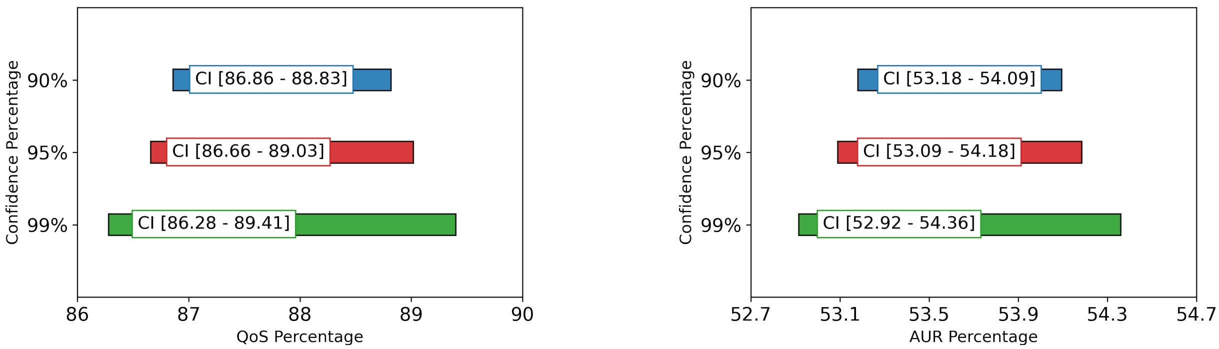
Criteria	Scenario #1	Scenario #2	Scenario #3
$QoS_{1minute}$	80%	87%	88%
AUR	41%	53%	54%
Agent Labor Hours	177	135	135

Recalling our observation of Table 1, a schedule with higher total agent labor hours did not necessarily contribute to higher performance criteria. Despite scenario #2 having 24% fewer agent labor hours than scenario #1 and the same volume of incoming calls, better results in the form of a higher QoS and AUR were realized. This indicates the possibility of lower agent labor hours leading to better performance criteria. An increase is also seen in both the QoS and AUR of scenario #3 with respect to scenario #2, despite having the same number of agent labor hours. This indicates that we have successfully adjusted the optimized schedule and that the manner in which the agent schedules are planned has a direct effect on the outputs of our simulation. As our results represent the average of 100 replications, we are able to plot the QoS and AUR confidence intervals of scenario #3 as shown in Figures 9a and 9b respectively.

Based on our simulation results, we can conclude that we are indeed able to simulate different schedules using our simulation model and evaluate them as either being acceptable or insufficiently planned. Through the analysis of our model's outputs, an experienced schedule planner is able to adjust existing schedules. Based on such a planner's expertise, the re-scheduling, adding and removing of agent shifts could further improve the QoS and AUR performance metrics.

7 CONCLUSIONS AND FUTURE WORK

Within this paper, we have constructed a discrete-event simulation model to simulate a working day at the ANGUS call center with user-inputted agent schedules. By re-assigning agent shifts, we were able to test three different schedules: an empirically drawn schedule, an optimized schedule and an adjusted optimized



(a) (b)

Figure 9: QoS and AUR Confidence Intervals.

schedule. We validated the superiority of the optimized schedule over the empirically drawn one as better performance criteria were realized. With the aim of further improving these criteria, intelligent changes were introduced to the optimized schedule based on our simulation outputs. Through these manipulations, we successfully achieved our goal, as the best QoS and AUR were realized in scenario #3.

In the future, it could be interesting to evaluate the performance of our model with additional data and therefore more accurate input. Rather than performing an estimation of the call arrival profile based on historical data, we could adopt an advanced forecast of that profile for the day being planned. A non-randomized data-based inter-arrival time could also better simulate the arrival of incoming calls. As our model shapes the dynamics of ANGUS, a schedule adjustment framework could be developed by identifying this schedule's overstaffed and understaffed shifts. This framework would allow an experienced planner to properly manipulate these schedules, bringing us closer to ANGUS's desired performance objectives.

8 ACKNOWLEDGEMENT

This project is co-funded by ANGUS and by the *occitanie* region of France.

REFERENCES

Aksin, Z., M. Armony, and V. Mehrotra. 2007. "The Modern Call Center: A Multi-Disciplinary Perspective on Operations Management Research". *Production and Operations Management* 16(6):665–688.

Aldor-Noiman, S., P. D. Feigin, and A. Mandelbaum. 2009. "Workload Forecasting for a Call Center: Methodology and a Case Study". *The Annals of Applied Statistics* 3(4):1403–1447.

Andrews, B. H., and S. M. Cunningham. 1995. "LL Bean Improves Call-Center Forecasting". *Interfaces* 25(6):1–13.

Atlason, J., M. A. Epelman, and S. G. Henderson. 2008. "Optimizing Call Center Staffing Using Simulation and Analytic Center Cutting-Plane Methods". *Management Science* 54(2):295–309.

Avramidis, A. N., W. Chan, M. Gendreau, P. L'ecuyer, and O. Pisacane. 2010. "Optimizing Daily Agent Scheduling in a Multiskill Call Center". *European Journal of Operational Research* 200(3):822–832.

Avramidis, A. N., and P. L'Ecuyer. 2005. "Modeling and Simulation of Call Centers". In *Proceedings of the 2005 Winter Simulation Conference*, edited by M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 144–152. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Chiu, C., M. J.-J. Wu, Y.-T. Tsai, N.-H. Chiu, M. S.-H. Ho, and H.-J. Shyu. 2009. "Constrain-Based Particle Swarm Optimization (CBPSO) for Call Center Scheduling". *International Journal of Innovative Computing, Information and Control* 5(12):4541–4549.

Chromy, E., T. Misuth, and M. Kavacky. 2011. "Erlang C Formula and Its Use in the Call Centers". *Advances in Electrical and Electronic Engineering* 9(1):7–13.

Gans, N., G. Koole, and A. Mandelbaum. 2003. "Telephone Call Centers: Tutorial, Review, and Research Prospects". *Manufacturing & Service Operations Management* 5(2):79–141.

Gans, N., H. Shen, Y.-P. Zhou, N. Korolev, A. McCord, and H. Ristock. 2015. "Parametric Forecasting and Stochastic Programming Models for Call-Center Workforce Scheduling". *Manufacturing & Service Operations Management* 17(4):571–588.

Ibrahim, R., H. Ye, P. L'Ecuyer, and H. Shen. 2016. "Modeling and Forecasting Call Center Arrivals: A Literature Survey and a Case Study". *International Journal of Forecasting* 32(3):865–874.

Statista Business Intelligence. 2019. "Call Centers in the U.S.". https://www.statista.com/study/23767/call-centers-in-the-us-statista-dossier/. Accessed 26th September.

Jouini, O., and A. Roubos. 2014. "On Multiple Priority Multi-Server Queues with Impatience". *Journal of the Operational Research Society* 65(5):616–632.

Mabert, V. A. 1985. "Short Interval Forecasting of Emergency Phone Call (911) Work Loads". *Journal of Operations Management* 5(3):259–271.

Mandelbaum, A. 2006. "Call Centers (Centres): Research Bibliography with Abstracts". Technical Report V. 7, Industrial Engineering and Management, Israel Institute of Technology, Haifa, Israel.

Mehrotra, V., and J. Fama. 2003. "Call Center Simulation Modeling: Methods, Challenges, and Opportunities". In *Proceedings of the 2003 Winter Simulation Conference*, edited by S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, 135–143. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Pehlivan, S. A., C. Pehlivan, C. Martinez, N. Cellier, F. Fontanili, and E. Lamine. 2021. "Performance Evaluation and Statistical Data Analysis of a Call Center for the Deaf Community". In *IEEE/ACS 18th International Conference on Computer Systems and Applications*. November 30$^{\text{th}}$-December 3$^{\text{rd}}$, Tangier, Morocco, 1–6.

Petitdemange, E., E. Lamine, F. Fontanili, and M. Lauras. 2020. "Enhancing Emergency Call Centers' Performance Through a Data-driven Simulation Approach". In *ISCRAM 17th International conference on Information Systems for Crisis Response and Management*. May 23$^{\text{th}}$-30$^{\text{th}}$, Blacksburg, Virginia, 218–227.

Robbins, T. R., D. J. Medeiros, and T. P. Harrison. 2010. "Does the Erlang C Model Fit in Real Call Centers?". In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 2853–2864. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Tanir, O., and R. J. Booth. 1999. "Call Center Simulation in Bell Canada". In *Proceedings of the 1999 Winter Simulation Conference*, edited by P. A. Farrington, H. B. Nembhard, D. T. Sturrock, and G. W. Evans, 1640–1647. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

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