CSC5800 - Class Project Report

Vehicular Queue Length Classification from High Resolution Stop Bar Detection Data

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Abstract:

This project uses high resolution (HiRes) data obtained from a real-life City of Detroit Intersection and attempts to predict the classification under which the vehicle queue for that approach falls (No Queue, Low Queue, or High Queue). This helps the decision makers in understanding the performance of the signal and potentially adjust traffic signal timing (cycle and phase times) in order to improve signal performance. The high resolution data is collected from a single source 360° fisheye camera providing high-accuracy stop bar pulse and presence data paired with high resolution traffic signal telemetry (phase status and timings).

An extensive data extraction procedure was conducted through APIs, data was converted into usable formats, sorted and tabulated, and finally processed under multiple detailed tables in order to make reflective of the conditions it was measuring. Outliers were eliminated, and a final per-cycle amalgamation of a series of different data features were combined into a single data set for statistical evaluation and model development. The Final data set consisted of 21 features and one classifier.

This project attempted to be a first step in that direction by processing a one-day long set of data for an approach at an intersection and deriving the statistical relationships between the chosen attributes. Additionally, various prediction classification models were test to provide a comparison (Logistic Regression, Decision Tree, Linear Discriminant Analysis, K Nearest Neighbors, Gaussian Naïve Bayes, SVM, and NN -Multilayer Perceptron).

Based on the statistical analyses performed, we reached interesting inferences regarding intersection queue formation and the potential implication on traffic signal performance. For instance, some of the investigated analyses: highly correlated continuous input Attributes, distribution pattern for attributes, models that predict our objective accurately, the decision boundaries, and the Receiver operating characteristic curve (ROC) for two class-problem.

Based on the classification prediction models developed we managed to predict the three classes of Queue Status – No Queue (NQ=1), Light Queue (LQ=2), Full Queue (FQ=3) with varying degrees of success for a balanced accuracy. Out of the tested methods, **K nearest neighbor (KNN) seems to be outperforming the other methods** (even the Neural Network based Multi-Level Perceptron). However, due to a ramification of an uneven class distribution (with much lower instances of FQ compared with the other two classes), potential data accuracy issues, review of analysis methods and configurations, and the need for a larger data pool, the results were not as strongly along the entire data range. Prediction of the FQ class specifically fell short in all methods and needs further investigation. However, for the NQ and LQ, the model seems to be highly accurate.

I. INTRODUCTION

Understanding traffic signal performance (TSP) has been one of traffic engineering's most challenging problems. In order to do so, traffic engineers need to have a number of detectors set up at various locations of the intersection in order to completely and accurately translate real-life conditions into quantifiable and useful metrics. Data is then converted into Traffic Signal Performance Measures (TSPM) to directly enhance the operational performance and to indirectly improve upon the safety of a traffic signal. The TSPMs could be used either for real-time traffic operations or for after-the-fact evaluation or assessment of the performance of a traffic signal. Traffic operations is usually assessed by the common Level-of-Service ranking based on intersection or approach delay. However, in recent years Perdu University, Iowa State, and Utah DOT amongst others have been developing and innovating with automating the process of those TSPM in order to make them practical and useful. In addition to the basic performance measures of Approach Volume and turning movement counts, there's been a number of more advanced Automated Traffic Signal Performance Measures (ATSPM) that have been developed such as the Purdue Phase Determination, Split Monitoring, Pedestrian Delay, Preemption, Split Failures, Approach Delay, and Arrivals on Red. However, there are a few others that are a little more involved that haven't been as popular such as Yellow-and-Red actuation, Headway, and Speed.

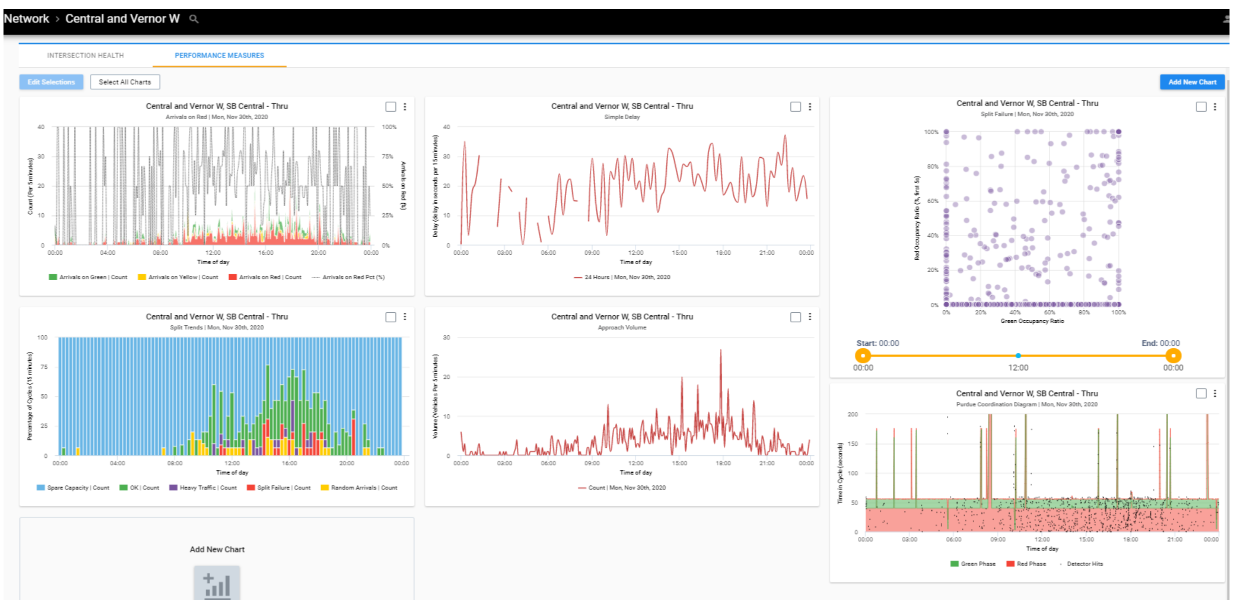


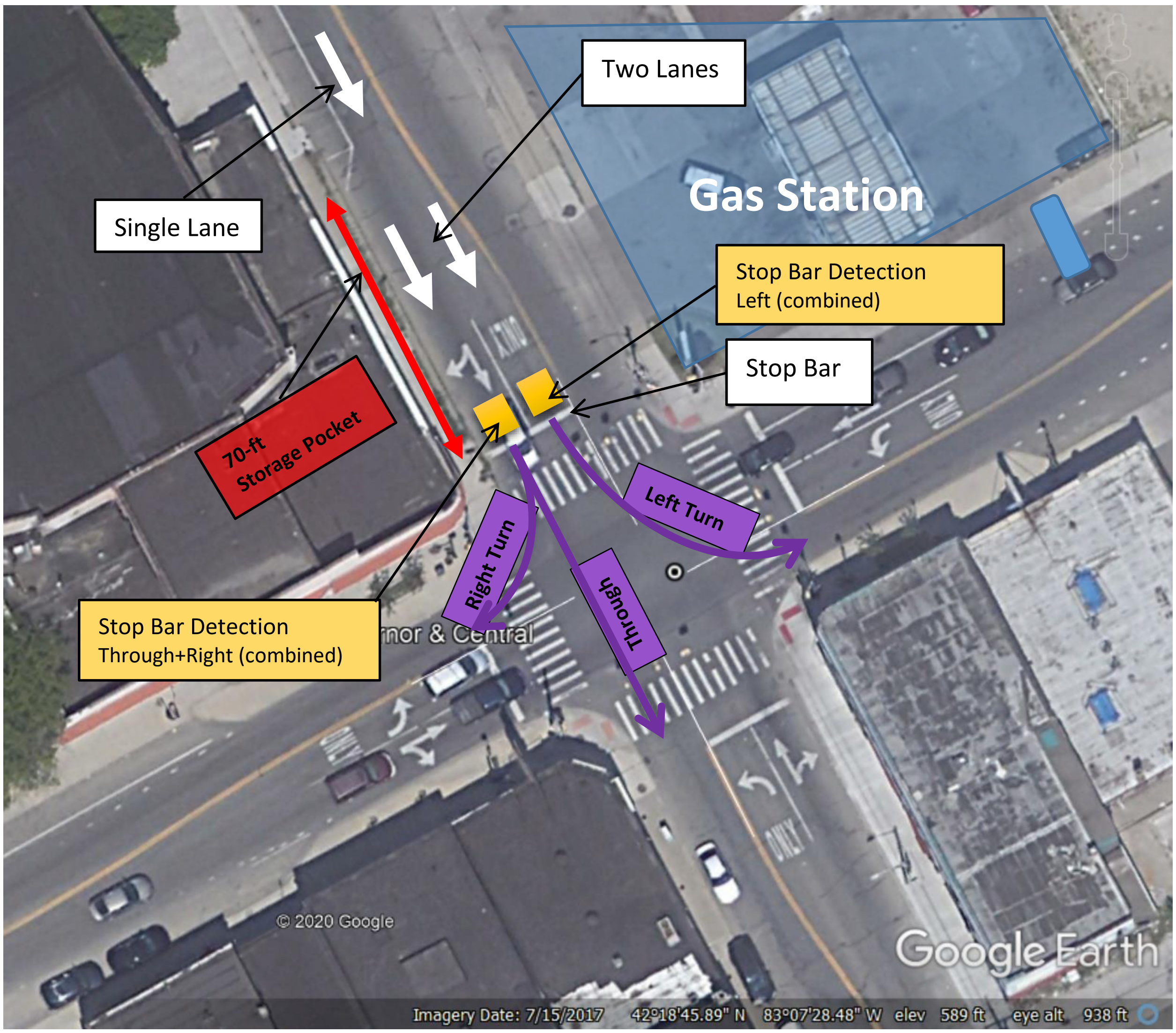
Figure: Miovision provided ATSPM's (Central & Vernor)

As powerful as those measures are, they come at a very hefty resource investment and cost for installation, operations, and maintenance in order to achieve their accuracy levels. In order to predict all those TSPM, at a minimum a set of two detectors are needed per approach and then connected to a data collection device in the cabinet. Many agencies may not have the financial means to initiate such a solution regardless of the benefit it may bring. However, stop-bar detection alone is more attainable and cheaper for smaller agencies. Those could be in the form of in-pavement detection pucks, loops, or single source 360° fisheye cameras and they provide high-accuracy stop bar pulse and presence data. This project aims at using high resolution (HiRes) stop bar detection data alone to try identifying features with the highest correlation to queue and which could potentially predict the queue with the highest accuracy (without the hefty investment in infrastructure).

a. **Chosen location, configuration, and timing**

The intersection location of Central Ave and Vernor Hwy in the southwest side of Detroit was chosen as the test location. This intersection was chosen for its typical 4-leg configuration and two-phase signal timing. In order to simplify the evaluation development process, one approach was selected: Southbound Central Avenue approach. This approach

The 60-second pre-timed cycle with a 40/20 Red/Green split. i.e.: for the southbound approach, every 60 second cycle consisted of 40 seconds of red and 20 seconds of green. This pre-timed cycle information makes it easier to identify missing information and timing errors.



The lane configurations of this approach consist of one approach lane that branches out into two lanes about 70 feet from the stop bar. In the most ideal of situations, this allows for approximately a storage pocket capacity of two (2) vehicles for the left turn lane (permissive movement) and five (5) vehicles for the through+right turn lane. In order for the approach to be considered blocked (maximum queue), there would need to be between 5 to 7 vehicles in the storage pockets. That is dependent on which movement lane the cars are stacking up in.

To add more complexity and potential error to the configuration, there is a gas station in the northeast quadrant of the intersection which has vehicles accessing it from Central Avenue and potentially disrupting typical flow and operation of the signal.

b. Detection and Data Accuracy

For this project a single source 360° fisheye camera providing high-accuracy stop bar pulse and presence data was used paired with high resolution traffic signal telemetry (phase status and timings). Additionally, the Camera capabilities were used to get accurate vehicle type classification (car, heavy, pedestrian, or bicycle) and Turning Movement Count (TMC) data in order to be used for the analyses and for the actual queue calculations used in training the model. The team attempted to use an advance detection box for this purpose however, the camera was exceeding its detection ranges and the data was inaccurate and unusable.

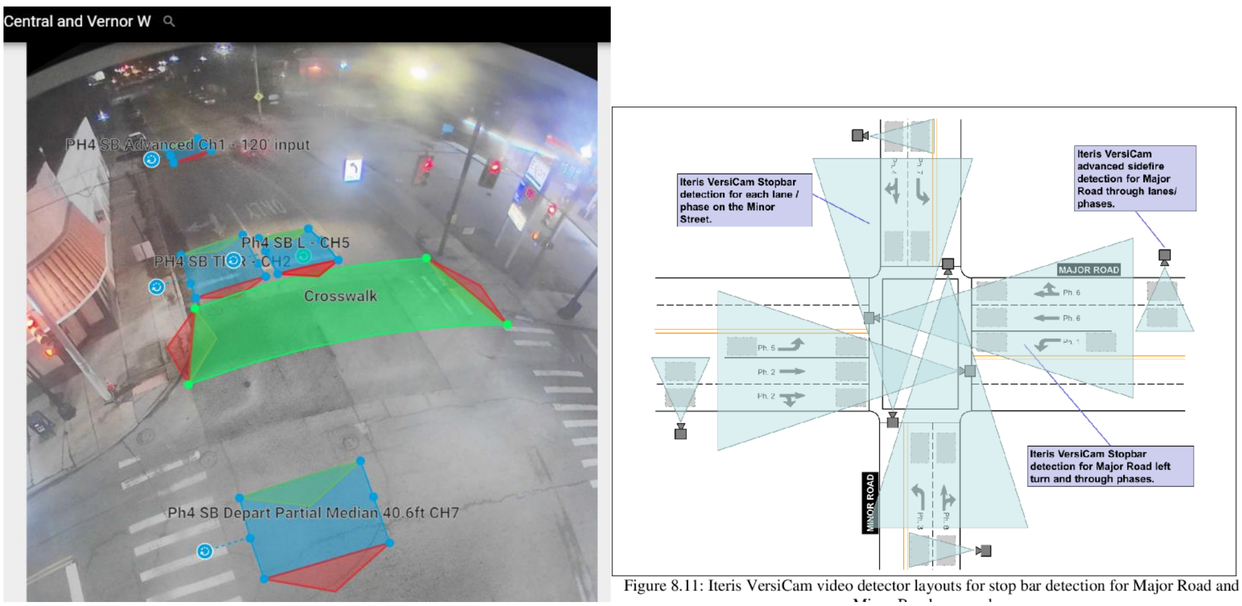


Figure: Single Camera Detection Box Configuration (left) vs. full lane-specific detection configuration (right)

Limited stop-bar detection, allows the traffic engineer to get a sense of what's happening at the stop-bar of the signal. When paired with traffic signal telemetry (signal phase and time) data, a better replication of the signal is possible. And just like with forensic evidence, the pieces of the puzzle are put together to try to come up with the intended queue prediction. The concern here is the limited view of the intersection that this approach starts with and the consequential limitation in accuracy. In order to offset those it was necessary to interpret the raw high resolution detector data and pair it with the high resolution signal telemetry to better tell the story of the arrival and departure of the vehicles. C

c. Problem statement (Research Question)

i. How can we leverage existing HiRes stop bar video detection in the City of Detroit to predict performance (queuing[TG1]) at Urban intersections?

ii. If so, how accurately can that be done relative to existing state of the practice metrics?

iii. Are there other existing data that can be leveraged to improve the accuracy of the performance metrics[TG2]?

d. Objective statement

i. Collect and Visualize existing High Resolution Signal Controller data at an intersections in the city of Detroit.

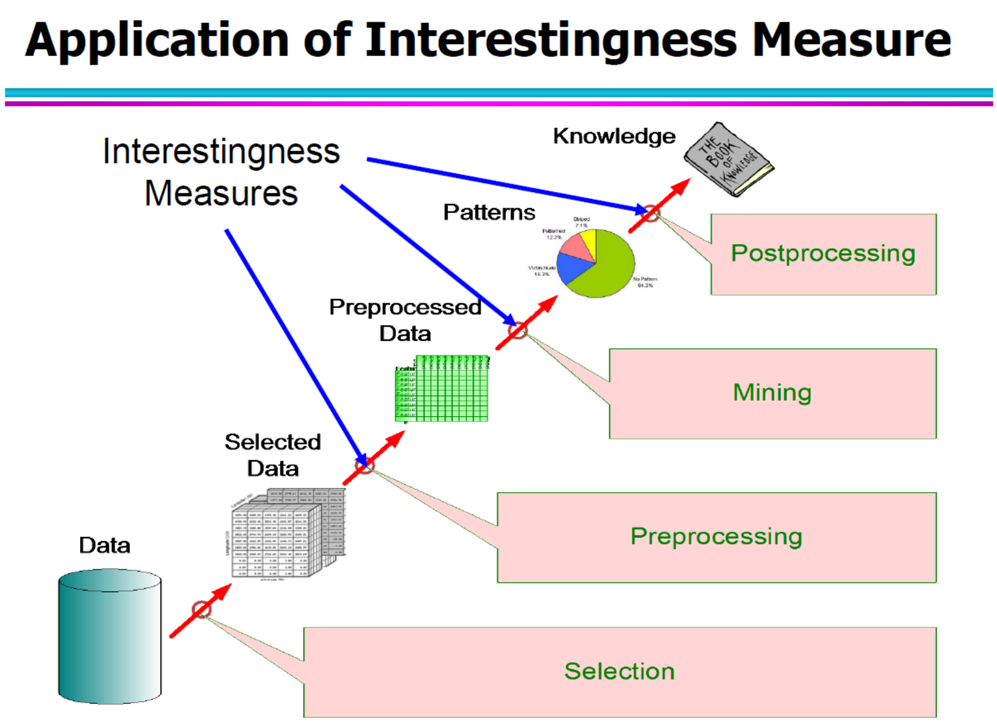
ii. Attempt to create a Methodology to define the performance measure logic using stop bar detection

iii. Compare performance measures using advanced detection (real world) with performance measures using stop bar detection

iv. Allow method to be able to Scale and measure the performance difference between advanced and stop bar logic.

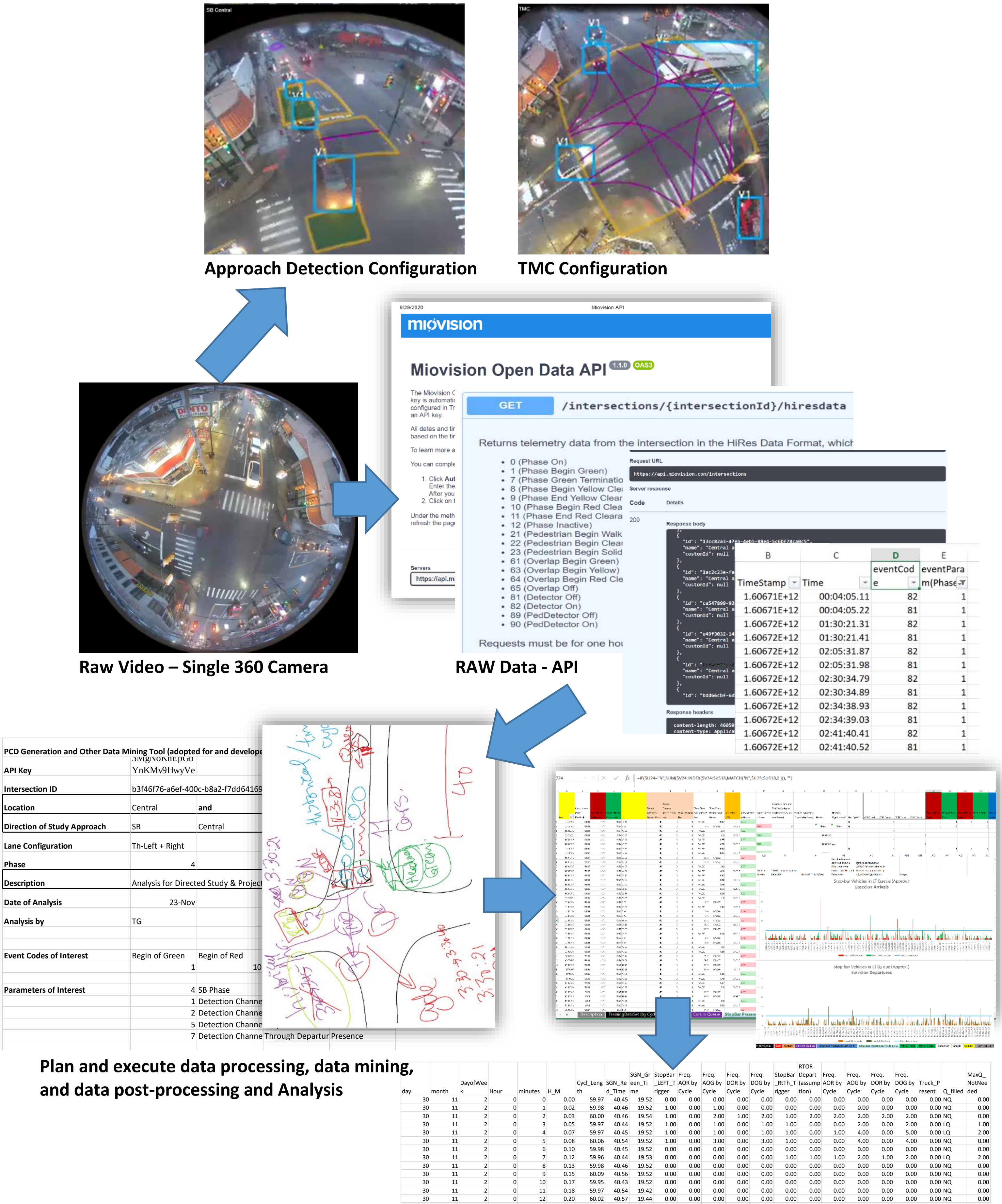
II. METHODOLOGY

The entire data development process is described below in bullet points up to the data analysis and modeling section. The entire process was very cumbersome as it accounted for a full effort to select the data, extract it, preprocess it, process it to make it usable and relevant, and organize the tables with usable attributes. The data set was preprocessed using excel, however, it is recommended for this process to be automated using python in the future.



Source: Steven F. Ashby Center for Applied Scientific Computing Month DD, 1997 (Lecture Notes – Introduction to Data Mining)

- Data Extracted from Miovision API –
    - November 30th was chosen
    - Day within the last month with highest southbound movement and overall signal volume for the day and per hour to account for worst case scenario.
    - High Resolution (HiRes) Data Extracted:
        - Stop-Bar Detection data
        - Advance Pulse-Box Detection data
        - Turning Movement Counts data (TMC)
    - Aggregated 1-minute Data Extracted"
        - Turning Movement Counts
- Account for Timestamp time in extraction (based on UTC time for the HiRes data and local time for the TMC) – HiRes had to be converted to local time.
- Extracted HiRes files were a series of 1-hr groups in JSON format that needed conversion and joining
- JSON converted to .txt files then worked with as .csv
- Timestamp converted to regular time with millisecond precision (functional time accuracy is to 100 millisecond [i.e.: 0.1 seconds])
- Data was checked for errors and gaps (missing data)
- A queue estimation model was built from advanced and stop-bar detection boxes (paired with the traffic signal status [red or green]). However, error was high.
    - Alternatively, a queue estimation model was used from the HiRes TMC data.
- Visualization:
    - HiRes Stop Bar Detection data was graphed for visual inspection of the arrivals on Red and Green.
- Recreated Stop-Bar Detection, signal status (and time left on red or green), headway (closeness of vehicles), speed, and historical TMC (some of those items were not accurate enough and were not used in the model).
- Model – Queue prediction (classification) discussed next section



SB Central
TMC
Approach Detection Configuration
TMC Configuration
miovision
Miovision Open Data API
GET /intersections/{intersectionId}/hiresdata
Returns telemetry data from the intersection in the HiRes Data Format, which
0 (Phase On)
1 (Phase Begin Green)
7 (Phase Green Terminatio
8 (Phase Begin Yellow Clea
9 (Phase End Yellow Clear
10 (Phase Begin Red Clea
11 (Phase End Red Cleara
12 (Phase Inactive)
21 (Pedestrian Begin Walk
22 (Pedestrian Begin Clear
23 (Pedestrian Begin Solid
61 (Overlap Begin Green)
63 (Overlap Begin Yellow)
64 (Overlap Begin Red Cle
65 (Overlap Off)
81 (Detector Off)
82 (Detector On)
89 (PedDetector Off)
90 (PedDetector On)
Requests must be for one hou
Request URL
https://api.miovision.com/intersections
Server response
TimeStamp
Time
eventCode
eventParam(Phase
Raw Video – Single 360 Camera
RAW Data - API
PCD Generation and Other Data Mining Tool (adopted for and develope
API Key
Intersection ID
Location
Direction of Study Approach
Lane Configuration
Phase
Description
Date of Analysis
Analysis by
Event Codes of Interest
Parameters of Interest
Plan and execute data processing, data mining, and data post-processing and Analysis

III. ANALYSIS (entire workbook can be found on GitHub)

https://github.com/rajratnapatil9/TRAFFIC-QUEUE-PREDICTION/blob/main/Queue%20Prediction.ipynb

DATA DIMENSION: 1343 x 19 (final set)

a. Schema:

List of Attributes and classifier are listed below with a short description and an example. Outliers and erroneous data points were eliminated from the original data set based on missing and off cycles. That reduced the data points from 1440 to 1343 over two steps.

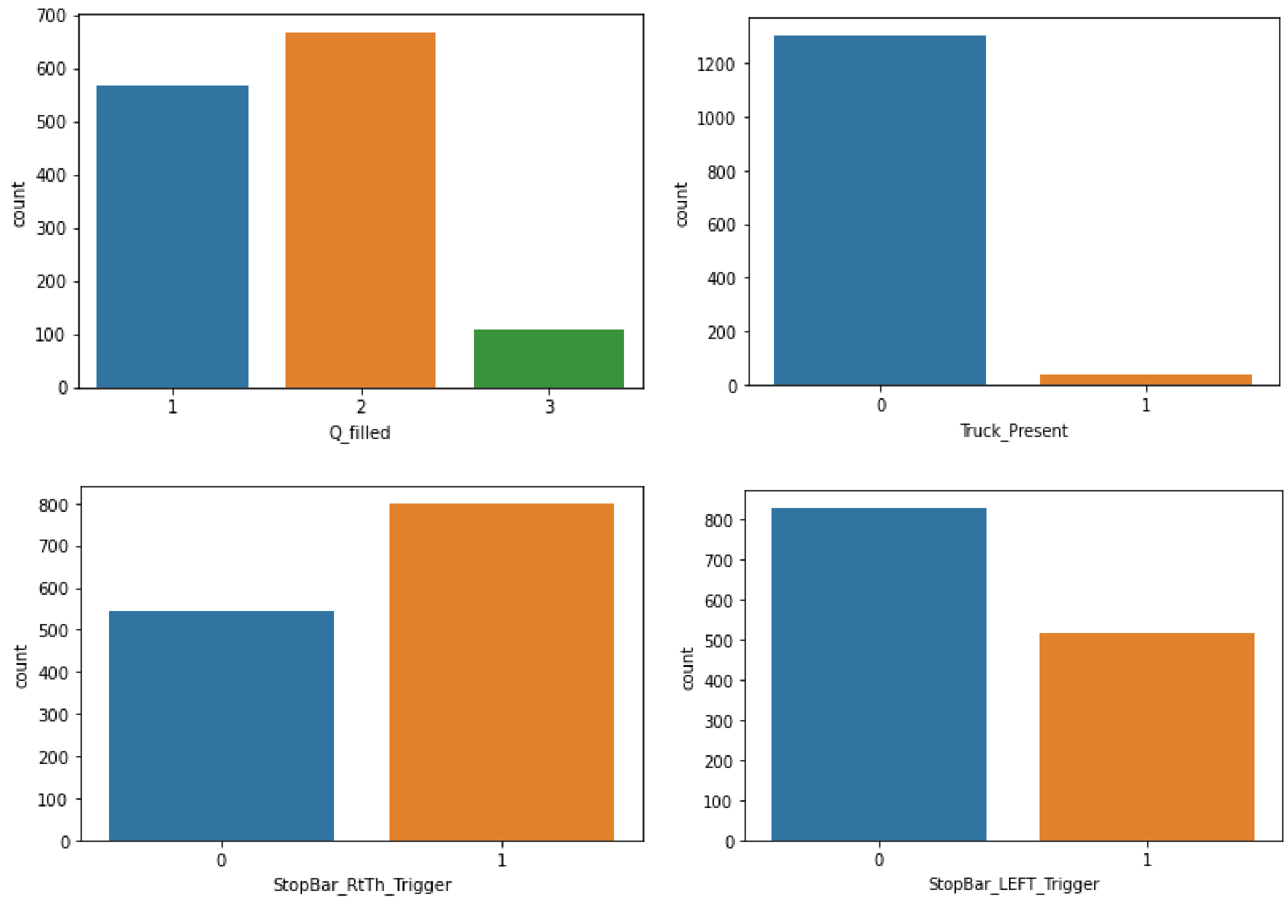
#	Attributes	Description	Example
1	Hour	Hour during which the data point occurred	10
2	minutes	Minute during which the data point occurred	20
3	H_M	Hour+Minute (fraction) during which the data point occurred	10.33
4	Cycl_Length	Cycle length in Seconds (to the 1/10th of a second)	59.97
5	SGN_Red_Time	Red Time in Seconds (to the 1/10th of a second)	40.55
6	SGN_Green_Time	Green Time in Seconds (to the 1/10th of a second)	19.42
7	StopBar_LEFT_Trigger	Trigger of detector box at stop bar during the cycle for the Left Turn lane	1
8	Freq. AOR by Cycle	Number of Vehicles Arriving on Red during Cycle (Left Turn)	1
9	Freq. AOG by Cycle	Number of Vehicles Arriving on Green during Cycle (Left Turn)	0
10	Freq. DOR by Cycle	Number of Vehicles Departing on Red during Cycle (Left Turn)	0
11	Freq. DOG by Cycle	Number of Vehicles Departing on Green during Cycle (Left Turn)	1
12	StopBar_RtTh_Trigger	Trigger of detector box at stop bar during the cycle for the Through+Right Turn lane	1
13	RTOR Depart (assumption)	Number of Vehicles Turning Right on Red (RTOR) during Cycle (Th+Rt lane)	0
14	Freq. AOR by Cycle	Number of Vehicles Arriving on Red during Cycle (Th+Rt lane)	1
15	Freq. AOG by Cycle	Number of Vehicles Arriving on Green during Cycle (Th+Rt lane)	0
16	Freq. DOR by Cycle	Number of Vehicles Departing on Red during Cycle (Th+Rt lane)	0
17	Freq. DOG by Cycle	Number of Vehicles Departing on Green during Cycle (Th+Rt lane)	1
18	Truck_Present	Presence of trucks during cycle	0
19	Q_filled	**Classification**: NQ, LQ, FQ (see provided table)	LQ

b. Distribution of Variables: NQ=1 , LQ=2, FQ= 3

Queue Classification Category	**NQ**	**LQ**	**FQ**
Category Numerical Code	**1**	**2**	**3**
Category Values	**0**	**1-5**	**6 and above**
Description	No cars during cycle	1 to 5 vehicles queued during cycle	6 or more vehicles queued during cycle
frequency	570	677	111

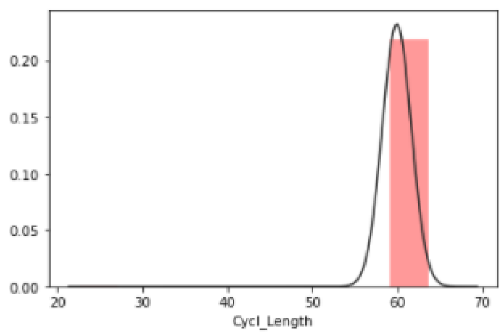
The derived actual queue lengths were categorized into three classes: NQ, LQ, and FQ (described above). Some basic descriptive statistics were performed to attempt to identify the class range, however, it was more crucial to follow a more practical approach that would yield useful results. The frequency of FQ is lower than LQ and NQ for our dataset. But we can't avoid this, as we need this information to accurately predict to improve traffic signal systems. NQ was used for when there are no queues present. FQ is used when the queue is expected to be full (backed up), and the LQ is the level incorporating everything in between. And because this is a sample data set, we didn't have a big data representation for the FQ level. However, with more days and locations to review in the future, it is expected that this category would be better represented.

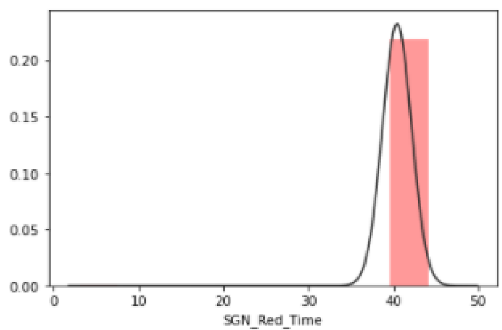
MaxQ_NotNeeded	
Mean	1.865243
Standard Error	0.058582
Median	1
Mode	0
Standard Deviation	2.158826
Sample Variance	4.66053
Kurtosis	0.039275
Skewness	1.010565
Range	8
Minimum	0
Maximum	8
Sum	2533
Count	1358
Confidence Level(95.0%)	0.114922

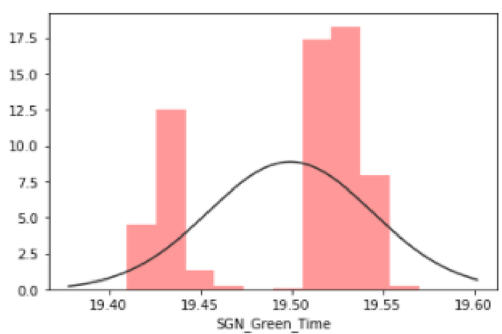


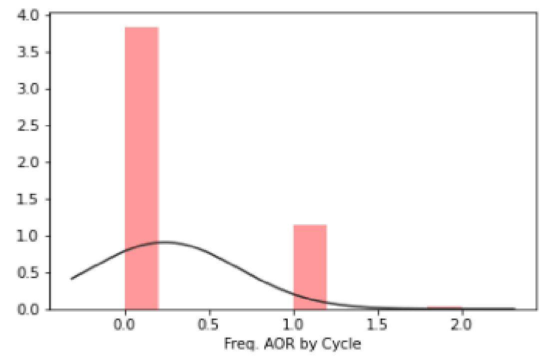
c. Histograms of select Independent Variables:

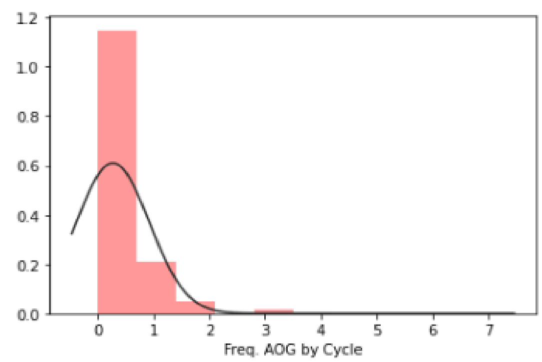
The following represent a set of histograms for a select number of independent variables.

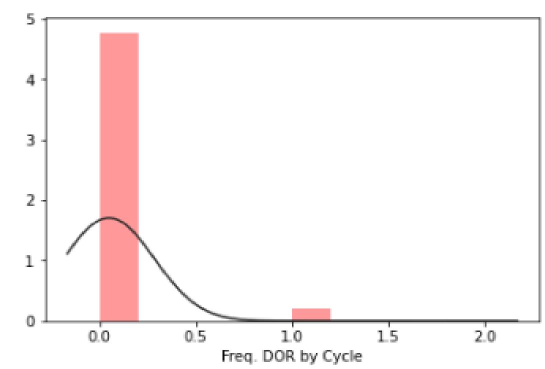


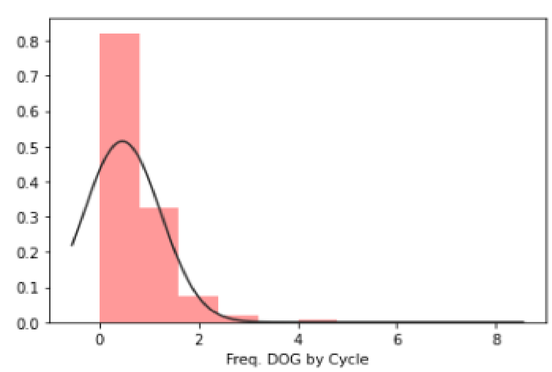












Uniformly Distributed (expected consistency)

Cycl_length

SGN_Red_Time

SGN_Green_Time

Non-uniformly Distributed (more random in nature)

Freq- AOR, AOG, DOR, DOG

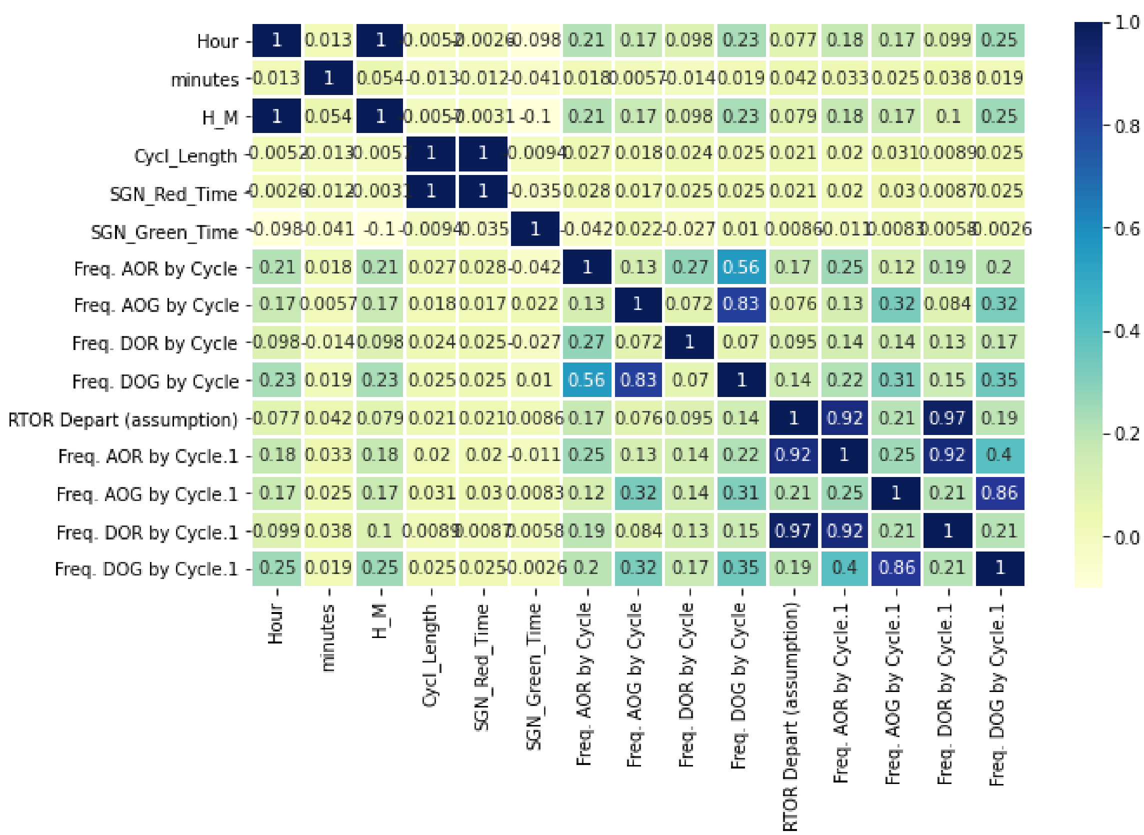
d. Correlations Analysis

According to the correlation coefficient matrix, there were six highly correlated attributes that stood out between. The most significant of which is: RTOR Depart (assumption) : Frequency DOR by Cycle.1 (0.97). This correlation is justified when the practical explanation of the Attribute is delved into. In this case the RTOR was derived from any DOR that occurs after 3 seconds. Additionally, RTOR seems to be occurring in correlation with vehicles arriving on red and departing on red (DOR).

Additionally, the data is indicating that most vehicles are arriving on green and departing on green for both lanes (that is a good value but could be improved with coordination with signals upstream). However, the final relationship is showing a high correlation between vehicles arriving on red (AOR) and departing on green (DOG) which is not a good indication of signal performance.

ATTRIBUTES	CORRELATION
RTOR Depart (assumption) : Frequency DOR by Cycle.1	0.97
RTOR Depart (assumption) : Frequency AOR by Cycle.1	0.92
Freq. AOR by Cycle.1 : Frequency DOR by Cycle.1	0.92
Freq. DOG by Cycle.1 : Freq. AOG by Cycle.1	0.86
Freq. DOG by Cycle : Freq. AOG by Cycle	0.83
Freq. DOG by Cycle: Freq. AOR by Cycle	0.56

The below correlation coefficient matrix represents the full relationship between the various continuous attributes. Categorical variables are not included.



e. MODEL BUILDING:

For Model Building, as our data is non-linear, we used these classification methods to search for accurate model. Seven models were investigated. The accuracy between the training and testing data sets for the following seven models is shown in the following table.

1. Logistic Regression

2. Decision Tree

3. Linear Discriminant Analysis

4. K nearest Neighbors

5. Gaussian Naïve Bayes

6. SVM

7. NN -Multilayer Perceptron

MODEL	TRAINING ACCURACY	TESTING ACCURACY
1. Logistic Regression	0.82	0.83
2. Decision Tree	1	0.75
3. Linear Discriminant Analysis	0.81	0.82
4. K Nearest Neighbors	**0.85**	**0.82**
5. Gaussian Naïve Bayes	0.52	0.52
6. SVM	**0.85**	**0.85**
7. NN -Multilayer Perceptron	**0.85**	**0.85**

f. Comparing the top performing classifiers

If we compare only the testing accuracies, then we have the following Top-3 Classifiers:

- **SVM**
- **NN-Perceptron**
- **KNN-K-Nearest Neighbors**

Inferences:-

- If we compare other measures like confusion metrics, F-measure, Precision and Recall, then we see that KNN wins
- Also if we closely observe, KNN gives us a balanced classification accuracy, for instance it predicts class FQ=3 more accurately than other two classifiers**.**

```
print('Confusion Matrix and Precision-Recall for SVM')
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
pred3 = svm.predict(X_test)
print(confusion_matrix(y_test, pred3))
print(classification_report(y_test, pred3))
```

```
Confusion Matrix and Precision-Recall for SVM
[[160   8   0]
 [ 22 180   1]
 [  2  27   3]]
              precision    recall  f1-score   support

           1       0.87      0.95      0.91       168
           2       0.84      0.89      0.86       203
           3       0.75      0.09      0.17        32

    accuracy                           0.85       403
   macro avg       0.82      0.64      0.65       403
weighted avg       0.84      0.85      0.83       403
```

```
#MLP
print('Confusion Matrix and Precision-Recall for MLP')
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
pred = clf.predict(X_test)
print(confusion_matrix(y_test, pred))
print(classification_report(y_test, pred))
```

```
Confusion Matrix and Precision-Recall for MLP
[[160   8   0]
 [ 22 179   2]
 [  0  28   4]]
              precision    recall  f1-score   support

           1       0.88      0.95      0.91       168
           2       0.83      0.88      0.86       203
           3       0.67      0.12      0.21        32

    accuracy                           0.85       403
   macro avg       0.79      0.65      0.66       403
weighted avg       0.84      0.85      0.83       403
```

```
#KNN
print('Confusion Matrix and Precision-Recall for KNN')
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
pred2 = knn.predict(X_test)
print(confusion_matrix(y_test, pred2))
print(classification_report(y_test, pred2))
```

```
Confusion Matrix and Precision-Recall for KNN
[[150  18   0]
 [ 21 174   8]
 [  0  24   8]]
              precision    recall  f1-score   support

           1       0.88      0.89      0.88       168
           2       0.81      0.86      0.83       203
           3       0.50      0.25      0.33        32

    accuracy                           0.82       403
   macro avg       0.73      0.67      0.68       403
weighted avg       0.81      0.82      0.81       403
```

	Correctly classified SVM	**Correctly classified MLP**	**Correctly classified KNN**
NQ=1	**160**	**160**	**150**
LQ=2	**180**	**179**	**174**
FQ=3	**3**	**4**	**8**

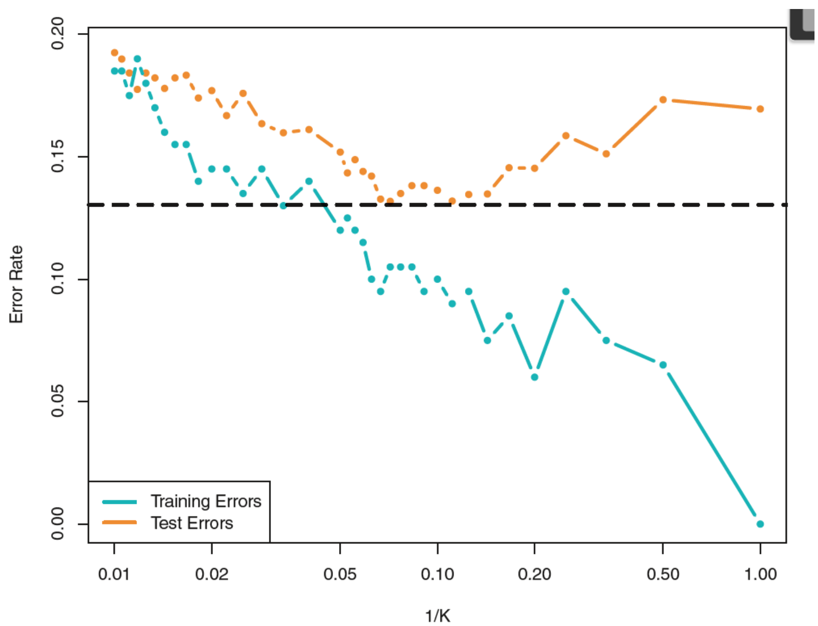
As we can see, although Accuracy of other models are equivalent for NQ=1 and LQ=2, Class FQ=3 is lagging behind with only a fraction of the data points correctly classified. Out of the three methods, FQ is more accurately classified under KNN (8 out of 32) which is a very important factor for Traffic signal regularization.

- K Nearest Neighbors **

We used k=5 because we felt it optimized the confusion matrix better for our test results

Theoretically: At K= 5, most case scenario observes a min Training and testing error rates. At K=5, 1/K = 0.2

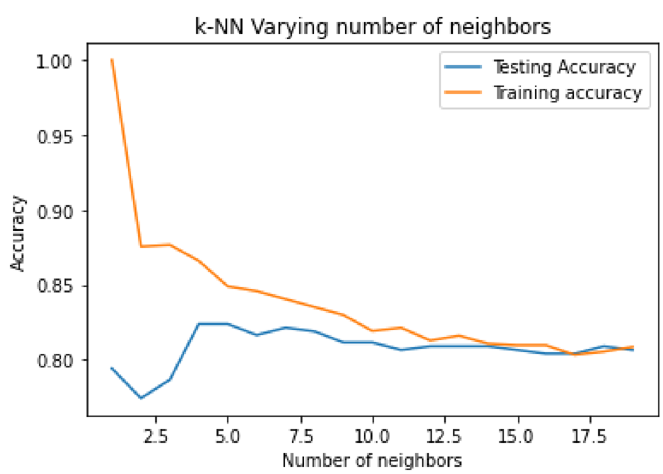
PG 42 of Textbook - An Introduction to Statistical Learning with Applications in R



Practically:

After plotting the graph we observed that at K=5, both Training and testing errors are minimum.

```
neighbors = np.arange(1,20)
train_accuracy =np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

for i,k in enumerate(neighbors):
    #Setup a knn classifier with k neighbors
    knn = KNeighborsClassifier(n_neighbors=k)

    #Fit the model
    knn.fit(X_train, y_train)

    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, y_train)

    #Compute accuracy on the test set
    test_accuracy[i] = knn.score(X_test, y_test)


plt.title('k-NN Varying number of neighbors')
plt.plot(neighbors, test_accuracy, label='Testing Accuracy')
plt.plot(neighbors, train_accuracy, label='Training accuracy')
plt.legend()
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
plt.show()
```

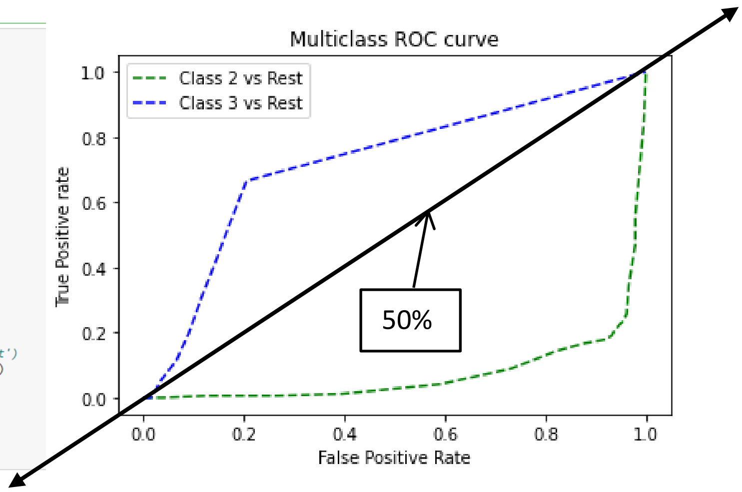


- **ROC-CURVE**

From ROC curve, we see for LQ=2 the KNN model is a very good model (above 50% chance) but for FQ=3, the KNN model current is a bad model (below 50%). But it is much better and balanced than any other model tried so far.

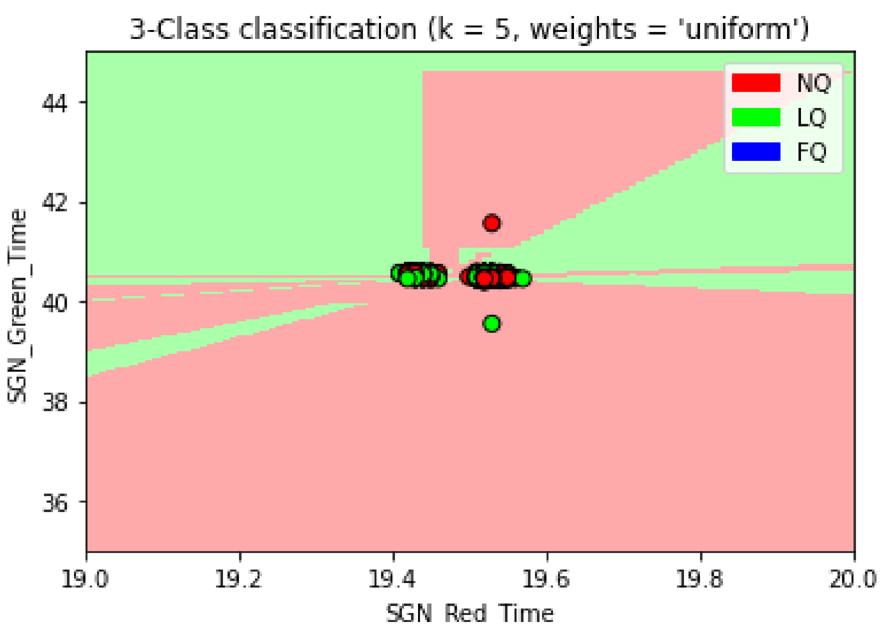
In this case, the penalization of one class prediction vs the other is subject to the objective and the cost function associated with it. This signifies that both of them are penalizing each other and tradeoff between these need to be decided based on the objective of the analysis. For our Analysis, we want both of these to be predicted accurately.

```
# 2-class classification

from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score


pred = knn.predict(X_test)
pred_prob = knn.predict_proba(X_test)

# roc curve for classes
fpr = {}
tpr = {}
thresh ={}

n_class = 3

for i in range(1,n_class):
    fpr[i], tpr[i], thresh[i] = roc_curve(y_test, pred_prob[:,i], pos_label=i)

# plotting
#plt.plot(fpr[0], tpr[0], linestyle='--',color='orange', label='Class 1 vs Rest')
plt.plot(fpr[1], tpr[1], linestyle='--',color='green', label='Class 2 vs Rest')
plt.plot(fpr[2], tpr[2], linestyle='--',color='blue', label='Class 3 vs Rest')
plt.title('Multiclass ROC curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive rate')
plt.legend(loc='best')
plt.savefig('Multiclass ROC',dpi=300);
```



- **Decision Boundary**

For NQ=1, LQ=2, FQ=3, as we can see, a clear boundary for FQ is missing which needs to improvised.



V. CONCLUSION

The issue of predicting queue classification solely from stop bar detection high resolution data is a hurdle that has not been addressed or resolved through research and industry due to the complexity it requires and the large set of data required to come to a reasonable selection process, method, and result interpretation. This project attempted to be a first step in that direction by processing a one-day long set of data for an approach at an intersection and deriving the statistical relationships between the chosen attributes. Additionally, various prediction classification models were test to provide a comparison (Logistic Regression, Decision Tree, Linear Discriminant Analysis, K Nearest Neighbors, Gaussian Naïve Bayes, SVM, and NN -Multilayer Perceptron).

Out of those methods, **K nearest neighbor (KNN) seems to be outperforming the other methods** (even the Neural Network based Multi-Level Perceptron). However, due to a ramification of an uneven class distribution (with much lower instances of FQ compared with the other two classes), potential data accuracy issues, review of analysis methods and configurations, and the need for a larger data pool, the results were not as strongly along the entire data range. Prediction of the FQ class specifically fell short in all methods and needs further investigation. However, for the NQ and LQ, the model seems to be highly accurate.

VI. REFERENCES

The following references were used throughout this report:

Model Analysis: https://github.com/rajratnapatil9/TRAFFIC-QUEUE-PREDICTION/blob/main/Queue%20Prediction.ipynb

PG 42 of Textbook - An Introduction to Statistical Learning with Applications in R http://faculty.marshall.usc.edu/gareth-james/ISL/

Steven F. Ashby Center for Applied Scientific Computing Month DD, 1997 (Lecture Notes – Introduction to Data Mining)

Rahman, R., Hasan, S. Real-time signal queue length prediction using long short-term memory neural network. *Neural Comput & Applic* (2020). https://doi.org/10.1007/s00521-020-05196-9

Solving A Simple Classification Problem with Python — Fruits Lovers' Edition https://towardsdatascience.com/solving-a-simple-classification-problem-with-python-fruits-lovers-edition-d20ab6b071d2

K-Nearest Neighbors, Boxplot, Standard Score, Feature Scaling, Curse of Dimensionality, Missing Values, Confusion Matrix, Classification Report, ROC-Curve, AUROC https://limebit-jupyter-notebooks.s3.eu-central-1.amazonaws.com/jupyter-KNN-und-SVM.html

AUC-ROC Curve in Machine Learning Clearly Explained https://www.analyticsvidhya.com/blog/2020/06/auc-roc-curve-machine-learning/

KNN for Classification using Scikit-learn https://www.kaggle.com/amolbhivarkar/knn-for-classification-using-scikit-learn

ROC Curve explained using a COVID-19 hypothetical example: Binary & Multi-Class Classification Tutorial https://towardsdatascience.com/roc-curve-explained-using-a-covid-19-hypothetical-example-binary-multi-class-classification-bab188ea869c

TRAFFIC-QUEUE-PREDICTION / Queue Prediction.ipynb

rajratnapatil9 Add files via upload History

1 contributor

Raw Blame

1659 lines (1659 sloc) | 412 KB

In [2]:
```
import numpy as np
import csv
import matplotlib.pyplot as plt
import pandas as pd
```

In [117]:
```
data = pd.read_csv("Data_CSV.csv")
data.head()
```

Out[117]:

	Hour	minutes	H_M	Cycl_Length	SGN_Red_Time	SGN_Green_Time	StopBar_LEFT_Trig
0	0	0	0.00	59.97	40.45	19.52	0
1	0	1	0.02	59.98	40.46	19.52	1
2	0	2	0.03	60.00	40.46	19.54	1
3	0	3	0.05	59.97	40.44	19.52	1
4	0	4	0.07	59.97	40.45	19.52	1

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1343 entries, 0 to 1342
Data columns (total 19 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Hour                     1343 non-null   int64
 1   minutes                  1343 non-null   int64
 2   H_M                      1343 non-null   float64
 3   Cycl_Length              1343 non-null   float64
 4   SGN_Red_Time             1343 non-null   float64
 5   SGN_Green_Time           1343 non-null   float64
 6   StopBar_LEFT_Trigger     1343 non-null   int64
 7   Freq. AOR by Cycle       1343 non-null   int64
 8   Freq. AOG by Cycle       1343 non-null   int64
 9   Freq. DOR by Cycle       1343 non-null   int64
 10  Freq. DOG by Cycle       1343 non-null   int64
 11  StopBar_RtTh_Trigger     1343 non-null   int64
 12  RTOR Depart (assumption) 1343 non-null   int64
 13  Freq. AOR by Cycle.1     1343 non-null   int64
 14  Freq. AOG by Cycle.1     1343 non-null   int64
 15  Freq. DOR by Cycle.1     1343 non-null   int64
 16  Freq. DOG by Cycle.1     1343 non-null   int64
 17  Truck_Present            1343 non-null   int64
 18  Q_filled                 1343 non-null   int64
dtypes: float64(4), int64(15)
memory usage: 199.5 KB
```

In [118]:
```
data['StopBar_LEFT_Trigger'] = data['StopBar_LEFT_Trigger'].astype('category')
data['StopBar_RtTh_Trigger']=data['StopBar_RtTh_Trigger'].astype('category')
data['Truck_Present']=data['Truck_Present'].astype('category')
data['Q_filled']=data['Q_filled'].astype('category')

data.info()
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1343 entries, 0 to 1342
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype   
---  ------                  --------------  -----   
 0   Hour                    1343 non-null   int64   
 1   minutes                 1343 non-null   int64   
 2   H_M                     1343 non-null   float64 
 3   Cycl_Length             1343 non-null   float64 
 4   SGN_Red_Time            1343 non-null   float64 
 5   SGN_Green_Time          1343 non-null   float64 
 6   StopBar_LEFT_Trigger    1343 non-null   category
 7   Freq. AOR by Cycle      1343 non-null   int64   
 8   Freq. AOG by Cycle      1343 non-null   int64   
 9   Freq. DOR by Cycle      1343 non-null   int64   
 10  Freq. DOG by Cycle      1343 non-null   int64   
 11  StopBar_RtTh_Trigger    1343 non-null   category
 12  RTOR Depart (assumption) 1343 non-null   int64   
 13  Freq. AOR by Cycle.1    1343 non-null   int64   
 14  Freq. AOG by Cycle.1    1343 non-null   int64   
 15  Freq. DOR by Cycle.1    1343 non-null   int64   
 16  Freq. DOG by Cycle.1    1343 non-null   int64   
 17  Truck_Present           1343 non-null   category
 18  Q_filled                1343 non-null   category
dtypes: category(4), float64(4), int64(11)
memory usage: 163.1 KB
```

In [321]:
```
(data['Q_filled']==1).sum()
```

Out[321]: 567

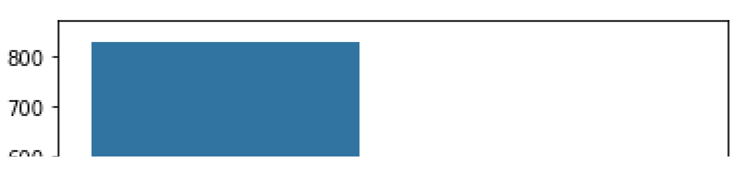
In [322]:
```
(data['Q_filled']==2).sum()
```

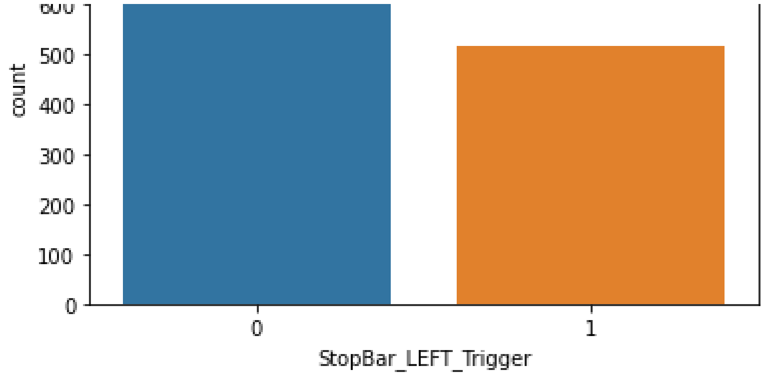
Out[322]: 668

In [323]:
```
(data['Q_filled']==3).sum()
```

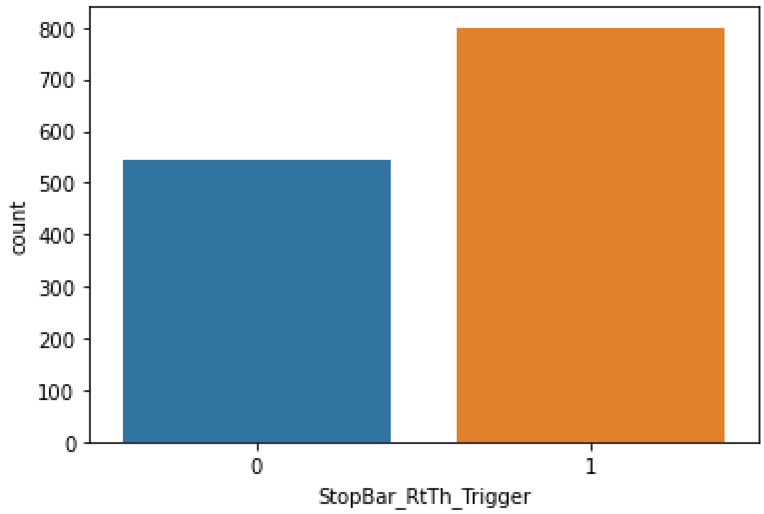
Out[323]: 108

In [5]:
```
import seaborn as sns
sns.countplot(data['StopBar_LEFT_Trigger'],label="Count of NT/T")
plt.show()

import seaborn as sns
sns.countplot(data['StopBar_RtTh_Trigger'],label="Count of NT/T")
plt.show()

import seaborn as sns
sns.countplot(data['Truck_Present'],label="Count of NT/T")
plt.show()

sns.countplot(data['Q_filled'],label="Count of NT/T")
plt.show()
```

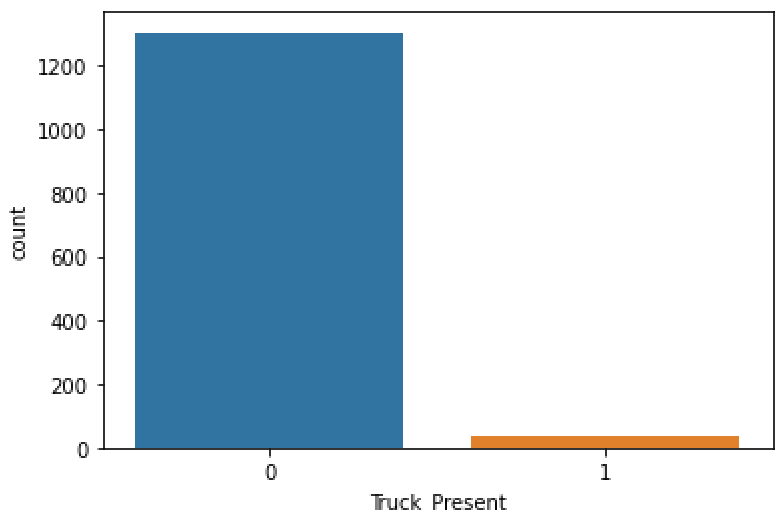




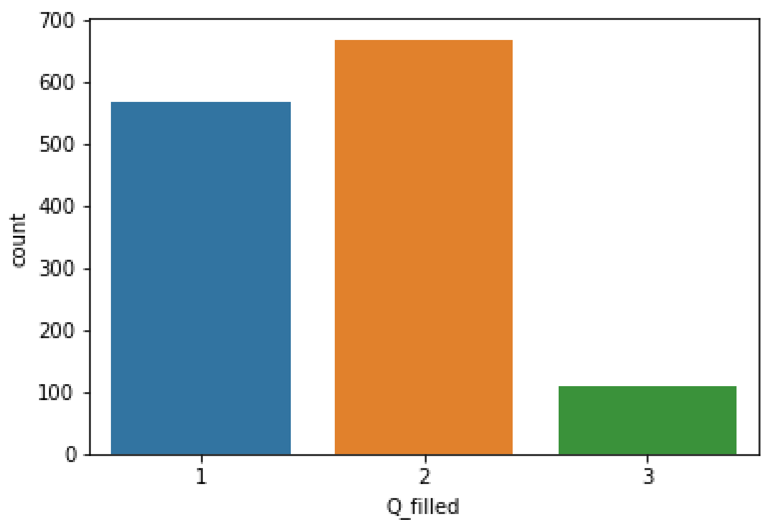
count
StopBar_LEFT_Trigger



count
StopBar_RtTh_Trigger



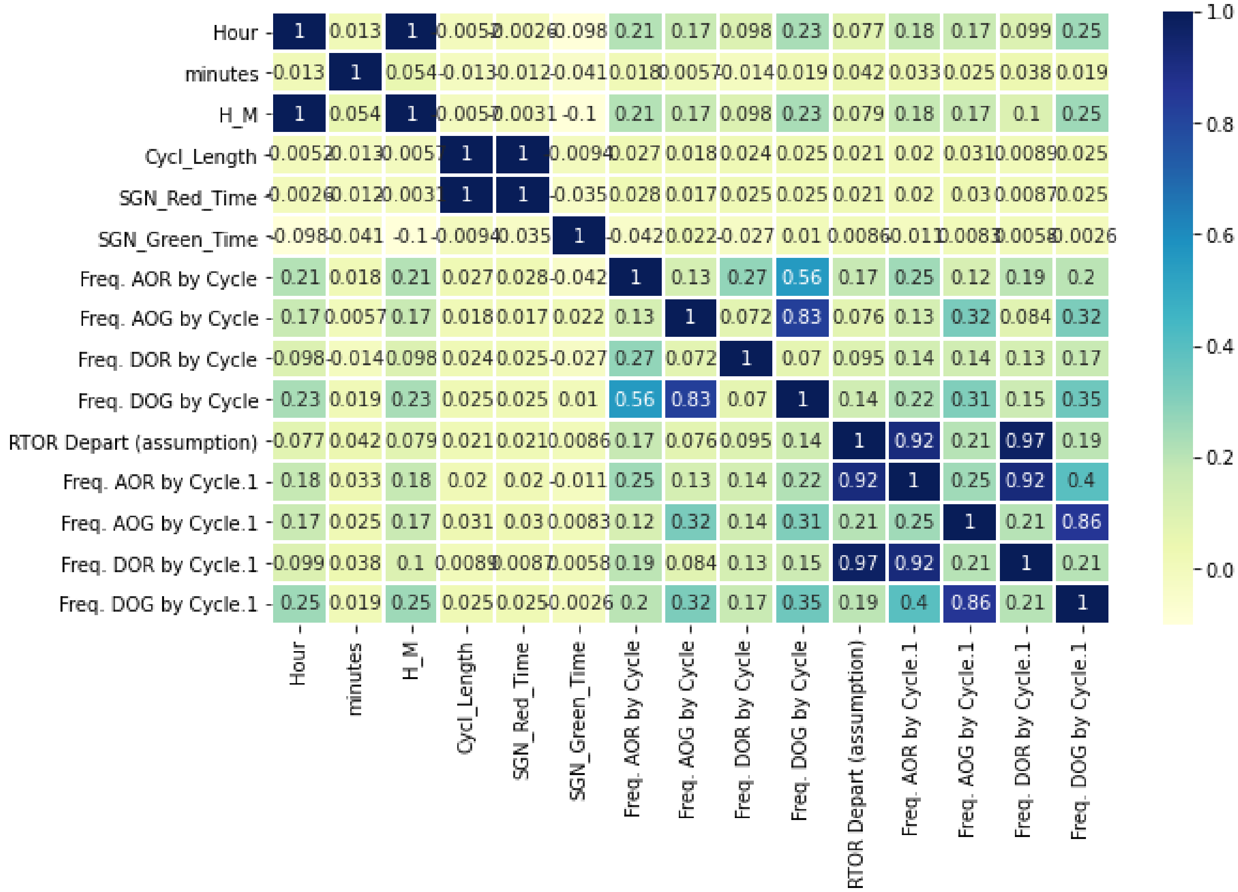
count
Truck_Present



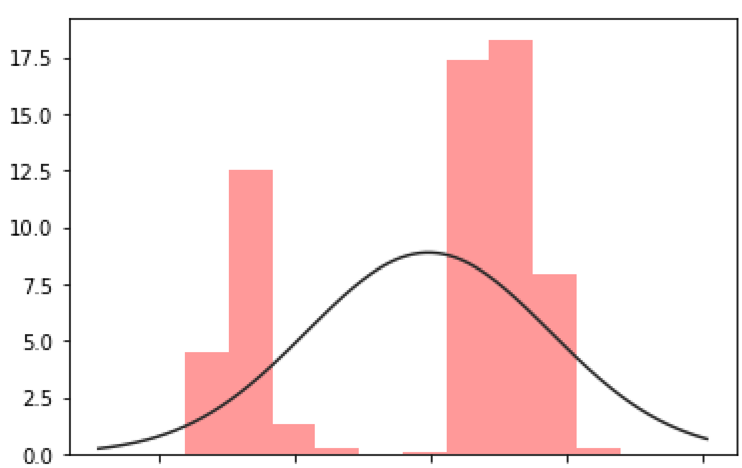
count
Q_filled

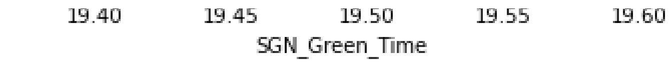
Correlation Plot for Continuous Attributes

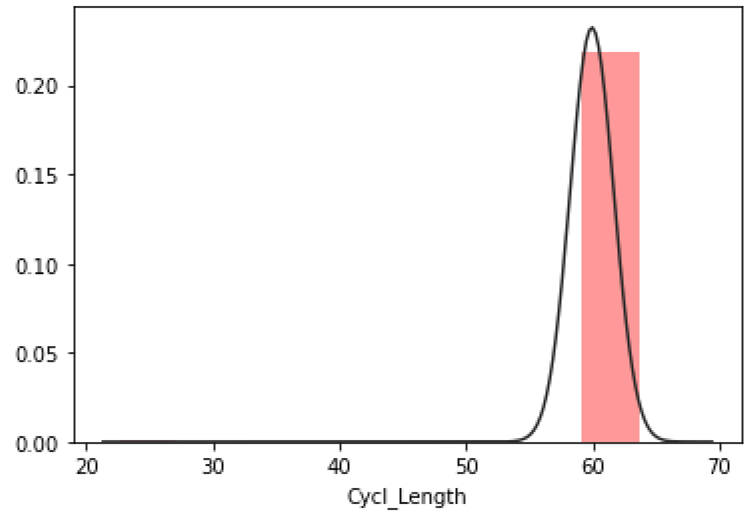
In [324]:
```
plt.figure(figsize=(10,6))
sns.heatmap(data.corr(), annot=True, linecolor = 'white', linewidths = 1, cmap="Y
lGnBu")
plt.show()
```

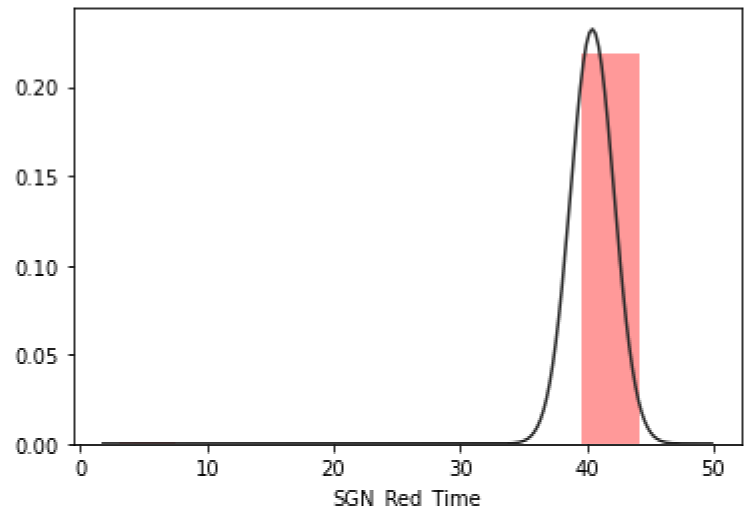


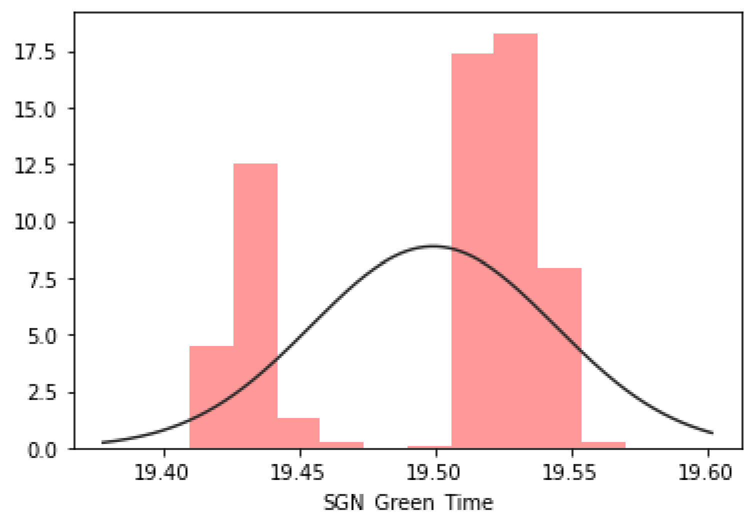
In [316]:
```
sns.distplot(data.SGN_Green_Time, color = 'red',  bins=10,fit=norm, kde=False)
plt.show()

sns.distplot(data.Cycl_Length, color = 'red', bins=10,fit=norm, kde=False)
plt.show()
sns.distplot(data.SGN_Red_Time, color = 'red', bins=10,fit=norm, kde=False)
plt.show()
sns.distplot(data.SGN_Green_Time, color = 'red', bins=10,fit=norm, kde=False)
plt.show()
```

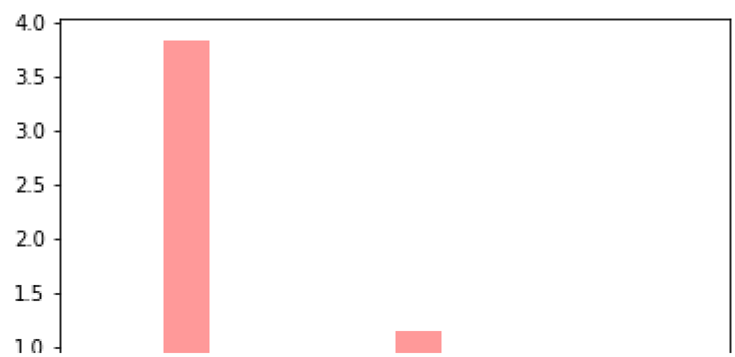


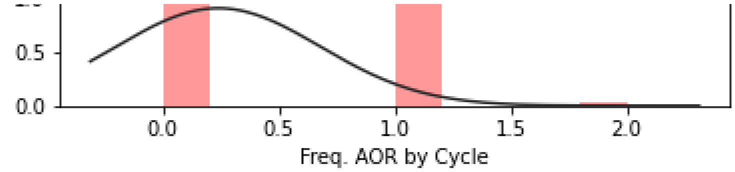

19.40
19.45
19.50
19.55
19.60
SGN_Green_Time

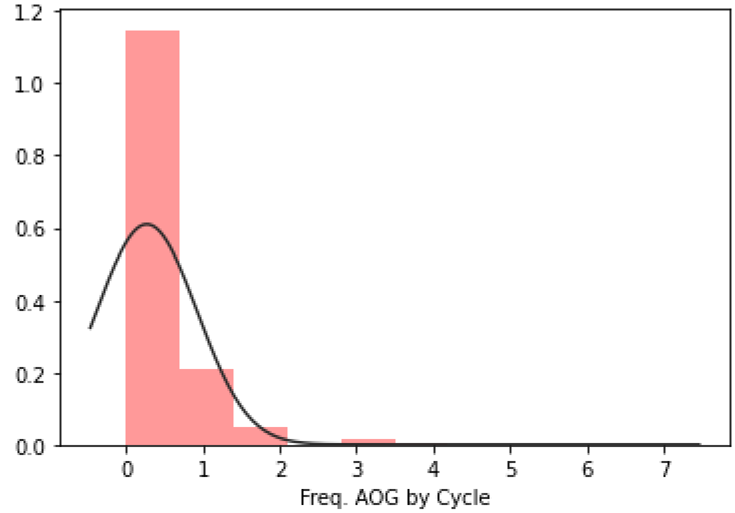

0.20
0.15
0.10
0.05
0.00
20
30
40
50
60
70
Cycl_Length

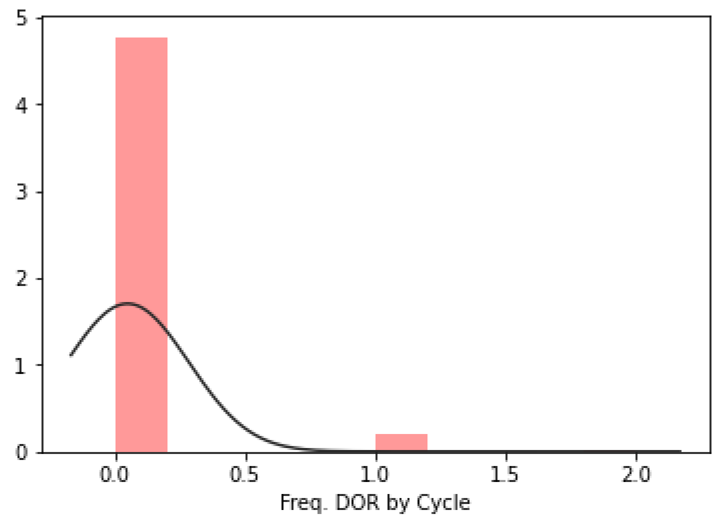

0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
50
SGN_Red_Time

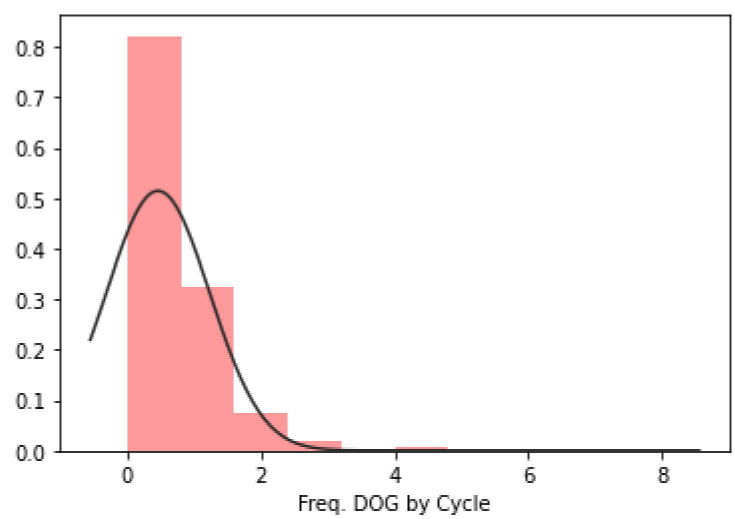

17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
19.40
19.45
19.50
19.55
19.60
SGN_Green_Time


4.0
3.5
3.0
2.5
2.0
1.5
1.0





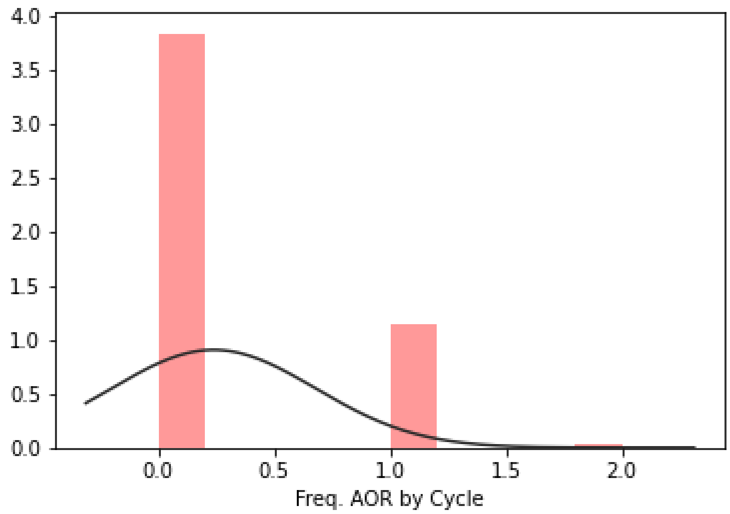


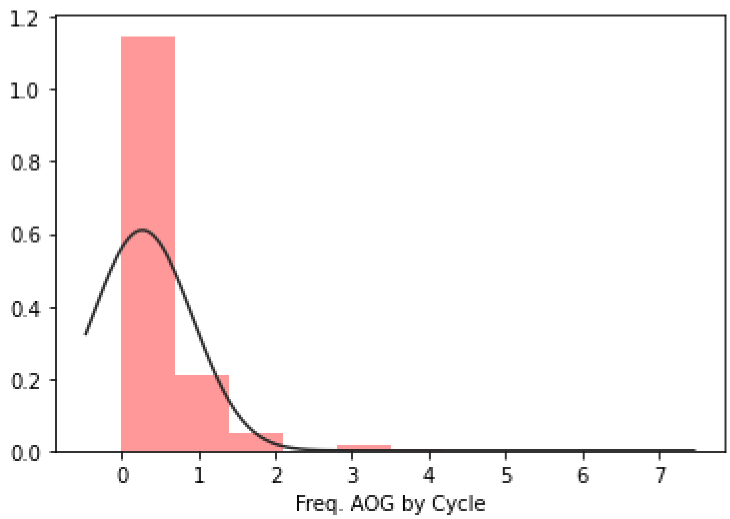


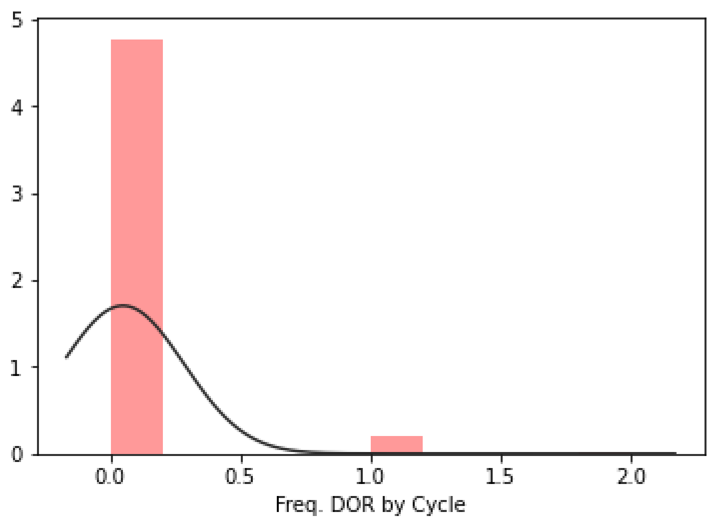
In [317]:

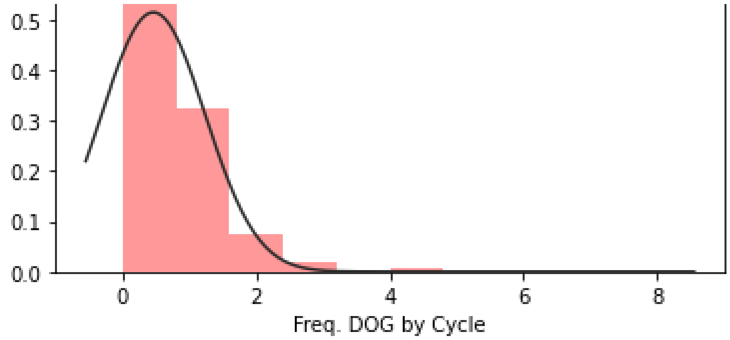
```
sns.distplot(data['Freq. AOR by Cycle'], color = 'red', bins=10,fit=norm, kde=False)
plt.show()
sns.distplot(data['Freq. AOG by Cycle'], color = 'red', bins=10,fit=norm, kde=False)
plt.show()
```

```
sns.distplot(data['Freq. DOR by Cycle'], color = 'red', bins=10,fit=norm, kde=False)
plt.show()
sns.distplot(data['Freq. DOG by Cycle'], color = 'red', bins=10,fit=norm, kde=False)
plt.show()
```









1. Splitting data into continuous and categorical Attributes

2. Scaling and Normalizing COntinous Attributes

3. Combining them into single dataset

In [119]:

```
data.catX= data[['StopBar_LEFT_Trigger', 'StopBar_RtTh_Trigger' , 'Truck_Present'
,'Q_filled']]
data.continuous = data[['Hour','minutes','H_M', 'Cycl_Length','SGN_Red_Time','SGN
_Green_Time', 'Freq. AOR by Cycle','Freq. AOG by Cycle' ,'Freq. DOR by Cycle','Fr
eq. DOG by Cycle', 'RTOR Depart (assumption)', 'Freq. AOR by Cycle.1','Freq. AOG
 by Cycle.1', 'Freq. DOR by Cycle.1','Freq. DOG by Cycle.1']]
data.catX.head()
data.continuous.head()
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data.continuous = scaler.fit_transform(data.continuous)
data.continuous = scaler.transform(data.continuous)
data.continuous = pd.DataFrame(data=data.continuous, columns=['Hour','minutes','H
_M', 'Cycl_Length','SGN_Red_Time','SGN_Green_Time', 'Freq. AOR by Cycle','Freq. A
OG by Cycle' ,'Freq. DOR by Cycle','Freq. DOG by Cycle', 'RTOR Depart (assumptio
n)', 'Freq. AOR by Cycle.1','Freq. AOG by Cycle.1', 'Freq. DOR by Cycle.1','Freq.
DOG by Cycle.1'])
data.continuous.head()

data.norm=(data.continuous-data.continuous.min())/(data.continuous.max()-data.con
tinuous.min())
data.norm.head(2)

data1 = pd.concat([data.norm, data.catX],axis=1)
data1.head(2)
```

```
<ipython-input-119-270207f77d5e>:1: UserWarning: Pandas doesn't allow columns to
be created via a new attribute name - see https://pandas.pydata.org/pandas-docs/s
table/indexing.html#attribute-access
  data.catX= data[['StopBar_LEFT_Trigger', 'StopBar_RtTh_Trigger' , 'Truck_Presen
t','Q_filled']]
<ipython-input-119-270207f77d5e>:2: UserWarning: Pandas doesn't allow columns to
be created via a new attribute name - see https://pandas.pydata.org/pandas-docs/s
table/indexing.html#attribute-access
  data.continuous = data[['Hour','minutes','H_M', 'Cycl_Length','SGN_Red_Time','S
GN_Green_Time', 'Freq. AOR by Cycle','Freq. AOG by Cycle' ,'Freq. DOR by Cycl
e','Freq. DOG by Cycle', 'RTOR Depart (assumption)', 'Freq. AOR by Cycle.1','Fre
```

```
q. AOG by Cycle.1', 'Freq. DOR by Cycle.1','Freq. DOG by Cycle.1']]
<ipython-input-119-270207f77d5e>:12: UserWarning: Pandas doesn't allow columns to be created via a new attribute name - see https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access
  data.norm=(data.continuous-data.continuous.min())/(data.continuous.max()-data.continuous.min())
```

Out[119]:

	Hour	minutes	H_M	Cycl_Length	SGN_Red_Time	SGN_Green_Time	Freq. AOR by Cycle	Freq. AOG by Cycle
0	0.0	0.000000	0.000000	0.820153	0.820333	0.6875	0.0	0.00000
1	0.0	0.016949	0.000834	0.820372	0.820552	0.6875	0.0	0.14285

Splitting data into Training and Testing sets.

In [139]:
```
from sklearn.model_selection import train_test_split
X= data1.iloc[0:,0:18]
y= data1["Q_filled"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=0)
X_train.head()
```

Out[139]:

	Hour	minutes	H_M	Cycl_Length	SGN_Red_Time	SGN_Green_Time	Freq. AOR by Cycle	F A b C
467	0.347826	0.118644	0.338757	0.820591	0.822743	0.1250	0.0	0
477	0.347826	0.593220	0.357947	0.820591	0.820771	0.7500	0.0	0
472	0.347826	0.254237	0.344180	0.820372	0.820552	0.6875	0.0	0
503	0.391304	0.050847	0.377555	0.820372	0.820552	0.6875	0.0	0
97	0.043478	0.677966	0.069670	0.820153	0.822524	0.1250	0.0	0

1. Logistic Regression

In [49]:
```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
print('Accuracy of Logistic regression classifier on training set: {:.2f}'
     .format(logreg.score(X_train, y_train)))
print('Accuracy of Logistic regression classifier on test set: {:.2f}'
     .format(logreg.score(X_test, y_test)))
```

```
Accuracy of Logistic regression classifier on training set: 0.82
Accuracy of Logistic regression classifier on test set: 0.83
```

2. Decision Tree

2. Decision Tree

In [50]:
```
from sklearn.tree import DecisionTreeClassifier
clf = DecisionTreeClassifier().fit(X_train, y_train)
print('Accuracy of Decision Tree classifier on training set: {:.2f}'
     .format(clf.score(X_train, y_train)))
print('Accuracy of Decision Tree classifier on test set: {:.2f}'
     .format(clf.score(X_test, y_test)))
```

```
Accuracy of Decision Tree classifier on training set: 1.00
Accuracy of Decision Tree classifier on test set: 0.75
```

3. K-Nearest Neighbors

In [212]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
print('Accuracy of K-NN classifier on training set: {:.2f}'
     .format(knn.score(X_train, y_train)))
print('Accuracy of K-NN classifier on test set: {:.2f}'
     .format(knn.score(X_test, y_test)))
```

```
Accuracy of K-NN classifier on training set: 0.85
Accuracy of K-NN classifier on test set: 0.82
```

4. Linear Discriminant Analysis

In [52]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
lda = LinearDiscriminantAnalysis()
lda.fit(X_train, y_train)
print('Accuracy of LDA classifier on training set: {:.2f}'
     .format(lda.score(X_train, y_train)))
print('Accuracy of LDA classifier on test set: {:.2f}'
     .format(lda.score(X_test, y_test)))
```

```
Accuracy of LDA classifier on training set: 0.81
Accuracy of LDA classifier on test set: 0.82
```

5. Gaussian Naive Bayes

In [53]:
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb.fit(X_train, y_train)
print('Accuracy of GNB classifier on training set: {:.2f}'
     .format(gnb.score(X_train, y_train)))
print('Accuracy of GNB classifier on test set: {:.2f}'
     .format(gnb.score(X_test, y_test)))
```

```
Accuracy of GNB classifier on training set: 0.52
Accuracy of GNB classifier on test set: 0.52
```

6. Support Vector Machine

In [219]:
```
from sklearn.svm import SVC
svm = SVC(C=1, kernel='poly')
svm.fit(X_train, y_train)
print('Accuracy of SVM classifier on training set: {:.2f}'
     .format(svm.score(X_train, y_train)))
print('Accuracy of SVM classifier on test set: {:.2f}'
     .format(svm.score(X_test, y_test)))
```

```
Accuracy of SVM classifier on training set: 0.85
Accuracy of SVM classifier on test set: 0.85
```

7. NN-Multilayer Perception

In [189]:
```
from sklearn.neural_network import MLPClassifier
clf=MLPClassifier(activation='relu', alpha=1e-05, batch_size='auto',
beta_1=0.9, beta_2=0.999, early_stopping=False,
epsilon=1e-08, hidden_layer_sizes=(5,2),
learning_rate='constant', learning_rate_init=0.001,
max_iter=2000, momentum=0.9, n_iter_no_change=10,
nesterovs_momentum=True, power_t=0.9, random_state=1,
shuffle=True, solver='lbfgs', tol=0.0001,
validation_fraction=0.1, verbose=False, warm_start=False)

clf2=clf.fit(X_train, y_train)
clf.fit(X_train, y_train)
print('Accuracy of MLP classifier on training set: {:.2f}'
     .format(clf.score(X_train, y_train)))
print('Accuracy of MLP classifier on test set: {:.2f}'
     .format(clf.score(X_test, y_test)))
```

```
Accuracy of MLP classifier on training set: 0.85
Accuracy of MLP classifier on test set: 0.85
```

WINNER MODEL -- MLP VS KNN VS SVM

MLP

In [218]:
```
#MLP
print('Confusion Matrix and Precision-Recall for MLP')
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
pred = clf.predict(X_test)
print(confusion_matrix(y_test, pred))
print(classification_report(y_test, pred))
```

```
Confusion Matrix and Precision-Recall for MLP
[[160   8   0]
 [ 22 179   2]
 [  0  28   4]]
              precision    recall  f1-score   support

           1       0.88      0.95      0.91       168
           2       0.83      0.88      0.86       203
           3       0.67      0.12      0.21        32
```

```
    accuracy                           0.85       403
   macro avg       0.79      0.65      0.66       403
weighted avg       0.84      0.85      0.83       403
```

KNN

In [217]:
```
#KNN
print('Confusion Matrix and Precision-Recall for KNN')
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
pred2 = knn.predict(X_test)
print(confusion_matrix(y_test, pred2))
print(classification_report(y_test, pred2))
```

```
Confusion Matrix and Precision-Recall for KNN
[[150  18   0]
 [ 21 174   8]
 [  0  24   8]]
              precision    recall  f1-score   support

           1       0.88      0.89      0.88       168
           2       0.81      0.86      0.83       203
           3       0.50      0.25      0.33        32

    accuracy                           0.82       403
   macro avg       0.73      0.67      0.68       403
weighted avg       0.81      0.82      0.81       403
```

SVM

In [221]:
```
#SVM
print('Confusion Matrix and Precision-Recall for SVM')
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
pred3 = svm.predict(X_test)
print(confusion_matrix(y_test, pred3))
print(classification_report(y_test, pred3))
```

```
Confusion Matrix and Precision-Recall for SVM
[[160   8   0]
 [ 22 180   1]
 [  2  27   3]]
              precision    recall  f1-score   support

           1       0.87      0.95      0.91       168
           2       0.84      0.89      0.86       203
           3       0.75      0.09      0.17        32

    accuracy                           0.85       403
   macro avg       0.82      0.64      0.65       403
weighted avg       0.84      0.85      0.83       403
```

Comparing other scores for KNN vs MLP vs SVM

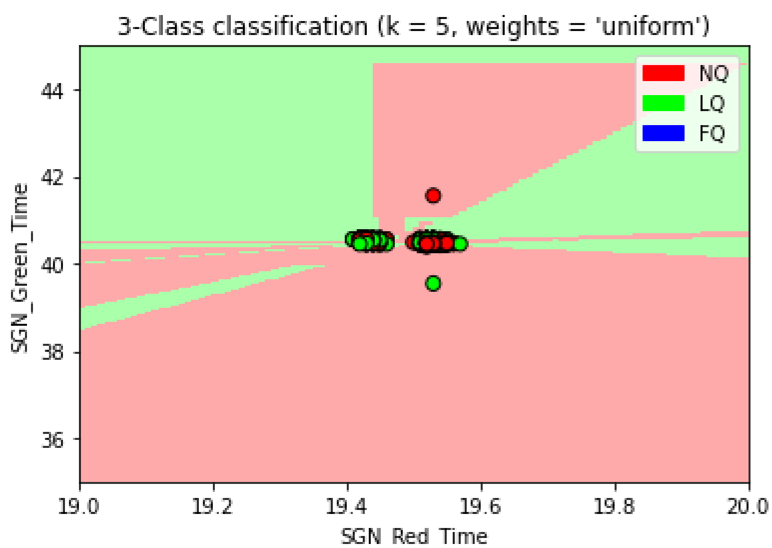
KNN wins as it balances the prediction for all three classes more correctly.

Drawing Decision Boundary

In [223]:

```
import matplotlib.cm as cm
from matplotlib.colors import ListedColormap, BoundaryNorm
import matplotlib.patches as mpatches
import matplotlib.patches as mpatches

#X = fruits[['mass', 'width', 'height', 'color_score']]
#y = fruits['fruit_label']
#X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
#X1= X_train.to_numpy(X_train)
#y1=y_train.to_numpy(y_train)


def plot_Queue_knn(X_train, y_train, n_neighbors, weights):
    #XX1= pd.DataFrame(X_train)
    #XXX= XX1.iloc[0:,0:18]
    #yy1= pd.DataFrame(y_train)
    #yyy= yy1.iloc[0:19]
    #XXX= XXX.to_numpy()
    #yyy= yyy.to_numpy()

    XXX= data[['SGN_Green_Time','SGN_Red_Time']]
    #XXX= X_train.iloc[0:,3:4]
    yyy= data['Q_filled']

    #X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
    X_mat = XXX.to_numpy()
    y_mat = yyy.to_numpy()

    # Create color maps
    cmap_light = ListedColormap(['#FFAAAA', '#AAFFAA', '#AAAAFF'])
    cmap_bold  = ListedColormap(['#FF0000', '#00FF00', '#0000FF'])

    knn2 = KNeighborsClassifier(n_neighbors, weights=weights)
    knn2.fit(X_mat, y_mat)

    # Plot the decision boundary by assigning a color in the color map
    # to each mesh point.

    mesh_step_size = .01  # step size in the mesh
    plot_symbol_size = 50

    x_min, x_max = X_mat[:, 0].min() - 1, X_mat[:, 0].max() + 1
    y_min, y_max = X_mat[:, 1].min() - 1, X_mat[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, mesh_step_size),
                         np.arange(y_min, y_max, mesh_step_size))
    Z = knn2.predict(np.c_[xx.ravel(), yy.ravel()])

    # Put the result into a color plot
```

```
    Z = Z.reshape(xx.shape)
    plt.figure()
    plt.pcolormesh(xx, yy, Z, cmap=cmap_light)

    # Plot training points
    plt.scatter(X_mat[:, 0], X_mat[:, 1], s=plot_symbol_size, c=y, cmap=cmap_bold
, edgecolor = 'black')
    #plt.xlim(xx.min(), xx.max())
    plt.xlim(19, 20)
    plt.ylim(35, 45)

    patch0 = mpatches.Patch(color='#FF0000', label='NQ')
    patch1 = mpatches.Patch(color='#00FF00', label='LQ')
    patch2 = mpatches.Patch(color='#0000FF', label='FQ')
    #patch3 = mpatches.Patch(color='#AFAFAF', label='lemon')
    plt.legend(handles=[patch0, patch1, patch2])


    plt.xlabel('SGN_Red_Time')
    plt.ylabel('SGN_Green_Time')
    plt.title("3-Class classification (k = %i, weights = '%s')"
              % (n_neighbors, weights))

    plt.show()

plot_Queue_knn(X_train,y_train,  5, 'uniform')
```

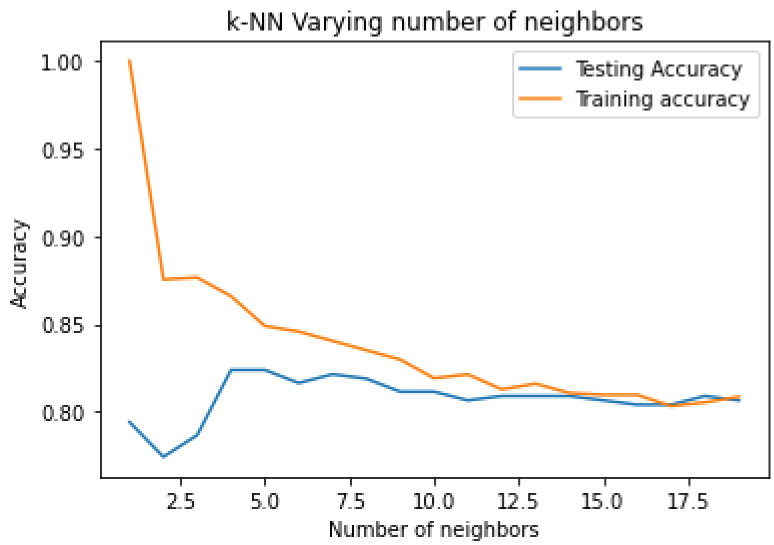


Drawing Nearest Neighbours VS Accuracy

We find k=5 to be optimum for modelling

In [264]:
```
neighbors = np.arange(1,20)
train_accuracy =np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

for i,k in enumerate(neighbors):
    #Setup a knn classifier with k neighbors
    knn = KNeighborsClassifier(n_neighbors=k)

    #Fit the model
    knn.fit(X_train, y_train)
```

```
    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, y_train)

    #Compute accuracy on the test set
    test_accuracy[i] = knn.score(X_test, y_test)


plt.title('k-NN Varying number of neighbors')
plt.plot(neighbors, test_accuracy, label='Testing Accuracy')
plt.plot(neighbors, train_accuracy, label='Training accuracy')
plt.legend()
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
plt.show()
```



Plotting ROC curve for LQ=2 and FQ=3

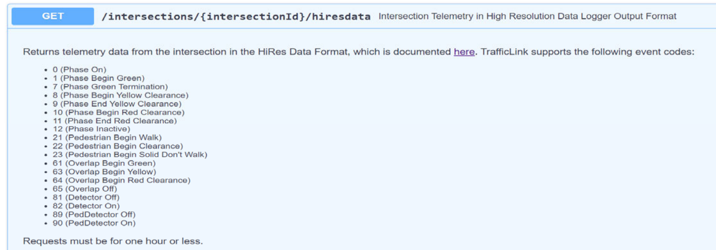
In [291]:
```
# 2-class classification

from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score


pred = knn.predict(X_test)
pred_prob = knn.predict_proba(X_test)

# roc curve for classes
fpr = {}
tpr = {}
thresh ={}

n_class = 3
```

PCD Generation and Other Data Mining Tool (adopted for and developed for CSC5800)

API Key	bYnKMv9Hwy			
Intersection ID	b3f46f76-a6ef-400c-b8a2-f7dd64169b8d			
Location	Central	**and**	Vernor	
Direction of Study Approach	SB	Central		
Lane Configuration	Th-Left + Right			
Phase	4			
Description	Analysis for Directed Study & Project for CSC5800			
Date of Analysis	23-Nov			
Analysis by	TG			
Event Codes of Interest	Begin of Green	Begin of Red	Detector on	Detector Off
	1	10	82	81

Parameters of Interest

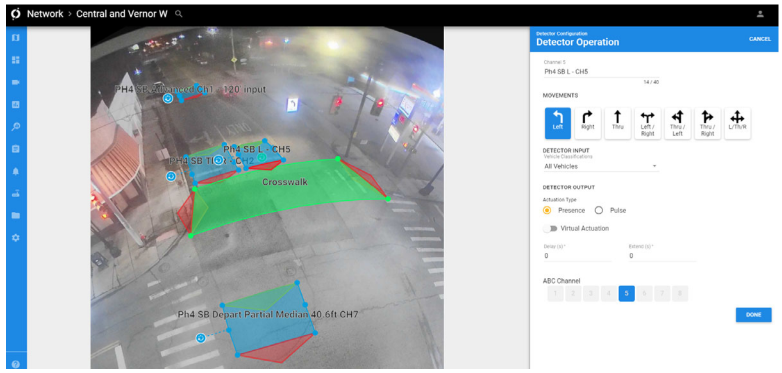
4	SB Phase	
1	Detection Channe Advanced	Pulse
2	Detection Channe Stop-bar RT+TH	Presence
5	Detection Channe Stop-bar LT	Presence
7	Detection Channe Through Departur	Presence


GET /intersections/{intersectionId}/hiresdata Intersection Telemetry in High Resolution Data Logger Output Format

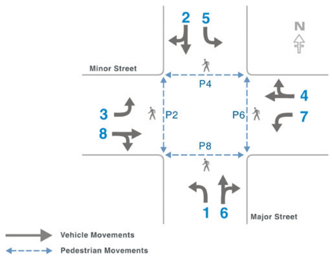
Returns telemetry data from the intersection in the HiRes Data Format, which is documented here. TrafficLink supports the following event codes:

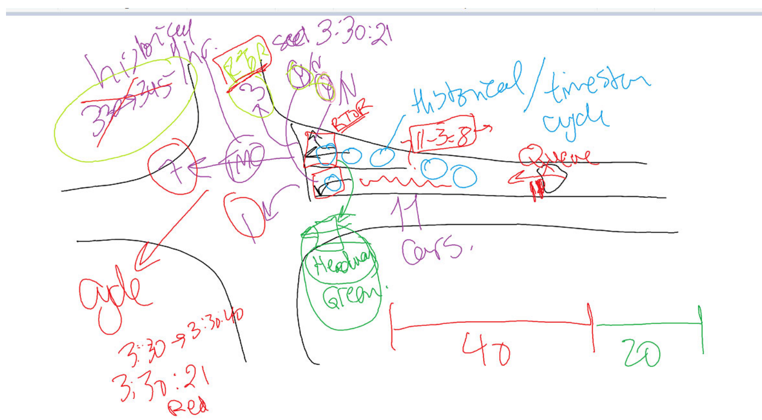
- 0 (Phase On)
- 1 (Phase Begin Green)
- 7 (Phase Green Termination)
- 8 (Phase Begin Yellow Clearance)
- 9 (Phase End Yellow Clearance)
- 10 (Phase Begin Red Clearance)
- 11 (Phase End Red Clearance)
- 12 (Phase Inactive)
- 21 (Pedestrian Begin Walk)
- 22 (Pedestrian Begin Clearance)
- 23 (Pedestrian Begin Solid Don't Walk)
- 61 (Overlap Begin Green)
- 63 (Overlap Begin Yellow)
- 64 (Overlap Begin Red Clearance)
- 65 (Overlap Off)
- 81 (Detector Off)
- 82 (Detector On)
- 89 (PedDetector Off)
- 90 (PedDetector On)

Requests must be for one hour or less.



Assumtions and Configurations
Red or Green
30 mph ~ 45 ft/sec
~150 ft advance pulse Detector
No residual queue assumed





Notes from Dec-3 2020
check for: should a Protected left term be required?
LT Permit?
We also have TMC for oposing traffic (allowing us to look at gap and ability to turn left)

Performance Measure
Data driven approach
Cross product HCM method vs. Actual data driven method.

Sensitivity Analysis
is it with in a percentage? (~10%)

Maybe try it out on Jefferson with higher dat and more coordination
Issue with Trucks
more peds

Elevator Pitch and Parameter Summary Schematic

Training Set
We need to fill in the blanks (Asume Missing Data) for the cycles highlighted in yellow and marked as Missing
or identify and ignore the outliers (just as spikes in TMC/Queue when some data is missing)
Input attributes (featuers) are marked in green "use" on top
Ignor all Columns with a balck "No" or "Do not Use"
Neural Network

Test Set to follow
Do we need a validation set as well?

Assuming no residual queue for now
In the future we can add that based on Headway below a certain threashhold and **TMC** counts about a certain value

Big questions for later:
Distinguish between Arival on Green (AOG) and Pass of Green (POG)
POG is when the vehivle is already in the queue but passes on green
AOG indicates that it arived and crosed on Green
When the Vehicle arrives on Green or Red at the Channel box is very important to the decision on the Queue.
for Ch-2 if there is much DOR, then the length of presense for the last AOR is important to identify vehicle status

There's a very credible corelation between the RTOR achieved from the TMC and that identified from movement on RED at CH2 detector that need to be investigated (LATER)

time	event Code (10)	event Param (4)	Missing Data?	New "N" Cycle Used	day	month	Dayof Week	Time	Hour	minutes	H_M	Current Cycle Red Time Start	Current Cycle Green Start Time	Cycl_Length	SGN_Red_Time	SGN_Green_Time	Missing Data?
00:00:15.5	10	4			30	11	2	0:00:15.5	0	0.0	0.00	00:00:15.5	00:00:56.0	59.97	40.45	19.52	
00:01:15.5	10	4		N	30	11	2	0:01:15.5	0	1.0	0.02	00:01:15.5	00:01:55.9	59.98	40.46	19.52	
00:02:15.5	10	4		N	30	11	2	0:02:15.5	0	2.0	0.03	00:02:15.5	00:02:55.9	60.00	40.46	19.54	
00:03:15.5	10	4		N	30	11	2	0:03:15.5	0	3.0	0.05	00:03:15.5	00:03:55.9	59.97	40.44	19.52	
00:04:15.4	10	4		N	30	11	2	0:04:15.4	0	4.0	0.07	00:04:15.4	00:04:55.9	59.97	40.45	19.52	
00:05:15.4	10	4		N	30	11	2	0:05:15.4	0	5.0	0.08	00:05:15.4	00:05:55.9	60.06	40.54	19.52	
00:06:15.5	10	4		N	30	11	2	0:06:15.5	0	6.0	0.10	00:06:15.5	00:06:55.9	59.98	40.45	19.52	
00:07:15.4	10	4		N	30	11	2	0:07:15.4	0	7.0	0.12	00:07:15.4	00:07:55.9	59.96	40.44	19.53	
00:08:15.4	10	4			30	11	2	0:08:15.4	0	8.0	0.13	00:08:15.4	00:08:55.9	59.98	40.46	19.52	
00:09:15.4	10	4			30	11	2	0:09:15.4	0	9.0	0.15	00:09:15.4	00:09:55.9	60.09	40.56	19.52	
00:10:15.5	10	4			30	11	2	0:10:15.5	0	10.0	0.17	00:10:15.5	00:10:55.9	59.95	40.43	19.52	
00:11:15.4	10	4			30	11	2	0:11:15.4	0	11.0	0.18	00:11:15.4	00:11:56.0	59.97	40.54	19.42	
00:12:15.4	10	4			30	11	2	0:12:15.4	0	12.0	0.20	00:12:15.4	00:12:56.0	60.02	40.57	19.44	
00:13:15.4	10	4			30	11	2	0:13:15.4	0	13.0	0.22	00:13:15.4	00:13:55.9	60.03	40.50	19.53	
00:14:15.4	10	4		N	30	11	2	0:14:15.4	0	14.0	0.23	00:14:15.4	00:14:55.9	59.99	40.45	19.54	
00:15:15.4	10	4			30	11	2	0:15:15.4	0	15.0	0.25	00:15:15.4	00:15:55.9	60.00	40.48	19.52	
00:16:15.4	10	4			30	11	2	0:16:15.4	0	16.0	0.27	00:16:15.4	00:16:55.9	59.96	40.42	19.54	
00:17:15.4	10	4		N	30	11	2	0:17:15.4	0	17.0	0.28	00:17:15.4	00:17:55.8	59.99	40.45	19.53	
00:18:15.4	10	4		N	30	11	2	0:18:15.4	0	18.0	0.30	00:18:15.4	00:18:55.9	60.00	40.47	19.53	
00:19:15.4	10	4			30	11	2	0:19:15.4	0	19.0	0.32	00:19:15.4	00:19:55.8	59.99	40.47	19.52	
00:20:15.4	10	4			30	11	2	0:20:15.4	0	20.0	0.33	00:20:15.4	00:20:55.9	60.01	40.57	19.44	
00:21:15.4	10	4			30	11	2	0:21:15.4	0	21.0	0.35	00:21:15.4	00:21:55.9	60.09	40.56	19.53	
00:22:15.5	10	4		N	30	11	2	0:22:15.5	0	22.0	0.37	00:22:15.5	00:22:55.9	60.01	40.46	19.55	
00:23:15.5	10	4		N	30	11	2	0:23:15.5	0	23.0	0.38	00:23:15.5	00:23:55.9	60.00	40.46	19.54	
00:24:15.5	10	4		N	30	11	2	0:24:15.5	0	24.0	0.40	00:24:15.5	00:24:55.9	60.00	40.46	19.54	
00:25:15.5	10	4			30	11	2	0:25:15.5	0	25.0	0.42	00:25:15.5	00:25:56.0	60.09	40.56	19.53	
00:26:15.6	10	4			30	11	2	0:26:15.6	0	26.0	0.43	00:26:15.6	00:26:56.0	60.00	40.47	19.53	
00:27:15.6	10	4			30	11	2	0:27:15.6	0	27.0	0.45	00:27:15.6	00:27:56.1	60.00	40.48	19.52	
00:28:15.6	10	4			30	11	2	0:28:15.6	0	28.0	0.47	00:28:15.6	00:28:56.0	59.98	40.46	19.52	
00:29:15.6	10	4			30	11	2	0:29:15.6	0	29.0	0.48	00:29:15.6	00:29:56.0	59.99	40.45	19.54	
00:30:15.5	10	4			30	11	2	0:30:15.5	0	30.0	0.50	00:30:15.5	00:30:56.1	59.99	40.57	19.42	
00:31:15.5	10	4			30	11	2	0:31:15.5	0	31.0	0.52	00:31:15.5	00:31:56.1	60.08	40.56	19.52	
00:32:15.6	10	4		N	30	11	2	0:32:15.6	0	32.0	0.53	00:32:15.6	00:32:56.1	60.01	40.47	19.54	
00:33:15.6	10	4			30	11	2	0:33:15.6	0	33.0	0.55	00:33:15.6	00:33:56.1	59.99	40.45	19.54	
00:34:15.6	10	4		N	30	11	2	0:34:15.6	0	34.0	0.57	00:34:15.6	00:34:56.1	59.98	40.46	19.52	
00:35:15.6	10	4			30	11	2	0:35:15.6	0	35.0	0.58	00:35:15.6	00:35:56.1	60.07	40.55	19.52	
00:36:15.7	10	4			30	11	2	0:36:15.7	0	36.0	0.60	00:36:15.7	00:36:56.1	59.99	40.46	19.53	
00:37:15.6	10	4			30	11	2	0:37:15.6	0	37.0	0.62	00:37:15.6	00:37:56.1	59.97	40.45	19.53	
00:38:15.6	10	4			30	11	2	0:38:15.6	0	38.0	0.63	00:38:15.6	00:38:56.2	59.97	40.54	19.43	
00:39:15.6	10	4		N	30	11	2	0:39:15.6	0	39.0	0.65	00:39:15.6	00:39:56.2	59.99	40.56	19.43	
00:40:15.6	10	4		N	30	11	2	0:40:15.6	0	40.0	0.67	00:40:15.6	00:40:56.1	60.08	40.54	19.54	
00:41:15.7	10	4		N	30	11	2	0:41:15.7	0	41.0	0.68	00:41:15.7	00:41:56.1	59.99	40.45	19.53	
00:42:15.6	10	4			30	11	2	0:42:15.6	0	42.0	0.70	00:42:15.6	00:42:56.1	59.98	40.45	19.53	
00:43:15.6	10	4	missing - 2		30	11	2	0:43:15.6	0	43.0	0.72	00:43:15.6	00:46:08.2	180.04	172.54	7.50	missing - 2
00:46:15.7	10	4			30	11	2	0:46:15.7	0	46.0	0.77	00:46:15.7	00:46:56.1	59.98	40.46	19.52	
00:47:15.6	10	4		N	30	11	2	0:47:15.6	0	47.0	0.78	00:47:15.6	00:47:56.1	59.98	40.45	19.53	
00:48:15.6	10	4			30	11	2	0:48:15.6	0	48.0	0.80	00:48:15.6	00:48:56.1	59.95	40.43	19.52	
00:49:15.6	10	4		N	30	11	2	0:49:15.6	0	49.0	0.82	00:49:15.6	00:49:56.1	59.96	40.55	19.42	
00:50:15.5	10	4			30	11	2	0:50:15.5	0	50.0	0.83	00:50:15.5	00:50:56.1	60.09	40.55	19.53	
00:51:15.6	10	4			30	11	2	0:51:15.6	0	51.0	0.85	00:51:15.6	00:51:56.1	59.99	40.46	19.53	
00:52:15.6	10	4		N	30	11	2	0:52:15.6	0	52.0	0.87	00:52:15.6	00:52:56.1	59.96	40.45	19.51	
00:53:15.6	10	4			30	11	2	0:53:15.6	0	53.0	0.88	00:53:15.6	00:53:56.1	60.07	40.56	19.51	
00:54:15.6	10	4			30	11	2	0:54:15.6	0	54.0	0.90	00:54:15.6	00:54:56.1	59.99	40.46	19.53	
00:55:15.6	10	4			30	11	2	0:55:15.6	0	55.0	0.92	00:55:15.6	00:55:56.1	59.99	40.45	19.54	
00:56:15.6	10	4			30	11	2	0:56:15.6	0	56.0	0.93	00:56:15.6	00:56:56.1	59.98	40.46	19.52	
00:57:15.6	10	4			30	11	2	0:57:15.6	0	57.0	0.95	00:57:15.6	00:57:56.1	59.98	40.46	19.52	
00:58:15.6	10	4			30	11	2	0:58:15.6	0	58.0	0.97	00:58:15.6	00:58:56.1	60.07	40.55	19.52	
00:59:15.6	10	4		N	30	11	2	0:59:15.6	0	59.0	0.98	00:59:15.6	00:59:56.1	60.00	40.46	19.54	
01:00:15.6	10	4			30	11	2	1:00:15.6	1	0.0	1.00	01:00:15.6	01:00:56.1	59.98	40.45	19.53	
01:01:15.6	10	4		N	30	11	2	1:01:15.6	1	1.0	1.02	01:01:15.6	01:01:56.2	60.06	40.54	19.52	
01:02:15.7	10	4		N	30	11	2	1:02:15.7	1	2.0	1.03	01:02:15.7	01:02:56.1	59.97	40.45	19.52	
01:03:15.7	10	4		N	30	11	2	1:03:15.7	1	3.0	1.05	01:03:15.7	01:03:56.2	59.99	40.55	19.43	
01:04:15.6	10	4		N	30	11	2	1:04:15.6	1	4.0	1.07	01:04:15.6	01:04:56.2	59.99	40.56	19.43	
01:05:15.6	10	4		N	30	11	2	1:05:15.6	1	5.0	1.08	01:05:15.6	01:05:56.2	60.00	40.56	19.44	
01:06:15.6	10	4			30	11	2	1:06:15.6	1	6.0	1.10	01:06:15.6	01:06:56.1	60.01	40.48	19.54	
01:07:15.6	10	4			30	11	2	1:07:15.6	1	7.0	1.12	01:07:15.6	01:07:56.1	59.99	40.46	19.53	
01:08:15.6	10	4			30	11	2	1:08:15.6	1	8.0	1.13	01:08:15.6	01:08:56.1	59.99	40.47	19.52	
01:09:15.6	10	4			30	11	2	1:09:15.6	1	9.0	1.15	01:09:15.6	01:09:56.2	60.07	40.55	19.52	
01:10:15.7	10	4			30	11	2	1:10:15.7	1	10.0	1.17	01:10:15.7	01:10:56.1	59.96	40.45	19.51	
01:11:15.7	10	4		N	30	11	2	1:11:15.7	1	11.0	1.18	01:11:15.7	01:11:56.2	60.06	40.53	19.53	
01:12:15.7	10	4		N	30	11	2	1:12:15.7	1	12.0	1.20	01:12:15.7	01:12:56.2	59.99	40.45	19.54	
01:13:15.7	10	4		N	30	11	2	1:13:15.7	1	13.0	1.22	01:13:15.7	01:13:56.1	59.95	40.42	19.52	
01:14:15.7	10	4			30	11	2	1:14:15.7	1	14.0	1.23	01:14:15.7	01:14:56.2	60.02	40.58	19.44	
01:15:15.7	10	4		N	30	11	2	1:15:15.7	1	15.0	1.25	01:15:15.7	01:15:56.2	59.98	40.56	19.42	
01:16:15.7	10	4			30	11	2	1:16:15.7	1	16.0	1.27	01:16:15.7	01:16:56.2	60.08	40.57	19.51	
01:17:15.7	10	4		N	30	11	2	1:17:15.7	1	17.0	1.28	01:17:15.7	01:17:56.2	60.01	40.49	19.52	
01:18:15.7	10	4		N	30	11	2	1:18:15.7	1	18.0	1.30	01:18:15.7	01:18:56.2	59.97	40.44	19.53	
01:19:15.7	10	4		N	30	11	2	1:19:15.7	1	19.0	1.32	01:19:15.7	01:19:56.2	60.00	40.46	19.54	
01:20:15.7	10	4			30	11	2	1:20:15.7	1	20.0	1.33	01:20:15.7	01:20:56.3	59.98	40.56	19.42	
01:21:15.7	10	4			30	11	2	1:21:15.7	1	21.0	1.35	01:21:15.7	01:21:56.2	60.07	40.55	19.53	
01:22:15.8	10	4			30	11	2	1:22:15.8	1	22.0	1.37	01:22:15.8	01:22:56.2	59.99	40.46	19.53	
01:23:15.7	10	4			30	11	2	1:23:15.7	1	23.0	1.38	01:23:15.7	01:23:56.2	59.98	40.45	19.53	
01:24:15.7	10	4			30	11	2	1:24:15.7	1	24.0	1.40	01:24:15.7	01:24:56.3	60.07	40.55	19.52	
01:25:15.8	10	4			30	11	2	1:25:15.8	1	25.0	1.42	01:25:15.8	01:25:56.3	59.90	40.47	19.44	
01:26:15.7	10	4			30	11	2	1:26:15.7	1	26.0	1.43	01:26:15.7	01:26:56.2	60.07	40.55	19.52	
01:27:15.8	10	4			30	11	2	1:27:15.8	1	27.0	1.45	01:27:15.8	01:27:56.2	59.96	40.44	19.53	
01:28:15.7	10	4			30	11	2	1:28:15.7	1	28.0	1.47	01:28:15.7	01:28:56.2	59.97	40.45	19.52	
01:29:15.7	10	4			30	11	2	1:29:15.7	1	29.0	1.48	01:29:15.7	01:29:56.2	60.03	40.46	19.56	
01:30:15.7	10	4		N	30	11	2	1:30:15.7	1	30.0	1.50	01:30:15.7	01:30:56.2	59.97	40.45	19.52	
01:31:15.7	10	4			30	11	2	1:31:15.7	1	31.0	1.52	01:31:15.7	01:31:56.2	59.99	40.47	19.53	
01:32:15.7	10	4			30	11	2	1:32:15.7	1	32.0	1.53	01:32:15.7	01:32:56.2	59.98	40.46	19.52	
01:33:15.7	10	4			30	11	2	1:33:15.7	1	33.0	1.55	01:33:15.7	01:33:56.1	59.98	40.45	19.53	
01:34:15.7	10	4			30	11	2	1:34:15.7	1	34.0	1.57	01:34:15.7	01:34:56.1	59.97	40.46	19.52	
01:35:15.6	10	4			30	11	2	1:35:15.6	1	35.0	1.58	01:35:15.6	01:35:56.2	59.99	40.55	19.44	
01:36:15.6	10	4			30	11	2	1:36:15.6	1	36.0	1.60	01:36:15.6	01:36:56.2	59.98	40.55	19.43	
01:37:15.6	10	4			30	11	2	1:37:15.6	1	37.0	1.62	01:37:15.6	01:37:56.2	60.07	40.55	19.52	
01:38:15.7	10	4			30	11	2	1:38:15.7	1	38.0	1.63	01:38:15.7	01:38:56.1	59.98	40.46	19.52	
01:39:15.7	10	4			30	11	2	1:39:15.7	1	39.0	1.65	01:39:15.7	01:39:56.1	59.98	40.46	19.52	
01:40:15.6	10	4			30	11	2	1:40:15.6	1	40.0	1.67	01:40:15.6	01:40:56.2	59.97	40.55	19.43	
01:41:15.6	10	4			30	11	2	1:41:15.6	1	41.0	1.68	01:41:15.6	01:41:56.2	59.99	40.56	19.43	
01:42:15.6	10	4		N	30	11	2	1:42:15.6	1	42.0	1.70	01:42:15.6	01:42:56.1	60.05	40.54	19.52	
01:43:15.7	10	4			30	11	2	1:43:15.7	1	43.0	1.72	01:43:15.7	01:43:56.1	59.98	40.45	19.53	
01:44:15.6	10	4			30	11	2	1:44:15.6	1	44.0	1.73	01:44:15.6	01:44:56.1	59.99	40.45	19.54	
01:45:15.6	10	4		N	30	11	2	1:45:15.6	1	45.0	1.75	01:45:15.6	01:45:56.1	59.98	40.45	19.53	
01:46:15.6	10	4			30	11	2	1:46:15.6	1	46.0	1.77	01:46:15.6	01:46:56.1	59.91	40.48	19.44	
01:47:15.5	10	4			30	11	2	1:47:15.5	1	47.0	1.78	01:47:15.5	01:47:56.1	60.09	40.57	19.53	
01:48:15.6	10	4			30	11	2	1:48:15.6	1	48.0	1.80	01:48:15.6	01:48:56.1	59.99	40.47	19.53	
01:49:15.6	10	4			30	11	2	1:49:15.6	1	49.0	1.82	01:49:15.6	01:49:56.0	59.97	40.44	19.53	
01:50:15.6	10	4		N	30	11	2	1:50:15.6	1	50.0	1.83	01:50:15.6	01:50:56.0	59.98	40.46	19.53	
01:51:15.5	10	4			30	11	2	1:51:15.5	1	51.0	1.85	01:51:15.5	01:51:56.0	59.97	40.45	19.52	
01:52:15.5	10	4			30	11	2	1:52:15.5	1	52.0	1.87	01:52:15.5	01:52:56.1	59.98	40.56	19.42	
01:53:15.5	10	4			30	11	2	1:53:15.5	1	53.0	1.88	01:53:15.5	01:53:56.0	59.98	40.55	19.43	
01:54:15.5	10	4	missing - 2	N	30	11	2	1:54:15.5	1	54.0	1.90	01:54:15.5	01:56:56.0	180.06	160.51	19.55	missing - 2
01:57:15.5	10	4			30	11	2	1:57:15.5	1	57.0	1.95	01:57:15.5	01:57:56.0	59.96	40.43	19.53	
01:58:15.5	10	4			30	11	2	1:58:15.5	1	58.0	1.97	01:58:15.5	01:58:56.0	60.00	40.47	19.53	
01:59:15.5	10	4			30	11	2	1:59:15.5	1	59.0	1.98	01:59:15.5	01:59:56.0	60.00	40.47	19.53	
02:00:15.5	10	4		N	30	11	2	2:00:15.5	2	0.0	2.00	02:00:15.5	02:00:56.0	59.99	40.47	19.52	
02:01:15.5	10	4			30	11	2	2:01:15.5	2	1.0	2.02	02:01:15.5	02:01:56.0	59.97	40.54	19.43	
02:02:15.5	10	4			30	11	2	2:02:15.5	2	2.0	2.03	02:02:15.5	02:02:56.0	60.08	40.55	19.52	
02:03:15.5	10	4			30	11	2	2:03:15.5	2	3.0	2.05	02:03:15.5	02:03:56.0	59.98	40.46	19.52	
02:04:15.5	10	4			30	11	2	2:04:15.5	2	4.0	2.07	02:04:15.5	02:04:56.1	60.06	40.54	19.52	
02:05:15.6	10	4		N	30	11	2	2:05:15.6	2	5.0	2.08	02:05:15.6	02:05:56.0	59.98	40.46	19.52	
02:06:15.6	10	4			30	11	2	2:06:15.6	2	6.0	2.10	02:06:15.6	02:06:56.0	60.01	40.46	19.55	
02:07:15.6	10	4			30	11	2	2:07:15.6	2	7.0	2.12	02:07:15.6	02:07:56.0	59.98	40.45	19.53	
02:08:15.6	10	4			30	11	2	2:08:15.6	2	8.0	2.13	02:08:15.6	02:08:56.1	59.98	40.53	19.45	
02:09:15.5	10	4			30	11	2	2:09:15.5	2	9.0	2.15	02:09:15.5	02:09:56.1	60.07	40.55	19.52	
02:10:15.6	10	4			30	11	2	2:10:15.6	2	10.0	2.17	02:10:15.6	02:10:56.1	59.98	40.46	19.52	
02:11:15.6	10	4			30	11	2	2:11:15.6	2	11.0	2.18	02:11:15.6	02:11:56.0	59.99	40.45	19.54	
02:12:15.6	10	4			30	11	2	2:12:15.6	2	12.0	2.20	02:12:15.6	02:12:56.1	59.99	40.56	19.43	
02:13:15.5	10	4			30	11	2	2:13:15.5	2	13.0	2.22	02:13:15.5	02:13:56.1	60.09	40.55	19.53	
02:14:15.6	10	4			30	11	2	2:14:15.6	2	14.0	2.23	02:14:15.6	02:14:56.1	59.97	40.43	19.54	
02:15:15.6	10	4			30	11	2	2:15:15.6	2	15.0	2.25	02:15:15.6	02:15:56.2	59.98	40.55	19.42	
02:16:15.6	10	4			30	11	2	2:16:15.6	2	16.0	2.27	02:16:15.6	02:16:56.1	60.07	40.54	19.53	
02:17:15.7	10	4			30	11	2	2:17:15.7	2	17.0	2.28	02:17:15.7	02:17:56.1	60.00	40.47	19.53	
02:18:15.7	10	4			30	11	2	2:18:15.7	2	18.0	2.30	02:18:15.7	02:18:56.1	59.98	40.46	19.53	
02:19:15.6	10	4			30	11	2	2:19:15.6	2	19.0	2.32	02:19:15.6	02:19:56.2	60.08	40.56	19.53	
02:20:15.7	10	4			30	11	2	2:20:15.7	2	20.0	2.33	02:20:15.7	02:20:56.2	60.00	40.46	19.54	
02:21:15.7	10	4			30	11	2	2:21:15.7	2	21.0	2.35	02:21:15.7	02:21:56.2	59.99	40.46	19.52	
02:22:15.7	10	4			30	11	2	2:22:15.7	2	22.0	2.37	02:22:15.7	02:22:56.2	59.99	40.46	19.53	
02:23:15.7	10	4			30	11	2	2:23:15.7	2	23.0	2.38	02:23:15.7	02:23:56.1	59.96	40.45	19.52	
02:24:15.7	10	4			30	11	2	2:24:15.7	2	24.0	2.40	02:24:15.7	02:24:56.2	60.07	40.54	19.52	
02:25:15.7	10	4			30	11	2	2:25:15.7	2	25.0	2.42	02:25:15.7	02:25:56.2	59.97	40.44	19.53	
02:26:15.7	10	4		N	30	11	2	2:26:15.7	2	26.0	2.43	02:26:15.7	02:26:56.2	60.00	40.46	19.53	
02:27:15.7	10	4		N	30	11	2	2:27:15.7	2	27.0	2.45	02:27:15.7	02:27:56.3	59.99	40.57	19.42	
02:28:15.7	10	4			30	11	2	2:28:15.7	2	28.0	2.47	02:28:15.7	02:28:56.2	59.98	40.56	19.43	
02:29:15.7	10	4			30	11	2	2:29:15.7	2	29.0	2.48	02:29:15.7	02:29:56.2	60.08	40.54	19.54	
02:30:15.7	10	4		N	30	11	2	2:30:15.7	2	30.0	2.50	02:30:15.7	02:30:56.2	60.00	40.46	19.54	
02:31:15.7	10	4			30	11	2	2:31:15.7	2	31.0	2.52	02:31:15.7	02:31:56.2	59.93	40.48	19.46	
02:32:15.7	10	4			30	11	2	2:32:15.7	2	32.0	2.53	02:32:15.7	02:32:56.2	60.02	40.49	19.54	
02:33:15.7	10	4			30	11	2	2:33:15.7	2	33.0	2.55	02:33:15.7	02:33:56.2	59.95	40.49	19.46	
02:34:15.7	10	4		N	30	11	2	2:34:15.7	2	34.0	2.57	02:34:15.7	02:34:56.1	60.02	40.49	19.54	
02:35:15.7	10	4			30	11	2	2:35:15.7	2	35.0	2.58	02:35:15.7	02:35:56.2	60.01	40.48	19.53	
02:36:15.7	10	4		N	30	11	2	2:36:15.7	2	36.0	2.60	02:36:15.7	02:36:56.2	60.03	40.48	19.54	
02:37:15.7	10	4			30	11	2	2:37:15.7	2	37.0	2.62	02:37:15.7	02:37:56.2	59.96	40.52	19.45	
02:38:15.7	10	4			30	11	2	2:38:15.7	2	38.0	2.63	02:38:15.7	02:38:56.2	59.96	40.55	19.42	
02:39:15.6	10	4			30	11	2	2:39:15.6	2	39.0	2.65	02:39:15.6	02:39:56.2	59.99	40.56	19.43	
02:40:15.6	10	4			30	11	2	2:40:15.6	2	40.0	2.67	02:40:15.6	02:40:56.2	60.08	40.54	19.54	
02:41:15.7	10	4		N	30	11	2	2:41:15.7	2	41.0	2.68	02:41:15.7	02:41:56.2	59.97	40.45	19.52	
02:42:15.7	10	4			30	11	2	2:42:15.7	2	42.0	2.70	02:42:15.7	02:42:56.2	59.98	40.55	19.43	
02:43:15.7	10	4			30	11	2	2:43:15.7	2	43.0	2.72	02:43:15.7	02:43:56.2	60.07	40.54	19.53	
02:44:15.7	10	4			30	11	2	2:44:15.7	2	44.0	2.73	02:44:15.7	02:44:56.2	59.97	40.45	19.52	
02:45:15.7	10	4			30	11	2	2:45:15.7	2	45.0	2.75	02:45:15.7	02:45:56.2	59.96	40.54	19.43	
02:46:15.7	10	4			30	11	2	2:46:15.7	2	46.0	2.77	02:46:15.7	02:46:56.2	60.07	40.55	19.52	
02:47:15.7	10	4			30	11	2	2:47:15.7	2	47.0	2.78	02:47:15.7	02:47:56.2	59.99	40.46	19.53	
02:48:15.7	10	4		N	30	11	2	2:48:15.7	2	48.0	2.80	02:48:15.7	02:48:56.3	59.97	40.56	19.42	
02:49:15.7	10	4			30	11	2	2:49:15.7	2	49.0	2.82	02:49:15.7	02:49:56.2	60.07	40.55	19.52	
02:50:15.8	10	4		N	30	11	2	2:50:15.8	2	50.0	2.83	02:50:15.8	02:50:56.2	59.98	40.45	19.52	
02:51:15.7	10	4		N	30	11	2	2:51:15.7	2	51.0	2.85	02:51:15.7	02:51:56.2	59.99	40.45	19.53	
02:52:15.7	10	4			30	11	2	2:52:15.7	2	52.0	2.87	02:52:15.7	02:52:56.3	59.97	40.55	19.42	
02:53:15.7	10	4			30	11	2	2:53:15.7	2	53.0	2.88	02:53:15.7	02:53:56.3	60.08	40.55	19.52	
02:54:15.8	10	4			30	11	2	2:54:15.8	2	54.0	2.90	02:54:15.8	02:54:56.2	59.96	40.44	19.52	
02:55:15.7	10	4			30	11	2	2:55:15.7	2	55.0	2.92	02:55:15.7	02:55:56.2	59.99	40.45	19.54	
02:56:15.7	10	4			30	11	2	2:56:15.7	2	56.0	2.93	02:56:15.7	02:56:56.2	59.99	40.47	19.52	
02:57:15.7	10	4		N	30	11	2	2:57:15.7	2	57.0	2.95	02:57:15.7	02:57:56.3	59.98	40.54	19.44	
02:58:15.7	10	4		N	30	11	2	2:58:15.7	2	58.0	2.97	02:58:15.7	02:58:56.2	60.06	40.54	19.52	
02:59:15.8	10	4			30	11	2	2:59:15.8	2	59.0	2.98	02:59:15.8	02:59:56.2	60.00	40.45	19.55	
03:00:15.8	10	4			30	11	2	3:00:15.8	3	0.0	3.00	03:00:15.8	03:00:56.2	59.97	40.45	19.52	
03:01:15.7	10	4			30	11	2	3:01:15.7	3	1.0	3.02	03:01:15.7	03:01:56.3	60.08	40.54	19.54	
03:02:15.8	10	4			30	11	2	3:02:15.8	3	2.0	3.03	03:02:15.8	03:02:56.3	59.99	40.46	19.53	
03:03:15.8	10	4			30	11	2	3:03:15.8	3	3.0	3.05	03:03:15.8	03:03:56.2	59.98	40.44	19.54	
03:04:15.8	10	4			30	11	2	3:04:15.8	3	4.0	3.07	03:04:15.8	03:04:56.3	60.07	40.55	19.52	
03:05:15.9	10	4		N	30	11	2	3:05:15.9	3	5.0	3.08	03:05:15.9	03:05:56.3	59.98	40.44	19.54	
03:06:15.8	10	4	missing - 2	N	30	11	2	3:06:15.8	3	6.0	3.10	03:06:15.8	03:06:56.3	179.98	40.46	139.52	missing - 2
03:09:15.8	10	4			30	11	2	3:09:15.8	3	9.0	3.15	03:09:15.8	03:09:56.4	59.98	40.55	19.43	
03:10:15.8	10	4			30	11	2	3:10:15.8	3	10.0	3.17	03:10:15.8	03:10:56.4	60.08	40.55	19.53	
03:11:15.9	10	4			30	11	2	3:11:15.9	3	11.0	3.18	03:11:15.9	03:11:56.3	59.99	40.46	19.53	
03:12:15.9	10	4			30	11	2	3:12:15.9	3	12.0	3.20	03:12:15.9	03:12:56.3	59.97	40.44	19.53	
03:13:15.8	10	4			30	11	2	3:13:15.8	3	13.0	3.22	03:13:15.8	03:13:56.4	60.07	40.55	19.53	
03:14:15.9	10	4			30	11	2	3:14:15.9	3	14.0	3.23	03:14:15.9	03:14:56.4	59.98	40.46	19.52	
03:15:15.9	10	4			30	11	2	3:15:15.9	3	15.0	3.25	03:15:15.9	03:15:56.3	59.95	40.43	19.52	
03:16:15.8	10	4			30	11	2	3:16:15.8	3	16.0	3.27	03:16:15.8	03:16:56.4	59.98	40.55	19.43	
03:17:15.8	10	4			30	11	2	3:17:15.8	3	17.0	3.28	03:17:15.8	03:17:56.4	59.97	40.54	19.43	
03:18:15.8	10	4			30	11	2	3:18:15.8	3	18.0	3.30	03:18:15.8	03:18:56.3	60.06	40.54	19.52	
03:19:15.8	10	4			30	11	2	3:19:15.8	3	19.0	3.32	03:19:15.8	03:19:56.3	60.00	40.47	19.53	
03:20:15.8	10	4			30	11	2	3:20:15.8	3	20.0	3.33	03:20:15.8	03:20:56.3	59.98	40.44	19.54	
03:21:15.8	10	4		N	30	11	2	3:21:15.8	3	21.0	3.35	03:21:15.8	03:21:56.3	59.97	40.44	19.53	
03:22:15.8	10	4			30	11	2	3:22:15.8	3	22.0	3.37	03:22:15.8	03:22:56.3	59.96	40.54	19.42	
03:23:15.8	10	4			30	11	2	3:23:15.8	3	23.0	3.38	03:23:15.8	03:23:56.3	59.99	40.55	19.44	
03:24:15.7	10	4	missing - 2	N	30	11	2	3:24:15.7	3	24.0	3.40	03:24:15.7	03:27:09.3	180.04	173.53	6.51	missing - 2
03:27:15.8	10	4			30	11	2	3:27:15.8	3	27.0	3.45	03:27:15.8	03:27:56.2	59.97	40.44	19.52	
03:28:15.8	10	4			30	11	2	3:28:15.8	3	28.0	3.47	03:28:15.8	03:28:56.3	59.96	40.54	19.42	
03:29:15.7	10	4			30	11	2	3:29:15.7	3	29.0	3.48	03:29:15.7	03:29:56.3	60.01	40.57	19.45	
03:30:15.7	10	4			30	11	2	3:30:15.7	3	30.0	3.50	03:30:15.7	03:30:56.3	60.00	40.55	19.45	
03:31:15.7	10	4			30	11	2	3:31:15.7	3	31.0	3.52	03:31:15.7	03:31:56.3	60.08	40.56	19.52	
03:32:15.8	10	4			30	11	2	3:32:15.8	3	32.0	3.53	03:32:15.8	03:32:56.3	59.98	40.46	19.52	

time	eventCode (81&82)	eventParam (5 - LT)	PrevRed	Cycle Length (from PrevRed)	Red Time in Cycle (sec)	Green Time in Cycle (sec)	tic	Posted Approach Speed (ft/sec)	Approx. Distance (pulse to stop bar)	Time - Pulse to Bar	Time Since Beginning of Red	Time Since Beginning of Green	Wait Time (LT)	Arrive on Red or Green	Depart on Red or Green	Departure Time after Red (sec) (May be eliminated or values over 5 secs)	Exclude Data point? (Depart after 5 secs)	Headway	Headway Significance?	New Cycle?	AOR Count	AOG Count	DOR Count	DOG Count	Freq. AOR by Cycle	Freq. AOG by Cycle	Freq. DOR by Cycle	Freq. DOG by Cycle	Max. Queue (cars)
00:02:14.9	82	5	00:01:15.5	59.98	40.46	19.52	59.43	45	0	0	FALSE	18.97		AOG						N		1			0	1	0	0	5
00:02:18.5	81	5	00:02:15.5	60.00	40.46	19.54	3.08	45	0	0	3.08	FALSE	00:03.6		DOR	3.1		#REF!	#REF!	N			1		0	2	1	2	5
00:02:59.3	82	5	00:02:15.5	60.00	40.46	19.54	43.80	45	0	0	FALSE	3.34		AOG								1							5
00:03:02.1	81	5	00:02:15.5	60.00	40.46	19.54	46.67	45	0	0	FALSE	6.21	00:02.9		DOG			00:00:43.6						1					5
00:03:02.5	82	5	00:02:15.5	60.00	40.46	19.54	47.01	45	0	0	FALSE	6.55		AOG								1							5
00:03:02.7	81	5	00:02:15.5	60.00	40.46	19.54	47.22	45	0	0	FALSE	6.76	00:00.2		DOG			00:00:00.6	yes					1					5
00:04:12.4	82	5	00:03:15.5	59.97	40.44	19.52	56.97	45	0	0	FALSE	16.53		AOG						N		1			0	1	0	1	5
00:04:12.8	81	5	00:03:15.5	59.97	40.44	19.52	57.38	45	0	0	FALSE	16.94	00:00.4		DOG			00:01:10.2						1					5
00:04:54.9	82	5	00:04:15.4	59.97	40.44	19.53	39.52	45	0	0	39.52	FALSE		AOR						N					0	1	0	1	5
00:04:55.8	81	5	00:04:15.4	59.97	40.44	19.53	40.34	45	0	0	40.34	FALSE	00:00.8		DOR	40.3	Exclude												5
00:04:59.7	82	5	00:04:15.4	59.97	40.45	19.52	44.27	45	0	0	FALSE	3.82		AOG								1							5
00:05:00.2	81	5	00:04:15.4	59.97	40.45	19.52	44.81	45	0	0	FALSE	4.36	00:00.5		DOG			00:00:04.5	yes					1					5
00:06:02.6	82	5	00:05:15.4	60.06	40.54	19.52	47.17	45	0	0	FALSE	6.63		AOG						N		1			0	3	0	3	5
00:06:05.2	81	5	00:05:15.4	60.06	40.54	19.52	49.79	45	0	0	FALSE	9.26	00:02.6		DOG			00:01:05.0						1					5
00:06:05.4	82	5	00:05:15.4	60.06	40.54	19.52	50.00	45	0	0	FALSE	9.46		AOG								1							5
00:06:07.3	81	5	00:05:15.4	60.06	40.54	19.52	51.86	45	0	0	FALSE	11.33	00:01.9		DOG			00:00:02.1	yes					1					5
00:06:07.8	82	5	00:05:15.4	60.06	40.54	19.52	52.44	45	0	0	FALSE	11.90		AOG								1							5
00:06:08.1	81	5	00:05:15.4	60.06	40.54	19.52	52.65	45	0	0	FALSE	12.11	00:00.2		DOG			00:00:00.8	yes					1					5
00:14:25.4	82	5	00:14:15.4	59.99	40.50	19.50	9.92	45	0	0	9.92	FALSE		AOR						N	1				1	0	0	1	5
00:14:58.7	81	5	00:14:15.4	59.99	40.45	19.54	43.29	45	0	0	FALSE	2.84	00:33.4		DOG			00:08:50.7						1					5
00:17:20.3	82	5	00:17:15.4	59.99	40.42	19.57	4.93	45	0	0	4.93	FALSE		AOR						N					0	0	0	0	5
00:17:20.8	81	5	00:17:15.4	59.99	40.42	19.57	5.40	45	0	0	5.40	FALSE	00:00.5		DOR	5.4	Exclude												5
00:18:36.9	82	5	00:18:15.4	60.00	40.45	19.55	21.55	45	0	0	21.55	FALSE		AOR						N					1	0	0	1	5
00:18:50.6	81	5	00:18:15.4	60.00	40.45	19.55	35.18	45	0	0	35.18	FALSE	00:13.6		DOR	35.2	Exclude												5
00:18:52.0	82	5	00:18:15.4	60.00	40.45	19.55	36.62	45	0	0	36.62	FALSE		AOR							1								5
00:19:02.2	81	5	00:18:15.4	60.00	40.47	19.53	46.82	45	0	0	FALSE	6.34	00:10.2		DOG			00:00:11.6						1					5
00:41:24.3	82	5	00:41:15.7	59.99	40.54	19.44	8.65	45	0	0	8.65	FALSE		AOR						N					0	0	0	0	5

Red or Green

~150 ft advance pulse Detector

30 mph ~ 45 ft/sec

Residual queue can't be known. Guessed from historical TMC and headway

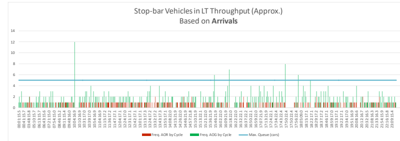
Ignore consecutive AOR/DOR and eliminate those data points (also, adjust configuration)

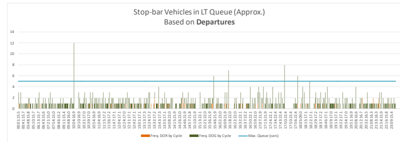
Steps

Bring in High res data for Event Code 81 and 82 & Parameter 2

If Channel 2 and 5 are brought together, the delete the other one

Needs work - are we aggregating by cycle length again?????





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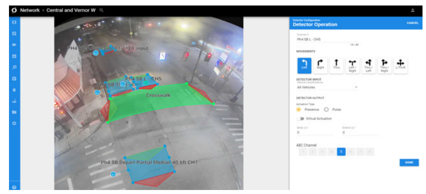
Data driver
Cross prodi

Sensitivity



time	eventCode (81&82)	eventParam (2 - Th+RT)	PrevRed	Cycle Length (from PrevRed)	Red Time in Cycle (sec)	Green Time in Cycle (sec)	tic	Posted Approach Speed (ft/sec)	Approx. Distance (pulse to stop bar)	Time - Pulse to Bar	Time Since Beginning of Red	Time Since Beginning of Green	Wait Time (RT or Th)	Arrive on Red or Green	Depart on Red or Green	Departure Time after Red (sec) (RTOR or RLR)	Assumed RTOR (Depart after 5 secs)	Headway	Headway Significance? (<5 secs)	New Cycle?	AOR Count	AOG Count	DOR Count	DOG Count	RTOR Depart (assumption)	Freq. AOR by Cycle	Freq. AOG by Cycle	Freq. DOR by Cycle	Freq. DOG by Cycle	Max. Queue (cars)
00:02:38.0	82	2	00:02:15.5	60.00	40.46	19.54	22.582	45	0	0	22.58	FALSE		AOR						N	1				2	2	2	2	2	5
00:02:41.7	81	2	00:02:15.5	60.00	40.46	19.54	26.235	45	0	0	26.23	FALSE	00:03.7		DOR	26.2	RTOR	#REF!	#REF!				1							5
00:02:42.5	82	2	00:02:15.5	60.00	40.46	19.54	27.002	45	0	0	27.00	FALSE		AOR							1									5
00:02:42.7	81	2	00:02:15.5	60.00	40.46	19.54	27.208	45	0	0	27.21	FALSE	00:00.2		DOR	27.2	RTOR	00:00:01.0	yes				1							5
00:03:02.1	82	2	00:02:15.5	60.00	40.46	19.54	46.672	45	0	0	FALSE	6.21		AOG								1								5
00:03:02.5	81	2	00:02:15.5	60.00	40.46	19.54	47.014	45	0	0	FALSE	6.55	00:00.3		DOG			00:00:19.8	yes					1						5
00:03:02.7	82	2	00:02:15.5	60.00	40.46	19.54	47.222	45	0	0	FALSE	6.76		AOG								1								5
00:03:03.0	81	2	00:02:15.5	60.00	40.46	19.54	47.53	45	0	0	FALSE	7.07	00:00.3		DOG			00:00:00.5	yes					1						5
00:04:12.8	82	2	00:03:15.5	59.97	40.44	19.52	57.382	45	0	0	FALSE	16.94		AOG						N		1			0	0	2	0	2	5
00:04:14.3	81	2	00:03:15.5	59.97	40.44	19.52	58.801	45	0	0	FALSE	18.36	00:01.4		DOG			00:01:11.3						1						5
00:04:14.8	82	2	00:03:15.5	59.97	40.44	19.52	59.331	45	0	0	FALSE	18.89		AOG								1								5
00:04:15.1	81	2	00:03:15.5	59.97	40.44	19.52	59.641	45	0	0	FALSE	19.20	00:00.3		DOG			00:00:00.8	yes					1						5
00:04:55.8	82	2	00:04:15.4	59.97	40.44	19.53	40.343	45	0	0	40.34	FALSE		AOR						N	1				0	1	4	0	5	5
00:04:58.3	81	2	00:04:15.4	59.97	40.45	19.52	42.895	45	0	0	FALSE	2.44	00:02.6		DOG			00:00:43.2						1						5
00:04:58.4	82	2	00:04:15.4	59.97	40.45	19.52	42.997	45	0	0	FALSE	2.54		AOG								1								5
00:04:58.5	81	2	00:04:15.4	59.97	40.45	19.52	43.1	45	0	0	FALSE	2.65	00:00.1		DOG			00:00:00.2	yes					1						5
00:04:58.7	82	2	00:04:15.4	59.97	40.45	19.52	43.305	45	0	0	FALSE	2.85		AOG								1								5
00:04:59.3	81	2	00:04:15.4	59.97	40.45	19.52	43.86	45	0	0	FALSE	3.41	00:00.6		DOG			00:00:00.8	yes					1						5
00:04:59.4	82	2	00:04:15.4	59.97	40.45	19.52	43.962	45	0	0	FALSE	3.51		AOG								1								5
00:04:59.5	81	2	00:04:15.4	59.97	40.45	19.52	44.064	45	0	0	FALSE	3.61	00:00.1		DOG			00:00:00.2	yes					1						5
00:05:00.2	82	2	00:04:15.4	59.97	40.45	19.52	44.814	45	0	0	FALSE	4.36		AOG								1								5
00:05:03.1	81	2	00:04:15.4	59.97	40.45	19.52	47.668	45	0	0	FALSE	7.22	00:02.9		DOG			00:00:03.6	yes					1						5
00:06:05.2	82	2	00:05:15.4	60.06	40.54	19.52	49.793	45	0	0	FALSE	9.26		AOG						N		1			0	0	4	0	4	5
00:06:05.4	81	2	00:05:15.4	60.06	40.54	19.52	49.999	45	0	0	FALSE	9.46	00:00.2		DOG			00:01:02.3						1						5
00:06:07.3	82	2	00:05:15.4	60.06	40.54	19.52	51.863	45	0	0	FALSE	11.33		AOG								1								5
00:06:07.8	81	2	00:05:15.4	60.06	40.54	19.52	52.436	45	0	0	FALSE	11.90	00:00.6		DOG			00:00:02.4	yes					1						5
00:06:08.1	82	2	00:05:15.4	60.06	40.54	19.52	52.649	45	0	0	FALSE	12.11		AOG								1								5
00:06:10.0	81	2	00:05:15.4	60.06	40.54	19.52	54.584	45	0	0	FALSE	14.05	00:01.9		DOG			00:00:02.1	yes					1						5

Red or Green

~150 ft advance pulse Detector

30 mph ~ 45 ft/sec

Residual queue can't be known. Guessed from historical TMC and headway

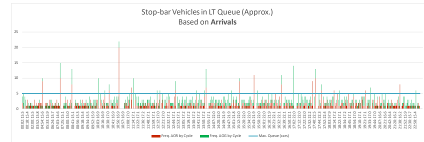
Ignore consecutive AOR/DOR and eliminate those data points (also, adjust configuration)

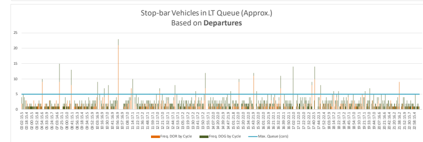
Steps

Bring in High res data for Event Code 81 and 82 & Parameter 2

If Channel 2 and 5 are brought together, the delete the other one

Needs work - are we aggregating by cycle length again?????





time	eventParam (7 - Advance)	eventCode (81 - Detector off)	time	eventParam (2 - Th+RT)	eventCode (81 - Detector off)	Match from Chan	Time difference	speed (ft/sec)	Speed (mi/hr)
15:59:10.2	7	81	16:00:10.1	2	81	#N/A	#N/A	0.0	0.0
16:00:02.7	7	81	16:00:15.0	2	81	#N/A	#N/A	0.0	0.0
16:00:11.3	7	81	16:01:07.3	2	81	16:00:10.1	00:00:01.2	42.2	28.7
16:00:17.5	7	81	16:01:15.7	2	81	16:00:15.0	00:00:02.4	20.6	14.0
16:00:32.7	7	81	16:02:09.9	2	81	16:00:15.0	00:00:17.6	2.8	1.9
16:00:35.1	7	81	16:02:22.8	2	81	16:00:15.0	00:00:20.1	2.5	1.7
16:00:42.8	7	81	16:03:14.5	2	81	16:00:15.0	00:00:27.8	1.8	1.2
16:01:10.3	7	81	16:03:18.4	2	81	16:01:07.3	00:00:03.0	16.8	11.5
16:01:13.4	7	81	16:04:00.1	2	81	16:01:07.3	00:00:06.1	8.2	5.6
16:01:15.9	7	81	16:04:06.5	2	81	16:01:15.7	00:00:00.2	243.9	166.3
16:01:56.7	7	81	16:04:08.3	2	81	16:01:15.7	00:00:41.1	1.2	0.8
16:02:19.9	7	81	16:04:29.7	2	81	16:02:09.9	00:00:10.0	5.0	3.4
16:02:24.7	7	81	16:04:51.8	2	81	16:02:22.8	00:00:01.9	25.7	17.5
16:02:37.2	7	81	16:05:13.2	2	81	16:02:22.8	00:00:14.4	3.5	2.4
16:02:43.2	7	81	16:06:10.6	2	81	16:02:22.8	00:00:20.4	2.4	1.7
16:03:10.8	7	81	16:06:37.5	2	81	16:02:22.8	00:00:48.0	1.0	0.7
16:03:13.7	7	81	16:07:04.8	2	81	16:02:22.8	00:00:50.9	1.0	0.7
16:03:16.3	7	81	16:07:22.1	2	81	16:03:14.5	00:00:01.8	27.5	18.7
16:03:24.7	7	81	16:08:16.5	2	81	16:03:18.4	00:00:06.3	7.9	5.4
16:03:30.5	7	81	16:08:22.1	2	81	16:03:18.4	00:00:12.1	4.1	2.8
16:04:01.7	7	81	16:08:36.3	2	81	16:04:00.1	00:00:01.6	30.9	21.1
16:04:11.0	7	81	16:09:21.2	2	81	16:04:08.3	00:00:02.7	18.8	12.8
16:05:09.4	7	81	16:10:16.8	2	81	16:04:51.8	00:00:17.7	2.8	1.9
16:05:12.3	7	81	16:10:21.5	2	81	16:04:51.8	00:00:20.5	2.4	1.7
16:05:15.9	7	81	16:10:22.3	2	81	16:05:13.2	00:00:02.7	18.6	12.7
16:05:47.4	7	81	16:10:26.6	2	81	16:05:13.2	00:00:34.2	1.5	1.0
16:05:55.6	7	81	16:11:10.9	2	81	16:05:13.2	00:00:42.4	1.2	0.8
16:06:54.9	7	81	16:11:14.3	2	81	16:06:37.5	00:00:17.4	2.9	2.0
16:07:23.9	7	81	16:11:16.9	2	81	16:07:22.1	00:00:01.8	27.5	18.8
16:07:30.1	7	81	16:12:12.0	2	81	16:07:22.1	00:00:07.9	6.3	4.3
16:07:54.2	7	81	16:12:16.8	2	81	16:07:22.1	00:00:32.1	1.6	1.1
16:08:23.9	7	81	16:14:13.0	2	81	16:08:22.1	00:00:01.8	27.5	18.8
16:09:17.5	7	81	16:14:38.3	2	81	16:08:36.3	00:00:41.2	1.2	0.8
16:09:24.1	7	81	16:15:18.5	2	81	16:09:21.2	00:00:03.0	16.8	11.5
16:09:34.0	7	81	16:15:22.4	2	81	16:09:21.2	00:00:12.9	3.9	2.6
16:10:18.6	7	81	16:16:06.6	2	81	16:10:16.8	00:00:01.8	27.2	18.5
16:10:33.5	7	81	16:16:54.9	2	81	16:10:26.6	00:00:06.9	7.2	4.9
16:11:09.6	7	81	16:17:15.2	2	81	16:10:26.6	00:00:43.0	1.2	0.8
16:11:16.7	7	81	16:17:22.8	2	81	16:11:14.3	00:00:02.4	20.8	14.2
16:11:18.7	7	81	16:17:27.3	2	81	16:11:16.9	00:00:01.8	27.2	18.6
16:11:31.4	7	81	16:17:58.0	2	81	16:11:16.9	00:00:14.5	3.5	2.4
16:11:35.0	7	81	16:18:06.8	2	81	16:11:16.9	00:00:18.1	2.8	1.9
16:12:09.8	7	81	16:18:12.3	2	81	16:11:16.9	00:00:52.9	0.9	0.6
16:12:11.7	7	81	16:19:21.9	2	81	16:11:16.9	00:00:54.8	0.9	0.6
16:12:14.5	7	81	16:19:27.4	2	81	16:12:12.0	00:00:02.5	19.8	13.5
16:12:18.7	7	81	16:20:17.7	2	81	16:12:16.8	00:00:01.9	26.3	18.0
16:13:51.3	7	81	16:20:22.1	2	81	16:12:16.8	00:01:34.5	0.5	0.4
16:14:13.7	7	81	16:21:19.9	2	81	16:14:13.0	00:00:00.8	66.1	45.1
16:14:31.4	7	81	16:21:23.3	2	81	16:14:13.0	00:00:18.5	2.7	1.8
16:15:09.8	7	81	16:22:10.6	2	81	16:14:38.3	00:00:31.5	1.6	1.1
16:15:12.1	7	81	16:22:15.1	2	81	16:14:38.3	00:00:33.8	1.5	1.0
16:15:14.0	7	81	16:22:18.9	2	81	16:14:38.3	00:00:35.7	1.4	1.0
16:15:17.2	7	81	16:23:10.6	2	81	16:14:38.3	00:00:39.0	1.3	0.9
16:15:51.0	7	81	16:23:16.3	2	81	16:15:22.4	00:00:28.6	1.7	1.2
16:16:09.5	7	81	16:23:37.6	2	81	16:16:06.6	00:00:02.8	17.6	12.0
16:17:14.2	7	81	16:23:37.8	2	81	16:16:54.9	00:00:19.3	2.6	1.8
16:17:17.3	7	81	16:23:38.5	2	81	16:17:15.2	00:00:02.0	24.8	16.9
16:17:25.5	7	81	16:23:41.3	2	81	16:17:22.8	00:00:02.7	18.4	12.5
16:17:34.3	7	81	16:24:06.2	2	81	16:17:27.3	00:00:07.0	7.2	4.9
16:17:41.1	7	81	16:24:55.3	2	81	16:17:27.3	00:00:13.8	3.6	2.5
16:17:57.5	7	81	16:25:00.7	2	81	16:17:27.3	00:00:30.2	1.7	1.1
16:18:00.2	7	81	16:25:06.4	2	81	16:17:58.0	00:00:02.2	22.2	15.2
16:18:10.3	7	81	16:25:51.9	2	81	16:18:06.8	00:00:03.6	14.0	9.5
16:18:14.6	7	81	16:25:52.9	2	81	16:18:12.3	00:00:02.3	21.6	14.7
16:18:35.9	7	81	16:27:25.5	2	81	16:18:12.3	00:00:23.6	2.1	1.4
16:18:38.4	7	81	16:28:22.7	2	81	16:18:12.3	00:00:26.2	1.9	1.3
16:18:59.1	7	81	16:30:16.6	2	81	16:18:12.3	00:00:46.8	1.1	0.7
16:19:09.9	7	81	16:31:12.3	2	81	16:18:12.3	00:00:57.7	0.9	0.6
16:19:13.9	7	81	16:31:18.8	2	81	16:18:12.3	00:01:01.6	0.8	0.6
16:19:21.9	7	81	16:31:22.4	2	81	16:19:21.9	00:00:00.0	0.0	0.0
16:19:24.5	7	81	16:31:43.0	2	81	16:19:21.9	00:00:02.6	19.2	13.1
16:19:36.0	7	81	16:33:07.0	2	81	16:19:27.4	00:00:08.5	5.9	4.0
16:19:38.6	7	81	16:33:29.1	2	81	16:19:27.4	00:00:11.2	4.5	3.0
16:20:10.3	7	81	16:33:30.1	2	81	16:19:27.4	00:00:42.8	1.2	0.8
16:20:17.4	7	81	16:33:53.4	2	81	16:19:27.4	00:00:49.9	1.0	0.7
16:20:36.1	7	81	16:34:17.9	2	81	16:20:22.1	00:00:14.0	3.6	2.4
16:20:56.2	7	81	16:35:08.3	2	81	16:20:22.1	00:00:34.2	1.5	1.0
16:20:59.4	7	81	16:36:14.1	2	81	16:20:22.1	00:00:37.3	1.3	0.9
16:21:14.7	7	81	16:36:20.5	2	81	16:20:22.1	00:00:52.6	1.0	0.6
16:21:15.9	7	81	16:37:16.9	2	81	16:20:22.1	00:00:53.9	0.9	0.6
16:21:19.2	7	81	16:37:42.1	2	81	16:20:22.1	00:00:57.2	0.9	0.6
16:22:08.4	7	81	16:37:45.7	2	81	16:21:23.3	00:00:45.1	1.1	0.8
16:22:11.4	7	81	16:37:48.2	2	81	16:22:10.6	00:00:00.8	65.9	44.9
16:22:14.8	7	81	16:37:48.8	2	81	16:22:10.6	00:00:04.2	11.9	8.1
16:22:17.1	7	81	16:37:53.1	2	81	16:22:15.1	00:00:02.0	25.3	17.2
16:22:21.0	7	81	16:37:55.4	2	81	16:22:18.9	00:00:02.1	23.8	16.2
16:22:57.4	7	81	16:37:57.0	2	81	16:22:18.9	00:00:38.5	1.3	0.9
16:23:13.7	7	81	16:38:06.0	2	81	16:23:10.6	00:00:03.1	16.3	11.1
16:23:31.1	7	81	16:38:06.9	2	81	16:23:16.3	00:00:14.9	3.4	2.3
16:23:43.3	7	81	16:38:14.3	2	81	16:23:41.3	00:00:02.0	25.1	17.1
16:24:12.3	7	81	16:38:21.6	2	81	16:24:06.2	00:00:06.1	8.2	5.6
16:24:14.8	7	81	16:39:11.7	2	81	16:24:06.2	00:00:08.5	5.9	4.0
16:24:36.9	7	81	16:39:14.7	2	81	16:24:06.2	00:00:30.7	1.6	1.1
16:24:37.8	7	81	16:40:17.5	2	81	16:24:06.2	00:00:31.6	1.6	1.1
16:24:40.3	7	81	16:40:22.0	2	81	16:24:06.2	00:00:34.1	1.5	1.0
16:25:09.2	7	81	16:40:45.3	2	81	16:25:06.4	00:00:02.8	17.7	12.1
16:25:31.4	7	81	16:41:22.3	2	81	16:25:06.4	00:00:25.0	2.0	1.4
16:25:35.2	7	81	16:41:51.1	2	81	16:25:06.4	00:00:28.8	1.7	1.2
16:25:49.2	7	81	16:42:11.5	2	81	16:25:06.4	00:00:42.8	1.2	0.8
16:26:37.2	7	81	16:42:12.1	2	81	16:25:52.9	00:00:44.3	1.1	0.8
16:27:12.4	7	81	16:42:17.1	2	81	16:25:52.9	00:01:19.5	0.6	0.4
16:27:15.2	7	81	16:43:15.2	2	81	16:25:52.9	00:01:22.3	0.6	0.4
16:27:20.4	7	81	16:43:50.6	2	81	16:25:52.9	00:01:27.4	0.6	0.4
16:27:31.9	7	81	16:44:12.8	2	81	16:27:25.5	00:00:06.4	7.8	5.3
16:27:36.4	7	81	16:44:16.8	2	81	16:27:25.5	00:00:10.9	4.6	3.1
16:28:10.7	7	81	16:46:29.5	2	81	16:27:25.5	00:00:45.2	1.1	0.8
16:28:22.6	7	81	16:47:07.4	2	81	16:27:25.5	00:00:57.1	0.9	0.6
16:28:31.0	7	81	16:47:11.4	2	81	16:28:22.7	00:00:08.3	6.0	4.1
16:28:34.7	7	81	16:48:05.8	2	81	16:28:22.7	00:00:12.0	4.2	2.8
16:28:47.9	7	81	16:48:16.2	2	81	16:28:22.7	00:00:25.1	2.0	1.4
16:28:59.8	7	81	16:49:21.9	2	81	16:28:22.7	00:00:37.0	1.4	0.9
16:29:31.6	7	81	16:49:27.5	2	81	16:28:22.7	00:01:08.9	0.7	0.5
16:29:34.0	7	81	16:50:13.7	2	81	16:28:22.7	00:01:11.3	0.7	0.5
16:30:10.7	7	81	16:50:21.8	2	81	16:28:22.7	00:01:48.0	0.5	0.3
16:30:19.5	7	81	16:50:50.8	2	81	16:30:16.6	00:00:02.9	17.3	11.8
16:31:12.2	7	81	16:51:12.3	2	81	16:30:16.6	00:00:55.6	0.9	0.6
16:31:20.6	7	81	16:52:17.8	2	81	16:31:18.8	00:00:01.7	28.6	19.5
16:34:20.1	7	81	16:53:10.3	2	81	16:34:17.9	00:00:02.2	22.8	15.5
16:35:11.2	7	81	16:53:17.0	2	81	16:35:08.3	00:00:02.9	17.5	11.9
16:35:58.8	7	81	16:53:20.8	2	81	16:35:08.3	00:00:50.5	1.0	0.7
16:36:08.4	7	81	16:53:51.5	2	81	16:35:08.3	00:01:00.1	0.8	0.6
16:36:17.6	7	81	16:54:08.7	2	81	16:36:14.1	00:00:03.5	14.2	9.7
16:36:22.3	7	81	16:55:07.0	2	81	16:36:20.5	00:00:01.8	27.3	18.6
16:37:14.3	7	81	16:56:07.1	2	81	16:36:20.5	00:00:53.8	0.9	0.6
16:37:16.6	7	81	16:56:17.6	2	81	16:36:20.5	00:00:56.2	0.9	0.6
16:37:19.0	7	81	16:57:15.1	2	81	16:37:16.9	00:00:02.1	24.3	16.6
16:38:13.9	7	81	16:57:18.7	2	81	16:38:06.9	00:00:06.9	7.2	4.9
16:38:37.7	7	81	16:57:21.4	2	81	16:38:21.6	00:00:16.1	3.1	2.1
16:38:46.9	7	81	16:58:17.8	2	81	16:38:21.6	00:00:25.4	2.0	1.3
16:39:09.9	7	81	16:58:20.6	2	81	16:38:21.6	00:00:48.3	1.0	0.7
16:39:13.2	7	81	16:59:18.6	2	81	16:39:11.7	00:00:01.4	35.0	23.9
16:39:16.5	7	81				16:39:14.7	00:00:01.9	26.8	18.3
16:39:57.1	7	81				16:39:14.7	00:00:42.5	1.2	0.8
16:40:10.2	7	81				16:39:14.7	00:00:55.5	0.9	0.6

Distance b **50**

s=d/t

20.64 ft/sec

14.0727 mph

Make sure the Signal is green when then moved (Eliminatirn RTOR)

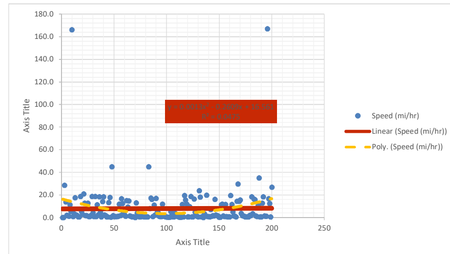
Maybe: Speed measurement with differnet ways (validation) - but th

Can we add this to the calc for approximate speed?

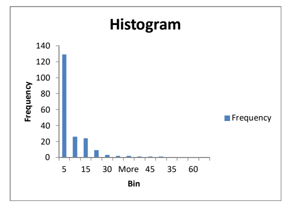
Can the TMc be used to eliminate RTOR movement?

Has to be speed when Signal is Green - for find beginning of Red and only account for through movement in that cycle

5
10
15
20
25
30
35
40
45
50
55
60
65



Bin	*Frequency*	*Bin*	*Frequency*
5	129	5	129
10	9	20	26
15	24	15	24
20	26	10	9
25	2	30	3
30	3	25	2
35	0	More	2
40	1	40	1
45	1	45	1
50	1	50	1
55	0	35	0
60	0	55	0
65	0	60	0
More	2	65	0



datetime_bin	entry_dir_name	exit_dir_name	classification	confidence	laneID	time	movement	volume	Through	Right	Left	Total	Ped	PrevRed	Cycle Length (from PrevRed)	Red Time in Cycle (sec)	Green Time in Cycle (sec)	TIC (Red Time)	Estimated Speed for Movement (ft/sec)	Approx. Distance (pulse to stop bar)	Time - Bar to mid-point	Time Since Beginning of Red	Time Since Beginning of Green	Crossing on Red or Green	New Cycle?	COR Right Count	COG Right Count	COR Thru Count	COG Thru Count	COR Left Count	COG Left Count	COR Ped Count	COG Ped Count	Freq. COR (Right) by Cycle	Freq. COG (Right) by Cycle	Freq. COR (thru) by Cycle	Freq. COG (Thru) by Cycle	Freq. COR (Left) by Cycle	Freq. COG (Left) by Cycle	Freq. COR (Ped) by Cycle	Freq. COG (Ped) by Cycle	Count by Vehicle Class - Car	Count by Vehicle Class - Heavy Combined	Vehicle Class - Articulated truck	Vehicle Class - Truck	Vehicle Class - Bus	Count by Vehicle Class - Pedestrian
2020-11-30 00:02:19.000-05:00	N	E	Light			00:02:19.0	left	1			1	1		00:02:15.5	60.00	40.46	19.54	3.54	22	37	1.681818	3.54	FALSE	COR	N					1				1	0	0	1	1	0	0	0	3.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:02:42.000-05:00	N	W	Light			00:02:42.0	right	1		1		1		00:02:15.5	60.00	40.46	19.54	26.54	22	23	1.045455	26.54	FALSE	COR		1																					
2020-11-30 00:03:04.000-05:00	N	S	Light			00:03:04.0	thru	1	1			1		00:02:15.5	60.00	40.45	19.54	48.54	44	37	0.840909	FALSE	8.08	COG					1																		
2020-11-30 00:04:14.000-05:00	N	W	Light			00:04:14.0	right	1		1		1		00:03:15.5	59.97	40.44	19.52	58.54	22	23	1.045455	FALSE	18.10	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:05:00.000-05:00	N	W	Light			00:05:00.0	right	1		1		1		00:04:15.4	59.97	40.45	19.52	44.57	22	23	1.045455	FALSE	4.12	COG	N		1							0	1	0	1	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:05:03.000-05:00	N	S	Light			00:05:03.0	thru	1	1			1		00:04:15.4	59.97	40.45	19.52	47.57	44	37	0.840909	FALSE	7.12	COG					1																		
2020-11-30 00:06:07.000-05:00	N	W	Light			00:06:07.0	right	1		1		1		00:05:15.4	60.06	40.54	19.52	51.60	22	23	1.045455	FALSE	11.06	COG	N		1							0	2	0	0	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:06:11.000-05:00	N	W	Light			00:06:11.0	right	1		1		1		00:05:15.4	60.06	40.54	19.52	55.60	22	23	1.045455	FALSE	15.06	COG			1																				
2020-11-30 00:07:34.000-05:00	N	W	Light			00:07:34.0	right	1		1		1		00:07:15.4	59.96	40.45	19.51	18.56	22	23	1.045455	18.56	FALSE	COR	N	1								1	1	0	1	0	0	0	0	3.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:08:11.000-05:00	N	W	Light			00:08:11.0	right	1		1		1		00:07:15.4	59.96	40.44	19.53	55.56	22	23	1.045455	FALSE	15.12	COG			1																				
2020-11-30 00:08:13.000-05:00	N	S	Light			00:08:13.0	thru	1	1			1		00:07:15.4	59.96	40.44	19.53	57.56	44	37	0.840909	FALSE	17.12	COG					1																		
2020-11-30 00:15:00.000-05:00	N	E	Light			00:15:00.0	left	1			1	1		00:14:15.4	59.99	40.45	19.54	44.56	22	37	1.681818	FALSE	4.11	COG	N						1			0	0	0	1	0	1	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:15:03.000-05:00	N	S	Light			00:15:03.0	thru	1	1			1		00:14:15.4	59.99	40.45	19.54	47.56	44	37	0.840909	FALSE	7.11	COG					1																		
2020-11-30 00:18:02.000-05:00	N	W	Light			00:18:02.0	right	1		1		1		00:17:15.4	59.99	40.45	19.53	46.61	22	23	1.045455	FALSE	6.16	COG	N		1							0	2	0	0	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:18:07.000-05:00	N	W	Light			00:18:07.0	right	1		1		1		00:17:15.4	59.99	40.45	19.53	51.61	22	23	1.045455	FALSE	11.16	COG			1																				
2020-11-30 00:18:27.000-05:00	N	W	Light			00:18:27.0	right	1		1		1		00:18:15.4	60.00	40.45	19.55	11.62	22	23	1.045455	11.62	FALSE	COR	N	1								2	0	0	0	0	1	0	0	3.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:18:48.000-05:00	N	W	Light			00:18:48.0	right	1		1		1		00:18:15.4	60.00	40.45	19.55	32.62	22	23	1.045455	32.62	FALSE	COR		1																					
2020-11-30 00:19:02.000-05:00	N	E	Light			00:19:02.0	left	1			1	1		00:18:15.4	60.00	40.47	19.53	46.62	22	37	1.681818	FALSE	6.15	COG							1																
2020-11-30 00:23:16.000-05:00	N	S	Light			00:23:16.0	thru	1	1			1		00:23:15.5	60.00	40.46	19.54	0.51	44	37	0.840909	0.51	FALSE	COR	N			1						0	0	1	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:24:45.000-05:00	N	W	Light			00:24:45.0	right	1		1		1		00:23:15.5	60.00	40.46	19.54	29.51	22	23	1.045455	29.51	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:32:40.000-05:00	N	N	Pedestrian			00:32:40.0	CCW	1				0	1	00:32:15.6	60.01	40.56	19.45	24.39			0	24.39	FALSE	COR	N							0		0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	1.00
2020-11-30 00:33:06.000-05:00	N	S	Light			00:33:06.0	thru	1	1			1		00:32:15.6	60.01	40.47	19.54	50.39	44	37	0.840909	FALSE	9.92	COG					1																		
2020-11-30 00:35:02.000-05:00	N	S	Light			00:35:02.0	thru	1	1			1		00:34:15.6	59.98	40.46	19.52	46.39	44	37	0.840909	FALSE	5.93	COG	N				1					0	1	0	1	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:35:13.000-05:00	N	W	Light			00:35:13.0	right	1		1		1		00:34:15.6	59.98	40.46	19.52	57.39	22	23	1.045455	FALSE	16.93	COG			1																				
2020-11-30 00:40:15.000-05:00	N	S	Light			00:40:15.0	thru	1	1			1		00:39:15.6	59.99	40.56	19.43	59.40	44	37	0.840909	FALSE	18.85	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:41:01.000-05:00	N	W	Light			00:41:01.0	right	1		1		1		00:40:15.6	60.08	40.54	19.54	45.42	22	23	1.045455	FALSE	4.88	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:41:28.000-05:00	N	W	Light			00:41:28.0	right	1		1		1		00:41:15.7	59.99	40.54	19.44	12.34	22	23	1.045455	12.34	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:48:04.000-05:00	N	E	Light			00:48:04.0	left	1			1	1		00:47:15.6	59.98	40.45	19.53	48.35	22	37	1.681818	FALSE	7.90	COG	N						1			0	0	0	0	0	1	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:50:03.000-05:00	N	W	Light			00:50:03.0	right	1		1		1		00:49:15.6	59.96	40.55	19.42	47.43	22	23	1.045455	FALSE	6.88	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 00:52:33.000-05:00	N	N	Pedestrian			00:52:33.0	CCW	1				0	1	00:52:15.6	59.96	40.46	19.50	17.38			0	17.38	FALSE	COR	N							0		0	0	0	0	0	0	0	0	0.00	0.00	0.00	0.00	0.00	1.00
2020-11-30 01:00:01.000-05:00	N	S	Light			01:00:01.0	thru	1	1			1		00:59:15.6	60.00	40.46	19.54	45.35	44	37	0.840909	FALSE	4.89	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:02:12.000-05:00	N	W	Light			01:02:12.0	right	1		1		1		01:01:15.6	60.06	40.54	19.52	56.37	22	23	1.045455	FALSE	15.84	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:03:56.000-05:00	N	W	Light			01:03:56.0	right	1		1		1		01:03:15.7	59.99	40.45	19.54	40.34	22	23	1.045455	40.34	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:05:24.000-05:00	N	W	Light			01:05:24.0	right	1		1		1		01:05:15.6	60.00	40.56	19.44	8.37	22	23	1.045455	8.37	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:12:01.000-05:00	N	S	Light			01:12:01.0	thru	1	1			1		01:11:15.7	60.06	40.53	19.53	45.34	44	37	0.840909	FALSE	4.81	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:13:02.000-05:00	N	S	Light			01:13:02.0	thru	1	1			1		01:12:15.7	60.03	40.45	19.54	46.28	44	37	0.840909	FALSE	5.83	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:14:02.000-05:00	N	S	Light			01:14:02.0	thru	1	1			1		01:13:15.7	59.95	40.42	19.52	46.29	44	37	0.840909	FALSE	5.87	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:16:05.000-05:00	N	S	Light			01:16:05.0	thru	1	1			1		01:15:15.7	59.98	40.56	19.42	49.32	44	37	0.840909	FALSE	8.76	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:18:07.000-05:00	N	S	Light			01:18:07.0	thru	1	1			1		01:17:15.7	60.01	40.49	19.52	51.27	44	37	0.840909	FALSE	10.78	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:19:12.000-05:00	N	W	Light			01:19:12.0	right	1		1		1		01:18:15.7	59.97	40.45	19.53	56.26	22	23	1.045455	FALSE	15.82	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:20:02.000-05:00	N	S	Light			01:20:02.0	thru	1	1			1		01:19:15.7	60.00	40.46	19.54	46.29	44	37	0.840909	FALSE	5.83	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:31:01.000-05:00	N	E	Light			01:31:01.0	left	1			1	1		01:30:15.7	59.97	40.45	19.52	45.27	22	37	1.681818	FALSE	4.82	COG	N						1			0	0	0	0	0	1	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:43:02.000-05:00	N	W	Light			01:43:02.0	right	1		1		1		01:42:15.6	60.05	40.54	19.52	46.40	22	23	1.045455	FALSE	5.87	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:46:04.000-05:00	N	S	Light			01:46:04.0	thru	1	1			1		01:45:15.6	59.98	40.45	19.53	48.38	44	37	0.840909	FALSE	7.93	COG	N				1					0	0	0	2	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:46:14.000-05:00	N	S	Light			01:46:14.0	thru	1	1			1		01:45:15.6	59.98	40.45	19.53	58.38	44	37	0.840909	FALSE	17.93	COG					1																		
2020-11-30 01:51:02.000-05:00	N	E	Light			01:51:02.0	left	1			1	1		01:50:15.6	59.98	40.46	19.53	46.44	22	37	1.681818	FALSE	5.98	COG	N						1			0	0	0	0	0	1	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 01:55:12.000-05:00	N	W	Light			01:55:12.0	right	1		1		1		01:54:15.5	180.06	40.55	139.51	56.53	22	23	1.045455	FALSE	15.97	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:01:03.000-05:00	N	S	Light			02:01:03.0	thru	1	1			1		02:00:15.5	59.99	40.47	19.52	47.50	44	37	0.840909	FALSE	7.03	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:06:02.000-05:00	N	S	Light			02:06:02.0	thru	1	1			1		02:05:15.6	59.98	40.46	19.52	46.42	44	37	0.840909	FALSE	5.96	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:27:12.000-05:00	N	S	Light			02:27:12.0	thru	1	1			1		02:26:15.7	60.00	40.46	19.53	56.31	44	37	0.840909	FALSE	15.84	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:27:28.000-05:00	N	W	Light			02:27:28.0	right	1		1		1		02:27:15.7	59.99	40.46	19.53	12.31	22	23	1.045455	12.31	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:35:02.000-05:00	N	S	Light			02:35:02.0	thru	1	1			1		02:34:15.7	60.02	40.49	19.54	46.35	44	37	0.840909	FALSE	5.86	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:37:02.000-05:00	N	S	Light			02:37:02.0	thru	1	1			1		02:36:15.7	60.03	40.48	19.54	46.32	44	37	0.840909	FALSE	5.83	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:42:04.000-05:00	N	E	Light			02:42:04.0	left	1			1	1		02:41:15.7	59.97	40.45	19.52	48.29	22	37	1.681818	FALSE	7.84	COG	N						1			0	0	0	0	0	1	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:51:02.000-05:00	N	S	Light			02:51:02.0	thru	1	1			1		02:50:15.8	59.98	40.46	19.52	46.24	44	37	0.840909	FALSE	5.79	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:52:01.000-05:00	N	S	Light			02:52:01.0	thru	1	1			1		02:51:15.8	59.99	40.45	19.53	45.26	44	37	0.840909	FALSE	4.81	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:58:07.000-05:00	N	S	Light			02:58:07.0	thru	1	1			1		02:57:15.8	59.98	40.54	19.44	51.28	44	37	0.840909	FALSE	10.74	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 02:58:45.000-05:00	N	W	Light			02:58:45.0	right	1		1		1		02:58:15.7	60.06	40.54	19.52	29.30	22	23	1.045455	29.30	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:06:42.000-05:00	N	E	Light			03:06:42.0	left	1			1	1		03:06:15.8	179.98	40.44	139.54	26.16	22	37	1.681818	26.16	FALSE	COR	N					1				0	0	0	0	1	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:22:01.000-05:00	N	S	Light			03:22:01.0	thru	1	1			1		03:21:15.8	59.97	40.44	19.53	45.18	44	37	0.840909	FALSE	4.74	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:25:07.000-05:00	N	S	Light			03:25:07.0	thru	1	1			1		03:24:15.7	180.04	40.57	139.48	51.26	44	37	0.840909	FALSE	10.69	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:37:12.000-05:00	N	W	Light			03:37:12.0	right	1		1		1		03:36:15.8	60.00	40.47	19.53	56.22	22	23	1.045455	FALSE	15.74	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:41:03.000-05:00	N	S	Light			03:41:03.0	thru	1	1			1		03:40:15.8	59.99	40.56	19.43	47.21	44	37	0.840909	FALSE	6.65	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:43:01.000-05:00	N	S	Light			03:43:01.0	thru	1	1			1		03:42:15.9	59.90	40.48	19.43	45.13	44	37	0.840909	FALSE	4.66	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:47:01.000-05:00	N	S	Light			03:47:01.0	thru	1	1			1		03:46:15.8	59.97	40.45	19.52	45.17	44	37	0.840909	FALSE	4.72	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:49:02.000-05:00	N	E	Light			03:49:02.0	left	1			1	1		03:48:15.8	59.98	40.56	19.42	46.21	22	37	1.681818	FALSE	5.65	COG	N						1			0	0	0	0	0	1	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:51:16.000-05:00	N	S	Light			03:51:16.0	thru	1	1			1		03:51:15.8	60.02	40.46	19.56	0.22	44	37	0.840909	0.22	FALSE	COR	N			1						0	0	1	0	0	1	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:52:02.000-05:00	N	E	Light			03:52:02.0	left	1			1	1		03:51:15.8	60.02	40.49	19.52	46.22	22	37	1.681818	FALSE	5.73	COG							1																
2020-11-30 03:53:01.000-05:00	N	S	Light			03:53:01.0	thru	1	1			1		03:52:15.8	59.98	40.45	19.53	45.21	44	37	0.840909	FALSE	4.76	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:55:00.000-05:00	N	W	Light			03:55:00.0	right	1		1		1		03:54:15.8	59.98	40.46	19.53	44.24	22	23	1.045455	FALSE	3.79	COG	N		1							0	1	0	1	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 03:55:02.000-05:00	N	S	Light			03:55:02.0	thru	1	1			1		03:54:15.8	59.98	40.45	19.53	46.24	44	37	0.840909	FALSE	5.79	COG					1																		
2020-11-30 03:59:41.000-05:00	N	W	Light			03:59:41.0	right	1		1		1		03:59:15.7	59.99	40.45	19.55	25.27	22	23	1.045455	25.27	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:06:03.000-05:00	N	S	Light			04:06:03.0	thru	1	1			1		04:05:15.8	60.00	40.47	19.53	47.23	44	37	0.840909	FALSE	6.76	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:08:01.000-05:00	N	W	Light			04:08:01.0	right	1		1		1		04:07:15.8	59.98	40.45	19.53	45.25	22	23	1.045455	FALSE	4.80	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:11:52.000-05:00	N	W	Light			04:11:52.0	right	1		1		1		04:11:15.8	60.00	40.55	19.45	36.24	22	23	1.045455	36.24	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:21:43.000-05:00	N	W	Light			04:21:43.0	right	1		1		1		04:21:15.7	59.97	40.45	19.52	27.35	22	23	1.045455	27.35	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:23:38.000-05:00	N	W	Light			04:23:38.0	right	1		1		1		04:23:15.7	59.95	40.55	19.40	22.31	22	23	1.045455	22.31	FALSE	COR	N	1								2	0	0	0	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:23:41.000-05:00	N	W	Light			04:23:41.0	right	1		1		1		04:23:15.7	59.95	40.55	19.40	25.31	22	23	1.045455	25.31	FALSE	COR		1																					
2020-11-30 04:28:04.000-05:00	N	E	Light			04:28:04.0	left	1			1	1		04:27:15.7	59.96	40.44	19.52	48.32	22	37	1.681818	FALSE	7.88	COG	N						1			0	0	0	0	0	1	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:32:05.000-05:00	N	E	Light			04:32:05.0	left	1			1	1		04:31:15.7	59.99	40.47	19.52	49.30	22	37	1.681818	FALSE	8.83	COG	N						1			0	1	0	0	0	1	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:32:07.000-05:00	N	W	Light			04:32:07.0	right	1		1		1		04:31:15.7	59.99	40.47	19.52	51.30	22	23	1.045455	FALSE	10.83	COG			1																				
2020-11-30 04:39:01.000-05:00	N	W	Light			04:39:01.0	right	1		1		1		04:38:15.7	59.97	40.45	19.53	45.32	22	23	1.045455	FALSE	4.87	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:43:01.000-05:00	N	S	Light			04:43:01.0	thru	1	1			1		04:42:15.6	59.98	40.55	19.43	45.37	44	37	0.840909	FALSE	4.83	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:44:56.000-05:00	N	W	Light			04:44:56.0	right	1		1		1		04:44:15.6	60.09	40.55	19.54	40.42	22	23	1.045455	40.42	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:46:05.000-05:00	N	W	Light			04:46:05.0	right	1		1		1		04:45:15.7	59.98	40.44	19.54	49.32	22	23	1.045455	FALSE	8.88	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:49:30.000-05:00	N	W	Light			04:49:30.0	right	1		1		1		04:49:15.7	59.99	40.55	19.44	14.34	22	23	1.045455	14.34	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:52:53.000-05:00	N	W	Light			04:52:53.0	right	1		1		1		04:52:15.6	60.07	40.54	19.53	37.41	22	23	1.045455	37.41	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:55:10.000-05:00	N	W	Light			04:55:10.0	right	1		1		1		04:54:15.6	60.00	40.46	19.54	54.38	22	23	1.045455	FALSE	13.92	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 04:56:02.000-05:00	N	S	Light			04:56:02.0	thru	1	1			1		04:55:15.6	59.98	40.45	19.52	46.38	44	37	0.840909	FALSE	5.93	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:00:01.000-05:00	N	E	Light			05:00:01.0	left	1			1	1		04:59:15.7	59.97	40.46	19.52	45.35	22	37	1.681818	FALSE	4.89	COG	N						1			0	0	0	0	0	1	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:02:44.000-05:00	N	W	Light			05:02:44.0	right	1		1		1		05:02:15.7	59.98	40.54	19.43	28.31	22	23	1.045455	28.31	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:04:09.000-05:00	N	W	Light			05:04:09.0	right	1		1		1		05:03:15.7	60.00	40.48	19.52	53.34	22	23	1.045455	FALSE	12.85	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:06:03.000-05:00	N	W	Light			05:06:03.0	right	1		1		1		05:05:15.6	60.05	40.54	19.51	47.36	22	23	1.045455	FALSE	6.82	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:10:31.000-05:00	N	E	Light			05:10:31.0	left	1			1	1		05:10:15.7	59.98	40.45	19.52	15.30	22	37	1.681818	15.30	FALSE	COR	N					1				0	0	0	0	1	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:12:01.000-05:00	N	W	Light			05:12:01.0	right	1		1		1		05:11:15.7	60.07	40.55	19.52	45.32	22	23	1.045455	FALSE	4.77	COG	N		1							0	2	0	0	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:12:02.000-05:00	N	W	Light			05:12:02.0	right	1		1		1		05:11:15.7	60.07	40.55	19.52	46.32	22	23	1.045455	FALSE	5.77	COG			1																				
2020-11-30 05:14:42.000-05:00	N	W	Light			05:14:42.0	right	1		1		1		05:14:15.7	60.11	40.55	19.56	26.30	22	23	1.045455	26.30	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:19:13.000-05:00	N	S	Light			05:19:13.0	thru	1	1			1		05:18:15.8	60.00	40.48	19.52	57.16	44	37	0.840909	FALSE	16.68	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:22:35.000-05:00	N	W	Light			05:22:35.0	right	1		1		1		05:22:15.8	60.07	40.54	19.53	19.15	22	23	1.045455	19.15	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:23:48.000-05:00	N	W	Light			05:23:48.0	right	1		1		1		05:23:15.9	59.97	40.55	19.42	32.08	22	23	1.045455	32.08	FALSE	COR	N	1								1	0	0	1	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:24:01.000-05:00	N	S	Light			05:24:01.0	thru	1	1			1		05:23:15.9	59.97	40.45	19.52	45.08	44	37	0.840909	FALSE	4.63	COG					1																		
2020-11-30 05:25:56.000-05:00	N	W	Light			05:25:56.0	right	1		1		1		05:25:16.0	60.00	40.56	19.44	40.03	22	23	1.045455	40.03	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:27:04.000-05:00	N	E	Light			05:27:04.0	left	1			1	1		05:26:16.0	59.99	40.46	19.54	48.03	22	37	1.681818	FALSE	7.57	COG	N						1			0	0	0	0	0	2	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:27:07.000-05:00	N	E	Light			05:27:07.0	left	1			1	1		05:26:16.0	59.99	40.46	19.54	51.03	22	37	1.681818	FALSE	10.57	COG							1																
2020-11-30 05:28:30.000-05:00	N	W	Light			05:28:30.0	right	1		1		1		05:28:15.9	59.97	40.45	19.52	14.06	22	23	1.045455	14.06	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:34:01.000-05:00	N	S	Light			05:34:01.0	thru	1	1			1		05:33:15.9	154.71	40.55	114.16	45.07	44	37	0.840909	FALSE	4.52	COG	N				1					0	1	0	2	0	1	0	0	4.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:35:01.000-05:00	N	W	Light			05:35:01.0	right	1		1		1		05:33:15.9	154.71	40.55	114.16	105.07	22	23	1.045455	FALSE	64.52	COG			1																				
2020-11-30 05:35:04.000-05:00	N	S	Light			05:35:04.0	thru	1	1			1		05:33:15.9	154.71	40.55	114.16	108.07	44	37	0.840909	FALSE	67.52	COG					1																		
2020-11-30 05:35:05.000-05:00	N	E	Light			05:35:05.0	left	1			1	1		05:33:15.9	154.71	40.55	114.16	109.07	22	37	1.681818	FALSE	68.52	COG							1																
2020-11-30 05:35:59.000-05:00	N	W	Light			05:35:59.0	right	1		1		1		05:35:50.6	25.33	5.81	19.52	8.36	22	23	1.045455	FALSE	2.55	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:42:54.000-05:00	N	W	Light			05:42:54.0	right	1		1		1		05:42:15.8	59.90	40.46	19.45	38.16	22	23	1.045455	38.16	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:47:05.000-05:00	N	W	Light			05:47:05.0	right	1		1		1		05:46:15.7	59.96	40.45	19.52	49.30	22	23	1.045455	FALSE	8.85	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:48:18.000-05:00	N	W	Light			05:48:18.0	right	1		1		1		05:48:15.6	59.97	40.45	19.52	2.35	22	23	1.045455	2.35	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:56:03.000-05:00	N	S	Light			05:56:03.0	thru	1	1			1		05:55:15.5	59.97	40.54	19.43	47.48	44	37	0.840909	FALSE	6.94	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:58:05.000-05:00	N	W	Light			05:58:05.0	right	1		1		1		05:57:15.6	59.98	40.44	19.54	49.43	22	23	1.045455	FALSE	8.99	COG	N		1							0	1	0	0	0	1	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 05:58:15.000-05:00	N	E	Light			05:58:15.0	left	1			1	1		05:57:15.6	59.98	40.44	19.54	59.43	22	37	1.681818	FALSE	18.99	COG							1																
2020-11-30 05:59:37.000-05:00	N	W	Light			05:59:37.0	right	1		1		1		05:59:15.5	59.98	40.47	19.51	21.45	22	23	1.045455	21.45	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:02:06.000-05:00	N	S	Light			06:02:06.0	thru	1	1			1		06:01:15.6	60.00	40.56	19.44	50.39	44	37	0.840909	FALSE	9.83	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:03:53.000-05:00	N	W	Light			06:03:53.0	right	1		1		1		06:03:15.7	60.07	40.55	19.52	37.32	22	23	1.045455	37.32	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:08:08.000-05:00	N	W	Light			06:08:08.0	right	1		1		1		06:07:15.8	59.99	40.46	19.53	52.22	22	23	1.045455	FALSE	11.75	COG	N		1							0	2	0	0	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:08:09.000-05:00	N	W	Light			06:08:09.0	right	1		1		1		06:07:15.8	59.99	40.46	19.53	53.22	22	23	1.045455	FALSE	12.75	COG			1																				
2020-11-30 06:11:59.000-05:00	N	S	Light			06:11:59.0	thru	1	1			1		06:11:15.7	60.06	40.54	19.52	43.29	44	37	0.840909	FALSE	2.76	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:14:02.000-05:00	N	E	Light			06:14:02.0	left	1			1	1		06:13:15.7	59.99	40.46	19.52	46.26	22	37	1.681818	FALSE	5.79	COG	N						1			0	0	0	0	0	1	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:15:08.000-05:00	N	W	Light			06:15:08.0	right	1		1		1		06:14:15.7	59.97	40.54	19.43	52.27	22	23	1.045455	FALSE	11.73	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:16:17.000-05:00	N	S	Light			06:16:17.0	thru	1	1			1		06:16:15.8	59.97	40.54	19.43	1.21	44	37	0.840909	1.21	FALSE	COR	N			1						0	0	1	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:24:02.000-05:00	N	S	Light			06:24:02.0	thru	1	1			1		06:23:15.7	59.98	40.46	19.52	46.27	44	37	0.840909	FALSE	5.81	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:24:56.000-05:00	N	W	Light			06:24:56.0	right	1		1		1		06:24:15.7	60.00	40.46	19.54	40.29	22	23	1.045455	40.29	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:30:03.000-05:00	N	S	Light			06:30:03.0	thru	1	1			1		06:29:15.6	60.01	40.57	19.44	47.39	44	37	0.840909	FALSE	6.81	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:33:51.000-05:00	N	W	Light			06:33:51.0	right	1		1		1		06:33:15.9	59.97	40.45	19.53	35.33	22	23	1.045455	35.33	FALSE	COR	N	1								1	0	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:35:03.000-05:00	N	W	Light			06:35:03.0	right	1		1		1		06:34:15.6	59.97	40.55	19.43	47.36	22	23	1.045455	FALSE	6.81	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:37:02.000-05:00	N	S	Light			06:37:02.0	thru	1	1			1		06:36:15.7	59.89	40.47	19.42	46.32	44	37	0.840909	FALSE	5.85	COG	N				1					0	0	0	1	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:38:06.000-05:00	N	W	Light			06:38:06.0	right	1		1		1		06:37:15.6	59.98	40.46	19.44	50.43	22	23	1.045455	FALSE	9.87	COG	N		1							0	1	0	0	0	0	0	0	1.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:40:02.000-05:00	N	S	Light			06:40:02.0	thru	1	1			1		06:39:15.6	59.90	40.46	19.44	46.36	44	37	0.840909	FALSE	5.91	COG	N				1					0	1	0	1	0	0	0	0	2.00	0.00	0.00	0.00	0.00	0.00
2020-11-30 06:40:05.000-05:00	N	W	Light			06:40:05.0	right	1		1		1		06:39:15.6	59.90	40.45	19.45	49.36	22	23	1.045455	FALSE	8.91	COG			1																				