

PUBLIC TRANSPORT SECTOR DRIVER BEHAVIOUR: Measuring recklessness using speed and acceleration

A.S. ZEEMAN and M.J. BOOYSEN

Department of E&E Engineering, Stellenbosch University, Private Bag X1, Matieland, 7602

Tel: 021 808-4013; Email: mjbooyesen@sun.ac.za

ABSTRACT

The informal transport industry in Sub-Saharan Africa is notoriously dangerous, leading to many fatalities annually. This paper presents an innovative way of monitoring driver behaviour, in real-time, by taking into account road design standards and vehicle dynamics. A theoretical model is presented that combines acceleration and speed data into an erratic driving detection algorithm. The model presents a novel use of commonly used civil engineering principles, used in road design. Evaluation of the models, using actual minibus taxi data, demonstrates that it successfully detect reckless driving. An online platform is presented to visualise the tracked vehicle and the driving behaviour.

1 INTRODUCTION

In Sub-Saharan Africa in general, and South Africa in particular, the minibus taxi sector dominates the informal public transportation system and has grown enormously in the last 20 years. Not only is it the most available mode of transport, it is also affordable to the public. In 2008 it held 67.9% of the collective transport market share. The sector originally evolved to meet the demand of mobility, but unfortunately, at the cost of personal safety.

The World Health Organization (WHO) African Region (WHO, 2009) has some of the world's highest road traffic fatality rates globally with more than 32 deaths per 100,000 population annually, making it the 9th leading cause of death in the region. The African region has less than 2% of the world's registered vehicles, but almost 20% of the global traffic deaths. According to the March 2011 Road Traffic Report (2011), there were 285,858 registered minibuses in South Africa, of which 1,408 were involved in fatal collisions during 2010-11, with 1,795 fatalities. A special maximum speed limit of 100km/h has been set for minibus taxis, 20km/h lower than the norm on highways, due to the high number of fatalities.

Research by Hickman (2005), have found that being monitored leads to safer driving behaviour. Seven key characteristics of a well performing urban transport system were identified by the SSATP (2005), with affordability and safety being the first two characteristics.

Sudden changes of direction, or travelling at a high speed around curves, or braking and accelerating result in forces acting on a vehicle and its passengers. High g-force values around a curve can also result in side slip and loss of control over the vehicle. Schietekat (2013) has shown that various reckless events are associated with high levels of lateral and/or longitudinal acceleration. Rapid acceleration also decreases the driver's ability to react as a result of increased speed and limited reaction times.

2 RELATED WORK

Numerous studies have been completed on driving behaviour and modelling thereof. The main differences between these studies are in the specific application area and the sensing method employed. An overview of the work done on driver modelling over the past few decades is given by Plöchl (2007). This overview focused on automatic vehicle control or driver assistance, such as path following, lane change assist and overtake assist. Nigro (2003) proposes a system named Intelligent Driving Recognition with Expert System (IDRES), which uses a two-level rule-based system that uses measurements from vehicle mounted cameras that face the road to determine lateral position delimiting the lanes of the road.

Driving patterns classification using Hidden Markov Models (HMM) is proposed by Oliver (2000) as a framework for machine learning for modelling and recognizing driver behaviour. Information sensed from a steering wheel angle sensor, brake pedal, speedometer, acceleration throttle, gear and GPS unit are used as inputs for the HMM. An adaptive assistance system to determine or predict driver's behaviour using HMM has been developed by Dapzol (2005). Four cameras are installed in the vehicle (view of front, rear, driver head, and his feet) to monitor the vehicle's sensors (speedometer, steering wheel, acceleration throttle and brake pedal) and the driver.

Imkamon (2008) proposes an erratic driving detection system using Fuzzy Logic. This system consists of a 3-axis accelerometer, a camera and an on-board diagnostics (OBD-II) reader, which provides the fuzzy logic model with speed and engine readings. The system output is a driving-risk level ranging from 1 to 3.

Visual monitoring makes use of cameras to monitor the driver's behaviour, and radar and lasers to determine the vehicles speed and position relative to obstacles on the road. Recently, research focus has shifted from visual monitoring to the use of vehicle-mounted motion sensors. Motion sensors, such as accelerometers and gyroscopes, measure the vehicle's acceleration, in g-force, and orientation. The popularity of these sensors is mostly due to their simplicity, robustness, and low cost.

A Neural Network (NN)-based model for driving pattern classification is proposed by (Di, 2009). Bi-axial accelerometer and GPS data are combined to characterize driving patterns using neural networks. A geo-referenced database was developed to empirically compare positioning data and to disregard outliers and anomalies.

An embedded sensory system to measure the comfort in public transportation has been developed by (Castellanos, 2011). The system consists of a tri-axial accelerometer, global positioning system (GPS) receiver, temperature sensor and SD Card storage. Three techniques were proposed to determine the comfort level: threshold detection of acceleration peaks; threshold-jerk detection based on the derivative of acceleration (jerk); and comfort assessment from weighted RMS accelerations based on the ISO2631-1 standard.

Eren (2012) estimates driver behaviour using an accelerometer, gyroscope and magnetometer. A threshold determines the occurrence of an event and a Dynamic Time Warping (DTW) algorithm compares the occurred event to a set of predefined templates to find an optimal path. Bayesian classification is used to determine how risky or safe the driving habits of the driver are.

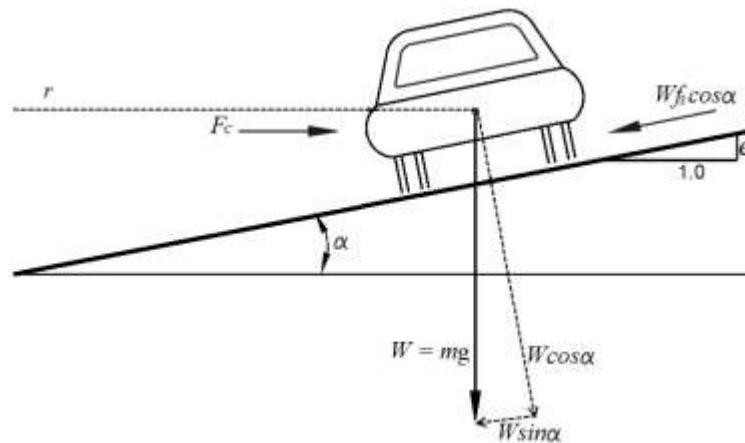


Figure 1 Forces acting on a vehicle travelling on a horizontal curve section of a road. Image adapted from Garber (2009).

Schietekat (2013) has shown that a simple setup that uses only a three-axes accelerometer and filtering software goes a long way towards detecting and classifying reckless driving behaviour. However, the acceleration alone does not provide sufficient information at lower speeds.

2.1 Contribution

Although various contributions have also been made in the field of modelling driver behaviour, there are shortcomings in the research field – existing approaches lack an algorithm where the relationship between speed and acceleration are *simultaneously* taken into account to accurately identify reckless driving. Most of the existing proposed platforms are also not appropriate for informal public transport in Sub-Saharan SSA, because the abundance of sensors used and complexity of the proposed solutions hamper robustness and make the solutions expensive and susceptible to failure or tampering.

This paper presents an innovative way of monitoring driver behaviour using an electronic unit with two sensors, namely a GPS and accelerometer, and a theoretical model, which *simultaneously* includes both acceleration and speed data, to detect and report erratic driving of a minibus taxi. The model is based on standards used in road design, and takes into account the relationship between a vehicle's tyres and the road surface. An online visualization is presented to allow remote monitoring and notification of driving behaviour. To aid in the reconstruction of crashes, the electronic system also contains a storage facility, which is used as a black-box. Driver behaviour and warning notifications are transmitted to an online platform in real-time and also delivered as an audible notification inside the vehicle.

This paper is an extension of the work presented by Zeeman (2013). The authors were invited to present this revised work at a local South African regional conference by engineers in the Civil Engineering fraternity.

3 DESIGN

In this section the techniques used to identify reckless driving manoeuvres in augmenting acceleration data with vehicle speed, and occupancy information are discussed.

Before a reckless driving detection system can be developed, the differences between urban and freeway driving manoeuvres were empirically investigated, so that both can be accommodated. Some significant differences were observed. The main differences between urban and highway events are listed in Table 1.

Table 1: Observed differences between minibus taxis on urban and highway roads

Property	Urban roads	Freeways
Typical legal travelling speeds	below 70km/h	below 100km/h
Maximum detected speed	below 80km/h	above 140km/h
Frequency of longitudinal event occurrences	high	low
Frequency of lateral event occurrences	high	medium
Typical duration of longitudinal event	short (13s)	long (19s)
Typical duration of lateral event	short (9s)	long (17s)
Accidents	injuries and some fatal accidents	high fatality rate
Types of manoeuvres/events	turns, braking, pull-over	circular road curve following, swerving, braking

3.1 Reckless driving acceleration threshold from road design principles

Roads are designed to optimize efficiency and safety, whilst minimizing cost and environmental damage. Worn out tyres, heavy rainfall and light rain after a long dry spell significantly reduce the friction between the road and a vehicle's tyres Keay (2006). This applies particularly to areas where the road surface is polluted by rubber and oil spills, as is the case in urban areas and the immediately surrounding rural areas. In road design, the friction relationship between a vehicle's tyres and the road surface is represented by a friction coefficient. For the purposes of road design, it is desirable to design for a friction coefficient lower than the value at which skidding is expected, since any of these determined factors are likely to present on any given road.

In this paper, the correlation between the friction coefficient (used for the design of roads) and in-vehicle inertial acceleration is utilised to enable reckless driving detection. The correlation between the friction coefficient and acceleration provides two conservative reckless acceleration thresholds: one for lateral manoeuvres and the other for longitudinal.

A key determinant of the safeness of a curvature in the road is the curve radius. A vehicle moving around a circular curve experiences a radial force, referred to as the centrifugal force. This outward radial force is opposed by the centripetal acceleration acting towards the centre of the curvature. The amount of centrifugal force the vehicle can withstand before slipping outwards depends on the side friction between the tyres and the road and the vehicle's weight. Roads are designed with an incline to aid the centripetal acceleration in balancing out the centrifugal force. This inclination of the roadway is known as superelevation. The forces acting on the vehicle are illustrated in Figure 1.

The inclination of the road is denoted with α , and the component of weight (W) along the inclined surface is $W\sin(\alpha)$. The force of friction down the inclined surface is $Wf_s\cos(\alpha)$, where f_s is the coefficient of side friction. The centrifugal force, F_c is given as

$$F_c = \frac{W a_c}{g} = \frac{W u^2}{g r} \quad (1)$$

since the equation for centripetal acceleration is

$$a_c = \frac{u^2}{r} \quad (2)$$

where a_c represents the acceleration for curvilinear motion, u the speed (m/s), r the radius of the curve, W the weight of the vehicle, and g the gravity (9.8 m/s^2).

From (1) it can be seen that increasing the curve radius reduces the amount of centrifugal force experienced by the vehicle. However, a minimum curve radius is desired to minimize the cost and environmental damage. An expression of the minimum curve radius has therefore been developed by civil engineers for designing roadways.

A conservative approach to calculating the minimum radius of a curvature is to assume a zero superelevation (no incline). The maximum centrifugal acceleration (conservative approach) that a vehicle can experience before slipping is

$$a_c = g f_s \quad (3)$$

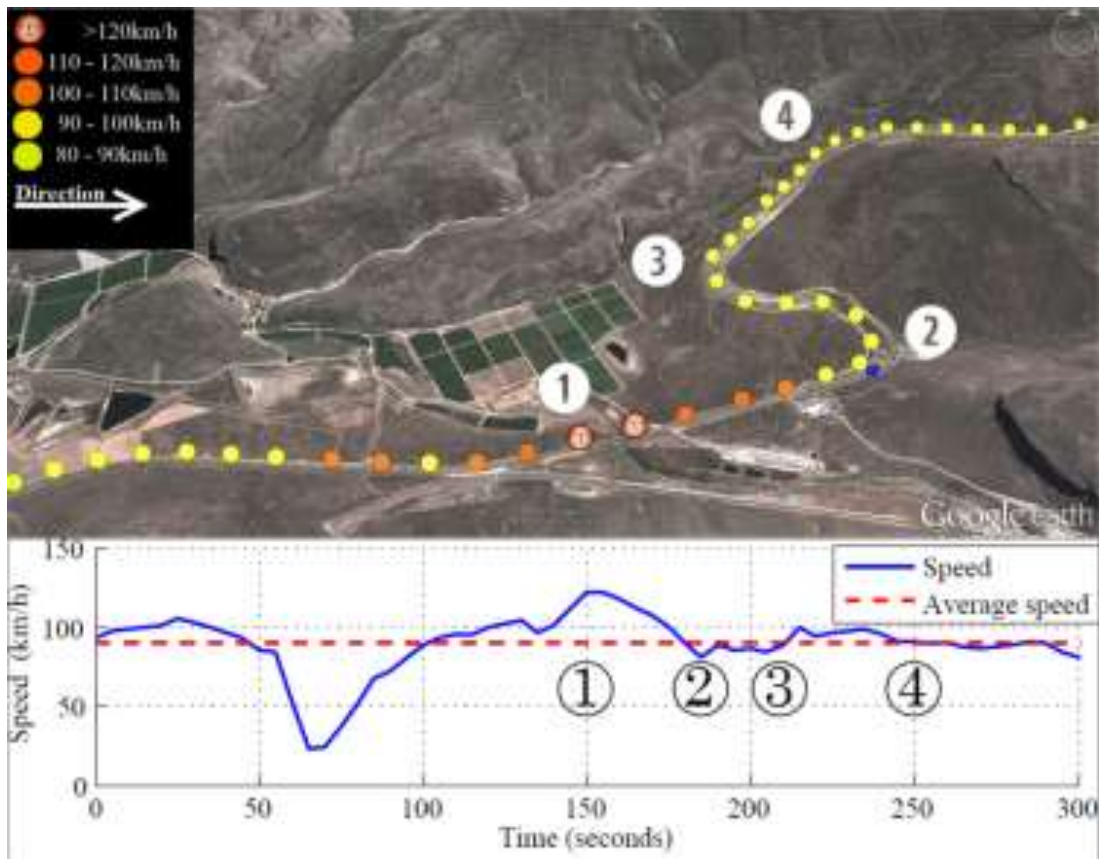


Figure 2 Map and speed plot of a minibus taxi travelling eastwards

The maximum centrifugal acceleration is therefore represented in terms of gravity and the side friction coefficient. According to CSIR Geometric Design Guidelines (2003), the coefficient of side-friction is

$$f_s = 0.21 - 0.001U \quad (4)$$

where U is the vehicle speed in km/h.

Combining gives

$$\frac{a_c}{g} = f_s = 0.21 - 0.001U \quad (5)$$

Since g-force (G) is a_c/g , (5) can therefore be written as

$$G_{lat} = 0.21 - 0.001U \quad (6)$$

which gives the maximum lateral g-force threshold around a curve.

For longitudinal manoeuvres, a nominal deceleration rate of $3.5m/s^2$ is recommended by AASHTO (American Association of State Highway and Transportation Officials), which relates to approximately 0.35G, although most drivers stop at a rate higher than $4.5m/s^2$ when confronted with the need to stop for an unexpected object in the roadway. This is a conservative and comfortable longitudinal deceleration rate for most drivers and is within a driver's capability to stay within the road lane and maintain steering control during the braking manoeuvre on wet surfaces.

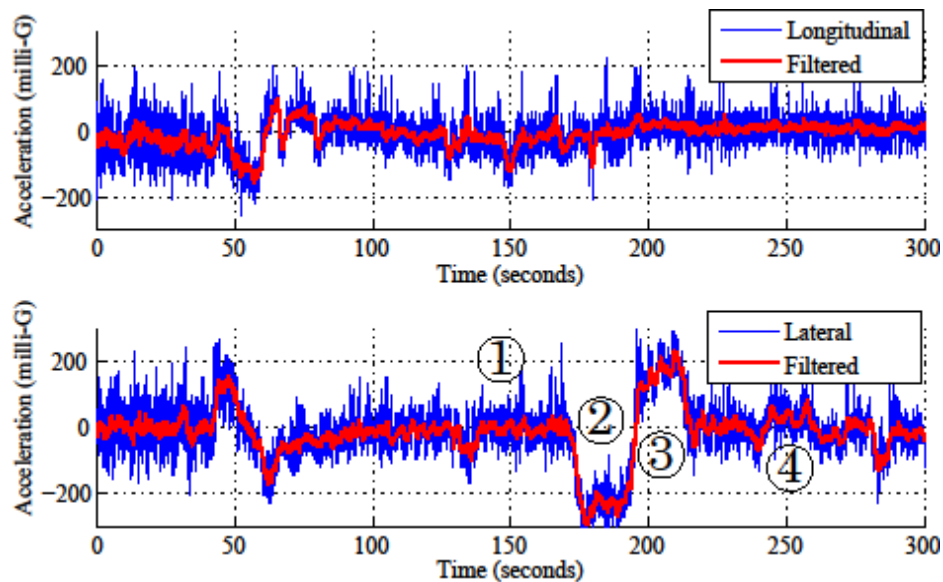


Figure 3 Low pass filtered acceleration of a minibus taxi. Left (nr. 2) and right (nr. 3) turns respectively relate to negative and positive values

A lateral reckless acceleration threshold, that is dependent on the vehicle's speed, and a longitudinal threshold, which is static at 0.35G, have therefore been designed. The thresholds use in-vehicle inertial measurements and road curvature design to give an indication of potential reckless events. Filtered acceleration data is then compared to the corresponding reckless acceleration threshold. The acceleration value above the threshold is calculated when the acceleration exceeds the threshold, and the severity of a reckless manoeuvre can be determined from this value.

3.2 Signal filter design

Raw acceleration data captured by the accelerometer sensor is digitally filtered with a low pass filter (LPF) to remove high frequency noise picked up from the vehicle and sensor. An exponential moving average (EMA) is chosen as the LPF since it results in shorter effective lag than a simple moving average. The derivative of the filtered acceleration data is then taken with respect to time to determine the rate of change of acceleration, i.e. the jerk. High acceleration peaks over a small Δt , results in high jerk values. Analysis of the jerk can be used to determine sharp driving actions, and therefore reckless driving manoeuvres.

Gradually increasing acceleration, or constant high acceleration, will not result in high jerk values, although it may be dangerous. Jerk can therefore not be used alone as an indication of reckless driving. This problem is overcome by summing the jerk samples over a moving window. High concentrations of changes in acceleration are identified, which indicates an erratic lateral or longitudinal driving event. The summation of the acceleration data essentially performs Riemann integration over the jerk, back to acceleration, removing the unwanted stationary offset caused by gravitation.

4 RESULTS

This section evaluates reckless driving detection model proposed in section 3, based on some of the experiments completed in minibus taxis. Thirty-six hours of acceleration and speed data were collected on South African and Ugandan roads from 41 minibus taxis, of which 25% is from urban driving.

One of the journeys undertaken includes a trip in a minibus taxi from Cape Town to the Eastern Cape (total distance: 580km, travelling time: 6 hours). Acceleration and GPS (speed and location) data were captured on the prototype's memory card and post-processed. As an example, and to test and demonstrate the effectiveness of the model, a road section of the trip was identified where the passenger felt unsafe, which happens to coincide with a high lateral g-force exerted on the minibus taxi. The selected 6 km road section, which was also regarded the most erratic for the journey by the passenger, is shown in Figure 2. The selected road section is a mountain pass (Hex River) notorious for its road accidents.

The minibus taxi's speed through the road section is shown in Figure 2. An average speed of 91km/h is maintained, despite a speed limit of 50km/h. The minibus taxi was travelling at a speed of 89km/h turning into the hairpin bend. On the straight (nr. 1), before the left turn, a top speed of 122km/h was reached, 22km/h above the absolute maximum legal limit for minibus taxis. The minibus taxi driver was therefore clearly speeding on this road segment.

The raw acceleration values (unprocessed values) for this road section are low pass filtered using the LPF with $N = 20$ samples, and the EMA's $\alpha = 0.0476$. The raw and low-pass filtered acceleration results are shown in Figure 3, which illustrates that the LPF filter removes the high frequency noise, keeping the valid content in the measured signal. The blue plot is the unfiltered noisy acceleration and the red plot the filtered acceleration.

Left (nr. 2) and right (nr. 3) turns in Figure 2's map respectively relate to negative and positive values in Figure 3. The filtered output clearly illustrates the high acceleration experienced through the turns. The acceleration plot shows that the first turn induces in the highest acceleration and the last turn, at nr. 4, is the lowest.

The results show the weakness in the approach of using only an accelerometer threshold, without considering speed, to model reckless driving: The road segment for an initial turn at 50 seconds on the speed and acceleration plots is not indicated in the map part of Figure 2. At this turn the road bends to the right and then joins the highway at a junction, where the minibus taxi turns left. The initial peaks in Figure 3 (at 50 seconds) would have triggered a simple threshold approach, even though they happen at a low speed. The system described in this work, however, distinguishes between the two scenarios: The initial peaks in acceleration in Figure 4 (at 50 seconds) are significantly lower than the latter peaks since our proposal takes the speed into account.

The summed values of the jerk, which essentially partially integrates the jerk back to acceleration, are illustrated in Figure 4. High concentrations of acceleration are observed at 50 seconds for both longitudinal and lateral, and at 200 seconds for lateral which corresponds with the LPF acceleration and jerk results. Comparing the peaks of the lateral jerk-summation plot at 200 seconds, with the LPF acceleration, we see that the values are similar.

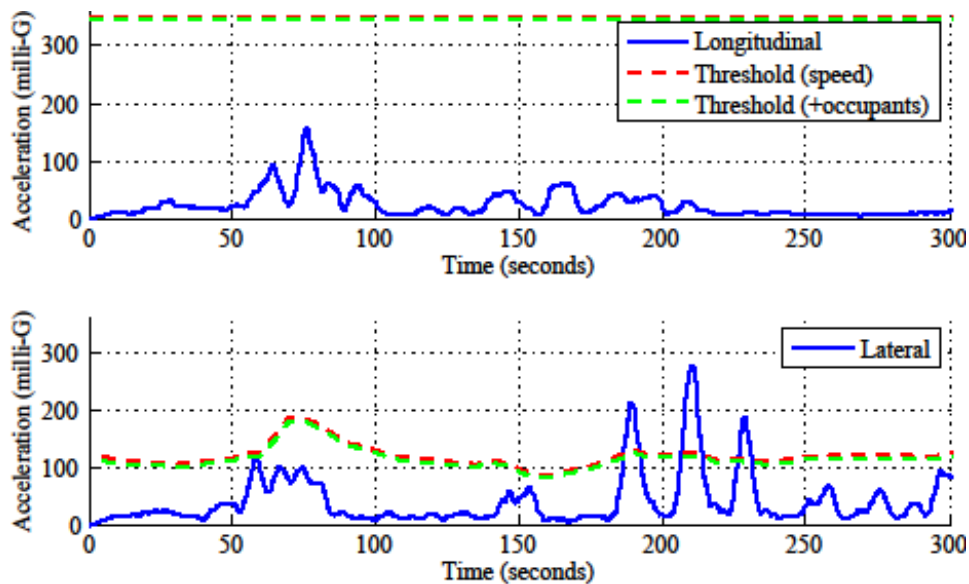


Figure 4 Longitudinal and lateral summed EMA-jerk plot with adaptive threshold.

The dip in speed when the taxi slows down at the road junction is seen at 70 seconds on Figure 2, and as a result the threshold increases (in Figure 4), thereby allowing higher acceleration around the bend. The effect on the lateral threshold can be seen in Figure 3 as the red dashed line. Clear erratic events were detected at 185sec, 205sec, and 225sec, which result in acceleration differences of 93milli-G, 151milli-G and 72milli-G respectively. These results are transmitted to an online platform in real time, from where the responsible parties can be notified of these infringements.

The longitudinal acceleration results with the road design erratic driving threshold can also be seen in Figure 4. No erratic driving events were identified. Longitudinal erratic events are less often identified on highway data since minibus taxis stop less frequently than in urban regions. From the collected data, the longitudinal events rarely exceed the threshold, and only exceed the threshold in harsh braking situations, probably due to the weight of a taxi.

The proposed dynamic threshold is therefore a realisable alternative solution. It takes the vehicle's current speed into account and reduces the acceleration threshold accordingly, therefore restricting the driver to stay within a safe travelling speed and acceleration.

5 ONLINE PLATFORM

This section describes the online reporting system. Data captured are reported wirelessly by the central controller, which uses a cellular modem to transmit the status of all the seats in the taxi to the online platform. Trinity Telecoms' SMART platform is used to store and visualise the occupancy and tracking information. This platform simplifies duplication and aggregation of remote data on a large scale, which is suited to the large minibus taxi industry. Moreover, the platform allows a hierarchy of access accounts and browser access, which allows each owner to view their own taxis on their own mobile phones, but also allows the taxi associations and road authorities to view the aggregated information at regional or national level. The online platform is shown in 5. Online tracking is provided as an additional benefit. Email and SMS notification are sent when the dynamic thresholds are exceeded, or when the speed limit is exceeded.

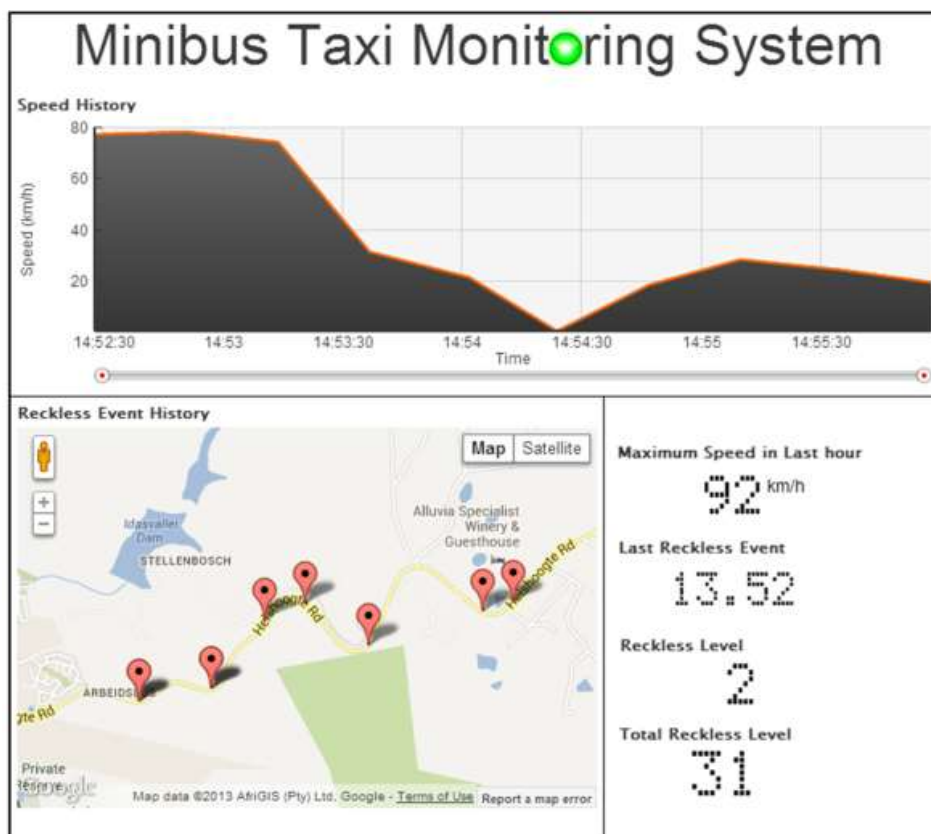


Figure 5 Online minibus taxi monitoring system's online dashboard.

6 CONCLUSION

This paper presents a reckless driving detection system, which was validated in minibus taxis on South African and Ugandan roads. Acceleration and speed results collected show a clear correlation to driving manoeuvres and are used as a measure of recklessness. The designed accelerometer data filtering system's results show the removal of high frequencies and unwanted offsets. The reckless driving detection system is based on novel techniques used to identify reckless driving manoeuvres in augmenting acceleration data with vehicle speed information. The designed model is based on principles used in road design, which takes into account the relationship between a vehicle's tyres and the road surface, i.e. the friction coefficient. Two thresholds (lateral and longitudinal) are developed from the model for comparison to the vehicle's inertial acceleration. The results clearly show the speed dependent lateral threshold, and the longitudinal threshold. The reckless driving detection system was successfully developed and tested, and could be used to make public transport in Sub-Saharan Africa safer.

7 ACKNOWLEDGEMENT

The authors would like to thank Trinity Telecoms (Trintel) for their support through provision of communications equipment, access to their online platform, and technical support.

REFERENCES

- Booyesen, M.J., Andersen, S.J., Zeeman, A.S., "Informal public transport in Sub-Saharan Africa as a vessel for Novel Intelligent Transport Systems", IEEE Intelligent Transport Systems, 6-9 Oct 2013, Den Haag, Netherlands.
- Castellanos, J et al., "Embedded sensor system and techniques to evaluate the comfort in public transportation," in IEEE Conference on Intelligent Transportation Systems, 2011.
- Dapzol, N, "Driver's behaviour modelling using the Hidden Markov Model formalism," in ECTRI Young researchers seminar, The Hague, the Netherlands, 2005.
- Di Lecce, V and Calabrese, M, "Nn-based measurements for driving pattern classification," in IEEE Instrumentation and Measurement Technology Conference, 2009.
- Eren, H, et al. "Estimating driving behavior by a smartphone," in IEEE Intelligent Vehicles Symposium, 2012
- Hickman, J, and Geller, E, "Self-management to increase safe driving among short-haul truck drivers," Journal of Organizational Behavior Management, 23 (4), 2005
- Imkamon, T et al., "Detection of hazardous driving behavior using fuzzy logic," in IEEE International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, 2008.
- Mohan, P et al., "Nericell: Rich monitoring of road and traffic conditions using mobile smartphones," in Proceedings of the ACM conference on embedded network sensor systems, 2008.
- Nigro, JM, and Rombaut, M, "Idres: A rule-based system for driving situation recognition with uncertainty management," Information Fusion, 4, (4), 2003.
- Oliver, N, and Pentland, A, "Graphical models for driver behaviour recognition in a smartcar" in Proceedings of the IEEE Intelligent Vehicles Symposium, 2000.
- Plöchl M, and Edelmann, J, "Driver models in automobile dynamics application," Vehicle System Dynamics, 45 (7-8), 2007.
- Schietekat, J M et al, "Detection of reckless driving in the Sub-Saharan informal public transportation system using acceleration-sensing telematics", Eurocon 2013, July 2013, Zagreb, Croatia.
- Smith, A, "A study of institutional, financial and regulatory frameworks of urban transport in large Sub-Saharan cities," SSATP Working Paper No. 82, 2005
- WHO, Status report on road safety in countries of the African region, 2009.
- Zeeman, AS and Booyesen, MJ, "Combining speed and acceleration to detect reckless driving in the informal public transport industry", IEEE Intelligent Transport Systems, 6-9 Oct 2013, Den Haag, Netherlands.