JMP® ACADEMIC CASE STUDY

JMP029: Call Center Improvement

Visual Six Sigma, 2nd Edition

A revision of the Visual Six Sigma: Making Data Analysis Lean case study by Andrew Ruddick and Andy Liddle (Process Insight) and Malcolm Moore (JMP).

Revised with permission by Mia Stephens (JMP), March 2016.

jmp STATISTICAL DISCOVERY

Call Center Improvement
Visual Six Sigma

Key ideas

Exploratory data analysis using linked graphs, data filtering, Distribution, Tabulate, Graph Builder and recursive partitioning. Understanding process capability and characterizing the behavior of a process over time with Control Chart Builder. Confirmatory data analysis with multiple regression and the prediction profiler.

Background

The particular scenario relates to the handling of customer queries via an IT call center. Prior to initiating a call, a customer may or may not have attempted to resolve the issue through alternative contact mechanisms, such as FAQs via a Web site. Due to customer demand, this call center does not operate the traditional answering service, whereby the details of the call and issue are logged and then passed onto a service engineer capable of solving the problem. Instead, the first call is taken by a service engineer who becomes responsible for finding a solution.

The Situation

Benchmark analysis (not presented here) indicated that the company had lower customer satisfaction ratings than best-in-class competitors and that higher levels of customer satisfaction are driven by call center performance with respect to the speed with which calls are answered and problems correctly resolved. Further, customer satisfaction is the top driver of product revenues, and it is estimated that 8 percent revenue growth is possible if the company matches call center performance of best in class.

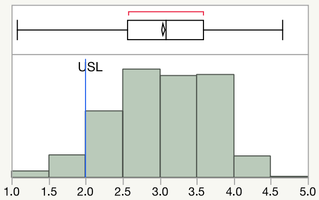
The performance goals to match best-in-class performance are:

- Time to answer should be no more than two minutes.
- 65 percent of calls must be solved in one iteration (or cycle) with a maximum service time of 1.5 hours;
- 85 percent of all calls must be solved with no more than two iterations with a maximum total service time of five hours; and
- 99 percent of all calls must be solved with no more than three iterations with a maximum total service time of 15 hours.

Figures 1, 2 and 3 summarize the time to answer calls and time to solve problems for service calls received in the prior month. These figures indicate that performance alongside these specifications is disappointing. It takes more than two minutes to answer 93.7 percent of calls, and very few problems are solved within the required time, irrespective of the number of times a customer contacts the call center before the problem is solved (iterations or cycles). Substantial reductions in time to answer calls and time to solve problems are necessary to meet the new performance specifications.

Figure 1: Time to Answer Capability Analysis

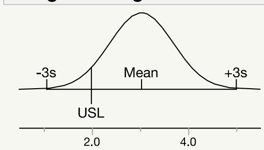
Time to Answer (Mins)



Capability Analysis

Specification	Value	Portion	% Actual
Lower Spec Limit	.	Below LSL	.
Spec Target	.	Above USL	93.6883
Upper Spec Limit	2	Total Outside	93.6883

Long Term Sigma



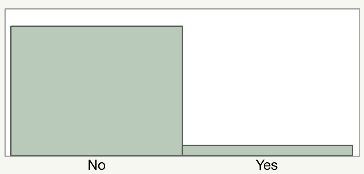
Sigma = 0.65627

Capability	Index	Lower CI	Upper CI
CP	.	.	.
CPK	-0.529	-0.547	-0.510
CPM	.	.	.
CPL	.	.	.
CPU	-0.529	-0.547	-0.510

Portion	Percent	PPM	Sigma Quality
Below LSL	.	.	.
Above USL	94.3671	943670.88	-0.086
Total Outside	94.3671	943670.88	-0.086

Figure 2: Acceptable Time to Answer

Acceptable t to answer?



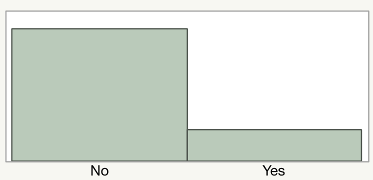
Frequencies

Level	Count	Prob
No	2657	0.93688
Yes	179	0.06312
Total	2836	1.00000

N Missing 0
2 Levels

Figure 3: Time to Solve

t to solve < 1.5 hours?

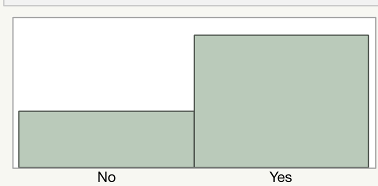


Frequencies

Level	Count	Prob
No	2305	0.81276
Yes	531	0.18724
Total	2836	1.00000

N Missing 0
2 Levels

t to solve < 5 hours?

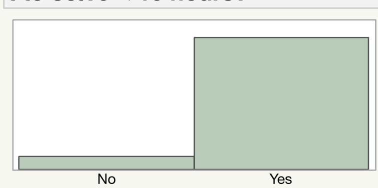


Frequencies

Level	Count	Prob
No	835	0.29443
Yes	2001	0.70557
Total	2836	1.00000

N Missing 0
2 Levels

t to solve < 15 hours?



Frequencies

Level	Count	Prob
No	233	0.08216
Yes	2603	0.91784
Total	2836	1.00000

N Missing 0
2 Levels

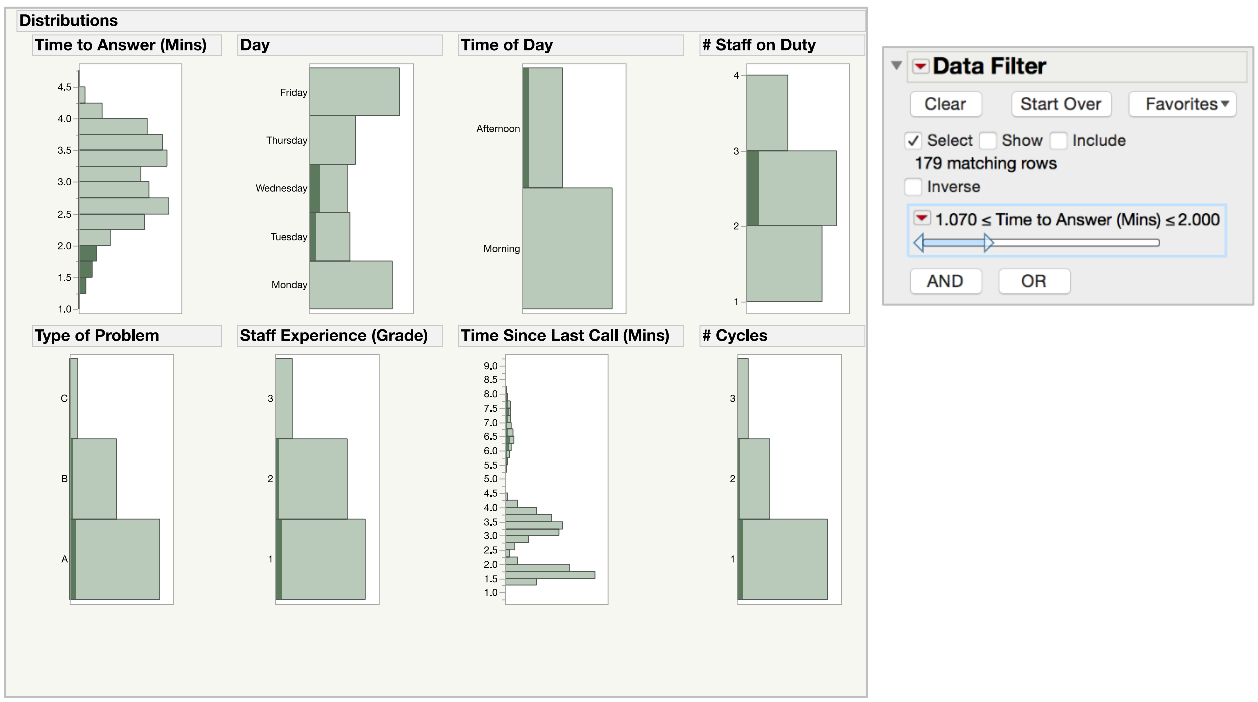
Exploring Potential Root Causes

A team was commissioned to investigate the call center process and dramatically improve process capability. The team applied the lean data analysis process and used cause-and-effect analysis to frame the problem with regard to identification of the potential causes of excessive time to answer and time to solve.

Data on these potential causes, along with time to answer, time to solve and number of cycles were collated for service calls received in the prior calendar month, which resulted in a data set consisting of 2836 rows. The data are in ***Call Center VSS.jmp***.

Figure 4 shows simple histograms of each variable, with calls having a time to answer of less than two minutes identified with darker shading (these rows were selected using the Data Filter). This tells us that the only time calls are answered in less than two minutes is on Tuesday and Wednesday afternoons when two staff are on duty. Further, calls are never answered in less than two minutes when three staff are on duty.

Figure 4: Distributions for Time to Answer and Inputs, and the Data Filter



This prompts us to explore what is different about the operation of the call center when three staff are on duty. By clicking on the bar for three staff on duty, we highlight the circumstances associated with calls received when three staff are on duty, as illustrated in Figure 5. This shows that only three staff are on duty on Friday mornings, which is one of the busiest periods.

Figure 5: Time to Answer with Three Staff on Duty

The distribution of time to answer when there are three staff on duty has a mean of approximately 2.6 minutes with a range from 2 to 3.2 minutes. Thus it appears that on some occasions, the staff loading of the call center has been adjusted to compensate for higher call volumes; however, the loading has not been optimized to achieve the new performance goals. To determine the impact of increasing staff loading by one person, it is necessary to perform the comparison between periods of similar call volumes. The tabulation in Figure 6 indicates an equivalent call volume occurs on Monday morning.

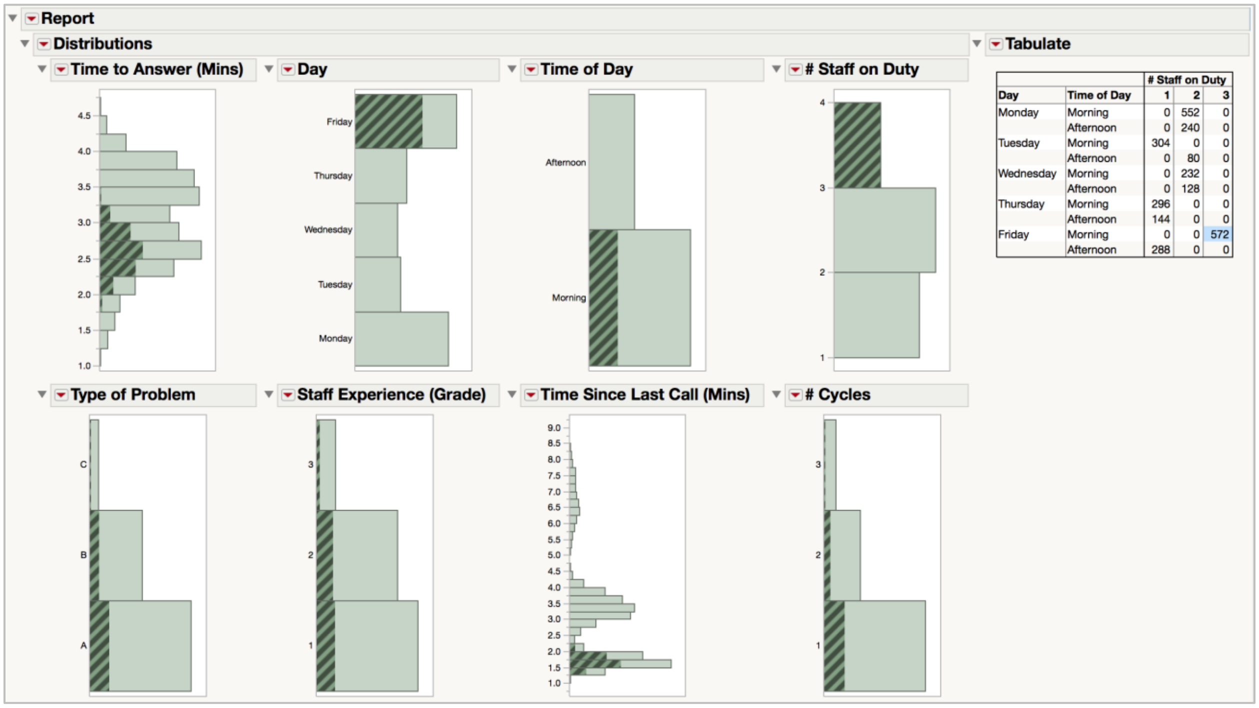
Figure 6: Tabulation of Staff on Duty

Tabulate

		# Staff on Duty		
Day	**Time of Day**	**1**	**2**	**3**
Monday	Morning	0	552	0
	Afternoon	0	240	0
Tuesday	Morning	304	0	0
	Afternoon	0	80	0
Wednesday	Morning	0	232	0
	Afternoon	0	128	0
Thursday	Morning	296	0	0
	Afternoon	144	0	0
Friday	Morning	0	0	572
	Afternoon	288	0	0

By combining the tabulation with the distribution output, we produce an interactive report. Alternately clicking on the Monday morning and Friday morning cells within the summary table, we see the impact of increasing the number of staff on duty by one between periods of equivalent activity, as illustrated in Figure 7.

Figure 7: Combined Reports for Distributions and Tabulate

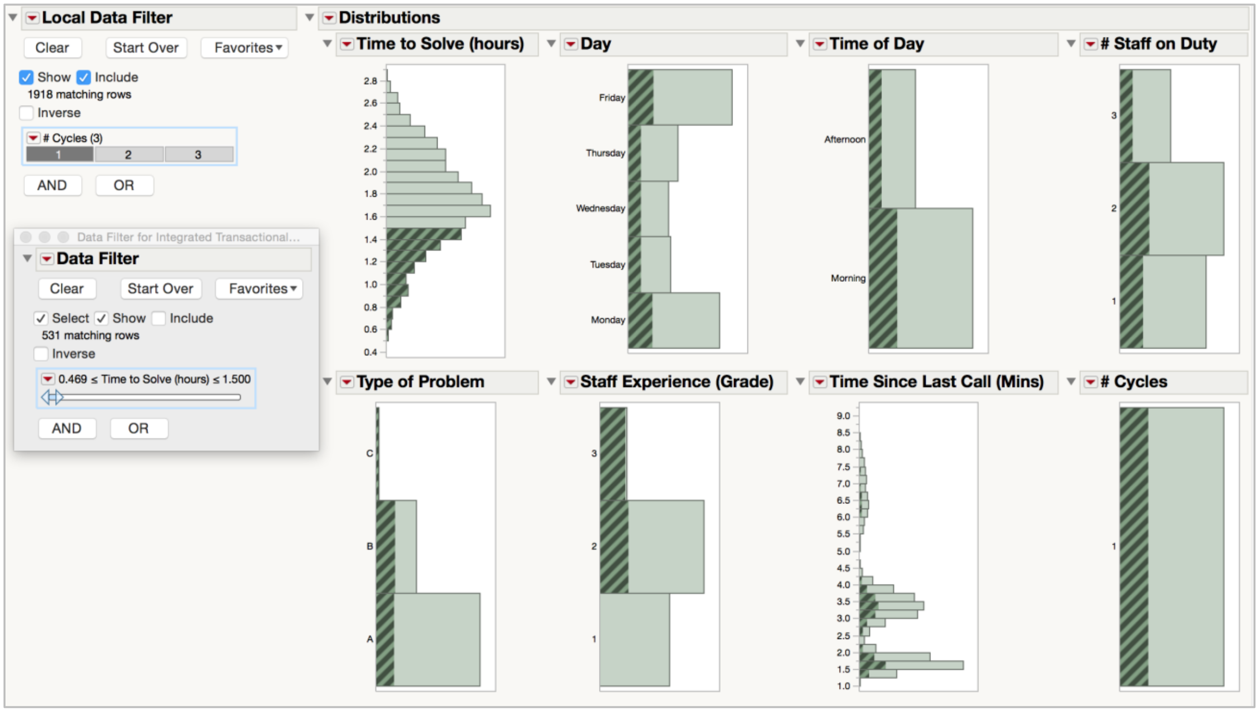


The impact of increasing the number of staff on duty by one is to reduce mean time to answer by roughly one minute (this can be further explored using the Distribution and the Data Filter). This visual model is confirmed by clicking on other cells with similar call volume but differing number of staff on duty, e.g., Wednesday afternoon vs. Thursday afternoon, but this is not shown in the interest of brevity.

The distribution of time to solve has three clusters of data points: the first, with a mean of around two hours, is associated with calls solved in the first cycle; the second, with a mean of around seven hours, is associated with calls solved in the second cycle; and the third, with a mean of around 24 hours, is associated with calls solved in the third cycle. Thus a separate visual analysis was performed for each of the three subgroups defined by number of cycles.

Figure 8 shows simple histograms of each variable when the number of cycles is one with calls with a time to solve of less than 1.5 hours, identified with darker shading. This indicates that staff experience followed by type of problem are the top drivers of variation in time to solve.

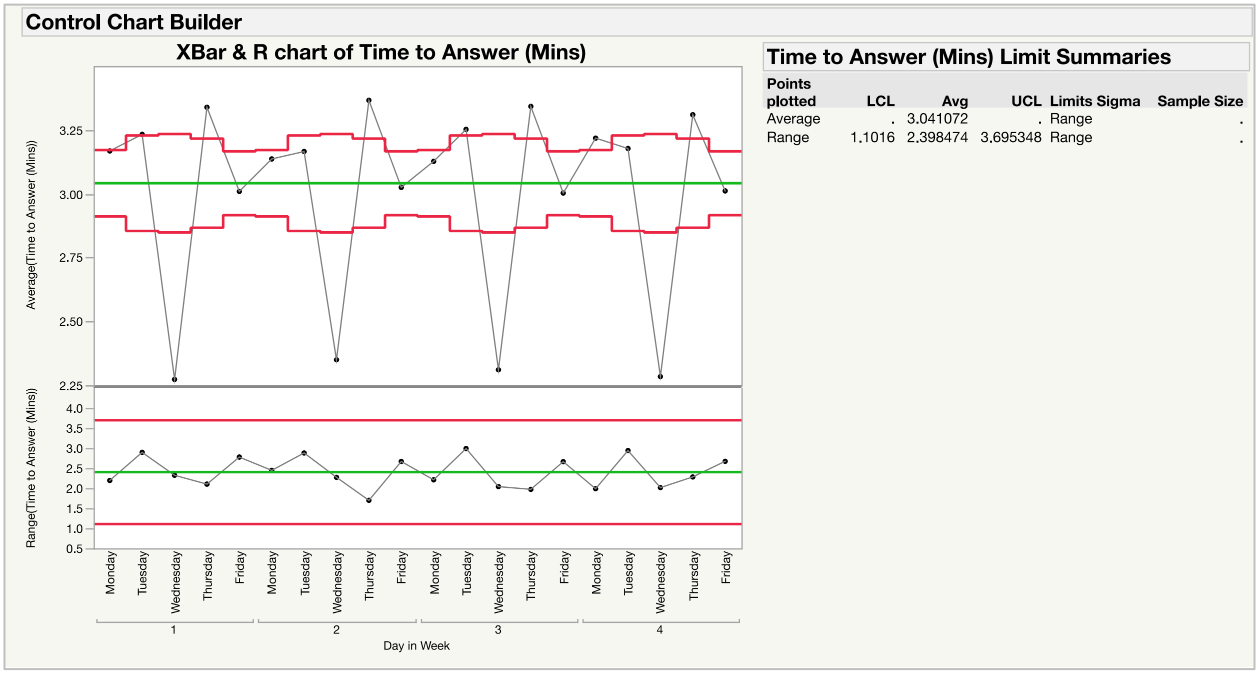
Figure 8: Time to Solve for Cycle 1, with Data Filters for Selection



Since we have time-ordered data, we can use a control chart to explore the behavior of the process over time. The XBar and R chart of time to answer, subgrouped by day and week, shows a repeatable pattern, with higher average times on Monday, Tuesday and Thursday and the lowest average times on Wednesday (see Figure 9).

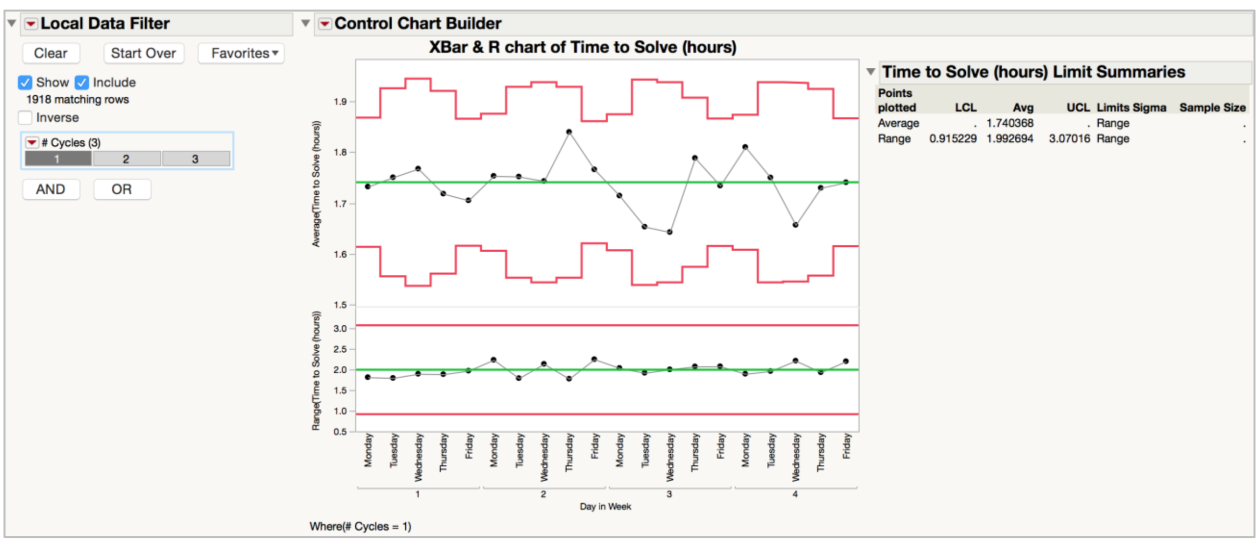
Further, the control limits are tighter on Monday and Wednesday, indicating that the call volume is higher on Mondays and Fridays than on other days.

Figure 9: Control Chart of Time to Answer



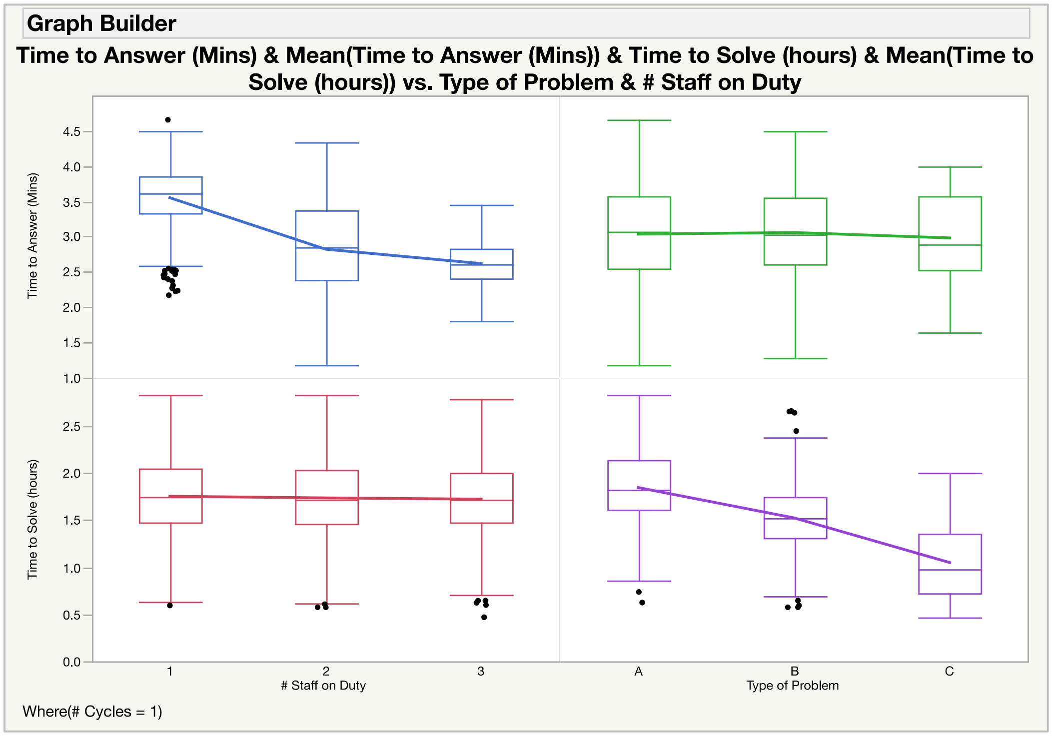
There is less of a time-ordered effect for the time to solve, as show in Figure 10. The points appear randomly scattered around the center line, with no obvious pattern over time.

Figure 10: Control Chart of Time to Solve, Cycle 1



To further explore potential relationships between the variables, we use the Graph Builder. For calls answered in one cycle, we can see that the number of staff on duty seems to be related to the time to answer but is not related to the type of problem (see Figure 11). The opposite appears true for time to solve - the type of problem appears to a factor, while the number of staff isn't a factor.

Figure 11: Graph Builder for Time to Solve and Time to Answer



Exploring Potential Root Causes using Recursive Partitioning

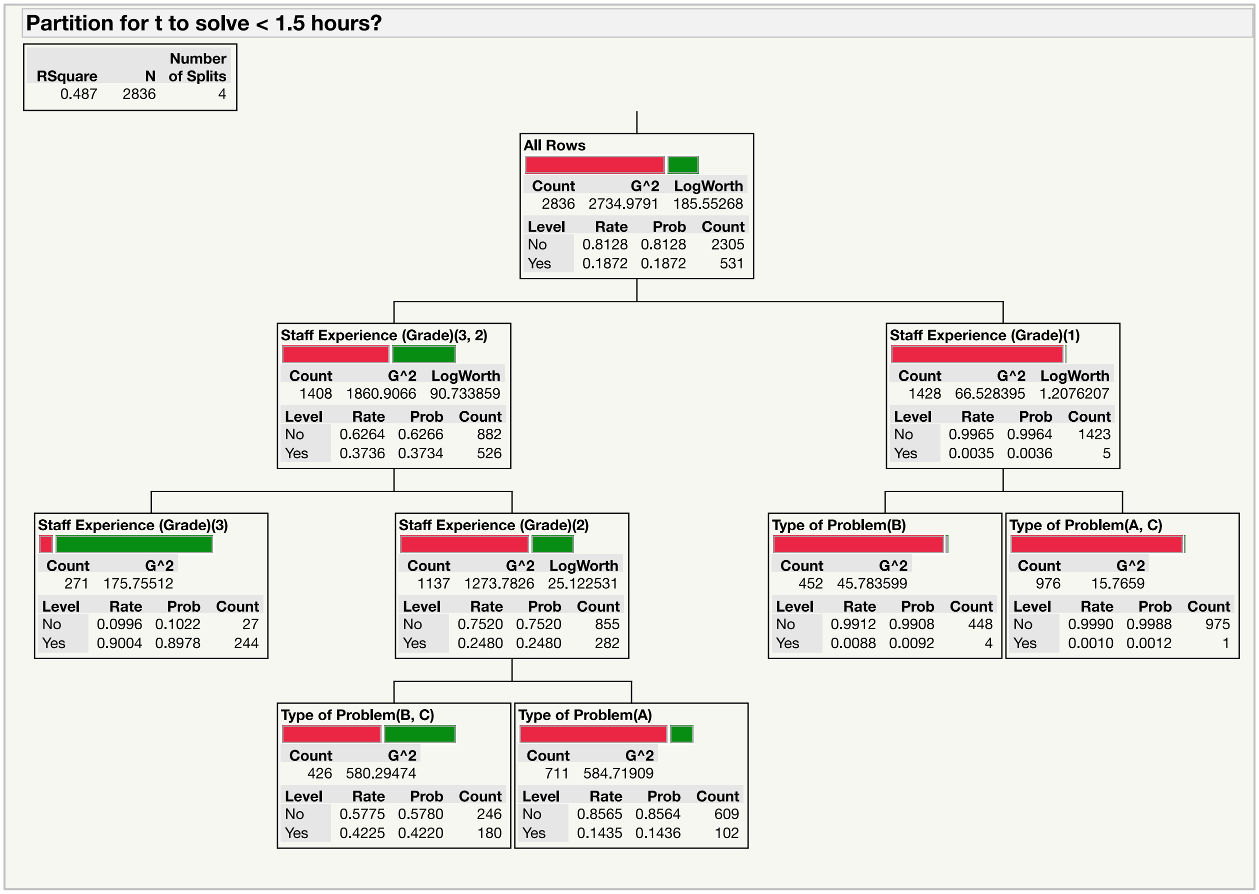
Another useful visual exploratory tool is recursive partitioning. This method repeatedly partitions data according to a relationship between the input variables and an output variable, creating a tree of partitions. It finds the critical input variables and a set of cuts or groupings of each that best explain process variation.

Figure 12 shows the resulting decision tree using recursive partitioning to explore the main drivers of variation in acceptable time to solve when the number of cycles is one. The tree displays the inputs, and their values, that are most associated with calls with a solution time of less than 1.5 when the number of cycles is one.

The hot X's are confirmed as staff experience and type of problem. Each node of the decision tree represents a subgroup, the criteria by which the subgroup was determined and the probability of solving problems in less than 1.5 hours. The four nodes of the decision tree tell us:

- Roughly 90% of all calls routed to staff at level 3 experience are solved in less than 1.5 hours.
- Roughly 25% of the calls routed to staff at level 2 experience are solved in less than 1.5 hours.
- 42.5% percent of calls routed to staff with level 2 experience are solved in less than 1.5 hours when the problem is category B or C.
- 14.5% of calls routed to staff with level 2 experience are solved in less than 1.5 hours when the problem is category A.
- Almost none of the calls routed to staff with level 1 experience are solved in less than 1.5 hours.

Figure 12: Recursive Partitioning for Time to Solve < 1.5 Hours



Exploratory Data Analysis – What Have We Learned?

These exploratory methods have collectively identified the hot X's:

- Day, time of day and number of staff on duty are the drivers of variation in time to answer.
- Staff experience and type of problem are the drivers of variation in time to solve, and analysis of time to solve is conditional on the number of cycles.

Exploratory analysis has also indicated some potential solutions:

- Determine staff loading required in each of the 10 time periods defined by the combination of day and time of day to ensure calls are consistently answered in less than two minutes, using the approximate rule that an increase in one staff on duty will reduce mean time to answer by one minute.
- Ensure that time to solve is acceptable by training call center staff to the equivalent of level 3 experience.

Confirmatory Analysis of Root Causes

The effects of this subset of input variables upon time to answer and time to solve were investigated in more detail using multiple linear regression. Day, time of day and number of staff on duty are confirmed as the drivers of variation in time to answer (see Figure 13).

Figure 13: Multiple Regression Time to Answer – Effects Tests

Response Time to Answer (Mins)

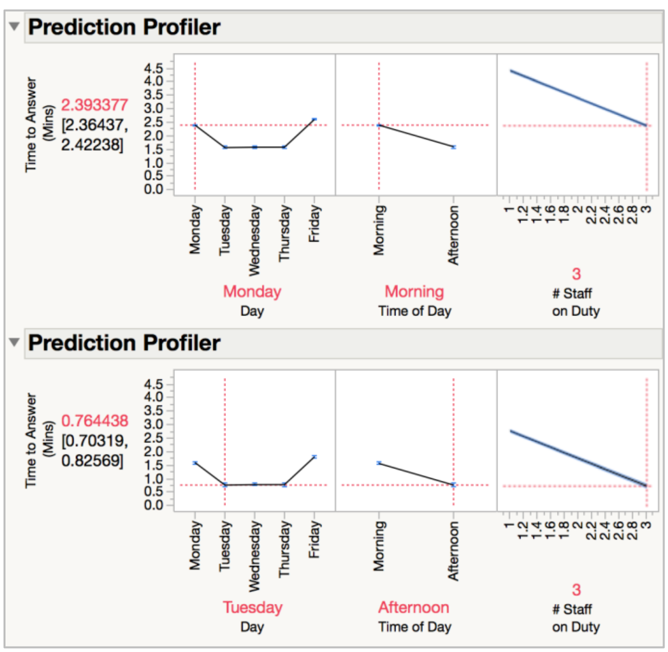
Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Day	4	4	393.92382	1118.804	<.0001*
Time of Day	1	1	304.39916	3458.162	<.0001*
# Staff on Duty	1	1	672.58050	7640.929	<.0001*
Type of Problem	2	2	0.27867	1.5829	0.2056
Staff Experience (Grade)	2	2	0.39538	2.2459	0.1060
Type of Problem*Staff Experience (Grade)	4	4	0.41431	1.1767	0.3190

The regression model for time to answer, with only these three significant input variables, was explored using the Prediction Profiler (this is a red triangle option in the regression analysis window). The contours for the variables in the profiler show how the predicted response will change as you change values of each input (at the current value of the other inputs). Drag the lines for an input to change the value, or, you can type in the value by clicking on the current value above the variable name.

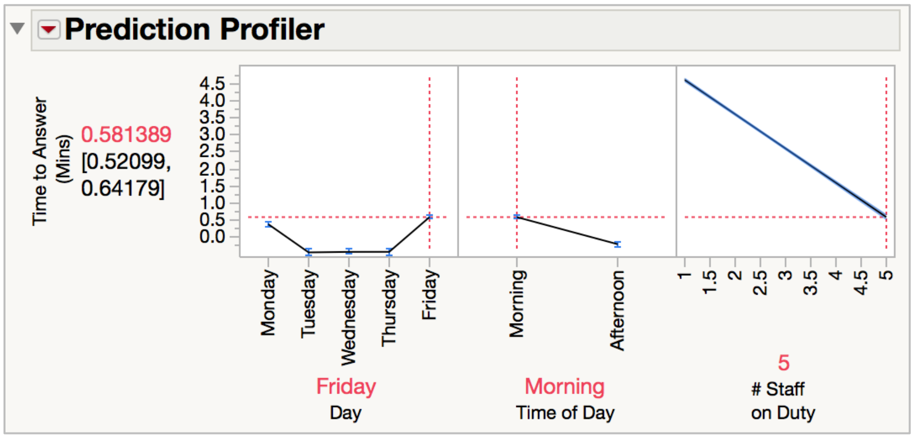
In Figure 14 we can see that the average time to answer is higher on Mondays and Fridays, is higher in the morning, and is much higher with lower staffing. The average predicted time to answer on Monday morning with 3 staff on duty is roughly 2.4 minutes (top, in Figure 14). In contract, the average time to answer on Tuesday afternoon with 3 staff on duty is only 0.76 minutes.

Figure 14: Prediction Profiler Time to Answer (With Only Significant Effects)



Clearly, staffing is strongly related to the time to answer. To explore the impact of increased staffing on time to answer on Friday afternoons, we extrapolate. We change the number of staff to five (again, by clicking on the number above the variable name and typing the number 5). We realize there is risk in extrapolation, since the maximum number of staff on duty at any time was only three. But, this gives us an indication of the potential improvement if we were to change the staffing level to five (Figure 15).

Figure 15: Time to Answer on Friday Morning, with Staffing Increased to Five



For time to solve (all cycles), staff experience, type of problem and the interaction between these two variables are confirmed as the drivers of variation (see Figure 16). By entering an interaction into the model we are able to test whether the impact of staff experience on the time to solve depends upon the type of problem (and vise versa). This interaction is explored in the profiler in Figure 17.

Figure 16: Multiple Regression Time to Solve – Effects Tests

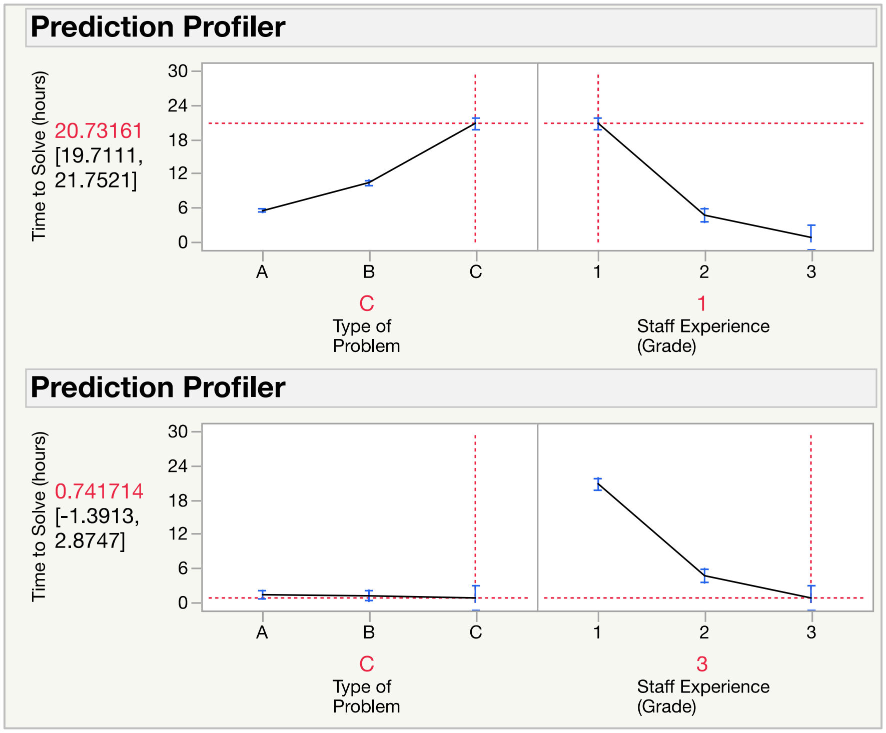
Response Time to Solve (hours)

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Day	4	4	14.312	0.1589	0.9590
Time of Day	1	1	21.727	0.9652	0.3260
# Staff on Duty	1	1	5.830	0.2590	0.6109
Type of Problem	2	2	3641.537	80.8838	<.0001*
Staff Experience (Grade)	2	2	26626.850	591.4210	<.0001*
Type of Problem*Staff Experience (Grade)	4	4	9062.494	100.6456	<.0001*

From Figure 17, we can clearly see that staff at level 1 experience have trouble solving some problem types, while staff at level 3 experience can quickly solve all types of problems.

Figure 17: Prediction Profiler for Time to Solve



Conclusions

These exploratory and confirmatory analyses have lead to the following decisions:

- All staff must be trained to level 3, and staff with level 3 experience should be used at all times.
- Five staff should be on duty on Monday and Friday mornings.
- Four staff should be on duty on Monday and Friday afternoons; Tuesday, Wednesday and Thursday mornings.
- Three staff should be on duty at all other times.

Note that, for the sake of brevity in this case study, these solutions may be naïve. Additional analysis would be required to determine feasibility and cost implications of such changes, and other potential solutions may be explored.

Improving the Process

These staffing changes are implemented as a pilot. Only staff at level 3 are used in the call center while accelerated training is conducted for staff at level 1 and 2. The results, after one month, are captured in the file ***Call Center VSS Pilot.jmp.***

Exercises:

1. Use the pilot data and the tools covered in the **Exploring Potential Root Causes** section of this case study to explore whether the implemented changes have been successful in elevating the call center to best-in-class performance levels. Use the tools introduced in this case study, including:

    - Histograms with dynamic linking
    - Capability analysis
    - Bar charts
    - Control charts
    - Tabulation
    - Graph Builder
    - Data Filter

2. Summarize what you have learned in Exercise 1 above:

    a. Were the required new staffing levels used at all times? If not, why do you think required staffing was not always used?
    b. Record the initial performance levels (in the language used in the background section) and the performance levels based on the pilot period.
    c. Was the pilot a success? Explain.
    d. Based on these results, would you recommend fully implementing the proposed solutions? If not, explain why.

3. Why was a pilot used first (rather than fully implementing the proposed solutions)?