Optimized staffing between product lines for a technical support center

by

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ABSTRACT

Technical support for products after the sale is commonplace in today's businesses. Original Equipment Manufacturers (OEMs) provide technical support to their dealer channel for resolution of complex product issues. Technical support staffing levels can vary by product type, product complexity, and production volumes, and case volumes.

This research seeks a better understanding of appropriate staffing levels between three product lines for one OEM. The objective of this paper is to develop a model for monthly and weekly average case volumes for the three product lines, based off of historical case volume data. This data is used to predict a product line's (platform's) workload based off the month of the year. The output of each platform's monthly case volume is then used in an optimization model to determine optimal staffing levels for each platform, based off the time of the year.

The models developed for each platform use a linear relationship which regresses workload on a set of binary variable for the months of the year. Each of the models developed provided statistically significant coefficients for months which contain the platform's highest workload. The outputs from these models are used in a mixed integer nonlinear programming optimization model to determine staff level of full time equivalent (FTE) employees at each platform. Each of the three scenarios utilized in this research provide similar trends and staffing levels for each of the three product lines. Results of this research are of interest for the management of technical support staffing.

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CHAPTER I: INTRODUCTION

1.1 Background Information

Original Equipment Manufacturers (OEMs) are producing ever more complex products. Product complexity, coupled with high frequency of changes, makes it difficult for dealerships of OEM products to be experts on service issues with each of these products. Many OEM's provide a service to their dealer groups to assist with issues they might encounter with the OEM's product.

One such OEM provides technical support to its dealer channels through a technical assistance center. If a dealership cannot resolve a product issue through the use of technical manuals, parts catalogs, or technical service bulletins, they will contact technical support for assistance. The dealership must provide all relevant information to the factory, after which the factory will contact the dealer by phone or email. Each interaction between the dealer group and OEM is considered one case.

Each of OEM's product lines has its own dedicated group of individuals to provide technical assistance to dealerships. These individuals have the experience and additional resources to assist the dealer in resolving their product related issue. Each technical support specialist will work several cases per day, ranging from 5 to 50 cases. Total case volume for each platform (i.e. range of products) ranges from 30 to 300 cases per day. Cases can be submitted in several different languages, and resources are staffed globally for each language.

There are four different priorities for technical support cases:

- Critical: This case type receives the highest priority and fastest response time. This is reserved for machine-down type issues, where the technician is at the machine and the customer has an immediate need for the piece of equipment.

- Reopen: This occurs when a technician needs additional assistance with a case that started as one of the other three priorities. When the case is resubmitted it will be designated with “Reopen”.
- Normal: This case type will have a lower priority than Critical, but higher than an Information Only. Typical response times are within an hour, but no longer than twelve hours.
- Information Only: This case type does not have a specified response time. This is used to tell the factory of issues discovered, or if a technician fixed an issue and provides their solution.

Each of the case priorities has a metric for acceptance and response times. For example, a critical case must be accepted by an analyst in 20 minutes, and response must be given in 2 hours. A normal or reopen case must be accepted by an analyst in two hours, and response must be given within twelve. There are different goals at the enterprise and platform levels for each metric.

1.2 Purpose and Objectives

For the scope of this thesis, I will be analyzing three platforms. A platform is a grouping of similar products that share engineering, marketing, manufacturing, and product support. For the purposes of this thesis, the platforms will be referenced as Platform A, Platform B, and Platform C. Each of these platforms have different peak seasons, with the ability to share resources (people) between the platforms. Management of the technical support group wishes to better understand the workload of each platform and how to effectively share manpower between the groups. The client has previously shared resources between these groups, but would like to have a better way of determining how to effectively share these resources.

The purpose of this thesis is to better understand how to efficiently or optimally allocate resources, specifically labor, between the three platforms to meet the OEM's clients' technical needs. This purpose will be achieved be meeting two objectives:

Objective 1: First, a model will be developed for each platform. These models will predict the number of cases expected for different time intervals (week and month). This data can be used at the platform level to predict workload.

Objective 2: An optimization model combining the three platforms will be created. The model will be used to determine the appropriate staffing for each of the platforms, based on the time of the year. The optimization will place minimum and maximum values for the number of resources for each platform, based on the time of year. These constraints are required due to minimum staffing requirements and work space for personnel at each platform. There are 22 full time equivalent staff members between the three platforms.

These models and optimization will be extremely useful to the client. Staffing for a seasonal business can be very difficult, but in the client's case these three platforms each have a different peak season. Using the models, the client can determine the staffing requirements of each platform throughout the year, as well as determine how to best share resources between the platforms. This provides the best experience for the client's dealer network.

Deliverables for this thesis will include a written report, oral defense, and usable models for the client. The client can then use the base models to develop models for additional platforms. Other platforms are outside the scope of this thesis, but the same methods presented here would apply for such work. For this thesis, the daily case volumes for the last five years will be needed. This data is located on an internal database of the client's. This data has already been collected and sorted by the author.

CHAPTER 2: LITERATURE REVIEW

There is varying research in relation to technical support staffing. Most of the literature around modeling workload relates to customer call centers or information technology technical support. There are also several published works on staff modelling within the healthcare industry. While these types of staffing issues are not the exact same as a dealership support center, many of the guiding concepts apply.

2.1 Staffing of Call Centers and Related Industries

Mahadevan and Overstreet (2012), found that using warranty data would be a key metric for determining call volume in a call center, when supporting a new product. This logically makes sense, as if you have higher warranty claims on a product, you are likely to get more calls from customers about the product. While this paper will not cover the causes of technical support volume, warranty inputs would be a major contributor to case volume. Mahadevan and Overstreet's paper also includes some key theories on forecasting call center calls. They mention that the two main objectives for call center management fall into two categories; soft skills (such as handling a difficult customer over the phone) and mathematical modelling. Another key point was the importance of distinguishing between seasonal and non-seasonal data when performing regression analyses.

There has also been research in the staffing call centers with "Skill-Based Routing" (Whitt and Wallace 2005). Some call centers staff so that all individuals have the skills to meet a caller's needs, while others may have staff with particular skill sets or tiered levels of support. The end goal is to support the customer, but different approaches can place different burdens on staffing requirements. Whitt and Wallace (2005) find that a small amount of cross training or multiple skills, can have almost the same impact as providing agents all the skills. Thus, it may not be necessary for every team member to possess every skill, but having a team of individuals where all those skills are adequately represented is what is important. Having a mix of employee skills can greatly reduce training time for new employees, as well as finding team members with a broad range of skill sets. Munoz and Bastian's (2016) research aligns with Whitt and Wallace's (2005) research. Their experiments found that dual skill servers were more economical in the long-run when compared to single skill or total skill servers.

Skill based routing lends its way to cross training of employees. Iravani et al. (2007) published research focusing on cross-training in call centers. Their research finds that many call centers are staffing individuals that can handle issues in many areas, such as sales, customer service, and diagnostics. With cross training though, there is a point of diminishing returns. It is cost prohibitive to train every employee to handle every type of issue they might encounter. The group developed a model to show how two alternative cross training activities would affect customer wait times. This tool is called a work sharing network where the average shortest path length is computed (WS-APL). This model can also be used as a tool to gauge how effective training activities might be. The model was found to easily compute the better of two cross training alternatives.

Research in the area of daily workload for a call center has been summarized by Avramidis et al. (2004). Their paper looks at three different conceptual models for a call center. The group theorizes that calls from customers, or demand, can have random variation and must be accounted for with appropriate models. They developed three different models to predict the demand for one day in the call center. The three models can be summarized as a Poisson model (random arrival rate), a flexible covariance matrix (differences in arrival intensity), and covariance of volumes with respect to different time periods (Avramidis, Deslauriers and L'Ecuyer. 2004). This research suggested that calls today would be affected by calls the previous day. Another key finding was that call volume within a certain timeframe of the day would also create a change in customer demand. Each of the models developed served a different purpose, but could be used in conjunction with each other to make informed staffing decisions for a call center.

Another relevant topic is in the space of service interruptions for a service provider. This could be for waiting in line at your local grocery store or on the phone with your internet provider, trying to resolve an issue. Pang and Whitt (2009) performed research on how service (support) outages affect customers requesting the service. Their research found that use of large scale servers was not necessarily the best approach, as downtime would have a more profound effect. The authors recommended having a goal close to the most efficient use of the servers, but not at the maximum. The incremental cost of the inefficiency is not worth the incremental gain at the extremes of the operational spectrum.

2.2 Staffing in the healthcare industry

In the healthcare industry, there has been significant research in the area of staffing, particularly within nursing. Stevenson (2004) looked at using financial tools to predict staffing needs. He proposed five different steps that should be used when managing staffing levels. His steps included having staffing standards, which are clear metrics for minimum and maximum staffing levels. Another tool is a staffing calculator that uses inputs from the standards, as well as best predicted customer demand. From this, there must be a feedback loop from the process, as well as appropriate reporting of results. Each one of these steps can reduce the financial burden from overstaffing or issues with high demand and understaffing.

Similar to Iravani et al. (2007), there has been research on cross training in the nursing industry. Gnanlet and Gilland (2014) focused on the impact of productivity changes with different cross training configurations in a hospital (2014). Their research also looked at centralized versus decentralized decision making for staffing and training, and the productivity therein. According to their study, "chaining" of resources provided a cost savings over partial flexibility. Chaining is where each unit was cross trained for one other unit, with no overlap. Centralized decision making also yielded a cost savings over decentralized decision making.

2.3 Impacts of Customer Interactions on Business Performance

Customer interactions, customer support, and customer relationship management (CRM) has been extensively researched in many areas. One key area is how CRM affects business performance. Many think of CRM as a tool or software package to handle the relationship with customers. CRM can be used for warranty claims, billing, product questions, etc. A study by Hendricks et al. (2007) showed that purely implementing a CRM system does not have a measureable impact on business profitability. Mahadevan et al. (2012) argued that companies will only see the benefits of CRM with strong guiding principles applied to CRM.

2.4 Behavioral Management Theory

George and Jones (2012) text on behavioral management shows some key theories relevant to this topic. The three platforms analyzed in this thesis perform have "pooled task interdependence". That is to say, that each of an individual's contributions is recognizable and the sum of all the individuals work is the total group output. This distinction is important, as adding more individuals to this type of group, should increase a group's marginal capacity.

CHAPTER III: METHODOLOGY

In this chapter, the data and methods of analysis will be discussed. Each of the three platforms has their own respective case volumes throughout the year. For the scope of this project, English cases for each of the platforms are analyzed, looking at all case priorities other than information only. Data range is from January 1st, 2012 to December 31st, 2016. At the time of research this date range was the most recent with full year values. Uses for the data include models for each platform's workload, as well as the optimization between platforms.

The three platforms being analyzed are referenced as Platform A, Platform B, and Platform C. Each platform has its own group of machinery that they are responsible for. Each of the platform's products perform specific tasks that customers require. Each platform has its own manufacturing and engineering support.

3.1 Data on Dealer Satisfaction with Technical Support

After a dealer has interacted with the technical support service via a case, they are given a survey on their experience. The questions asked are summarized in table 3.1

Table 3.1: Dealer Survey Questions after Interaction with Technical Support

Question	Responses				
	Worst or Bad				Best
Rate your satisfaction with the specialist's response time for this specific case	1	2	3	4	5
Rate the specialist who assisted you with his/her professionalism	1	2	3	4	5
Rate the specialist on his/her ability to provide a helpful solution	1	2	3	4	5
Overall, rate your experience based on this case	1	2	3	4	5
Was the problem resolved?	Yes	No	N/A		

For each of the first four questions, a scale of one to five is used. In this case, a “1” would represent a worst or bad experience and a “5” would be the best experience for the customer. A metric called dealer satisfaction index (DSI) is calculated based on the dealer’s overall experience (Question 4 in Table 3.1). A score of 5 would be 100%, and a score of 1 would be equal to 20%. One might argue that a 1 should be 0%, but what is important is the range in value. DSI is an average of all survey responses for a certain platform, with typical ranges in the 80 to 90 percent range. The company as a whole has a metric for the average of DSI scores, with individual platforms possibly having higher goals. This goal is a minimum threshold, so platforms strive to be above the DSI metric.

The second survey question comes down to the individual specialist, and how they are able to help the dealer. There is not a specific metric tied to this question. The third question can become a bit difficult to quantify. There are times when there is a new issue with a product and there might not be a clear solution at the present time. Dealers might also be dissatisfied with the solution, in either cost or time to complete said solution. For these reasons, response time is most prevalent for use in this thesis. Response time is one of the key factors for an overall good experience and also one of the metrics that the specialists have the most control over. Having enough specialists staffed at appropriate hours ensures better response times.

DSI data could be used as an indicator for how staffing changes between the platforms are affecting the customer (dealer). One would theorize that with lower staff levels, response times would go up, and could lead to lower DSI scores. At the time of this study the DSI data was available, as well as the baseline staff levels. However, there is no historical data with purposefully varied staff levels. That data, when available, could be used in the future to monitor how staff levels are affecting DSI. Similar to section 2.3, this data could be used as a CRM tool to make business decisions for customer satisfaction.

3.2 Case Data and Seasonality for Platforms

Figure 3.1 below shows how Platform A's case volumes change throughout the year. Peak volumes happen in between the August through October timeframe. This is when the majority of use of this product family happens. There is a large decline in activity in the late winter and early spring. Table 3.2 provides summary statistics for Platform A

Figure 3.1: Monthly Case volume for the previous five years for Platform A

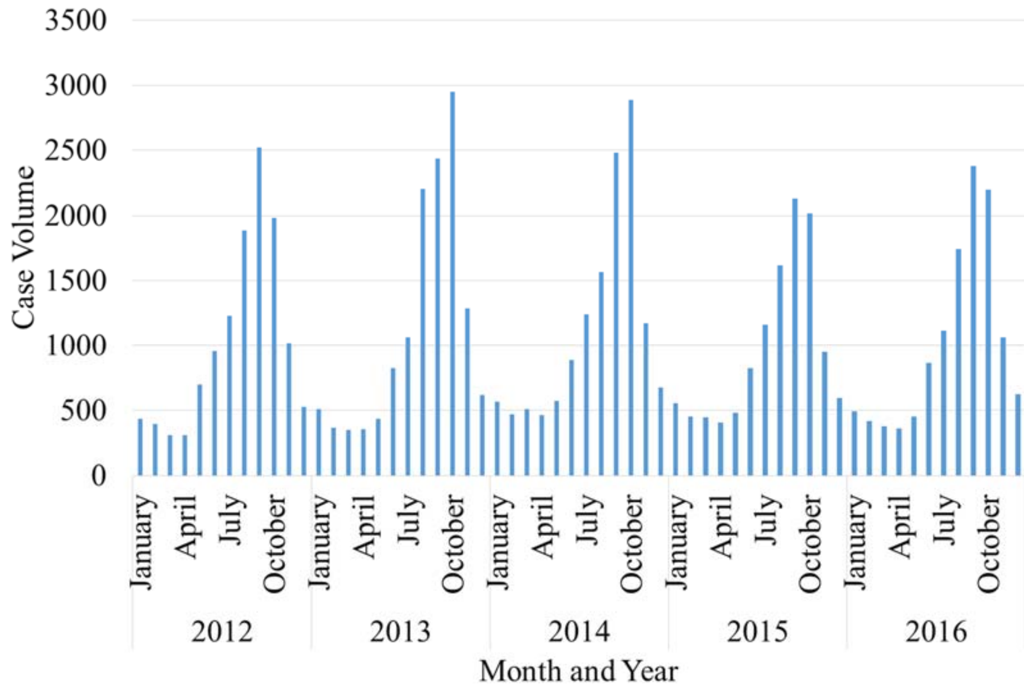


Table 3.2: Case Summary Statistics by month for Platform A

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year
Average	513	423	400	380	530	872	1164	1805	2391	2409	1100	609	12598
Min	434	371	312	313	439	823	1068	1565	2136	1985	951	528	11658
Max	567	471	510	468	698	954	1243	2207	2523	2949	1286	677	13510
St. Deviation	54	41	79	59	107	54	75	257	153	473	132	54	824

Figure 3.2 summarizes the case volumes for Platform B. There is a very large peak in volume in the April and May timeframe, when the majority of hours are accumulated on this platform's products. We see a significant decline in the off season compared to Platform A. Table 3.3 provides summary statistics for Platform A.

Figure 3.2: Monthly Case volume for the previous five years for the Platform B

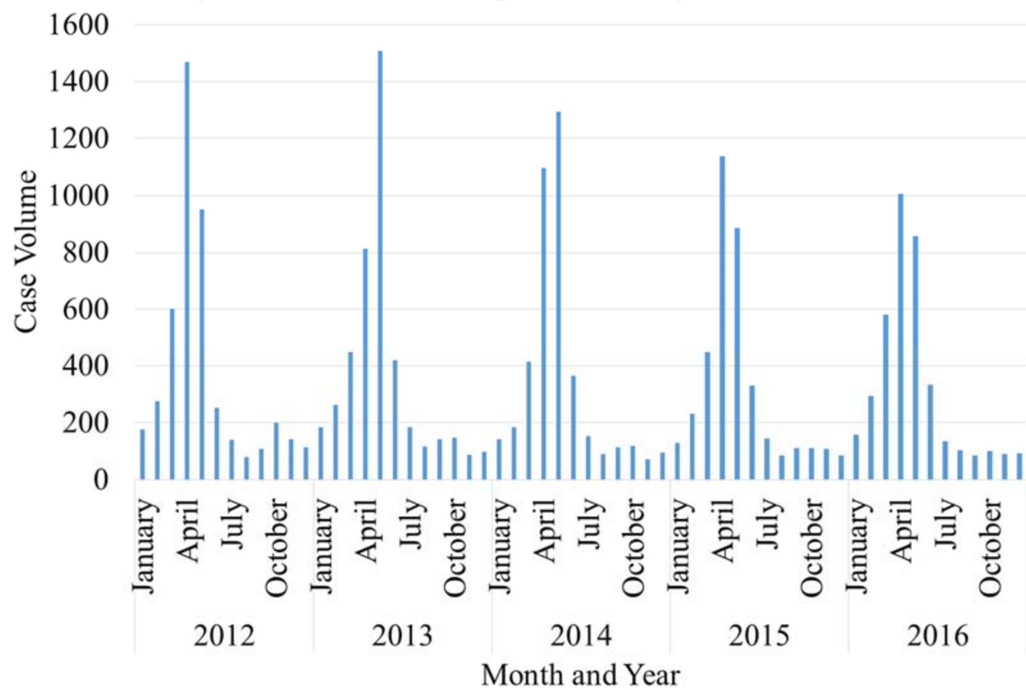


Table 3.3: Case Summary Statistics by month for Platform B

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year
Average	158	250	499	1104	1100	339	151	95	112	136	100	97	4140
Min	129	185	415	814	857	251	135	79	86	101	72	86	3805
Max	183	293	601	1470	1509	418	184	117	142	200	141	113	4508
St. Deviation	23	43	86	239	288	61	19	15	20	40	26	10	322

Figure 3.3 summarizes the case volumes for Platform C. Here the peak season is during the months of April, May, and June. This platform also has less variation between peak and off-season times. Table 3.4 provides summary statistics for Platform C.

Figure 3.3: Monthly Case volume for the previous five years for Platform C

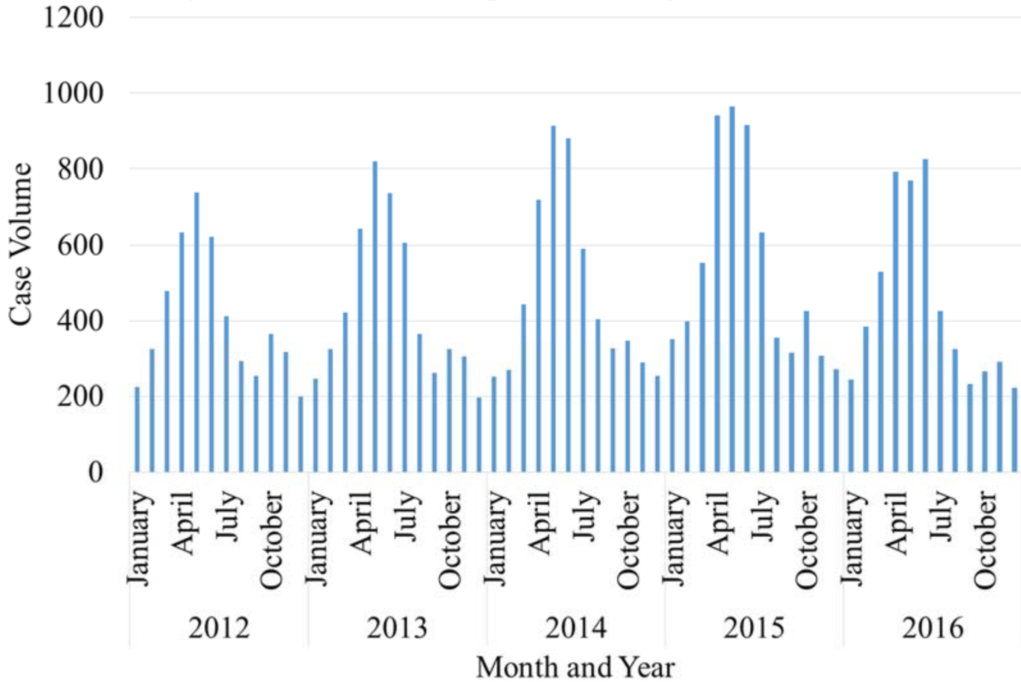


Table 3.4: Case Summary Statistics by month for Platform C

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year
Average	263	340	485	746	842	796	534	349	278	346	302	228	5508
Min	224	270	422	634	740	622	412	293	233	266	289	197	4862
Max	351	399	554	940	965	916	634	405	326	425	317	271	6432
St. Deviation	50	52	56	126	95	118	106	42	40	58	12	33	594

Figure 3.4 summarizes the total case volume for each of the platforms in this study. When all of the platforms are combined, the peak season is between April and October, with the largest peaks in the fall due to Platform C's high case volumes. Table 3.5 provides summary statistics for all cases between the three platforms.

Figure 3.4: Monthly Case volume for the previous five years for all platforms in this study

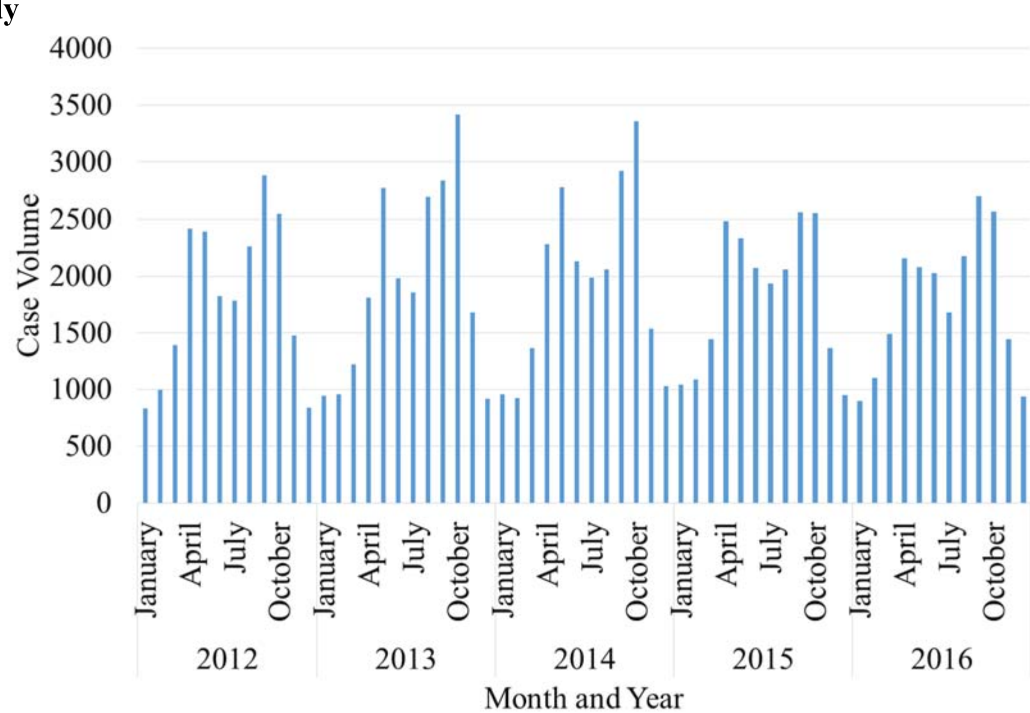


Table 3.5: Case Summary Statistics by month for all platforms combined

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year
Average	934	1013	1384	2231	2471	2008	1849	2249	2781	2891	1502	934	22246
Min	835	926	1223	1813	2082	1827	1678	2060	2560	2551	1366	839	21258
Max	1039	1099	1491	2483	2779	2134	1986	2690	2924	3420	1679	1025	23337
St. Deviation	76	77	102	265	300	116	123	260	150	455	117	67	913

3.3 Workload Platform Regression Models

One of the main objectives of this project is to develop a working model to predict each platform's workload. For the purposes of this project, workload is defined as the number of cases received in a given time period (day, week, month, year). The individuals working on each of these platforms perform tasks other than assisting with technical cases, but this type of work comprises the majority of their workload.

The regression model is assumed to be linear. The model will have the same form for each of the platforms, with the output changing based on the selected platform. The regression model regresses workload on a set of binary variables for each of the respective months. The models are summarized in the equation below.

$$Y_i = \beta_{0i} + \beta_{1i} * January + \beta_{2i} * February + \beta_{3i} * March + \beta_{4i} * April + \beta_{5i} * May + \beta_{6i} * June + \beta_{7i} * July + \beta_{8i} * August + \beta_{9i} * September + \beta_{10i} * October + \beta_{11i} * November$$

Where Y_i = Case volume for a given time period (week, month) and platform, and the months represent binary variable for the month a case volume falls within. This form of equation differs from those proposed for other staffing models from section 2.1. Here, month of the year is deemed the most critical factor in determining workload. This is similar to Avramidis et al's (2004) work looking a timing during certain periods of the day, but on a larger time interval (year).

There will be six different models developed. A case per week and case per month model for each of the respective platforms. A summary of the 6 models is listed in table 3.6 below. For this project the daily case volume will not be analyzed, as the day of the week has high variability depending on the time of year. A Saturday in October is much more likely to be busy than a Saturday in January. Monthly and weekly based models were chosen to provide two different levels specificity for analyses. Using a monthly model, there are five data points for each month, while with a weekly model there are approximately twenty. For the weekly model, total case volumes for a full week are analyzed as partial weeks (not a full seven day period) may be present. The weekly and monthly model for each platform is essentially the same, other than one uses monthly data and one uses weekly data. This does provide different coefficients, therefore two models for each platform are defined.

Table 3.6: Model Names and Description of Dependent Variables

Model Name	Description
$Y_{A\ Month}$	Amount of Platform A cases for a given month
$Y_{A\ Week}$	Amount of Platform A cases for a given week
$Y_{B\ Month}$	Amount of Platform B cases for a given month
$Y_{B\ Week}$	Amount of Platform B cases for a given week
$Y_{C\ Month}$	Amount of Platform C cases for a given month
$Y_{C\ Week}$	Amount of Platform C cases for a given week

3.4 Optimization

Once a workload model is estimated for each platform, a baseline case volume will be forecasted for each platform, based on the monthly or weekly time interval. For example: For the month of June, the $Y_{A\ June}$ model predicts 900 cases, the $Y_{B\ June}$ model predicts 350 cases, and the $Y_{C\ June}$ model predicts 800 cases. This gives a total volume between the three platforms of 2050 cases (Y_{June}). This value is the workload that must be shared between employees for a given time period.

The objective of the optimization will be to minimize the cases worked per person, for a given time period (week, month). Since resources will be shared between the respective platforms, the goal is to have the average cases per person per time period for each platform be as close to one another as possible. This is accomplished by using an aggregate case per person measure. Average case per person figure is computed for each platform. This value is then multiplied by the platform's share of the total case volume. These three values are summed to give a weighted average case per day measure.

For the three platforms, there are 22 full time equivalent employees. Full time equivalent (FTE) is used, as more than twenty-two people assist these platforms with technical support, but the majority of their time is comprised of other duties. Platform A has 12 full time equivalent employees, and both Platform B and Platform C have 5 FTEs.

The models will be constrained by minimum and maximum staffing levels for each platform, as well as the total labor pool. Minimum staffing requirements are necessary to ensure there is always staffing, and to account for sick days, vacation days, and other tasks outside of technical support cases. Maximum staffing levels are set for physical space requirements in the office. The minimum and maximum staffing requirements are summarized in table 3.7 below.

Table 3.7: Minimum and Maximum Staffing Levels for Each Platform

Platform	Normal Staffing Level	Minimum Staffing	Maximum Staffing
Platform A	12	6	15
Platform B	5	3	9
Platform C	5	3	9

The optimization model will be developed as a mixed integer nonlinear programming (MINLP) model. The nonlinear programming (NLP) model is summarized below.

The decision variables include:

X_A= Number of people (FTEs) working on Platform A

X_B= Number of people (FTEs) working on Platform B, and

X_C= Number of people (FTEs) working on Platform C

The objective of the MINLP model is to minimize the weighted average cases per person, which is calculated as:

$$\left(\frac{Y_{A\ Month}}{X_A} \times \frac{Y_{A\ Month}}{Y_{Total\ Month}}\right) + \left(\frac{Y_{B\ Month}}{X_B} \times \frac{Y_{B\ Month}}{Y_{Total\ Month}}\right) + \left(\frac{Y_{C\ Month}}{X_C} \times \frac{Y_{C\ Month}}{Y_{Total\ Month}}\right)$$

OR

$$\left(\frac{Y_{A\ Week}}{X_A} \times \frac{Y_{A\ Week}}{Y_{Total\ Week}}\right) + \left(\frac{Y_{B\ Week}}{X_B} \times \frac{Y_{B\ Week}}{Y_{Total\ Week}}\right) + \left(\frac{Y_{C\ Week}}{X_C} \times \frac{Y_{C\ Week}}{Y_{Total\ Week}}\right)$$

depending on the timeframe chosen. The objective is subject to the following constraints as presented earlier:

$$X_A + X_B + X_C = 22$$

$$X_A, X_B, X_C = Integer$$

$$6 \leq X_A \leq 15$$

$$3 \leq X_B \leq 9$$

$$3 \leq X_C \leq 9$$

The model is solved using EXCEL with the built-in Solver Add-In and the GRG nonlinear programming algorithm (Excel 2013).

In Chapter 4, additional scenarios will be ran with the MINLP model for sensitivity analysis. Changes to the bounds for each platform, as well as changing the number of FTE's will be analyzed.

3.5 Summary of Methodology

In summary, six models are developed to predict the monthly and weekly case volume based on the month of the year. These values represent an average volume based on week or month. Each of these model's outputs is then used in an optimization model. This optimization's goal is to assign people to different platforms, based on the respective case volume for a given time period.

CHAPTER IV: RESULTS AND DISCUSSION

This chapter presents the regression models for forecasting weekly and monthly cases for each platform. Regression models were estimated using ordinary least squares (OLS) in EXCEL. A full presentation of model outputs with summary statistics can be found in the appendix.

4.1 Platform A Models

Below is the monthly model equation for Platform A, using the coefficients from the regression model output. The standard error for each coefficient is listed below the coefficient in parentheses. This model predicts the monthly case total for a particular month.

$$
\begin{aligned}
Y_{A\,Month} = \frac{608.6}{(78.3)} - \frac{95.4}{(110.8)} * January - \frac{185.4}{(110.8)} * February - \frac{208.2}{(110.8)} * March \\
- \frac{228.2}{(110.8)} * April - \frac{79}{(110.8)} * May + \frac{263.4}{(110.8)} * June + \frac{555.6}{(110.8)} * July \\
+ \frac{1196.8}{(110.8)} * August + \frac{1782.8}{(110.8)} * September + \frac{1800.4}{(110.8)} * October \\
+ \frac{491.8}{(110.8)} * November
\end{aligned}
$$

The monthly Platform A model has a R-Squared value of 0.96. The coefficients for the intercept, July, August, September, October, and November are all statistically significant at the 1% level. The coefficients on the months of June and April are significant at the 5% level, and March is significant at the 10% level. The coefficients for the months of January, February, and May are not statistically significant. The months with the highest frequency of cases do have statistically significant coefficients.

Below is the weekly model equation for Platform A, using the coefficients from the regression model output. This model predicts the weekly total of cases during a particular month.

$$Y_{A\,Week} = \frac{128.6}{(13.5)} - \frac{15.7}{(19.1)} * January - \frac{24.4}{(20.0)} * February - \frac{36.4}{(19.4)} * March - \frac{40.2}{(19.7)} * April - \frac{10.5}{(19.7)} * May + \frac{80.1}{(19.7)} * June + \frac{131.9}{(19.7)} * July + \frac{288.3}{(19.7)} * August + \frac{436.0}{(19.7)} * September + \frac{398.9}{(20.0)} * October + \frac{128.6}{(19.7)} * November$$

The weekly Platform A model has a R-Squared value of 0.89. The coefficients for the intercept, June, July, August, September, October, and November are statically significant at the 1% level. The coefficient for the month of April is significant at the 5% level, and the coefficient for the month of March is significant at the 10% level. The coefficients for the months of January, February, and May are not statistically significant. As with the monthly model, the months with the highest frequency of cases are statistically significant at the 1% level.

4.2 Platform B Models

Below is the monthly model equation for Platform B, using the coefficients from the regression model output. This model predicts the monthly case total for a particular month.

$$Y_{B\,Month} = \frac{96.8}{(51.1)} + \frac{60.8}{(72.3)} * January + \frac{152.8}{(72.3)} * February + \frac{401.8}{(72.3)} * March + \frac{1007.6}{(72.3)} * April + \frac{1002.8}{(72.3)} * May + \frac{242.6}{(72.3)} * June + \frac{54.4}{(72.3)} * July - \frac{2}{(72.3)} * August + \frac{15.2}{(72.3)} * September + \frac{39.2}{(72.3)} * October + \frac{3}{(72.3)} * November$$

The monthly Platform B regression model has a R-Squared value of 0.92. The coefficients for the months of March, April, May, and June are statistically significant at the 1% level. The coefficient for the month of February is significant at the 5% level, and the intercept is significant at the 10% level. The coefficients for the months of January, July, August, September, October, and November are not statistically significant. The months with the highest frequency of cases do have statistically significant coefficients.

Below is the weekly model equation for Platform B, using the coefficients from the regression model output. This model predicts the weekly total of cases during a particular month.

$$Y_{B\,Week} = \frac{21.6}{(9.4)} + \frac{12.7}{(13.3)} * January + \frac{39.3}{(13.9)} * February + \frac{93.1}{(13.5)} * March + \frac{235.8}{(13.7)} * April + \frac{230.6}{(13.7)} * May + \frac{58.9}{(13.7)} * June + \frac{12.9}{(13.7)} * July + \frac{0.6}{(13.7)} * August + \frac{5.1}{(13.7)} * September + \frac{9.5}{(13.9)} * October + \frac{0.7}{(13.7)} * November$$

The weekly Platform B regression model has a R-Squared value of 0.80. The coefficients for the months of February, March, April, May, and June are statistically significant at the 1% level. The intercept is significant at the 5% level. The months of January, July, August, September, October and November are not statistically significant. As with the monthly model, the months with the highest frequency of cases are statistically significant at the 1% level.

4.3 Platform C Models

Below is the monthly model equation for Platform C, using the coefficients from the regression model output. This model predicts the monthly case total for a particular month.

$$Y_{C\ Month} = \frac{228.2}{(33.3)} + \frac{35}{(47.1)} * January + \frac{112}{(47.1)} * February + \frac{257}{(47.1)} * March + \frac{517.8}{(47.1)} * April + \frac{613.6}{(47.1)} * May + \frac{568}{(47.1)} * June + \frac{305.4}{(47.1)} * July + \frac{120.8}{(47.1)} * August + \frac{49.4}{(47.1)} * September + \frac{117.4}{(47.1)} * October + \frac{73.4}{(47.1)} * November$$

The monthly Platform C model has a R-Squared value of 0.91. The coefficients for the intercept, March, April, May, June and July are statistically significant at the 1% level. The coefficients for the month of February, August, and October are statistically significant at the 5% level. The coefficients for the months of January, September, and November are not statistically significant. The months with the highest frequency of cases do have statistically significant coefficients.

Below is the weekly model equation for Platform C using the coefficients from the regression model output. This model predicts the weekly total of cases during a particular month.

$$Y_{C\,Week} = \frac{48.3}{(5.0)} + \frac{10.2}{(7.0)} * January + \frac{33.7}{(7.3)} * February + \frac{61.8}{(7.1)} * March + \frac{123.8}{(7.2)} * April + \frac{148.2}{(7.2)} * May + \frac{137.9}{(7.2)} * June + \frac{72.6}{(7.2)} * July + \frac{31.9}{(7.2)} * August + \frac{15.4}{(7.2)} * September + \frac{29.3}{(7.3)} * October + \frac{22.9}{(7.2)} * November$$

The weekly Platform C model has a R-Squared value of 0.84. The coefficients for the intercept, February, March, April, May, June, July August, October and November are statistically significant at the 1% level. September is significant at the 5% level, and the month of January is not statistically significant.

4.4 MINLP Weekly and Monthly Platform Staffing Model Results

Table 4.1 below uses each of the above equations to create a monthly total, or weekly average by month for each of the six models. These baseline numbers are to be used in the optimization MINLP model to examine staffing levels for each platform.

Table 4.1: Forecasted monthly and weekly volumes by platform and month

Model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
$Y_{A\ Month}$	513	423	400	380	530	872	1164	1805	2391	2409	1100	609
$Y_{A\ Week}$	113	104	92	88	118	209	260	417	565	527	257	129
$Y_{B\ Month}$	158	250	499	1104	1100	339	151	95	112	136	100	97
$Y_{B\ Week}$	34	61	115	257	252	80	34	22	27	31	22	22
$Y_{C\ Month}$	263	340	485	746	842	796	534	349	278	346	302	228
$Y_{C\ Week}$	58	82	110	172	197	186	121	80	64	78	71	48

The above data were then used to run the MINLP staffing optimization model. The model was ran for each month, using monthly and weekly forecasted data. The summary of the model output is contained in tables 4.2 and 4.3 respectively. A screenshot from the EXCEL spreadsheet can be found in the appendix.

Table 4.2: Optimal staffing levels for each platform, based on the monthly MINLP Platform Staffing model

Staff Level	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
X_A	12	9	6	6	6	9	13	15	15	15	15	14
X_B	4	6	8	9	9	4	3	3	3	3	3	3
X_C	6	7	8	7	7	9	6	4	4	4	4	5

Table 4.3: Optimal staffing levels for each platform, based on the weekly MINLP Platform Staffing model

Staff Level	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
X_A	12	9	6	6	6	10	13	15	15	15	15	14
X_B	4	6	8	9	9	4	3	3	3	3	3	3
X_C	6	7	8	7	7	8	6	4	4	4	4	5

Both models (weekly and monthly) provided the same results for staffing except for the month of June. This time is unique as Platform A and Platform C demand starts to rise, and Platform C volumes drop off sharply. Graphical representations of the staff levels for the monthly and weekly models can be found in figures 4.1 and 4.2 respectively.

Figure 4.1: Optimal staffing levels for each platform based on the monthly model

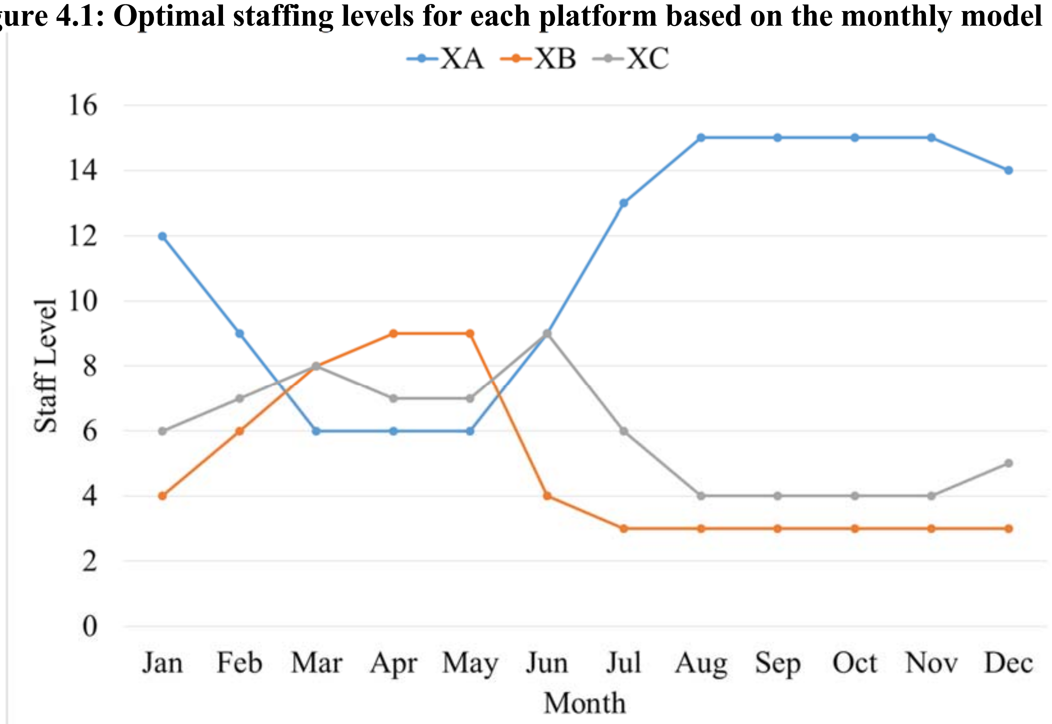
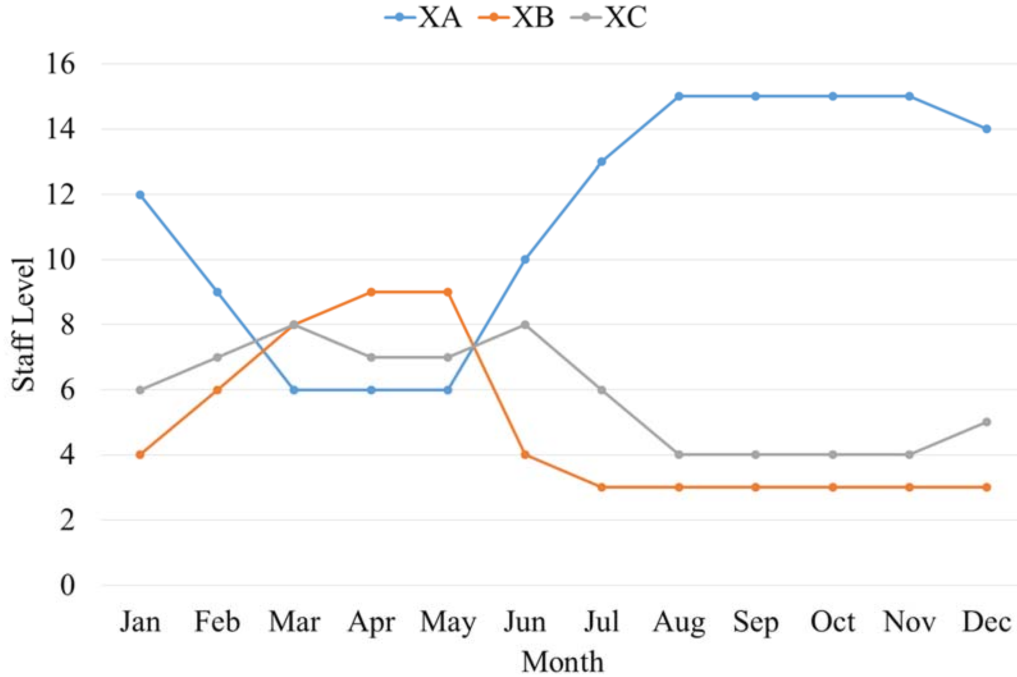


Figure 4.2: Optimal staffing levels for each platform based on the weekly model



4.5 Sensitivity report and Lagrange Multiplier

A sensitivity report was ran for each month of the original optimization model. This optimization is solved as a non-linear so a shadow price is not provided via Excel. Since the original equation had each of the FTE values equaling an integer, that constraint had to be removed to get an appropriate Lagrange Multiplier. For each of the months of the year, the Lagrange Multiplier ranged from -1.73 to -5.85. This results signifies that if the total number of FTE's are increased, the average cases per person per month will go down for each of the respective months.

4.6 Sensitivity analysis of models combined by month

In reviewing the optimization model, the limits for several of the platforms were met in certain months. Two of the platforms went to the maximum or minimum constraint for several months. To assess these constraints, sensitivity analysis was conducted on the bounds for the staffing constraints from section 3.4. These are changed to:

$$4 \leq X_A \leq 17$$

$$2 \leq X_B \leq 10$$

$$2 \leq X_C \leq 10$$

Tables 4.4 and 4.5 below show the results with the wider bounds for the staffing levels for each platform.

Table 4.4: Optimal staffing levels for each platform, based on the revised (bounds) monthly MINLP Platform Staffing model

Staff Level	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
X_A	12	9	6	4	5	9	14	17	17	17	16	15
X_B	4	6	8	10	10	4	2	2	2	2	2	2
X_C	6	7	8	8	7	9	6	3	3	3	4	5

Table 4.5: Optimal staffing levels for each platform, based on the revised (bounds) weekly MINLP Platform Staffing model

Staff Level	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
X_A	12	9	6	4	5	10	14	17	17	17	16	14
X_B	4	6	8	10	10	4	2	2	2	2	2	3
X_C	6	7	8	8	7	8	6	3	3	3	4	5

With the revised limits for the optimization model, some changes are noted in the spring and fall timeframes. The total staffing for Platform A is smaller in the spring and higher in the fall, with the opposite being found for Platform B. Platform C also produced some changes, but is closer to the original optimization results when compared to the other two platforms. A graphical representation of the revised staff levels for the monthly and weekly models can be found in figures 4.3 and 4.4 respectively.

Figure 4.3: Optimal staffing levels for each platform based on the revised (bounds) monthly model

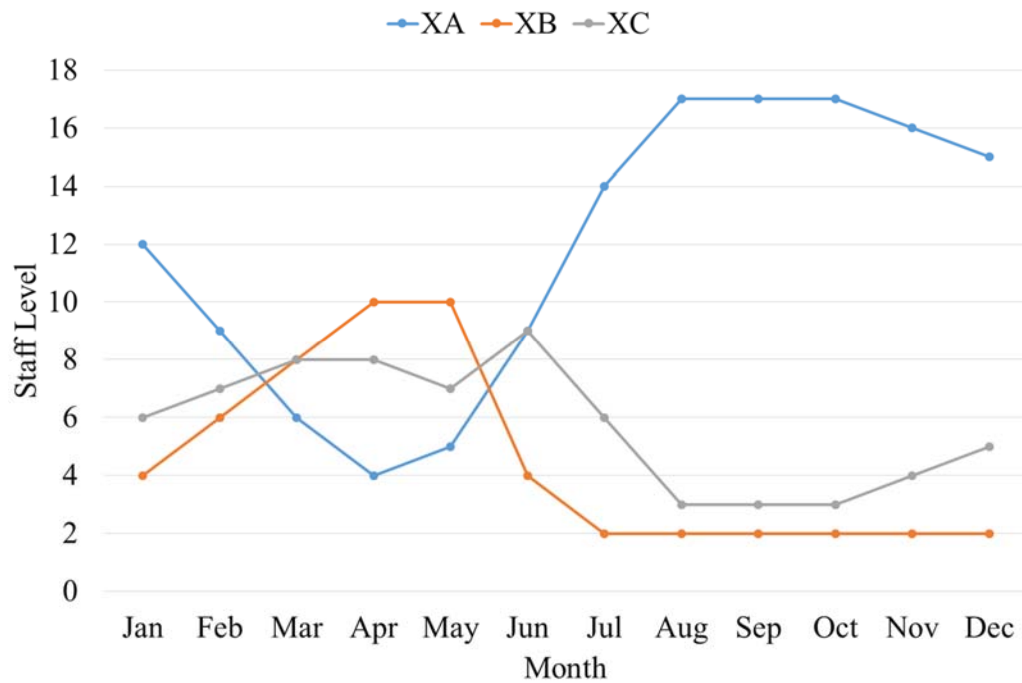
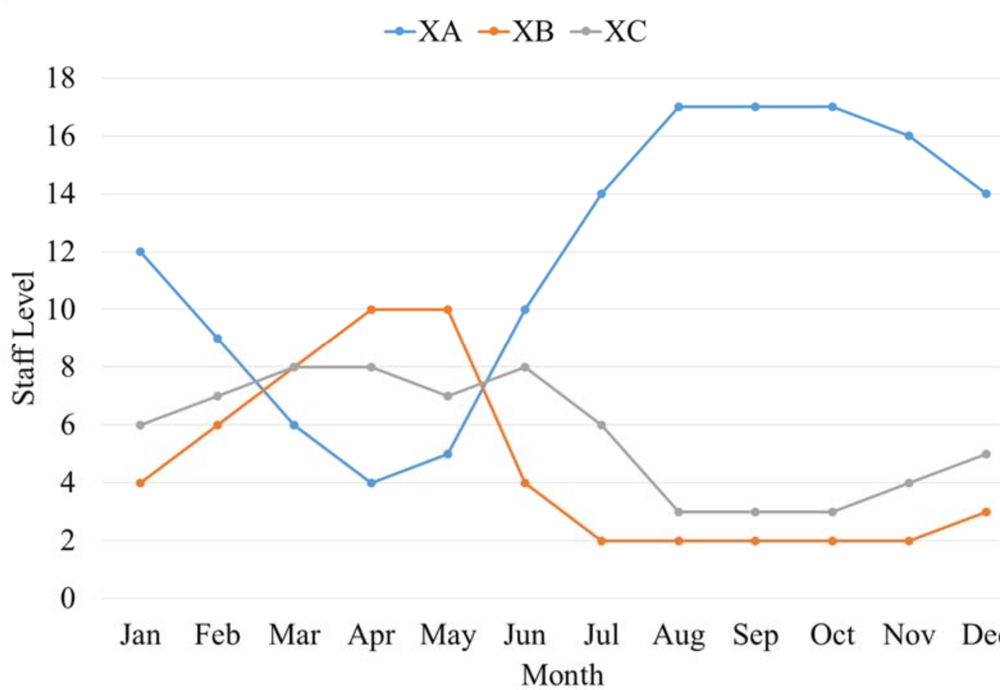


Figure 4.4: Optimal staffing levels for each platform based on the revised (bounds) weekly model



4.7 Analysis of increased full time equivalent employees

Additional analysis was conducted by increasing the number of FTE employees by approximately 18 percent. This value would add 2 FTE employees to Platform A, and 1 to Platform B and Platform C. The MINLP discussed in section 3.4 was modified as follows:

$$X_A + X_B + X_C = 26$$

$$4 \leq X_A \leq 17$$

$$2 \leq X_B \leq 10$$

$$2 \leq X_C \leq 10$$

The bounds for each platform were selected from the analysis conducted in section 4.5. Tables 4.6 and 4.7 below show the results with the increased FTE level and the wider bounds from the previous section.

Table 4.6: Optimal staffing levels for each platform, based on the revised (FTE) monthly MINLP Platform Staffing model

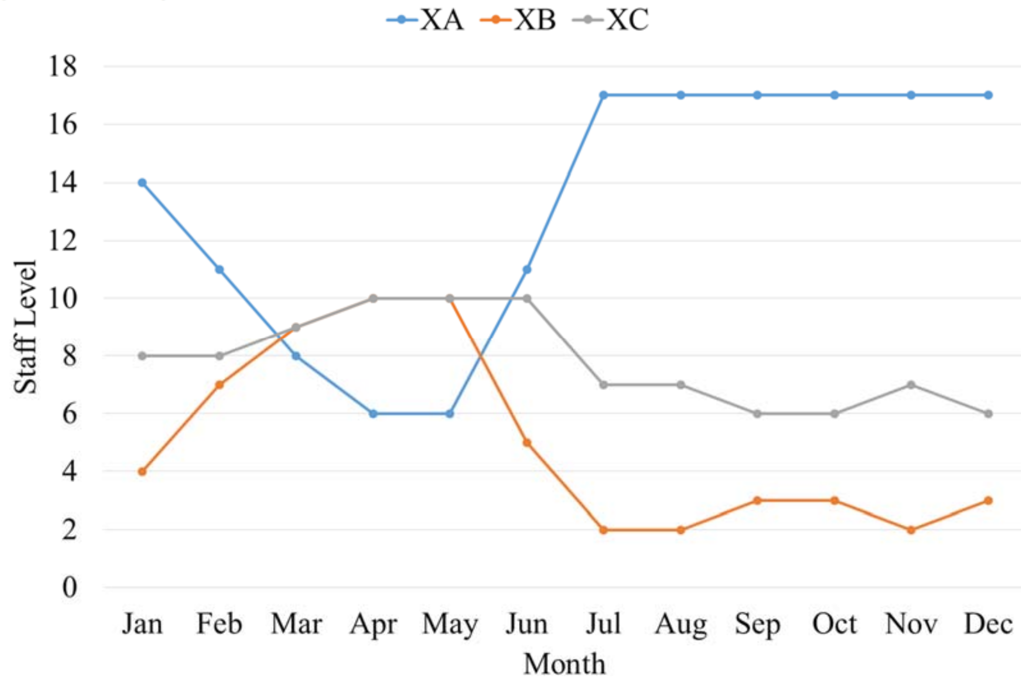
Staff Level	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
X_A	14	11	8	6	6	11	17	17	17	17	17	17
X_B	4	7	9	10	10	5	2	2	3	3	2	3
X_C	8	8	9	10	10	10	7	7	6	6	7	6

Table 4.7: Optimal staffing levels for each platform, based on the revised (FTE) weekly MINLP Platform Staffing model

Staff Level	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
X_A	14	11	8	6	6	11	17	17	17	17	17	17
X_B	4	7	9	10	10	5	2	2	3	3	2	3
X_C	8	8	9	10	10	10	7	7	6	6	7	6

With the revised FTE model, we see a few changes compared to the first two optimization. The monthly and weekly model are now exactly the same in terms of optimal staffing level. It is also noted that Platform C is more consistent with its staffing level throughout the year. Once again, Platform A and Platform B go to the bounds of their staffing level during the peak seasons. A graphical representation of the FTE model is in figure 4.5 below.

Figure 4.5: Optimal staffing levels for each platform based on the revised (FTE) monthly and weekly model



4.8 Summary of results

Each regression model has produced a forecasting tool to predict the average number of cases per month or week based on the month of the year. When this data is used with an optimization model, an appropriate staffing level is generated. Each of the three scenarios for optimization has produced similar trends with regards to staffing levels. Platform A and Platform B both experience larger swings in their staffing levels, while Platform C is more consistent throughout the year.

CHAPTER V: CONCLUSIONS

Efficient utilization of resources for employers continues to be a top priority. In the instance of an OEM, staffing of technical support centers for “after the sale” support is one of these situations. Technical support centers seek to provide a high level of service to its end users, while also effectively using its available manpower. This research focused on one such OEM’s use of technical support staff across 3 different product lines.

Regression analysis was performed for each platform based on weekly and monthly case volume data. For each of the platforms, the regression produced a forecast model which can be used to predict the monthly or weekly case average (volume), based on the month of the year. Each model produced statistically significant coefficients for the months in which they see the highest case volume. These models can be used as a tool for managers for staffing, as well as bench marking case volumes in future years.

Using the monthly average data from the previous regressions, an optimization was preformed to determine proper staffing levels based on the month of the year. Six different optimization scenarios were analyzed, based on the monthly and weekly data regression and using three different bounds of staffing levels. All six of the optimizations show the same trends, with slightly different numbers for the maximum and minimums, based on the bounds from the original equation. This shows that regardless of the actual value of total FTE’s or FTE’s at each platform, each platform has a different requirement based on the time of year.

The staffing levels that are recommended by the model have been reviewed by the technical support center’s management. The staffing levels proposed similar to what has been done in the past, but shows that more resources are needed for certain platforms peak seasons. Shifting these resources to those platforms should equate to better dealer experience and faster problem resolution.

Further considerations for this research would involve looking at the effect of dealer satisfaction (DSI) based on the staffing level of each platform. The scope of this research was focused on appropriate staff levels, which should correlate to appropriate response times to dealers. To verify this, DSI scores would have to be compared to different staffing levels for which data is not available presently. Management is hesitant to lower staffing levels during peak times to test this theory.

Another topic that has not been addressed in this paper is around cross-training of employees that must move between platforms. The reason this was excluded is due to the nature of work. Once an employee can diagnose a complex hydraulic, electrical, or engine related issue, they can do that for another platform as well. The basics of those three areas covers approximately 70 percent of the needed skill, and the other 30 percent specific to the platform can be learned on the job.

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APPENDIX A

Table A1: Platform A Monthly Regression Results from GRETL

Model 1: OLS, using observations 2012:01-2016:12 (T = 60)
Dependent variable: SumofCaseCount

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	608.6	78.3178	7.7709	<0.0001	***
January	−95.4	110.758	−0.8613	0.3933	
February	−185.4	110.758	−1.6739	0.1007	
March	−208.2	110.758	−1.8798	0.0662	*
April	−228.2	110.758	−2.0603	0.0448	**
May	−79	110.758	−0.7133	0.4791	
June	263.4	110.758	2.3782	0.0214	**
July	555.6	110.758	5.0163	<0.0001	***
August	1196.8	110.758	10.8055	<0.0001	***
September	1782.8	110.758	16.0963	<0.0001	***
October	1800.4	110.758	16.2552	<0.0001	***
November	491.8	110.758	4.4403	<0.0001	***

Mean dependent var	1049.817	S.D. dependent var	746.4931
Sum squared resid	1472083	S.E. of regression	175.1239
R-squared	0.955226	Adjusted R-squared	0.944965
F(11, 48)	93.09491	P-value(F)	1.74e-28
Log-likelihood	−388.3716	Akaike criterion	800.7433
Schwarz criterion	825.8754	Hannan-Quinn	810.5738
rho	0.298843	Durbin-Watson	1.397989

Table A2: Platform A Weekly Regression Results from GRETL

Model 1: OLS, using observations 1-219
Dependent variable: WEEKSUM

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	128.55	13.5327	9.4992	<0.0001	***
January	−15.65	19.1381	−0.8177	0.4144	
February	−24.3735	19.9646	−1.2208	0.2235	
March	−36.3921	19.3883	−1.8770	0.0619	*
April	−40.1611	19.6625	−2.0425	0.0424	**
May	−10.4944	19.6625	−0.5337	0.5941	
June	80.0611	19.6625	4.0718	<0.0001	***
July	131.894	19.6625	6.7079	<0.0001	***
August	288.283	19.6625	14.6616	<0.0001	***
September	435.95	19.6625	22.1716	<0.0001	***
October	398.862	19.9646	19.9785	<0.0001	***
November	128.561	19.6625	6.5384	<0.0001	***

Mean dependent var	236.3836	S.D. dependent var	174.3957
Sum squared resid	758170.6	S.E. of regression	60.51991
R-squared	0.885649	Adjusted R-squared	0.879573
F(11, 207)	145.7474	P-value(F)	4.92e-91
Log-likelihood	−1203.128	Akaike criterion	2430.256
Schwarz criterion	2470.925	Hannan-Quinn	2446.681
rho	0.154639	Durbin-Watson	1.688044

Table A3: Platform B Monthly Regression Results from GRETL

Model 1: OLS, using observations 2012:01-2016:12 (T = 60)
Dependent variable: SumofCaseCount

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	96.8	51.1025	1.8942	0.0642	*
January	60.8	72.2699	0.8413	0.4044	
February	152.8	72.2699	2.1143	0.0397	**
March	401.8	72.2699	5.5597	<0.0001	***
April	1007.6	72.2699	13.9422	<0.0001	***
May	1002.8	72.2699	13.8758	<0.0001	***
June	242.6	72.2699	3.3569	0.0015	***
July	54.4	72.2699	0.7527	0.4553	
August	−2	72.2699	−0.0277	0.9780	
September	15.2	72.2699	0.2103	0.8343	
October	39.2	72.2699	0.5424	0.5900	
November	3	72.2699	0.0415	0.9671	

Mean dependent var	344.9833	S.D. dependent var	374.9756
Sum squared resid	626752.4	S.E. of regression	114.2687
R-squared	0.924449	Adjusted R-squared	0.907136
F(11, 48)	53.39415	P-value(F)	4.29e-23
Log-likelihood	−362.7552	Akaike criterion	749.5104
Schwarz criterion	774.6425	Hannan-Quinn	759.3409
rho	−0.058010	Durbin-Watson	2.115379

Table A4: Platform B Weekly Regression Results from GRETL

Model 1: OLS, using observations 1-219
Dependent variable: WEEKSUM

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	21.55	9.40378	2.2916	0.0229	**
January	12.65	13.299	0.9512	0.3426	
February	39.2735	13.8733	2.8309	0.0051	***
March	93.1342	13.4728	6.9128	<0.0001	***
April	235.783	13.6634	17.2566	<0.0001	***
May	230.617	13.6634	16.8784	<0.0001	***
June	58.8944	13.6634	4.3104	<0.0001	***
July	12.8944	13.6634	0.9437	0.3464	
August	0.561111	13.6634	0.0411	0.9673	
September	5.11667	13.6634	0.3745	0.7084	
October	9.45	13.8733	0.6812	0.4965	
November	0.672222	13.6634	0.0492	0.9608	

Mean dependent var	79.32420	S.D. dependent var	92.23952
Sum squared resid	366105.0	S.E. of regression	42.05500
R-squared	0.802615	Adjusted R-squared	0.792125
F(11, 207)	76.51905	P-value(F)	1.10e-66
Log-likelihood	−1123.413	Akaike criterion	2270.826
Schwarz criterion	2311.495	Hannan-Quinn	2287.251
rho	0.107879	Durbin-Watson	1.784082

Table A5: Platform C Monthly Regression Results from GRETL

Model 1: OLS, using observations 2012:01-2016:12 (T = 60)
Dependent variable: SumofCaseCount

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	228.2	33.3073	6.8514	<0.0001	***
January	35	47.1036	0.7430	0.4611	
February	112	47.1036	2.3777	0.0214	**
March	257	47.1036	5.4561	<0.0001	***
April	517.8	47.1036	10.9928	<0.0001	***
May	613.6	47.1036	13.0266	<0.0001	***
June	568	47.1036	12.0585	<0.0001	***
July	305.4	47.1036	6.4836	<0.0001	***
August	120.8	47.1036	2.5646	0.0135	**
September	49.4	47.1036	1.0488	0.2995	
October	117.4	47.1036	2.4924	0.0162	**
November	73.4	47.1036	1.5583	0.1257	

Mean dependent var	459.0167	S.D. dependent var	223.6959
Sum squared resid	266249.6	S.E. of regression	74.47729
R-squared	0.909818	Adjusted R-squared	0.889151
F(11, 48)	44.02324	P-value(F)	2.80e-21
Log-likelihood	−337.0717	Akaike criterion	698.1433
Schwarz criterion	723.2755	Hannan-Quinn	707.9739
rho	0.636900	Durbin-Watson	0.720469

Table A6: Platform C Weekly Regression Results from GRETL

Model 1: OLS, using observations 1-219
Dependent variable: WEEKSUM

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	48.3	4.98044	9.6979	<0.0001	***
January	10.15	7.04341	1.4411	0.1511	
February	33.7	7.34758	4.5865	<0.0001	***
March	61.8053	7.13548	8.6617	<0.0001	***
April	123.756	7.23641	17.1018	<0.0001	***
May	148.2	7.23641	20.4798	<0.0001	***
June	137.867	7.23641	19.0518	<0.0001	***
July	72.5889	7.23641	10.0311	<0.0001	***
August	31.8667	7.23641	4.4037	<0.0001	***
September	15.3667	7.23641	2.1235	0.0349	**
October	29.2882	7.34758	3.9861	<0.0001	***
November	22.8667	7.23641	3.1599	0.0018	***

Mean dependent var	104.8904	S.D. dependent var	54.59649
Sum squared resid	102691.8	S.E. of regression	22.27320
R-squared	0.841966	Adjusted R-squared	0.833568
F(11, 207)	100.2588	P-value(F)	1.37e-76
Log-likelihood	−984.2180	Akaike criterion	1992.436
Schwarz criterion	2033.105	Hannan-Quinn	2008.861
rho	0.325029	Durbin-Watson	1.347206

Figure A1: Screenshot from EXCEL spreadsheet of the optimization model