

Vehicular Data Analytics for Smart Driving

Dilum Bandara, PhD

Dept. of Computer Science & Engineering

University of Moratuwa

Dilum.Bandara@uom.lk

International Symposium on Applied Analytics for a Smart Society – 2016

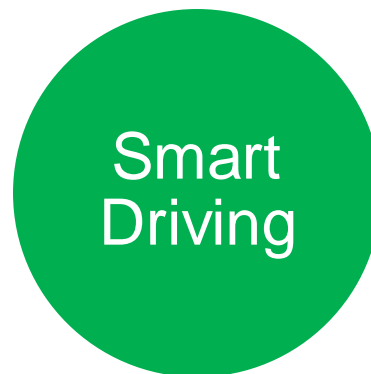
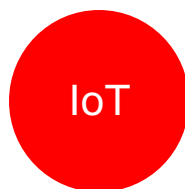
Why?



Reckless Driving



Fault Detection
& Prediction



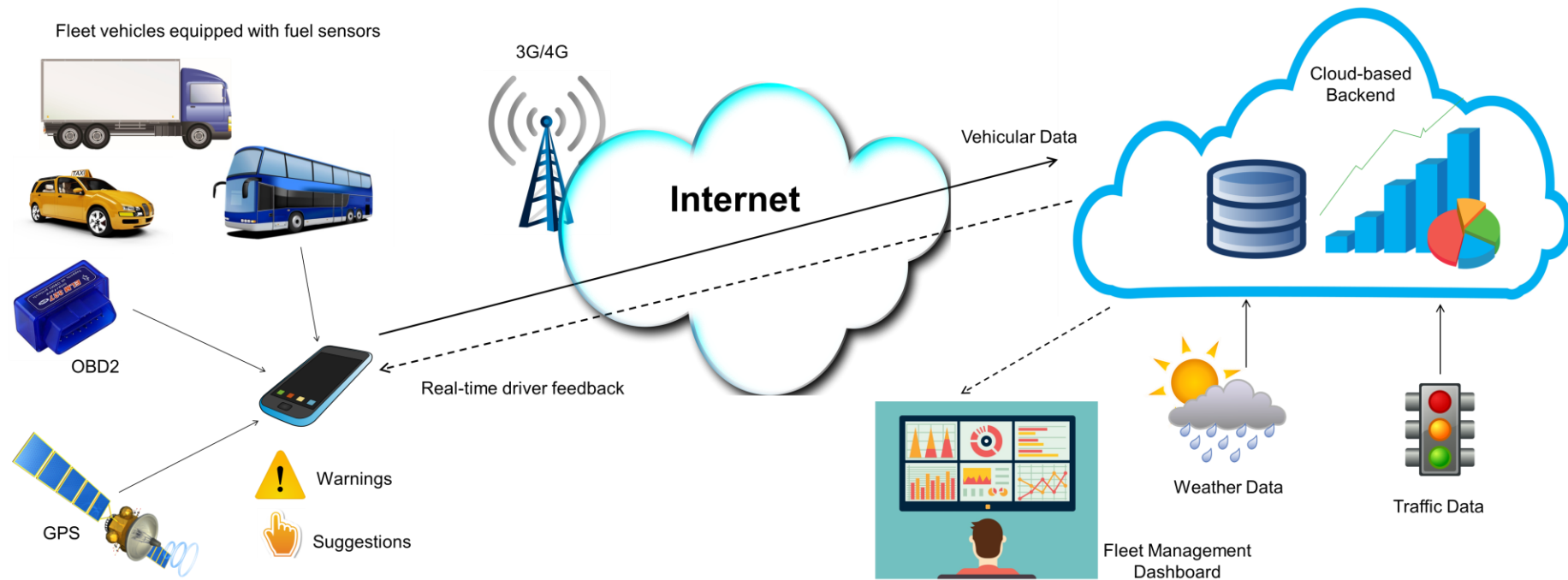
Fuel Fraud

Driving Anomaly
Detection



Tracking &
Surveillance

Solution Architecture



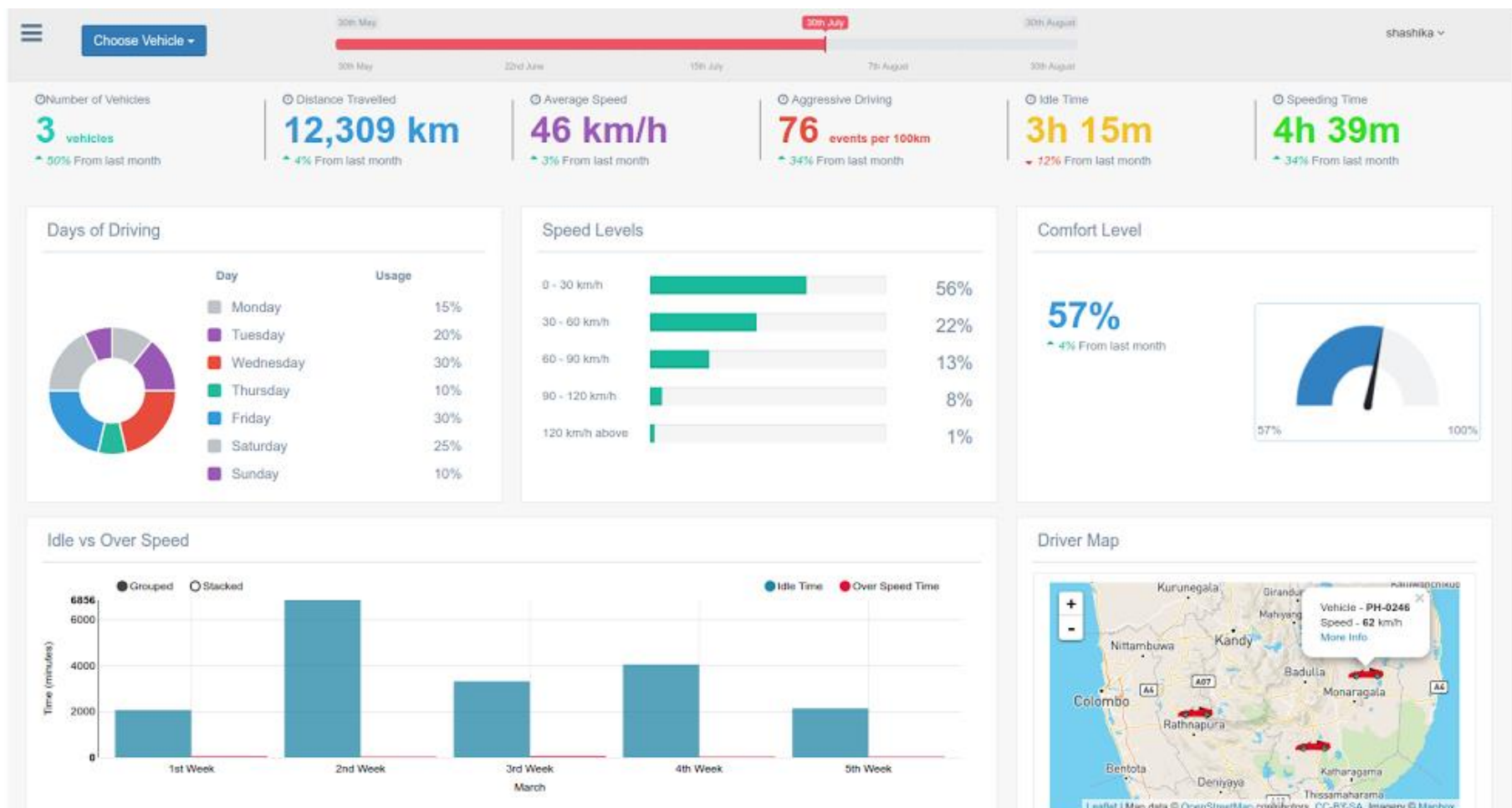
Real-time analysis

- Driving anomaly detection
- Fuel fraud
- Geo fencing
- Vehicle fault detection

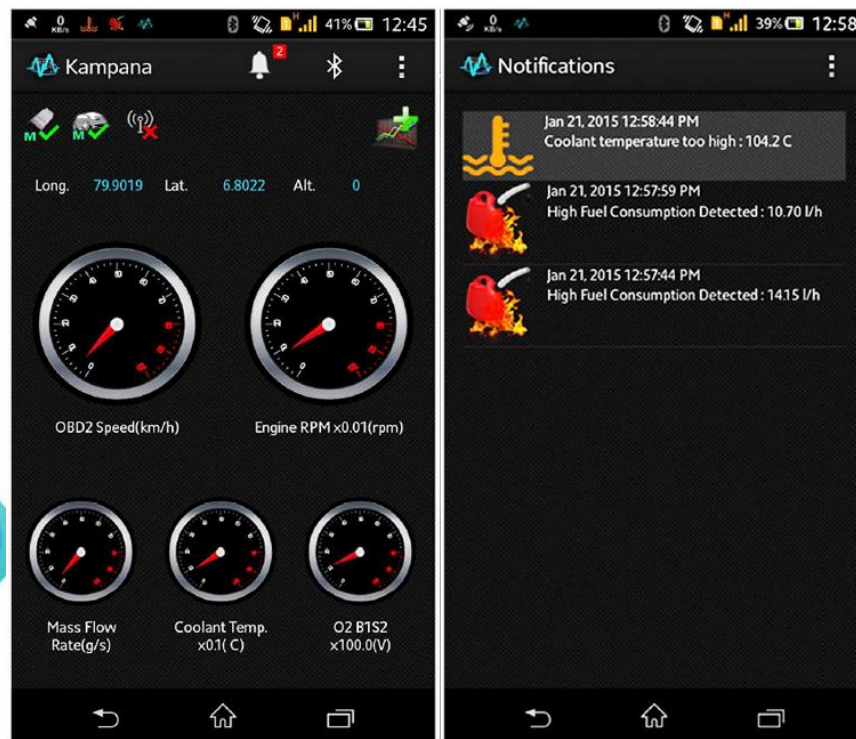
Historical analysis

- Driver profiling
- Driver coaching
- Predicting sensor failure
- Case analysis

Dashboard



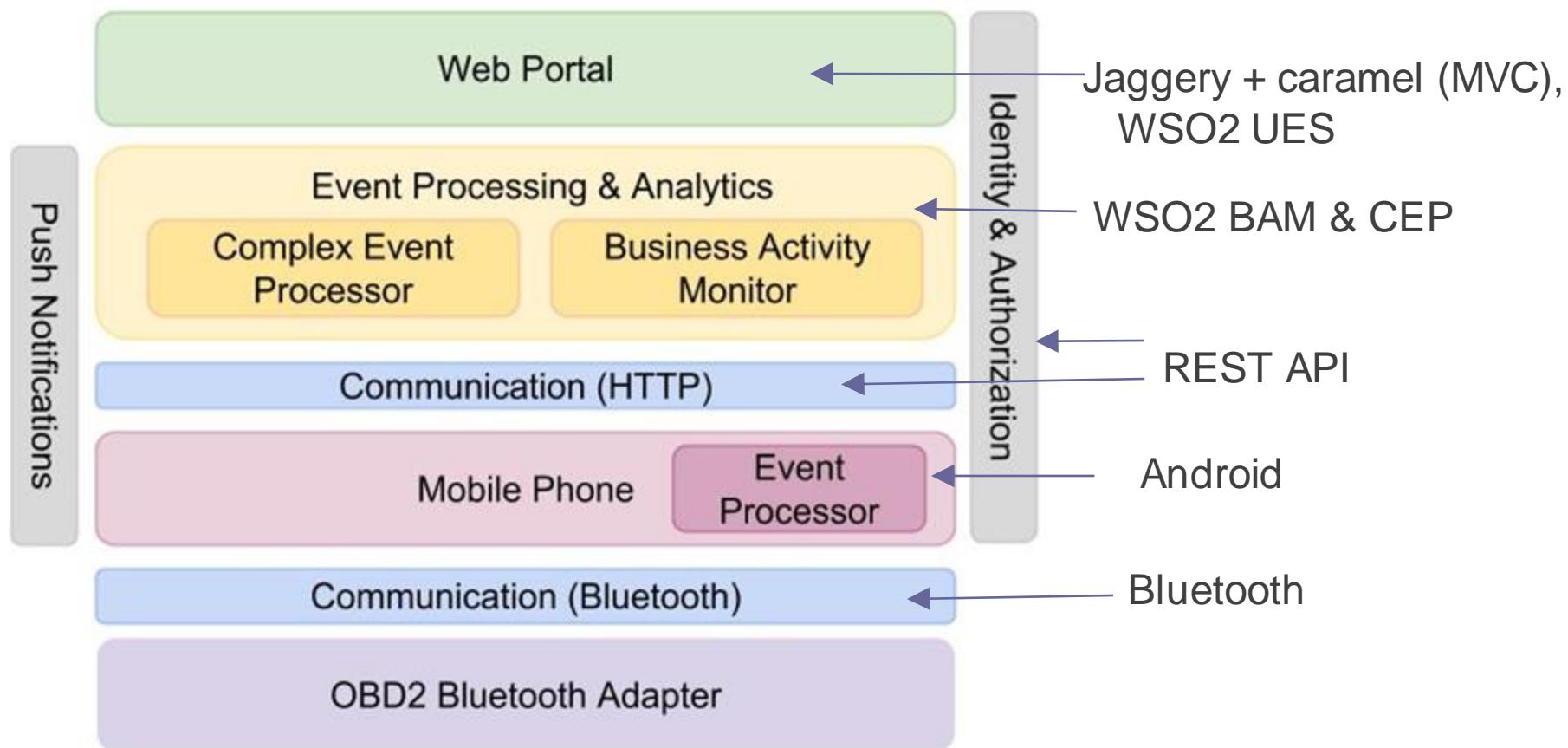
OBD2 Based Analysis



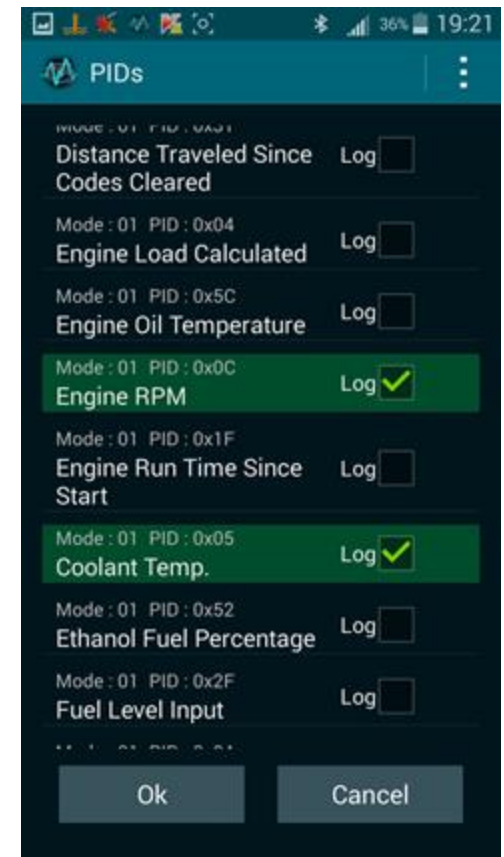
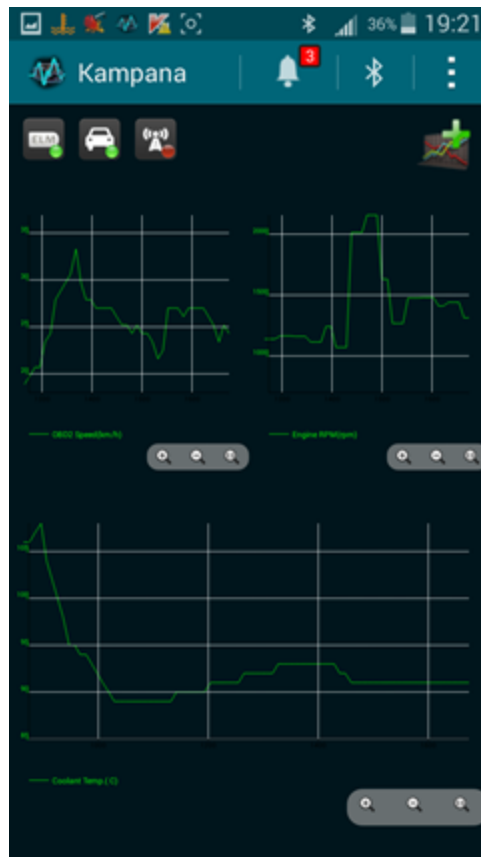
□ OBD – On Board Diagnostics

- Available in many vehicles since 1996
- OBD2 – In most vehicles since 2005
- Speed, RPM, Odometer, Coolant Temperature, Throttle Position, Oxygen, Mass Air Flow, etc.

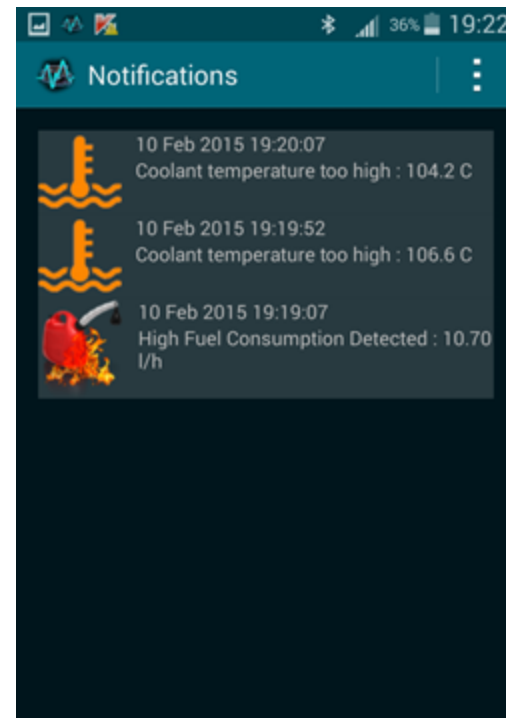
Solution Architecture



App-Level Processing – Real-Time Dashboard

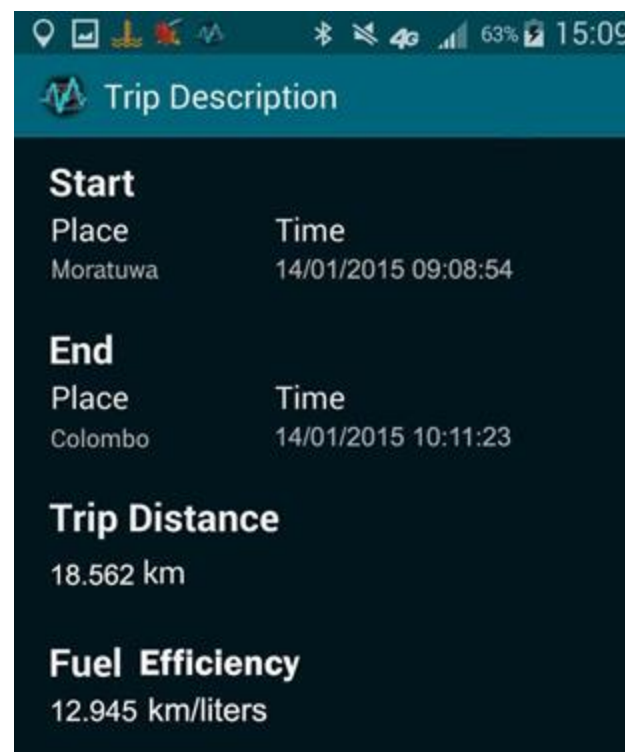
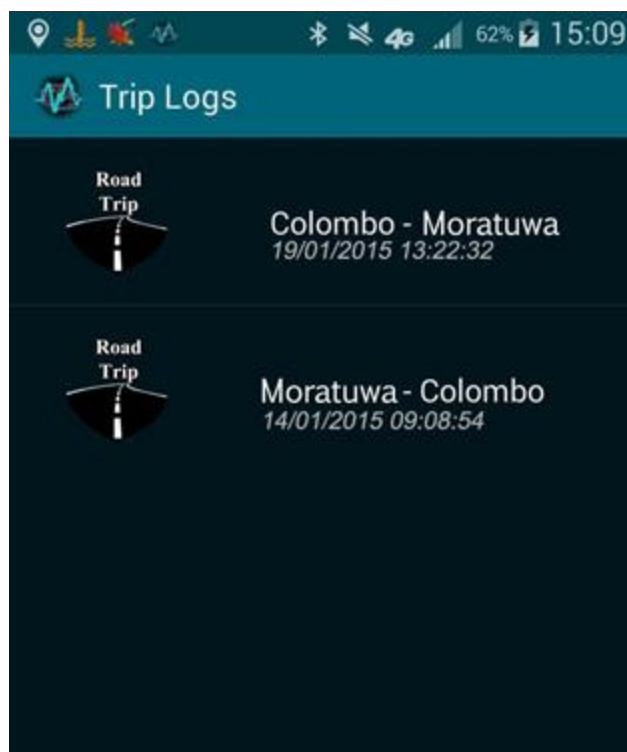


Fuel Economy & Coolant Temperature Monitoring



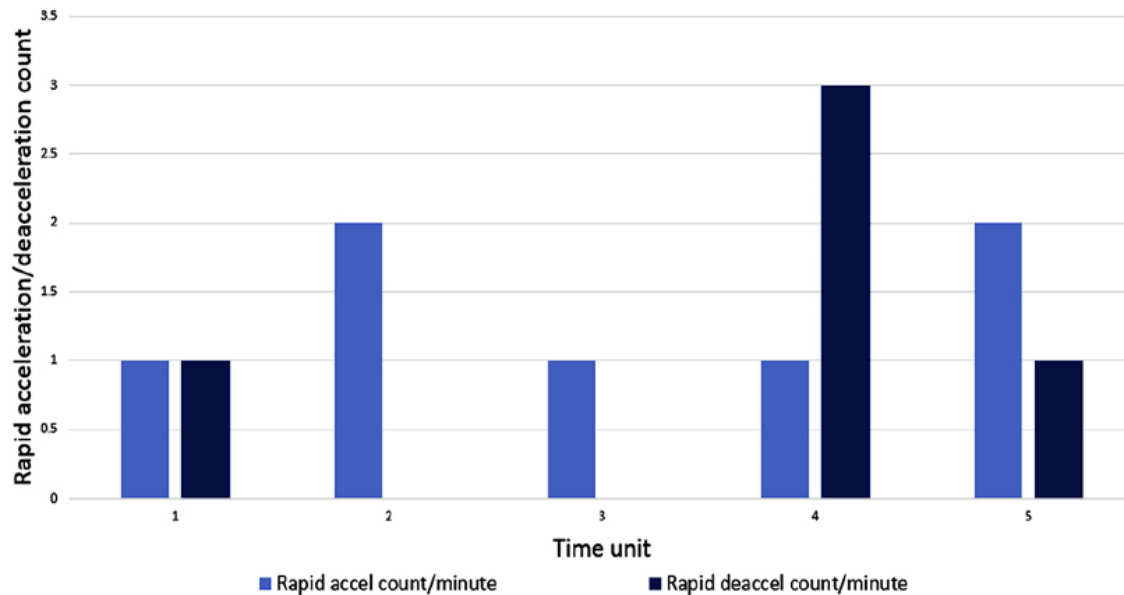
- ❑ Implemented using Siddhi CEP on smartphone
- ❑ Minimum impact on battery level
 - Bandwidth saving due to local processing → Reduce energy consumption

Trip Logs



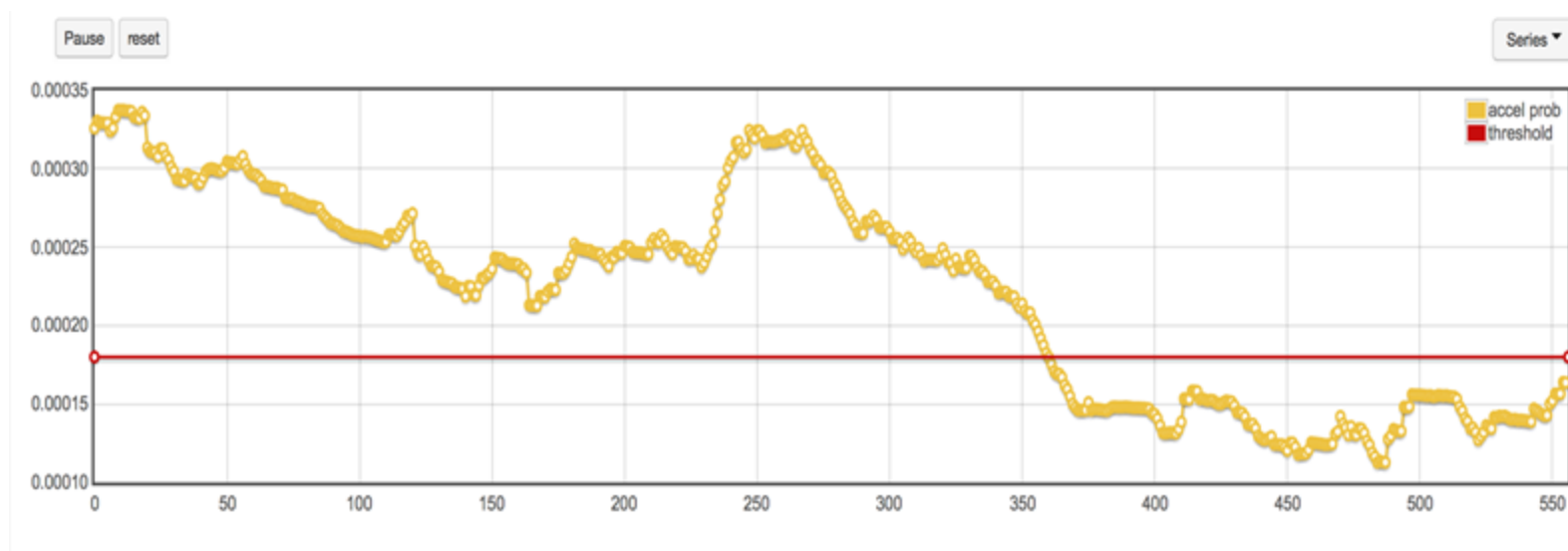
- Standard car → High-end Car

Backend Processing – Reckless Driving



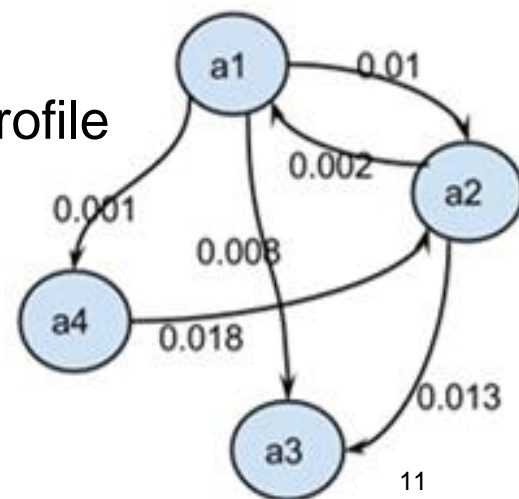
- Hard accelerations & deceleration count above a threshold
 - Per 100 Km
 - Per 1 Hour
- Count depends on average speed of vehicle in last t seconds
- Implemented using Siddhi CEP
- Computed values stored in RDBMS

Driver Profiling

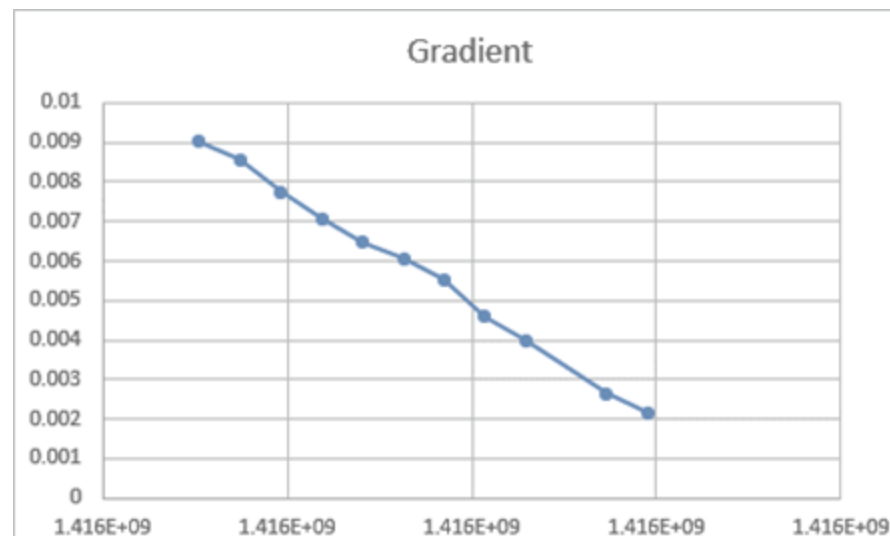
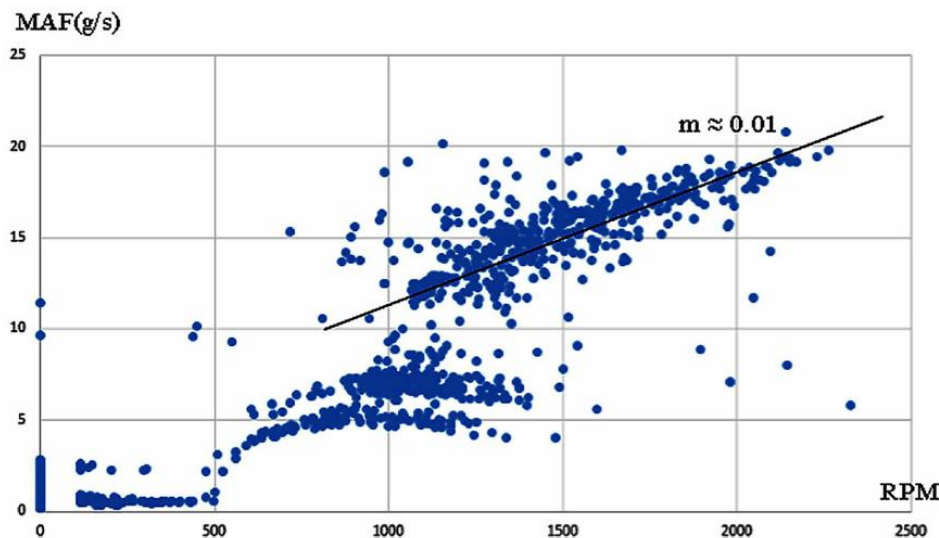


□ Detection of anomalies

- Hidden Markov Model based on acceleration profile
- Model implemented in BAM
- Validator implemented in CEP



Sensor Failure Prediction



- ❑ Mass Air Flow (MAF) sensor value has a linear relationship with engine RPM
- ❑ When sensor fails, gradient between MAF & RPM reduces with time
- ❑ Rate of change of gradient can predict date of failure

Fuel Consumption Prediction

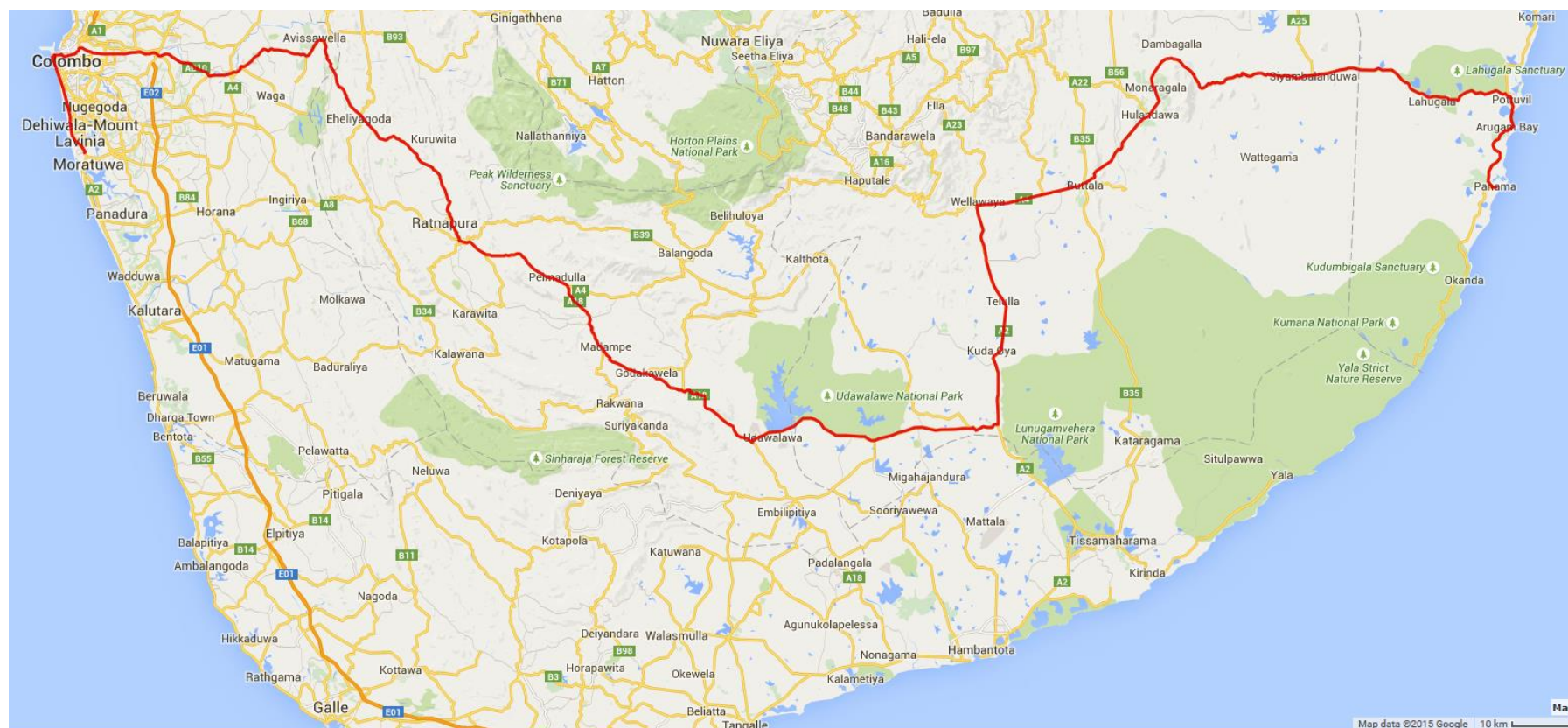
- Long-distance bus fitted with a GPS unit & high-precision fuel sensor
- Could you
 - explain variability in fuel consumption
 - predict fuel consumption of a journey
 - give tips to improve fuel consumption



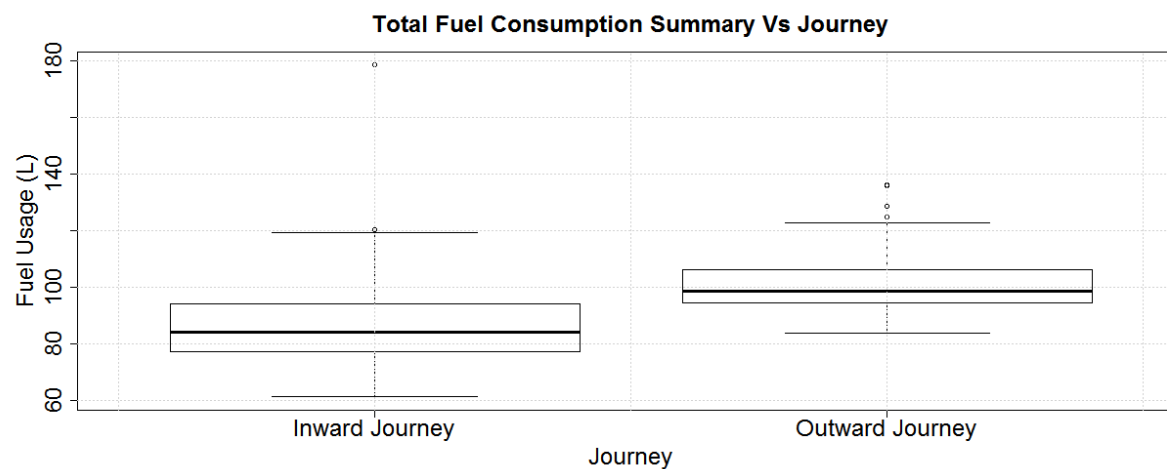
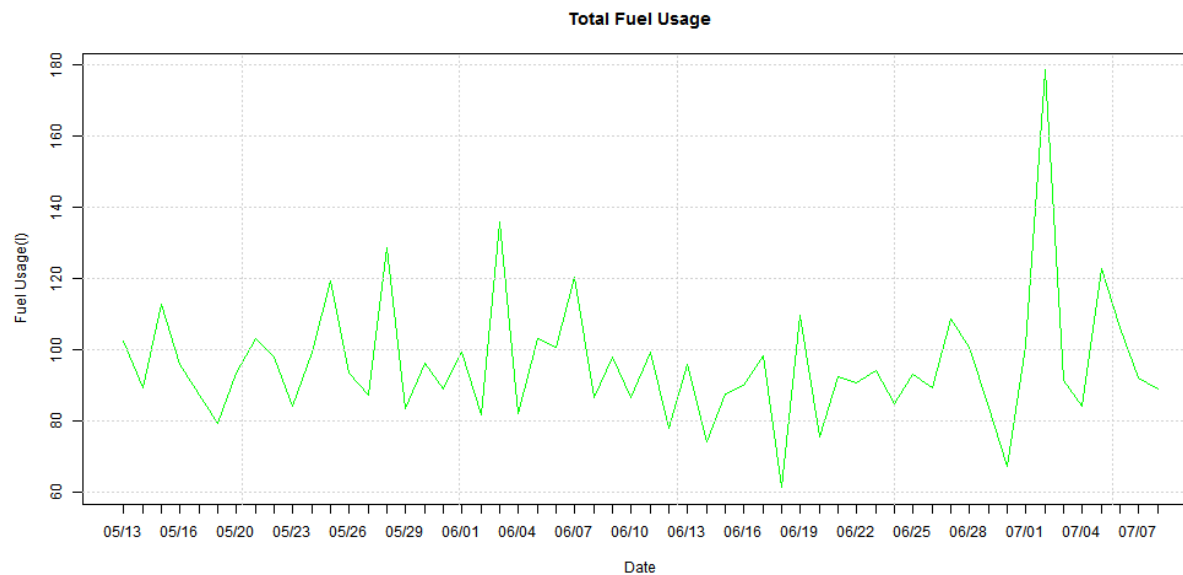
Dataset

- From 13 May 2015 – 31 August 2015
- Parameters
 - Timestamp (date and time)
 - Longitude (Min: 5.918611°N, Max: 9.835556° N)
 - Latitude (Min: 79.516667° E, Max: 81.879167° E)
 - Bearing (0° to 360°)
 - Elevation (Min: 0m, Max: 2,524m)
 - Distance traveled (km) – between two samples
 - Speed (kmh-1)
 - Acceleration (kmh-2)
 - Ignition status (1 – Ignition On or 0 – Ignition Off)
 - Current battery voltage (Min: 0v, Max: 29v)
 - Fuel level (Min: 0L, Max: 218L)
 - Fuel consumption (L)

Bus Route

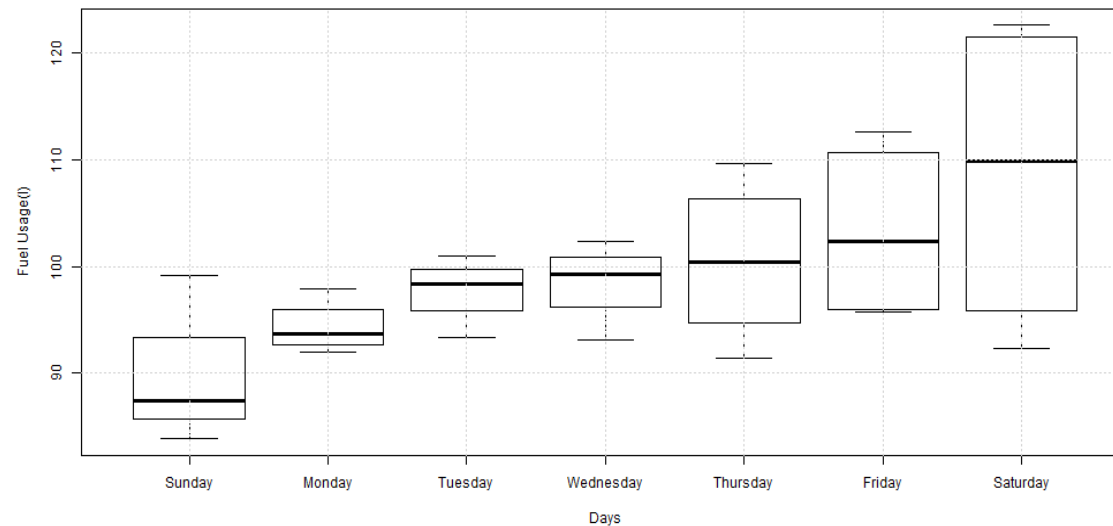


Fuel Usage

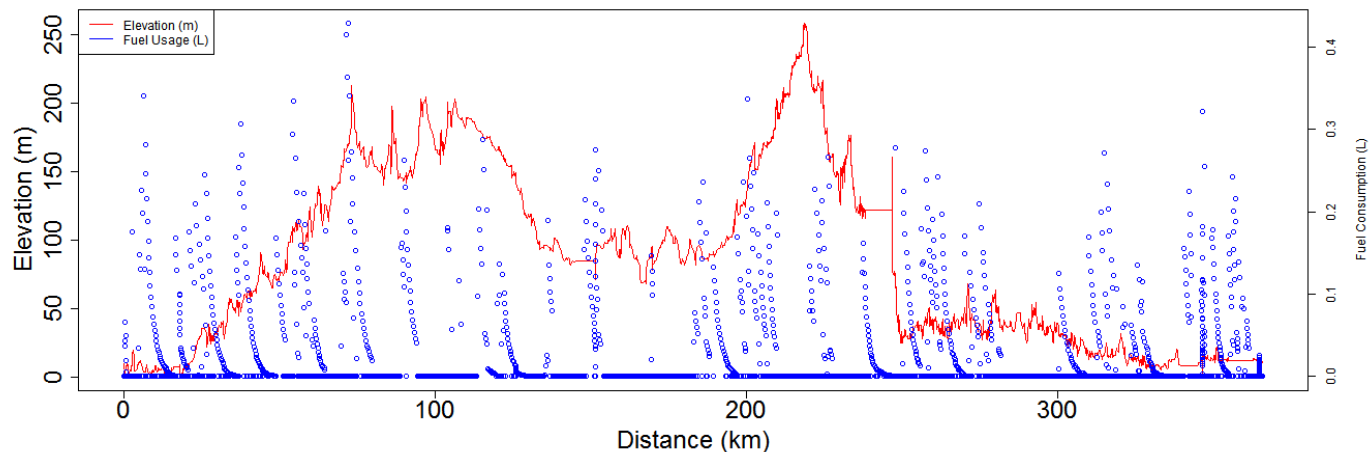


Factors Contributing to Fuel Usage

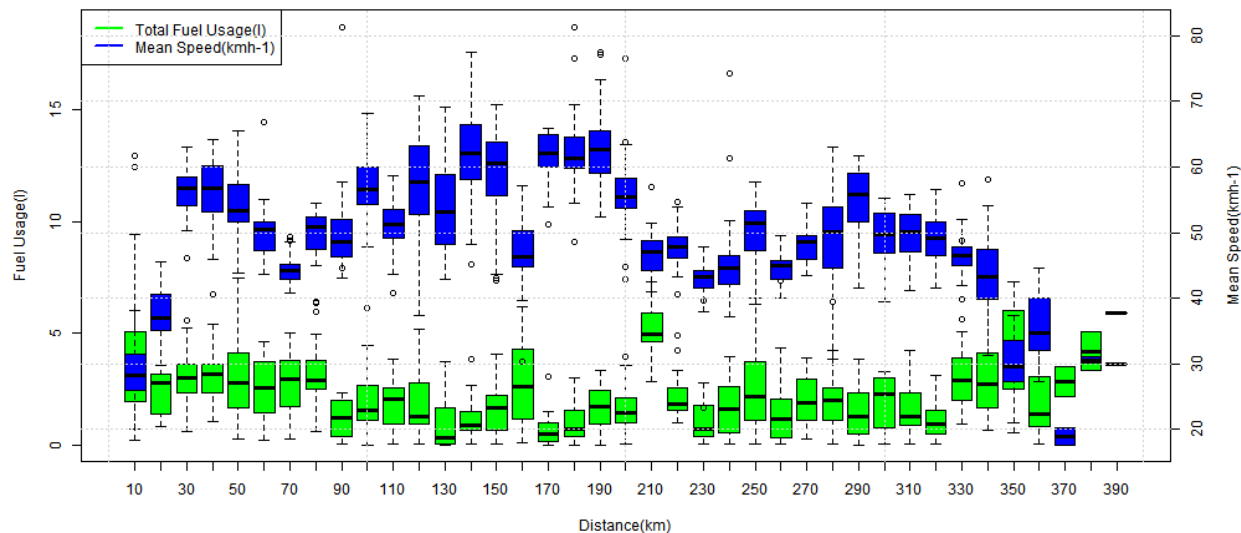
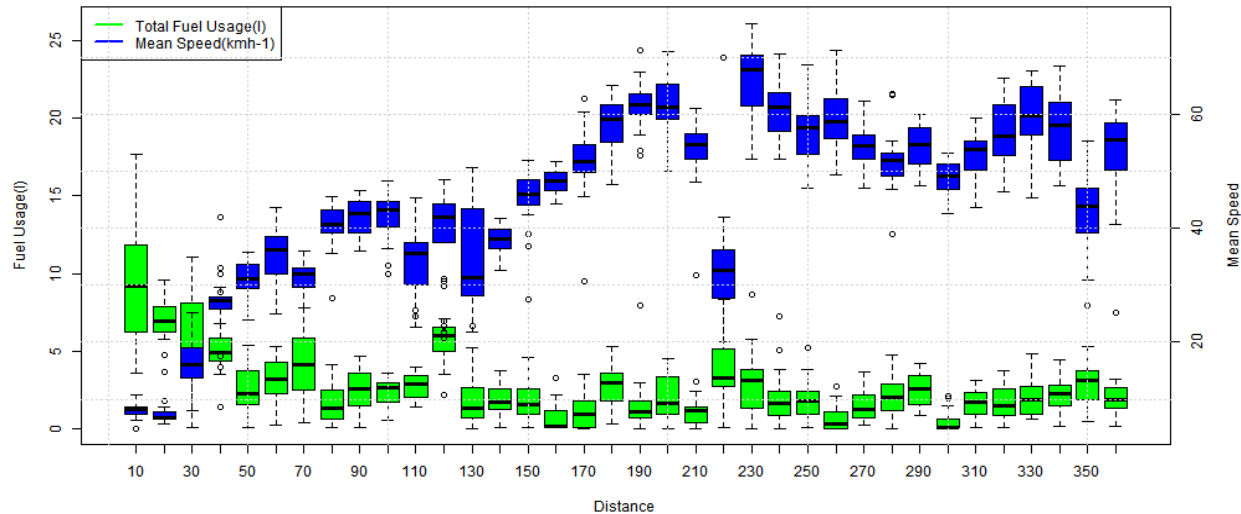
Total Fuel Consumption Summary Vs Day



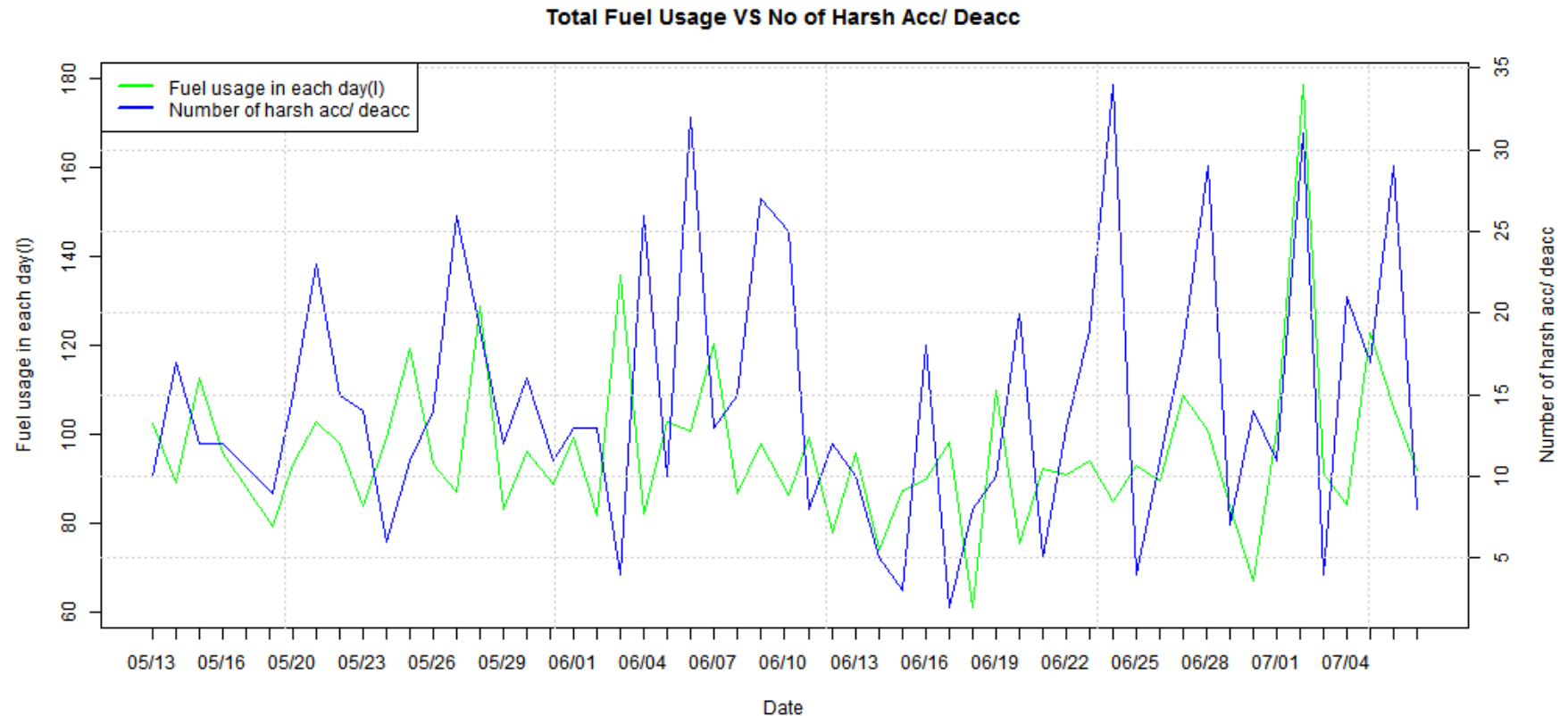
Fuel Consumption and Elevation



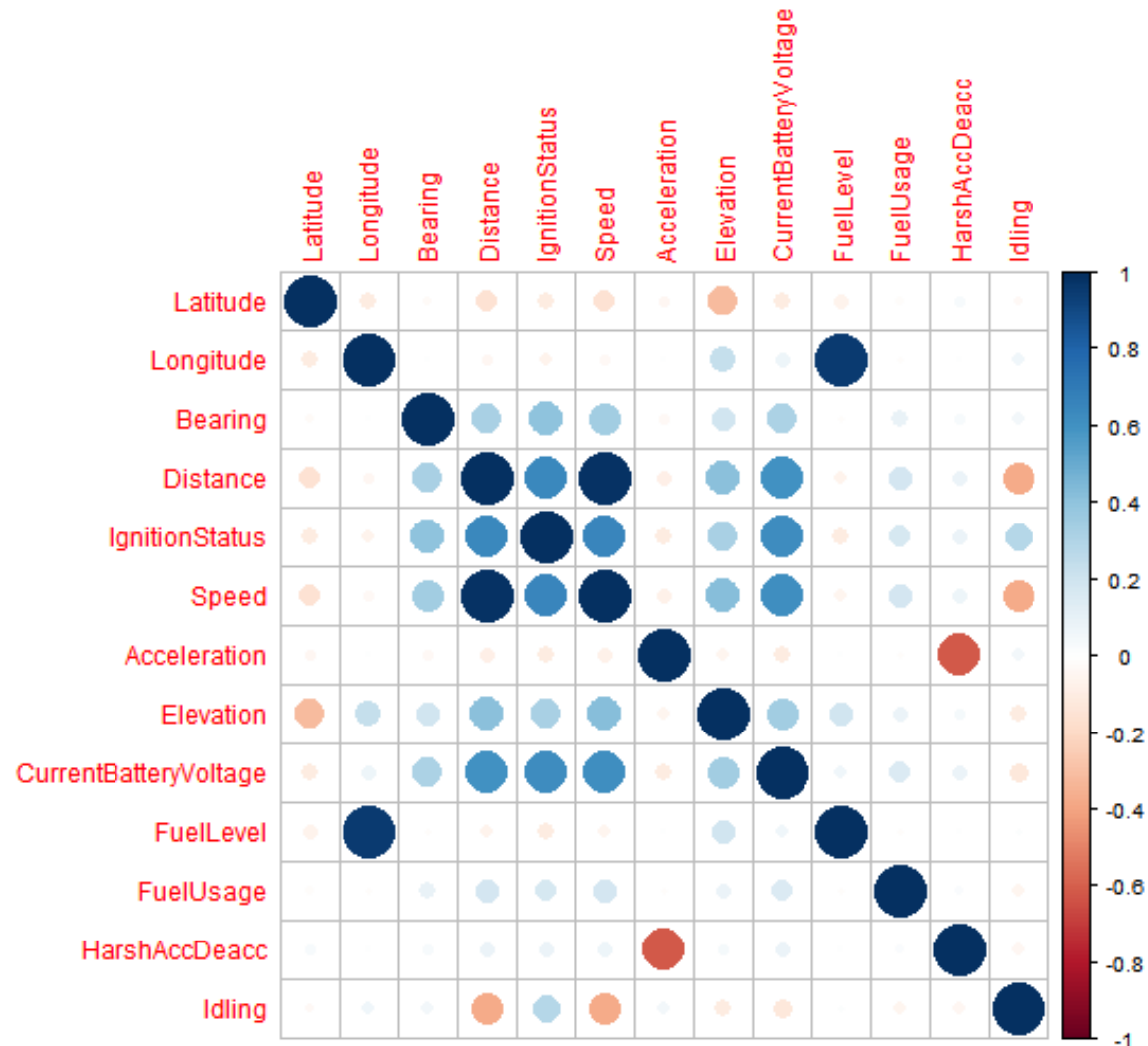
Factors Contributing to Fuel Usage (Cont.)



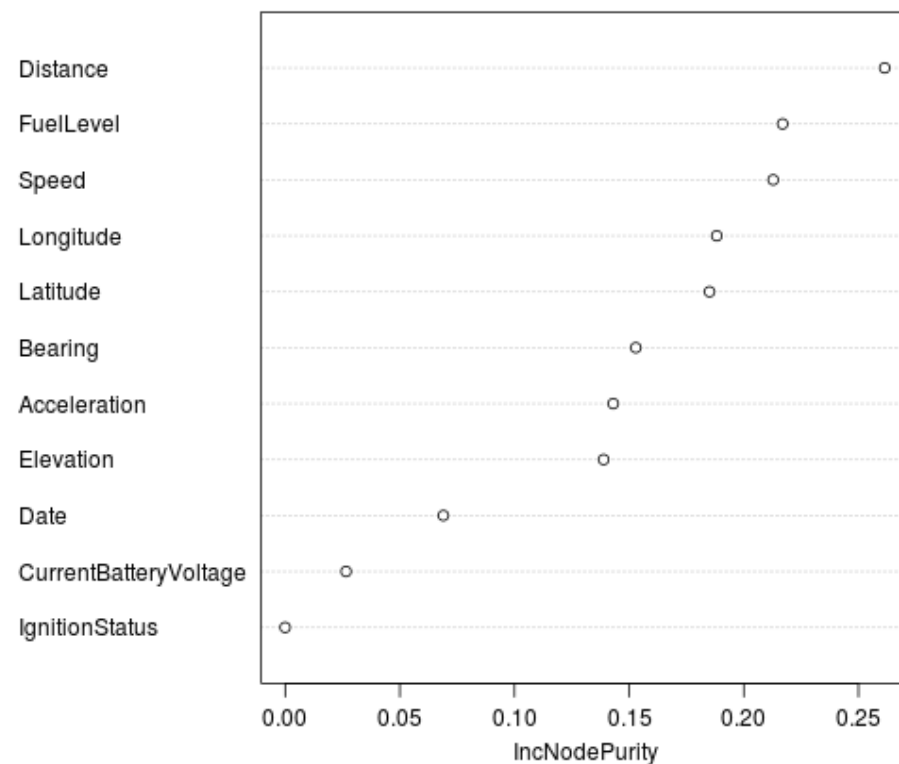
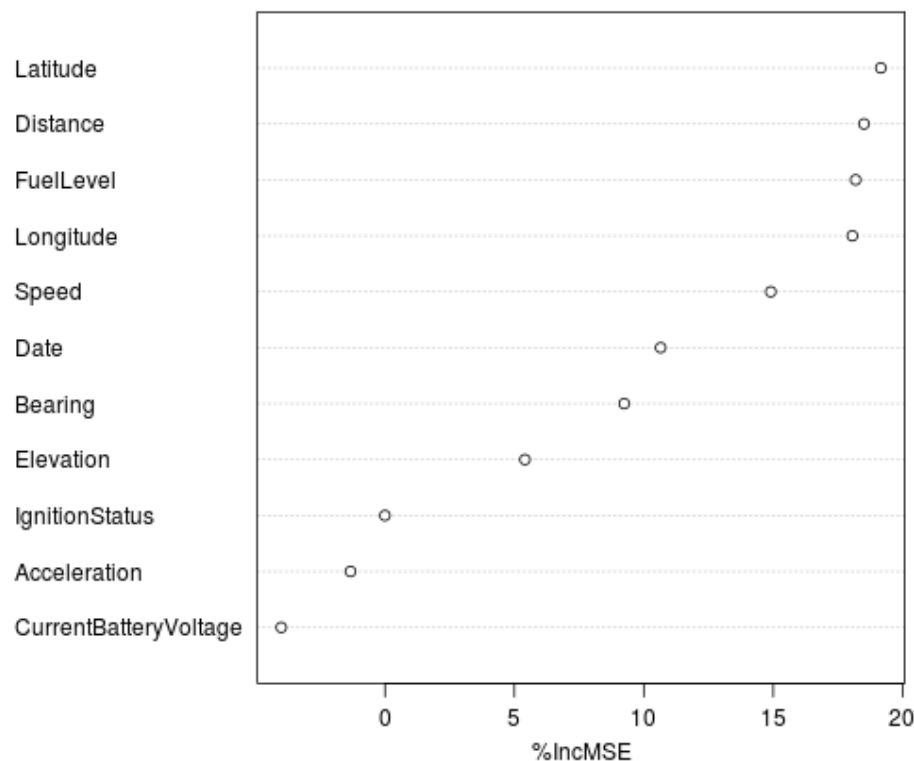
Factors Contributing to Fuel Usage (Cont.)



Factors Contributing to Fuel Usage (Cont.)

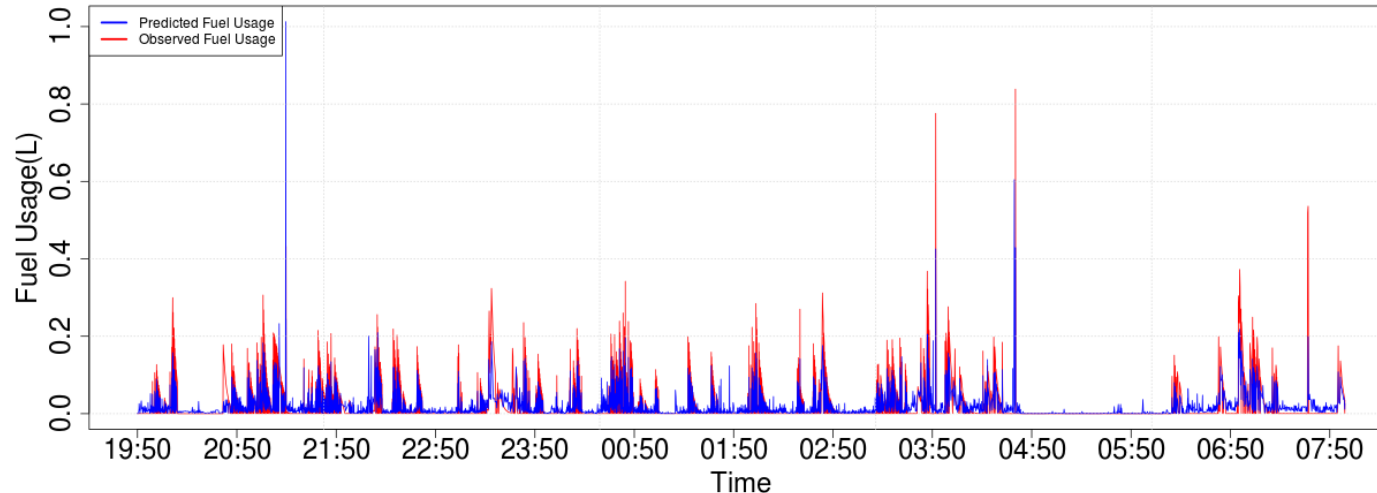


Variable Importance

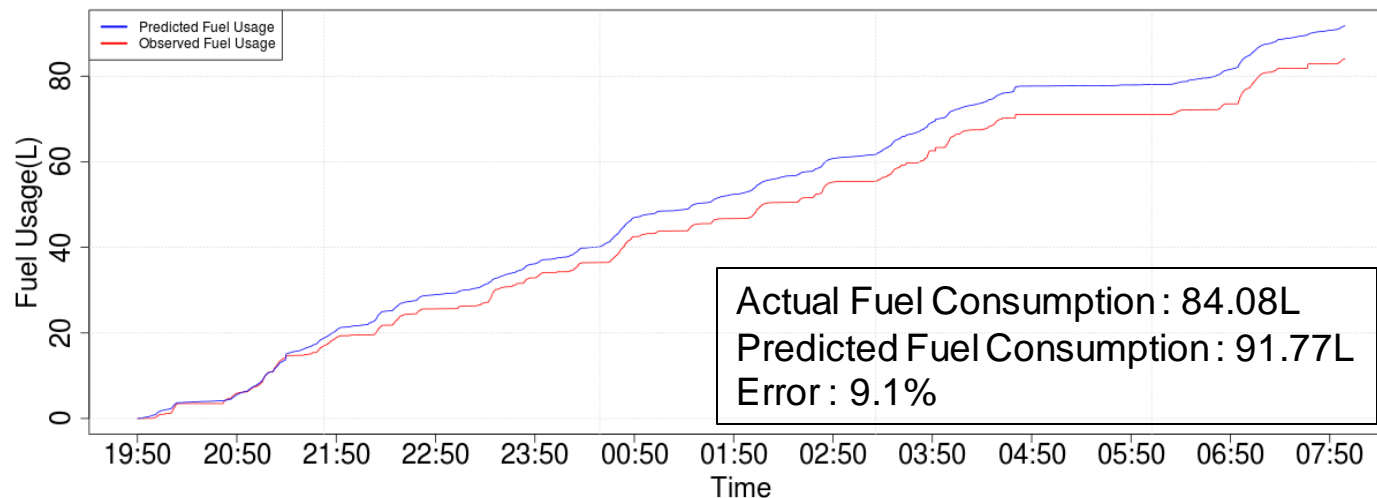


Predicting Fuel Consumption – Random Forrest

Fuel Usage Prediction

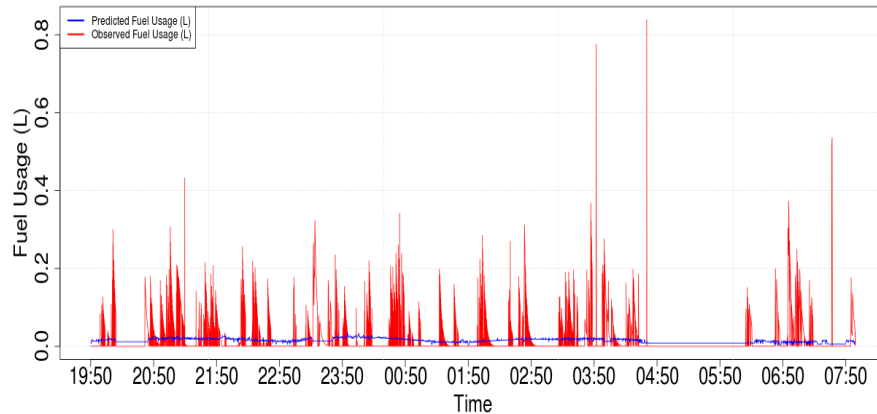


Fuel Usage Prediction

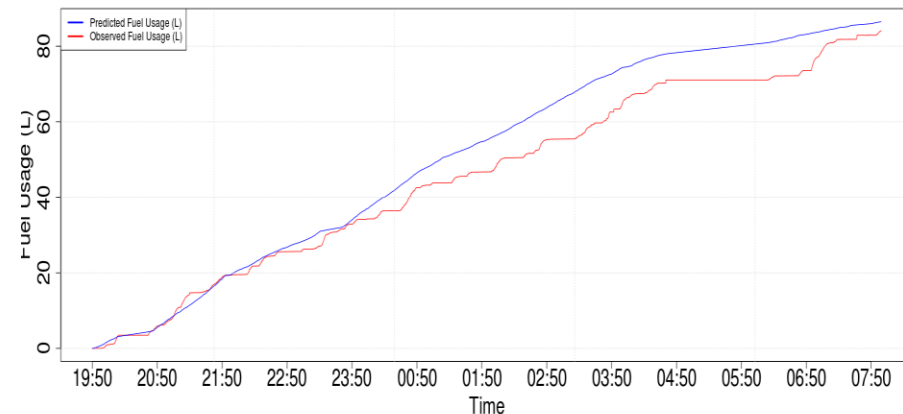


Predicting Fuel Consumption – Gradient Boosting & Neural Network

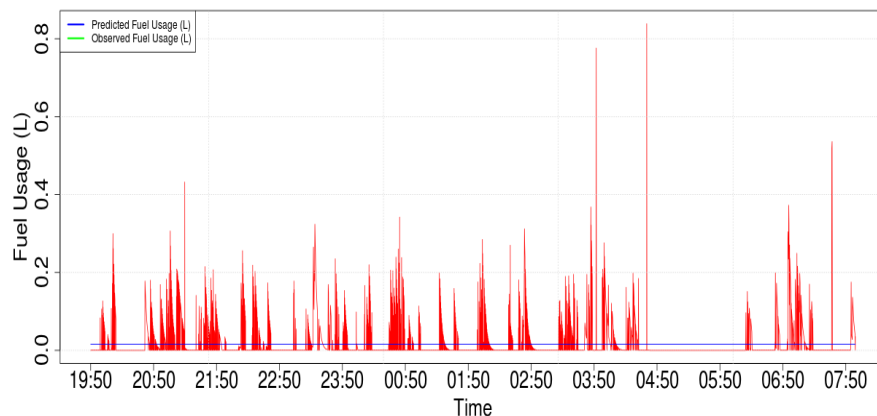
Fuel Usage Prediction



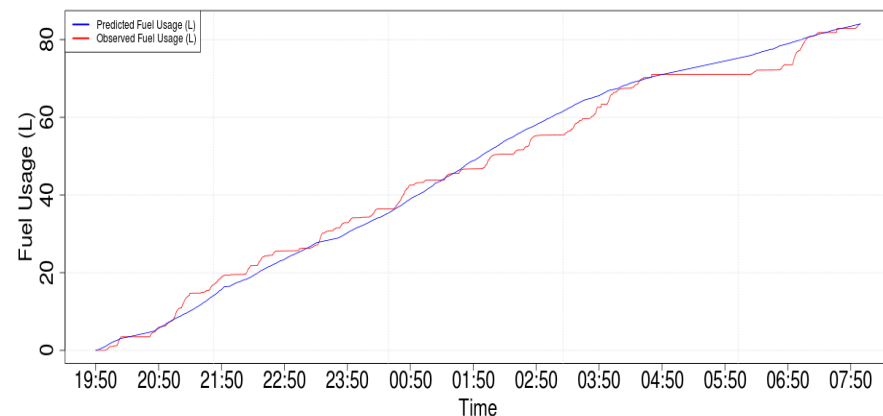
Fuel Usage Prediction



Fuel Usage Prediction



Fuel Usage Prediction



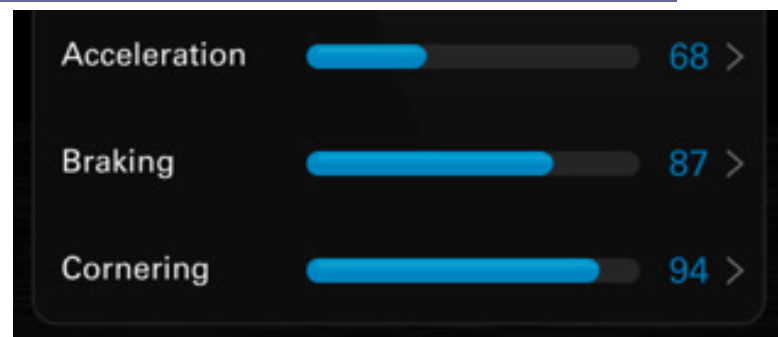
Predicting Fuel Consumption (Cont.)

Model	Nash-Sutcliffe Efficiency
RF	0.26189
GB	-0.00240
ANN	-0.01304

Error Statistics	RF	GB	ANN
BIAS	0.00477	0.00045	0.00274
MAE	0.02296	0.02585	0.02756
RMSE	0.04046	0.04715	0.04740

On Going Work

- Dashboard design
- Driver profiling
 - Beyond acceleration profile
 - Correlating with location, time, traffic, & weather
 - Usage-Based Insurance (UBI)
- Quantifying passenger comfort
- Case analysis
 - Traffic, weather
- Driver feedback
 - Real-time & long-term
- Process re-engineering



Comfort Level

57%
▲ 4% From last month



Research Challenges

- Lack of annotated data
 - Events, GIS, weather
- Optimum sampling frequency – 4Vs of big data
 - GPS 10 Hz, practically < 0.2 Hz
 - OBD2 ~ 10 Hz per PID
- Enhancing accuracy of detected events
- Correlating with location, time, traffic, & weather
 - Lack of (real-time) data
- Relating numbers to physical events such that drivers could understand

Publications

- ❑ M. Amarasinghe, S. Muramudalige, S. Kottegoda, A. L. Arachchi, and H. M. N. Dilum Bandara, “Cloud-Based Driver Monitoring and Vehicle Diagnostic with OBD2 Telematics,” Intl. J. of Handheld Computing Research (IJHCR), to appear.
- ❑ S. Wickramanayake and H.M.N.D. Bandara, “Poster: Enhancing Fuel Economy of Fleet Vehicles Through Real-Time Driver Monitoring and Feedback,” in Proc. 1st Asian Students Symposium on Emerging Technologies (ASSET 2016), June 2016.
- ❑ S. Muramudalige and H.M.N.D. Bandara, “Demo: Cloud-Based Vehicular Data Analytics Platform,” in Proc. 1st Asian Students Symposium on Emerging Technologies (ASSET 2016), June 2016.
- ❑ S. Wickramanayake and H.M.N.D. Bandara, “Fuel Consumption Prediction of Fleet Vehicles Using Machine Learning: A Comparative Study,” In Proc. 2nd Moratuwa Engineering Research Conference (MERCon 2016), Apr. 2016.
- ❑ M. Amarasinghe, S. Kottegoda, A. L. Arachchi, S. Muramudalige, H.M.N.D. Bandara, and A. Azeez, “Cloud-Based Driver Monitoring and Vehicle Diagnostic with OBD2 Telematics,” In Proc. Intl. Conf. on Advances in ICT for Emerging Regions (ICTer), Aug. 2015.

Acknowledgement

□ Students

- Sandareka Wickramanayake (MSc)
- Shashika Muramudalige (MSc, BSc)
- Asiri Liyana Arachchi (BSc)
- Malintha Amarasinghe (BSc)
- Sasikala Kottegoda (BSc)

□ Research partners

- Mr. Nishal Samarasekera (Dept. of TLM)

□ Data

- Nimbus Venture (Pvt) Ltd.
- Many other drivers who help us collected data

Q&A



Dilum.Bandara@uom.lk