FORECASTING AND OPTIMIZING CALL CENTER STAFFING

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Agenda

- Project Overview
- Literature Review and Cases Studies
  - Forecasting Methods
  - Queueing Model
  - Case Studies
- Data Analysis
  - IVR Calls
  - Skill Performance
  - Shrink
- Updated forecasting approach
  - Call Volume
  - Service Level and Service Time
  - Staffing

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PROJECT OVERVIEW

Objectives

- Develop models that can forecast the call volumes, and agent productivity and turn in a tool for determining the agent staff required in a call center
- The forecasting model should have minimum forecasting error and be easy to use
- Model will also need to provide a projected level of performance to goal based on actual net staffing (staff available vs required)

Methodology

- Conduct industry/literature review
- Statistical modelling techniques:
  - Regression analysis with Trend/Seasonal/Cyclical Components: Multivariate Linear Regression
  - Time-series analysis model: Holt-Winters' Method, ARIMA
- Software
  - Data analytics and modelling: Excel and R/Python
  - Data visualization: Tableau
- Data cleaning and processing: remove outliers, group and transform variables
- Descriptive analytics: explore distribution of important fields and relationship among variables
- Predictive analytics:
  - Separate the whole dataset into training and testing dataset: 2017 and 2018 data will be the training set to build up the model. 2019 data will be the testing set to verify the error
  - Build forecasting models for call volume, shrink, and number of staff
  - Tune and refine models
- Business Insights and Recommendations

Business Challenges and Potential Hypothesis

❑ Business Challenges

- How many staff members are needed at the call center to maintain an acceptable level of service at minimum cost? (80% of calls handled within 30 seconds)
- How can the model adjust to changes happening in real-time business conditions?

❑ Potential Hypothesis

- The volume of calls varies depending on specific weather conditions/unexpected events
- Call volumes are associated with seasonality and trend
- Staff productivity differs according to different skills in different seasons
- Number of required staff depends on events other than call volume such as staff's expertise and company's hiring policies.

LITERATURE REVIEW AND CASE STUDIES

Forecasting Method

- Important characteristics of telephone calls' arrival process
  - **Time-variability**: Arrival rates vary temporally over the course of a day. For example, peak hour arrival rate can be significantly higher than the level of the average daily arrival rate.
  - **Inter-day correlation:** There is significant dependency between arrival counts on successive days
  - **Intra-day correlation:** Successive periods within the same day exhibit strong correlations

- Forecasting methods:
  - ARIMA model
  - Bayesian technique
  - Neural Network

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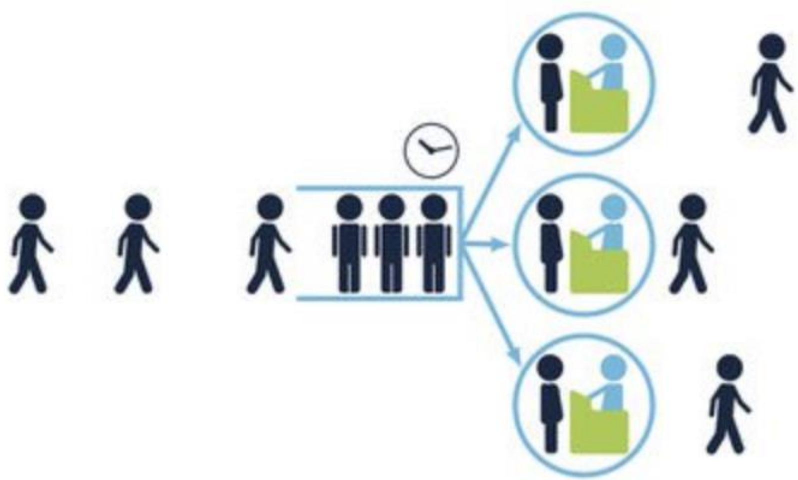
Queueing Models

- ❑ Erlang models follow "First come, first serve"
  - Erlang C: Poisson arrivals, exponential service times, one or more agents
  - Erlang A: Extension of Erlang C to accommodate abandonment
- ❑ Square-Root Safety Staffing (QED regime)



Reference: https://www.edx.org/course/queuing-theory-from-markov-chains-to-multi-server-systems-2

Case studies

- **Research Paper:** *"A Comparison of Univariate Time Series Methods for Forecasting Intraday Arrivals at a Call Center*" written by James W. Taylor - University of Oxford published on Management Science, 2008, Vol. 54

- **Data**: Five series of half-hourly arrivals at call centers operated by a retail bank in the UK for the **36-week period** from January 2004 to 10 September 2004.

- **Forecasting method**:
  - Seasonal ARMA modeling
  - Periodic AR modeling
  - Extension of Holt-Winters exponential smoothing for two seasonal cycles
  - Robust exponential smoothing
  - Dynamic harmonic regression

Case studies

- **Evaluation measurements:** Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Percentage Error (RMSPE)

- **Motivation to study**:
  - The data shows very clear seasonality
  - The data has a repeating intra-week cycle when the call volume generally peaks on Monday and is clearly much lower on Sundays
  - The intraday cycle from their data is quite similar to PECO data: there is a peak around 11 am and then followed by a second peak around 2 pm (in PECO data the second peak is at 3 pm)

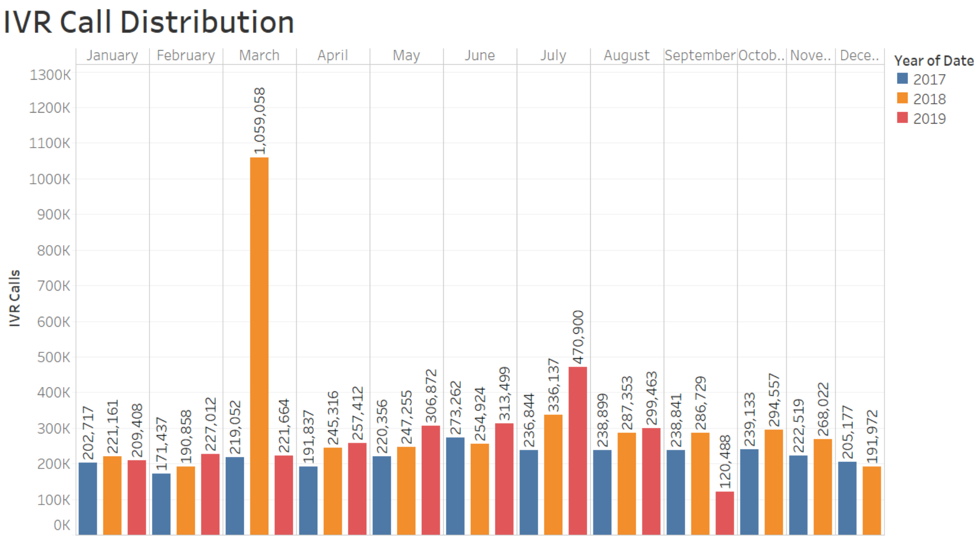
- **Major Findings: *Seasonal ARMA*** and ***the extension of Holt-Winters exponential smoothing*** showed the most accurate results to predict call volumes up to about two or three days ahead

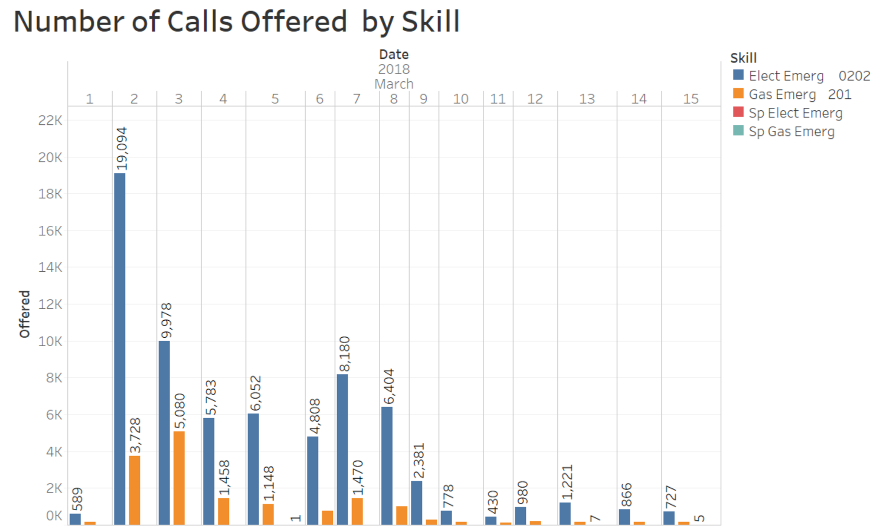
DATA ANALYSIS

Data Summary

- **Data Dimension:**
  - IVR and Call Data: 988 observations and 6 columns
  - Skill Performance Data: 185556 observations and 16 columns
  - Shrink Data: 21534 observations and 4 columns
- **Time period**:
  - 01/01/2017 - 09/15/2019 (IVR and Skill Performance Data), 01/01/2017 - 09/14/2019 (Shrink Data)
  - Daily without transfer for IVR dataset, 30-minute intervals with transfers for Skill Performance Dataset, and daily for Shrink dataset
- **Missing Data**:
  - IVR dataset: 15th June 2019 has an unusual data : Number of calls offered, handled, answer within target time and the service level is 0.
- **Data Type:**
  - IVR dataset: all numeric variables
  - Skill Performance dataset: variables ‘Skills’ and ‘Queue’ are character
  - Shrink Dataset: ‘Activity Code’ and ‘Activity Category’ is character

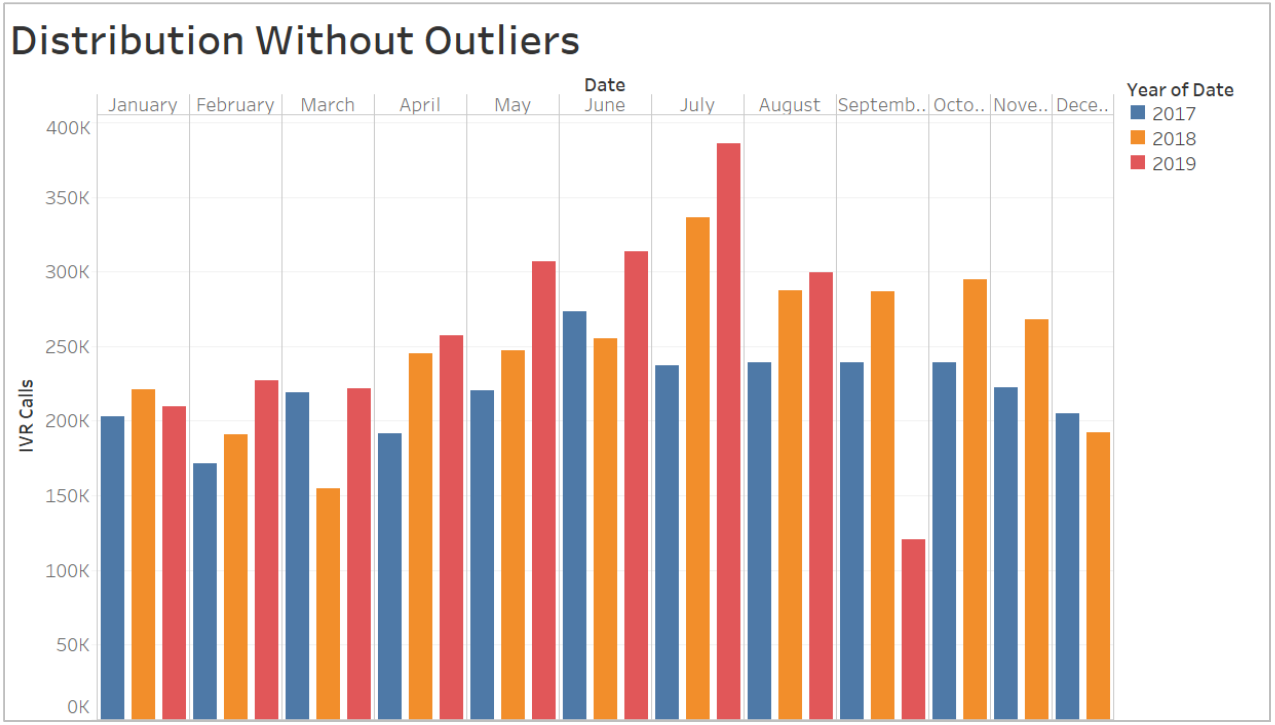
IVR And Calls Data





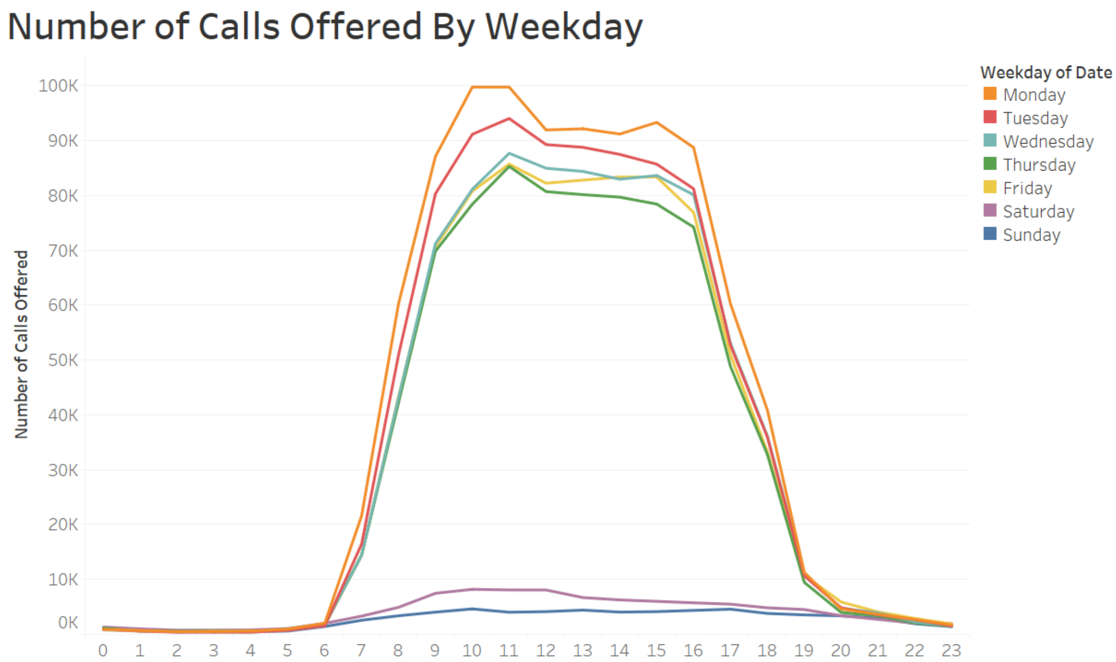
- 2018 has an unusual monthly pattern (March) due to the heavy snow which affected more than 750,000 PECO customers on Mar 2 – Mar 3
- Majority of call on these two days is from electric emergency queue, reporting power outages in PA area

IVR And Calls Data



- Number of call offered share the same pattern during 12 months over 3 years.
- July 22nd, 2019 has an unexpected high call volume reporting power outages due to strong wind and heavy rain.

IVR And Calls Data



- The weekdays Monday through Friday have a similar pattern. Weekends have completely different patterns from weekdays
- There are two major peaks during the day: 11 am and 3 pm. Monday has higher call volume compared to other weekdays.

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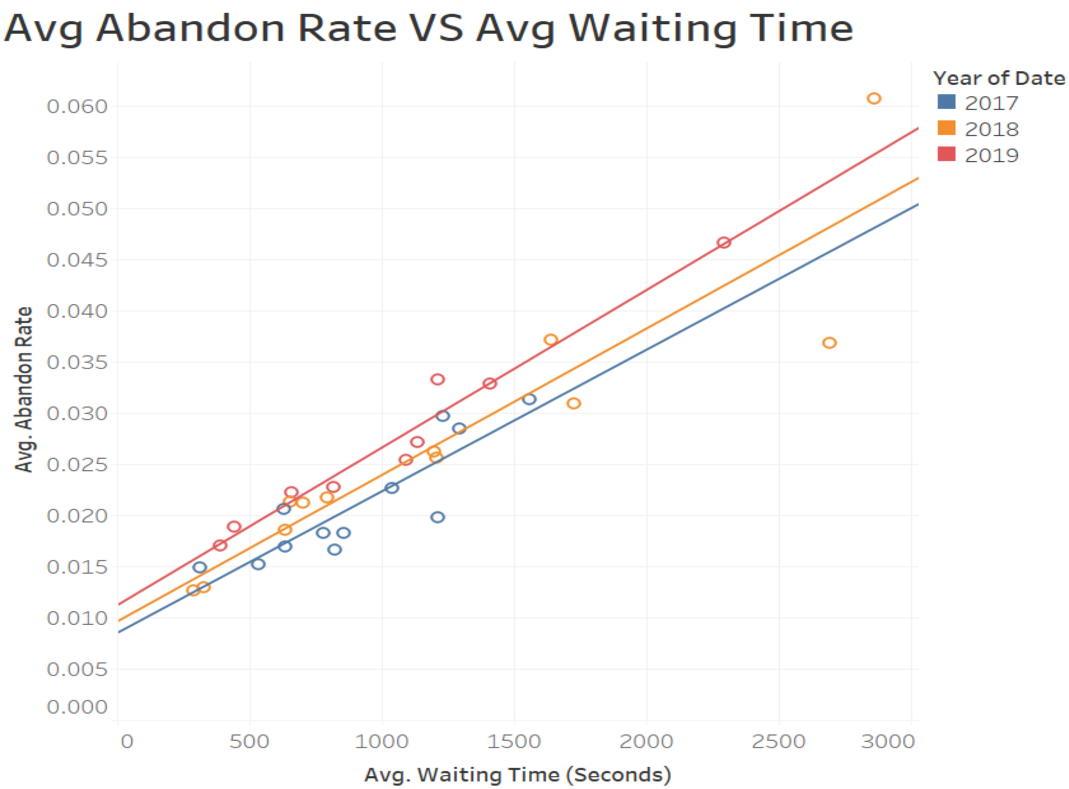
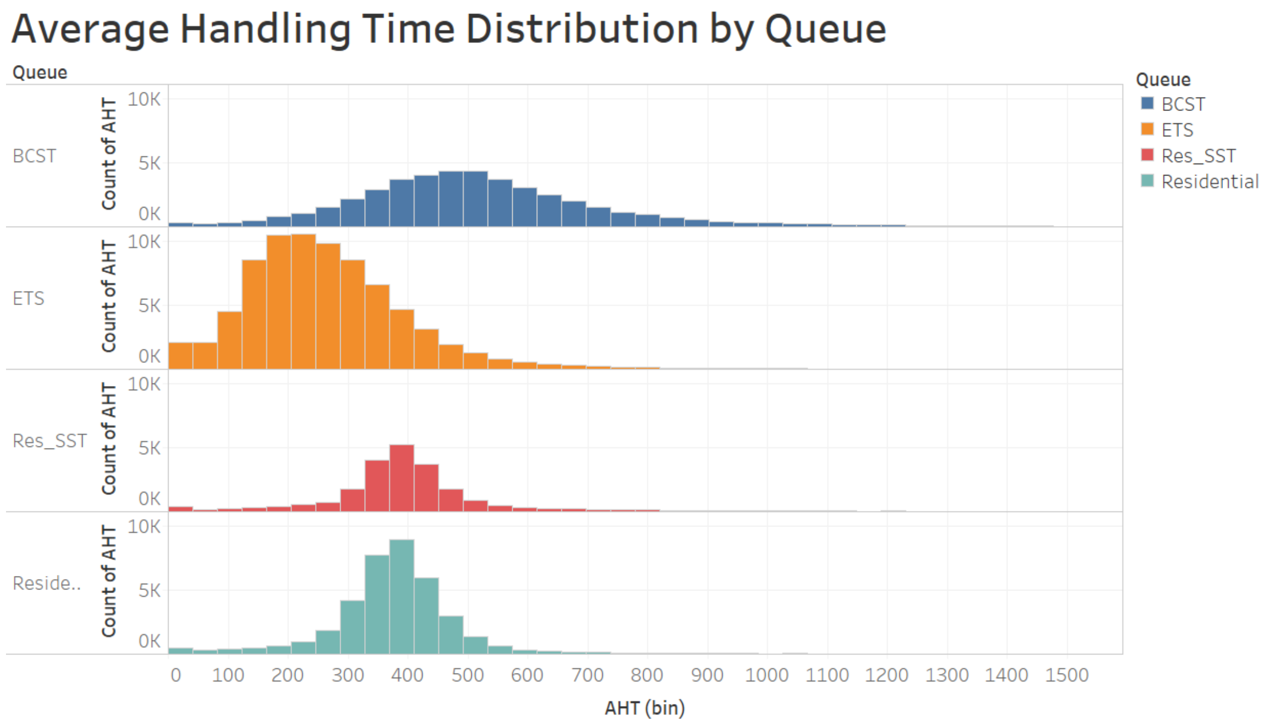
Skill Performance Data



- Abandon rate and waiting time (ASA) are positively correlated.
- The longer the customer has to wait for answer, the more likely he/she will hang up

Skill Performance Data

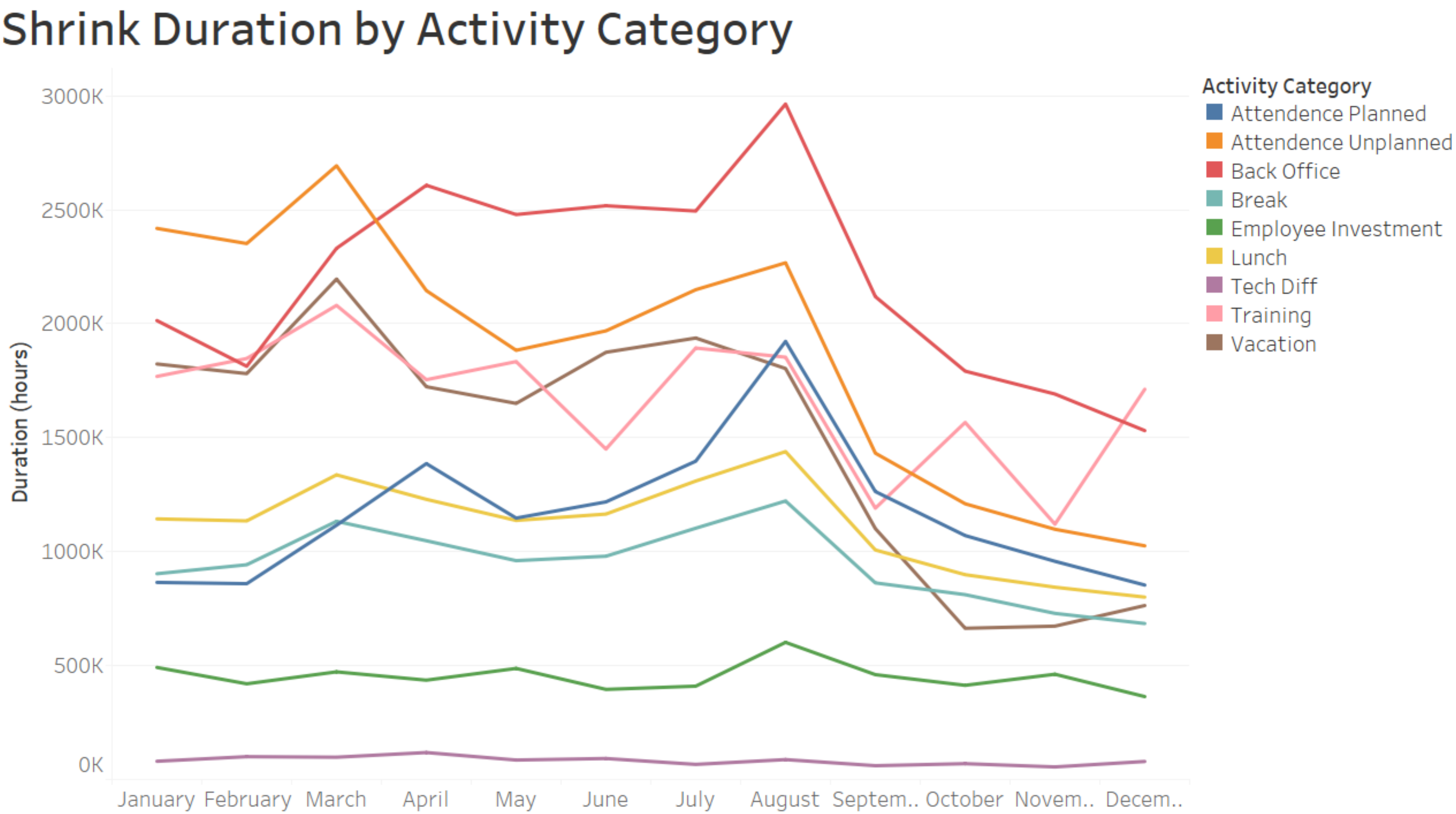


Measurement: seconds

	BSCT	ETS	RES_SST	Residential
Mean	532	268	416	383
Standard Deviation	260	151	217	149

Mean and Standard Deviation of Handling time in Each Queues

Shrink Data



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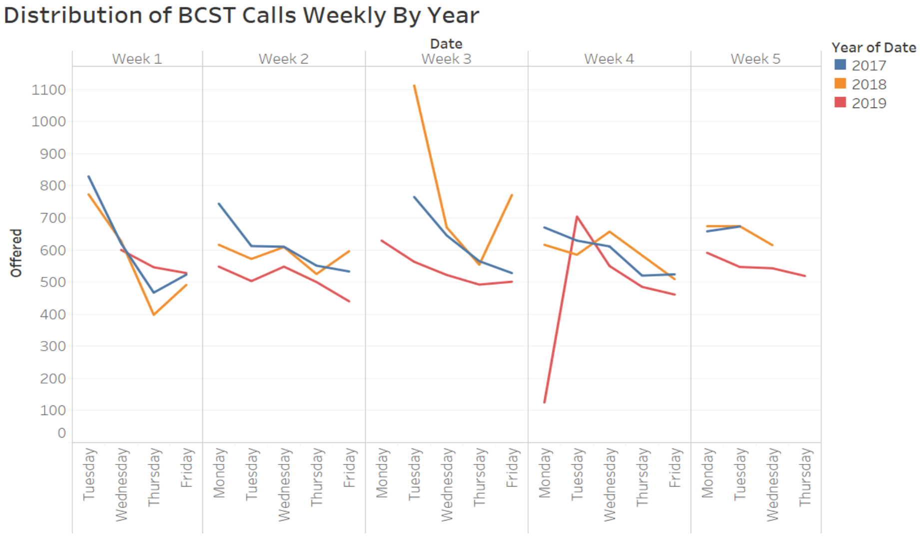
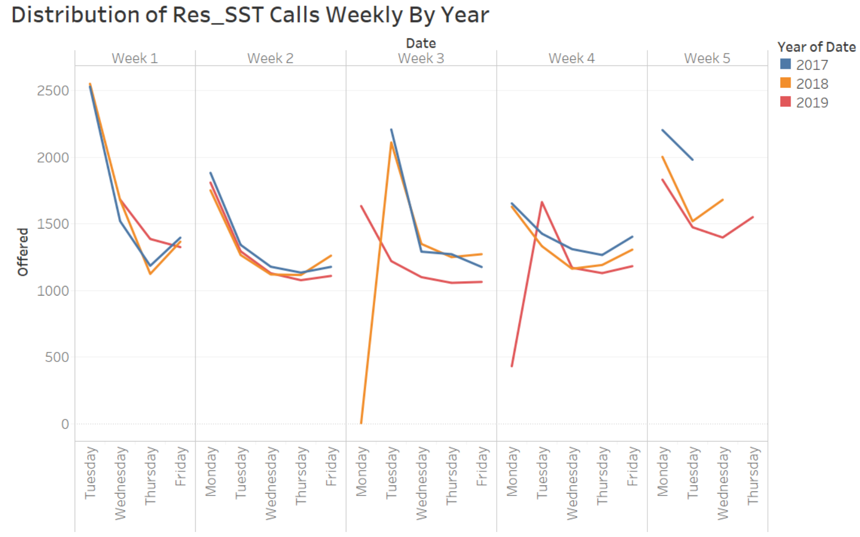
PROPOSED FORECASTING APPROACH

Call Volume

- Training data: Jan 1 - Jan 31, 2017 and Jan 1 - Jan 31, 2018
- Testing data: Jan 1- Jan 31, 2019
- Process:
  - Defined patterns during day-of-week, week-of-month and month-of-year
  - Call volume is forecasted based on different queues/skills
  - Use training data to fit different time-series models
  - Evaluate models using RMSE
  - Modify and optimize time-series forecasting model

Call Volume





- Number of offered calls through Commercial line (BCST) and Residential_transfer (Res_SST) follow the same pattern during the week over three years
- Number of offered calls are highest on Monday, then decrease during weekday and slightly increase when weekend is coming.

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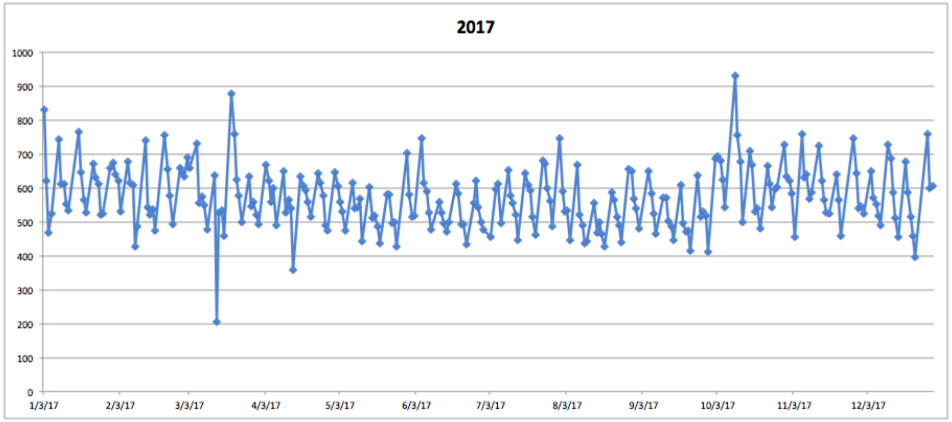
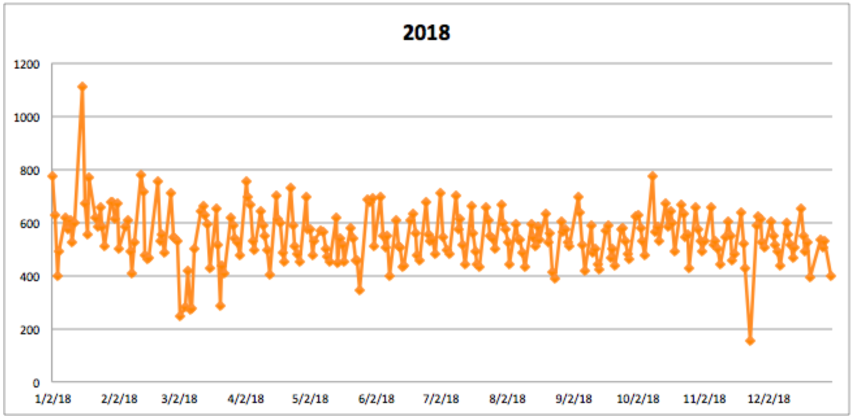
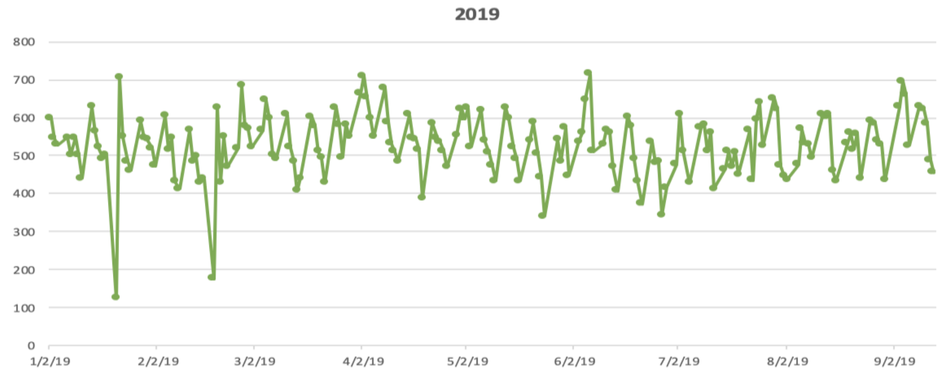
Call Volume







- Number of offered calls through Commercial line (BCST) in 2017 and 2018 are stationary
- Number of offered calls through Commercial line (BCST) in 2019 is also stationary but there are many outliners

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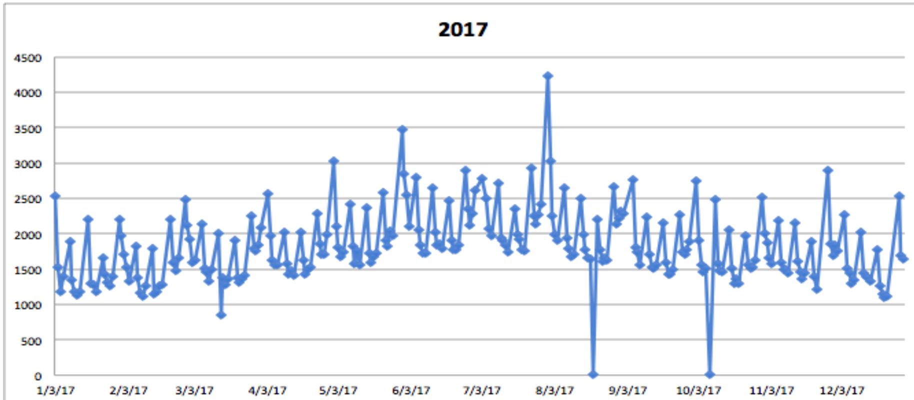
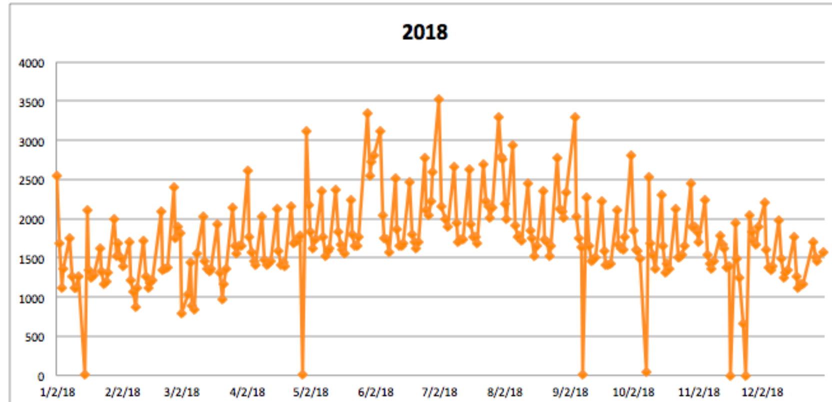
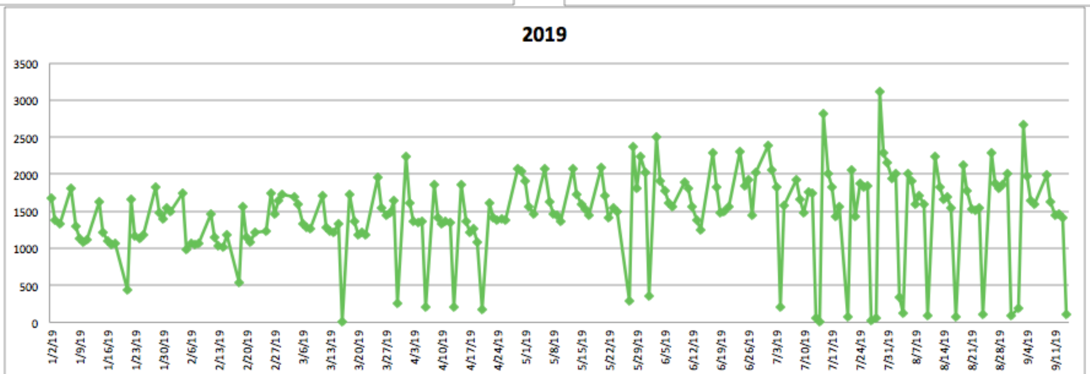
Call Volume







- Number of offered calls through Residential Transfer Line (Res_SST) in 2017 and 2018 have trend - like an arch, and "seasonality"
- In 2019 data we can still see the trend
- In 2019 we can see there is some weekly "seasonality"

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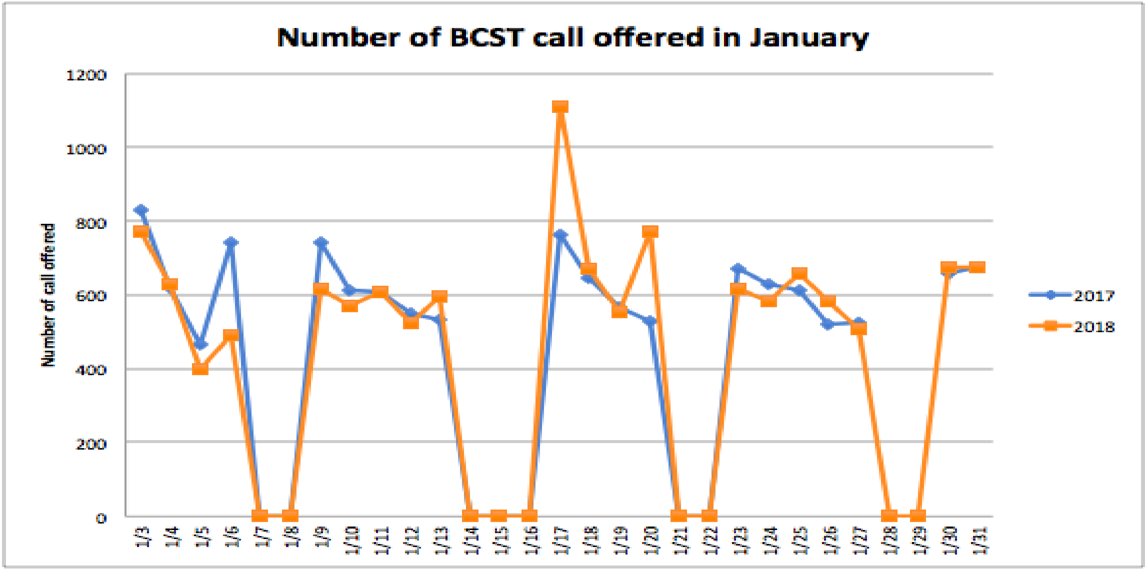
Call Volume – Exponential Smoothing



- The predicted values are weighted sum of the past observations
- Uses a smoothing factor that is selected by FITTING.
- This method gives larger weights to recent observations and decreases exponentially as observations become distant

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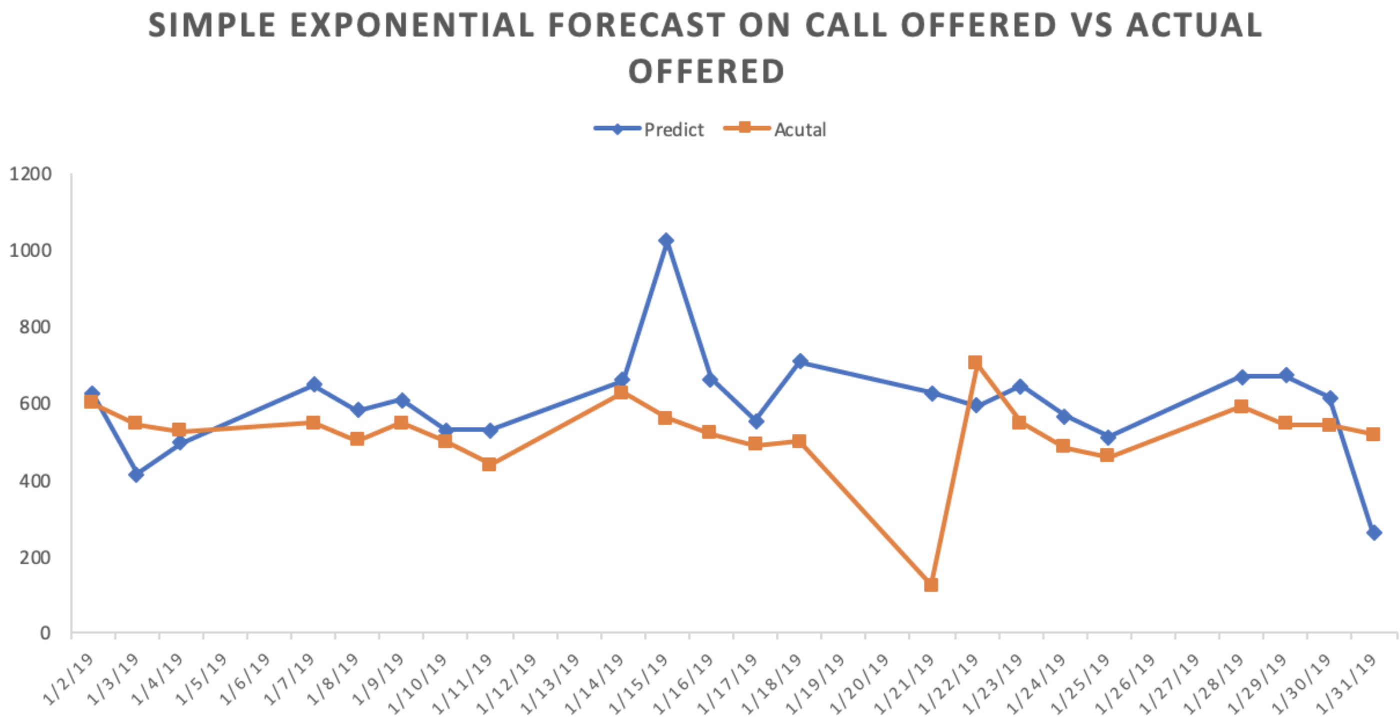
Call Volume – Exponential Smoothing



- Predicted data: BCST queue
- Train dataset: Jan 1 - Jan 31, 2017 and Jan 1 - Jan 31, 2018
- Testing data: Jan 1- Jan 31, 2019

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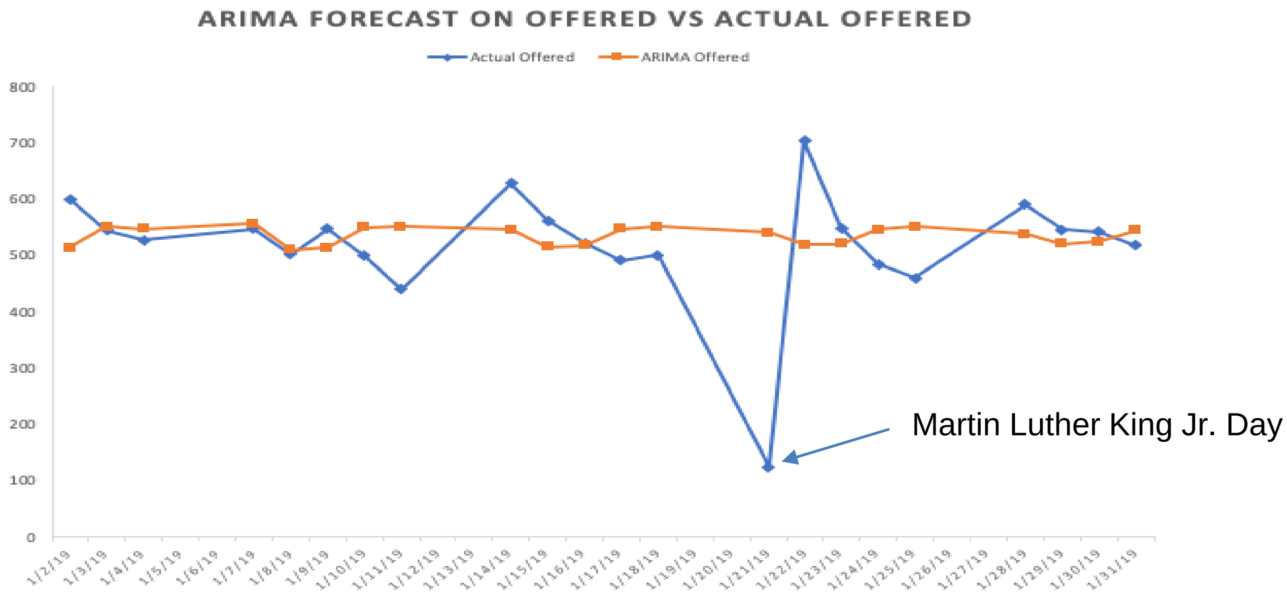
Call Volume - ARIMA

- Idea: Autocorrelation, Seasonality and Trend
- Initial result: ARIMA(4, 1, 0) model on BCST data
  - ARIMA model can easily be estimated with missing value(holidays) within the time series
  - We can use the whole dataset to predict the future, and consider trend and seasonality
  - Outliners don’t fit patterns

Predicted data:
BCST queue

Training dataset:
Jan 1 - Jan 31, 2017
Jan 1 - Jan 31, 2018

Testing data:
Jan 1- Jan 31, 2019



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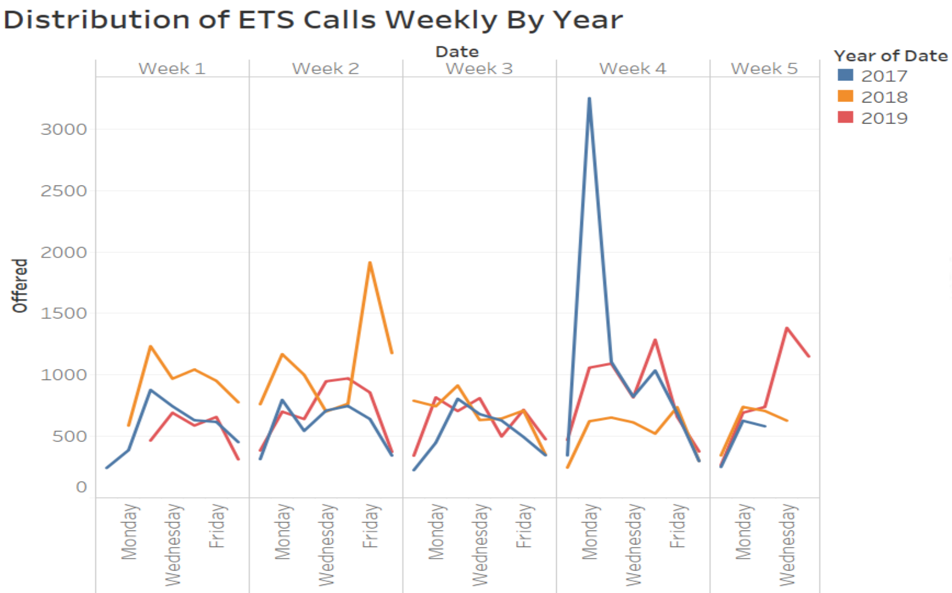
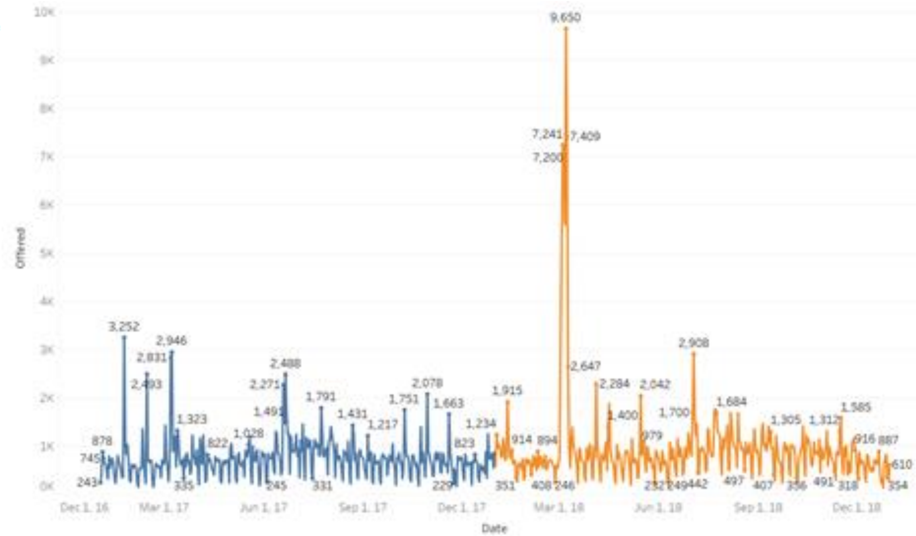
Special Modelling for Emergency Cases





- Emergency calls exhibited unsual patterns over differrent weekdays and over different months during the year
- Except from seasionality and trend components, emergency call volumes are affected by unexpected weather events such as snow storm, strong winds, and heavy rain.
- Separate the Gas Emergency and Electric Emergency since they are for different usage.

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Special Modelling for Emergency Cases

- Collecting Weather Data from Jan 1 to Jan 31 on 2017

- Important data points: Maximum, Minimum, Average Temperature, Wind Speed, Pressure, Humidity, Dew points and Precipitation, changes between days

- Model: Multivariate Linear Regression

- Findings:
  - Average Temperature, Maximum Dew point, Average Dew Point, Average humidity and minimum pressure are significant when forecasting the number of calls offered
  - Wind speed and pressure have stronger correlation with call volume.

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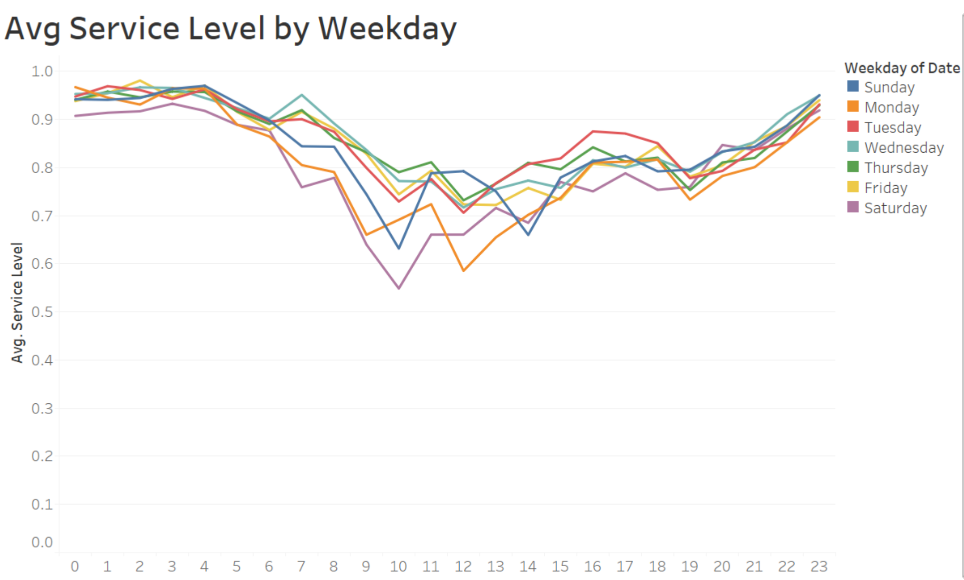
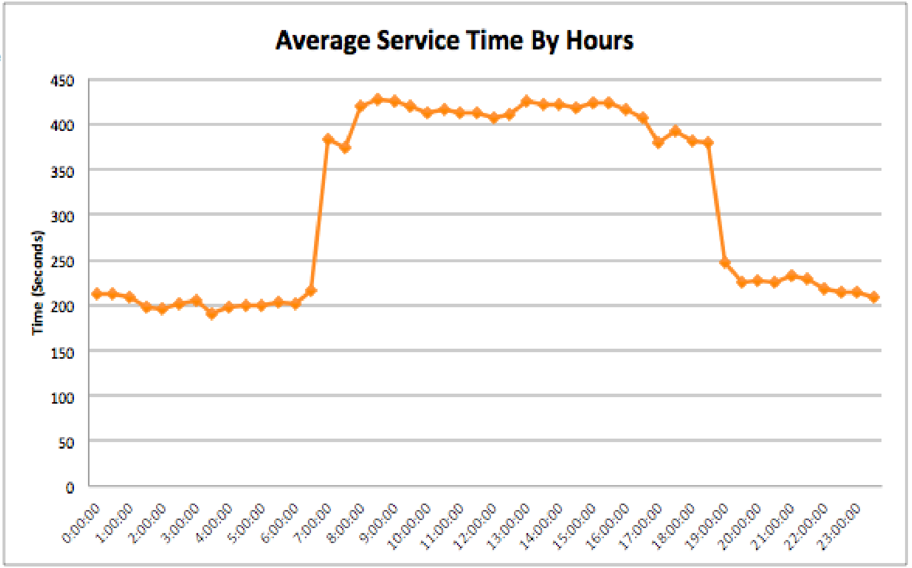
Service Time and Service Level





- Important variables to predict service time: the weekday and the hour period in each day
- Average service time patterns resemble a step function
- Predict models includes weekday-specific quadratic, linear daily trend effect, weekday - period interaction effect

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Staffing

- Queueing Model used: Modified Erlang C/ Erlang A

- Features of Erlang C model:
  - Constant arrival and service rate
  - Arrival process is assumed to follow a Poison distribution
  - Service times are assumed to be exponentially distributed and independent of each other
  - Blocking, abandonment, and retrials are ignored.
- Erlang A handles abandonments

- Quality – Efficiency Driven Regimes
  - Follow the square-root staffing model
  - Find optimal coefficient for linear waiting probability and expected service level

- Staffing and training schedule: Also good to know employee's turnover rate, Training duration required for different skills and Hiring Season

UPDATED FORECASTING MODEL

Call Volume Forecasting Overview

- Training data: Jan – December 2017 and Jan – December 2018
- Testing data: Jan 2019 – August 2019

- Model Performance Overview:
  - Forecasting models for BSCT, Residential and Emergency queues perform better than PECO's model in term of average error rate (%)

Table 1: Forecasting Error Rate Comparison

	Number of call offer (Actual) PECO				
	Total	Residential	Transfer	BCST	ETS
Jan	11.46%	20.73%	1.91%	11.71%	0.07%
Feb	5.58%	17.98%	7.72%	15.62%	28.46%
March	4.27%	10.74%	3.00%	7.49%	14.83%
April	1.27%	6.11%	0.63%	10.02%	29.87%
May	6.58%	24.48%	2.45%	5.31%	24.95%
June	8.47%	20.27%	4.54%	11.07%	14.52%
July	0.06%	12.90%	3.23%	14.71%	29.45%
August	0.47%	0.33%	1.21%	2.19%	2.46%
Average	4.77%	14.19%	3.08%	9.77%	18.08%

	Number of call offer (Actual) - Group 4				
	Total	Residential	Transfer	BCST	ETS
Jan	12.21%	18.51%	10.54%	9.96%	0.73%
Feb	1.35%	5.83%	7.76%	8.07%	18.01%
March	3.62%	0.92%	8.03%	6.79%	16.24%
April	6.22%	1.12%	12.36%	1.34%	13.77%
May	5.78%	2.71%	9.77%	1.88%	9.32%
June	9.91%	5.34%	15.17%	4.52%	15.17%
July	0.18%	4.84%	13.34%	7.05%	24.02%
August	2.69%	4.83%	9.26%	0.72%	10.57%
Average	5.24%	5.51%	10.78%	5.04%	13.48%

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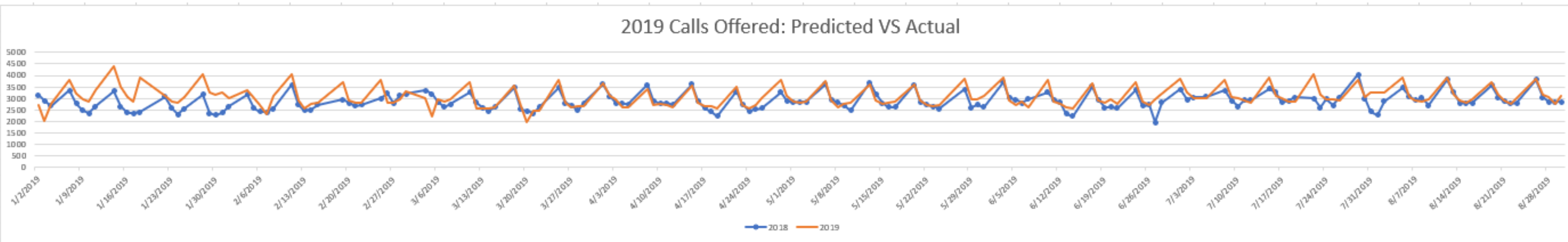
Call Volume Forecasting - Residential

- Triple Exponential Smoothing – Holt and Winters Method
- 3 smoothing factors: Alpha(Level), Beta(Trend), Gamma(Seasonality)
- 2019 Call Volume is predicted using 2018 Calls Volume
- Outliers such as Federal holidays and weekends are removed



	Residential		
	Actual	PECO Forecast	Group 4 forecast
RMSE	-	462	388
Average % difference	-	14.19%	5.51%
Mean	2010	2271	2105
S.D	1359	1552	1455

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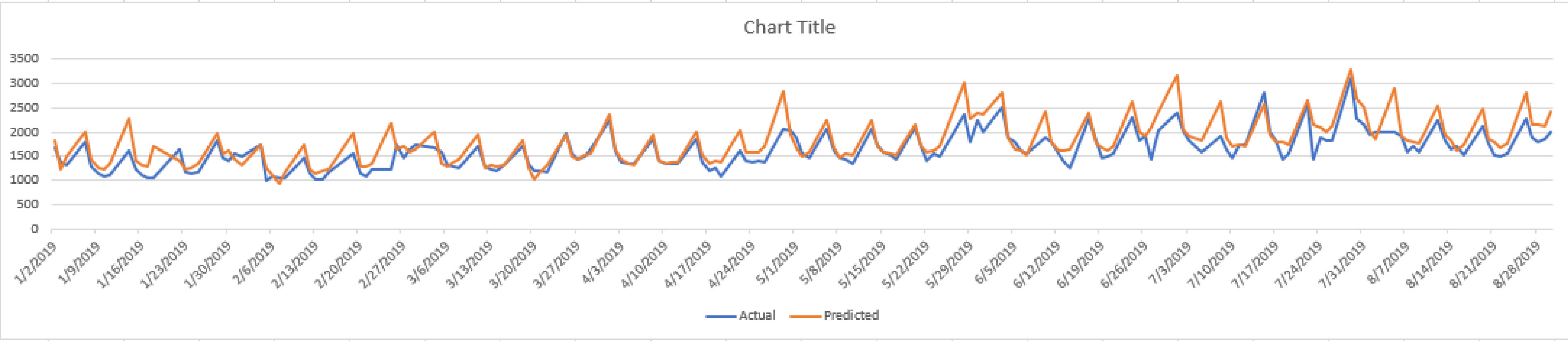
Call Volume Forecasting – Transfer (Res_SST)

- Triple Exponential Smoothing – Holt and Winters Method
- 3 smoothing factors: Alpha(Level), Beta(Trend), Gamma(Seasonality)
- 2019 Call Volume is predicted using 2018 Calls Volume



	Transfer		
	Actual	PECO Forecast	Group 4 forecast
RMSE	-	203	321
Average % difference	-	3.08%	10.78%
Mean	1134	1156	1251
S.D	791	829	913

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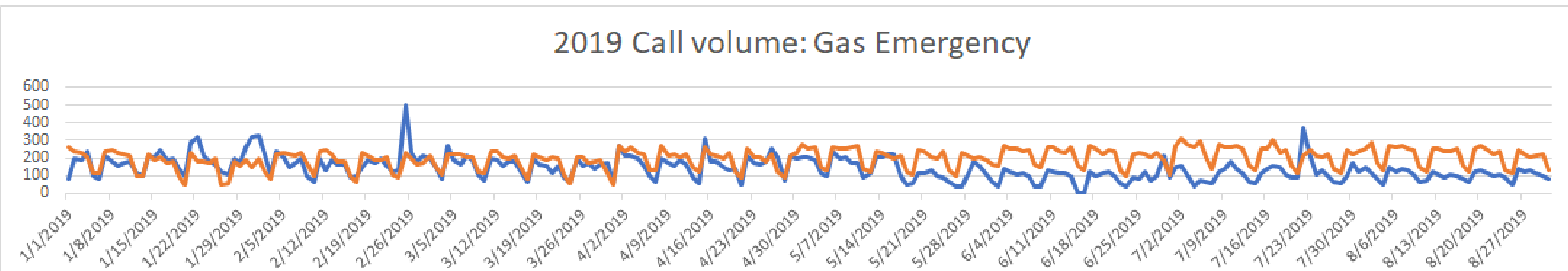
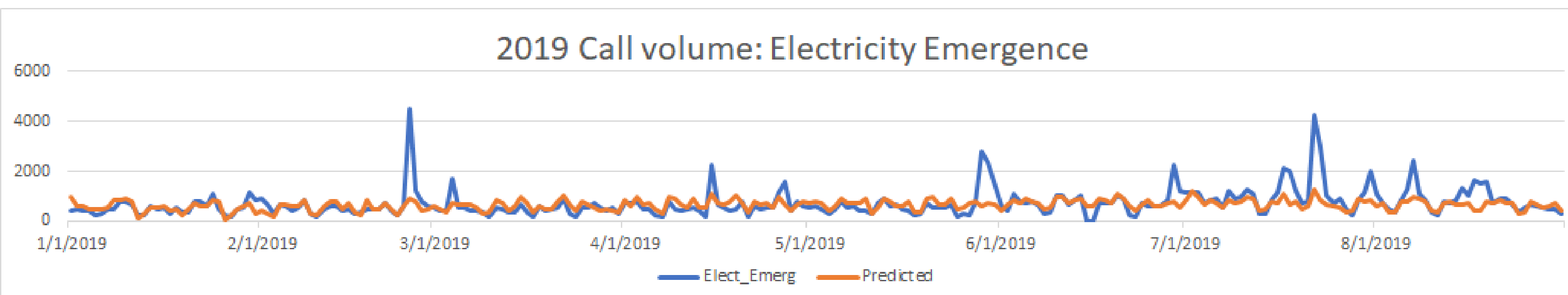
Call Volume Forecasting – Emergency (ETS)

- Use 2018 Gas/ Electricity Emergency daily data to build linear regression
- Use lasso to do the feature selection
- Remove the data in Mar.3- 8 2018 because there was an unexpected heavy snow
- The call volume for gas emergency entire lower from May and the model failed to predicted it. This might not relate to weather changing





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Call Volume Forecasting– Commercial (BCST)

- Number of offered calls through Commercial line (BCST) follows the same pattern during the week over three years
- Idea from simple exponential smoothing and moving average
- Using week on week to make prediction
    - Used Monday Week 1 from 2017 and 2018 to calculate the mean on Monday Week 1
    - Used the most recent value on the same week as the most recent observation entered model
    - Alpha = 0.5 on the mean of the week and the most recent observation

	BCST		
	Actual	PECO Forecast	Group 4 forecast
RMSE	-	75	109
Average % difference	-	9.77%	5.04%
Mean	369	402	380
S.D	252	274	267

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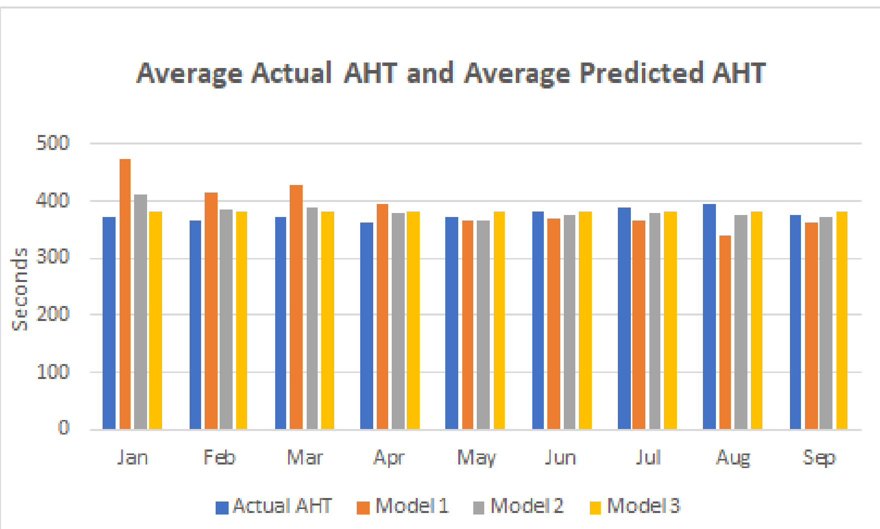
Service Time Forecasting

- Method: Multiple Linear Regression and Simple Moving Average
  - Model 1 Variables: Year, Month, Weekday, Time, Queue and Weekday*Queue
  - Model 2 Variables: Year, Month, Weekday, Time, Queue
  - Model 3: Simple Moving Average with 2 months period

- Model 1 performs better on training data but has over-fitting problem. Model 2 has lower R-squared on training data but has better prediction result on testing data.
- Model 2 performs better than naïve average prediction but still have larger error than moving average model. Our group choose to use result from moving average (Model 3) for calculating staffing



Model 1 Error	Model 2 Error	Model 3 Error	Average Prediction Error	Peco Prediction Error
27%	10%	3%	6%	1%
13%	5%	4%	3%	2%
14%	5%	3%	2%	1%
9%	4%	5%	0%	3%
1%	2%	3%	5%	1%
3%	1%	0%	4%	2%
6%	3%	2%	7%	4%
14%	5%	3%	7%	5%
4%	1%	2%	4%	0%
10.1%	**4.0%**	**2.8%**	**4.2%**	**2.1%**

Error Rate Comparison

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Service Level Forecasting

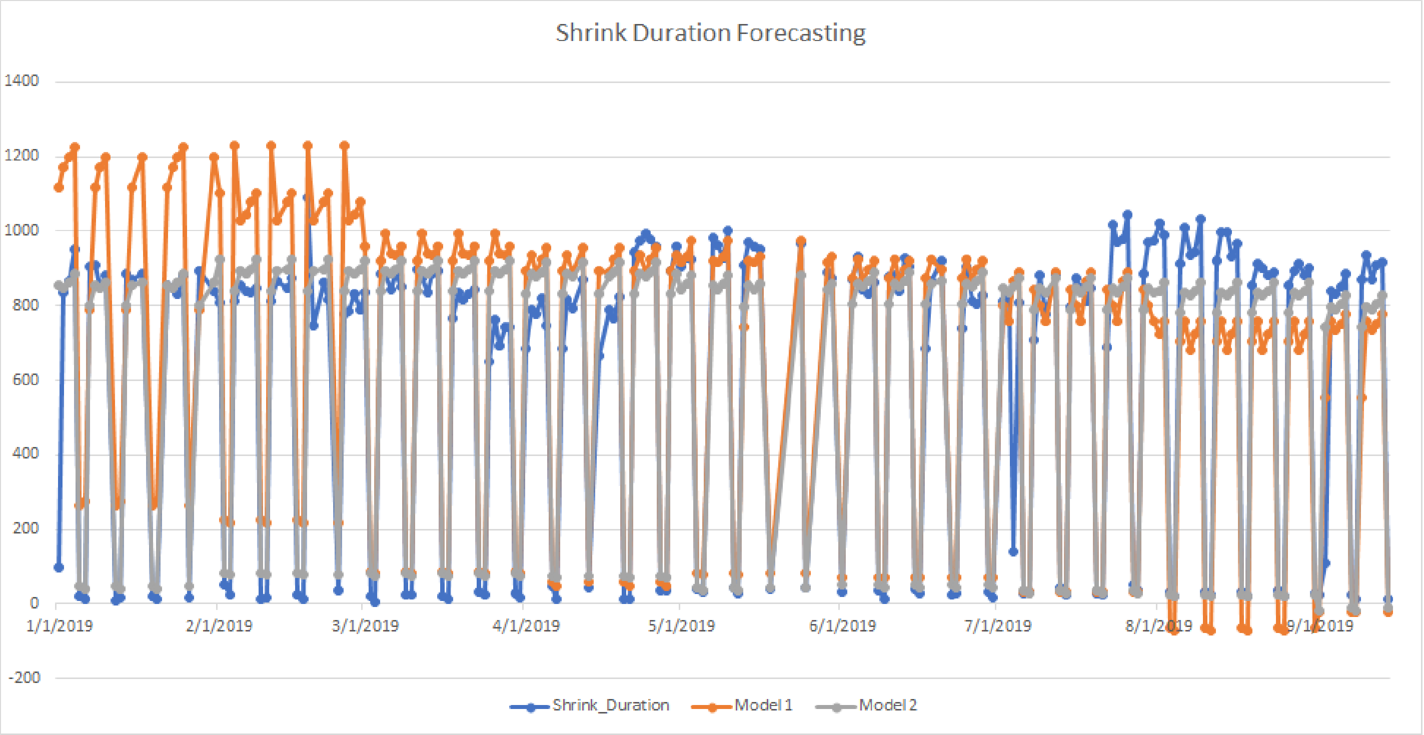
- **Method**: Linear Regression to estimate the relationship between service level and number of agents.
- Both train and test data is from 2019 data because there is shortage of data for number of agents for 2017 and 2018
- There is positive relationship between Service Level and Number of Agents while the relationship between Service Level and Call Volume and Abandon Rate is negative.
- The model can predict service level for ETS queue better than other queues

Month	BCST			ETS			Res_SST			Residential			Total		
	Actual	Forecast	Error	Actual	Forecast	Error	Actual	Forecast	Error	Actual	Forecast	Error	Actual	Forecast	Error
Jan	65%	51%	20%	93%	91%	2%	93%	84%	10%	89%	76%	14%	85%	78%	9%
Feb	71%	52%	26%	91%	90%	1%	91%	84%	8%	86%	76%	12%	85%	78%	9%
Mar	55%	51%	8%	92%	91%	1%	89%	83%	7%	78%	74%	5%	80%	76%	4%
Apr	53%	50%	6%	92%	91%	2%	82%	83%	0%	74%	74%	0%	77%	76%	2%
May	49%	50%	2%	92%	90%	2%	78%	82%	6%	69%	73%	5%	74%	75%	1%
Jun	37%	46%	24%	90%	91%	1%	70%	82%	17%	63%	72%	14%	69%	74%	8%
Jul	30%	44%	45%	86%	89%	4%	68%	78%	15%	56%	69%	23%	64%	72%	14%
Aug	35%	46%	33%	88%	91%	4%	78%	78%	0%	69%	74%	8%	69%	75%	8%
Sep	41%	46%	11%	93%	92%	1%	85%	81%	5%	77%	75%	3%	77%	77%	0%
Average Error Rate			**19%**			**2%**			**7%**			**9%**			**6%**

Service Level Forecasting Errors

Shrink Duration Forecasting

- Method: Multiple Linear Regression
- Model 1 Variables: Year + Month + Weekday + Year*Month + Month*Weekday
- Model 2 Variables: Year + Month + Weekday
- Model 2 performed better than Model 1 on both training and testing data. Both model can explain high proportion of variance in shrink duration using only 3 exploratory factors



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Shrink Duration Forecasting

- Model 2 performs better than naïve average percentage model in term of average error rate
- Model 2 has lowest mean absolute error rate among 3 models. Therefore, our group choose this model to predict shrink duration and then turned to shrink percentage using current non-shrink data.

Month	Actual Percentage	Predicted Percentage	Error	Average Percentage	Error
Jan	55.1%	56.0%	1.0%	55.8%	0.7%
Feb	54.3%	56.2%	2.0%	54.1%	0.1%
Mar	53.8%	56.5%	2.7%	53.4%	0.4%
Apr	54.0%	55.7%	1.6%	53.2%	0.8%
May	59.0%	56.8%	2.2%	53.4%	5.6%
Jun	54.6%	54.9%	0.3%	52.3%	2.3%
Jul	54.8%	54.9%	0.1%	51.5%	3.2%
Aug	56.2%	53.3%	2.9%	50.2%	6.0%
Sep	53.1%	52.4%	0.7%	50.3%	2.8%
Average Error Rate			1.49%		2.4%

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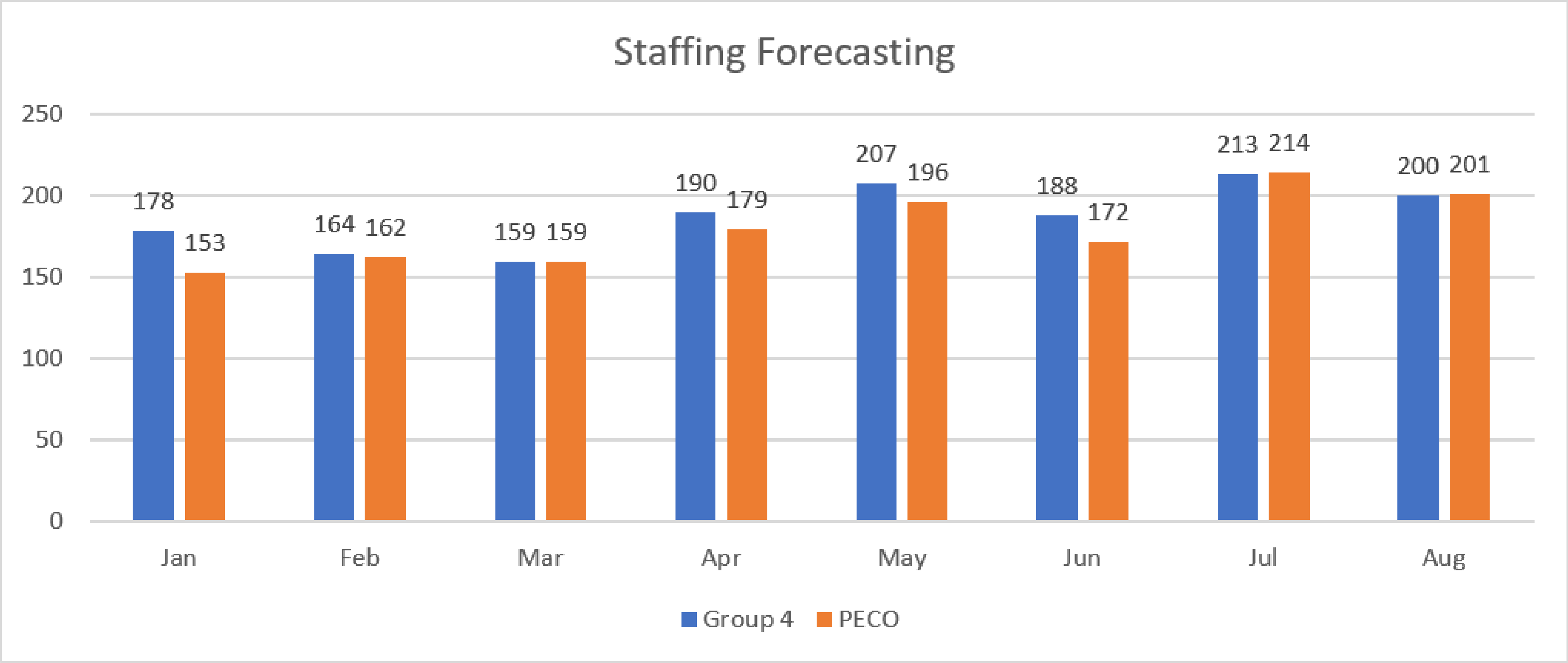
Staffing Forecasting

- **Method 1**: Using PECO formula, AHT and Shrink to calculate number of FTE. However, using our predicted call offered to compare our forecasting model and PECO's forecasting model

- January, April and June have the largest difference in our group's calculation and PECO due to the biggest difference between our forecasted call volume and PECO.



Staffing Forecasting

- **Method 2:** Changing the formula using: new abandon rate, our predicted call offered, AHT and Shrink.
- Our assumption: Each agent works 40h/weeks and 22 days a month. Occupancy remains the same with PECO's model.
- Further Model's Improvement:
  - Include Service level as a constraint and create simulation for different service level.
  - Recalculate Shrink percentage

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Call Offered	138,387	114,688	126,019	142,640	146,701	140,227	161,898	151,925
Abandon Rate	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%
Call Handle	133820	110903	121860	137933	141860	135600	156555	146911
AHT	383	382	382	382	382	382	382	382
Call Load (h)	14237	11768	12931	14636	15053	14389	16612	15589
Occupancy	81%	81%	81%	81%	81%	81%	81%	81%
Adjusted Call Load	17576	14528	15964	18069	18584	17764	20509	19246
Raw number of Agent	100	83	91	103	106	101	117	109
Shrink	56%	56.20%	56.50%	55.70%	56.80%	54.90%	54.90%	53.30%
FTE	178	147	161	184	186	184	212	205
PECO Forecast	153	162	159	179	196	172	214	201

Draft Staffing Calculation

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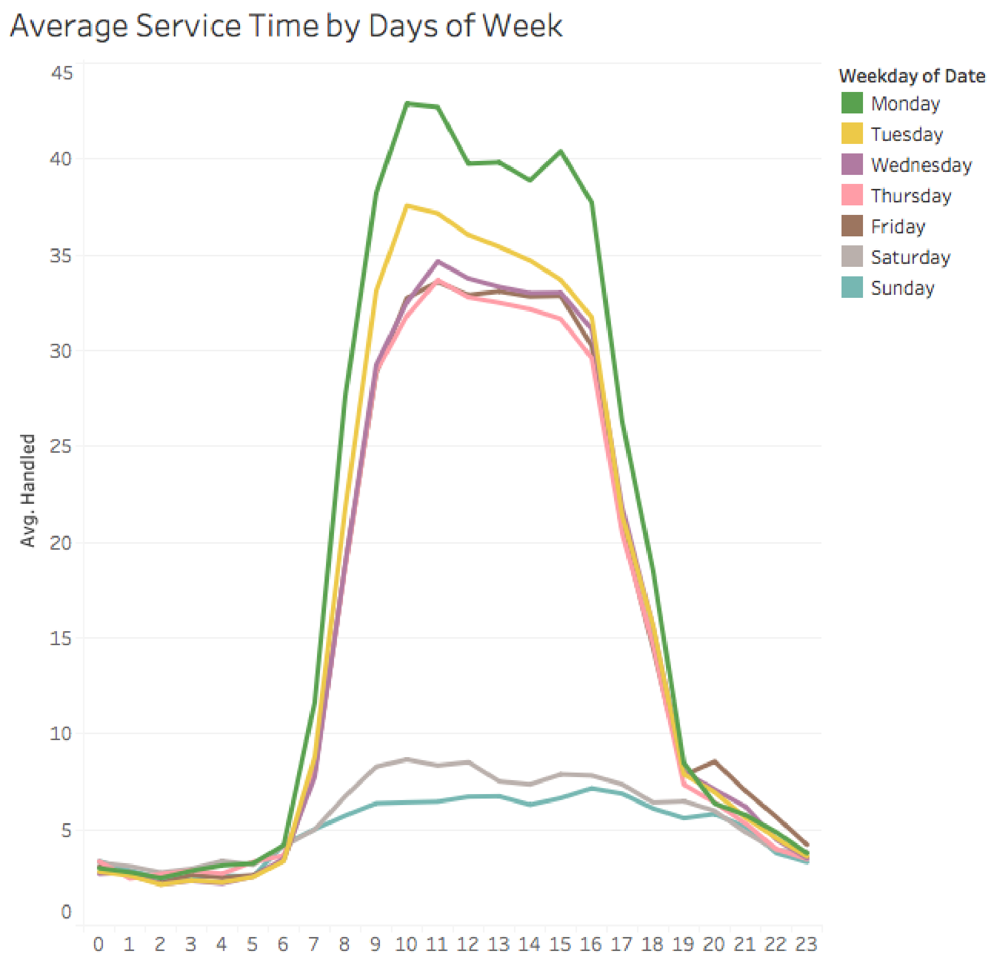
QUESTIONS & ANSWERS

Thank You

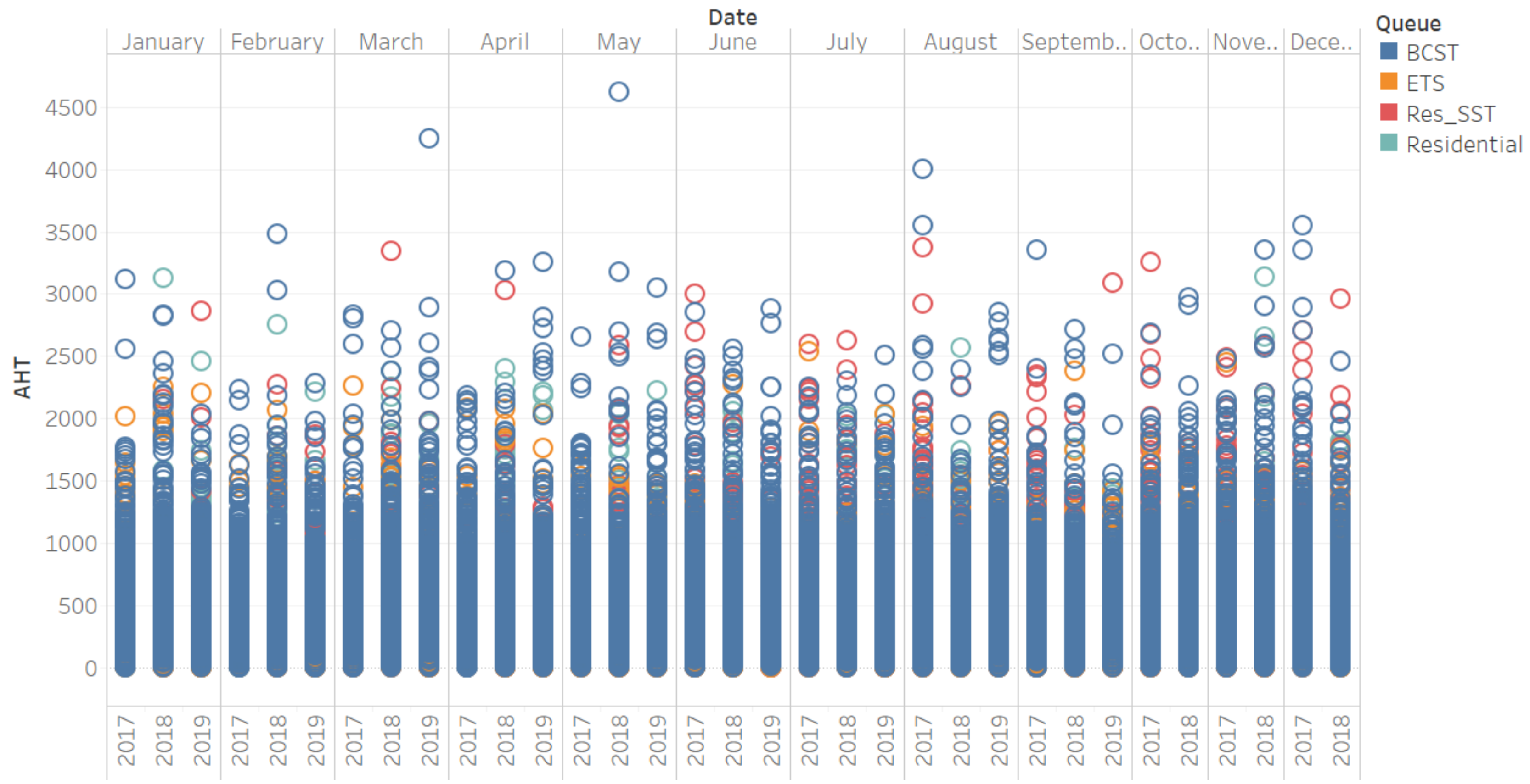
APPENDIX

Appendix – Service Time by Date

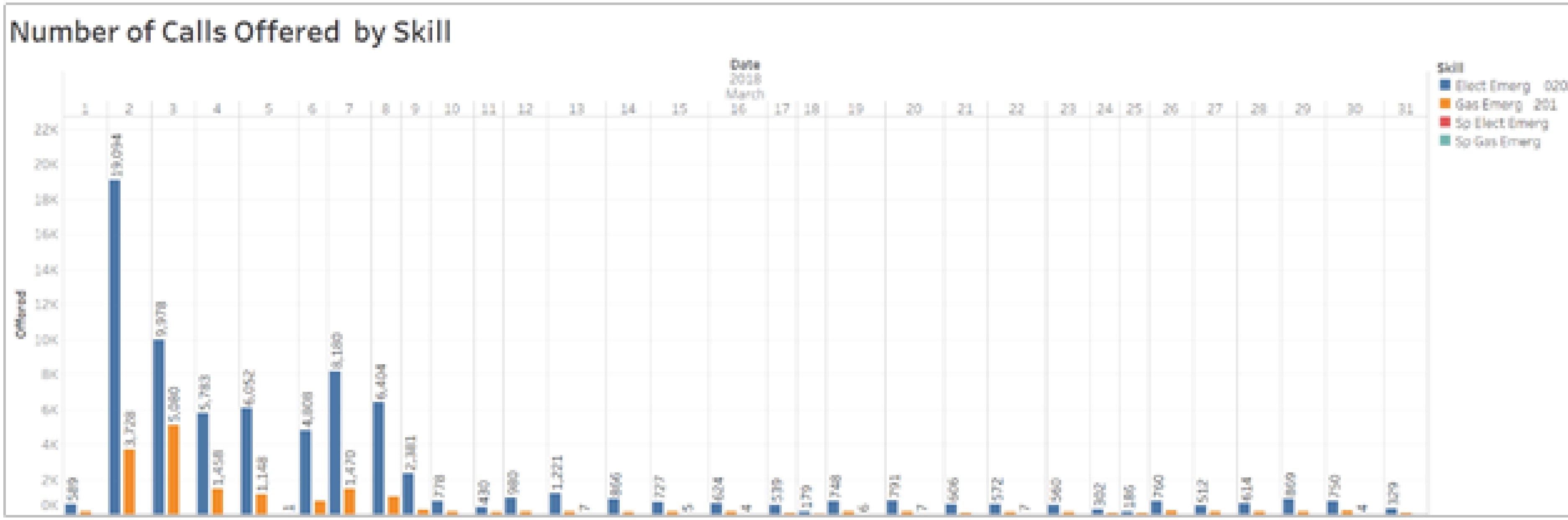


Appendix – Service Time by Queue

Sheet 29



Appendix – Number of Calls Offered by Skill (March 2018)



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Appendix – Simple Exponential Smoothing

Group.1	Actual		Group 2	Actual		Group 3	Acutal	Predicted
1/3/2017	829		1/2/2018	773		1/2/2019	600	592
1/4/2017	620		1/3/2018	627		1/3/2019	546	543
1/5/2017	467		1/4/2018	398		1/4/2019	528	527
1/6/2017	523		1/5/2018	491		1/7/2019	548	545
1/9/2017	744		1/8/2018	616		1/8/2019	503	505
1/10/2017	612		1/9/2018	572		1/9/2019	548	545
1/11/2017	610		1/10/2018	609		1/10/2019	500	502
1/12/2017	551		1/11/2018	525		1/11/2019	440	448
1/13/2017	533		1/12/2018	596		1/14/2019	629	618
1/17/2017	765		1/16/2018	1112		1/15/2019	563	559
1/18/2017	645		1/17/2018	670		1/16/2019	522	522
1/19/2017	565		1/18/2018	554		1/17/2019	492	495
1/20/2017	528		1/19/2018	771		1/18/2019	501	503
1/23/2017	670		1/22/2018	616		1/21/2019	125	165
1/24/2017	629		1/23/2018	585		1/22/2019	704	686
1/25/2017	611		1/24/2018	657		1/23/2019	550	547
1/26/2017	520		1/25/2018	583		1/24/2019	485	489
1/27/2017	524		1/26/2018	509		1/25/2019	461	467
1/30/2017	658		1/29/2018	674		1/28/2019	591	584
1/31/2017	673		1/30/2018	674		1/29/2019	547	544
			1/31/2018	615		1/30/2019	543	541
						1/31/2019	519	519

Appendix – ARIMA

```
Series: ts_bcst_train
ARIMA(4,1,0)(0,0,1)[5]

Coefficients:
          ar1      ar2      ar3      ar4     sma1
      -0.7596  -0.9185  -0.8324  -0.6944  -0.6571
s.e.   0.0952   0.0858   0.0975   0.1225   0.1596

sigma^2 estimated as 13732:  log likelihood=-382.06
AIC=776.12   AICc=777.64   BIC=788.88

Training set error measures:
                    ME     RMSE     MAE       MPE     MAPE      MASE        ACF1
Training set -22.03852 111.4622 75.0947 -10.11099 17.03462 0.7135473 -0.08838509
```

Appendix – Linear Regression Gas_Emergency

```
Step:  AIC=143.87
Gas_Emerg ~ Date + MaxTemp + AvgTemp + MinTemp + MaxDewPoint + 
    AvgDewPoint + MinDewPoint + MaxHumidity + AvgHumidity + MinHumidity + 
    MaxWindSpeed + AvgWindSpeed + MinWindSpeed + MaxPressure + 
    AvgPressure + MinPressure + weekday + MaxTemp_change + AvgTemp_change + 
    MinTemp_change + MaxDewPoint_change + AvgDewPoint_change + 
    MinDewPoint_change + MaxHumidity_change + AvgHumidity_change + 
    MinHumidity_change + AvgWindSpeed_change + AvgPressure_change

                      Df Sum of Sq     RSS    AIC
<none>                               494.8 143.88
+ TotalPrecipation     1       3.7   491.1 145.65
- AvgPressure_change   1     212.5   707.3 152.95
- MaxHumidity          1     241.7   736.5 154.21
- AvgTemp              1     304.7   799.5 156.75
- AvgHumidity          1     734.3  1229.1 170.08
- MinPressure          1    1378.5  1873.3 183.15
- MinTemp_change       1    1417.2  1912.0 183.78
- MaxWindSpeed         1    1863.3  2358.1 190.28
- MinWindSpeed         1    2779.7  3274.5 200.46
- MaxDewPoint_change   1    4394.7  4889.5 212.89
- AvgDewPoint_change   1    5039.7  5534.5 216.73
- MinTemp              1    5584.2  6079.0 219.64
- AvgDewPoint          1    5756.5  6251.3 220.50
- MaxHumidity_change   1    6605.3  7100.1 224.45
- MinHumidity          1    7276.6  7771.3 227.25
- MinDewPoint          1    7385.4  7880.2 227.68
- AvgWindSpeed         1    9063.6  9558.4 233.67
- MaxTemp              1    9872.6 10367.4 236.19
- Date                 1   10523.0 11017.8 238.07
- MaxPressure          1   11308.5 11803.3 240.21
- MaxDewPoint          1   11448.8 11943.6 240.57
- weekday              1   15065.6 15560.4 248.77
- AvgHumidity_change   1   15088.8 15583.6 248.82
- AvgTemp_change       1   15604.8 16099.6 249.83
- MaxTemp_change       1   15633.2 16128.0 249.88
- AvgPressure          1   15983.7 16478.5 250.55
- MinDewPoint_change   1   17047.7 17542.5 252.49
- MinHumidity_change   1   19301.6 19796.4 256.24
- AvgWindSpeed_change  1   30045.0 30539.8 269.68
```

Appendix – Linear Regression Gas_Emergency

```
Call:
lm(formula = Gas_Emerg ~ Date + MaxTemp + AvgTemp + MinTemp +
    MaxDewPoint + AvgDewPoint + MinDewPoint + MaxHumidity + AvgHumidity +
    MinHumidity + MaxWindSpeed + AvgWindSpeed + MinWindSpeed +
    MaxPressure + AvgPressure + MinPressure + weekday + MaxTemp_change +
    AvgTemp_change + MinTemp_change + MaxDewPoint_change + AvgDewPoint_change +
    MinDewPoint_change + MaxHumidity_change + AvgHumidity_change +
    MinHumidity_change + AvgWindSpeed_change + AvgPressure_change,
    data = dgas)

Coefficients:
       (Intercept)                Date             MaxTemp             AvgTemp             MinTemp         MaxDewPoint
         18571.975              -8.522              38.399             -18.406             -15.265             -66.384
       AvgDewPoint         MinDewPoint         MaxHumidity         AvgHumidity         MinHumidity        MaxWindSpeed
            89.981             -40.120              -1.697             -11.553              14.053               6.726
      AvgWindSpeed        MinWindSpeed         MaxPressure         AvgPressure         MinPressure             weekday
           -29.413              -8.889             537.575           -1312.795             181.544             -25.295
    MaxTemp_change      AvgTemp_change      MinTemp_change  MaxDewPoint_change  AvgDewPoint_change  MinDewPoint_change
          -603.366             585.079              -8.221               9.784               9.635              24.770
MaxHumidity_change  AvgHumidity_change  MinHumidity_change AvgWindSpeed_change  AvgPressure_change
           -10.725              17.462             -23.344              36.842             -59.914

>
```