Impact of Weather on Dropped Calls for the 4G LTE Network

Dr. Ron Bose
Naveen Jindal School of Management
The University of Texas at Dallas
Richardson, TX, USA
ron.bose@utdallas.edu

Kanak Kanti Roy
Naveen Jindal School of Management
The University of Texas at Dallas
Richardson, TX, USA
kanak.roy@utdallas.edu

Shreshtha Jha
Naveen Jindal School of Management
The University of Texas at Dallas
Richardson, TX, USA
shreshtha.jha@utdallas.edu

Roy Wickham
Individual Contributor
Westlake, TX, USA
N/A

Sankaran Ramanathan
Network Systems
Verizon
Basking Ridge, NJ, USA
sankaran.ramanathan@verizon.com

Shane Ronan
Network Systems
Verizon
Temple Terrace, FL, USA
shane.ronan@verizon.com

***Abstract*—Adverse weather is thought to have a significant impact on the percentage of dropped calls and handover failures for the 4G LTE Network. Temporary network degradation due to weather sometimes leads to increased technician dispatches to fix problems that the technician can do nothing about. This paper describes how machine learning (ML) models can be used to predict dropped call and handover percentage failures for the 4G LTE network under various weather conditions. These models can then be used to minimize unnecessary technician dispatches as well as identify network elements that are particularly vulnerable to adverse weather conditions. The ML models were developed and tested using network KPI data collected over a period of 12 months and hourly weather data covering 140 contiguous zip codes in the US collected over exactly the same time period.**

I. Introduction

Each year, the 4G LTE network appears to experience a large increase in % of dropped calls in the Spring when leaves come back on trees. There is also an increase in dropped calls on days with higher relative humidity, rainfall or higher temperatures. This is to be expected, since greater the moisture in the air, the higher the path loss, and hence, worse coverage and more drops. There is also a human behavior component as days with warm weather bring people outside, resulting in increased call volumes. Also days with rain creates slower automobile traffic, which increases network congestion and handoffs.

Fig. 1 (from a location in New York state) illustrates how dropped call rates go down in the winter and back up in the summer, but there are blips all throughout the year showing smaller cold and warm spells:

Fig. 1. Daily variation of SIP DC % for a sample geographic region

There are three reasons why models to predict the network impact of adverse weather are important:

1. Network engineers currently spend considerable manual effort identifying if network performance anomalies that are due to impact of weather. Building a robust predictive model would eliminate much of the time and cost associated with that effort.
2. Additional cost savings can come from preventing unnecessary technician dispatches to try and fix network performance problems that are due to weather or known seasonal changes, which the technician can do nothing about. Only if the measured network degradation (such as dropped call % or handover failure %) is higher than that predicted by our model should a technician be dispatched.
3. Understanding the impact of adverse weather on individual radios may allow the optimization of settings at these radios

and improve future equipment designs based on these findings.

Recognizing these three factors, we created ML models to predict the % of dropped calls and % of network handover failures based on a set of input weather parameters.

Understanding the impact of weather on network KPIs will become even more important with roll out of 5G, where path loss from moisture and leaves will be more destructive for millimeter waves. Since we have limited 5G data today, it is important we start with 4G LTE to understand the relationships amongst network KPIs and weather parameters and build performance models for current (4G LTE) and future (5G) use.

II. DATA COLLECTION

In this section, we specify the data that needed for our study and how it was collected.

A. Data Acquisition

a) Weather Source

One year of hourly weather data was acquired for a geographical area covering 140 contiguous zip codes in the southeastern US from a public data source - darksky.net [1].

The data was collected by using multiple API calls to darksky.net that generated a single file per day for each of the 140 zip codes. Each file contained hourly weather information for one zip code for a single day (hour 00 through hour 23). These daily files per zip code were generated and stored as separate JSON files. Each JSON file contained the following data for each of 24 hours:

- Time zone
- Offset
- Latitude
- Longitude
- Date
- Hour
- Apparent temperature
- Cloud cover
- Dewpoint
- Humidity
- Precipitation intensity
- Precipitation probability
- Pressure
- Temperature
- UV Index
- Visibility
- Wind bearing
- Wind gust
- Wind speed

b) KPI Source

Voice over LTE (VoLTE) Key Performance Indicator (KPI) data was extracted from a company owned and proprietary data cluster using Apache Spark and saved as CSV files. Hourly data was collected for each radio located in the 140 contiguous zip codes for which weather data had also been collected from darksky.net. Each CSV file contained the following data:

- Date
- Hour
- Zip code
- Radio Number
- Abnormal Releases
- Calls Answered
- Call Attempts
- Calls Completed
- Call Drops
- Call Drops including Handoff
- Call Setup Completions
- Adjusted SIP DC %
- Handover Attempts
- Handover Failures
- Handover Failure %
- Location ID

III. SOLUTION APPROACH

A. Data Pre-processing in Spark

The weather data and the KPI data were separate datasets obtained from two different sources – one public and the other proprietary. These two datasets were merged by first preprocessing both the datasets in Spark to create three columns – date, hour and zip code and then joining the datasets with respect to these columns. Upon joining, the final Spark data frame contained 36,735,339 records.

B. Correlation Analysis and Feature Selection using Python

It was important to understand the correlation between the features to accurately separate out the most important features. Feature selection is important to reduce the dimensions without loss of information. To extract the important features and see the performance of various ML models using these selected features, one-third of the data was randomly sampled and analyzed in Python, with the following correlation plot.

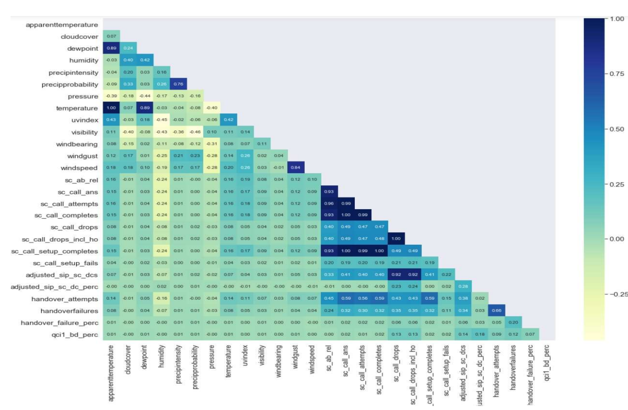

Fig. 2. Correlation plot among important features

Weather features (x-variables) selected because of least correlation were - Temperature, Pressure, Humidity, Wind speed, Precipitation intensity, UV index, Visibility, Cloud cover, Time of day (hour) and Radio number. The rest of the features were ignored and train-test split was done based on the selected features only. The y variables chosen were Adjusted SIP DC % and Handover Failure %.

C. Machine Learning Models on sample data using Python

In order to estimate the best machine learning models to predict Adjusted SIP DC % and Handover failure %, the training set from the sample subset of the data was fitted with supervised algorithms including Linear Regression, Decision Tree, K-Nearest Neighbors, Random Forest and Gradient Boosted Trees (LightGBM) using Python.

Based on the performance of the models, Random Forest and Gradient Boosted Trees gave us the best results. It is known that Random Forest is particularly useful when the input data is noisy with missing values, and also when the input data is high dimensional and we need high predictive accuracy for a data set with highly correlated features.

Both Random Forest and LightGBM are ensemble learning methods and predict by combining the outputs from individual decision trees. They differ in the way the trees are built and the way the results are combined. For our purposes, we were not concerned about the internal details of computation, but the speed and accuracy of the results.

The performance of the models were evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). It was confirmed that these two models had good predictive capability with low RMSE and MAE.

D. Model Deployment on Spark

Once the two models to estimate each Adjusted SIP DC % and Handover Failure % were identified, the production models were implemented in Spark [2] and deployed on the entire dataset in Spark. The models were deployed by splitting the entire dataset in the ratio of 70:30. 70% of the entire data was used for training the models and 30% was used to test the models. The processing time in Spark was recorded, along with the other model performance measures like Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

IV. NUMERICAL RESULTS

In this section, we briefly cover the results and how they were used to arrive at the best models to predict Adjusted SIP DC % and Handover Failure % using the weather parameters.

A. Model Performance in Python on Sample Data

The following tables list the various performance measures computed for the ML models using one-third of randomly sampled data in Python.

TABLE I. PERFORMANCE COMPARISON FOR ADJUSTED SIP SC DC % IN PYTHON

Models	*RMSE*	*MAE*
Random Forest	2.52	0.78
LightGBM	2.47	0.77

TABLE II. PERFORMANCE COMPARISON FOR HANDOVER FAILURE % IN PYTHON

Models	*RMSE*	*MAE*
Random Forest	2.79	1.27
LightGBM	2.76	1.24

From TABLE I and TABLE II. it is observed that the models implemented using Random Forest and Gradient Boosted Trees (LightGBM) algorithms are good models to predict Dropped Call % and Handover Failure % as these two models have low RMSE as well as low MAE.

B. Model Performance in Spark on entire data

The following tables list the various performance measures computed for Random Forest and LightGBM models on the entire data worth 36,735,339 records in Spark using the libraries available in SparkML.

TABLE III. PERFORMANCE COMPARISON FOR ADJUSTED SIP SC DC % IN SPARK ML

Models	Adjusted SIP SC DC%		
	Processing Time	*RMSE*	*MAE*
Random Forest	5-10 minutes	3.82	0.93
LightGBM	>4 hours	3.8	0.91

TABLE IV. PERFORMANCE COMPARISON FOR HANDOVER FAILURE % IN SPARK ML

Models	Handover Failure %		
	Processing Time	*RMSE*	*MAE*
Random Forest	5-10 minutes	3.28	1.33
LightGBM	3-4 hours	3.28	1.33

From TABLE III and TABLE IV, Random Forest proved to have significantly faster processing times with almost similar RMSE and MAE for the given data. Hence we recommend the use of the Random Forest model for this type of modeling and analysis for new weather data at other geographical regions.

The charts below show actual versus predicted dropped call % for all the radios combined and also for one specific radio using a 24 hour snapshot.

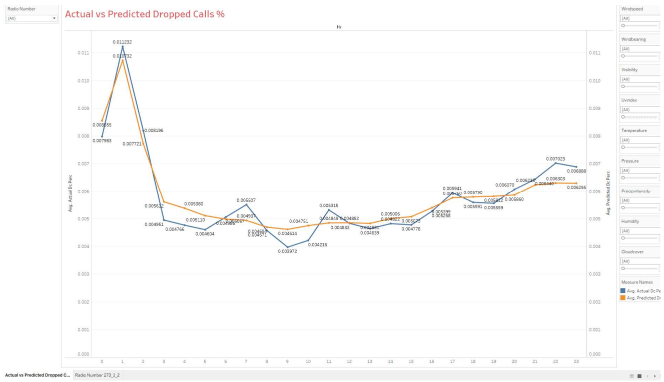

Fig. 3. Actual vs Predicted dropped call % for all Radios

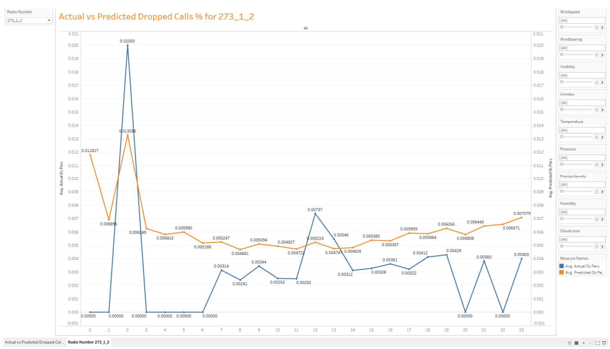

Fig. 4. Actual vs Predicted dropped call % for Radio Number 273-1-2

In each case the orange line was predicted by analyzing past weather and the blue line reflects actual data. In Fig. 3. we see that during hour one of the day there was a large spike in dropped calls. What is notable is the degree to which the model (shown in orange) predicted this spike.

In Fig. 4. We show a similar plot for one radio belonging to a specific vendor. The orange line is predicted and the blue line is actual. For this particular radio, actual performance appears to be better than predicted performance so there is no cause for concern. If we determine that a particular vendor's model of radio is highly susceptible to adverse weather, we can share this with the vendor in order to improve performance for future product releases.

V. CONCLUSION

There is a predictable impact of weather-related factors on network performance KPIs such as Adjusted SIP Dropped Call % or Handover Failure %. The Random Forest models found in Spark ML Lib provides a good way to predict this impact. These models can be used to make business decisions about whether a technician dispatch is required during weather incidents. This dispatch is required with measured Dropped Call % or Handover Failure % are higher than that predicted by the Random Forest model. In addition, we can look at predictions for individual radios to determine if their performance is susceptible to adverse weather, and provide appropriate guidance to the equipment vendor.

This study also suggest that similar studies be carried out when 5G KPI data is available, since the impact of weather on 5G waves likely to be much greater than for 4G.

VI. FUTURE WORK

This study was based on weather and KPI data for a small area of the US, comprising of 140 contiguous zip codes. This Random Forest model needs to be trained and tested on data from other geographical areas in the US to be considered truly robust.

In order to expand this use case into a useable nationwide model, it is necessary to determine a cost effective and reliable way to source hourly weather data based on zip codes. darksky.net is a good starting point for this weather data. At the same time, the corresponding KPI data must also be collected and stored.

REFERENCES

[1] https://darksky.net/dev

[2] https://spark.apache.org/docs/1.2.2/ml-guide.html