Towards Detection of Road Weather Conditions using Large-Scale Vehicle Fleets

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***Abstract*—Bad weather conditions such as heavy rain, black ice and fog can have a significant impact on road safety. Currently vehicle safety technologies such as the electronic stability program work reactive to hazardous situations. In this paper, we propose the use of crowd-sourced vehicle data to improve road-weather models and provide real-time local warnings for weather-related hazards. We present our initial results from a field test where we used vehicle CAN-bus data and low cost external sensors to observe local weather phenomena. The CAN-bus contains, among others, data on vehicle dynamics such as wheel speeds. Our approach is to isolate anomalies within these signals. Our initial research suggests some anomalies are weather related and can be used to describe local weather phenomena. Furthermore, the externally installed sensors provide more information on which we can build our assumptions. The results show that the gathered measurements are consistent with the reliable observations from road weather stations.**

***Index Terms*—Anomaly Detection, Vehicle Data, Can-Bus, Road Safety, Road Weather Conditions, Road Weather Models**

I. Introduction

Studies have shown that the type and intensity of road weather has a significant impact on the accident risk [1]. Factors such as heavy rain, snow, strong winds and limited visibility are challenging for drivers. Dedicated road weather models allow us to predict dangerous these road conditions. However, they typically depend on observations from conventional road weather stations, which are not available at the fine spatio-temporal scale needed to provide localized, real-time warnings. As a result, uncertainties in the forecast of environmental conditions can still pose a significant risk to driver safety. Advanced driver assistance technologies such as stability control, anti-lock brakes, on the other hand, are standard options in vehicles and can respond to local hazards. However, these applications are limited in their use as they work reactive to sensor measurements. Only when a hazardous situation is measured the technology can react to stabilize the vehicle. Hence, there is still much room for improvement. Proactive safety measures such as real-time local warnings could prevent such hazardous situations altogether. Early warnings for dangerous conditions such as heavy precipitation and fog, would allow the driver to anticipate and adjust their driving behavior, and aid road authorities with providing safer road management. Improving the resolution and accuracy of models and observations is a crucial step towards such a real-time, location-based warning systems. Fortunately, the rise of connected vehicles and their advanced sensing capabilities provide us with an opportunity to address this issue. The connected car market was worth \$13 billion in 2012 [2], \$42.6 billion in 2019 and is expected to be worth \$212.7 billion by 2027 [3]. When equipped with road-weather sensing capabilities, connected cars could provide us with with the dense observation network needed for real-time, local weather warnings.

For this purpose, a heterogeneous group of industrial stakeholders and researchers consisting of more than 30 partners from seven countries (Belgium, France, Portugal, Romania, Spain, Turkey and South Korea) initiated the Real-time location-aware road weather services composed from multi-modal data (SARWS) project[4]. The goal of SARWS is to provide real-time weather services by expanding the local data collection mechanisms from traditional data sources towards large-scale vehicle fleets. The Belgian consortium consists of Verhaert New Products & Services, Be-Mobile, Inuits, bpost, imec - IDLab (University of Antwerp) and the Royal Meteorological Institute of Belgium (RMI). Within this consortium, the aim is to use crowd-sourced vehicle data to enable real-time warning services for local weather phenomena and dangerous road conditions that surpass the accuracy and timeliness of current warning systems. In addition, these observations will be used to enhance and validate weather prediction models. Local weather data is gathered from the vehicle's Controller Area Network (CAN). The CAN-bus is used by the various Electronic Control Units controlling the vehicle to send sensor and system parameters to each other. From this data, more specifically from parameters related to vehicle dynamics, we can extract valuable road-weather information. For example, wheel speed data and data from the electronic stability program can indicate wheel slip. Changes in braking distance, on the other hand, can provide information on road surface wetness. This data is extended with additional sensor data (e.g., temperature, humidity) and sent to a cloud back-end using a data distribution framework. The collected

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data is then used for: (i) time-series data analysis on CAN-data for the detection of weather-related anomalous vehicle behaviour; (ii) validating and improving the accuracy of weather and road weather models by using the high resolution, real-time vehicle data as input for the models, and (iii) real-time weather services that warn drivers and other stakeholders (e.g. road authorities) about dangerous road conditions. The primary targeted weather conditions in the SARWS project are visibility (e.g. fog), local air and road surface temperature, and road surface condition (slipperiness, aquaplaning, snow, black ice), with a possible extension to precipitation (intensity, type) and wind gusts (crosswind in particular).

In this paper, we discuss the results of our first field test, assess the feasibility of extracting road weather conditions from vehicle data and analyze the reliability of low-cost, crowd-sourced sensor data. In Section II, we discuss the state of the art in road-weather assessment using mobile platforms. Section III discusses the proposed architecture of our solution. In Section IV, we elaborate on our field test setup and discuss the results of our measurement campaign and in section V we present our conclusions.

II. Related Work

The related work on road weather detection can be divided in two categories: (1) detection and analysis of weather-related vehicle dynamics, where we focus on extraction of anomalous behavior from CAN-data, and (2) improving existing weather models by ingesting crowd-sourced data.

A. Weather dependent Vehicle dynamics

Currently, detection of road conditions relies on a sparse network of road weather stations, combined with road weather models to fill in the gaps. The use of a vehicle fleet could significantly increase the density of observations, enabling improved models and real-time warnings for dangerous conditions. In this research, we focus specifically on road-weather-related vehicle behavior. The primary indicator of road-weather conditions is tire friction. Sudden changes in wheel speed, indicate a change in friction, which may be caused by dangerous, weather-related road conditions. Extracting road-weather information from this data, however, is challenging as there are many other variables, such as tire pressure, road surface condition, vehicle weight and acceleration, that influence the friction between vehicle and road. Hence, changes in wheel speed can also reflect numerous other anomalies that are not related to road-weather conditions. A railway crossing segment, for example, may wrongly be classified as glazed segment because of the inherent low friction between rubber tires and the metal rail. Eriksson et al. conclude that the presence of road-specific anomalies such as railway crossings or cobblestone pavements must be filtered out because unrepresentative samples may introduce biased results [5]. The road segment metadata needed for this filter operation is available in Geographic Information System (GIS) databases [6]. In addition, dependencies between features and vehicle speed can be problematic towards classification of the road condition. Perttunen et al. describe how these linear dependencies can be removed [7]. Finally, it is necessary to have sufficient insight in the interaction between the vehicle and the environment. To investigate this relation, simulation can be used. Simulation models of vehicle dynamics can help to identify the necessary parameters related to weather phenomena. Most models are created to evaluate the performance of the vehicle under different conditions. Li et al. highlight the importance of the road-tire friction coefficient [8]. This parameter is affected by road conditions, so changing this parameter on a calibrated model can provide valuable information on vehicle dynamics under different road-weather conditions. Once anomalies are detected, there is still the challenge of classifying (or even quantifying) them to provide insight in the local weather conditions. A first challenge lies in distinguishing weather-related events (e.g., aquaplaning) from anomalies from other sources such as poor road conditions (e.g., potholes). An added challenge, is classifying the weather-related events themselves, for example distinguishing between aquaplaning and sleet. Furthermore, classification of time series data, still poses a significant challenge, especially when considering multi-variate signals. Fawaz et al. provide an in depth review of possible supervised and unsupervised deep learning approaches to tackle time-series classification [9]. In summary, a combination of advances in anomaly detection, filtering and classification is needed to accurately extract road weather conditions from vehicle data.

B. Improved Weather Models and Real Time Warning Systems

Two types of models are considered in our use case: numerical weather prediction (NWP) models, which use mathematical models of the atmosphere to predict the weather based on current weather conditions, and road weather models (RWM), which are used to specifically forecast road weather related parameters, such as road surface condition and temperature. Physical models ([10], [11], [12]) typically make use of radiative balance equations at the road surface, while other models use a statistical approach [13].

RWMs use meteorological input from nowcasting and NWP models, and recent local observations from Road Weather Stations (RWS) can be used to improve the forecasts [11]. NWP models also benefit from the best possible estimate of the initial state of the atmosphere, using various techniques to incorporate recent meteorological observations through a process know as data assimilation [14]. Data assimilation already makes use of a great variety of different data sources such as observations from airplanes, ships and soundings. RMI's operational NWP model Alaro ([15], [16]) is currently run at a resolution of 4km, and is being validated at a higher resolution of 1.3km. Current NWP models still have difficulties reproducing very local weather phenomena, even at their highest resolutions. To provide real-time warnings for drivers, high resolution mobile weather observations have a lot of potential value, especially in weather situations with sharp discontinuities, for example the boundary between rain and snow, and local fog or severe precipitation events [17]. Various national meteorological services are investigating the use of crowd-sourced data and vehicle observations in particular [18]. The use of real-time vehicle data for data assimilation could lead to improvements in NWP forecasts, but only if sufficient quality can be guaranteed. For example, effects such as the impact of the vehicle speed on the observed air temperature should be properly quantified [18]. Quality control measures are an important aspect of the ongoing research within the SARWS project.

There is also ongoing research to improve dedicated RWMs. The Finnish Meteorological Institute (FMI) showed that correcting RWM output with real-time data from a commuter bus produced lower errors during a 22-day test [19]. More recently, mobile car data were included in the FMI's RWM during the winter of 2017-2018 and it was shown that this is an effective way of improving the performance in case of a sparse RWS network [20]. The results did not show any clear improvement when considering a dense RWS network, but the added value of mobile data is yet to be examined on itineraries with large variations of elevation, where it is expected to be greater, as well as during other seasons with higher daily variations of temperature [20]. In Austria, case studies combining RWS observations and the nowcasting system INCA were successfully conducted and resulted in minimal forecast errors with respect to road temperature observations [13]. The German weather office (DWD) also conducts tests in the frame of their project FloWKar to include car data into their weather nowcasting system [21]. The fact that mobile and RWS weather data have different reliability and accuracy, can be taken into account through calibration methods [22]. Finally, it was shown in [23] that air temperature observations from car sensors have utility for improving thermal mapping, which also aids road temperature forecasting.

With large-scale deployment in mind, the primary challenge is to achieve similar results using vehicle CAN-data and a limited set of broadly applicable low-cost sensors, such as humidity and temperature sensors. In addition to advances in NWP modelling, we expect that incorporation of real-time vehicle data will lead to improvements in state-of-the-art road weather services.

III. SARWS Proposed Architecture

Figure 1 schematically presents the general use case of the Belgian consortium with the data flows for the SARWS framework. Weather related data is gathered from connected bpost vehicles and sent to Inuits' data broker. In case of connection loss, data is temporarily buffered in the vehicle and transmitted once connectivity is restored. This data can be event-data (e.g., change in wiper speed, fog light enabled), sensor data from the on-board unit (e.g., temperature, humidity, camera data) or (partially) processed vehicle data (e.g., wheel speeds). The broker distributes this data towards imec's backend, to further analyse the vehicular behavior, and to Be-Mobile's mobility platform, where the data is processed and aggregated into maps. These maps are sent to RMI to improve and validate their NWP and RWM models. RMI, in turn, provides local

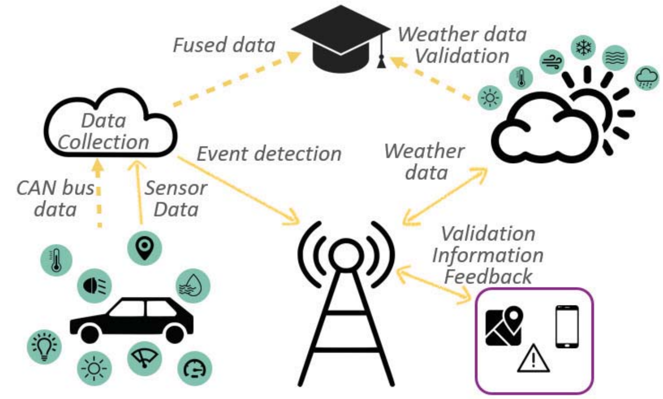


Fig. 1. Proposed architecture for the SARWS use case of the Belgian consortium.

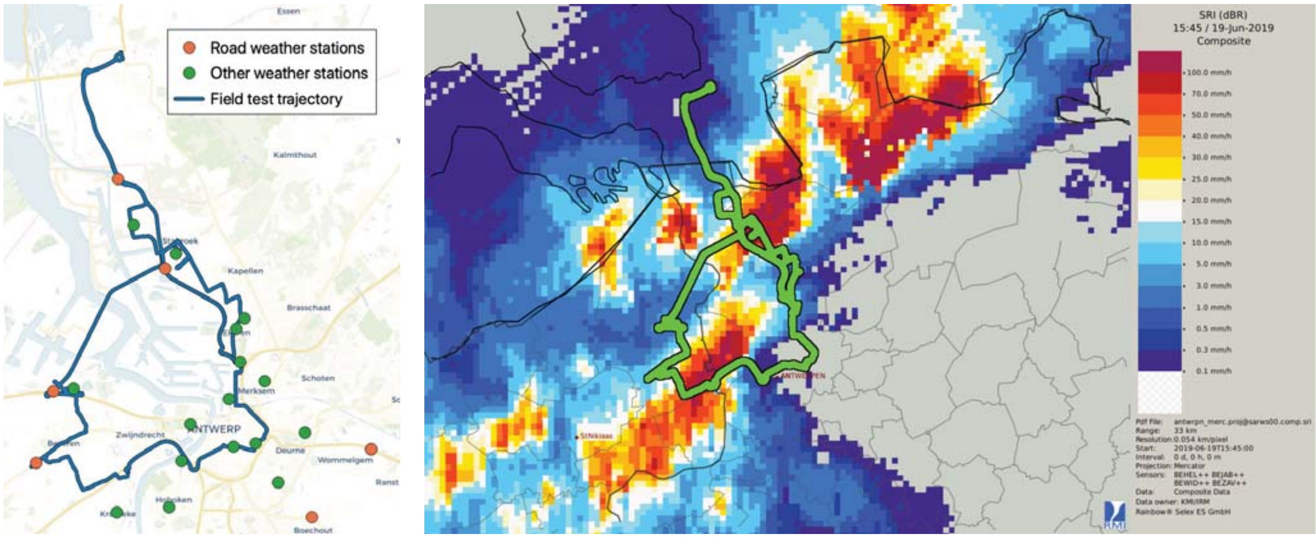
road weather data (road segment level) to Be-Mobile to enable its real-time warning system. This data, represented at the grid level, is also sent to imec's backend to train and validate the machine learning algorithms on vehicular data. In a final step, Be-Mobile sends real-time road-weather warnings to 3rd party stakeholders, such as drivers and road authorities. During the project up to 30 vehicles of the bpost fleet will be used for validation. A smartphone interface allows to collect feedback from the drivers for validation. After the project, the goal is to deploy the platform on all 6500 bpost vehicles and additional 3rd party fleets.

IV. Results

A. Test Setup

On 19 June 2019 a field test was conducted by the Belgian SARWS consortium with a convoy of three vehicles. A bpost Fiat Ducato postal van and a Citroen Grand C4 Picasso were equipped with an on-board unit (OBU) developed by Verhaert, communicating with the data distribution platform of project partner Inuits. This OBU records the GPS location with a GPS dongle fixed to the windscreen. The outside temperature and humidity were recorded by a sensor located at the air inlet under the hood. These parameters were sent through the SARWS platform for validation of the data pipeline. Towards validation, the weather during the test campaign was also recorded using a dash cam. The third vehicle, imec's BMW X5 test vehicle, was equipped with CAN logging setup and an accurate Septentrio GPS-system. The BMW was not connected to the SARWS cloud platform, but instead performed the logging of CAN-data offline.

The day of the field test was selected based on RMI's prediction for severe precipitation and thunderstorms arising from summer convection. The prepared trajectory, with a total length of 140.5 km, passed several weather stations, including dedicated RWS, which can be used for reference, validation and calibration of the registered sensor data. The route and an illustration of the heavy thunderstorm cells on the day of the field test are shown in Figure 2.



(a) (b)

Fig. 2. (a) The field test trajectory (blue) in and around Antwerp, with the location of the weather stations close to the trajectory. Orange markers indicate RWS operated by the Flemish road management agency (AWV). Green markers are other reference stations. (b) A snapshot of the weather radar imagery on the day of the field test (15:45 UTC). Red zones indicate thunderstorm cells with severe precipitation intensities.

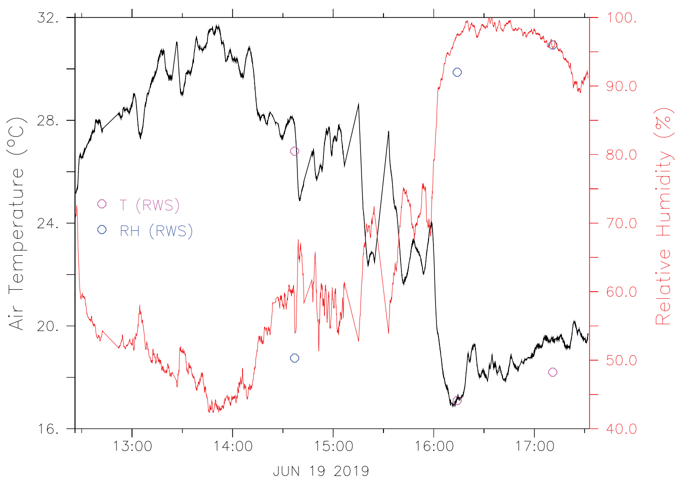


Fig. 3. Air temperature (black) and relative humidity (red) as measured by the bpost van. In purple and blue, respectively the 2 m-temperature and relative humidity as reported from 3 RWS when the car is closest in space and time. This reveals that the vehicle's measurements are consistent with the reliable RWS measurements with relatively small deviations.

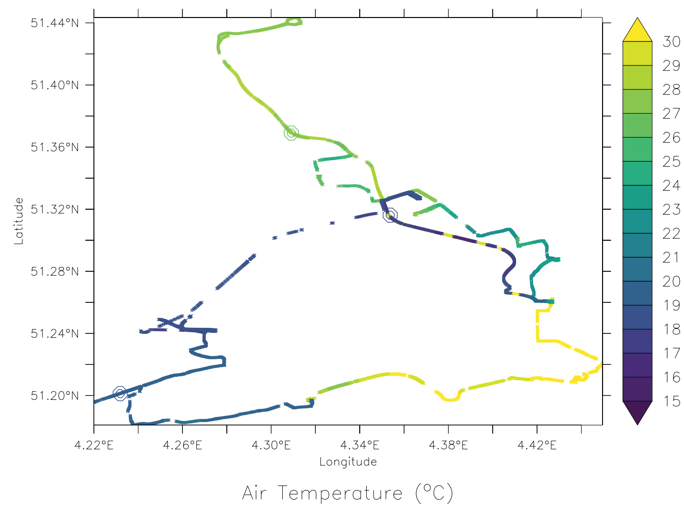


Fig. 4. Air temperature as reported by the bpost van (colored line) together with RWS observations (colored circles).

B. Vehicle Data Analysis

1) External Sensor Analysis: The measurements of air temperature (T2M), relative humidity (RH) and wipers status are plotted together with classic observations from the RWS or radar when relevant for consistency checking. The measurements of T2M and RH from the Citroen car have been discarded due to sensor biases induced by the vicinity of the engine block. The time is always expressed as UTC.

In Fig. 3, the air temperature as measured by the bpost van is consistent with the RWS observations. A sudden temperature drop is observed around 4 pm, associated with the onset of heavy precipitation as derived from the radar imagery. The relative humidity evolution is also shown for the same car. These car observations are also relatively close to the RWS data. Consistent with the temperature observations, a quick humidity increase occurred around 4 pm.

Since weather parameters vary in both time and space, a 2D-map of both temperature and relative humidity from the bpost van are shown in Fig. 4 and Fig. 5 respectively. The RWS measurements at the closest time of car passage, shown as colored circles, show once again the good consistency between mobile and static data. However, some issues remain to be addressed, such as the absence of data transmission in the central region of the domain.

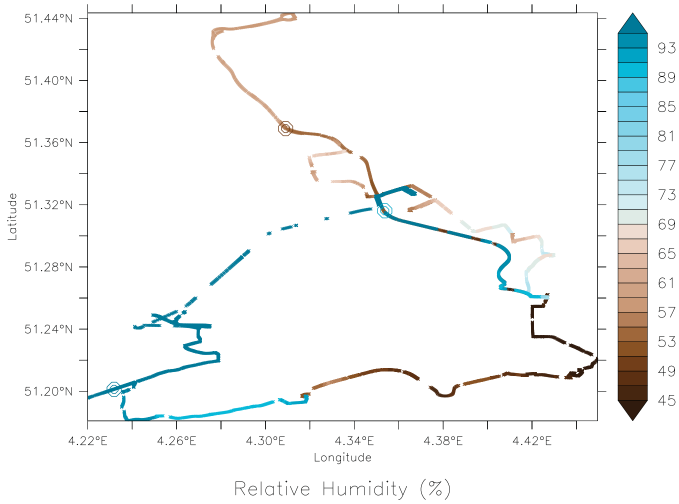


Fig. 5. Relative humidity as reported by the bpost van (colored line) together with RWS observations (colored circles).

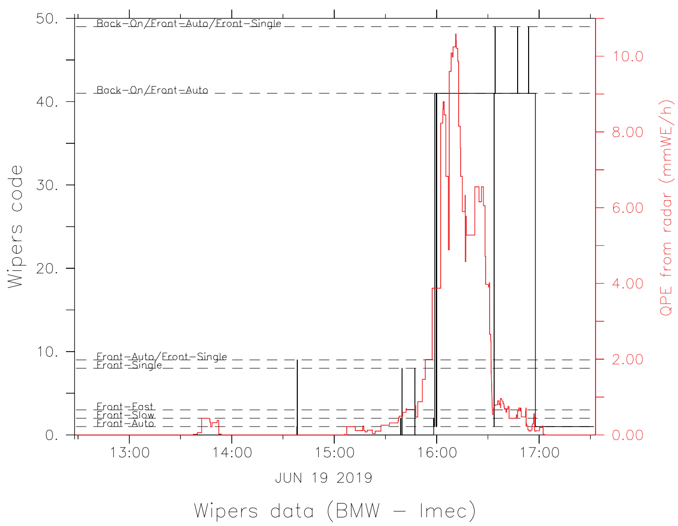


Fig. 6. Wiper status from the BMW car (black) and Quantitative Precipitation Estimate (red) from analysis of radar images.

2) CAN-bus Data Analysis: We now discuss the first results from analysing the CAN-bus data of the BWM X5. We analysed the wiper status data and performed a preliminary anomaly analysis of the wheel speeds to show that CAN data can be correlated to road weather conditions.

The wiper data collected for the BMW during the field test is shown in Fig. 6 together with a detailed estimate of the precipitation amount given by RMI's quantitative precipitation estimation (QPE) product [24]. The wipers status are given by discrete value codes. Separate codes for back/front and automatic/single mode are used, and are shown as dashed lines. For the QPE, we used a composite product made from four meteorological radars combined with gauge data, interpolated to GPS coordinates of the car. This product has a time resolution of 5 minutes. Around 4 pm, the wiper status changed from "No use" to "Back-on" and "Front-auto", which can be sensibly interpreted as occurrence of a precipitation event. This is consistent with the QPE, temperature drop, relative humidity increase, radar images, and video of the event.

In Fig. 7 the difference in wheel speeds between the rear-wheels is presented versus the difference at the front-wheels for the whole test drive. These are distributed around a straight line corresponding to equal differences. Furthermore, some outliers are observed that deviate from this line. These outliers or anomalies can be identified by considering the distance d between the point and the line of equal differences (see Fig. 7) which we interpret as an anomaly score.

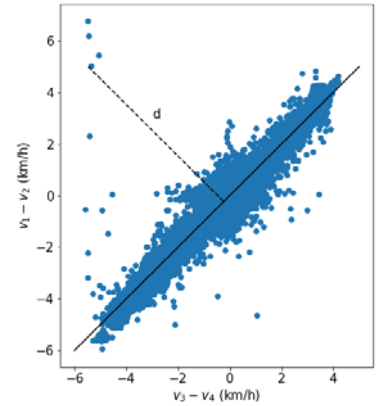


Fig. 7. Difference in wheel speeds (in km/h) at the front axle ($v_1 - v_2$) vs the difference at the rear-axle ($v_3 - v_4$). The differences are distributed around the line corresponding to equal differences, i.e. $v_1 - v_2 = v_3 - v_4$ (black solid line). The distance d between the points and the line (dashed line) can be interpreted as an anomaly score to detect the outliers.

These outliers correspond to an anomalous behavior of the relative wheel speeds which is typically related to slip behavior of the vehicle where one or more wheels lose their grip. In Fig. 8 the four wheel speeds are presented as a function of the time for two outliers. In the upper figure the left wheel at the back slips, which is then corrected by the electronic stability program (ESP) (the BMW has four-wheel drive). In the lower figure we see this behavior for the two left wheels. Note that only the lower figure was recorded after it started raining around 16:00. The first anomaly was not weather-related, further investigation of the anomaly showed that the acceleration of the wheel before slippage reached around 4.4 m/s^2. This acceleration is close to the maximum acceleration on a dry surface for the BMW X5 which indicates that the anomaly originated from a high acceleration. This reveals that further clustering of the anomalies is needed for a better distinction of the weather-related anomalies.

To validate that the anomaly score is correlated with road condition we consider two separate hours of the test-drive: one from 14:00 to 15:00 before it started raining and the road was dry and one from 16:15 to 17:15 when it was raining and the road was wet. Each hour is split in samples of one minute that are scored with the highest anomaly score of that minute. Predicting the 50% samples with the highest scores as being on wet road results in an accuracy of 65%. We note that since

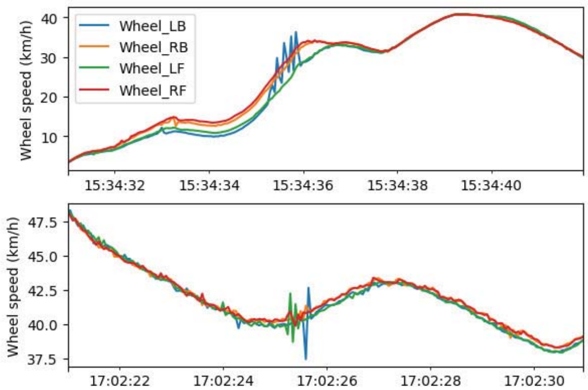


Fig. 8. Four wheel speeds for two detected anomalies where one or more wheels starts slipping, which is corrected by the electronic stability program.

we only have data from a single drive there might also be other factors that distinguish the two hours (such as differences in road conditions that are not related to the weather or driver behaviour).

This preliminary anomaly analysis of the CAN-bus data indicates a correlation between the CAN data and the road condition, but more data is needed to perform a proper validation. The detected anomalies could also be due to non-weather related phenomena such as driver behavior, potholes, speed bumps, etc.. Next steps in this research involve clustering of the detected anomaly to distinguish between non-weather related anomaly and weather related anomaly. To detect other types of anomalies and other weather related events more advanced techniques are needed to take into account additional CAN-bus parameters and the temporal correlations between different parameters.

V. Conclusions and further work

These first results have shown that car measurements of both temperature and relative humidity are consistent with the reliable observations from the RWS, provided the car sensors are located far from the engine block. These direct observations are also consistent with wipers data (a plausible proxy for rain), which were successfully compared to estimates of precipitation from radar measurements. Similarly, changes in wiper status have also shown to provide an indication of precipitation events. This convergence of various sources of weather data strengthens the confidence in the added value of car weather data, in particular when considering the small spatio-temporal scales that cannot be resolved by a conventional RWS network. Currently, the RWM used at the RMI is launched each hour and provides forecasts of road surface temperature and road conditions corresponding to locations of the RWS network throughout Belgium. In the short-term, RMI plans to incorporate real-time vehicle data in this RWM which will run at a higher time resolution for each 250 m-road segment in the region of Antwerp.

A preliminary analysis of CAN-bus data has also shown that anomalies related to road conditions can be extracted from time-series data such as wheel speeds, indicating that it can be an additional data source for RMI's models and can be of significant value in setting up real-time warning services for dangerous conditions. Future work will focus on optimizing the detection algorithm to evaluate more relations present in the vehicle data such as temporal or higher order dependencies. This might be achieved using temporal auto-encoders or other deep learning approaches. Although a distinction can be made between weather an non-weather-related events, further research in time-series classification will also be needed to further automate the process.

Acknowledgment

The SARWS (Real-time location-aware road weather services composed from multi-modal data[4]) Celtic-Next project (October 2018-2021) combines the expertise of commercial partners Verhaert New Products & Services, Be-Mobile, Inuits and bpost with the scientific expertise of research partners imec - IDLab (University of Antwerp) and the Royal Meteorological Institute of Belgium, together with an international consortium with partners in Portugal, France, South-Korea, Turkey, Romania and Spain. The Flemish project was realised with the financial support of Flanders Innovation & Entrepreneurship (VLAIO, project nr. HBC.2017.0999).

References

[1] F. Malin, I. Norros, and S. Innamaa, "Accident risk of road and weather conditions on different road types," *Accident Analysis & Prevention*, vol. 122, pp. 181–188, 2019.

[2] GSMA mAutomotive. (2013, jun) Connected car forecast: Global connected car market to grow threefold within five years. [Online]. Available: https://www.gsma.com/iot/wp-content/uploads/2013/06/cl_ma_forecast_06_13.pdf

[3] Markets and Markets. (2019, nov) Connected car market. [Online]. Available: https://www.marketsandmarkets.com/Market-Reports/connected-car-market-102580117.html

[4] Celtic-Next SARWS. (2019) Real-time location-aware road weather services composed from multi-modal data. [Online]. Available: https://www.celticnext.eu/project-sarws/

[5] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, and H. Balakrishnan, "The pothole patrol: using a mobile sensor network for road surface monitoring," in *Proceedings of the 6th international conference on Mobile systems, applications, and services*. ACM, 2008, pp. 29–39.

[6] O. contributors. Planet dump retrieved from https://planet.osm.org. [Online]. Available: https://www.openstreetmap.org

[7] M. Perttunen, O. Mazhelis, F. Cong, M. Kauppila, T. Leppänen, J. Kantola, J. Collin, S. Pirttikangas, J. Haverinen, T. Ristaniemi *et al.*, "Distributed road surface condition monitoring using mobile phones," in *International conference on ubiquitous intelligence and computing*. Springer, 2011, pp. 64–78.

[8] L. Li, K. Yang, G. Jia, X. Ran, J. Song, and Z.-Q. Han, "Comprehensive tire–road friction coefficient estimation based on signal fusion method under complex maneuvering operations," *Mechanical Systems and Signal Processing*, vol. 56, pp. 259–276, 2015.

[9] H. I. Fawaz, G. Forestier, J. Weber, L. Idoumghar, and P.-A. Muller, "Deep learning for time series classification: a review," *Data Mining and Knowledge Discovery*, vol. 33, no. 4, pp. 917–963, 2019.

[10] L.-P. Crevier and Y. Delage, "Metro: A new model for road-condition forecasting in canada," *Journal of applied meteorology*, vol. 40, no. 11, pp. 2026–2037, 2001.

[11] M. Kangas, M. Heikinheimo, and M. Hippi, "Roadsurf: a modelling system for predicting road weather and road surface conditions," *Meteorological applications*, vol. 22, no. 3, pp. 544–553, 2015.

[12] V. Karsisto, S. Tijm, and P. Nurmi, "Comparing the performance of two road weather models in the netherlands," *Weather and Forecasting*, vol. 32, no. 3, pp. 991–1006, 2017.
[13] Z. Yin, J. Hadzimustafic, A. Kann, and Y. Wang, "On statistical nowcasting of road surface temperature," *Meteorological Applications*, vol. 26, no. 1, pp. 1–13, 2019.
[14] E. Kalnay, *Atmospheric modeling, data assimilation and predictability*. Cambridge university press, 2003.
[15] O. Giot, P. Termonia, D. Degrauwe, R. De Troch, S. Caluwaerts, G. Smet, J. Berckmans, A. Deckmyn, L. De Cruz, P. De Meutter *et al.*, "Validation of the alaro-0 model within the euro-cordex framework," *Geoscientific Model Development*, vol. 9, no. 3, pp. 1143–1152, 2016.
[16] P. Termonia, C. Fischer, E. Bazile, F. Bouyssel, R. Brožková, P. Bénard, B. Bochenek, D. Degrauwe, M. Derková, R. El Khatib *et al.*, "The aladin system and its canonical model configurations arome cy41t1 and alaro cy40t1," *Geoscientific Model Development*, vol. 11, pp. 257–281, 2018.
[17] W. P. Mahoney III and J. M. O'Sullivan, "Realizing the potential of vehicle-based observations," *Bulletin of the American Meteorological Society*, vol. 94, no. 7, pp. 1007–1018, 2013.
[18] K. S. Hintz, K. O'Boyle, S. L. Dance, S. Al-Ali, I. Ansper, D. Blaauboer, M. Clark, A. Cress, M. Dahoui, R. Darcy *et al.*, "Collecting and utilising crowdsourced data for numerical weather prediction: Propositions from the meeting held in copenhagen, 4–5 december 2018," *Atmospheric Science Letters*, vol. 20, no. 7, p. e921, 2019.
[19] V. Karsisto and P. Nurmi, "Using car observations in road weather forecasting," in *International Road Weather Conference*, 2016.
[20] V. Karsisto and L. Lovén, "Verification of road surface temperature forecasts assimilating data from mobile sensors," *Weather and Forecasting*, vol. 34, no. 3, pp. 539–558, 2019.
[21] A. Bouras, J. W. Acevedo, M. Hellweg, T. Kratzsch, J. Nachtigall, Z. Paschaldi, and H. Riede, "The challenge of using high-resolution crowdsourcing data from vehicle sensors for a comprehensive observation network," in *EMS Annual Meeting Abstracts*, vol. 16. EMS2019-934, 2019.
[22] L. Lovén, V. Karsisto, H. Järvinen, M. J. Sillanpää, T. Leppänen, E. Peltonen, S. Pirttikangas, and J. Riekki, "Mobile road weather sensor calibration by sensor fusion and linear mixed models," *PloS one*, vol. 14, no. 2, 2019.
[23] Y. Hu, E. Almkvist, T. Gustavsson, and J. Bogren, "Modeling road surface temperature from air temperature and geographical parameters—implication for the application of floating car data in a road weather forecast model," *Journal of applied meteorology and climatology*, vol. 58, no. 5, pp. 1023–1038, 2019.
[24] E. Goudenhoofdt and L. Delobbe, "Generation and verification of rainfall estimates from 10-yr volumetric weather radar measurements," *Journal of Hydrometeorology*, vol. 17, no. 4, pp. 1223–1242, 2016.