Enhancing the Customer Service Experience in Call Centers Using Preemptive Solutions and Queuing Theory

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ABSTRACT

The security alarms services market in the United States delivers hardware equipment and services to homeowners and businesses to help monitor and enhance personal property protection. Customer satisfaction via wait time reduction, first call resolution, and cost minimization are key drivers of success to players in this market. Most companies invest heavily in customer service systems including call centers. Our client, AlarmCo, a top provider of property protection, manages an inbound call center that supports a range of questions from customers who call within thirty days from the alarm installation date. Often, security companies fail to utilize strategic solutions when managing inbound customer call traffic and default to reactive measures which unnecessarily increase customer wait times. The key question the team aims to address in this thesis is: "How can we improve the customer service experience for customers of a major security service provider in the United States?"

For this thesis, MIT partnered with OnProcess Technology, a managed services provider specializing in complex, global service supply chain operations, to develop a robust framework to preemptively reduce the number of inbound customer calls, and thereby improve customer service. Using ABC segmentation, the team categorized customers by reason code and demographics. To simulate the client's call center queue, the team calculated the key inputs for the queuing model including average wait time, interarrival rates and number of servers. The team then chose and developed the M/M/n stochastic queuing model for the simulation. The M/M/n queue reflects a simple system with parallel servers, arrivals with a Poisson distribution and service times that are exponentially distributed. Next, the customer segmentation was used to develop targeted preemptive solutions. Taking into account feasibility ratings, the team assigned success rates to each solution and adjusted the inbound call data accordingly. By analyzing the outputs of the simulation before and after adjusting the dataset, the team quantified the impact of preemptive solutions on the call center queue. Ultimately, narrowing to twelve strategic preemptive solutions led to the enhancement of the as-is queuing model by reducing average wait time by up to 35%.

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-Nisha & Qiao

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-Nisha

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-Qiao

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1. INTRODUCTION

The security alarms service market has seen significant growth in the last twenty years with the growing prevalence of cybersecurity and remote monitoring as well as a rapidly growing middle class segment of the US population. In fact, the home alarm securities and automation market was estimated to be $13 billion in 2013 and is estimated to grow to $48 billion by 2018 (Morea 2016). This industry is comprised of establishments that produce security systems and also provide other services such as installation and monitoring. The supply market for this industry consists of electricians, equipment and security services while the demand market can be anyone from individual consumers to retail or public establishments. These households and businesses have decided to outsource security services rather than taking on the logistical and cost liability of safeguarding their properties themselves.

The major players that sell security services include ADT, Vivint, Monitronics, Slomins, and Protection 1, which account for nearly 38% of the market share in 2016 (IBISWorld). While ADT is the largest provider accounting for nearly 25% of the market share, Vivint has seen a 15% CAGR growth since 2006. The remaining share reflects a largely fragmented supplier base and the industry is expected to undergo several mergers and acquisitions in the next decade. The leading players all offer similar types of services including alarm system sales and monitoring, burglary alarm system sales, monitoring and repairs.

Many security alarm services companies have not realized the promise of waves of new technologies that are creating breakthroughs in the sector of inbound service queue management. Some of these major developments include the transition from voice based service to automated web services and the transition from live phone call issue resolutions to intelligent voice recognition (IVR.) For the purposes of this thesis, we have teamed up with OnProcess Technology (OPT) to provide a planning framework that utilizes these breakthroughs to allow our client company, AlarmCo, a major security service provider, to shift from inbound service queues to preemptive next issue avoidance using queuing theory and predictive analytics.

1.1. Problem Description

Homeowners and security companies commonly communicate through online channels and inbound and outbound phone calls. Inbound calls are defined as calls that originate from the customers, mostly consisting of general inquiries or issues with service. Outbound calls generally consist of sales calls originating from the company. Customer service teams need to be accessible twenty-four hours a day via most channels in order to resolve customer concerns, especially during an alarm sounding event. High levels of customer service, particularly at call centers, have thus become a growing concern for security service companies due to the time sensitive nature of most inbound calls.

Some key performance indicators used by security providers to assess call center performance include customer satisfaction, wait time and cost. Often times, however, home security companies provide reactive measures to solve a customer problem. An example of a reactive solution is dispatching an agent to fix an alarm system after a customer has called in with a complaint. Reactive approaches such as these cause challenging problems for security companies trying to improve service to customers. Some examples of these issues include:

- Backed up customer queues,
- High levels of wait times for customers making inbound calls,
- Underutilized service agents at call centers,

- Costs due to excess dispatching of truck rolls (technicians called to fix alarm system at customer home), and
- Costs associated with potential excess labor.

Our project helped deliver a framework that can allow AlarmCo to preemptively reduce inbound customer call requests while holistically advance customer service performance. Developing preemptive measures in place of reactive solutions could cut queue length, reduce average wait times, and free up agent capacity. In order to develop a robust analysis, the team also utilized current industry reports, best practices in customer segmentation, and historically significant case studies in customer segmentation, call center queuing and queuing theory. Due to confidentiality, all the numbers used throughout the thesis are for illustrative purposes only and are not necessarily indicative of the actual performance of AlarmCo.

1.2. The Case of AlarmCo Call Center

AlarmCo represents a major player in the security services industry, with global and US based operations. This company is primarily a business-to-customer (B2C) player with a very small percentage of business-to-business (B2B) customers. AlarmCo, in an effort to improve its operations at a US based call center, is looking to switch from a reactive inbound phone queue (drawing negative customer reviews and ~$400M annual operating cost to the company) to a new paradigm of leveraging operational data, the internet of things and predictive analytics.

Currently, the AlarmCo Inbound Call Center (AICC) supports a range of questions from customers calling within thirty days from the installation date of their security system and is looking to answer calls within agreed service levels. Though 95% of calls are inbound (customers call the 1-800 customer service line), the remaining consists of outbound calls, when customers request a call back. The calls may include service issues, financial questions or technical issues. A significant portion of the call volume falls under "general inquiry." The AICC is equipped to track time of call, reason for call and resolutions offered to the customer. All calls that get escalated fall out of the queue and get handled separately by an escalation management team. The company tracks its service levels using the following metrics:

- 95% of the incoming calls to be answered within thirty seconds
- Wait Time (Speed of Answer) should be less than thirty seconds
- Abandoned Rate must be less than 5% of the total incoming calls
- Business rules around Abandoned calls:
    - If a customer drops the call within thirty seconds, call is not "Abandoned"
    - If a customer drops after thirty seconds, the call is "Abandoned"
    - A call completed in any time interval will be considered not "Abandoned"

Major costs associated with running this call center include fixed costs as well as labor costs that average to $31.50 per service agent per hour. This labor cost consists of wage, benefits, unscheduled absences, training, telephony, software licenses and other overhead costs. The main cost that AlarmCo bears for servicing homeowners is the cost of acquisition (including truck rolls, technician cost, material cost) of $1250/year. Homeowners are charged the following by AlarmCo:

- Cost of Alarm Installation: $100 - $200/year
- Bolt on Charges (service, battery changes): $10/month
- Billing Charge: $45 - $50

OnProcess Technology, on behalf of AlarmCo, is looking to answer the following specific questions and concerns:

1 How do the key performance indicators (including wait time, queue length, interarrival times) perform at the AICC?

2 What are the potential preemptive solutions that may be able to reduce wait time? What are the costs and effectiveness of each solution? What are the advantages and disadvantages associated with each potential preemptive solution? Which preemptive solutions will best serve the AlarmCo customer base?

3 What is the trade-off of implementing preemptive solutions versus reactive measures to address customer concerns? How will the current queuing simulation be impacted?

1.3. Research Motivation

Players in the security service market try to maximize customer satisfaction by creating highly efficient and high performing call centers. Typical benchmarks used to assess this performance include service level, average speed to answer, call duration, first call resolution rate and abandoned rate. Agents track these variables in dashboards that are highly advanced and have innovative reporting mechanisms including weekly metrics reports, labor attrition reports, schedule adherence reports, agent ranking reports, and call resolution reports. While service agents at these call centers accurately maintain and update dashboards to track this level of data, there is still a large gap when it comes to producing reactive measures rather than proactive measures to avoid customer calls in the first place.

To give a more specific example, a customer can call with a general inquiry regarding a product upgrade. A reactive measure to solve this issue is to have a live representative or agent explain to the customer how to upgrade the alarm system. A preemptive measure would be to include a quick tutorial on a web channel on how to perform the upgrade. The objective of this thesis is to address the three key questions posed in the previous section by AlarmCo and OnProcess Technology and minimize inbound calls to the AICC by providing a preemptive framework to the client.

1.4. Research Outline and Scope

The three main datasets used in this project were inbound call data, demographic customer data, and agent resource plans. The key measures when analyzing the first dataset, inbound calls to a call center queue, include interarrival rates (time between customer calls), wait time (time a customer waits before being greeted by a service agent) and number of servers available (call center agents). To develop a targeted preemptive framework that minimizes inbound calls, customers must first be segmented by demographic and call reason code. Then, preemptive solutions per industry best practices were vetted by a team of industry specialists and assigned a feasibility rating. The previous customer segmentation served to narrow preemptive solutions by appropriate customer group. Thorough analysis of the inbound call data allowed the team to accurately calculate inputs to several potential queuing models. These inputs include interarrival rates, service time and number of service agents.

$$Service\ time = \text{Wait time} + \text{Handling time} + \text{Wrap time}$$

Equation 1. Service Time Calculation

Eventually, the M/M/n model was chosen based on the data consistency between the empirical data and the output data generated by the model. As a final step, the team compared the inbound call dataset both before and after the preemptive solutions were to be implemented. These targeted preemptive solutions aim to decrease average customer wait time, reduce average queue length and overall improve the customer service experience for the AlarmCo customer base.

This research focuses on a call center located in the United States with fifteen to twenty service agents and an average of 150,000 incoming calls annually. We assumed that the customer queue follows a single queue system wherein a customer calls the call center number and is placed in one single queue. Calls are then assigned to one service agent at random. Arrival times follow a Poisson distribution under the assumption that an occurrence of one event (or call) does not affect the probability of another event occurring and that two calls cannot take place at the exact same time. Service times follow an exponential distribution which describes the time of an agent serving a customer.

1.5. Thesis Structure

The thesis continues as follows. In Chapter 2, we assess and summarize relevant literature and approach used in other research that is applicable to our study of call centers. In Chapter 3, we discuss the methodology, assumptions and conceptual framework of our research and queuing model. In Chapter 4, we document the queuing model, provide results of each queuing simulation run, and review the finalized preemptive solutions with their impacts on the inbound call system. In the final chapter, Chapter 5, we conclude by providing general observations and implications of our research, key insights, and recommendations for any potential future research.

2. LITERATURE REVIEW

2.1. Customer Segmentation

In order to provide an effective and efficient framework of preemptive actions which will aim to reduce the number of inbound customer support calls, the team needed to develop and segment critical customer groups instead of targeting the general customer population. Customer segmentation is a common best practice when identifying principal customer groups. There are many different ways of clustering members of a population, including the K-means algorithm, bi-clustering and ABC segmentation. These examples of segmentations can generally be categorized into broader segmentation models: a priori, clustering-based, flexible, and componential (Wind, Yoram 1978). A priori is the most traditional model. It segments the customers based on pre-defined variables of either the product or user specific characteristics. The clustering-based model approaches the data using machine learning methods which segment the data based on their similarities without a pre-defined group type. Both flexible and componential are relatively new models which are used mainly for new product offering and market prediction.

2.1.1. K-Means Algorithm

After doing research and considering the particular needs of the client, the team decided to explore the use of a clustering-based model to understand major user groups. One well known method of a clustering-based model is called the K-Means algorithm (Pascal, Ozuomba, Kalu 2015). K-Means is a machine learning algorithm which can be categorized as unsupervised learning. Unsupervised learning is characterized as not requiring labeled data before classification. The algorithm itself will enable segmentation of customer level data into different groups as long as the number of groups is pre-specified. Furthermore, a robust data mining technique will allow effective segmentation of customers based on market characteristics in order to improve customer service, coinciding with the underlying research goal.

There are four steps to perform the K-Means algorithm for customer segmentation:

1. feature normalization: a data preparation stage to adjust all data elements to a common scale,
2. centroid initialization: initial centroids or means were randomly chosen,
3. assignment stage: each data point is assigned to the closest centroid, and
4. updating stage: perform multiple iterations of clustering by moving the centroids.

In a case study by Pascal, a team utilized MATLAB software to illustrate the effectiveness of this four-step methodology. The sample data was first collected from a mega retail company called Nigeria. Two features of customer purchase data including average number of visits per month and average amount of goods purchased per month, were then used to classify the customers. Eventually, four classes were created using the K-Means algorithm: High-Buyers-Regular-Visitors (HBRV), High-Buyers-Irregular-Visitors (HBIV), Low- Buyers-Regular-Visitors (LBRV), and Low-Buyers-Irregular-Visitors (LBIV). The development of these unique classes ultimately helped the business plan its customer service strategy and focus efforts on the more critical customer groups, including HBRV and HBIV.

A similar approach can be used to segment the customers in a call center and identify a hierarchy of customer groups. While in the Nigeria case example, customers were segmented by buying rates and visiting frequency, neighborhood demographics and reason code metrics could be used to segment the customers of AlarmCo. Some other relevant data features to be explored and potentially segmented include customer call wait time and customer call frequency.

2.1.2. Bi-clustering Based Method

As a traditional way of classifying customers, the K-Means algorithm discussed above has several advantages including ease of use, fast computation and tight clusters. However, this algorithm only takes into consideration certain characteristics and fails to consider customers with partial similarities. In other words, the K-Means algorithm classifies customers based on generic features, which may or may not produce meaningful groupings. It may also overlook the subgroups which share similar (but not obvious) characteristics defined as general features. For example, the customer pain point is a very important characteristic which is not explicitly represented by features used in K-Means algorithm. In order to resolve this issue, a bi-clustering based method could be used which takes into account the customer pain points while using it for customer segmentation (Wang, Miao, Zhao, Jin, Chen 2016). The bi-clustering based method was first developed for biological data analysis, and it has been around for many years. Not until recent years has computing power advanced enough to accept bi-clustering across many different applications, mainly because this method involves NP-hard problems.

The BCBimax, a more specific bi-clustering algorithm that segments by binary numbers, consists of five steps:

- data collection
- data transformation
- algorithm selection
- data analysis

- data application

While this method enables the effective use of issue codes to segment the customer base, there are still some limitations when applying this algorithm to call center optimization. One limitation lies in the data transformation step where the customer pain points are transformed into binary numbers. We need to consider the different severity of the pain points rather than simply assigning a binary tag. In addition, the paper uses this method of clustering for product design purposes rather than customer service improvement. The data application step in the case of call centers requires a different, more concentrated approach to interpret results. Another important consideration is the ability to group results with the ones produced by the traditional K-Means segmentation. We believe results can be combined and leveraged to discover more informative segmentations. For example, K-means method can be used to produce general groups of customers based on their demographic information, while bi-clustering based method can be used to create sub-groups which are addressing different customer paint points, or vice versa.

2.1.3. ABC Customer Classification

The final option for segmentation is ABC classification. According to an article by Oracle, ABC analysis is a well-recognized method for classifying object (inventory, suppliers, or customers) according to their level of importance based on pre-specified criteria (JD Edwards World, 2016). Essentially, ABC analysis is a method of analysis that divides the subject up into three (or more) categories: A, B and C. Category A represents the most common products, suppliers, or customers that you have, Category B represents the "middle ground" customers and

Category C (and beyond) represent the small, fragmented customers that are the tail of the customer Pareto graph.

ABC analysis can be used to improve analysis of large and complex data sets by breaking them down into more comprehensible groups. The groups that are created based on different customer characteristics help define the priority of the data. ABC segmentation allows teams to tackle and analyze data in a meaningful way. For example, when customers are segmented at a call center, preemptive solutions should aim to serve 80% of the population and the order in which customers are served should be based on ABC priority. While ABC classification is often used to segment inventory, many businesses are finding value in segmenting suppliers and customers to maximize customer service and optimize supplier relationship management. ABC segmentation proves especially useful for datasets that require segmentation using quantitative and qualitative variables. This segmentation often takes into account sales or spend as the primary method of prioritizing customers. While this is an important measure, other criteria for segmentation will also be explored, namely demographics and customer pain points.

2.1.4. Issues and Advances in Segmentation

There are several issues and advances in the segmentation research which should also be considered. The main problems and perspectives of segmentation originate from five areas (Wind 1978):

- Problem definition
- Research design consideration
- Data collection approaches
- Data analysis procedures

- Data interpretation and implementation

Wind and Yoram focus on marketing usage rather than improving customer service and thus certain issues are not relevant to security service customer segmentation. The K-Means, Bi-clustering, or ABC methods may resolve some of these aforementioned concerns, but supplementary information could still prove useful to further this study. According to Wind and Yoram, one common concern with clustering-based segmentation is the lack of stability. For example, preset segmentation may make sense with the original data but because data is continuously evolving, the segmentation may become obsolete overtime. Additionally, with the rapid change in technology and market adoption, it is hard to ensure segmentation stability. To solve this issue, Wind suggests comparing the results of alternative clustering procedures and developing a combined approach to segmenting the population.

This way, the segmentation will be based on several variables and will be more malleable to change. Per Wind and Yoram, the most relevant step is data interpretation and implementation. To be more specific, two important questions need to be answered in this area to guarantee the effective usage of any segmentation results. First, how should we select the "target" segment? This depends on the financial impact of the segment to the business as well as the resource capacity and ability to implement any segmented strategy against the target. Second, how do we translate segmentation findings into a tangible strategy? This is determined by three major factors: the creativity and tenacity of the researcher, in our case, the MIT thesis team, the involvement of different teams, including meetings and interviews with different stakeholders and subject matter experts, and the insights from risk analysis of different potential strategies.

2.2. Queuing Theory

With the boom of the economy in the last century, there has been increased emphasis on the value of time and improving general customer service. In a study by Consumer Advocate, customer service and monitoring services account for 40% in the weighted qualities to rank the best company. These issues are highly applicable in queuing theory (Consumer Advocate, 2015). Simply speaking, when all customers in a line are not able to be serviced at once, a queue is formed. Queuing theory is a special application of discrete and stochastic process theory that can give deep insight into the efficiency of many different types of queuing systems. The queuing problem is most easily identified in real world environments such as supermarket lines, toll stations, and computer networks. Optimization of queues, including wait time reduction, labor staff efficiency and queue length reduction, prove helpful to marketing, operations and technical teams. The motivations behind optimizing queues are most commonly cost reduction and service improvement (via reduced wait times).

2.2.1. Modeling a Call Center Queue

In order to develop an optimum call center queuing model, accurate and complete data must be readily available and analyzed. Fortunately, most modern call centers are backed up with strong technological infrastructures that allow them to store and access data as needed. Thus, the problem is not data availability or data integrity but rather a lack of expert knowledge on how to develop relevant and usable insight from call center data. Interestingly, the number of call center operators is often selected based on "rule of thumb" and best practices, rather than being derived from a data driven approach (Brezavšček, Baggia 2014).

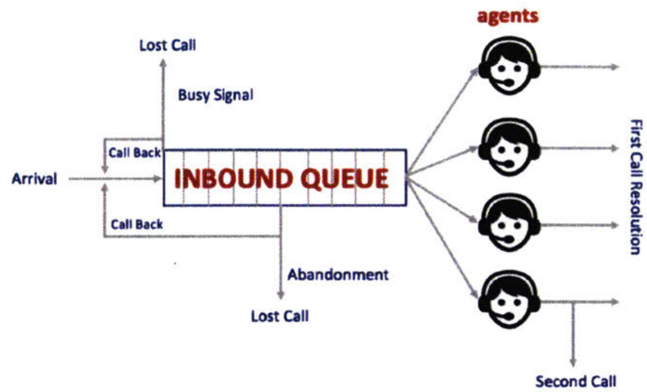


Figure 1. Call Center as a Queuing System

Most queuing systems are comprised of servers, computer generated and live agents, customers with various arrival rates, and a channel of service. More specifically to a call center queue, this consists of service agents to answer phone calls, customers who call the customer service number and are placed in a single queue (before being served by an agent) and a call center telephonic software system. The components should be reviewed thoroughly to ensure accurate input selection into the queuing model. Thorough analysis of this input data, including distributions of service times, interarrival rates, and agent prevalence by unit of time serves to link the data set with an appropriate and optimized queuing model. Brezavšček states in a September 2013 queuing theory conference paper that the key inputs to analyze in a call center queuing model include queue populations (segmenting the population into different call reasons), interarrival times (the average time between incoming phone calls), probability distribution functions of service times, and queuing disciplines such as first in first out (FIFO), last in first out (LIFO), and randomization (Brezavšček, Baggia 2014). Tan Chai, however, argues that there are only two key inputs in any queuing model: interarrival rates and service rates (the time it takes between servicing two adjacent customers in a queue) while the key outcome is the average time a customer remains in a queue waiting for a customer service agent to answer his or her call. As described in QUT system modelling and simulation lecture, Poisson distribution is the most commonly used distribution to represent the interarrival rates and services rates in a queuing model (Joshi, 2017). This approach is robust and can be used to approximate a large number of data patterns. These inputs have been historically analyzed to identify distributions and commonalities between queues using modeling software systems such as Arena, Oracle, Matlab, Jaamsim, and Mathematica.

In another simulation project by Fariborz Jolai and Seyed Mohammad Asadzadeh, the team developed a queuing model in the rescue services industry that ultimately found the best priority assignment for queues in disaster situations, thus improving customer service in dire situations (Jolai, Asadzadeh, Ghodsi, Bagheri-Marani 2016). People in the queue were prioritized not only by arrival time but also by urgency of health issue. In this scenario, customer arrivals were random and thus a stochastic model was implemented.

2.2.2. Queuing Validation

While a model can be used to represent a system, a simulation expands that model and identifies the performance of the system under different conditions. After a reliable model is built that can accurately represent system behavior, simulations via "what if" scenarios are valuable when authenticating the simulation of a queue. Simulation validation and verification are a key step to ensure expected outcomes of system queues are correctly simulated. For example, if a call center simulation depicts a long wait time for customers who call for service requests, there is an expectation that the actual data reflects a similar characterization. In an attempt to optimize queues at a university customer service center, Tai Chan Xian and Chai Weng

Hong ran their simulation model five times to verify that the correlation between the model and real system fell within a +/- 10% validity level (Xian, Hong, Hawari 2016). In each instance, average wait time in queue, maximum wait time in queue, average total time in system, maximum total time in system, number of people in queue, and agent utilization percentage fell within the required validity levels of the actual data. Validation of simulation models is also helpful because it can lead to a discovery of system bottlenecks. For example, in a study by Xian, long wait times were causing customers to exit the queue early in frustration (potentially a future monetary risk to the university) (Xian, Hong, Hawari 2016). The team thus reworked the model and simulation to include a minimum requirement for waiting time. This adjustment eliminated outlier customers who left the queue early without direct contact with a service agent.

2.3. Conclusion

Technological advances have shaped a new wave of customer service. While 75% of customers still communicate with brands via call centers, companies are expanding avenues to communicate with the customers to include social media, websites, live chats, and email. In fact, according to a report by Gartner, 20% of the 500 largest global businesses will introduce video-based chat by 2018 (Gartner 2017). Social media has become a main avenue for customers to reach companies and it is expected that customer communication channels will continue to grow with complexity.

While minimizing costs and lead times are often considered core supply chain functions, many companies are looking to improve their supply chain by addressing the latest needs of customers more efficiently. In order to provide a preemptive framework that reduces the number of customer inbound calls utilizing the latest technology, the team studied the most critical customer groups (from the customer segmentation) with special emphasis on caller criteria (i.e. call reason code, customer age, customer income levels and success rates of the solutions provided by service agents). In summary, the team simulated the AlarmCo customer queue, proposed and derived the impact of the suggested preemptive solutions on the current queue and proved the optimization using queue simulation.

3. METHODOLOGY

A six step process was followed to solve the problem of reducing inbound calls using preemptive solutions. This systematic approach helped break the problem into manageable actions and adhere to a structured timeline. The team first requested three separate sets of data including details on inbound customer calls, customer demographics and labor resource plans. We then performed preliminary data analysis to understand the top customer reason codes and solutions for the inbound traffic. This step was critical in narrowing our focus to avoid developing a loose and inapplicable customer service framework for every call reason and solution.

Next, customers were segmented by demographic groups and prevalence of top reason codes. Customer segmentation led to the development of different preemptive solutions addressing major call reasons codes. At the same time, we were able to select the appropriate queuing model for our queuing simulation based on the inbound call center data. This gave us the “as is” scenario of call center queuing at the AICC. Calculating the impact of the recommended preemptive solutions on the inbound queue along with a feasibility ranking allowed us to update the simulation and provide a new queuing scenario to the client. Finally, we worked with stakeholders to develop a risk assessment for each potential preemptive solution and were able to develop a hierarchical ranking of solutions based on both risk and feasibility.

Throughout the project, the team held weekly meetings with AlarmCo to define the scope of the project, request and understand company data, update on research progress, discuss next steps, and resolve any issues. Below is a pictorial view of the six step process utilized to structure the AlarmCo and OPT prompt.

Figure 2. Holistic Six Step Project Methodology

3.1. Scope Identification and Data Request

The first step entailed confirming the scope and appropriate stakeholders with AlarmCo. A set of questions was formulated to identify client objectives as well as distinguish top priority call center metrics. Here the team learned that costs associated with any process improvement should be studied but should not be a major constraint. Also, solutions should strategically target the appropriate customer groups who contribute most of the top reason codes, which ultimately minimized queue inefficiencies.

Following scope clarification, the team requested a full year of data to calculate inputs required to segment the call population and run the queuing model. Three sets of data were requested: inbound call data (including key information like call wait times, call handling times and agent/customer IDs), demographic data (including the age, economic position and language proficiency of each customer), and finally, labor resource data (reflecting the utilization of each agent by day of month and week). The original data was transferred to the MIT team via Microsoft Excel with over 150,000 lines of data, spanning a one-year time period for a single representative call center.

3.2. Preliminary Data Analysis

The team imported all data tables into an SQL database and conducted preliminary data analysis for each dataset in Tableau. This helped us understand top call reason and solution codes, high traffic time periods, data seasonality and outliers. Building a Pareto of top reason codes and solution codes helped us assess which issues account for a majority of the inbound calls. Knowing this information is critical in developing concentrated solutions. Other analyses including heat maps of high traffic time segments and seasonality by day and month were critical in understanding the trends in the inbound call volume and any correlated variables.

3.2.1. Data Received

The data was provided in separate batches which led to iterative discussions with AlarmCo to understand its content and identify missing information. The first and largest dataset received from the client was the inbound customer call data. Below in Table 1 are the key fields pulled by the team. With this information, the team was able to analyze reason codes and solution codes as well as to identify which contributed to 80% of the inbound traffic.

#	Unique Identifiers	Queuing Inputs	Reason Codes	Solution Codes
1	OPT Sequence number (primary key)	Date Modified (the time and date of call)	Success and failure tags	Abandoned calls
2	Unique Call ID (foreign key)	Wait Time (time to respond to the incoming call, typically speed of answer (in seconds)	Reasons for calling	Inbound general queries
3	Agent ID (foreign key)	Handling Time (the number of seconds conversation is in progress)	Failure drilldowns	Warm transfers
4	Customer ID (foreign key)	Wrap Time for after call work (in seconds)		Issue escalation
5	Customer time receipt (foreign key)	Hold time for abandoned calls (in seconds)		

6	Geo ID (foreign key)			

Table 1. Unique Identifiers for Inbound Customer Call Data

The next set of data received from the client was the demographic level detail which was especially critical in performing different types of segmentation. Each caller had a demographic tag (unique identifier) that linked the individual to a certain neighborhood and an associated proportion of demographics related to age, income level, English proficiency, family type, and work information. The client provided this data format to ensure confidentiality while still providing comprehensive information to assist in customer segmentation. This data format required the team to normalize and restructure so that each customer can be easily identified by a systematic combination of key segments. Below in Table 2 is the key demographic detail provided by OPT. The team decided to narrow in on three important variables in customer segmentation including age, family income, and language proficiency (highlighted below).

#	Age	Income Level	English Proficiency	Family Type	Work
1	***Sex By Age***	***Family Income In The Past 12 Months***	***Age By Language Spoken At Home (5 Years And Over)***	Household Type	Sex Of Workers By Place Of Work
2	Sex By Educational Attainment For The Population 25 Years And Over	Aggregate Income Deficit For Families By Family Type		Own Children Under 18 Years By Family Type And Age	Means Of Transportation To Work
3		Poverty Status By Household Type By Age Of Householder		Relationship By Household Type (65 Years And Over)	Aggregate Travel Time To Work
4		Poverty Status Of Individuals By Living Arrangement		Family Type By Presence And Age Of Own Children Under 18 Years	
5		Poverty Status Of Families By Family Type By Presence Of Related Children			

6		Nonfamily Household Income			

Table 2. Demographic Attributes

Lastly, the team was given labor resource plans detailing overall agent performance efficiencies. Agent efficiency is defined as a percentage of time a service agent is servicing customer inbound calls. This data was an addition to the inbound customer call data. It generalized the queue data presented in the inbound customer call data and added one key variable of the number of agents. All data was provided hourly by day of week and month.

#	Inbound Customer Call	Resource Allocation	Queue
1	Call Time	Number of Agents	Inbound Lines
2	Call Arrivals	Agent Efficiency	Average Speed to Answer
3	Handling Time		Average Queued
4	Wrap Time		

Table 3. Queuing Inputs and Outputs

3.2.2. Dataset Normalization

A database that is not normalized often includes redundant data and superfluous naming conventions. Normalization reduces these redundancies and errors in the data and often has the unexpected benefit of familiarization of the dataset and deep knowledge of the interdependent relationships between variables. Normalization is a pertinent first step in any data analysis because skipping this step can lead to many issues including security concerns, low disk space capacity, slow speed of queries, inefficiency of database updates, and perhaps most importantly, lack of data integrity.

To avoid these risks, the team spent significant time upfront to accurately normalize the data, or more specifically, ensure congruent terminology, unique attributes, and compatible units of measure. We found that some fields shared commonalities, for example, "price incorrect," "special price unavailable," and "special price incorrect" all implied similar customer issues. In cases like this, the team developed a new, unified naming convention for issue codes. Another key step in normalizing the data was creating unique identifiers and developing primary and foreign keys for each data table. For example, the team concatenated customer ID, call ID, and demographic ID to create a unique identifier for each individual call in the database. Developing unique identifiers for each table was critical because it allowed us to update and link values seamlessly.

Initial analysis of the data revealed the need for more updates to the data and the team thus performed a second iteration of normalization. First, data was incomplete for the month of June (possibly due to a data outage), so the team extrapolated the data to populate these missing fields. Service times and arrival rates were randomized for this additional subset of data in June. In addition, reason and solution codes with similar data definitions were combined while infrequent codes were categorized as "other." The data showed time of call but did not show interarrival time (times between calls) and required further calculation to create this value. Lastly, in order to derive total service time on call, the team combined and summed handling time and wrap time.

Following normalization, the data was imported into a database server for efficient analysis and queries. Unique identifiers served as primary or foreign keys that were required to build relationships between tables and run queries using multiple tables in MySQL software.

3.2.3. Stakeholder Interviews

A total of six interviews were conducted with various stakeholders, subject matter experts, data technicians and AlarmCo leadership in order to understand common key performance indicators for call centers in the industry. Additionally, stakeholder interviews were critical in developing risk assessments and feasibility scores for each of the current and proposed preemptive solutions. The team went through many iterations of this scoring to ensure accurate ranking of solutions.

3.2.4. Data Analysis

The next step was to conduct a more thorough analysis on the normalized datasets. The first thing we wanted to learn was how many calls fall within each issue. After analyzing count of calls by this variable, we pulled in solution as a second variable, for example, determining the number of people who called with a general inquiry issue and what percentage of these customers were provided an acceptable solution. We plotted the calls by both days of week and month and were able to study seasonality trends over a one-year time period. With this analysis, we could see dips in the data and heat maps that reflected times with the highest inbound call volumes.

To analyze demographics, we joined the demographic and inbound call data tables by "Geo ID" and "OPT Sequence Number", the unique identifiers for each table respectively. With deeper analysis, we learned many interesting insights regarding the customer base of nearly 142,000 customers. Namely, we studied what proportion of the customers were of various age groups, poverty levels, income levels, average household size, average travel time to work and language proficiencies. Examination of the resource plans helped us understand the distribution of service agents on any given day as well as average call volume by agent. This dataset also gave us a clearer view of agent utilization in terms of available hours per day.

Our final analysis consisted of building histograms and determining distributions of service times and arrival times. The aggregated data reflected in the histograms were pulled into excel, where the team was able to conduct a goodness of fit test and select a particular distribution for each variable. The distributions would later help with selection of an appropriate queuing model.

3.3. Customer Segmentation

Once the data was vetted and investigated, the team segmented the customers based on demographics and call reason codes. An initial analysis was conducted using excel to identify customer demographic groups. An advanced analysis was then conducted using a machine learning mechanism to tie the customer demographic groups to the customer pain points. After data retrieval, we found the most efficient method of clustering customers was via an ABC segmentation.

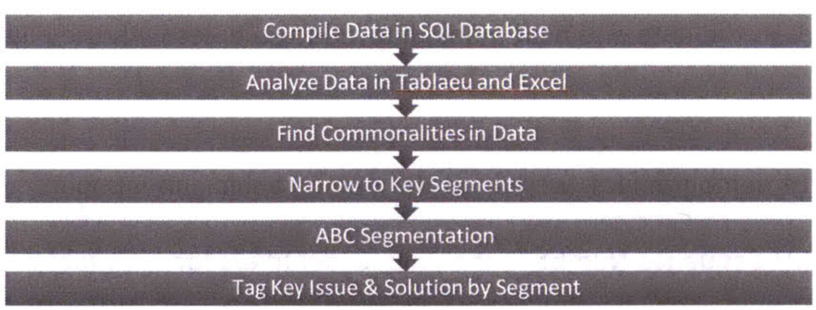


Figure 3. Customer Segmentation Process

3.3.1. Segmentation of Customer Base Using Caller Demographics

Customers are segmented by demographics using three key categories: age, income level, and English proficiency. The team chose age because this is strong indicator of technological tendencies (i.e. a millennial homeowner may be more likely to search YouTube for a tutorial on how to fix an alarm system rather than calling customer service.) Income level expresses the buying power of a customer (i.e. a customer that falls above the $200K income level will be more prone to require an immediate solution to ensure constant functional home security). English proficiency was the last important indicator of customers who will likely favor a transcribed solution to one via voice or video. In choosing the target segment, we focused on the homeowner segment of the market which accounts for the majority (~81%) of AlarmCo revenues. The sub-segments of homeowners were skillfully chosen based on combinations of customers who have similar demographic patterns in terms of income, age, and English level. By addressing each segment with a different solution category, such as automated responses or IVR, the team was able to translate segmentation findings into a tangible strategy for the client.

3.3.2 Segmentation of Customer Base Using Top Reason Codes

A decision tree is a simple representation of classifying segments of data and is commonly used in data mining. For the purposes of our research, we created a three tiered decision tree that asked questions regarding age, income and language. The advantages of using decision trees to segment our customers include that decision trees:

1. Can accept input data that is numerical and categorical,
2. Requires minimal data preparation,
3. Are easy to interpret, and
4. Perform well with large data sets (in our case, over 150,000 lines of data.)

The team built a customer market segmentation or decision tree to enable more focused efforts during the development of preemptive solutions. For example, if a large segment of a population who call about pricing errors are millennials, the team can assume this demographic will be more prone to accept a technological preemptive solution. The key steps involved in building an ABC classification of customers via decision trees include:

1. Select the top seven reason codes that account for 80% of calls and determine top solutions provided to customers who call for these reasons.
2. Narrow to most applicable decision variables when segmenting population (i.e. age, income, and language).
3. Create reasonable age and income brackets that segment the population without skewing the data.
4. Calculate the count of customers that fall in any one or several of these categories.

3.4. Queue Simulation

The main purpose of developing a queue simulation was to be able to simulate the impact of preemptive solutions on the inbound queue. In order to do so, a queuing model, based on several input variables, was selected to accurately represent the call center queue. Key performance indicators (KPIs) for a queue included the average queue length and customer wait time before getting served. These two characteristics were direct results of key call center data such as average interarrival time (the time between two inbound calls), average service time (the time each agent spent on resolving a call), and the average number of agents. Depending on the selected queuing model, Wolfram Mathematica software was used to quickly generate theoretical KPI data of queue length and wait time from existing inbound call data. The output theoretical KPI data was compared to the data from the original dataset to ensure the model was representative.

3.4.1. Simulation Approach

Queue simulation was done in two steps. First, we chose a queuing model with the strongest fit to the data, and second, we validated the model using the existing dataset. In order to choose the best fitted queuing model, the team researched on different queuing models and listed five important characteristics of the call center system that serve as inputs to all queuing models. The notation system for a queue in a single system is written as A/B/c/N/K where

A represents the interarrival time distribution,

B represents the service time distribution,

c represents the number of call service agents,

N represents the queue capacity (limitation on how many people can wait in the queue),

K represents the size of the calling population.

This notation required the team to first study the five characteristics of the queue and calculate variables that were missing. These characteristics were the essential inputs of a queuing model because they characterized the incoming load of a queue and the system capability to handle the load thus defining which model should be used. For example, different interarrival time distribution required a different queuing model simulation. Therefore, analysis and calculation for each input variable were performed to understand the queue and select an appropriate queuing model. Some potential distributions studied include:

M = Poisson distribution (Markovian)

E = Erlang distribution

G = General distribution

GI = General independent distribution.

Once the distributions of the input variables were finalized and the queuing model was selected based on these inputs, the model was validated by comparing theoretical output data from the simulation with the inbound customer call data received from AlarmCo. The outputs of the queuing model were the KPIs including average queue length and average wait time. The team chose a +/-10% validity level according to Tai Chan Xian and Chai Weng Hong's research which was discussed in literature review section 2.2.2. This means that if the theoretical data fell within 10% of the empirical data, the model exemplifies a suitable representation of the queue.

To summarize, the key simulation steps followed include:

1. Obtained inbound queue data and normalized
2. Performed preliminary analysis on the data and understood the characteristics of both input and output variables
3. Selected a suitable queuing model
4. Validated the queuing model

3.4.2. Simulation Software

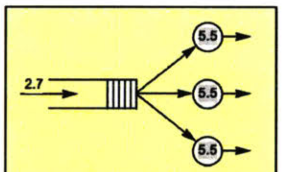
While the team had many options to simulate the queue in the given call center, we decided it was best to use a software that had functionality in data processing as well as a strong visual user experience. Wolfram Mathematica is a symbolic computation program, or a "computer algebra system," used in many academic disciplines including the sciences, engineering, quantitative, and computer science. While the system is commonly used for matrix and data manipulation, finite element analysis, discrete and continuous calculus and data mining, our team used it for its queue simulation and visualization functionalities.

Using Wolfram Mathematica, we were able to efficiently simulate the queue by generating queue KPIs based on inbound traffic. In addition, Wolfram Mathematica was used to construct the visual representation of the model and simulate the impact of potential changes to the queue. Wolfram Mathematica allowed our team to build a more user friendly, adaptive, and cost effective solution for OnProcess Technology. For example, an M/M/n queuing model could be easily simulated in Wolfram Mathematica by running several lines of commands which generated KPI measures of mean system size, mean system time, mean queue size and mean queue time.

```
In[473]:= Q = QueueingProcess[2.70, 5.58, 3]
          QueueProperties[Q]

Out[473]= QueueingProcess[2.7, 5.58, 3, ∞, 0]
```

Out[474]=



Basic Properties	
QueueNotation	M/M/3
ArrivalRate	2.7
ServiceRate	5.58
UtilizationFactor	0.16129
Throughput	2.7
ServiceChannels	3
SystemCapacity	∞
InitialState	0
Performance Measures	
MeanSystemSize	0.486538
MeanSystemTime	0.180199
MeanQueueSize	0.00266676
MeanQueueTime	0.000987689

Figure 4. Sample Queue KPI Calculation in Mathematica

3.5. Preemptive Solution Development

The MIT team partnered with subject matter experts to brainstorm preemptive solutions which focused on reducing 80% of the total calls that are associated with issue codes that can be automated with preemptive solutions. We not only focused on developing solutions for calls in which customers left dissatisfied and without a resolution, but also on calls tagged with a successful outcome (i.e. customer issue was solved on first call with no issue escalation). The idea of minimizing all inbound calls in the system allowed us to improve the customer experience for both disgruntled customers and customers who could be served better. All solutions were developed with the purpose of reducing repeat inbound calls, reducing repeat truck rolls (dispatching technicians) and better allocating labor resources at the call center.

The proposed preemptive solutions fell under five key categories:

- Automated Remote Service - Proactive upgrade or dispatch parts and components that are more likely to fail within two weeks or proactive triage for customers, for example, conduct in-depth diagnostics, decision trees, remote device reset, remote software upgrade.
- Education - Proactive outreach to customers to help them upgrade products that are at the end of their life cycle and can no longer be supported by original equipment manufacturer and education on top mentioned features that draw questions from customers.
- Online Resources – Online services that address key customer concerns such as a frequently asked questions (FAQ) page, video tutorials, automated web and video chats.

- Improved Telephonic Experience – Improved customer experience on the call while minimizing the live interaction of agents and customers. This can include IVR, an improved mobile application with alert features, and web based service tickets.
- Proactive Analysis – Exploration of search engine optimization (SEO) and search engine marketing (SEM) techniques to link customers with web based solutions prior to providing call center help phone numbers.

The team conducted market based research to aggregate all potential preemptive solutions that fall into one of the aforementioned categories and narrowed this list in a workshop with industry SMEs and members of the OnProcess Technology team. This list was narrowed based on validity, risk, and utility of the solutions.

3.6. Solution Impact and Scenario Analysis

Following this research, we estimated how much each preemptive solution would affect the number of inbound calls as well as which solutions were most feasible to AlarmCo. Essentially, the team reviewed three scenarios, deleted a predetermined set of calls associated with each, and calculated a new interarrival rate by scenario. This rate was fed back into the queuing simulation described in section 3.4 and allowed us to determine how each scenario of preemptive solutions can improve the queue. These improvements included an upfront reduction in wait time, a reduction in queue length, and finally, an insight on reallocation of service agent labor hours (using the average hourly pay by service agent.)

Scenario analysis is a process of investigating potential future events by studying all possible outcomes of a process, in this case the implementation of zero, partial or all of the proposed preemptive solutions. Scenario analysis reflects one of the most common methods of projection and is especially helpful because teams can gauge the incremental impact of any change to the simulation. We decided to implement scenario analysis to improve decision making by allowing consideration of multiple outcomes and their associated implications to the queue. We looked at three specific scenarios for AlarmCo:

1. As-is Scenario: If no preemptive solutions were implemented
2. Hybrid Scenario: If the most feasible solutions were implemented (targeting top reason codes and 80% of calls)
3. Cherry Pick Scenario: All proposed solutions were implemented (targeting 100% of calls, reflecting a generally unreachable target but helpful when benchmarking)

4. DATA ANALYSIS AND RESULTS

This section presents analysis of the base data, segmentation mapping results, and the queuing model results. First, a high level view of top reason codes, seasonality and demographic prevalence is presented based on call volume and call density. Additional detail is provided on assumptions, data extrapolation, and sensitivity of the queuing model. The consolidated view of top chosen preemptive actions are presented with a particular emphasis on cost, feasibility and risk to AlarmCo. Finally, the impact of a set of selected preemptive solutions were presented after running the queuing model with updated input queue data. This section focuses on presenting results, while the implications and insights are more thoroughly explored in the subsequent Discussion section.

4.1. Inbound Customer Call Data Analysis and Results

Analysis of call volume reveals that 80% of calls are made by customers with seven of the thirty possible issue codes.

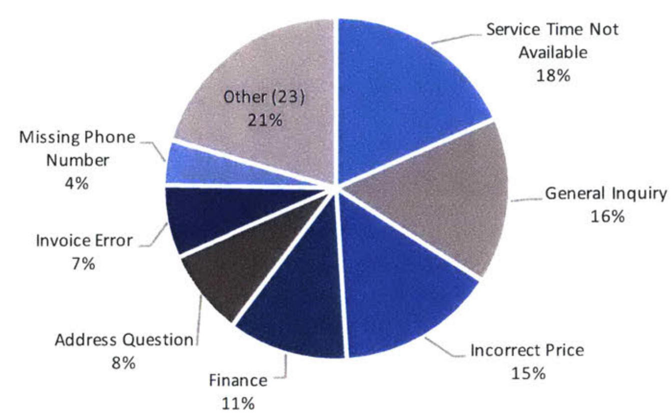


Figure 5. Percentage of Customer Calls by Reason Code

The number one reason customers call the AlarmCo help line was because a service was required in their homes such as machine reboots, upgrades, or replacements. The next most common reason for call, accounting for 16% of calls was due to general inquiries from the customer. The next two most common call reasons were incorrect price and finance questions. The final three top issue codes were attributed to questions on address (for technician dispatch and closest client location), invoice errors, and missing contact details.

Taking a closer look at these top issue codes, we found that a majority of calls were warm transfers to sales (agent transfers call, without concrete solution), solutions that were accepted by the customer, and resolved solutions to general questions. In the figure below, we see that 14% of customer calls were left unresolved.

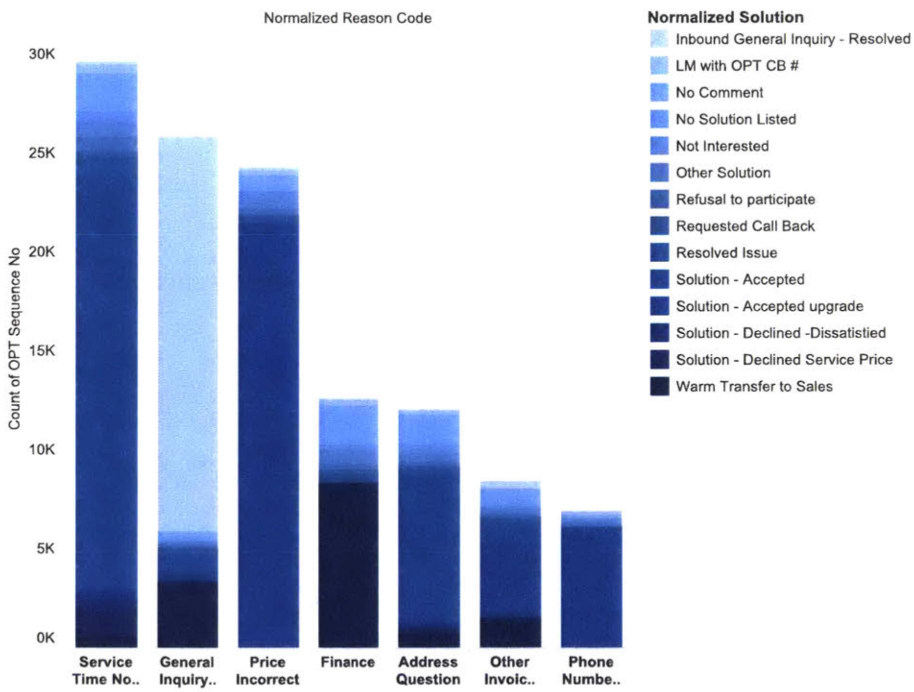


Figure 6. Solution Code Distribution by Top Reason Codes

Next we studied the seasonality of call volume by month. The data revealed that Sunday, Saturday, and Friday had the lowest call volumes while the days with the largest number of incoming calls were Monday, Tuesday and Wednesday. Additionally, we noticed a dip in total call density in the months of December and July.

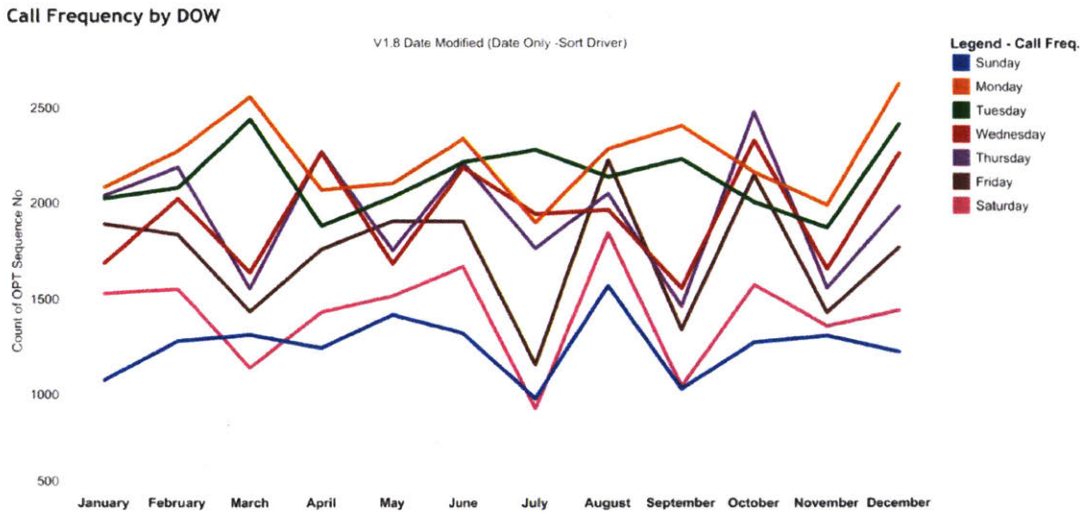


Figure 7. Call Frequency by Day of Week and Month

When studying the distribution of calls, we learned that the highest call count on any Sunday for the calendar year was 1500, nearly 40% lower than the maximum number of inbound calls on Monday.

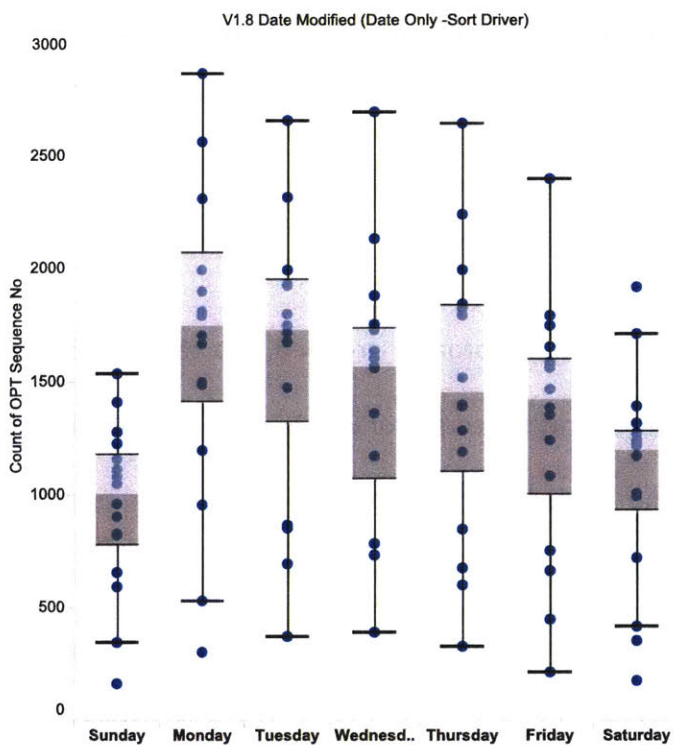


Figure 8. Box Plot of Call Frequency by Day of Week

The top three issue codes were "Service Time Not Available", "General Inquiry", and "Incorrect Price." Further analysis on these variables revealed that the majority of calls occurred in the afternoon between 2:30 PM and 5:00 PM. Additionally, we see that the total time on call revealed a more normally distributed dataset with a peak at the middle of day.

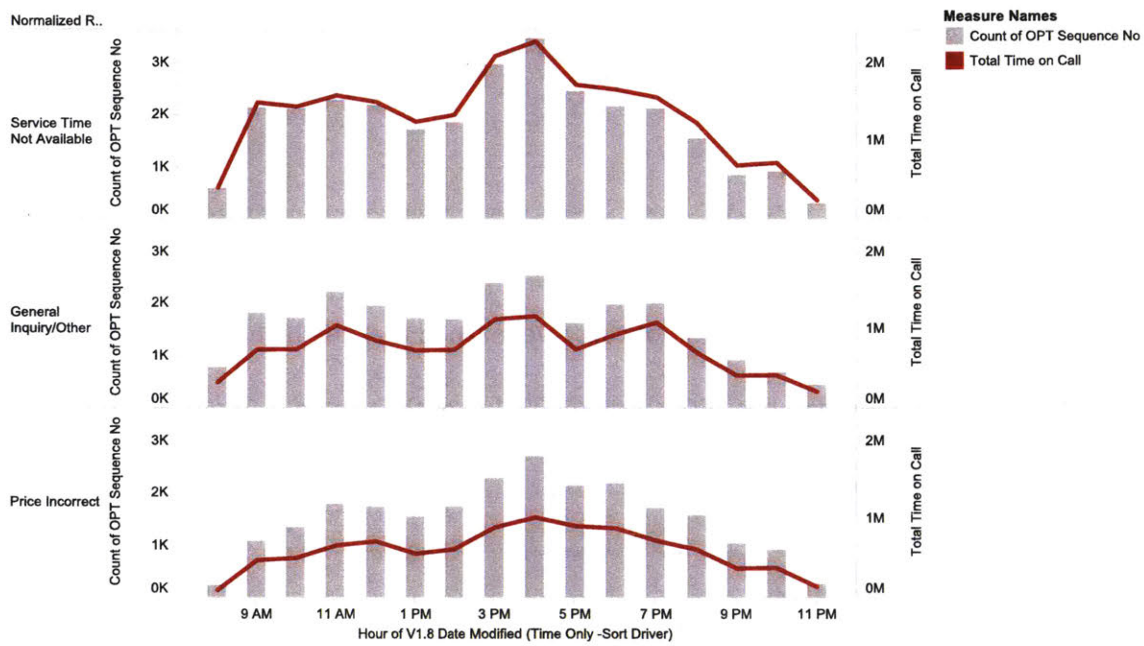


Figure 9. Call Time Distribution by Hour and Reason Code

For more aggregate details on the demand data, please refer to Appendix A.

4.2. Customer Segmentation Results

AlarmCo customers can be broadly grouped into two categories: business clients and homeowner clients. Homeowners account for 81% of sales while the business clients account for the remaining 19%. The homeowner category can be further broken down to platinum or premium customers accounting for 15% of customers, silver customers (average package holders) accounting for 58% of customers and finally, basic package holders, accounting for the remaining 27%. Total sales and customer count can be found in the following figure.

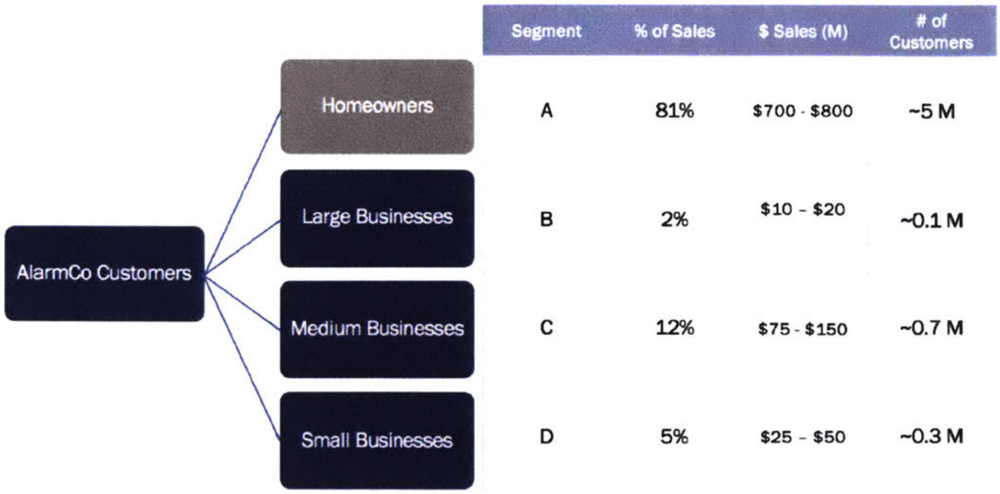
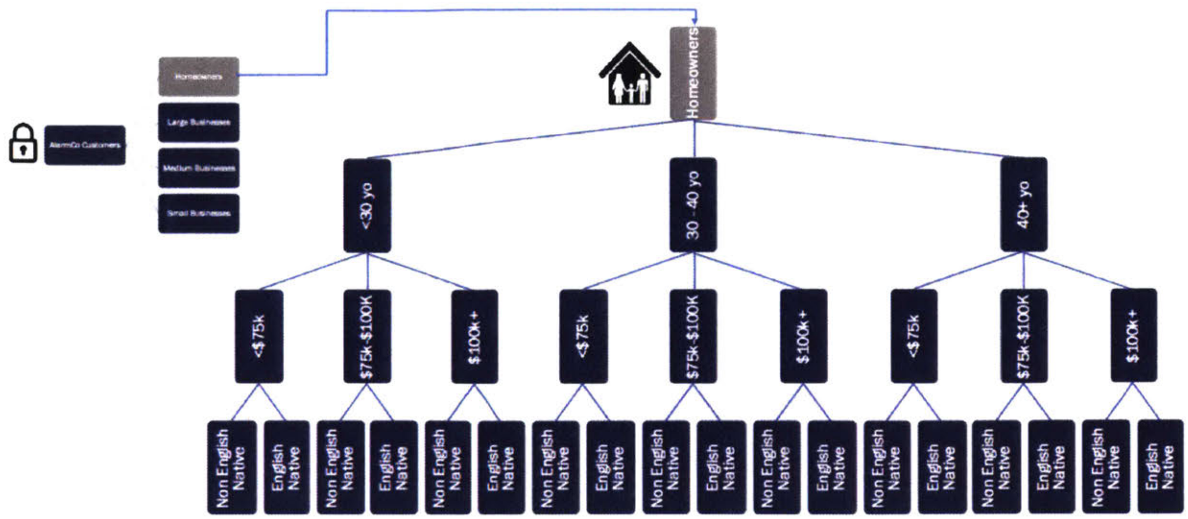


Figure 10. High Level Customer Segmentation

4.2.1. Customer Demographics Segmentation Results

Using homeowners as the target customer category, the team narrowed the demographic segmentation to three key characteristics that defined any one customer. These characteristics included age, income bracket, and English proficiency. Given there were three age groups, three income brackets, and a binary value for language proficiency, homeowners were tagged as one of eighteen categories (A1-A18). This segmentation served as a valuable reference point to build preemptive solutions that were more specifically catered to each receiving party or segment.



Category:	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18
# of Cust (k):	6.2	8.2	8.8	9.0	1.4	3.0	2.2	8.2	9.0	16.1	10.9	27.5	0.2	4.1	2.1	9.2	1.5	18.1
% of Cust:	4%	6%	6%	6%	1%	2%	2%	6%	6%	11%	7%	19%	0%	3%	1%	6%	1%	12%

Figure 11. ABC Detailed Segmentation (Category A)

4.2.2. Customer Segmentation and Top Reason Codes Mapping Results

After analyzing the most common historical solutions provided to customers who called for "general inquiries", we developed a preemptive framework per the narrowed scope of our previously defined segmentation. Here, we assumed that a younger, abler demographic will be more prone to accept a proactive upgrade and access a mobile FAQ before calling a customer representative. Similarly, we hypothesized that an older demographic (>40 years old) will require an approach similar to proactive outreach or an FAQ via desktop.

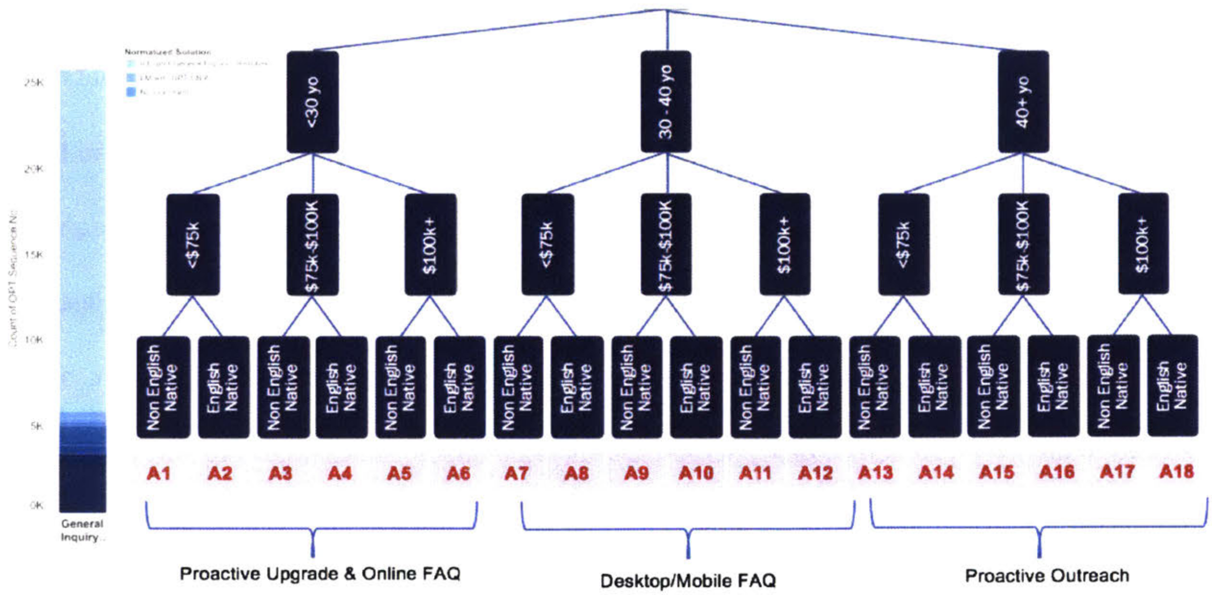


Figure 12. Sample Segmentation for Issue: General Inquiry (GI), Solution: GI Resolved

4.3. Queue Simulation

In order to quantify the impact of preemptive solutions to the as-is call center system, a thorough understanding of the call center performance was mandatory. The team decided to examine the as-is customer queue of a sample call center by selecting a representative queuing model and using the model to examine the queue quantitatively. The data analysis presented in this section has three key steps: select a representative queuing model, validate the queuing model, and understand the as-is queue.

4.3.1. Queuing Model Selection

As discussed in methodology section 3.4.1, a parallel server queue has the following notation: A/B/c/N/K where *"A"* represents the interarrival time distribution, *"B"* represents the service time distribution, *"c"* represents the number of parallel servers, *"N"* represents the system capacity, and *"K"* represents the size of the calling population.

In other words, these five variables together define a queuing model. They all serve as inputs to a queuing model which then generate KPIs for a particular queue as the outputs. This section discusses the analysis of each input and output variable. All of AlarmCo's inbound traffic fell into one general queue. The queue discipline was first-in-first-out (FIFO) which means the customers were being served in the sequence of their call in order. If a customer called, the individual waited in the general queue for the next available representative, unless he or she decided to drop the call before being served. During 8:00 AM to 12:00 AM, there was no capacity limit of the queue. No matter how many customers were waiting in line, as long as they decided to stay and wait for the next representative, their call would stay in the queue and the new calls would be added. This meant the system capacity, N, was infinite. There was no limitation on the calling population either. All inbound calls automatically join into the general queue. Therefore, the size of the calling population, K, was infinite as well. For the purposes of this research, we assumed that there was no major difference between the productivity of each call agent. We set the number of parallel servers, c, equal to the number of call agents staffed at a given time.

The interarrival time of any inbound call is the difference between the arrival time of one call and the previous one. For AICC inbound traffic, all calls arrived independently, meaning the arrival time of one customer call had no relationship with any previous calls or the current state of the system. A different way of interpreting interarrival time is to use interarrival rate. Interarrival rate is the number of incoming calls during a given time interval. In the resource plan dataset received, the time interval was defined per hour, which was the base time unit for all future calculations. The service time was defined as the handling time (the time spent on the call serving the customer) plus the wrap-up time (the time spent after the call to close the case).

Similar to the interarrival time, the service time of each call was independent. Service rate is defined the number of customers served during a given time interval (per hour).

The team decided to approximate the interarrival rate and service rate as a Poisson distribution with parameter (λ), the average number of arrivals or served customers during a particular time interval. There were three reasons for this assumption. First, a Poisson input implied that the interarrival time and service time should be independent, which was the case for the AICC inbound traffic. Second, as discussed in section 2.2.1, a Poisson distributed input is widely used in simple queuing models. Last, as stated in the same section, the Poisson distribution is an extremely robust distribution and could be used to approximate closely a large number of arrival and breakdown patterns in practice. For notation purposes, all Poisson inputs were represented as *M* (Markovian process.)

Per the preliminary analysis, the five input variables analyzed are summarized below:

#	Final Input Variables	Input Characteristics	Final Notation	Units
1	Interarrival rate	Poisson distribution	M	#/hr
2	Service rate	Poisson distribution	M	#/hr
3	Number of parallel servers	Same productivity for all agents	n	#
4	System capacity	Infinite (Ignored)	N/A	N/A
5	Calling population	Infinite (Ignored)	N/A	N/A

Table 4. Input Variables Preliminary Analysis

Output of the queuing model could be summarized as follows:

#	Final Output Variables	Notation	Units
1	Mean wait time in the queue	W_q	Seconds
2	Mean queue length	L_q	# of people

Table 5. Output Variables Preliminary Analysis

Therefore, following the aforementioned parallel server queuing model notation, the team decided to use the M/M/n queuing model to simulate the inbound customer call of AlarmCo.

4.3.2. Queuing Model Validation

In order to make sure the selected model, M/M/n, is representative of the AICC, the team extracted the empirical inputs and outputs from the customer queue data, and compared the theoretical outputs with the empirical data. If the difference fell within the 10% validity threshold, it could be concluded that the M/M/n model accurately emulates AlarmCo's sample call center inbound customer call queue.

AlarmCo gave the team different data points for 152,552 individual inbound calls. The queue specific data which contained all the input and output variables was organized by sixteen business hours a day and seven days a week. The data included average interarrival rate, average service rate and number of parallel agents for each business hour of a day, as well as corresponding average queue length and average wait time. By taking the average value per hour, the team not only developed representative values, but also made sure that the data was not overly generalized. Since there were sixteen business hours a day and seven days a week, the total lines of data which needed to run against the model were 112. Each line of data generated two output variables, therefore, 112 * 2 = 224 output variables were validated.

A sample validation table for Monday is presented in Table 6 below. For the comprehensive calculation for the remaining days, please refer to Appendix B.

Monday	Input Variables			Output Variables				Validation		Agents
	M	M	n	Theoretical KPI Outputs Generated from M/M/n model		Empirical data for AlarmCo's inbound customer call queue		Error		
Business Hours	Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Error for Lq (# of people)	Error % for Wq	Agents Efficiency
8:00 AM	10	7.79	4	0.0217	8.3485	0	8	0.02	4%	26%
9:00 AM	33	6.86	9	0.0756	8.2473	0	8	0.08	3%	40%
10:00 AM	27	5.85	9	0.0556	7.4133	0	7	0.06	6%	43%
11:00 AM	33	6.99	9	0.0658	7.1756	0	7	0.07	3%	46%
12:00 PM	37	6.99	10	0.0567	5.5205	0	6	0.06	-8%	44%
1:00 PM	27	6.62	8	0.0676	9.0096	0	9	0.07	0%	45%
2:00 PM	31	7.07	9	0.0379	4.4059	0	4	0.04	10%	39%
3:00 PM	48	5.83	14	0.0690	5.1736	0	5	0.07	3%	51%
4:00 PM	53	6.47	14	0.0657	4.4640	0	4	0.07	12%	50%
5:00 PM	42	6.47	11	0.1136	9.7339	0	10	0.11	-3%	45%
6:00 PM	43	5.75	13	0.0658	5.5049	0	5	0.07	10%	47%
7:00 PM	35	5.65	11	0.0770	7.9250	0	8	0.08	-1%	49%
8:00 PM	31	5.77	10	0.0638	7.4099	0	7	0.06	6%	45%
9:00 PM	22	6.03	8	0.0311	5.0900	0	5	0.03	2%	33%
10:00 PM	18	5.83	7	0.0340	6.7997	0	7	0.03	-3%	38%
11:00 PM	6	6.69	3	0.0296	17.7620	0	18	0.03	-1%	20%

Table 6. Validation Table for Monday

This table shows the validation data for Monday, a day with characteristic inbound traffic. Input variables calculated from the inbound traffic were presented for each business hour. The theoretical outputs were retrieved by running the queuing model, and the empirical data was retrieved from the dataset provided by AlarmCo. As shown in the Error columns, the output variable differential between theoretical and empirical data was within 10% validity levels except for one instance highlighted in yellow. In addition, based on the agent efficiency data given by AlarmCo, the agents had been idling for more than half of the time in any given hour. Since their efficiency was low, there were close to no callers waiting in line on average for any given hour. Therefore, we could safely disregard the comparison of the average queue length. Out of the 112 data points of average wait time validated, only four data points had an error percentage slightly over 10%. Therefore, we believe it was safe to state that the M/M/n model was representative of the inbound customer call queue of AlarmCo's call center.

4.4. Preemptive Solution Framework

AlarmCo's aim is to provide the right answer to the right customer and the right agent at the right time. With the use of predictive analytics, AlarmCo can implement proactive solutions that provide these answers immediately, often without the need for customer inbound calls. The team developed twenty potential preemptive solutions that fall within five categories. The five categories are automated remote service, education, online resources, telephonic services, and proactive analyses. Examples of each solution as well as the advantages and disadvantages of pursuing each solution can be found in the Appendix C.

4.4.1 Top Preemptive Solutions

The first solution that falls under "Automated Remote Services" is providing "Proactive Upgrades" to the customer. In this case, the client tracks machine signals and estimates when a security device needs to be upgraded. By tracking machine signals, alarm systems can be upgraded remotely before service is terminated, avoiding poor customer experience and unwanted churn. The second solution within this category is "Remote Device Resets." Similarly, if a machine is sending a failure signal to the client, remote action can fix the issue without customer intervention. Failure analysis indicates that 10% - 30% of returned materials are No-Trouble-Found (NTF) returns which means no actual issue was detected with the device. This means that the perceived issue could have been resolved without returning the equipment. The final solution in this category is "Automatic dispatch of parts and components." Often, alarm systems require a small update or need to be completely replaced. In either case, a signal from the machine can trigger an automatic dispatch of an alarm system or a specific component. Additionally, instead of shipping same-day replacement parts in response to a critical product malfunction, the client can send parts via two-day delivery before the malfunction and ensure your customers security system is not impacted by problems with the alarm system.

The second category of solutions is "Education." Different solutions proposed here include mailed brochures, video tutorials, self-install kits, and email FAQs. Using these avenues, AlarmCo can connect directly with the customer hassle free. Customers can be educated on how to fix or reset machines and be given details on eligibility, new products, and upgrade options. Within the kit, AlarmCo can enclose a manual, replacement parts, basic tools and also use this as a channel to market other products and services. There are five solutions that fall under the "Online Resources" category of preemptive solutions. The first solution in this category is the option of adding a detailed Frequently Asked Questions (FAQ) page to the AlarmCo website. Here, the client will be able to include answers to questions associated with most general inquiries. Other options to improve the online presence of AlarmCo as well as improve the customer experience is including live or automated web chats and video chats.

Regarding minimizing current call times, the client has many options in terms of improving telephonic assistance. AlarmCo already has a successful mobile application though it is missing an alert functionality when an alarm system needs an upgrade or reset. AlarmCo can also look to outsource labor to third party call centers during high traffic periods. On the other hand, the client can explore the option of advancing its Interactive Voice Response (IVR) services. IVR is a technology that allows humans to communicate with a computer with use of voice and dual tone multi-frequency signaling (DTMF) tones using the phone key pad. IVR can utilize both key pad numbers or speech recognition.

The final category of preemptive solutions is "Proactive Analysis." AlarmCo can look to invest more heavily in its Search Engine Optimization (SEO) and Search Engine Marketing (SEM) campaign with search providers such as Google, Bing and Yahoo. These campaigns could reissue keywords to direct customers to education related preemptive solutions before the customer is directed to the contact page on the AlarmCo website. Other solutions we explored in this category include better utilizing "machine failures" to forecast when failures are most likely and customer call back after purchase to ensure no malfunctions up to five-days post purchase.

4.4.2. Feasibility Study

A risk and feasibility assessment was developed to create a hierarchy of most viable preemptive solutions. Each of these solutions were assigned a success rate based on external market research as well as a stakeholder scoring exercise. We then took a weighted average of all responses looking at three key factors: implementation cost, feasibility, and risk to AlarmCo. Each factor has a different weight based on feedback from subject matter experts in the security industry. We then ran a sensitivity analysis and calculated the success rate probabilities found in Table 7.

Weights:		0.2	0.5	0.3			
Preemptive Category	Response	Implementation Cost Rating	OPT Feasibility Rating	Risk Assessment	Weighted Avg (rating)	Weighted Average Score	% Success Rate
Automated Remote Service	Response 1	3.0	2.3	2.0	2.4	2.6	51%
	Response 2	3.0	2.3	2.0	2.4		
	Response 3	2.0	2.3	3.0	2.5		
	Response 4	2.7	3.3	2.7	3.0		
Education	Response 1	4.6	1.0	1.2	1.8	2.7	53%
	Response 2	3.8	3.8	1.2	3.0		
	Response 3	3.6	3.2	2.2	3.0		
	Response 4	2.4	3.0	3.0	2.9		
Online Resource	Response 1	4.0	2.4	2.0	2.6	2.7	55%
	Response 2	3.2	3.8	1.6	3.0		
	Response 3	2.4	3.0	2.0	2.6		
	Response 4	3.0	3.0	2.2	2.8		
Proactive Analysis	Response 1	4.8	1.3	1.0	1.9	2.3	47%
	Response 2	3.5	3.3	1.3	2.7		
	Response 3	2.8	2.8	2.3	2.6		
	Response 4	2.8	2.3	1.8	2.2		
Telephonic Assistance	Response 1	3.0	2.0	2.0	2.2	2.8	56%
	Response 2	4.0	3.0	1.3	2.7		
	Response 3	2.7	3.7	2.7	3.2		
	Response 4	3.3	3.0	3.3	3.2		

Table 7. Success Rate Matrix

While an overall reduction of a total of 45% (35% + 10%) seems favorable, realizing this upper limit reduction is unlikely and would require significant switching and operating costs for AlarmCo. The team then looked to implement the most effective solutions while still recouping a majority of the wait time reductions. Using this conservative approach, we developed a hybrid model, using twelve preemptive solutions and achieving an overall wait time reduction of 35% when compared to the "as-is" model. The final preemptive solutions chosen can be found below:

#	Preemptive Category	Solution
1	Automated Remote Service	Proactive Upgrade
2	Automated Remote Service	Remote Device Reset
3	Automated Remote Service	Automatic Dispatch Parts/Components
4	Education	Send Brochure
5	Education	Video Tutorial
6	Education	Customer Call
7	Education	Email Tutorial
8	Education	Self-Install Kit
9	Online Resource	Frequently Asked Questions (FAQ)
10	Telephonic Assistance	Interactive Voice Response (IVR)
11	Proactive Analysis	Invest in SEO/SEM resources
12	Proactive Analysis	Additional Customer Service Metrics

Table 8. Selected Preemptive Solutions

4.5. Solution Impact and Scenario Analysis

4.5.1 Impact on the "As-is" Model

The main goal of implementing these preemptive solutions was to reduce the number of inbound calls of the call center. This section quantitatively shows the major impacts on the as-is model if all aforementioned twelve preemptive solutions were to be implemented in unison. In addition to wait time reduction, the team also calculated an average decrease of 6% in call avoidance with an average decrease of 3% in agent efficiency, assuming no resource was reallocated.

4.5.1.1. Inbound call avoidance

As explained the in previous section, the preemptive solutions aim to reduce the number of inbound calls. The hourly reduction percentage for each day of the week is summarized in the table below:

	Total Inbound Call Reduction Percentage For Each Business Hour						
Hour	Sunday	Monday	Tuesday	Wednesda	Thursday	Friday	Saturday
8.00	5.09%	6.35%	5.03%	6.46%	5.96%	6.06%	4.63%
9.00	5.74%	6.18%	6.92%	6.56%	6.34%	6.35%	6.71%
10.00	5.69%	6.36%	5.95%	6.99%	6.22%	6.13%	6.16%
11.00	5.83%	5.81%	6.05%	6.50%	5.76%	5.76%	6.12%
12.00	5.95%	5.54%	5.48%	6.14%	6.73%	5.99%	5.32%
13.00	5.46%	6.05%	6.59%	5.63%	6.46%	5.11%	5.46%
14.00	6.52%	6.13%	5.60%	6.77%	6.06%	5.46%	5.52%
15.00	5.91%	6.58%	6.28%	5.93%	6.09%	6.45%	5.35%
16.00	6.07%	6.53%	6.25%	6.08%	6.69%	5.53%	5.64%
17.00	6.50%	6.52%	6.00%	5.89%	6.27%	5.48%	6.32%
18.00	5.87%	5.66%	5.83%	5.96%	5.61%	6.30%	6.40%
19.00	5.58%	6.34%	6.34%	6.53%	6.25%	6.25%	6.14%
20.00	6.49%	5.74%	5.63%	5.54%	5.77%	6.00%	7.21%
21.00	5.09%	5.86%	5.49%	6.91%	5.69%	5.21%	5.80%
22.00	5.33%	5.43%	5.24%	5.85%	4.88%	5.13%	5.94%
23.00	7.56%	4.97%	5.79%	5.55%	4.60%	5.64%	7.07%
Average	5.92%	6.00%	5.90%	6.21%	5.96%	5.80%	5.99%

Table 9. Total Inbound Call Reduction Percentage for Each Business Hour

Following the reduction percentage above, every week the preemptive solutions would reduce around 169 inbound calls per the following equation.

$$Call\ reduction\ number = Orginal\ number\ of\ calls * (1 - Reduction\ Percentage)$$

Equation 2. Call Reduction Equation

Assuming fifty-two weeks per year, throughout a year, this system would help reduce around 8789 inbound calls annually.

	Daily Total Number of Calls		Daily Improvement Rate		Yearly Saving
	Before #	**After #**	**#**	**(%)**	**#**
Sunday	279.00	262.56	16.44	5.89%	855.03
Monday	496.00	465.75	30.25	6.10%	1572.75
Tuesday	474.00	445.55	28.45	6.00%	1479.18
Wednesd	428.00	401.35	26.65	6.23%	1385.83
Thursday	431.00	404.58	26.42	6.13%	1373.78
Friday	383.00	360.60	22.40	5.85%	1164.79
Saturday	310.00	291.58	18.42	5.94%	957.87
Total	2801.00	2631.98	169.02	[Avg] 6.03%	8789.23

Table 10. Total Number of Inbound Calls Reduced per Year

4.5.1.2. Average Wait Time Reduction

This inbound call avoidance effect had a direct impact on the queue because it reduced the average interarrival rate, an input to the queue. After updating the queuing model with the new interarrival rate, there was significant improvement in average wait time of the queue compared to original data generated by the model without the impact of preemptive solutions. Note that the average queue length would also be improved. However, due to the small original queue length (less than 1), the improvement of the queue length will not be the focus of this discussion. For the comprehensive comparison calculation, please refer to Appendix D.

Monday	Input Variables			Output Variables				Improvement	
	M	M	n	Original Theoretical KPI Outputs Generated from M/M/n model		New Theoretical KPI Outputs Generated from M/M/n model		Improvement after Implementing Preemptive Solutions	
Business Hours	Updated Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)
8:00 AM	9.36	7.79	4	0.0217	8.3485	0.0160	6.1436	-26%	-26%
9:00 AM	30.96	6.86	9	0.0756	8.2473	0.0574	6.6693	-24%	-19%
10:00 AM	25.28	5.85	9	0.0556	7.4133	0.0340	4.8451	-39%	-35%
11:00 AM	31.08	6.99	9	0.0658	7.1756	0.0421	4.8775	-36%	-32%
12:00 PM	34.95	6.99	10	0.0567	5.5205	0.0361	3.7190	-36%	-33%
1:00 PM	25.37	6.62	8	0.0676	9.0096	0.0438	6.2213	-35%	-31%
2:00 PM	29.10	7.07	9	0.0379	4.4059	0.0236	2.9187	-38%	-34%
3:00 PM	44.84	5.83	14	0.0690	5.1736	0.0358	2.8748	-48%	-44%
4:00 PM	49.54	6.47	14	0.0657	4.4640	0.0343	2.4912	-48%	-44%
5:00 PM	39.26	6.47	11	0.1136	9.7339	0.0649	5.9496	-43%	-39%
6:00 PM	40.57	5.75	13	0.0658	5.5049	0.0385	3.4127	-42%	-38%
7:00 PM	32.78	5.65	11	0.0770	7.9250	0.0446	4.8980	-42%	-38%
8:00 PM	29.22	5.77	10	0.0638	7.4099	0.0400	4.9229	-37%	-34%
9:00 PM	20.71	6.03	8	0.0311	5.0900	0.0203	3.5373	-35%	-31%
10:00 PM	17.02	5.83	7	0.0340	6.7997	0.0237	5.0056	-30%	-26%
11:00 PM	5.70	6.69	3	0.0296	17.7620	0.0242	15.2901	-18%	-14%
Total	465.75						Average	-36%	-32%

Table 11. Sample Calculation on the KPI Improvement of the Queue On Monday

Based on the updated hourly number of inbound calls and the updated average wait time per call during that hour, the updated daily total wait time was calculated by getting the product-sum of these two variables, the equation can be found below (*Wait Time = WT*).

$$NEW\ Daily\ Total\ WT = Sum((NEW\ Hourly\ \#\ of\ IB\ Calls) * (NEW\ Avg\ WT\ per\ Call))$$

Equation 3. Formula to Calculate New Daily Total Wait Time

Further analysis revealed that after implementing the selected preemptive solution, in this scenario, the average wait time would be reduced by 35.67% weekly. Assuming fifty-two weeks per year, the preemptive solutions would save 109.42 hours of wait time for all customers.

	Daily Total Wait Time		Daily Improvement Rate		Yearly Saving
	Before	After (min)	(min)	(%)	(hr)
Sunday	41.59	29.01	12.58	30.24%	10.90
Monday	55.92	34.75	21.17	37.85%	18.34
Tuesday	68.67	43.33	25.35	36.91%	21.97
Wednesd	49.68	31.18	18.50	37.24%	16.03
Thursday	48.71	30.04	18.67	38.33%	16.18
Friday	49.40	32.31	17.09	34.59%	14.81
Saturday	39.92	27.02	12.90	32.31%	11.18
Total	353.90	227.65	126.25	[Avg] 35.67%	109.42

Table 12. Summary of the Reduction in Wait time

4.5.1.3. Agent Efficiency Decrease

Although the queue system could be improved with fewer inbound calls and shorter wait time, we calculated that agents would have up to 3% reduction in their efficiency. This was calculated based on the assumption that the call center would keep the same agent staffing plan.

Agent Efficiency	Sunday		Monday		Tuesday		Wednesday		Thursday		Friday		Saturday	
Business Hours	Old Efficiency	New Efficiency	Old Efficiency	New Efficiency	Old Efficiency	New Efficiency	Old Efficiency	New Efficiency	Old Efficiency	New Efficiency	Old Efficiency	New Efficiency	Old Efficiency	New Efficiency
8:00 AM	26%	24%	32%	30%	38%	36%	33%	31%	32%	30%	26%	24%	25%	24%
9:00 AM	40%	38%	53%	50%	52%	48%	48%	45%	48%	45%	48%	45%	42%	39%
10:00 AM	43%	40%	51%	48%	51%	48%	53%	49%	45%	42%	46%	43%	40%	37%
11:00 AM	46%	43%	52%	49%	51%	48%	52%	49%	52%	49%	51%	48%	44%	42%
12:00 PM	44%	41%	53%	50%	56%	53%	53%	49%	55%	51%	53%	49%	49%	47%
1:00 PM	45%	42%	51%	48%	52%	49%	48%	45%	49%	46%	48%	46%	48%	45%
2:00 PM	39%	37%	49%	46%	55%	52%	47%	43%	49%	46%	51%	48%	44%	42%
3:00 PM	51%	48%	59%	55%	60%	56%	56%	52%	59%	55%	55%	52%	54%	51%
4:00 PM	50%	47%	58%	55%	58%	55%	60%	57%	58%	54%	58%	55%	53%	50%
5:00 PM	45%	42%	59%	55%	56%	52%	52%	49%	57%	54%	52%	49%	52%	49%
6:00 PM	47%	45%	58%	54%	59%	56%	51%	48%	54%	51%	52%	49%	46%	43%
7:00 PM	49%	46%	56%	53%	57%	53%	52%	48%	54%	51%	50%	47%	47%	44%
8:00 PM	45%	42%	54%	51%	52%	49%	47%	44%	45%	43%	46%	43%	43%	40%
9:00 PM	33%	31%	46%	43%	47%	45%	45%	42%	38%	36%	38%	36%	43%	40%
10:00 PM	38%	36%	44%	42%	47%	45%	41%	38%	39%	37%	39%	37%	31%	29%
11:00 PM	20%	19%	30%	28%	28%	26%	33%	31%	25%	24%	18%	17%	18%	17%
Average	41%	39%	50%	47%	51%	48%	48%	45%	47%	45%	46%	43%	42%	40%
Reduction		2%		3%		3%		3%		3%		3%		3%

Table 13. Summary of the Reduction in Agent Efficiency Level per Day

4.5.2. Solution Scenario Analysis

After calculating different success rates for each of the twenty preemptive solutions, we applied a weighted average percent reduction of interarrival rate for each day and hour. With these new and improved interarrival rates, the team was able to rerun the queuing simulation and compare three different scenarios: implementing no preemptive solutions (as-is state), implementing the most favorable (twelve) preemptive solutions, and finally, implementing all twenty solutions (cherry pick). After updating the queuing model interarrival rates, we see that wait times steadily decrease with implementation of each scenario. If AlarmCo implements all twenty solutions per the cherry pick scenario (best case), average wait times reduce from 6.88 seconds to 4.03 seconds in the morning, 7.74 seconds to 4.53 seconds in the afternoon, and 8.84 seconds to 5.17 seconds in the evening. If the client conservatively moves forward with twelve of the twenty solutions, average wait times reduce from 6.88 seconds to 4.47 seconds in the morning, 7.74 seconds to 5.03 seconds in the afternoon, and 8.84 seconds to 5.74 seconds in the evening.

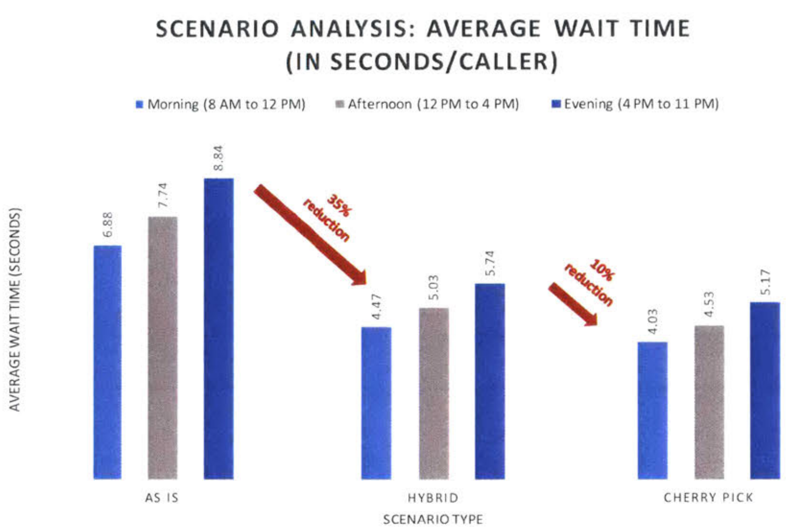


Figure 13. Scenario Analysis of Wait Time Reduction

5. DISCUSSION

After developing the segmentation methodology and queuing model in the previous sections, we analyzed how preemptive solutions impact the queuing model in terms of changes to average wait time, queue length and potential savings in labor hours. In the following section, we lay out the insights of our segment and issue code analysis, assess impact of preemptive solutions to our queuing model, and conduct a scenario analysis to develop the best combination of solutions for AlarmCo to pursue.

5.1. Issue Code and Demographic Analysis Insights

While ABC segmentation is generally performed on the basis of financial measure, customer service for AlarmCo is measured by other units including wait time, service time, and customer satisfaction level. Our approach was to first understand the overall sales of four types of customers: homeowners, large businesses, medium sized businesses, and small sized businesses. Our analysis of demographics data allowed us to further segment our core customer group, homeowners. Stakeholder alignment and appropriately distributed aggregate call volumes were key in developing the best suited sub-segments. Call data revealed interesting insights on which issue codes to tackle first. Additionally, the team was able to locate and correct many anomalies in the data with this preliminary analysis. The most critical learnings that came from this section were understanding the current state of the call center queue, learning that customer traffic is higher in the middle of the day, middle of the week but relatively cyclical throughout the year. Lastly, the call and demographic data allowed the team to develop accurate inputs and create a representative model of the call center queue. To ensure viability, we made sure to use conservative ranges when updating these input variables. While the data was manipulated to maintain confidentiality, we found wait times, queue lengths, and agent-customer interactions were emulated accurately by the queuing model.

5.2. Queuing Result Insights

There are three major insights that can be drawn from the process of applying queuing theory in this research:

- Poisson distribution is a robust model for a general queuing model
- Small changes in the number of inbound calls can have a large effect on the queue
- Tradeoffs have to be made between the service level and resources

Through the queuing model selection process, we found the Poisson distribution was indeed a very robust model. In order to select the queuing model, the team had to decide on the distribution for both interarrival rate and service rate. The distribution diagram of these two rates are presented below. Based on the data, it was not certain if Poisson would be representative for the distribution in the model. However, through the selection and validation process of the queuing model, it was proven that Poisson distribution was representative.

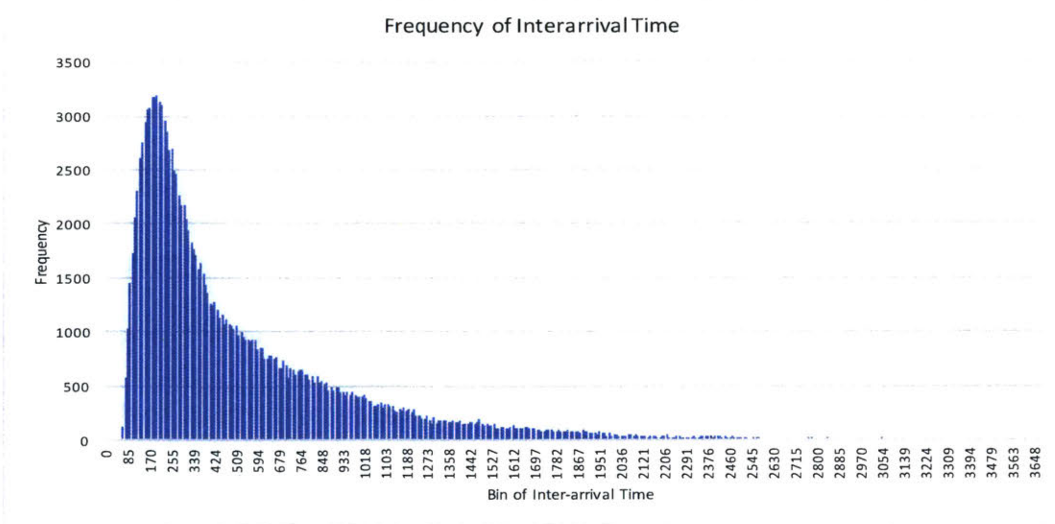


Figure 14. Frequency of Interarrival Time

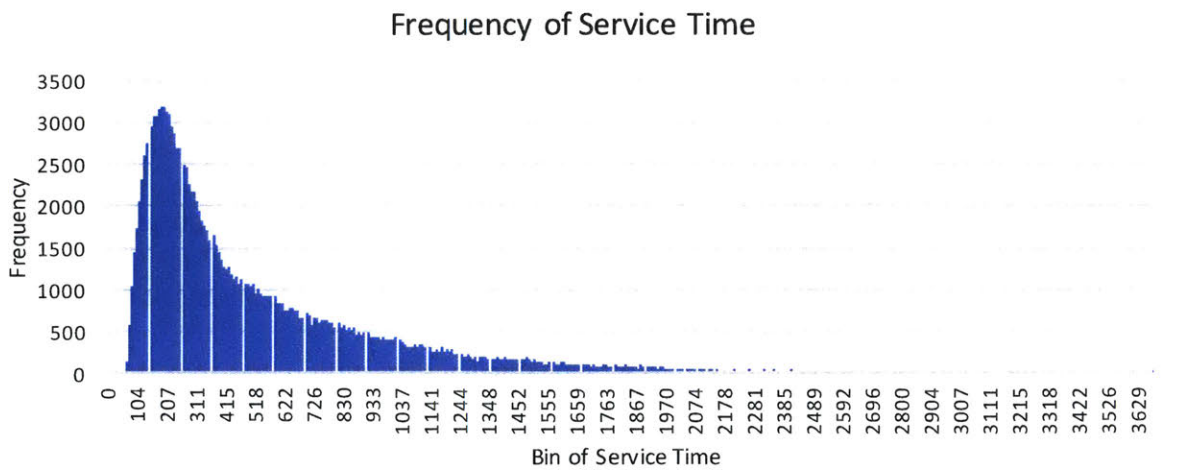


Figure 15. Frequency of Service Time

The second insight drawn from the impact of preemptive solutions to the as-is system is that small call avoidance can result in a large queue service level improvement. Based on the conservative calculation, implementing the twelve preemptive solutions would reduce the number of hourly inbound call by around 6% in general. However, this minimal 6% could result in an around 35% reduction in wait time and queue length. This means if a company implements effective preemptive solutions, the return on investment could be substantial in terms of the queue KPIs.

The last major insight is related to the resource allocation plan. As shown in the result section 4.4.3.3, if the number of call agents are kept constant, implementing preemptive solutions would reduce the working efficiency of each agent. Decreasing agent efficiency means more idle-time, which could be translated to either a reallocation of labor or a monetary loss depending on the wage rate of the agent. This tradeoff leaves the company leaves two questions: would the company spend the money to achieve a better service level, or would they rather reallocate the agents to some other tasks to make full use of the resources?

5.3. Scenario Model and Expectations

Our chosen hybrid model is a conservative and feasible approach in implementing preemptive solutions with the goal of minimizing inbound calls and reducing average wait time. The twelve solutions, though scattered across all five preemptive solution categories, have strong support from stakeholders and according to our research, have worked successfully with other players in the home alarm securities market. Our original expectation was that the cherry pick scenario would lead to a much larger incremental wait time reduction. However, after analyzing the feasibility scoring of the various AlarmCo stakeholders, we found that certain solutions such as outsourcing and live chats are preferred less due to high switching costs and additional labor requirements. Another expectation the team had was a significant improvement in agent efficiency. However, in the "as-is" case, agents are already being underutilized and instead have significant idle time on service center floor. We found that more beneficial impact our analysis can make is to improve the customer experience by minimizing wait time and call avoidance, with a reduced focus on agent utilization enhancements.

5.4. Risks and Special Considerations

When studying the preemptive solutions to pursue per the results of our segmentation and ranking system, it is important to consider the potential pitfalls of each solution. The first category of preemptive solutions, Automated Remote Services, will be tracked by machine signal data. The total actual failure rate for the ~145,000 customer security systems is 1.9%. In other words, a total of 2760 customers experienced a malfunction with their alarm systems, which accounts for 1.9% of all customers. To test the accuracy of machine data, we studied the prevalence of failures in a machine signaling AlarmCo that a reboot or replacement is required for a customer alarm system. A failure is defined as machine signal giving a false positive (signaling a malfunction when there was no malfunction) or a false negative (signaling no malfunction when there was an error.) The figure below gives the detailed breakdown of machine signal failures.

Alarm Signal to AlarmCo

Alarm Performance	Failure Signal	No Failure Signal	Grand Total
Actual Failure	130,088 *(89.28%)*	12,861 *(8.83%)*	142,949 *(98.11%)*
No Failure	224 *(0.15%)*	2,536 *(1.74%)*	2,760 *(1.89%)*
Grand Total	130,312 *(89.43%)*	15,397 *(10.57%)*	145,709 *(100%)*

Signal Failure

Figure 16. Machine Failure Prevalence

Another factor to consider is the variance in cost of implementation. For example, if the team decides to implement a more involved web-based chat or IVR solution, integration requirements of the required decision tree will be complex and difficult to quantify in terms of cost. Also, we have not considered integration costs of building a uniformed platform which may impact customer experience and trigger unnecessary dispatches.

Another risk we discovered in our research is in the use of ABC segmentation. Customers can move from one segment to another with a change in age, income and ability to speak English fluently, thus, customer segments are not fixed. The sub-segments of class "A" customers must be routinely analyzed to determine if this class still consists of primary customers. This process requires a much more cyclical method of data measurement and collection. Additionally, while homeowners who fall in segment A consist of the majority of AlarmCo's customer base, it is important to not lose sight of constantly improving customer service of business clients who on a per customer basis, provide significant revenues to the client.

5.5. Generalization to Other Companies

While the home security industry is unique in terms of the critical need to resolve customer issues on first call, the direct learnings of this thesis can be applied to other companies who have similar customer service KPIs and queuing systems. Similar approaches can also be adopted when analyzing a company in a different industry. The table below summarizes the special considerations when rolling out the methodology to analyze other companies who are trying to improve the performance at call centers.

#	Methodology Steps	Consideration Specific to AlarmCo	General Consideration for Rolling Out
1	Scope Identification & Data Request	- Improvement in customer service was the main objective - Cost should not be a constraint	- Define main objective and constraints of the company
2	Preliminary Data Analysis	- The unique identifiers were important for data analysis	- Realize KPIs specific to the industry. i.e. seasonality, trends
3	Customer Segmentation	- Customer demographics data was important to the home security company	-Consider factors to segment the customer group
4	Queue Simulation	- the M/M/n model was representative for the empirical queue data	- Select queuing model which fits the empirical data
5	Preemptive Solution Development and Scenario Analysis	- Preemptive solutions were finalized as a joint effort of both the research team and the industry professionals	- Perform feasibility study through experienced groups in that industry
6	Solution Finalization & Discussion	- Insights, risks, and future steps should be discussed with all stakeholders	- Similar to the AlarmCo case

Table 14. Special Consideration When Applying the Methodology to a Different Company

Note that the data presented in this paper was sample representative data (due to the client's confidentiality constraint). Because the average queue length was smaller than one, this paper did not put emphasis on the improvement of the queue length. However, when applying a similar approach to other companies, depending on that company's customer queue data, it may be important to consider the impact on both average queue length and average wait time.

5.6. Future Steps

While our analysis is not exact, it does represent anticipated performance of proactive solutions to improve customer service for home security providers. This analysis can help AlarmCo develop expectations of the impact of these solutions and utilize them in different segments of its business. This information adds direction to AlarmCo's approach on providing top customer service and anticipating the immediate needs of its customers. AlarmCo should consider further investigation to validate the hypotheses presented in this paper. To do this, the company can consider performing a pilot test with customers calling for a less prevalent issue code. Additionally, AlarmCo can segment its customer base across another business unit and test preemptive solutions on a smaller, less risky segment.

Next, AlarmCo should consider other methods of reducing wait time for its customers calling the call center. For example, with access to the accurate data, AlarmCo can implement multivariate programming to minimize wait times for customers. The MIT team explored the option of utilizing this technique and built a simple linear programming model to optimize the queuing process. Total system wait time can be calculated as a function of number of agents, average service time by agent, and average number of calls managed per server. Constraints that we considered in this preliminary analysis included maximum agent capacity, minimum service time required to resolve a call, and time constraints in terms of agent labor hours. Of course, a multivariate model will need a multitude of nominal, categorical, and binary variables to build a robust model.

6. CONCLUSION

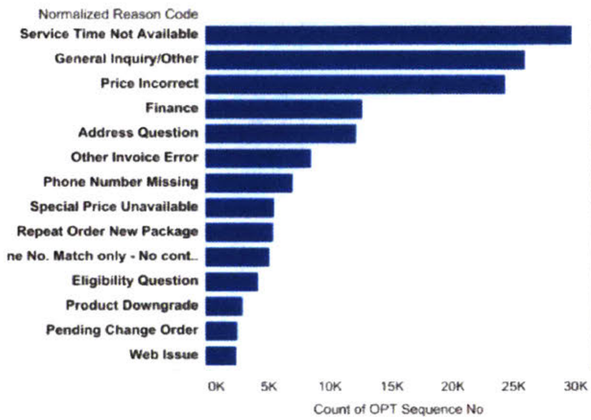
While the home security industry in the United States has seen vast change in the last decade in terms of technological innovation, security companies are still not able to fully utilize call center data to develop proactive solutions in place of reactive measures. In closing this gap, the team addressed the following question for AlarmCo: "How can we improve the customer service experience for customers of a major security service provider in the US?"

To understand the current call center system, the MIT thesis team simulated the queue of an AlarmCo call center by calculating interarrival rates, service time, and using the number of agents by hour and day of week. The team also strategically segmented the AlarmCo customer base and developed targeted preemptive solutions for prevalent segments. After adjusting the queuing inputs per the potential preemptive solutions, we were able to directly assess the quantifiable impact of introducing preemptive solutions to this industry.

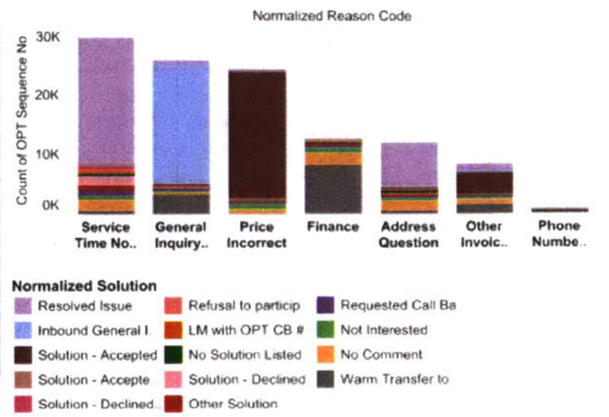
APPENDICES

Appendix A – Overall Summary of Demand Data

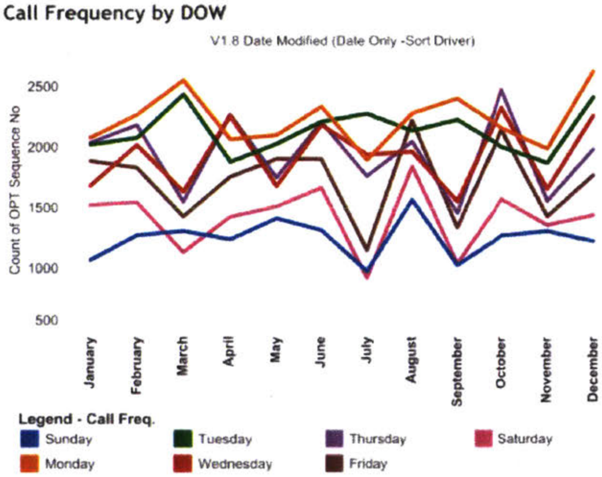
Reason Codes



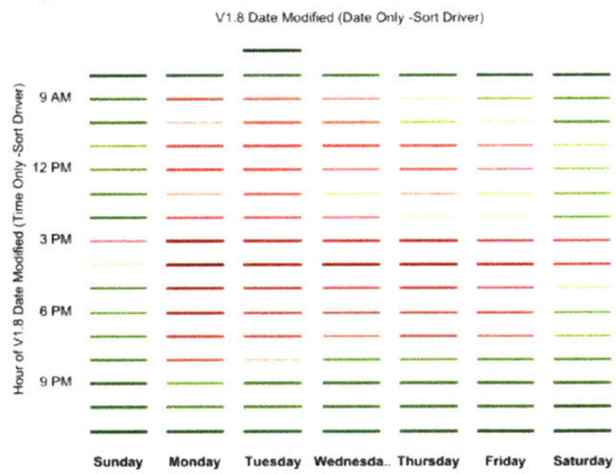
Reason and Solution Codes



Call Frequency by DOW



Daily Traffic



Appendix B – Calculations for Validating the M/M/n queuing model

Sunday:

Sunday	Input Variables			Output Variables				Validation		Agents
	M	M	n	Theoretical KPI Outputs Generated from M/M/n model		Empirical data for AlarmCo's inbound customer call queue		Error		
Business Hours	Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Error for Lq (# of people)	Error % for Wq	Agents Efficiency
8:00 AM	7	9.11	3	0.0162	8.3128	0	8	0.02	4%	26%
9:00 AM	15	7.44	5	0.0415	9.9671	0	10	0.04	0%	40%
10:00 AM	17	7.98	5	0.0549	11.6189	0	12	0.05	-3%	43%
11:00 AM	24	6.57	8	0.0304	4.5590	0	5	0.03	-9%	46%
12:00 PM	20	6.52	7	0.0326	5.8683	0	6	0.03	-2%	44%
1:00 PM	19	7.09	6	0.0506	9.5859	0	10	0.05	-4%	45%
2:00 PM	15	6.36	6	0.0232	5.5564	0	6	0.02	-7%	39%
3:00 PM	28	6.82	8	0.0722	9.2819	0	9	0.07	3%	51%
4:00 PM	26	7.38	7	0.0781	10.8150	0	11	0.08	-2%	50%
5:00 PM	21	6.65	7	0.0375	6.4232	0	7	0.04	-8%	45%
6:00 PM	22	6.64	7	0.0557	9.1133	0	9	0.06	1%	47%
7:00 PM	21	6.14	7	0.0685	11.7467	0	11	0.07	7%	49%
8:00 PM	18	6.69	6	0.0518	10.3545	0	10	0.05	4%	45%
9:00 PM	12	7.26	5	0.0141	4.2202	0	4	0.01	6%	33%
10:00 PM	11	7.19	4	0.0487	15.9525	0	16	0.05	0%	38%
11:00 PM	3	7.44	2	0.0174	20.8454	0	21	0.02	-1%	20%

Monday:

Monday	Input Variables			Output Variables				Validation		Agents
	M	M	n	Theoretical KPI Outputs Generated from M/M/n model		Empirical data for AlarmCo's inbound customer call queue		Error		
Business Hours	Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Error for Lq (# of people)	Error % for Wq	Agents Efficiency
8:00 AM	10	7.79	4	0.0217	8.3485	0	8	0.02	4%	26%
9:00 AM	33	6.86	9	0.0756	8.2473	0	8	0.08	3%	40%
10:00 AM	27	5.85	9	0.0556	7.4133	0	7	0.06	6%	43%
11:00 AM	33	6.99	9	0.0658	7.1756	0	7	0.07	3%	46%
12:00 PM	37	6.99	10	0.0567	5.5205	0	6	0.06	-8%	44%
1:00 PM	27	6.62	8	0.0676	9.0096	0	9	0.07	0%	45%
2:00 PM	31	7.07	9	0.0379	4.4059	0	4	0.04	10%	39%
3:00 PM	48	5.83	14	0.0690	5.1736	0	5	0.07	3%	51%
4:00 PM	53	6.47	14	0.0657	4.4640	0	4	0.07	12%	50%
5:00 PM	42	6.47	11	0.1136	9.7339	0	10	0.11	-3%	45%
6:00 PM	43	5.75	13	0.0658	5.5049	0	5	0.07	10%	47%
7:00 PM	35	5.65	11	0.0770	7.9250	0	8	0.08	-1%	49%
8:00 PM	31	5.77	10	0.0638	7.4099	0	7	0.06	6%	45%
9:00 PM	22	6.03	8	0.0311	5.0900	0	5	0.03	2%	33%
10:00 PM	18	5.83	7	0.0340	6.7997	0	7	0.03	-3%	38%
11:00 PM	6	6.69	3	0.0296	17.7620	0	18	0.03	-1%	20%

Tuesday:

Tuesday	Input Variables			Output Variables				Validation		Agents
	M	M	n	Theoretical KPI Outputs Generated from M/M/n model		Empirical data for AlarmCo's inbound customer call queue		Error		
Business Hours	Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Error for Lq (# of people)	Error % for Wq	Agents Efficiency
8:00 AM	13	8.59	4	0.0466	12.9162	0	13	0.05	-1%	26%
9:00 AM	31	6.68	9	0.0579	6.7249	0	7	0.06	-4%	40%
10:00 AM	32	6.26	10	0.0430	4.8427	0	5	0.04	-3%	43%
11:00 AM	35	7.58	9	0.0558	5.7376	0	6	0.06	-4%	46%
12:00 PM	37	7.33	9	0.1080	10.5052	0	10	0.11	5%	44%
1:00 PM	31	6.58	9	0.0648	7.5219	0	8	0.06	-6%	45%
2:00 PM	31	6.29	9	0.0905	10.5047	0	10	0.09	5%	39%
3:00 PM	43	5.97	12	0.1124	9.4083	0	9	0.11	5%	51%
4:00 PM	49	6.47	13	0.0738	5.4236	0	5	0.07	8%	50%
5:00 PM	37	5.52	12	0.0600	5.8392	0	6	0.06	-3%	45%
6:00 PM	36	5.51	11	0.1198	11.9798	0	12	0.12	0%	47%
7:00 PM	33	5.81	10	0.0988	10.7805	0	11	0.10	-2%	49%
8:00 PM	27	5.75	9	0.0632	8.4263	0	8	0.06	5%	45%
9:00 PM	16	5.66	6	0.0698	15.7159	0	16	0.07	-2%	33%
10:00 PM	16	5.67	6	0.0691	15.5535	0	16	0.07	-3%	38%
11:00 PM	7	6.32	4	0.0109	5.6286	0	6	0.01	-6%	20%

Wednesday:

Wednesd	Input Variables			Output Variables				Validation		Agents
	M	M	n	Theoretical KPI Outputs Generated from M/M/n model		Empirical data for AlarmCo's inbound customer call queue		Error		
Business Hours	Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Error for Lq (# of people)	Error % for Wq	Agents Efficiency
8:00 AM	13	7.84	5	0.0147	4.0796	0	4	0.01	2%	26%
9:00 AM	29	6.65	9	0.0364	4.5216	0	4	0.04	13%	40%
10:00 AM	30	7.10	8	0.0863	10.3603	0	10	0.09	4%	43%
11:00 AM	35	6.73	10	0.0493	5.0751	0	5	0.05	2%	46%
12:00 PM	29	6.88	8	0.0849	10.5390	0	11	0.08	-4%	44%
1:00 PM	25	6.55	8	0.0426	6.1373	0	6	0.04	2%	45%
2:00 PM	29	7.78	8	0.0361	4.4857	0	5	0.04	-10%	39%
3:00 PM	39	7.00	10	0.0849	7.8403	0	8	0.08	-2%	51%
4:00 PM	50	5.91	14	0.0894	6.4356	0	6	0.09	7%	50%
5:00 PM	32	6.15	10	0.0495	5.5734	0	6	0.05	-7%	45%
6:00 PM	32	6.25	10	0.0436	4.9046	0	5	0.04	-2%	47%
7:00 PM	29	5.61	10	0.0470	5.8395	0	6	0.05	-3%	49%
8:00 PM	21	5.59	8	0.0382	6.5413	0	7	0.04	-7%	45%
9:00 PM	15	5.55	6	0.0536	12.8710	0	13	0.05	-1%	33%
10:00 PM	13	5.34	6	0.0290	8.0235	0	8	0.03	0%	38%
11:00 PM	7	7.13	3	0.0423	21.7371	0	22	0.04	-1%	20%

Thursday:

Thursday	Input Variables			Output Variables				Validation		Agents
	M	M	n	Theoretical KPI Outputs Generated from M/M/n model		Empirical data for AlarmCo's inbound customer call queue		Error		
Business Hours	Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Error for Lq (# of people)	Error % for Wq	Agents Efficiency
8:00 AM	11	6.87	5	0.0122	4.0021	0	4	0.01	0%	26%
9:00 AM	26	6.72	8	0.0469	6.4872	0	7	0.05	-7%	40%
10:00 AM	24	7.61	7	0.0390	5.8486	0	6	0.04	-3%	43%
11:00 AM	33	6.39	10	0.0467	5.0923	0	5	0.05	2%	46%
12:00 PM	34	6.16	10	0.0789	8.3547	0	8	0.08	4%	44%
1:00 PM	28	6.39	9	0.0378	4.8540	0	5	0.04	-3%	45%
2:00 PM	26	6.59	8	0.0537	7.4308	0	7	0.05	6%	39%
3:00 PM	41	6.36	11	0.1072	9.4140	0	9	0.11	5%	51%
4:00 PM	49	6.53	13	0.0678	4.9843	0	5	0.07	0%	50%
5:00 PM	36	6.30	10	0.1036	10.3621	0	10	0.10	4%	45%
6:00 PM	33	6.74	9	0.0862	9.3990	0	9	0.09	4%	47%
7:00 PM	34	5.73	11	0.0538	5.6999	0	6	0.05	-5%	49%
8:00 PM	22	6.09	8	0.0290	4.7492	0	5	0.03	-5%	45%
9:00 PM	16	6.95	6	0.0208	4.6852	0	5	0.02	-6%	33%
10:00 PM	12	5.19	6	0.0214	6.4090	0	6	0.02	7%	38%
11:00 PM	6	5.97	4	0.0070	4.1781	0	4	0.01	4%	20%

Friday:

Friday	Input Variables			Output Variables				Validation		Agents
	M	M	n	Theoretical KPI Outputs Generated from M/M/n model		Empirical data for AlarmCo's inbound customer call queue		Error		
Business Hours	Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Error for Lq (# of people)	Error % for Wq	Agents Efficiency
8:00 AM	8	7.81	4	0.0076	3.4239	0	3	0.01	14%	26%
9:00 AM	23	6.84	7	0.0589	9.2204	0	9	0.06	2%	40%
10:00 AM	27	7.33	8	0.0333	4.4344	0	4	0.03	11%	43%
11:00 AM	28	6.88	8	0.0666	8.5589	0	9	0.07	-5%	46%
12:00 PM	29	6.12	9	0.0676	8.3930	0	8	0.07	5%	44%
1:00 PM	25	6.49	8	0.0454	6.5434	0	7	0.05	-7%	45%
2:00 PM	25	6.99	7	0.0876	12.6085	0	13	0.09	-3%	39%
3:00 PM	33	6.62	9	0.0984	10.7356	0	11	0.10	-2%	51%
4:00 PM	44	6.29	12	0.0871	7.1304	0	7	0.09	2%	50%
5:00 PM	30	6.42	9	0.0610	7.3150	0	7	0.06	5%	45%
6:00 PM	32	6.12	10	0.0515	5.7933	0	6	0.05	-3%	47%
7:00 PM	29	6.47	9	0.0447	5.5503	0	6	0.04	-7%	49%
8:00 PM	20	6.19	7	0.0456	8.2028	0	8	0.05	3%	45%
9:00 PM	14	7.33	5	0.0312	8.0197	0	8	0.03	0%	33%
10:00 PM	12	6.22	5	0.0329	9.8679	0	10	0.03	-1%	38%
11:00 PM	4	7.45	3	0.0040	3.5995	0	4	0.00	-10%	20%

Saturday:

Saturday	Input Variables			Output Variables				Validation		Agents
	M	M	n	Theoretical KPI Outputs Generated from M/M/n model		Empirical data for AlarmCo's inbound customer call queue		Error		
Business Hours	Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Error for Lq (# of people)	Error % for Wq	Agents Efficiency
8:00 AM	6	8.04	3	0.0144	8.6535	0	9	0.01	-4%	26%
9:00 AM	18	7.21	6	0.0336	6.7226	0	7	0.03	-4%	40%
10:00 AM	18	7.58	6	0.0250	5.0033	0	5	0.03	0%	43%
11:00 AM	24	7.71	7	0.0358	5.3763	0	5	0.04	8%	46%
12:00 PM	23	6.64	7	0.0713	11.1573	0	11	0.07	1%	44%
1:00 PM	22	6.55	7	0.0585	9.5698	0	10	0.06	-4%	45%
2:00 PM	21	6.81	7	0.0337	5.7824	0	6	0.03	-4%	39%
3:00 PM	31	6.34	9	0.0853	9.9067	0	10	0.09	-1%	51%
4:00 PM	35	6.64	10	0.0549	5.6454	0	6	0.05	-6%	50%
5:00 PM	25	5.37	9	0.0593	8.5381	0	9	0.06	-5%	45%
6:00 PM	22	5.96	8	0.0338	5.5231	0	6	0.03	-8%	47%
7:00 PM	23	6.13	8	0.0378	5.9209	0	6	0.04	-1%	49%
8:00 PM	18	5.99	7	0.0285	5.7081	0	6	0.03	-5%	45%
9:00 PM	13	6.08	5	0.0567	15.6992	0	16	0.06	-2%	33%
10:00 PM	8	8.70	3	0.0327	14.6949	0	15	0.03	-2%	38%
11:00 PM	3	5.58	3	0.0040	4.8245	0	5	0.00	-4%	20%

Appendix C – Summary of Preemptive Solutions

Count	Preemptive Category	Solution	Details	Example	Advantages	Potential Pitfalls
1	Automated Remote Service	Proactive Upgrade	Track machine signals, upgrade customers before their service was terminated to avoid a poor customer experience and unwanted churn.	Security device is updated by client per machine signal output	Minimal customer disturbance	Customer ease of use, interruption to machine functionality
2	Automated Remote Service	Remote Device Reset	Can also help you avoid No-Trouble-Found (NTF) returns. Failure analysis of returned parts and products indicates that 10% - 30% of returned materials are NTF, meaning the perceived issue could have been resolved without returning the equipment.	If the machine is sending failure signal, potentially a reset signal (or some remote action) could be used to try and fix the issue without the customer having to intervene	Savings on dispataching, minimal customer	Poor internet connectivity, reset malfunctions
3	Automated Remote Service	Automatic Dispatch parts/Components	Proactive upgrade of customer machines that are obsolete and generates positive machine signals, indicating propensity to fail within two weeks	Instead of shipping same-day replacement parts in response to a critical product malfunction, you can send parts via two-day delivery and ensure your customer's business isn't impacted by problems with your product.	On time delivery, customer preference	Dispatcher Scheduling Issues
4	Education	Send Brochure	Eligibility, New Products, Upgrade Options	Proactively reach out to customers to educate them about the need to swap out their modems and provide them with an upgrade path. Upon contact, educate customers on the benefits and provide them with upgrade options.	Decreased Truck Rolls, Improved Customer Service	High input Costs to Client
5	Education	Video Tutorial	Add video channel to website for most common problems	Customer googles "how to reset security device" and is directed to video channel, customer calls and is redirected to video channel	Minimized cost to client, Reduced truck rolls	Adoption by all customer segments
6	Education	Customer Call	Preemptive call to customer educating them on how to fix/reset machine	Client agent tracks machine signal prevalence and calls customer to suggestion quick solution	Face to face interaction, avoid dispatch cost	Added labor costs, customers may hang up
7	Education	Email Tutorial	Send mass email to customers that have machine signal implying upcoming failure in device	"Your device is eligible for a free upgrade, click below to learn more"	Quick implementation	Mass emails often get ignored
8	Education	Self Install Kit	Send kit to each customer to fix/update device	Box kit mained to customer - enclosed is a manual, replacement parts, basic tools, customer promise card	Detailed help kit, dispatcher cost savings, additional marketing potential, reduced truck rolls	Customer does not understand kit, customer may feel unequipped, low customer engagement
9	Online Resource	Frequently Asked Questions (FAQ)	Add questionairre to email or website addressing top customer concerns	Add top questions to avoid general inquiry calls for example, "How long is my warranty?"	Quick implementation, best practice in industry	Questions not answered in FAQ still lead to inbound calls
10	Online Resource	Automated Web Chat	Develop automated web chat to address key customer concern. Top Providers include Chatbot, Interactions, Inteliwise, Chatter (salesforce)	Customer enters client website and is met with bottom right automated pop up "Hello! My name is Jake. How can I help you today?"	Feeling of live interaction without the cost, data analytics	Customer dissatisfaction with user experience
11	Online Resource	Live Web Chat	Outsource live chat service - top providers include LivePerson, Comm100, BoldChat, Kayako Fusion, LiveHelpNow	Customer enters client website and is met with bottom right live pop up "Hello! My name is Jake. How can I help you today?"	High Customer engagement	Added labor costs
12	Online Resource	Video Chat	Provide video chat services with customers to solve issues	Link to "request video chat" on live text chat	Face to face interaction, avoid dispatch cost	Labor cost requirement, if issue unresolved - dispatch still required
13	Online Resource	Online Customer Service Ticket	Customers can open a ticket on client website and tickets can be addressed systematically	Customer enters name, chooses drop down category, types complaint - system outputs ticket number	Potential for data analytics	Customer may still want live conversation, high start up cost, resolution time is longer
14	Telephonic Assistance	Added mobile application functionailty	Add alert (via text or on application) to update device	Customer received text with weblink to solve issue	Potential adoption for younger demographic	User acceptance of mobile app
15	Telephonic Assistance	Interactive Voice Respone (IVR)	Customer calls security services client and is met with automated voice service	Prioritise which types of outbound calls to customers and other departments could be replaced by Agent-generated and/or automated SMS or email	Minimized labor costs, technilogical advances	Customer may still want live conversation, high start up cost
16	Telephonic Assistance	Outsource during high traffic	Explore viability of an outsourced contact centre acting as a overflow during periods of exceptionally busy inbound traffic.	The outsourcer could offer a range of options, from simply taking messages right up to e.g. setting appointments for Sales people or Engineers	High cost to outsource, poor quality of issue resolution	Poor customer service experience
17	Proactive Analysis	Machine Data	*Machine data logs from OEM: leverage historical machine data to create baseline for conditions, apply predictive analytics to baseline machine data to pre-emptively determine when a device is likely to experience disruption	AlarmCo learns the probability of machine failure and dispatches a technitian before the customer has to call in	Innovative and best practice in industry	False positives and false negatives may skey data
18	Proactive Analysis	SEO/SEM Resource Investment	Build online Seach Engine Optimization campaign to direct customers to [education] related solutions rather than customer service phone call	*Proactively release over the air updates, to avoid service disruption, prevent customer satisfaction decrease, and avoid unnecesary truck roll	Minimal customer disturbance	Interruption to machine functionality
19	Proactive Analysis	Add customer service metrics (aside from "routine metrics" to call center)	First Call resolution, how many calls have been wrongly escalated, calls required to resolve issue, internal transfer call count, misrouted internal transfer count, compaint count	Analysis of additional metrics for customer service agents to track (incentive system)	Cost Effective, low technology requirements	Data integrity requirements
20	Proactive Analysis	Analysis of calls 5 days post purchase	Target customers who often call right after purchase	20% of customer calls originate post purchase. Add live tutorial to installation appointment	Improves customer service at early stage of customer development	Data integrity requirements, labor costs increase

Appendix D – Calculations for The Impact of 12 Selected Preemptive Solutions

Sunday:

Sunday	Input Variables			Output Variables				Improvement	
	M	M	n	Original Theoretical KPI Outputs Generated from M/M/n model		New Theoretical KPI Outputs Generated from M/M/n model		Improvement after Implementing Preemptive Solutions	
Business Hours	Updated Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)
8:00 AM	6.64	9.11	3	0.0162	8.3128	0.0132	7.1320	-19%	-14%
9:00 AM	14.14	7.44	5	0.0415	9.9671	0.0304	7.7351	-27%	-22%
10:00 AM	16.03	7.98	5	0.0549	11.6189	0.0407	9.1480	-26%	-21%
11:00 AM	22.60	6.57	8	0.0304	4.5590	0.0206	3.2775	-32%	-28%
12:00 PM	18.81	6.52	7	0.0326	5.8683	0.0219	4.1937	-33%	-29%
1:00 PM	17.96	7.09	6	0.0506	9.5859	0.0366	7.3412	-28%	-23%
2:00 PM	14.02	6.36	6	0.0232	5.5564	0.0161	4.1336	-30%	-26%
3:00 PM	26.34	6.82	8	0.0722	9.2819	0.0463	6.3247	-36%	-32%
4:00 PM	24.42	7.38	7	0.0781	10.8150	0.0531	7.8314	-32%	-28%
5:00 PM	19.63	6.65	7	0.0375	6.4232	0.0254	4.6631	-32%	-27%
6:00 PM	20.71	6.64	7	0.0557	9.1133	0.0363	6.3101	-35%	-31%
7:00 PM	19.83	6.14	7	0.0685	11.7467	0.0454	8.2505	-34%	-30%
8:00 PM	16.83	6.69	6	0.0518	10.3545	0.0352	7.5214	-32%	-27%
9:00 PM	11.39	7.26	5	0.0141	4.2202	0.0110	3.4672	-22%	-18%
10:00 PM	10.41	7.19	4	0.0487	15.9525	0.0380	13.1269	-22%	-18%
11:00 PM	2.77	7.44	2	0.0174	20.8454	0.0134	17.3700	-23%	-17%
Total	262.56						Average	-29%	-24%

Monday:

Monday	Input Variables			Output Variables				Improvement	
	M	M	n	Original Theoretical KPI Outputs Generated from M/M/n model		New Theoretical KPI Outputs Generated from M/M/n model		Improvement after Implementing Preemptive Solutions	
Business Hours	Updated Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)
8:00 AM	9.36	7.79	4	0.0217	8.3485	0.0160	6.1436	-26%	-26%
9:00 AM	30.96	6.86	9	0.0756	8.2473	0.0574	6.6693	-24%	-19%
10:00 AM	25.28	5.85	9	0.0556	7.4133	0.0340	4.8451	-39%	-35%
11:00 AM	31.08	6.99	9	0.0658	7.1756	0.0421	4.8775	-36%	-32%
12:00 PM	34.95	6.99	10	0.0567	5.5205	0.0361	3.7190	-36%	-33%
1:00 PM	25.37	6.62	8	0.0676	9.0096	0.0438	6.2213	-35%	-31%
2:00 PM	29.10	7.07	9	0.0379	4.4059	0.0236	2.9187	-38%	-34%
3:00 PM	44.84	5.83	14	0.0690	5.1736	0.0358	2.8748	-48%	-44%
4:00 PM	49.54	6.47	14	0.0657	4.4640	0.0343	2.4912	-48%	-44%
5:00 PM	39.26	6.47	11	0.1136	9.7339	0.0649	5.9496	-43%	-39%
6:00 PM	40.57	5.75	13	0.0658	5.5049	0.0385	3.4127	-42%	-38%
7:00 PM	32.78	5.65	11	0.0770	7.9250	0.0446	4.8980	-42%	-38%
8:00 PM	29.22	5.77	10	0.0638	7.4099	0.0400	4.9229	-37%	-34%
9:00 PM	20.71	6.03	8	0.0311	5.0900	0.0203	3.5373	-35%	-31%
10:00 PM	17.02	5.83	7	0.0340	6.7997	0.0237	5.0056	-30%	-26%
11:00 PM	5.70	6.69	3	0.0296	17.7620	0.0242	15.2901	-18%	-14%
Total	465.75						Average	-36%	-32%

Tuesday:

Tuesday	Input Variables			Output Variables				Improvement	
	M	M	n	Original Theoretical KPI Outputs Generated from M/M/n model		New Theoretical KPI Outputs Generated from M/M/n model		Improvement after Implementing Preemptive Solutions	
Business Hours	Updated Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)
8:00 AM	12.35	8.59	4	0.0466	12.9162	0.0367	10.7097	-21%	-17%
9:00 AM	28.85	6.68	9	0.0579	6.7249	0.0339	4.2272	-42%	-37%
10:00 AM	30.10	6.26	10	0.0430	4.8427	0.0264	3.1597	-39%	-35%
11:00 AM	32.88	7.58	9	0.0558	5.7376	0.0350	3.8322	-37%	-33%
12:00 PM	34.97	7.33	9	0.1080	10.5052	0.0711	7.3192	-34%	-30%
1:00 PM	28.96	6.58	9	0.0648	7.5219	0.0390	4.8504	-40%	-36%
2:00 PM	29.26	6.29	9	0.0905	10.5047	0.0589	7.2525	-35%	-31%
3:00 PM	40.30	5.97	12	0.1124	9.4083	0.0638	5.7034	-43%	-39%
4:00 PM	45.94	6.47	13	0.0738	5.4236	0.0408	3.1960	-45%	-41%
5:00 PM	34.78	5.52	12	0.0600	5.8392	0.0348	3.5994	-42%	-38%
6:00 PM	33.90	5.51	11	0.1198	11.9798	0.0728	7.7300	-39%	-35%
7:00 PM	30.91	5.81	10	0.0988	10.7805	0.0591	6.8776	-40%	-36%
8:00 PM	25.48	5.75	9	0.0632	8.4263	0.0411	5.8008	-35%	-31%
9:00 PM	15.12	5.66	6	0.0698	15.7159	0.0501	11.9224	-28%	-24%
10:00 PM	15.16	5.67	6	0.0691	15.5535	0.0503	11.9524	-27%	-23%
11:00 PM	6.59	6.32	4	0.0109	5.6286	0.0083	4.5156	-24%	-20%
Total	445.55						Average	-36%	-32%

Wednesday:

Wednesd	Input Variables			Output Variables				Improvement	
	M	M	n	Original Theoretical KPI Outputs Generated from M/M/n model		New Theoretical KPI Outputs Generated from M/M/n model		Improvement after Implementing Preemptive Solutions	
Business Hours	Updated Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)
8:00 AM	12.16	7.84	5	0.0147	4.0796	0.0103	3.0553	-30%	-25%
9:00 AM	27.10	6.65	9	0.0364	4.5216	0.0219	2.9070	-40%	-36%
10:00 AM	27.90	7.10	8	0.0863	10.3603	0.0522	6.7344	-40%	-35%
11:00 AM	32.73	6.73	10	0.0493	5.0751	0.0289	3.1829	-41%	-37%
12:00 PM	27.22	6.88	8	0.0849	10.5390	0.0547	7.2366	-36%	-31%
1:00 PM	23.59	6.55	8	0.0426	6.1373	0.0284	4.3358	-33%	-29%
2:00 PM	27.04	7.78	8	0.0361	4.4857	0.0221	2.9459	-39%	-34%
3:00 PM	36.69	7.00	10	0.0849	7.8403	0.0525	5.1504	-38%	-34%
4:00 PM	46.96	5.91	14	0.0894	6.4356	0.0491	3.7610	-45%	-42%
5:00 PM	30.11	6.15	10	0.0495	5.5734	0.0305	3.6500	-38%	-35%
6:00 PM	30.09	6.25	10	0.0436	4.9046	0.0267	3.1930	-39%	-35%
7:00 PM	27.11	5.61	10	0.0470	5.8395	0.0275	3.6519	-42%	-37%
8:00 PM	19.84	5.59	8	0.0382	6.5413	0.0256	4.6524	-33%	-29%
9:00 PM	13.96	5.55	6	0.0536	12.8710	0.0351	9.0597	-34%	-30%
10:00 PM	12.24	5.34	6	0.0290	8.0235	0.0203	5.9682	-30%	-26%
11:00 PM	6.61	7.13	3	0.0423	21.7371	0.0337	18.3646	-20%	-16%
Total	401.35						Average	-36%	-32%

Thursday:

Thursday	Input Variables			Output Variables				Improvement	
	M	M	n	Original Theoretical KPI Outputs Generated from M/M/n model		New Theoretical KPI Outputs Generated from M/M/n model		Improvement after Implementing Preemptive Solutions	
Business Hours	Updated Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)
8:00 AM	10.34	6.87	5	0.0122	4.0021	0.0088	3.0600	-28%	-24%
9:00 AM	24.35	6.72	8	0.0469	6.4872	0.0296	4.3834	-37%	-32%
10:00 AM	22.51	7.61	7	0.0390	5.8486	0.0258	4.1210	-34%	-30%
11:00 AM	31.10	6.39	10	0.0467	5.0923	0.0291	3.3701	-38%	-34%
12:00 PM	31.71	6.16	10	0.0789	8.3547	0.0455	5.1660	-42%	-38%
1:00 PM	26.19	6.39	9	0.0378	4.8540	0.0229	3.1410	-39%	-35%
2:00 PM	24.42	6.59	8	0.0537	7.4308	0.0347	5.1124	-35%	-31%
3:00 PM	38.50	6.36	11	0.1072	9.4140	0.0636	5.9469	-41%	-37%
4:00 PM	45.72	6.53	13	0.0678	4.9843	0.0358	2.8192	-47%	-43%
5:00 PM	33.74	6.30	10	0.1036	10.3621	0.0622	6.6395	-40%	-36%
6:00 PM	31.15	6.74	9	0.0862	9.3990	0.0562	6.4909	-35%	-31%
7:00 PM	31.87	5.73	11	0.0538	5.6999	0.0313	3.5311	-42%	-38%
8:00 PM	20.73	6.09	8	0.0290	4.7492	0.0191	3.3180	-34%	-30%
9:00 PM	15.09	6.95	6	0.0208	4.6852	0.0147	3.5094	-29%	-25%
10:00 PM	11.41	5.19	6	0.0214	6.4090	0.0158	4.9983	-26%	-22%
11:00 PM	5.72	5.97	4	0.0070	4.1781	0.0056	3.5072	-20%	-16%
Total	404.58						Average	-35%	-31%

Friday:

Friday	Input Variables			Output Variables				Improvement	
	M	M	n	Original Theoretical KPI Outputs Generated from M/M/n model		New Theoretical KPI Outputs Generated from M/M/n model		Improvement after Implementing Preemptive Solutions	
Business Hours	Updated Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)
8:00 AM	7.52	7.81	4	0.0076	3.4239	0.0057	2.7299	-25%	-20%
9:00 AM	21.54	6.84	7	0.0589	9.2204	0.0386	6.4553	-34%	-30%
10:00 AM	25.35	7.33	8	0.0333	4.4344	0.0214	3.0345	-36%	-32%
11:00 AM	26.39	6.88	8	0.0666	8.5589	0.0441	6.0182	-34%	-30%
12:00 PM	27.26	6.12	9	0.0676	8.3930	0.0427	5.6351	-37%	-33%
1:00 PM	23.72	6.49	8	0.0454	6.5434	0.0315	4.7795	-31%	-27%
2:00 PM	23.64	6.99	7	0.0876	12.6085	0.0611	9.3087	-30%	-26%
3:00 PM	30.87	6.62	9	0.0984	10.7356	0.0600	6.9994	-39%	-35%
4:00 PM	41.57	6.29	12	0.0871	7.1304	0.0530	4.5913	-39%	-36%
5:00 PM	28.36	6.42	9	0.0610	7.3150	0.0401	5.0912	-34%	-30%
6:00 PM	29.98	6.12	10	0.0515	5.7933	0.0307	3.6824	-40%	-36%
7:00 PM	27.19	6.47	9	0.0447	5.5503	0.0276	3.6536	-38%	-34%
8:00 PM	18.80	6.19	7	0.0456	8.2028	0.0306	5.8546	-33%	-29%
9:00 PM	13.27	7.33	5	0.0312	8.0197	0.0235	6.3709	-25%	-21%
10:00 PM	11.38	6.22	5	0.0329	9.8679	0.0248	7.8566	-24%	-20%
11:00 PM	3.77	7.45	3	0.0040	3.5995	0.0032	3.0323	-21%	-16%
Total	360.60						Average	-33%	-28%

Saturday:

Saturday	Input Variables			Output Variables				Improvement	
	M	M	n	Original Theoretical KPI Outputs Generated from M/M/n model		New Theoretical KPI Outputs Generated from M/M/n model		Improvement after Implementing Preemptive Solutions	
Business Hours	Updated Average Inter-arrival Rate	Average Service Rate	Number of Agents	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)	Lq - Average Queue Length	Wq - Average Wait Time (s)
8:00 AM	5.72	8.04	3	0.0144	8.6535	0.0120	7.5336	-17%	-13%
9:00 AM	16.79	7.21	6	0.0336	6.7226	0.0223	4.7784	-34%	-29%
10:00 AM	16.89	7.58	6	0.0250	5.0033	0.0172	3.6575	-31%	-27%
11:00 AM	22.53	7.71	7	0.0358	5.3763	0.0238	3.8050	-34%	-29%
12:00 PM	21.78	6.64	7	0.0713	11.1573	0.0502	8.3003	-30%	-26%
1:00 PM	20.80	6.55	7	0.0585	9.5698	0.0408	7.0552	-30%	-26%
2:00 PM	19.84	6.81	7	0.0337	5.7824	0.0234	4.2370	-31%	-27%
3:00 PM	29.34	6.34	9	0.0853	9.9067	0.0567	6.9592	-34%	-30%
4:00 PM	33.02	6.64	10	0.0549	5.6454	0.0346	3.7695	-37%	-33%
5:00 PM	23.42	5.37	9	0.0593	8.5381	0.0364	5.6025	-39%	-34%
6:00 PM	20.59	5.96	8	0.0338	5.5231	0.0212	3.7080	-37%	-33%
7:00 PM	21.59	6.13	8	0.0378	5.9209	0.0243	4.0506	-36%	-32%
8:00 PM	16.70	5.99	7	0.0285	5.7081	0.0175	3.7813	-39%	-34%
9:00 PM	12.25	6.08	5	0.0567	15.6992	0.0414	12.1622	-27%	-23%
10:00 PM	7.52	8.70	3	0.0327	14.6949	0.0256	12.2619	-22%	-17%
11:00 PM	2.79	5.58	3	0.0040	4.8245	0.0030	3.9101	-25%	-19%
Total	291.58						Average	-31%	-27%

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