



Frederick County

Division of Emergency Management

Data ConQUEST



Our Team



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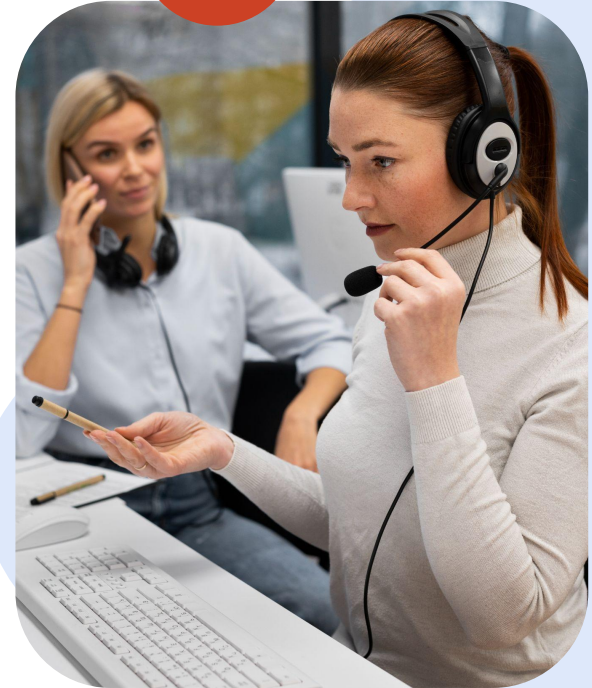
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Daniel Samuel
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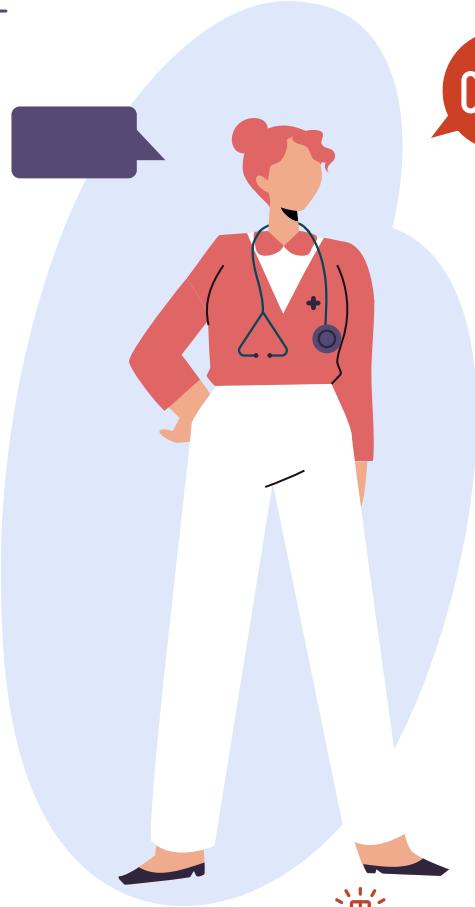




01

Objective & Scope





The Division of Emergency Management (DEM) handles 911 calls and dispatching for many different agencies.

PALS provides quality assistance to local governments while providing real-world experience for students.



Partnership for
Action Learning
in Sustainability





Objectives

- ◆ Assess staffing needs
- ◆ Utilize call volume data
- ◆ Identify **specific times and areas** where additional staffing is needed

Deliverable

Staffing allocation recommendations based on historical call trends



Project Scope



Analyze Historical
911 Call Data



Identify Peak
Staffing Needs



Focus on Quantifying
Shortfalls

Limitations



Existing DEM data



No Hourly Staffing Data





02

Data Received & Cleanup





Data Collection



Calls by Hour

Talk Group Usage



Calls by Day

Call Wait Time

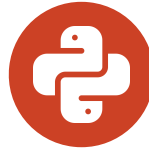


Data Processing & Cleanup



Excel Cleanup

Organize and clean raw data in Excel



Python Model

Manipulate the data in Python to create a regression model



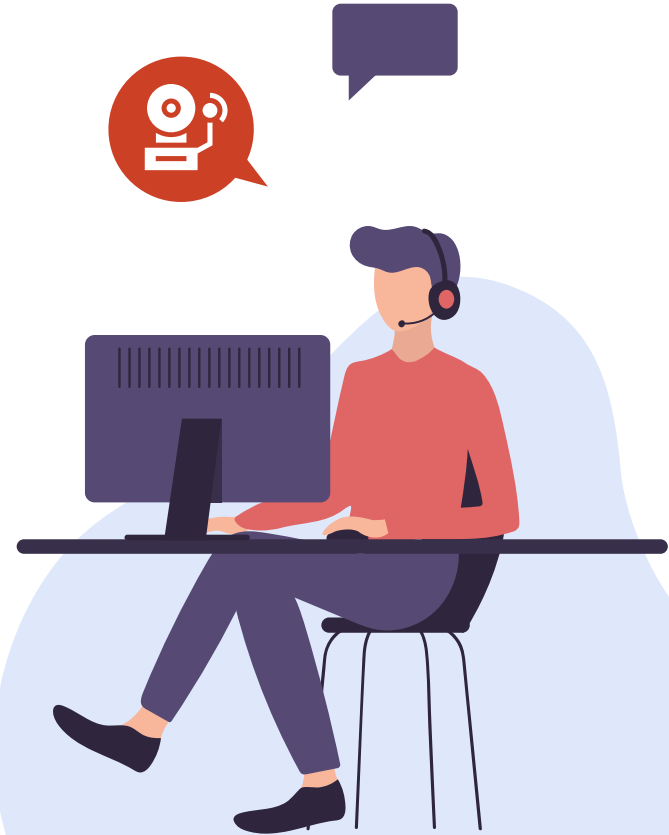
Tableau Visualization

Visualize the data in Tableau to reveal insights



03

Data Analysis

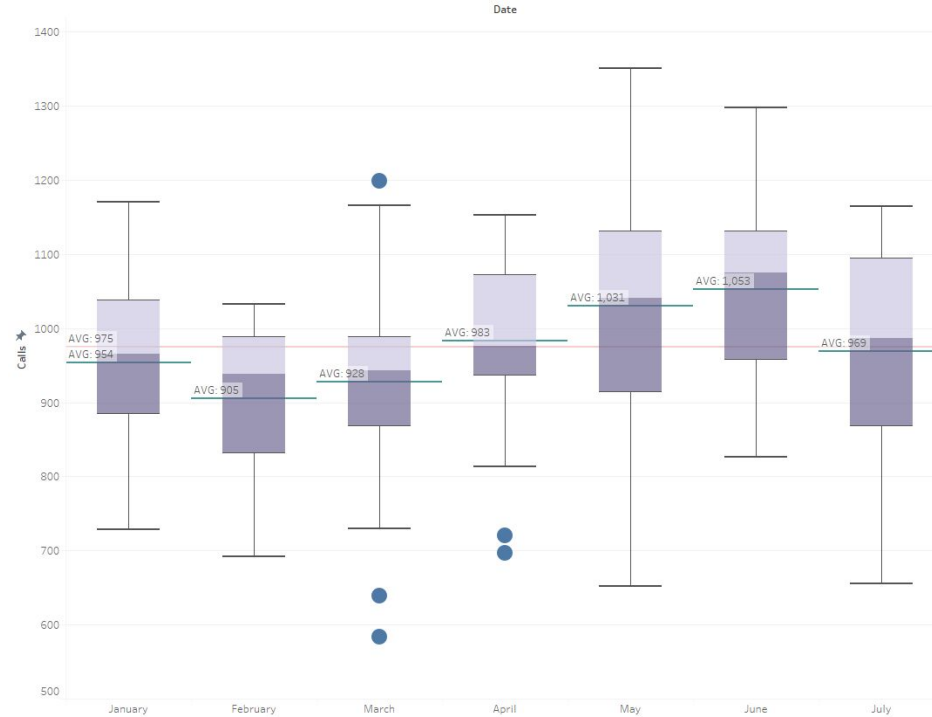


Initial Call Analysis

Calls by day tend to be **similar** across all months, with ~ **950–1000** per day

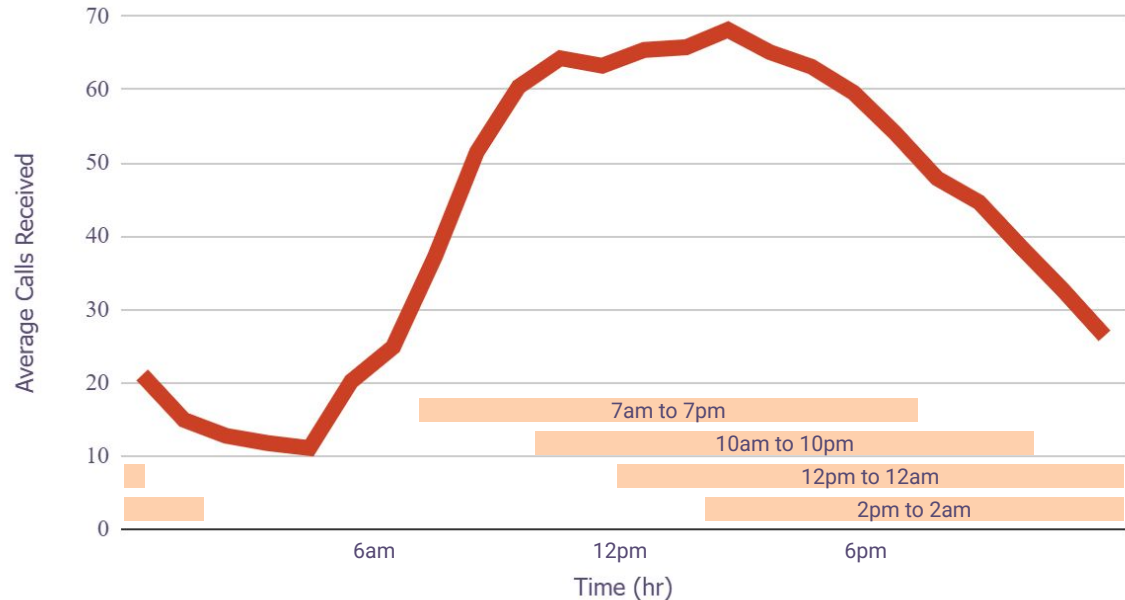
June has the highest **average and median** calls per day

May has the **greatest variance** in number of calls, ~ **700**



Weekday Calls by Hour

Average Calls By Hour



Weekday calls tend to follow the workday and normal waking hours

Current power shifts have most people working from 2 – 7 pm, while peak hours are 9 am – 5 pm

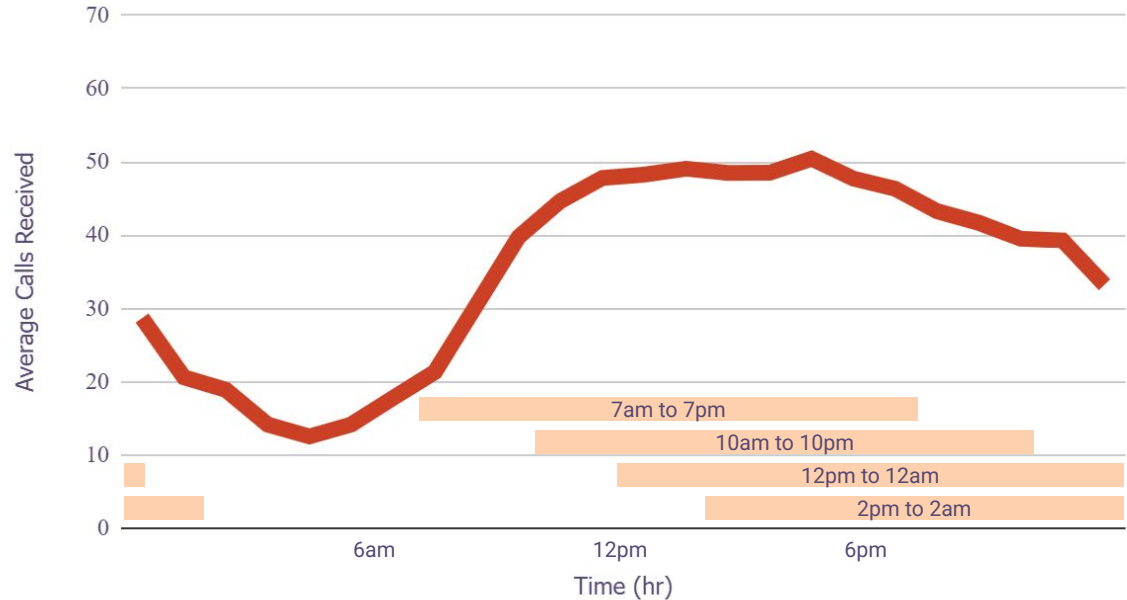


Weekend Calls by Hour

Weekend calls tend to be **lower** overall and are **flatter** throughout **waking hours**

Current power shifts have most people working from **2 – 7 pm**, while peak hours are **9 am – 9 pm**

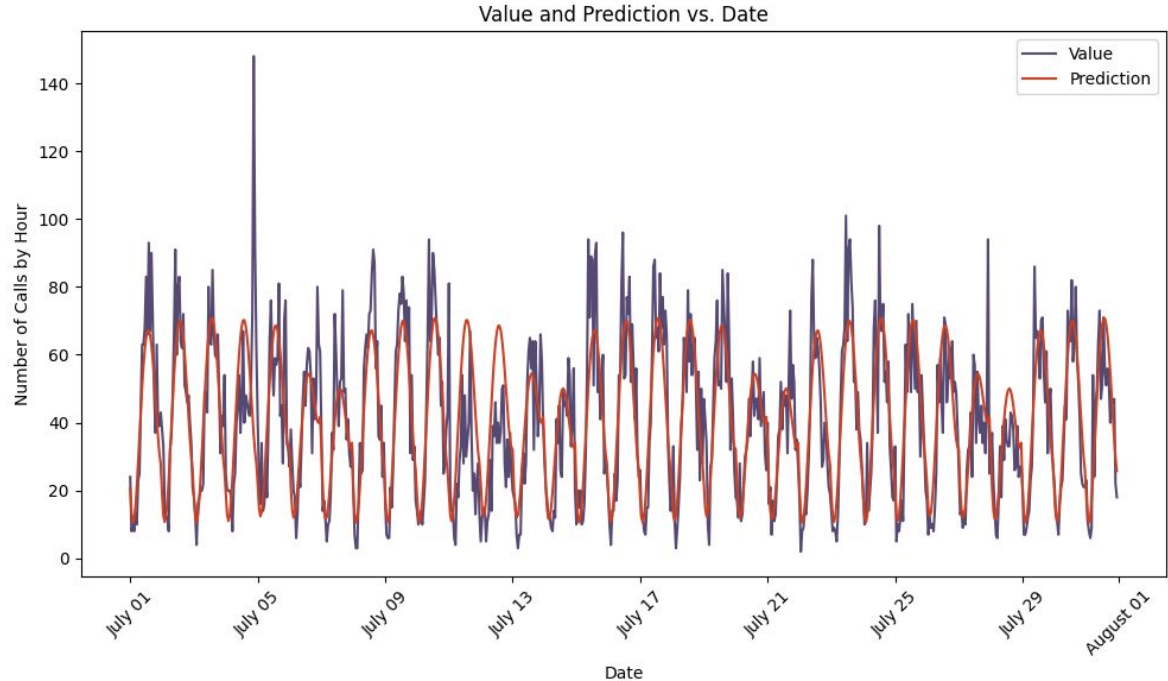
Average Calls By Hour



Python Polynomial Predictive Model

Regression analysis illustrated that **hour of the day** and **weekday / weekend** are **significant** to number of calls received

Create a **polynomial prediction model** to predict **calls by hour for July**





04

Recommendations



Modify the current
power shift schedule to
better adjust to:

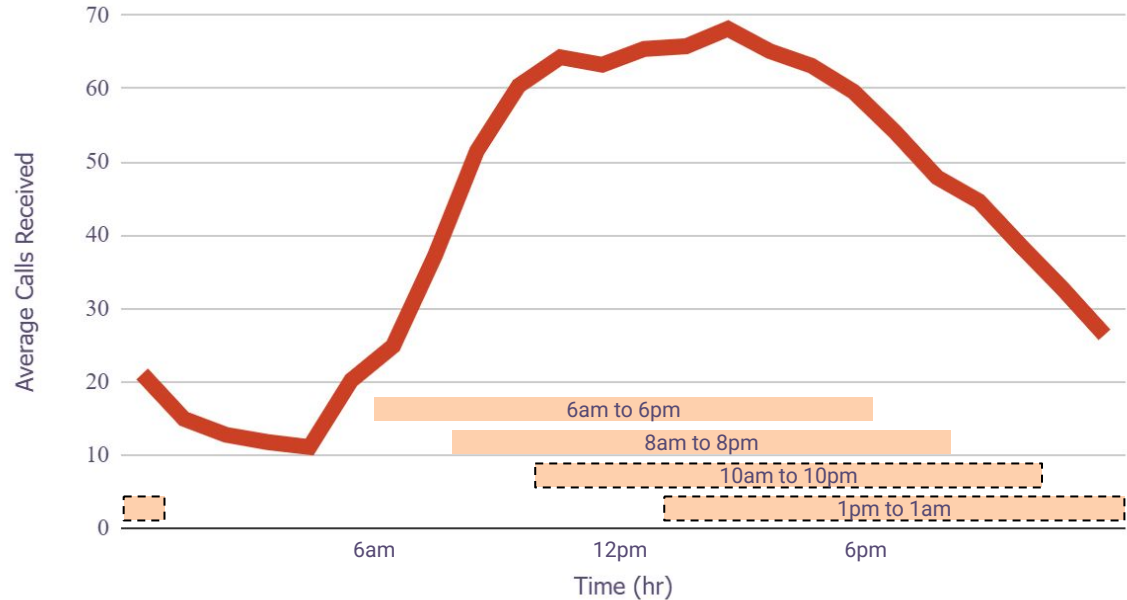
- ◆ Peak hours of the day
- ◆ Weekday / weekend status

Modified Weekday Shifts

Heavier earlier
power shifts cover
peak hours

Lighter later power
shifts provide
additional support in
higher volume (but
not peak) times

Average Calls By Hour

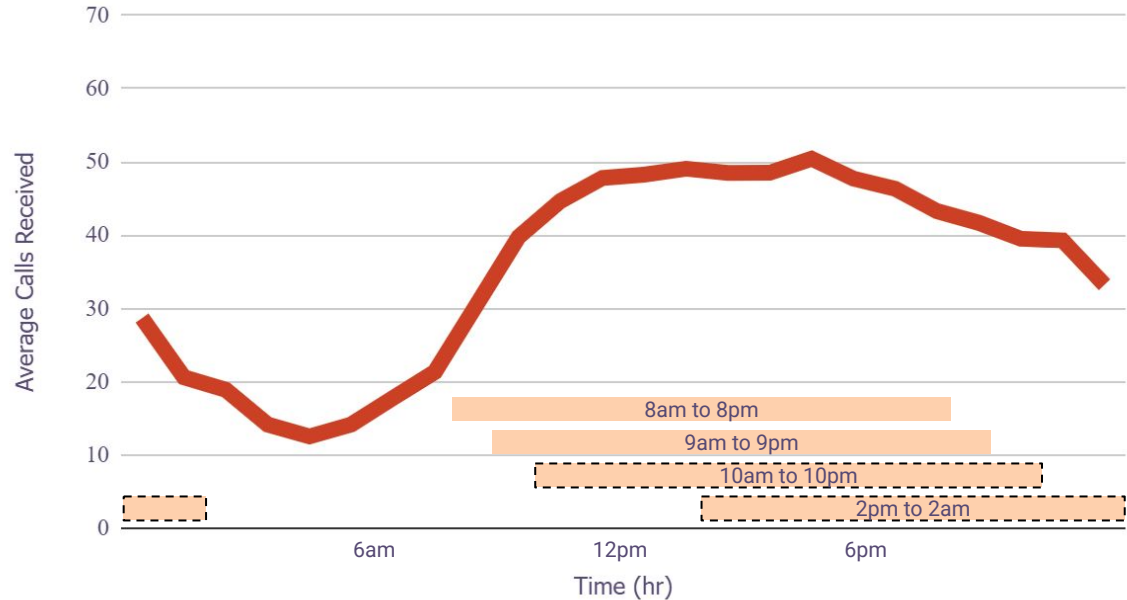


Modified Weekend Shifts

Heavier earlier
power shifts cover
peak hours

Lighter later power
shifts provide
additional support in
higher volume (but
not peak) times

Average Calls By Hour





05

Impact





Impact of Modified Shifts



Decrease Wait Time

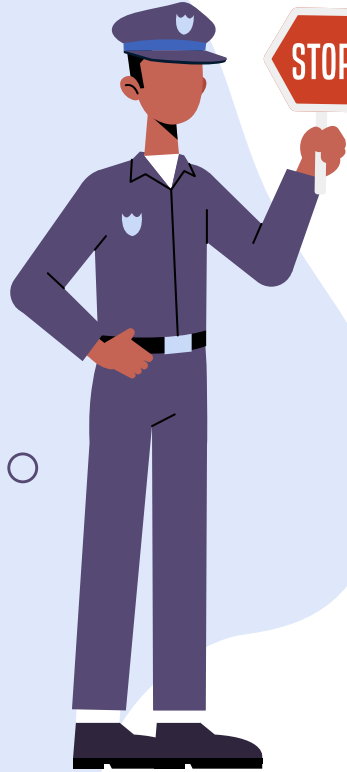
Reduce **wait time** for emergency call reception and dispatch



Future Forecast

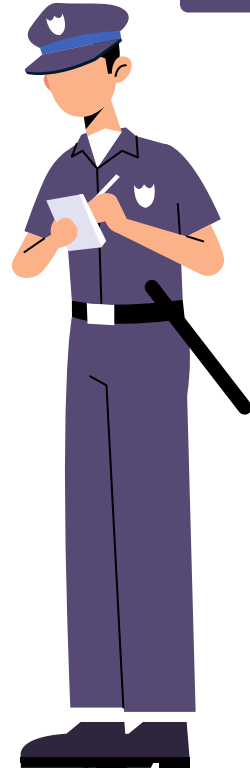
Forecast **approximate calls** based on hour of the day and day of the week

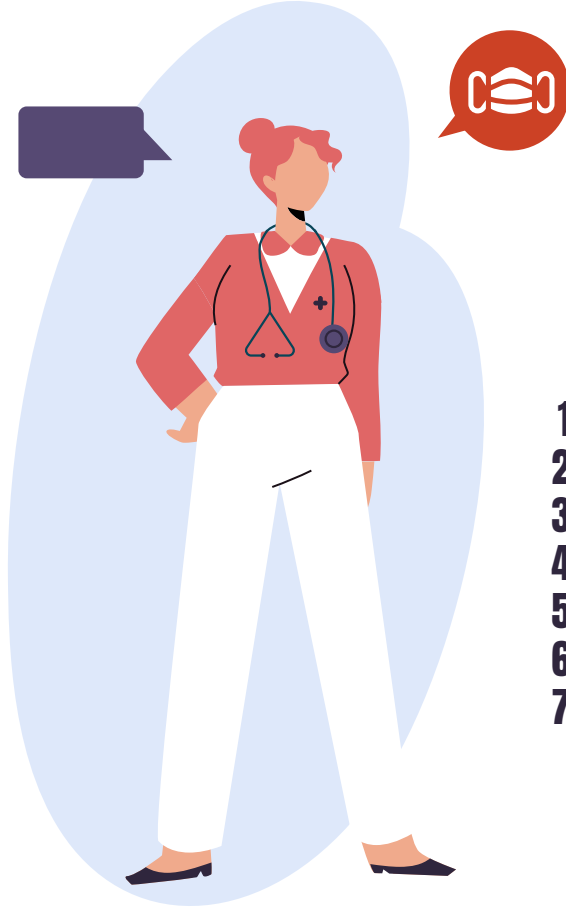




Thank You!

Questions?





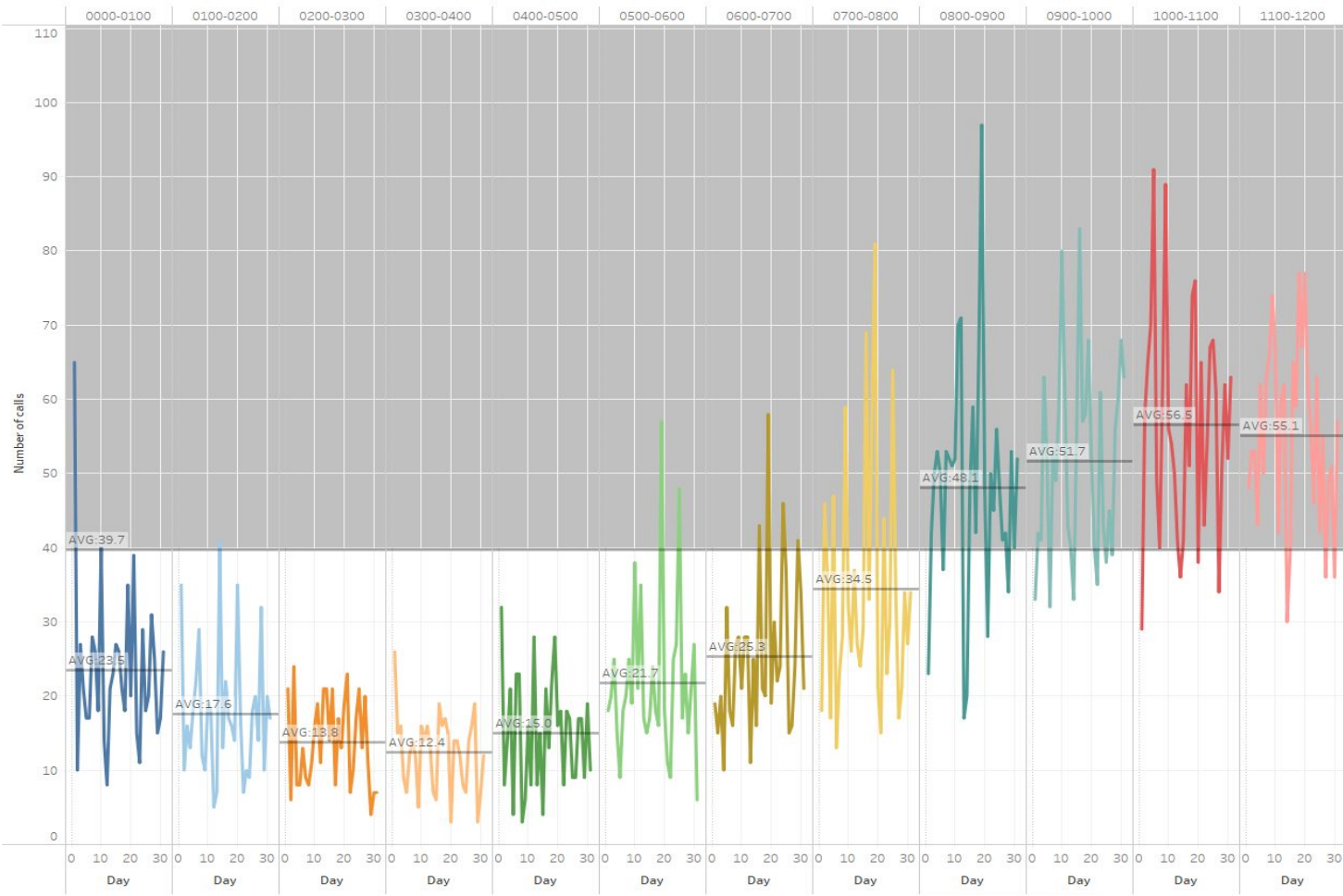
Appendices

1. CBH - January
2. CBH - February
3. CBH - March
4. CBH - April
5. CBH - May
6. CBH - June
7. CBH - July

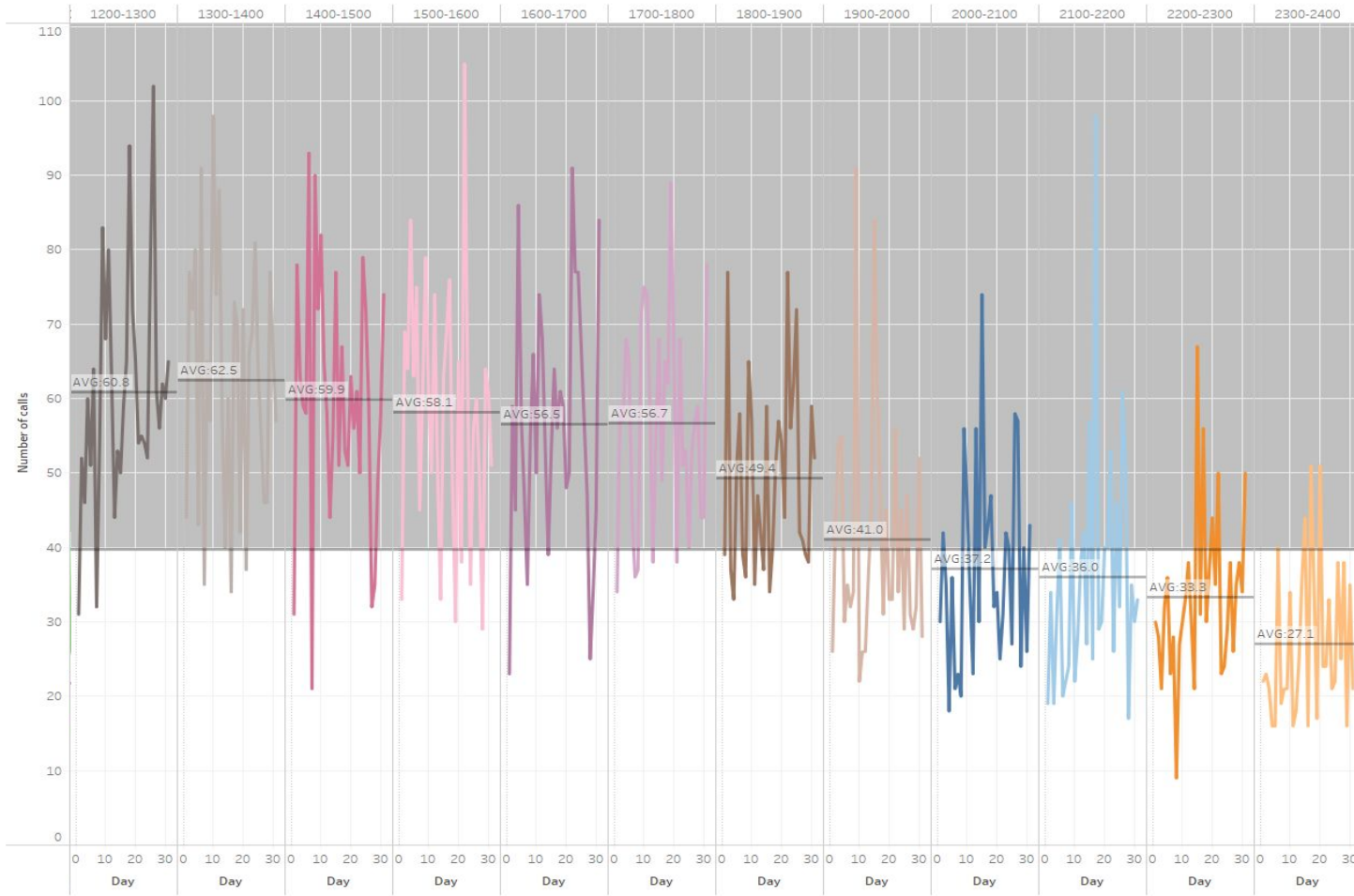
1. CBD - January
2. CBD - February
3. CBD - March
4. CBD - April
5. CBD - May
6. CBD - June
7. CBD - July

1. CBD - Regression
2. CBH - Regression
3. Polynomial Regression
4. CBD - Boxplot(Month)
5. CBD - Boxplot(Day)
6. Traditional Shift

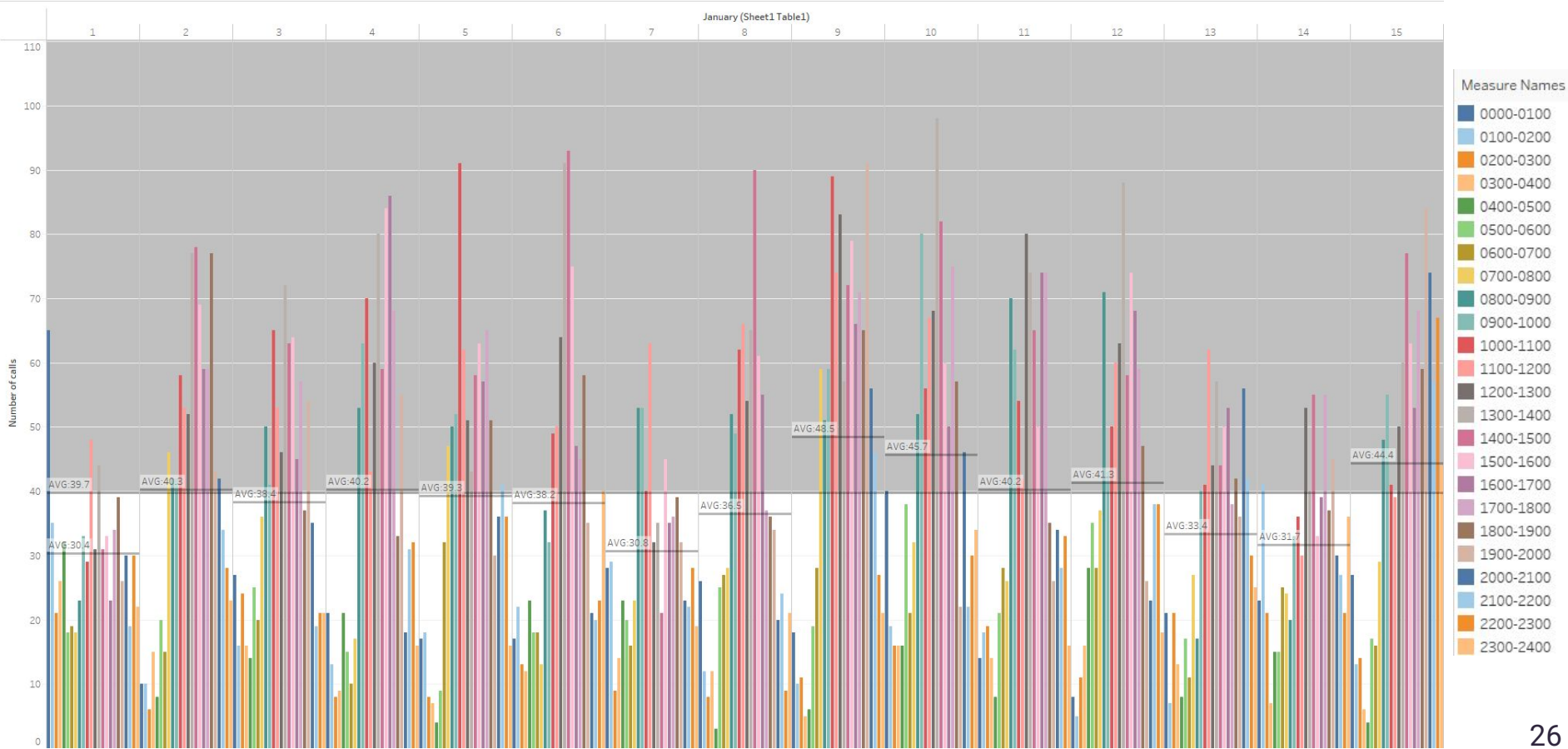
CBH - January(Hour 0 - Hour 12)



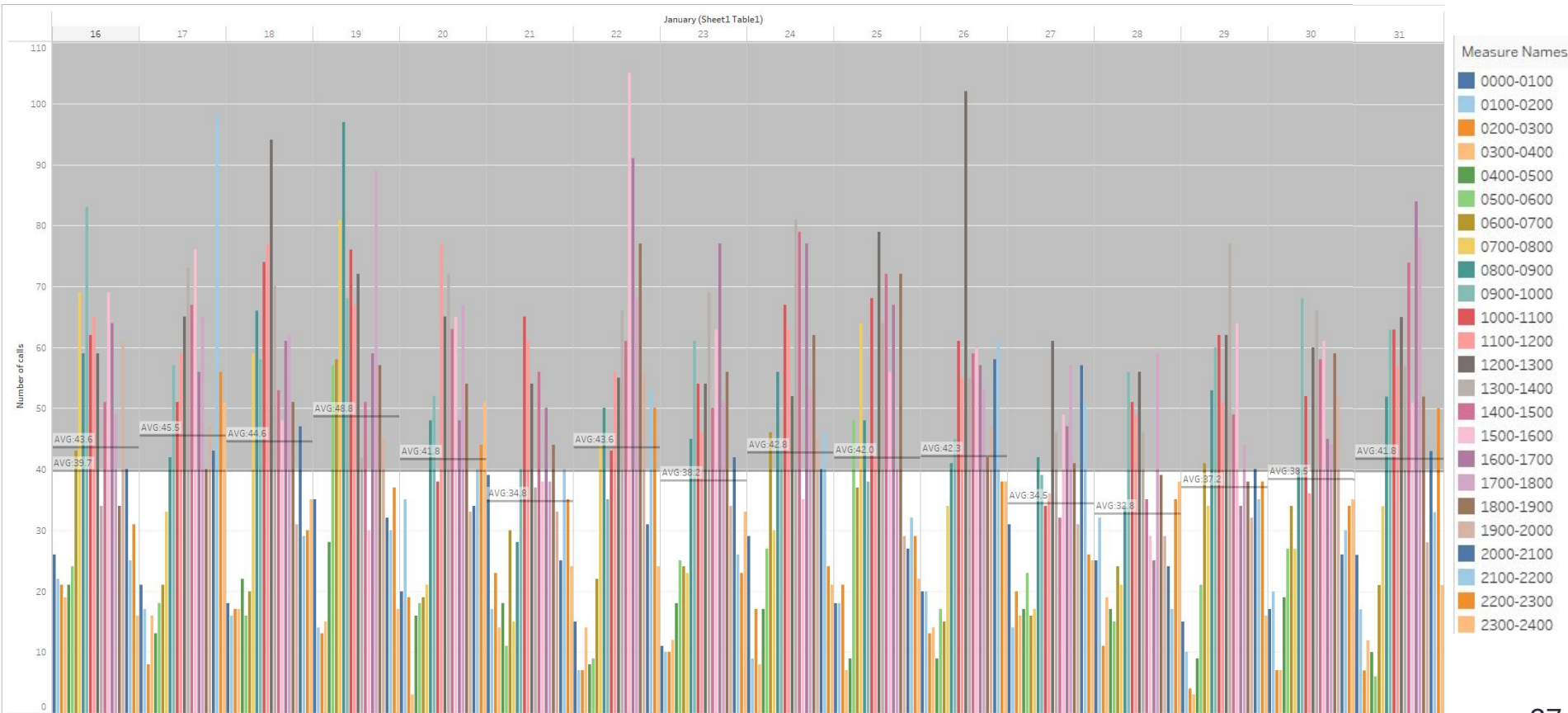
CBH - January(Hour 12 - Hour 24)



CBH - January(Day 1 - Day 15)

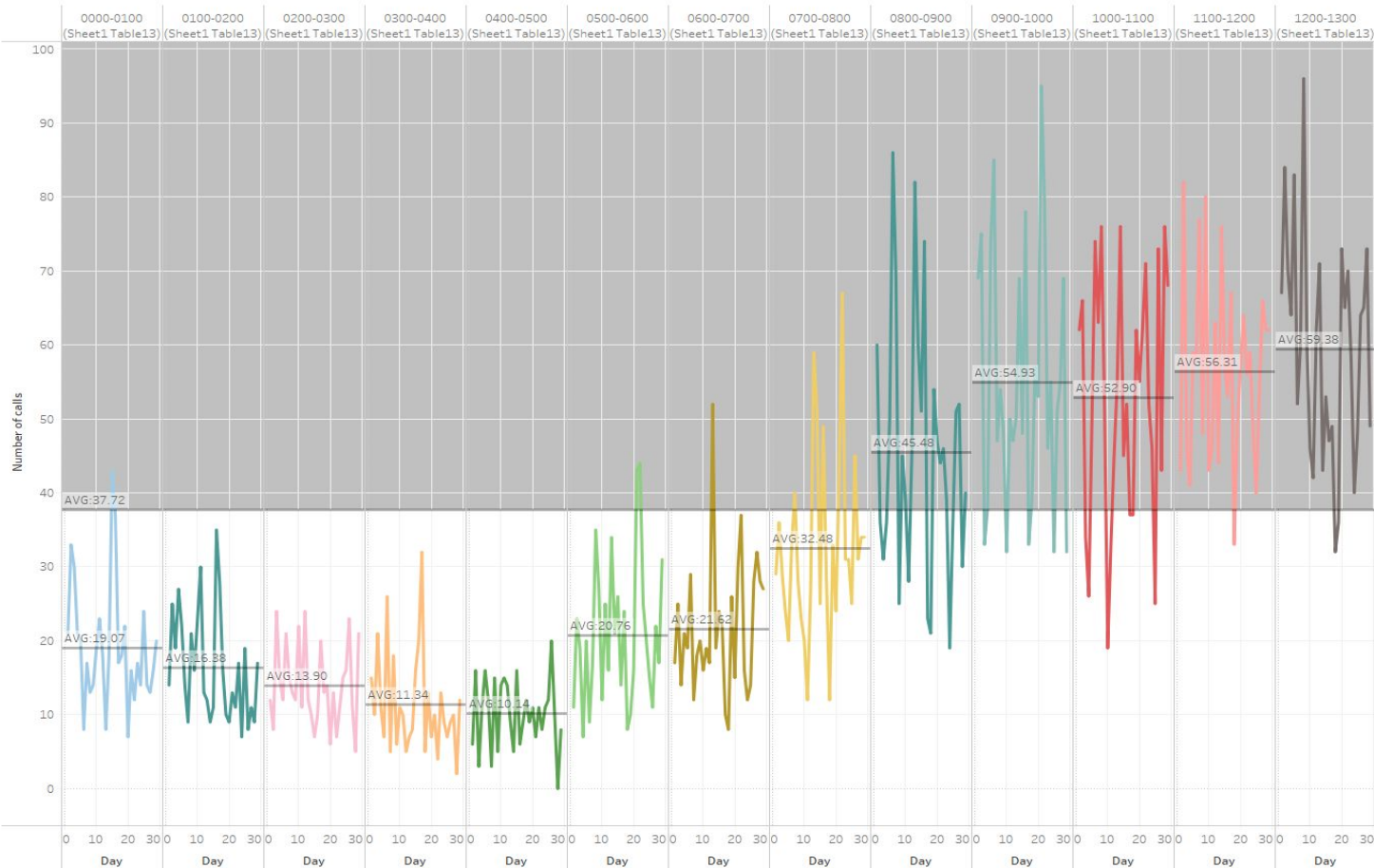


CBH - January(Day 15 - Day 31)

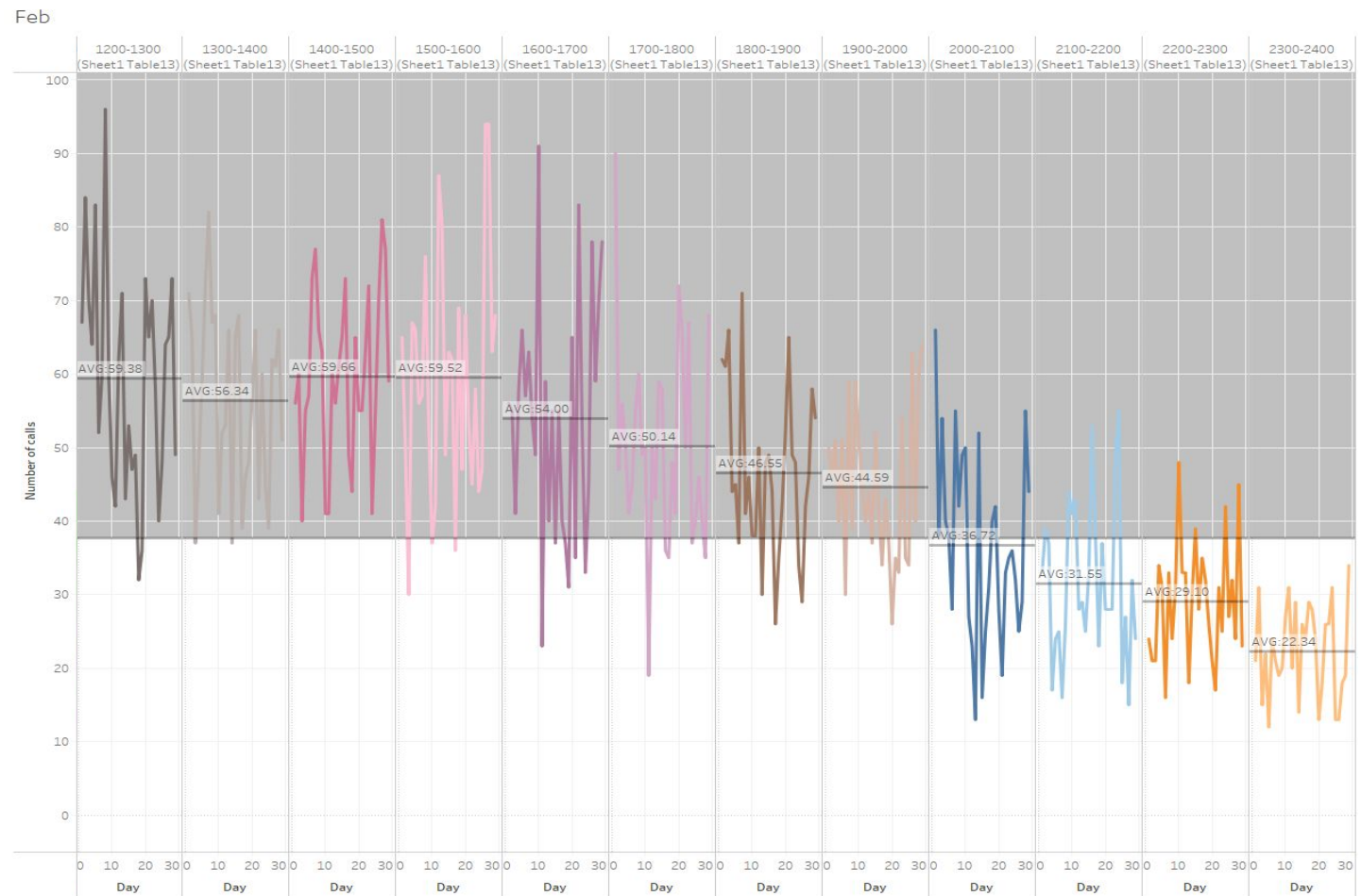


CBH - February(Hour 0 - Hour 12)

Feb

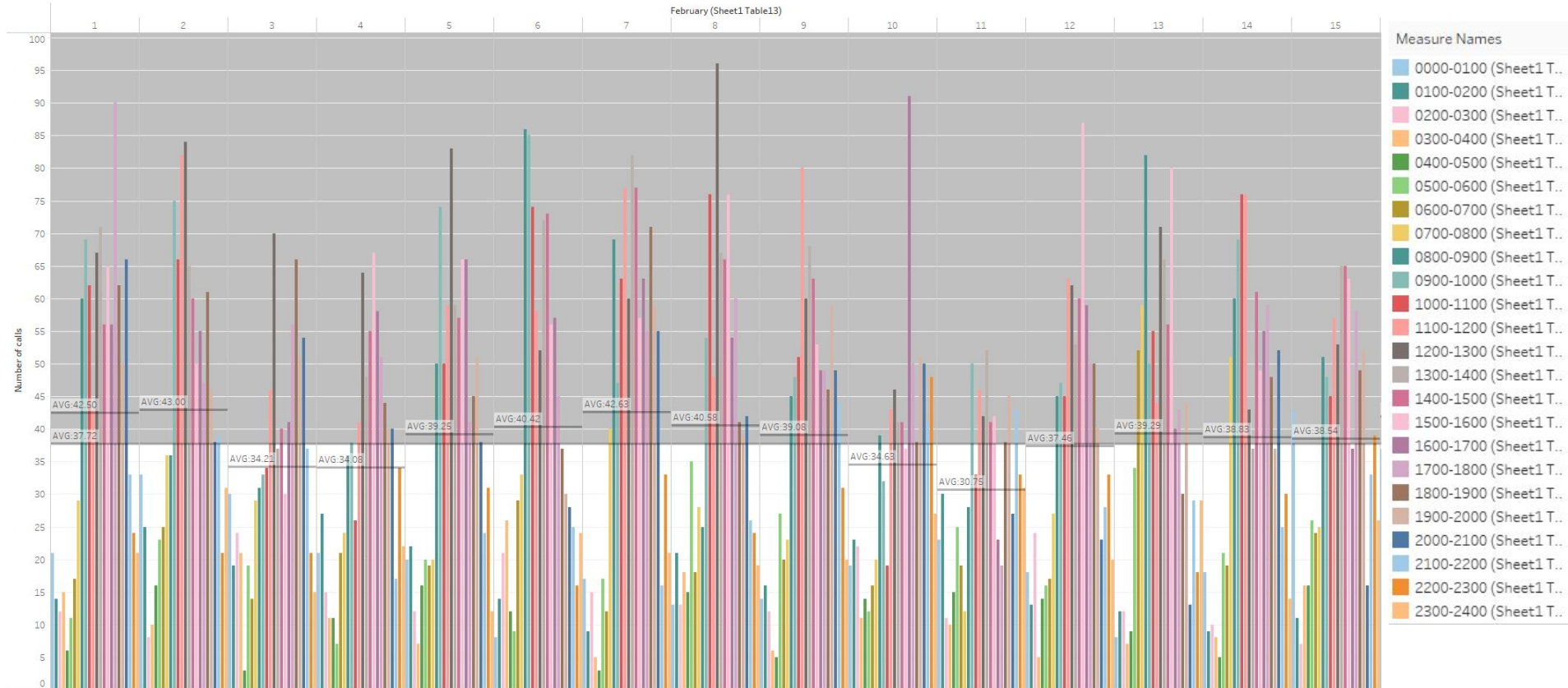


CBH - February(Hour 12 - Hour 24)



CBH - February(Day 1 - Day 15)

Feb (2)

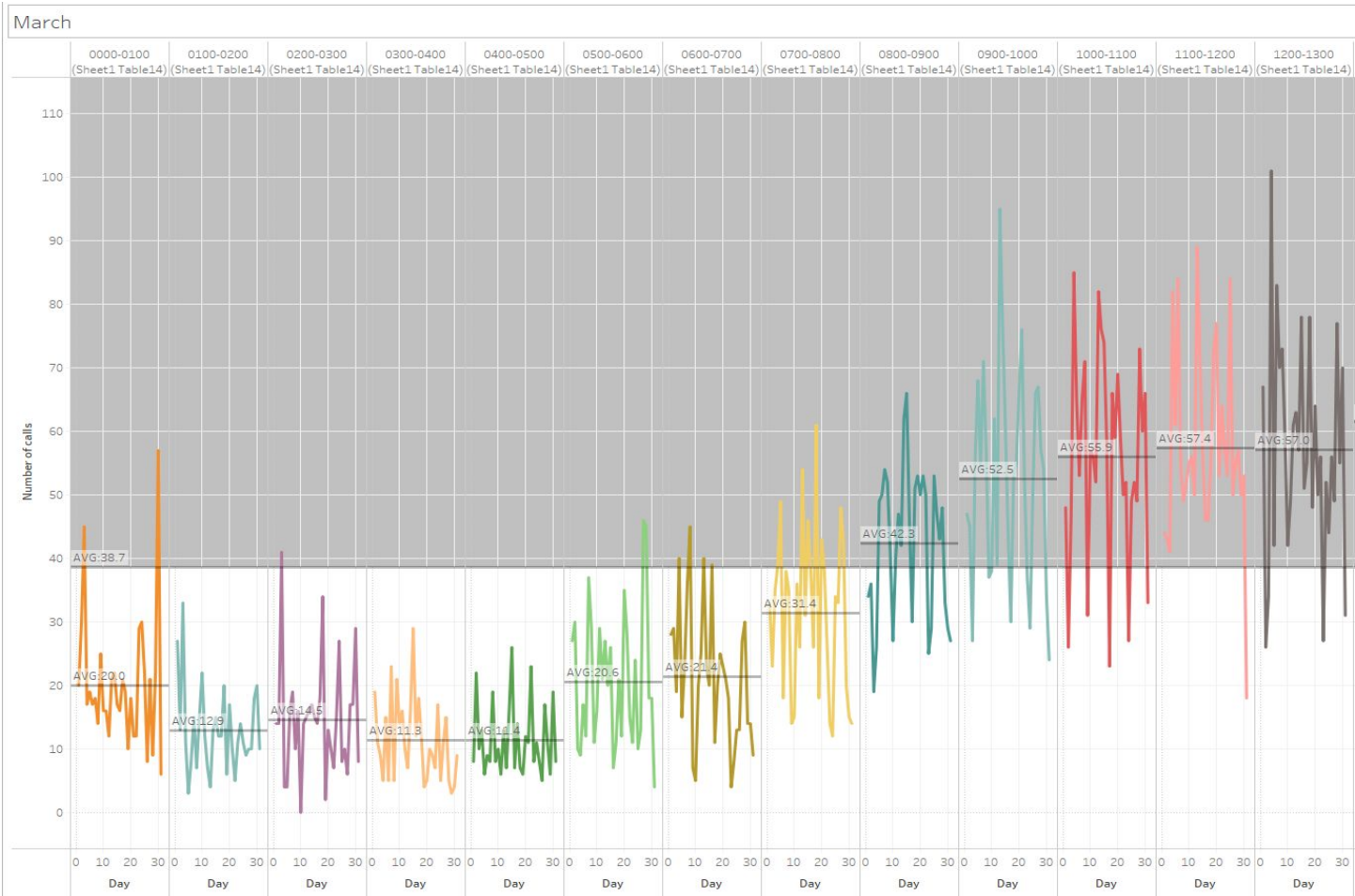


CBH - February(Day 16 - Day 28)

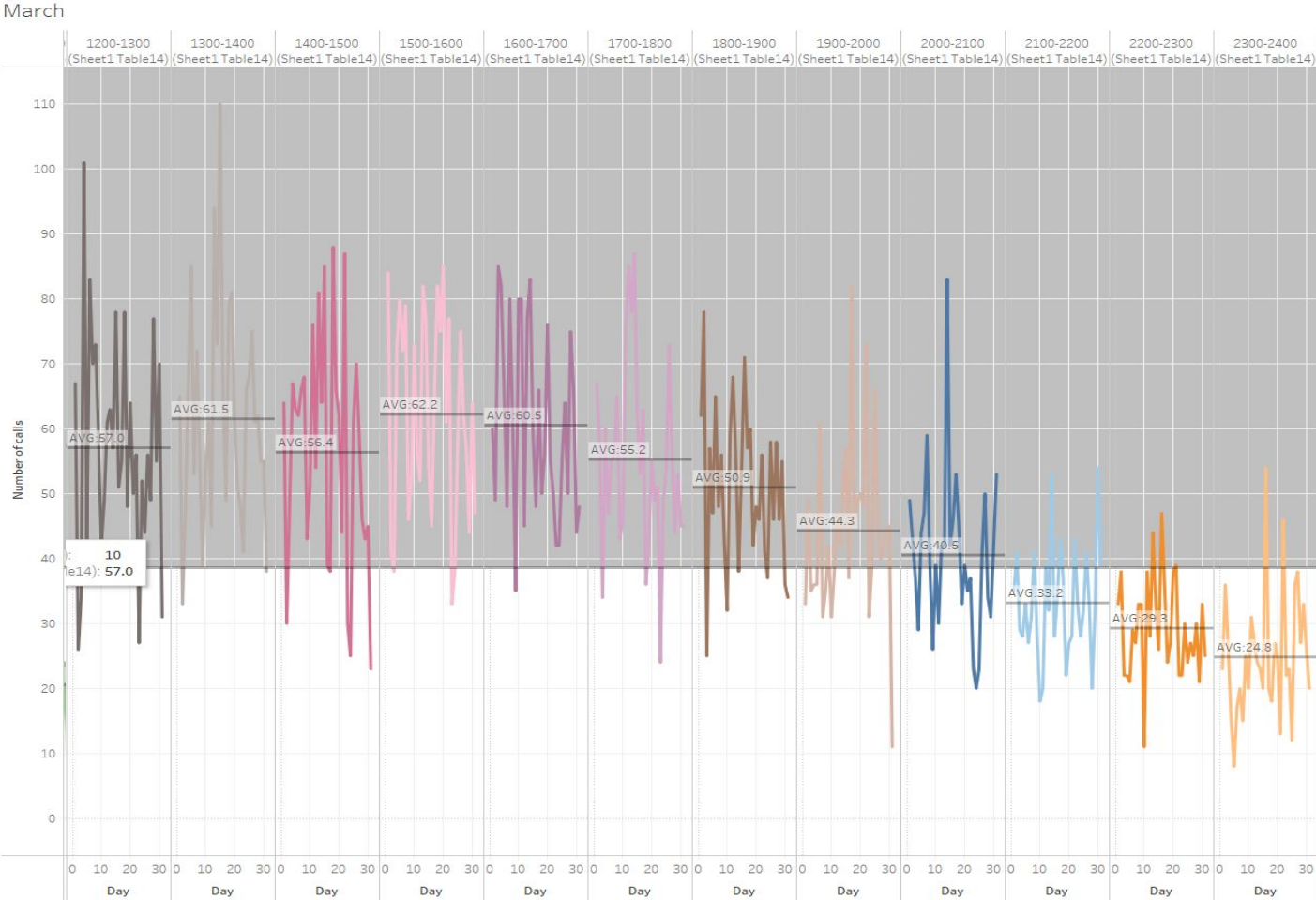
Feb (2)



CBH - March(Hour 0 - Hour 12)



CBH - March(Hour 12 - Hour 24)



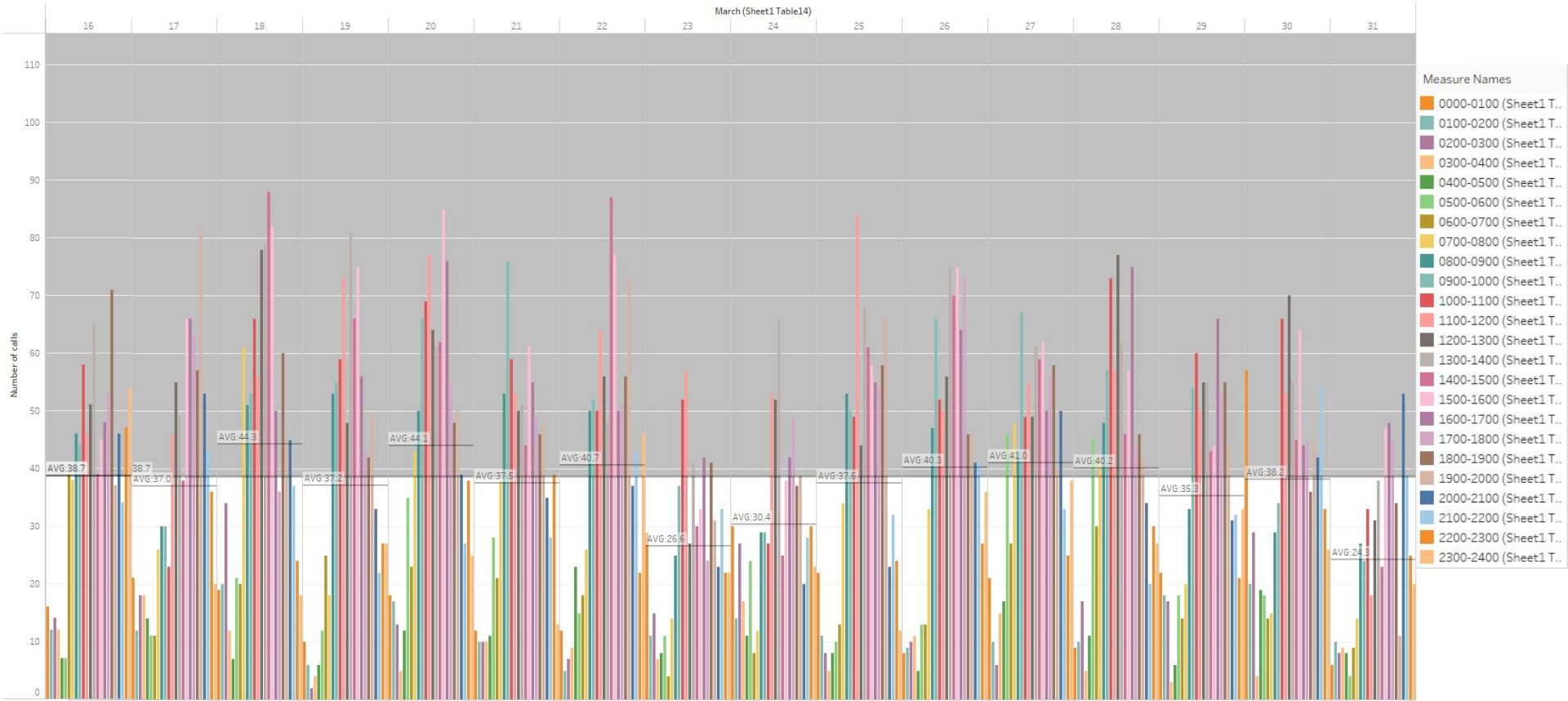
CBH - March(Day 1 - Day 15)

March (2)



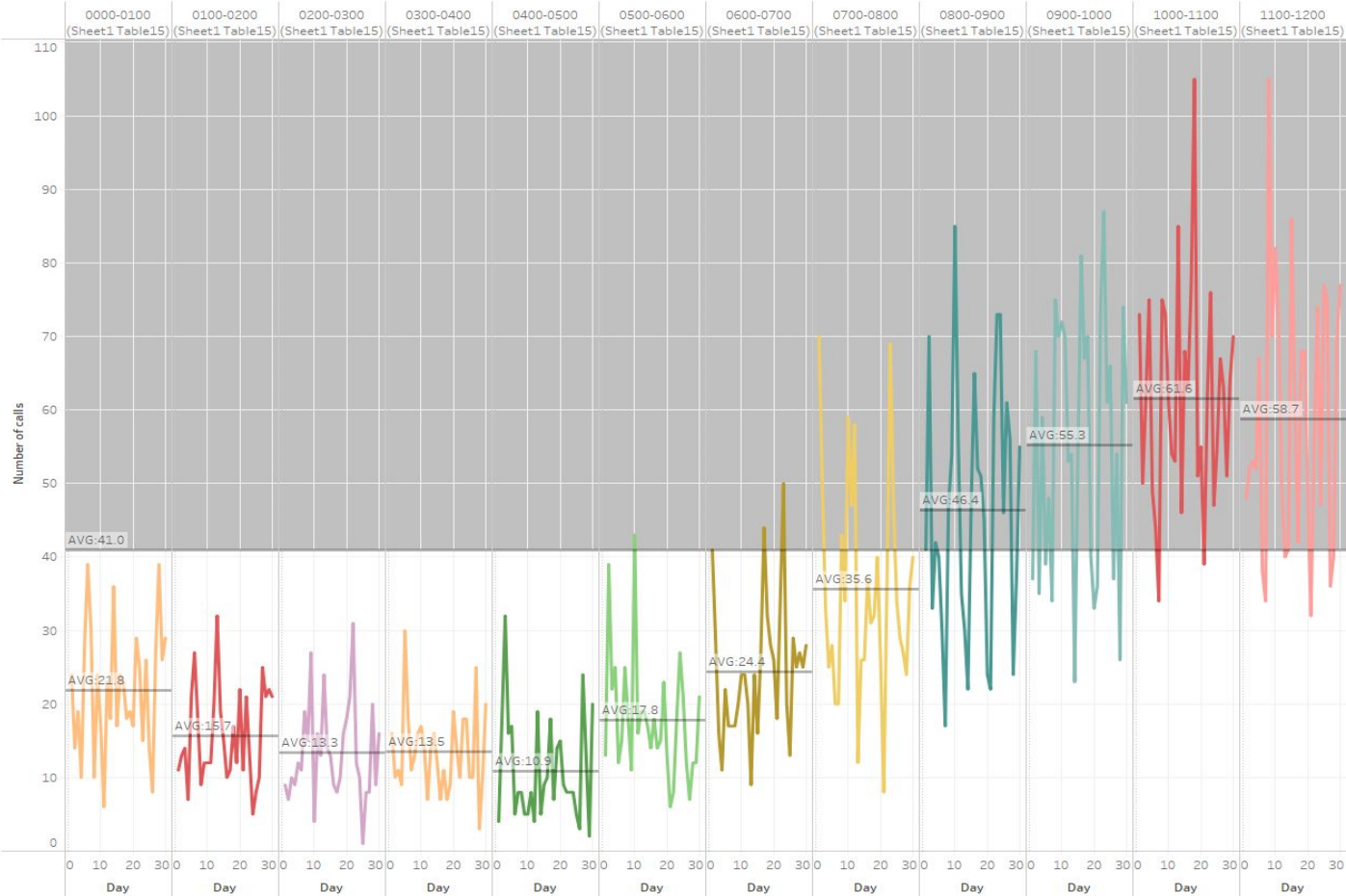
CBH - March(Day 16 - Day 31)

March (2)



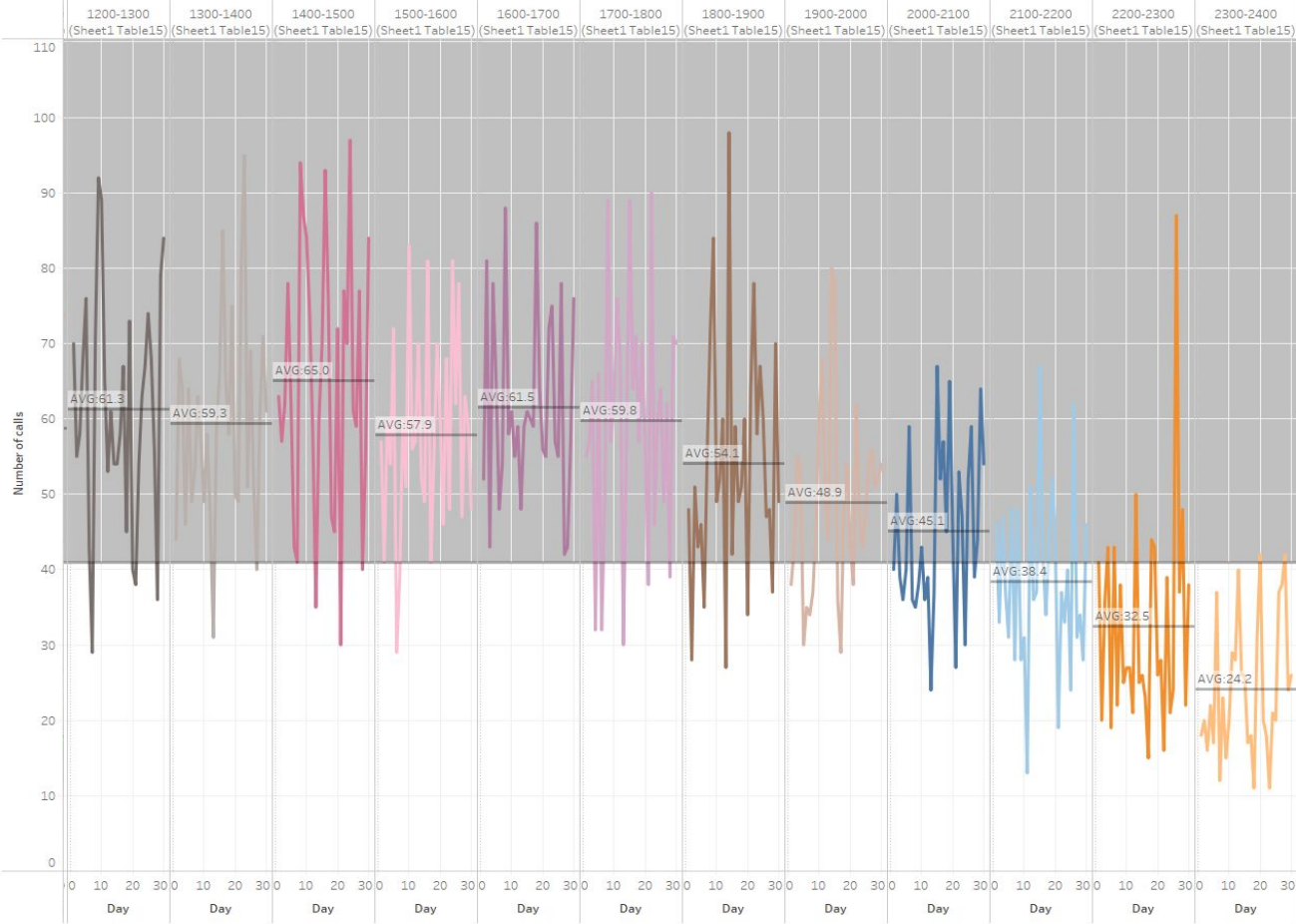
CBH - April(Hour 0 - Hour 12)

April



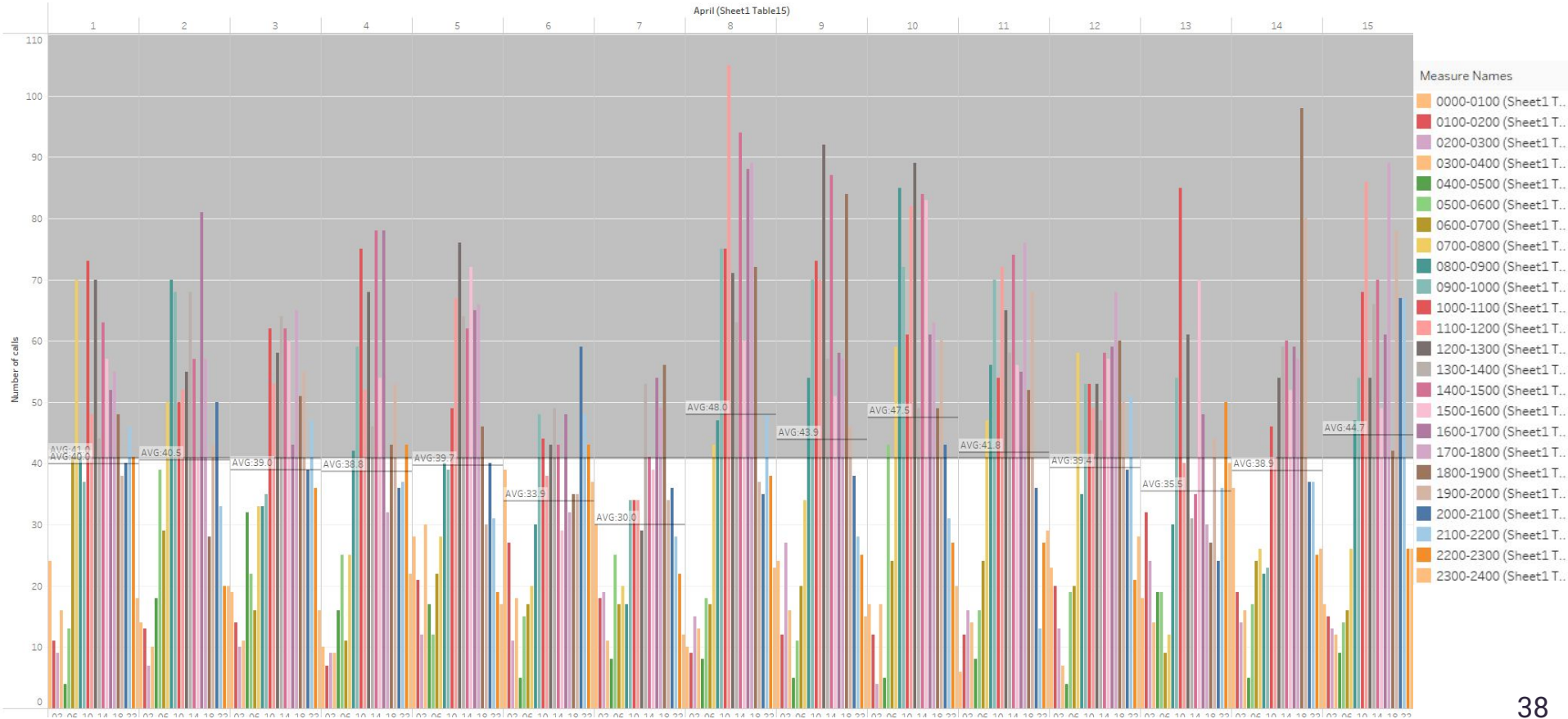
CBH - April(Hour 12 - Hour 24)

April



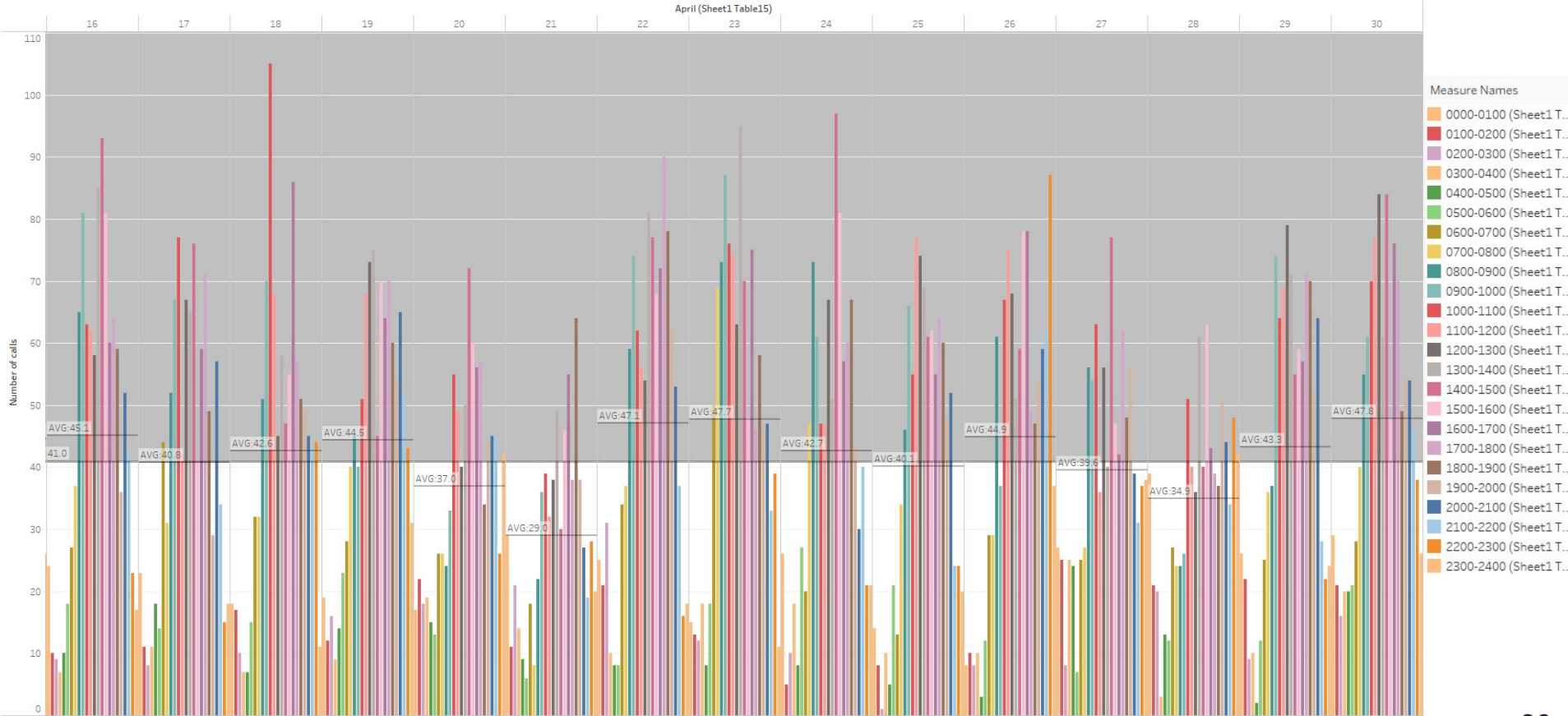
CBH - April(Day 1 - Day 15)

April (2)

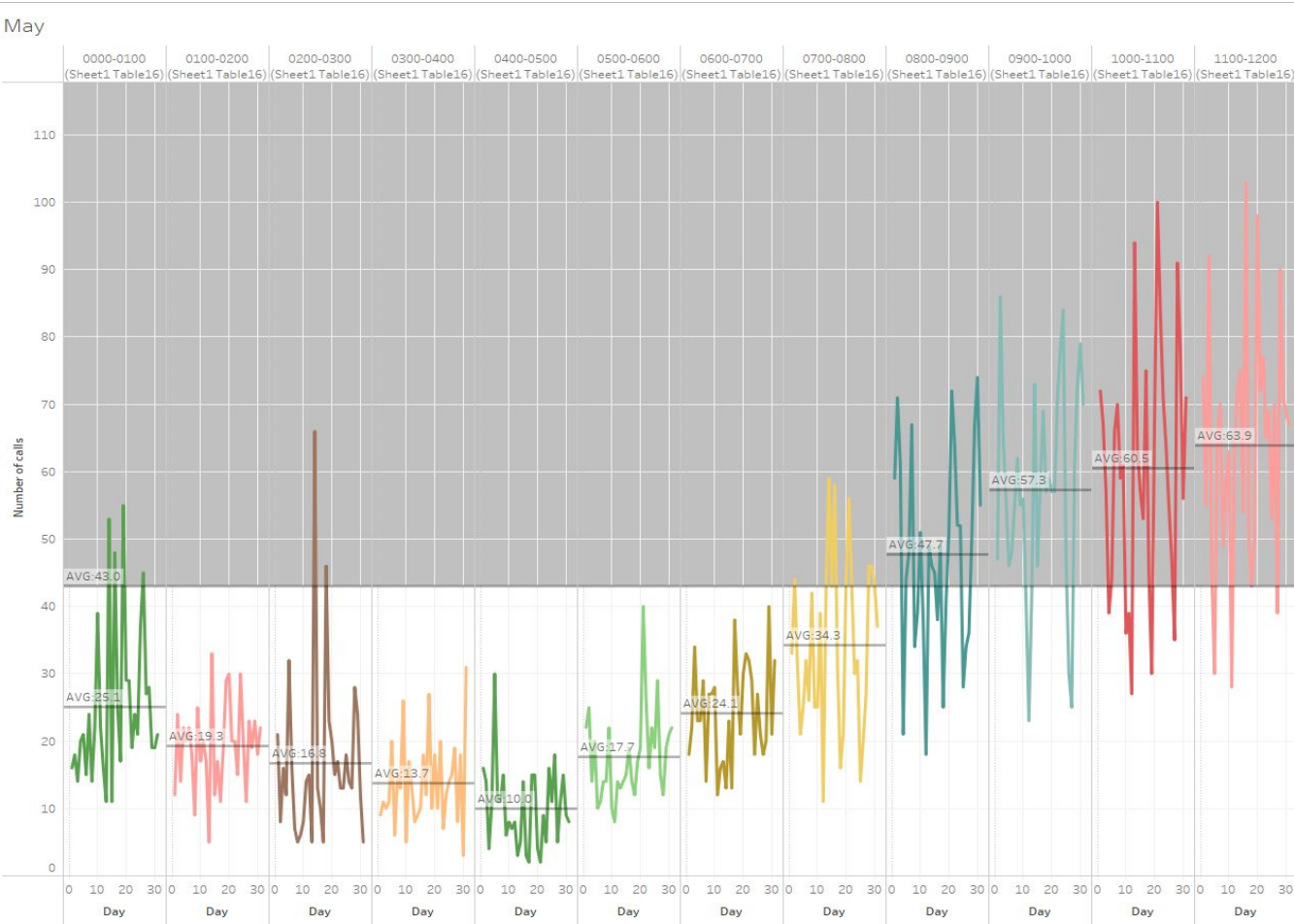


CBH - April(Day 16 - Day 30)

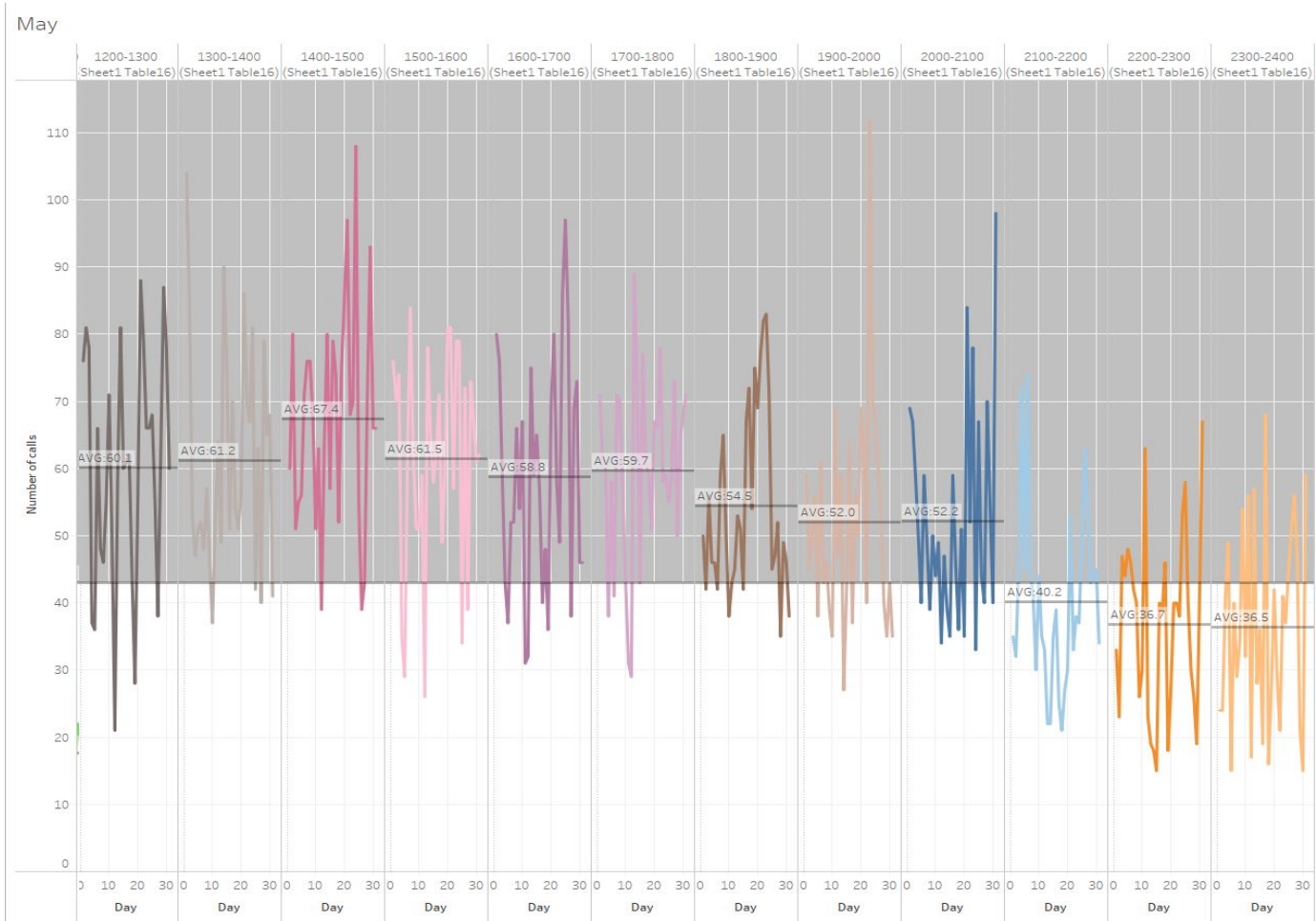
April (



CBH - May(Hour 0 - Hour 12)

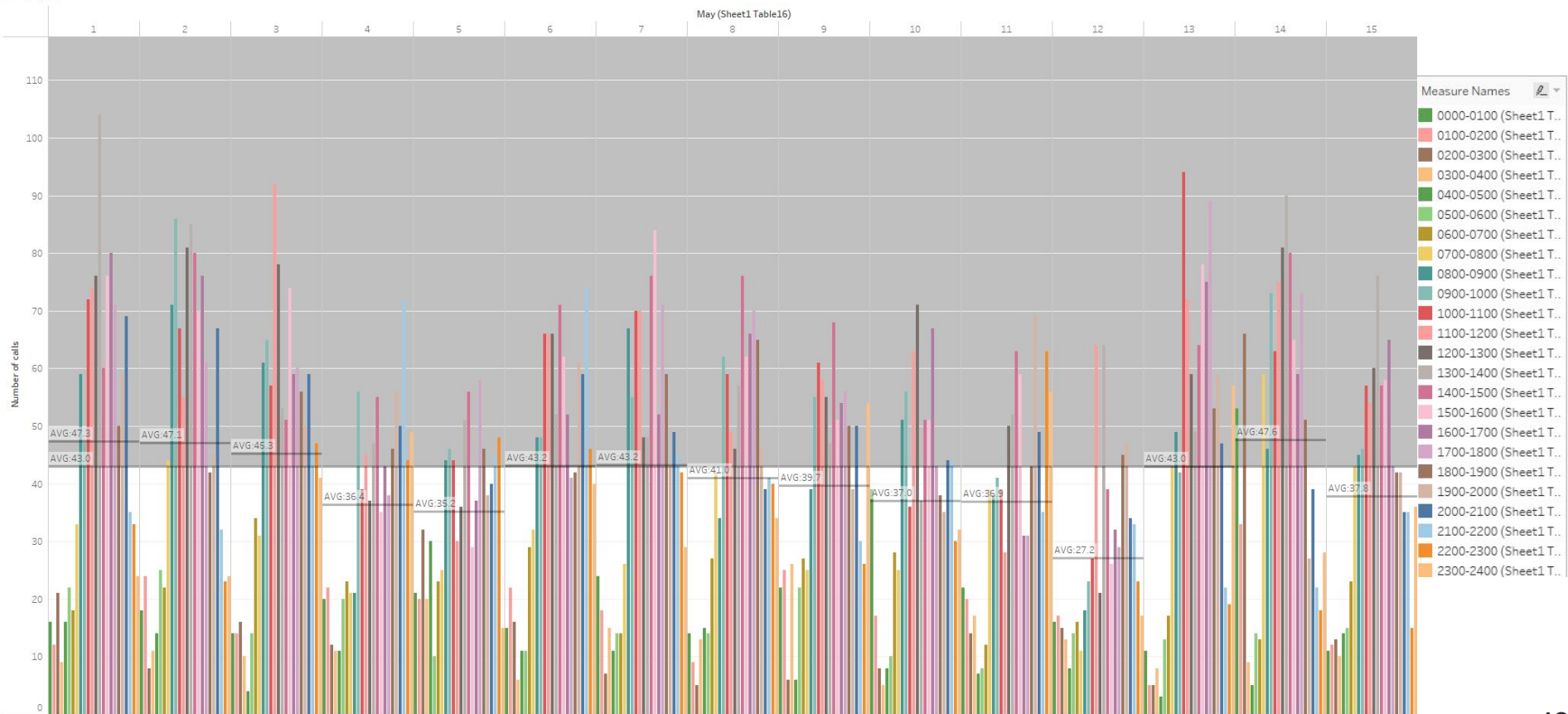


CBH - May(Hour 12 - Hour 24)

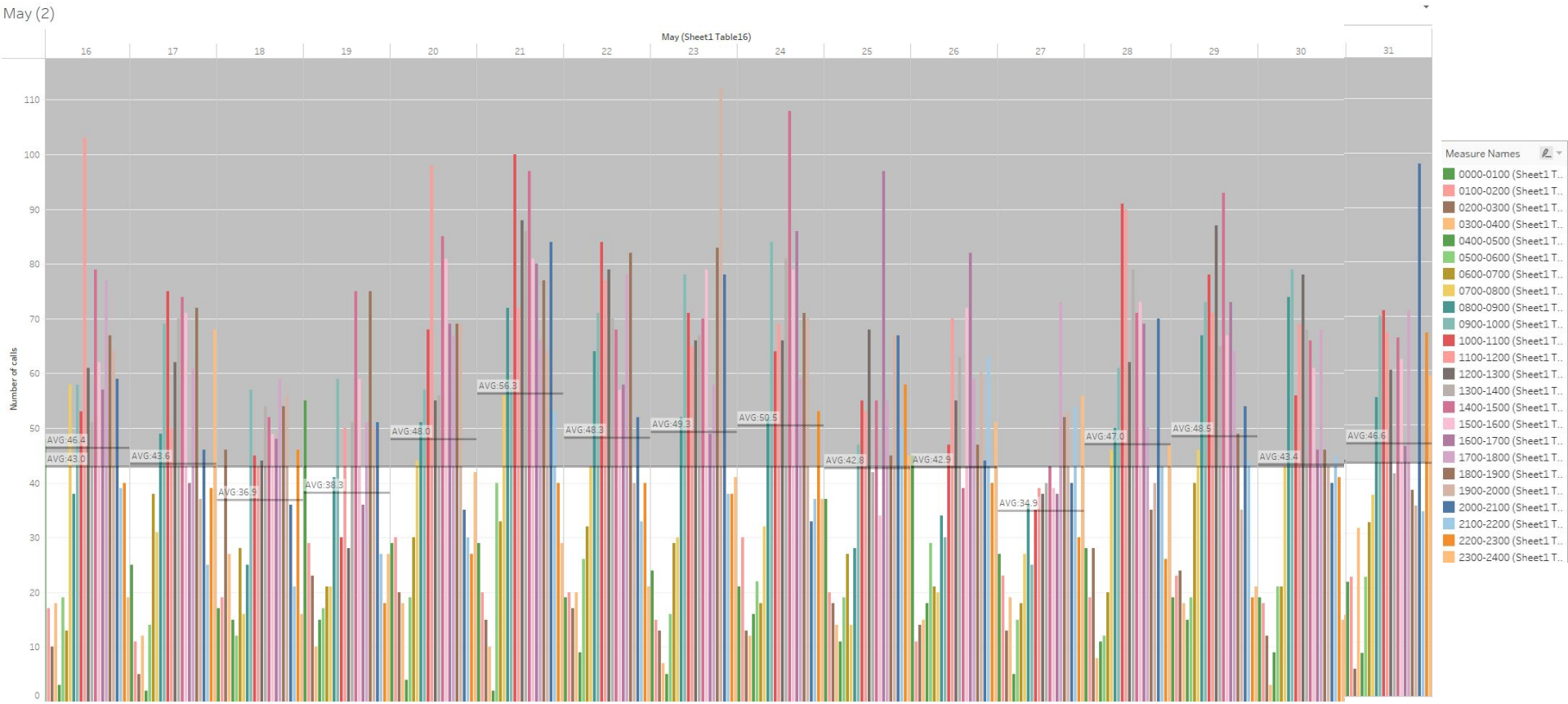


CBH - May(Day 1 - Day 15)

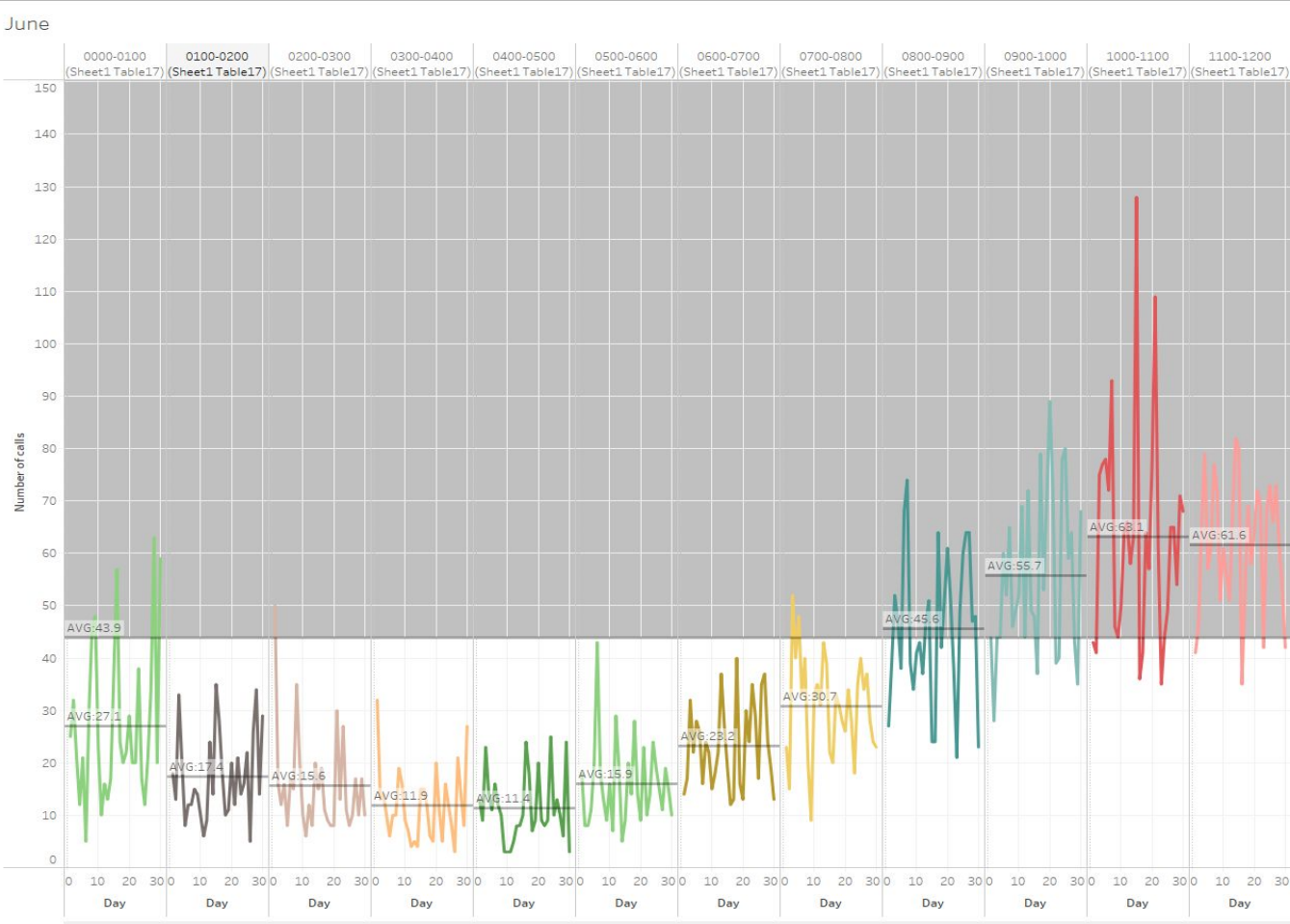
May (2)



CBH - May(Day 16- Day 31)

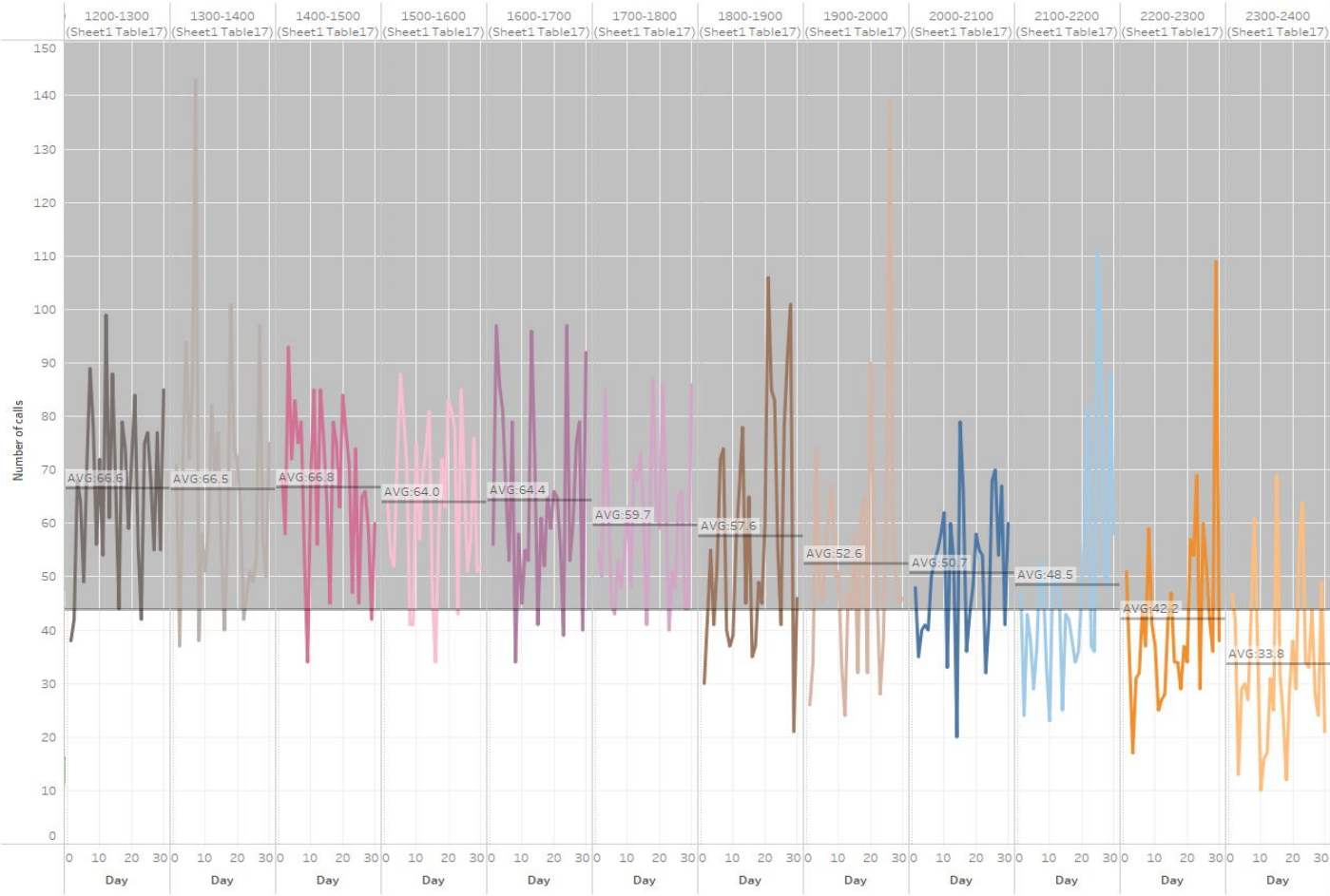


CBH - June(Hour 0 - Hour 12)



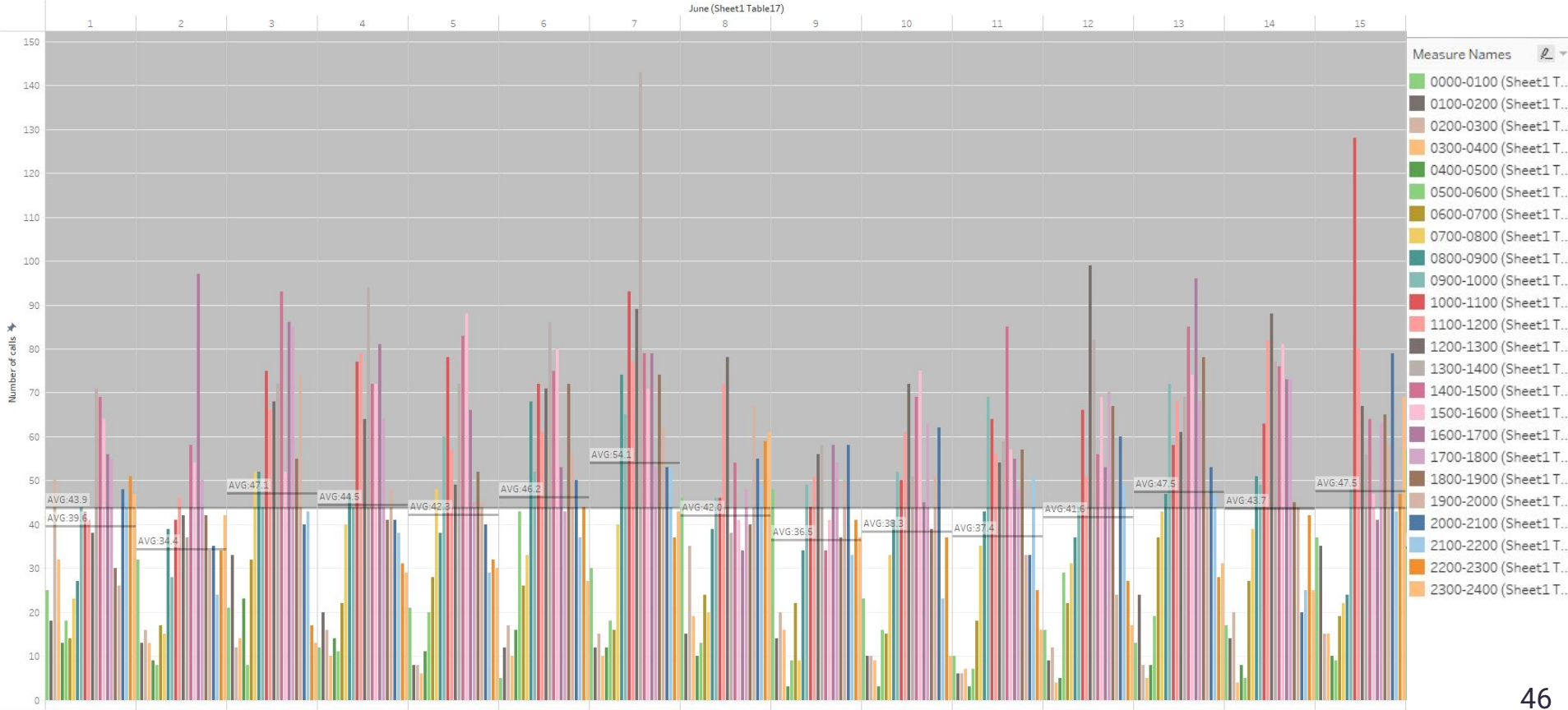
CBH - June(Hour 12 - Hour 24)

June

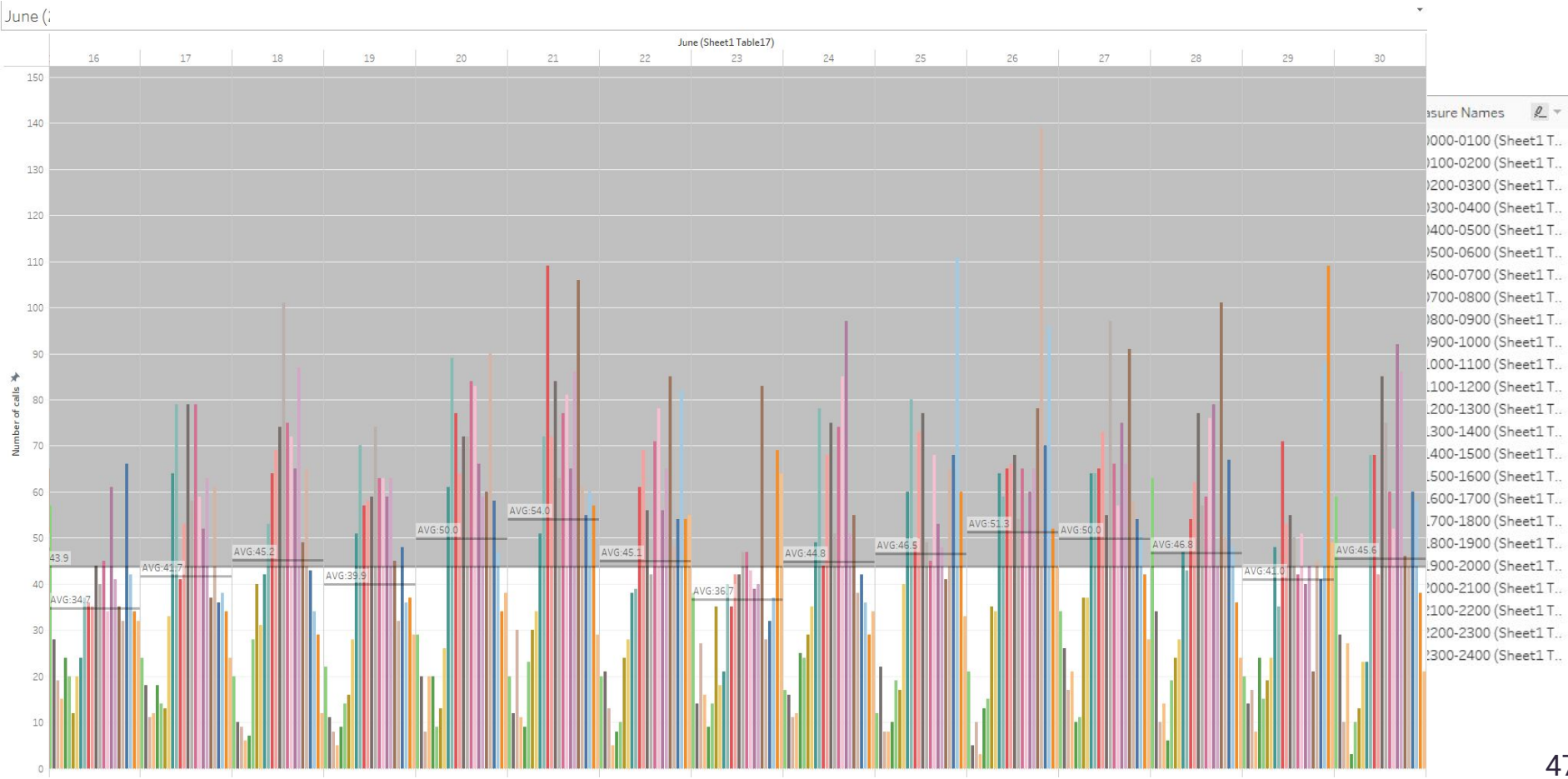


CBH - June(Day 1 - Day 15)

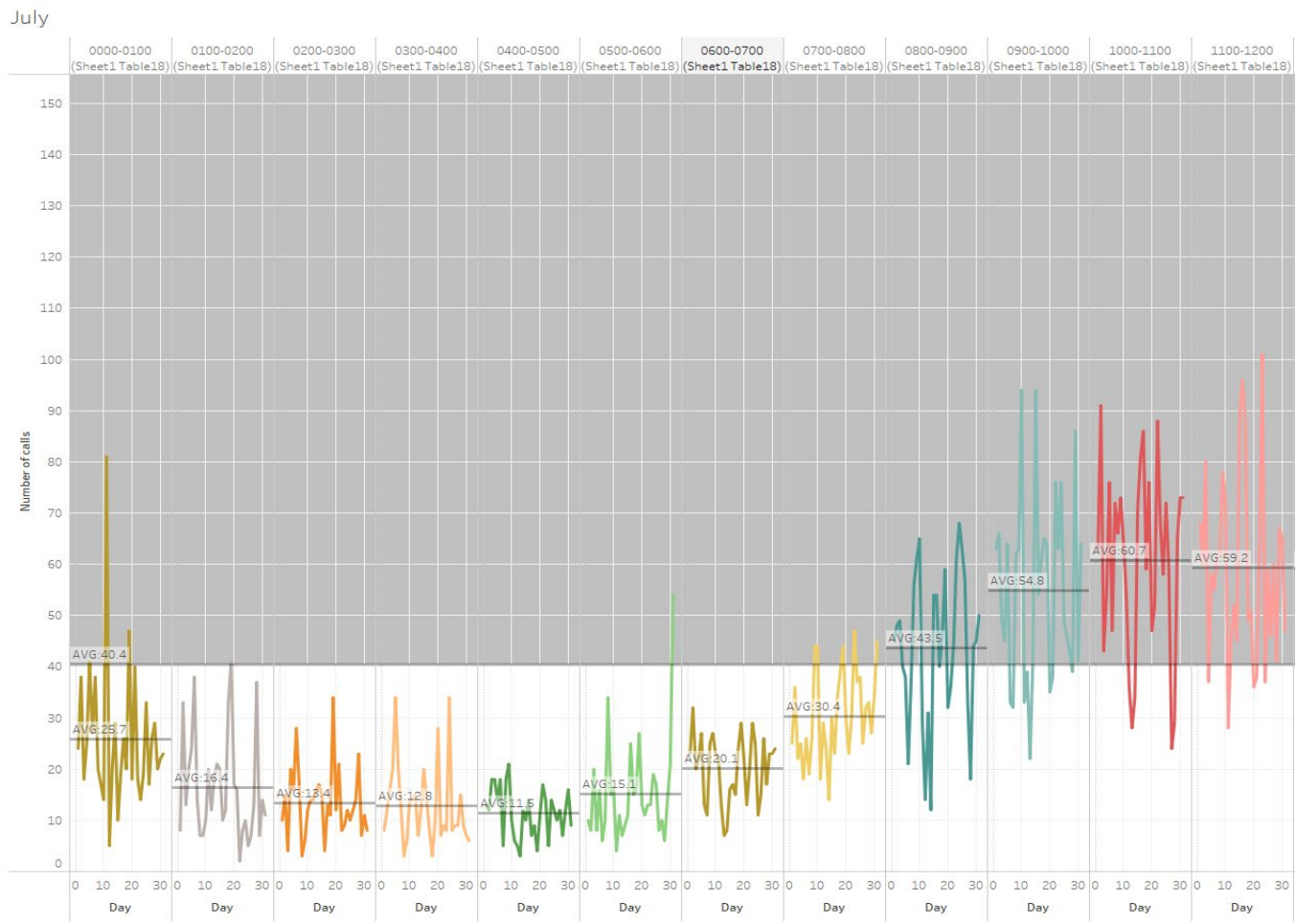
June (2)



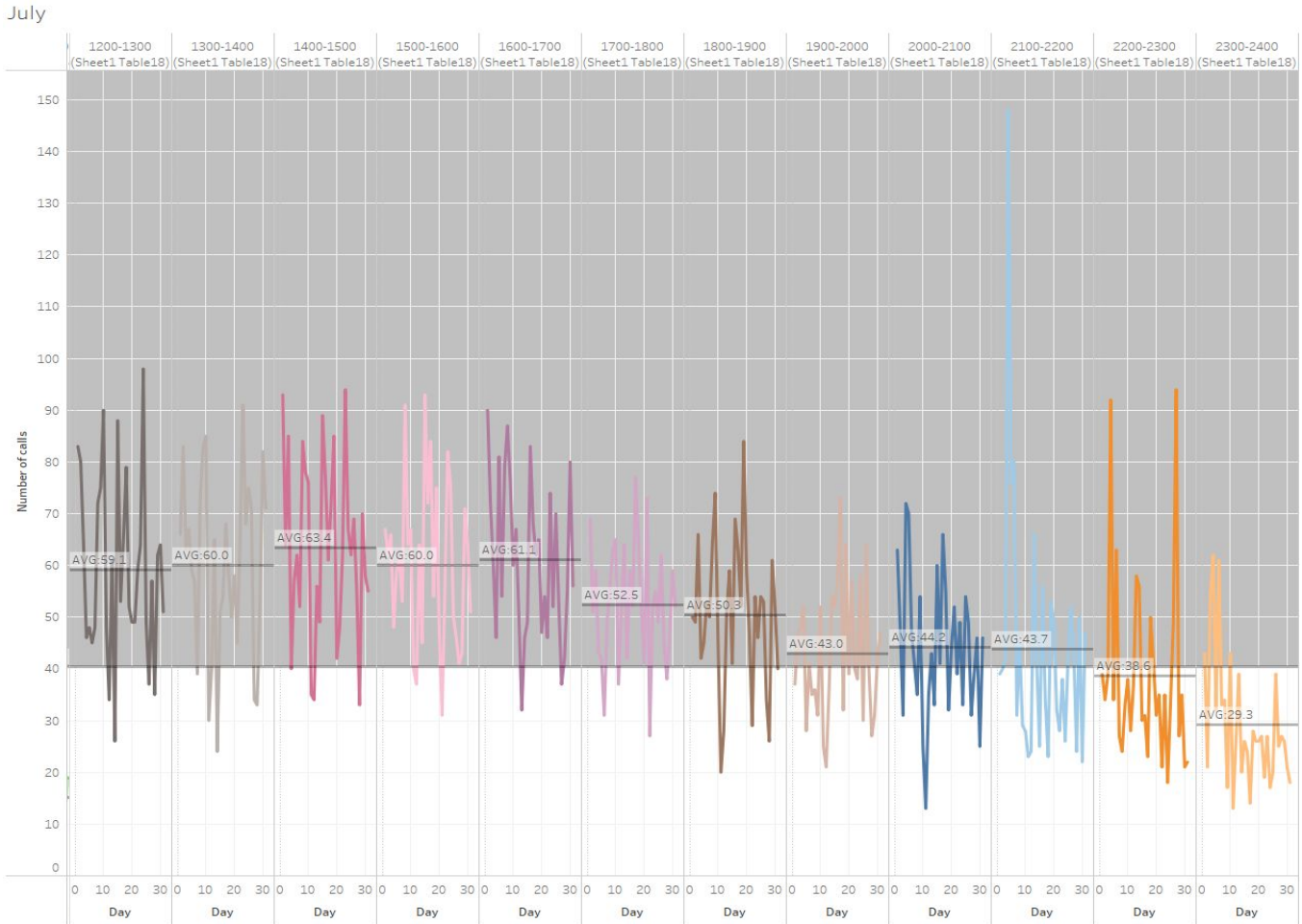
CBH - June(Day 16 - Day 30)



CBH - July(Hour 0 - Hour 12)

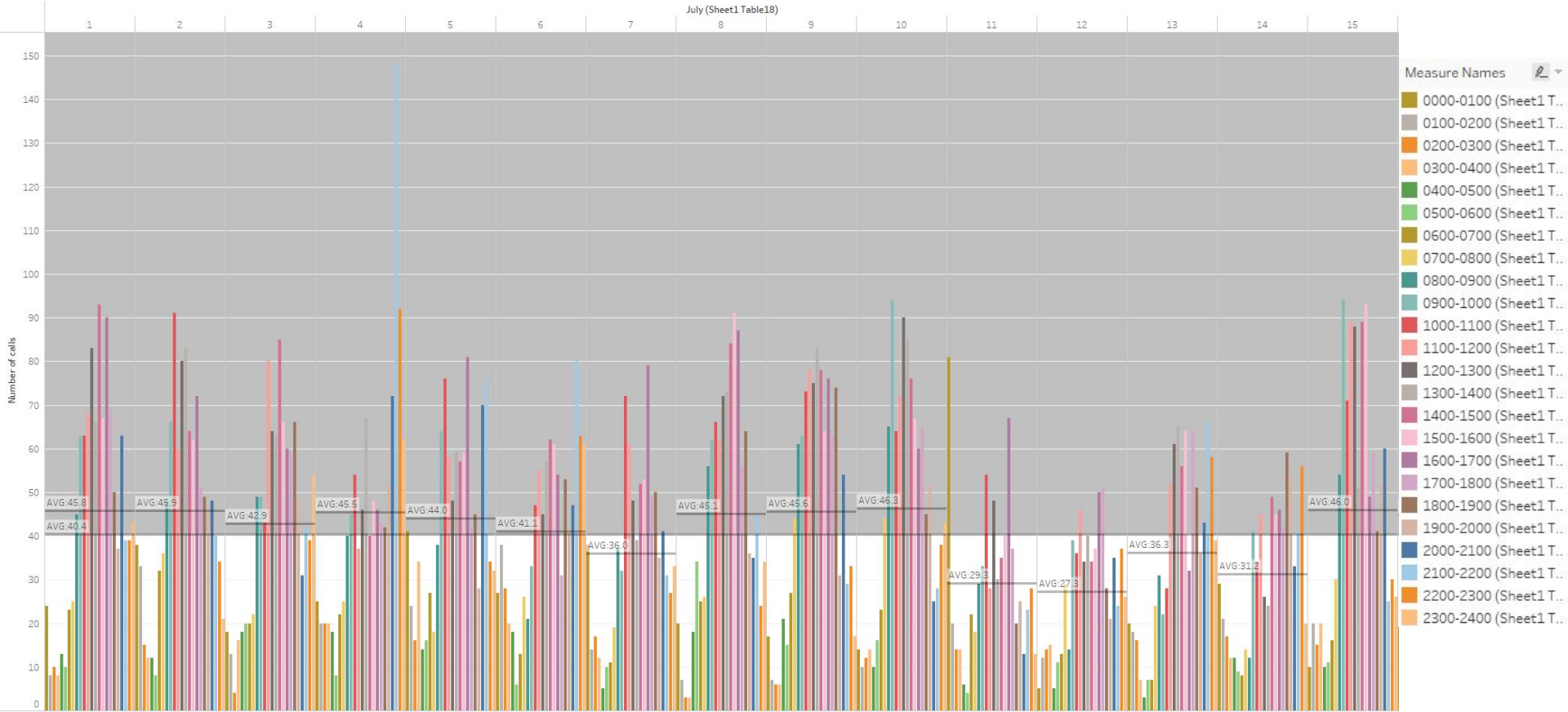


CBH - July(Hour 12 - Hour 24)



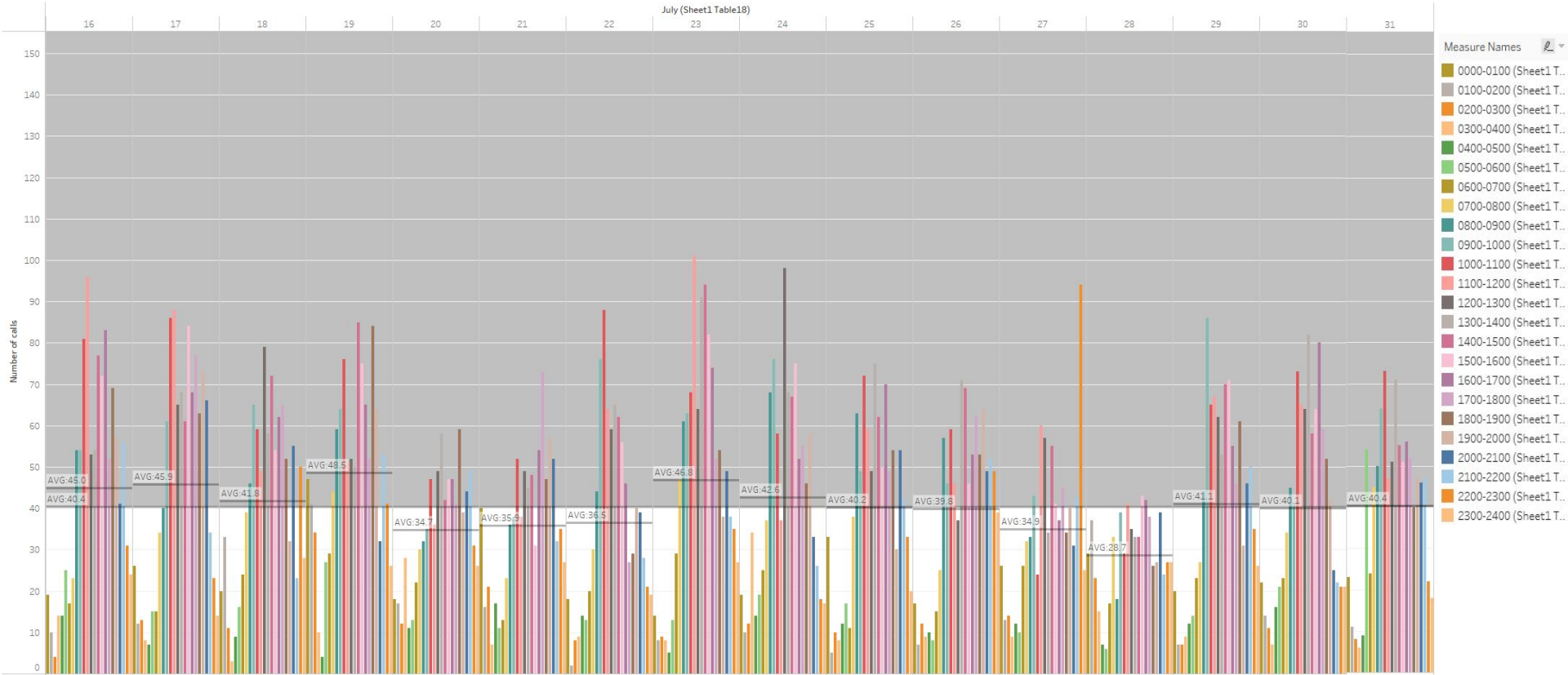
CBH - July(Day 1 - Day 15)

July (2)

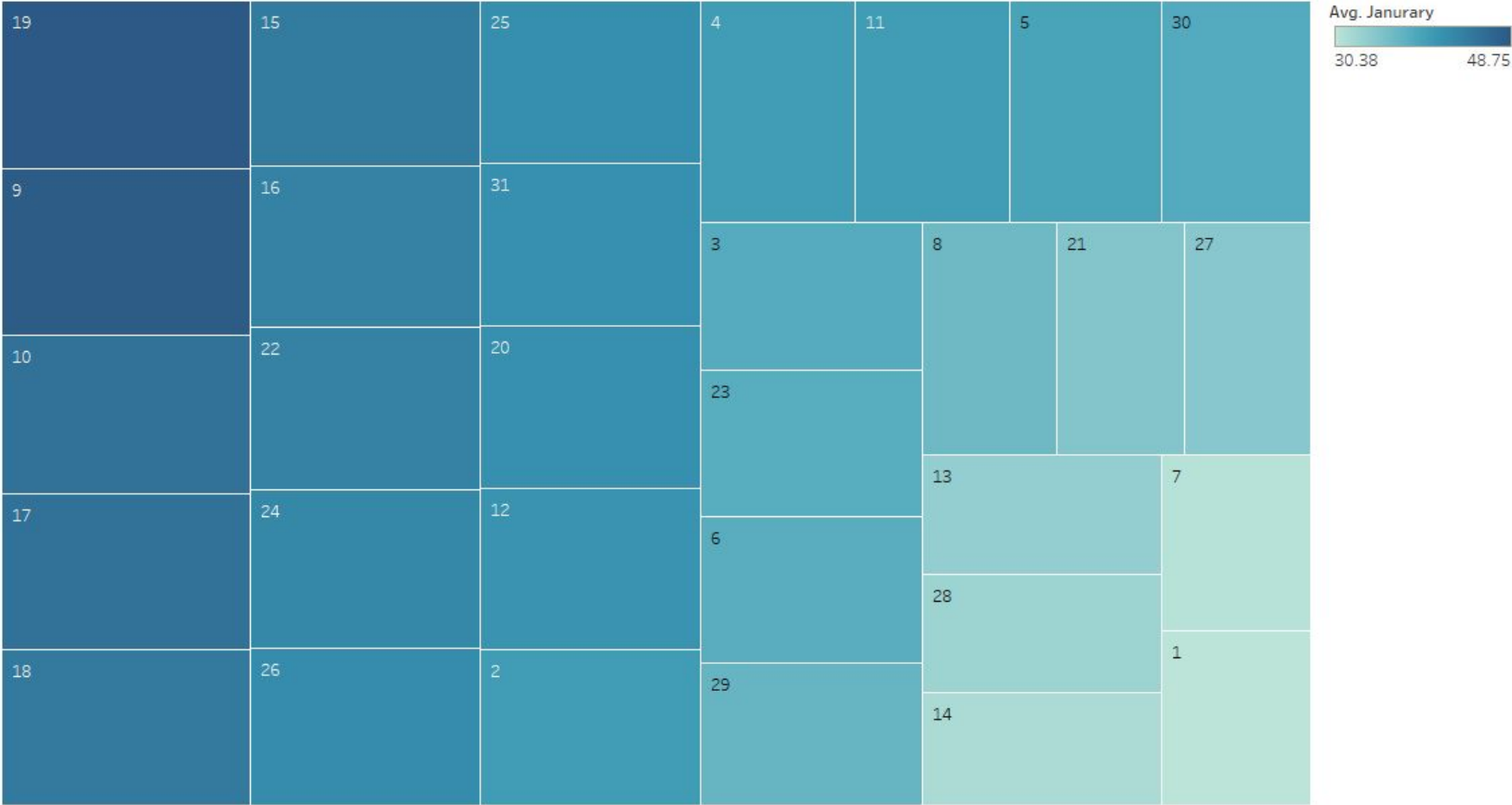


CBH - July(Day 16 - Day 31)

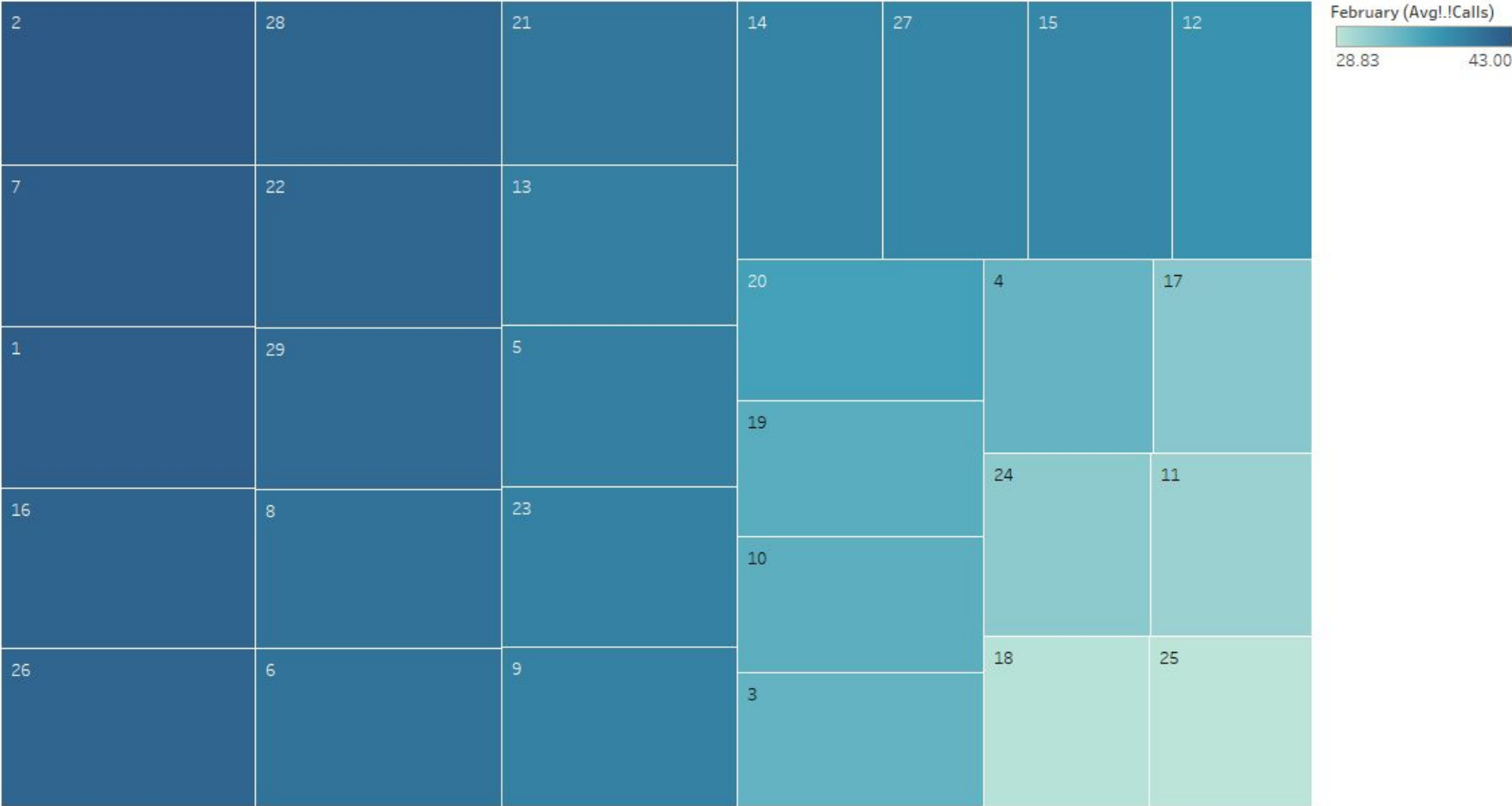
July (2)



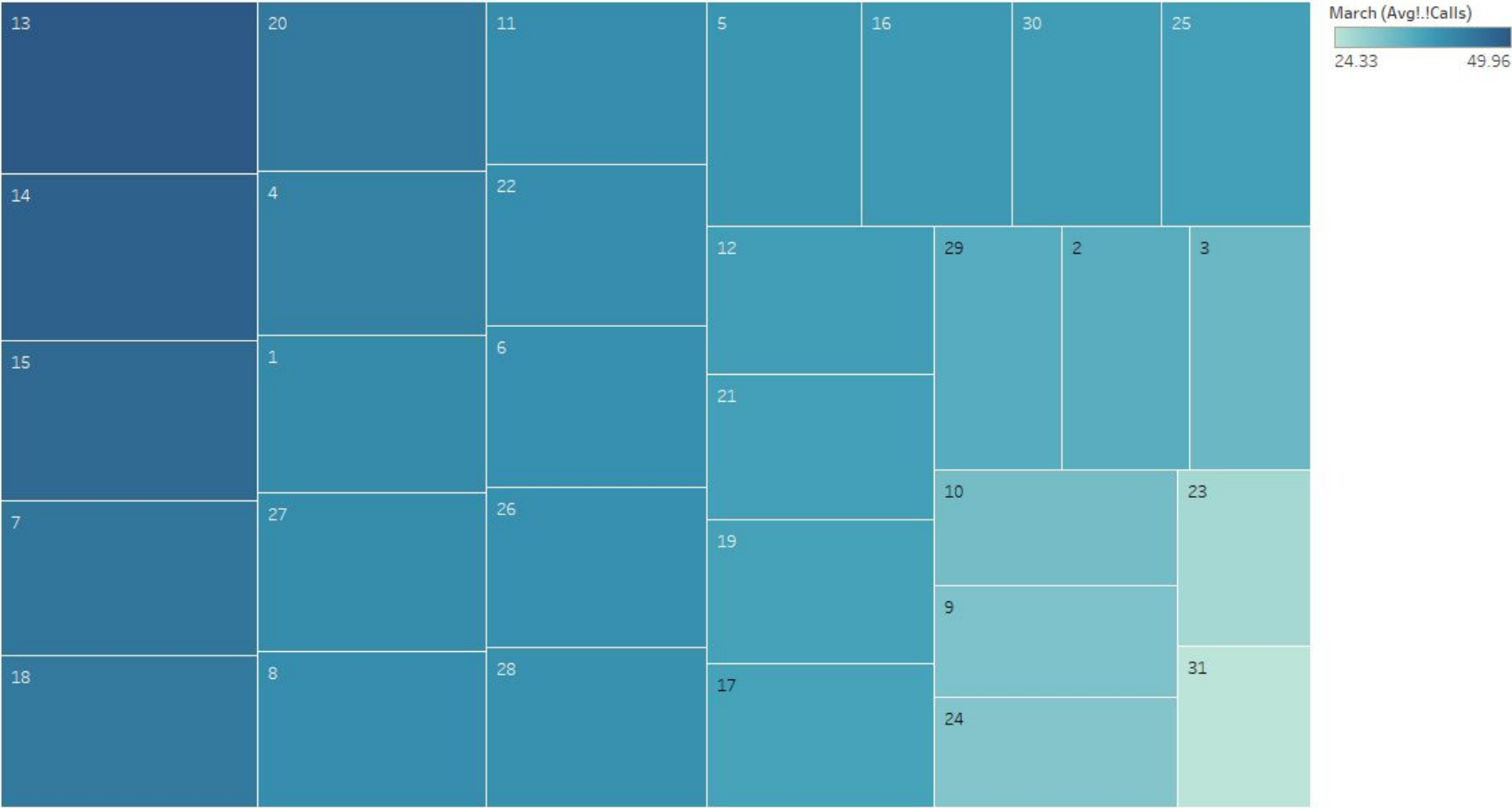
CBD- January



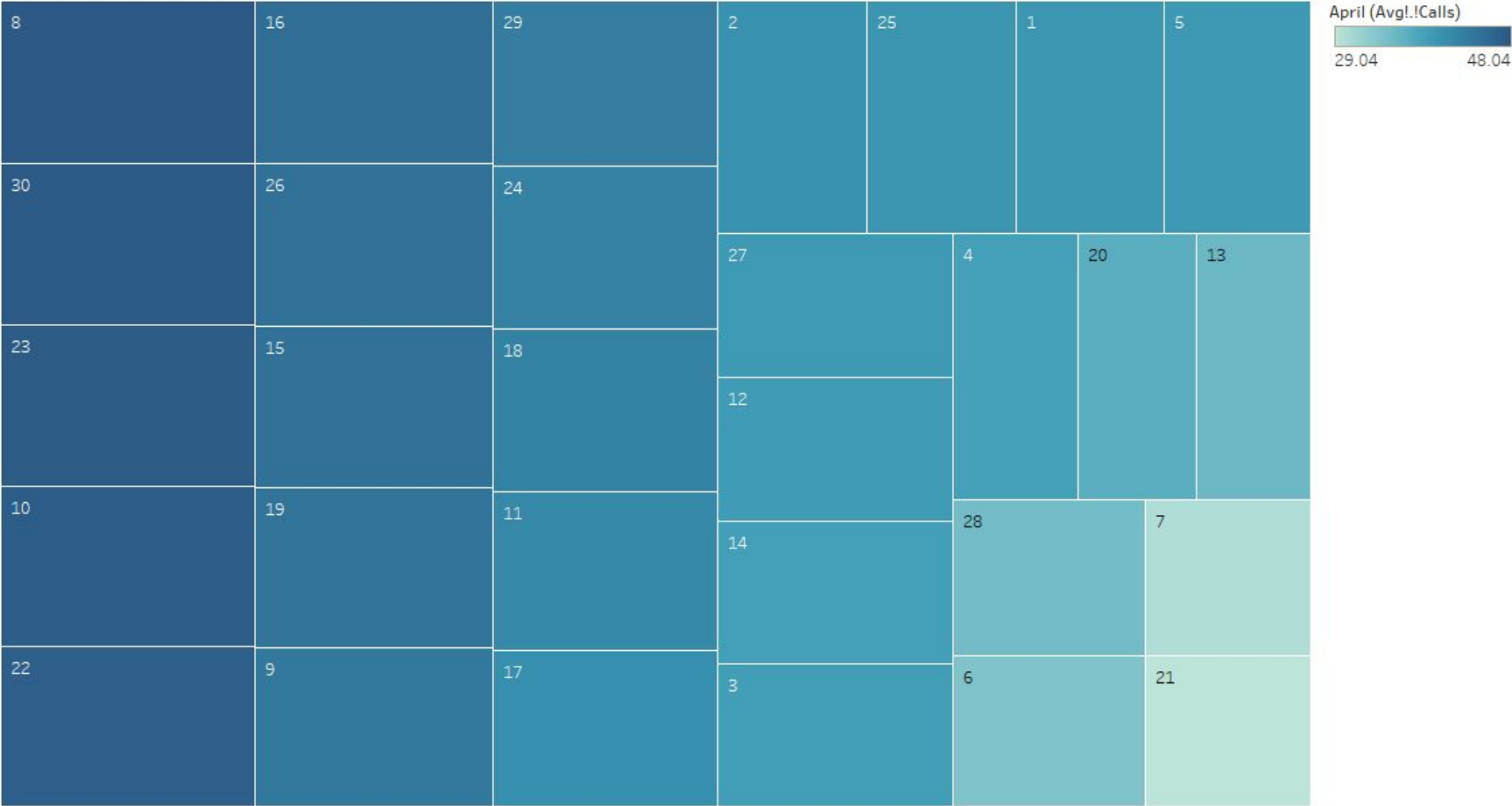
CBD- February



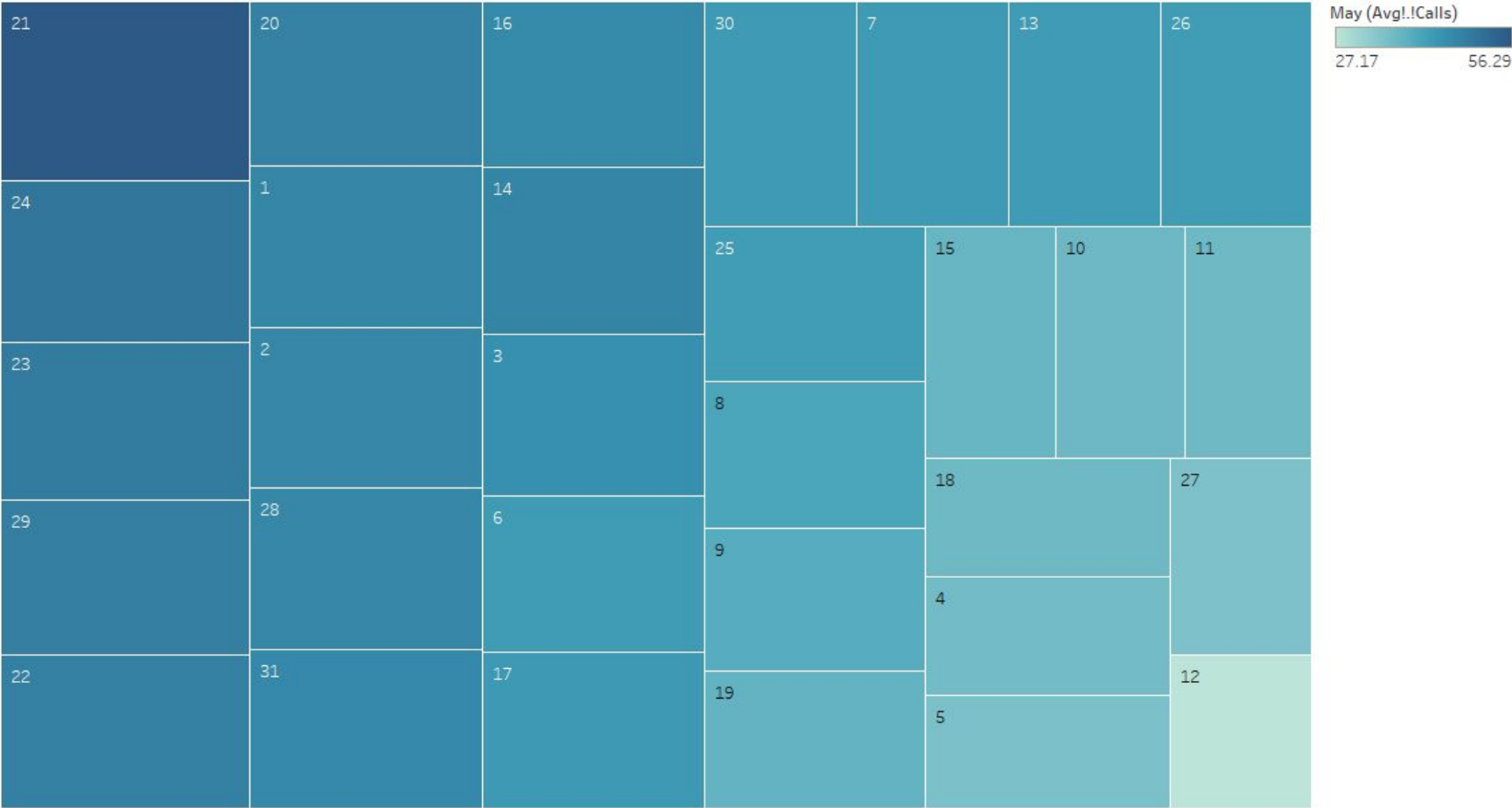
CBD- March



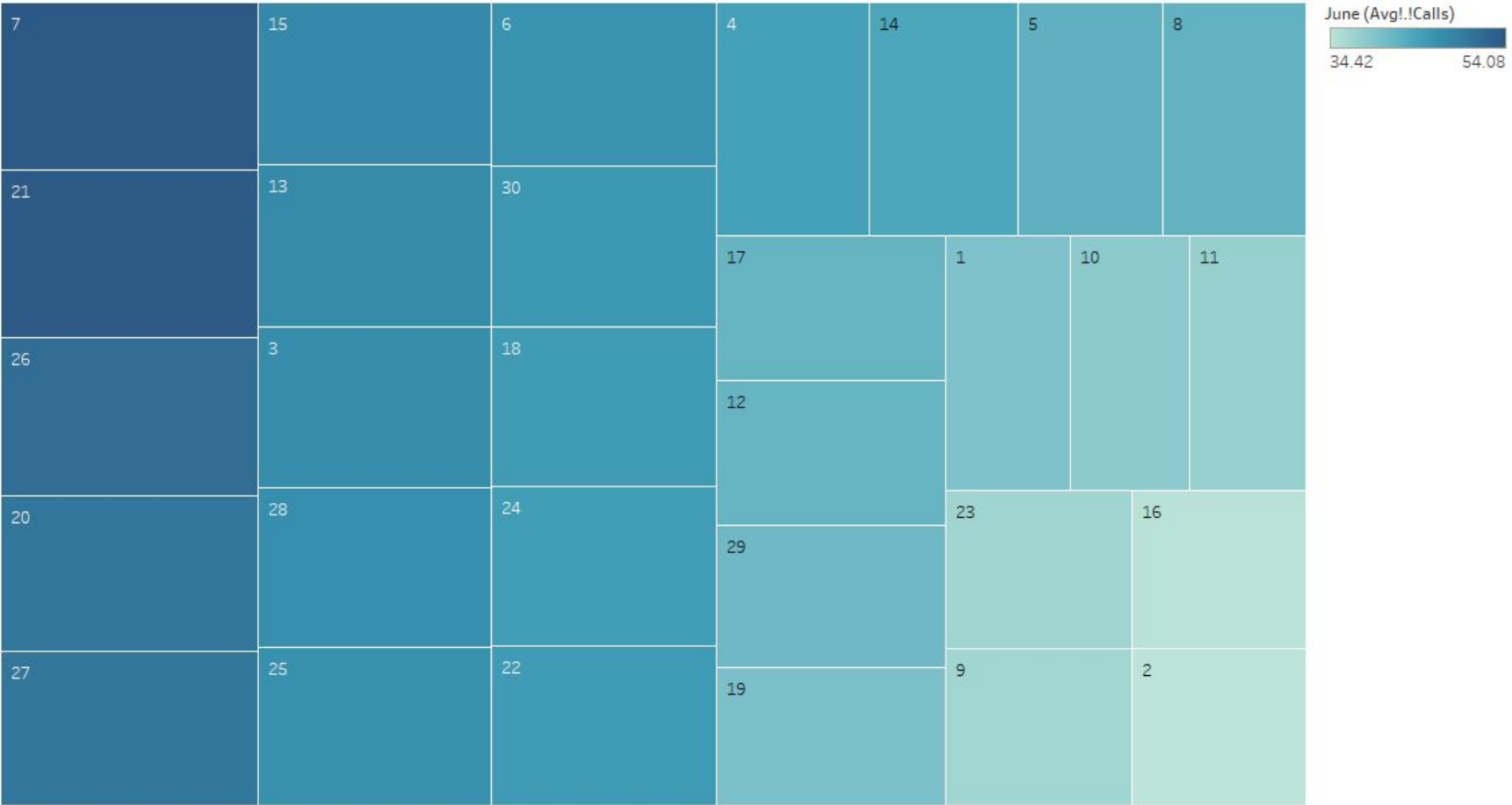
CBD- April



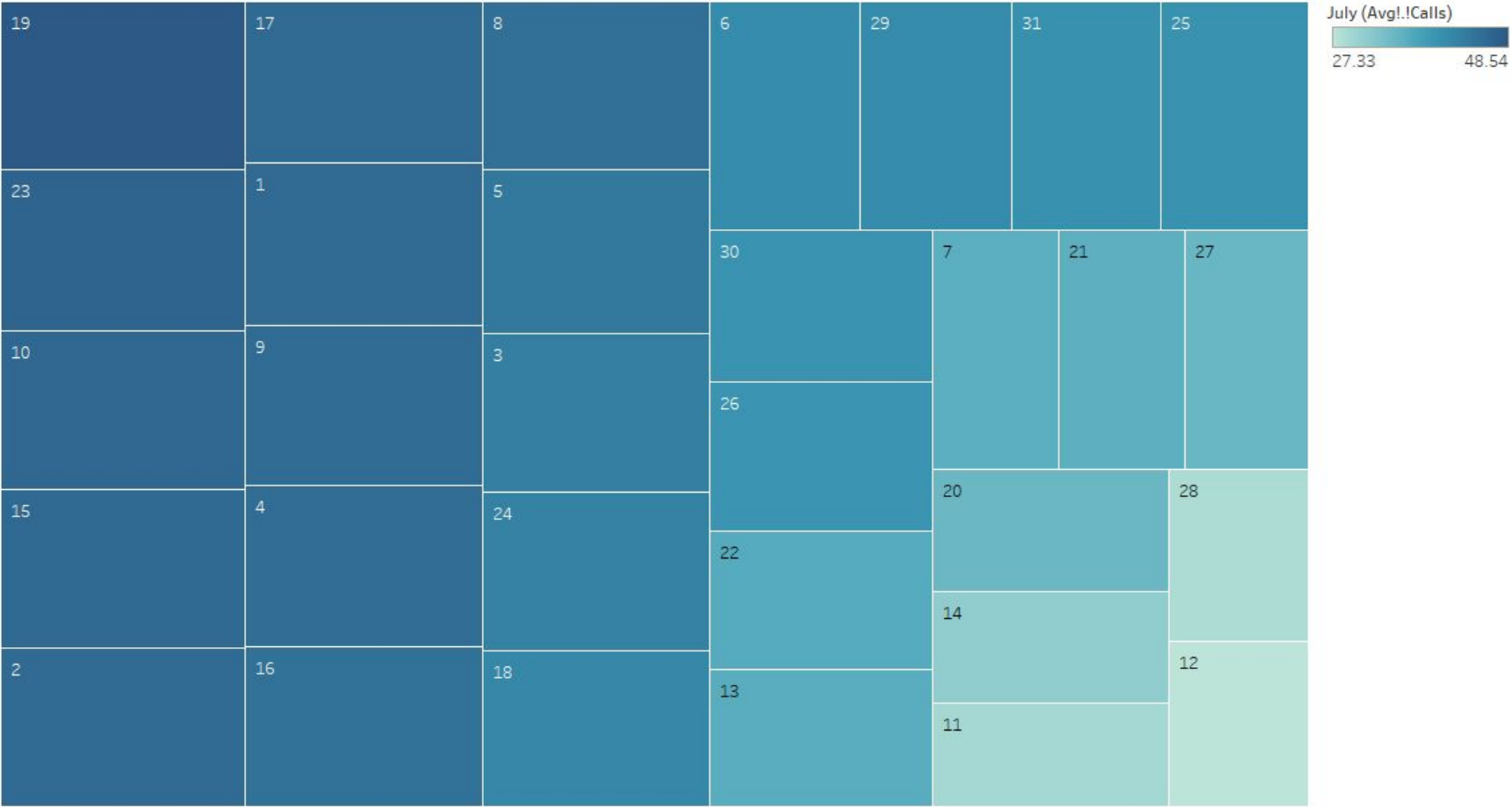
CBD- May



CBD- June



CBD- July



Calls by Day Regression Results (using date and weekday / weekend)

OLS Regression Results						
=====						
Dep. Variable:	January	R-squared:	0.461			
Model:	OLS	Adj. R-squared:	0.412			
Method:	Least Squares	F-statistic:	9.402			
Date:	Sun, 03 Nov 2024	Prob (F-statistic):	0.00112			
Time:	18:01:11	Log-Likelihood:	-147.68			
No. Observations:	25	AIC:	301.4			
Df Residuals:	22	BIC:	305.0			
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	758.3462	52.551	14.431	0.000	649.363	867.330
date	6.2213	2.632	2.364	0.027	0.762	11.680
weekday	165.5491	44.443	3.725	0.001	73.379	257.719
=====						
Omnibus:	0.055	Durbin-Watson:	1.545			
Prob(Omnibus):	0.973	Jarque-Bera (JB):	0.062			
Skew:	-0.028	Prob(JB):	0.969			
Kurtosis:	2.762	Cond. No.	49.6			
=====						

Calls by Hour Regression Results (using date and hour of the day)

OLS Regression Results						
Dep. Variable:	value	R-squared:	0.196			
Model:	OLS	Adj. R-squared:	0.195			
Method:	Least Squares	F-statistic:	139.9			
Date:	Sun, 03 Nov 2024	Prob (F-statistic):	4.82e-29			
Time:	18:13:29	Log-Likelihood:	-2574.7			
No. Observations:	576	AIC:	5153.			
Df Residuals:	574	BIC:	5162.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	23.7532	1.711	13.885	0.000	20.393	27.113
hour	1.5076	0.127	11.829	0.000	1.257	1.758
Omnibus:	35.156	Durbin-Watson:	0.835			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	40.019			
Skew:	0.636	Prob(JB):	2.04e-09			
Kurtosis:	3.217	Cond. No.	26.1			

Polynomial Regression Coefficients and Errors

Intercept: 20.6605

Coefficients:

1: 0.0000

Hour: -10.1176

Day of Week: -1.4675

Weekend: 0.0562

Hour²: 2.9040

Hour Day of Week: 1.2270

Hour Weekend: -0.4192

Day of Week²: -0.3679

Day of Week Weekend: 0.2018

Weekend²: 0.0562

Hour³: -0.1891

Hour² Day of Week: -0.0644

Hour² Weekend: 0.3218

Hour Day of Week²: -0.2805

Hour Day of Week Weekend: -1.1093

Hour Weekend²: -0.4192

Day of Week³: 0.3024

Day of Week² Weekend: 0.5325

Day of Week Weekend²: 0.2018

Weekend³: 0.0562

Hour⁴: 0.0036

Hour³ Day of Week: 0.0004

Hour³ Weekend: -0.0007

Hour² Day of Week²: 0.0135

Hour² Day of Week Weekend: -0.1001

Hour² Weekend²: 0.3218

Hour Day of Week³: -0.0021

Hour Day of Week² Weekend: 0.3725

Hour Day of Week Weekend²: -1.1093

Hour Weekend³: -0.4192

Day of Week⁴: -0.0242

Day of Week³ Weekend: -0.1963

Day of Week² Weekend²: 0.5325

Day of Week Weekend³: 0.2018

Weekend⁴: 0.0562

Results for the Polynomial Model (Predict July)

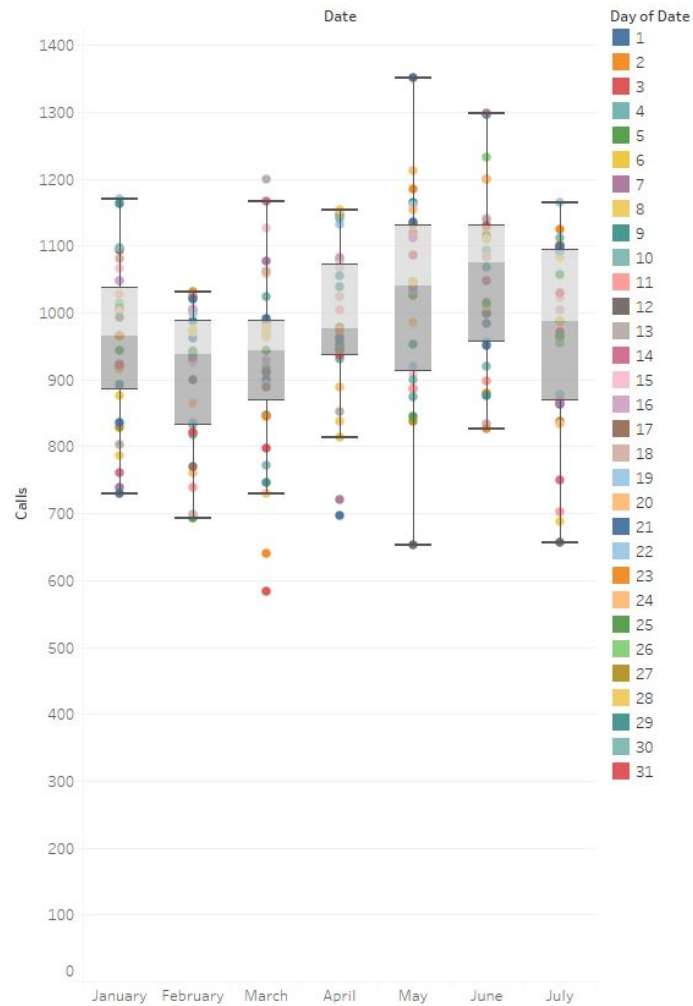
Mean Absolute Error (MAE): 10.08

Mean Squared Error (MSE): 190.18

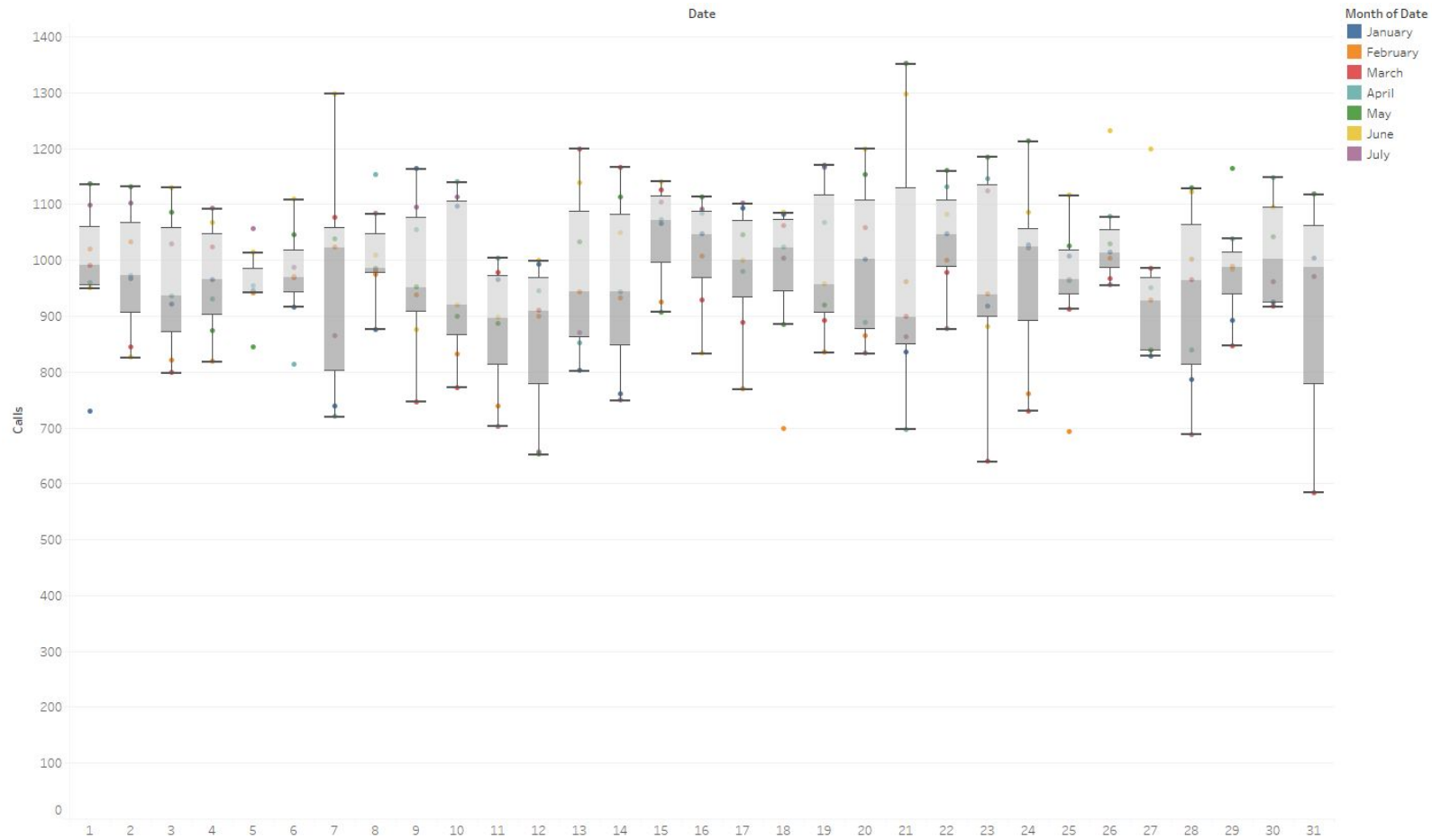
Root Mean Squared Error (RMSE): 13.79

R-squared (R²): 0.6385

Calls by Day - Boxplot (Month)



Calls by Day - Boxplot (Day)



Traditional and Power Shifters

EXAMPLE OF THE TRADITIONAL SHIFT SCHEDULE

A / B / C / D

D=6:00AM – 6:00PM; **N**=6:00PM – 6:00AM

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Week 1	D	D	N	N	OFF	OFF	OFF
Week 2	OFF	D	D	N	N	OFF	OFF
Week 3	OFF	OFF	D	D	N	N	OFF
Week 4	OFF	OFF	OFF	D	D	N	N

EXAMPLE OF THE POWER SHIFT SCHEDULE

E / F

10:00AM-10:00PM, 2:00PM-2:00AM

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Week 1	OFF	Work	Work	OFF	OFF	Work	Work
Week 2	Work	OFF	OFF	Work	Work	OFF	OFF
Week 3	OFF	Work	Work	OFF	OFF	Work	Work
Week 4	Work	OFF	OFF	Work	Work	OFF	OFF