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Use of Contextual Accident Prediction Methods for Road Traffic Regime Adaptation.

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Abstract

Emerging ITS technologies, such as connected vehicles and autonomous vehicles present new potential for optimizing the QoS of a transport network. The availability of massive data on road conditions is a great asset. Such data are required for transportation network safety, mobility and emission reduction. Predictive mechanisms are still needed for road safety to anticipate critical situations through appropriate actions. In order to maximize the accuracy of such predictions, it is important to identify the parameters that play a particular role at the precision level. A case study based on data from the City of Gatineau enable to identify areas potentially at risk. Associated road safety corrective measures based on accurate predictions have an impact on the ecology of the areas in question by considering the traffic density.

1. Introduction

Emerging ITS technologies such as CVs and AVs represent new potential for optimizing the overall operations of a road network. Nevertheless, having large amounts of data raises additional questions about the relative relevance of some data categories on others. With respect to road safety, the relevance of certain parameters is defined according to their contribution to accident predictions accuracy**.**

AI techniques are increasingly considered to make accident predictions. The diversity of these methods as well as the associated results accuracy have an impact on the measures to be taken against the detected risks on transportation network.
The approach developed in this paper is based on a methodology allowing an empirical study whose purpose is to identify the correlations between a prediction method and the input parameters that increase the precision of the results.

Another predictive action is to identify potential risk areas in order to take measures for impacts elimination or minimisation. The actions considered in this paper take into consideration the ecological aspect requirements on transportation networks.

This paper is structured as follows: Section 2 provides an overview of existing work on transportation networks assessment and required actions regarding safety and environment. Section 3 presents an empirical study based on data from the City of Gatineau followed by a new methodology for decision making regarding actions to be taken on risk zones. Section 4 presents a conclusion and future work.

2.Related Work

2.1 Network Assessment for risk zones identification

A set of data including the number of actual and predicted accidents is required to estimate the risks. Locations of risky accidents should be identified [1].
Transportation network monitoring and assessment with respect to road safety is based on accident environment data collection such as weather, road surface conditions, any information related to the road network infrastructure (intersection, segment), etc. The traffic model and density are also considered as important parameters regarding the occurrence of accidents.
The following parameters represent the main measures considered in road safety standards to assess the risks of road network areas [2], [3]

- F-a = number of fatal accidents,
- SI-a: number of serious injury accidents,
- MI-a: number of accidents with minor injuries,
- MDO-a: number of accidents with material damage only,
- T-a: total number of accidents.
- AADT: Annual average daily traffic of the considered areas.

A large number of mathematical operations are performed in order to evaluate criteria representing indices that qualify transport network areas according to accidents risks. Examples of indexes considered for network screening include: 1) frequency of accidents, 2) severity index, 3) accident rate and 4) critical accident rate [1].

Risk validation requires relationships between previous indexes. In particular, with respect to intersections one of the following relationships has to be satisfied:

- Accident rate above the critical rate,
- Severity index greater than the severity index calculated for the category of the area in question,
- Accident frequency greater than or equal to four accidents per intersection over five years.

2.2 Accident prediction and associated corrective measures

The variables surrounding the occurrence of accidents are of great diversity. Among these parameters, traffic patterns and traffic density play a crucial role in the occurrence of accidents [5], [6].

On the other hand, the effectiveness of actions that address the risk areas identified through the transport network assessment depends on the prediction accuracy levels. Nevertheless, many studies on accident prediction consider different methods of treatment with diverse input parameters, making accuracy measurements difficult [7].

Artificial intelligence techniques are increasingly used in the transport accident predictions. Nevertheless, the variables considered during these treatments are not uniform. Given the impact of methods and variables on prediction accuracy, optimizing prediction-based actions presents another challenge to AI techniques [8], [9], [10].

2.3 Measurement parameters relating to road safety

In terms of road safety, numerous sources of problems are identified during the processing of traffic accident data. Several measures are defined and associated with managers from different institutions such as Municipalities, Police and insurance services.

Speed limits and their variations represent solutions to road safety problems. In most cases, speed limitation is seen as a compromise between reducing travel time and reducing road accidents. Which increases the complexity of setting a speed limit and enforcing it.

The study presented in [13], consists of finding the optimal speed for the user and also the society at large. Numerous experiments are conducted in order to calculate the desired value. The presence of congestion is another source of problems leading to accidents. It is directly related to traffic models and density at particular sections.

2.4 Main sources of greenhouse gas emissions

In [14], it is shown that the frequency and occurrence of congestion has a direct impact on greenhouse emissions.

Exhaust emissions from vehicles traveling on urban road networks have detrimental effects exacerbated by the frequent occurrence of congestion. A literature review presented in [15] shows the role of traffic in pollution estimation. The passenger’s exposure time to combustion gasses is directly related to traffic congestion.

In [12], based on experiments, reducing maximum of certain speed limits may have no effect on greenhouse emissions. Policies surrounding speed limits remain a complex problem for which adaptations to specific transport networks are required.
Algorithms considering average speeds as inputs to the VERSIT + model provide increased accuracy in forecasting emissions [11]. VERSIT is a suite of models used to predict emissions and energy use factors based on fleets of vehicles traveling in specific areas. The study presented in [11] showed that reducing speed limits from 50 to 30 km / h reduces emissions by around 25%.

3. Case Study: Accident Data Processing for the City of Gatineau

3.1 Phase 1: Analysis of accident predictions details

3.1.1 Characteristics of the City of Gatineau accident data

In order to overcome the problem of prediction methods and variables diversity with regard to the accuracy of accident predictions, we present in this section an empirical study that makes it possible to locate the relative importance of certain variables. Among available data from the City of Gatineau regarding road accidents, we consider here some categories, including those presented in Table 1.
Two different AI prediction methods are considered to compare their respective results.

Number of variables	Meteo	Pavement	Speed limit
1	Other	Accumulation of water	0
2	Heavy rain	Dried	10
3	Fog / Mist	Muddy	20
4	Clear	Snow	30
5	Cloudy/Dark	Melting snow	40
6	Snow/Heavy	Iced	50
7	Rain/Drizzle	Wet	60
8	Blowing snow / Snowstorm	Hard snow	70
9	Strong wind	Sand Gravel	80
10	Ice	Other	90
11			100
12			

Table 1: Main variables associated with accidents – City of Gatineau

3.1.2 Experiment environment

Numerous data pre-processing are required before proceeding with the prediction methods. Three tools are considered for Phase 1 of this study:

- *A geographic information system*: Platform software for geolocation - Quantum GIS (QGIS) Version 2.14. It is considered to manage raster and vector image formats and databases. It is used as a graphical interface for sophisticated analysis of various geolocated data.
- *A database management system*: PostgreSQL: This system enables the manipulation of various data categories such as objects. It can create functions and establish links between these data such as inheritance links. It incorporates features of SQL.
- *Matlab-integrated AI toolbox*: (Matrix Laboratory)- Programming language to implement algorithms. AI methods based on neural networks are integrated within the toolbox. The Levenberg-Marquardt and Bayesian algorithms are considered in this study.

3.1.3 Experiment Scenarios

In order to set the importance of some variables over others in accident prediction, we identified a first sample of tests based on the combination of variables surrounding the occurrence of an accident. Both algorithms which are based on neural networks, are used to compare the accuracy of the prediction results. Table 2 illustrates examples of correlations between accident variables that have been tested and analyzed.

# Case	Combination of variables
Case #1	% 10 Meteos variables surface % 10 variables pavement surface
Case # 2	% 10 Meteos variables surface % 02 Traffic density variables % 10 variables pavement condition
Case # 3	% 10 Meteos variables % 02 Traffic density variables % 12 Speed limit variables
Case # 4	% 02 Variables - density %12 Variables - the speed limit % 10 Variables – pavement condition

Table 2: Examples of scenarios based on accident variables combinations

3.1.4 Experiment results analyzes

The three-year accident data from the City of Gatineau (2015-2017) is divided into two subsets. Data from the first two years are used for learning and data from the third year is considered for the test phase of the prediction methods. Table 3 illustrates the prediction accuracy rates obtained by each scenario case.

# Case	Experiment results on prediction accuracy
Case #1	81 % for Levenberg-Marquardt algorithm and 92 % for Bayesian algorithm
Case # 2	54 % for Levenberg-Marquardt algorithm and 69 % for Bayesian algorithm,
Case # 3	Bayesian algorithm 90 %, Inconclusive results for Levenberg-Marquardt algorithm
Case # 4	Results with both algorithms are inconclusive

Table 3: Experimental results of prediction algorithms

Generally speaking, the Bayesian algorithm performs better than the Levenberg-Marquardt one. The correlation with some parameters such as road surface condition and traffic density does not make it possible to make good predictions with both algorithms. More experiments are then required for these variables considering other categories of prediction algorithms. Those are out of the scoop of this paper

3.2 Identification of risk zones in the City of Gatineau

The purpose of this phase is to identify risk zones at the City of Gatineau level by considering provided data concerning the accidents and the characteristics of the considered areas infrastructure. Thanks to the geolocation tool and data processing to locate all accidents across the Cities, East and West regions of the City presenting the concentration of accidents across are identified.

Based on identified regions and the observations of the contents, it turned out that the criteria presented in Section 2 of this paper are not directly applicable. Nevertheless, given the importance of predictions and measurement, a set of operations using QGIs capabilities combined with the database management, correlations between various variables have generated areas of the City that require prediction treatments to avoid critical states according to the risk index presented in Section 2. Example of parameters to correlate: number of injuries, number of deaths, speed limit, accidents with material damage only. We present here two examples of identified risk zones.

Identified Zone 1:

Total of 116 Accidents over the three years fatal accidents 9 accidents with more than two injuries. 68% of accident occurred in streets at 50 km /h.

Table 4 : Parameters combination for zone 1 identification

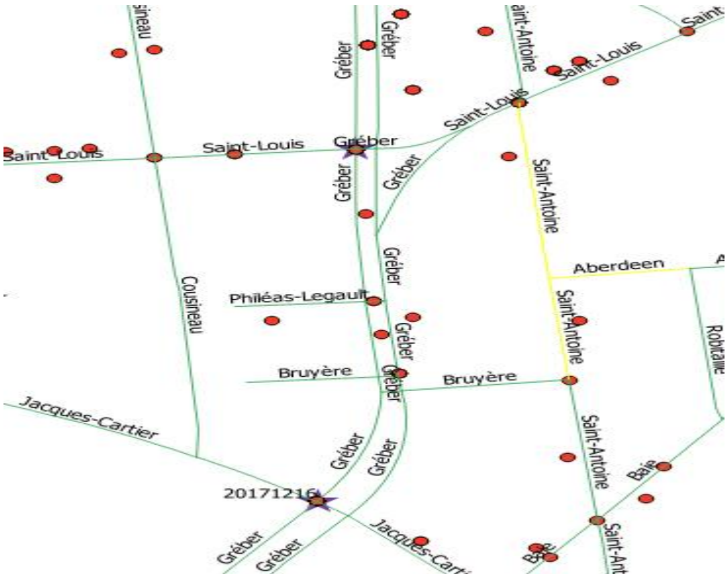

Figure 1 : Potential risk zone 1

Identified zone 2

Total of 18 accidents over the three years 1 fatal accident 3 accidents with more than two wounded 100% of accidents occur on dry pavements

Table 5 : Correlation parameters for zone 2 identification

Figure 2: Potential risk zone 2

Identified areas require processing to consider specific measures to minimize current risks and avoid trends towards risk indexes similar to those presented in Section 2. In the next section, we present a new methodology to best respond to the risk of road safety by integrating environmental considerations according to transport network QdS requirements.

3.3 Towards safe and Green zones in the City of Gatineau

Each zone identified as at risk must be the subject of various measures in order to limit or even eliminate redundant risks. In this paper we consider measures that both reduce greenhouse effects and safety risks. Step 1 of this phase is then based on an experimental simulation-based approach before proceeding to a real-life test bed.

3.3.1 Experimental environment of step 1 corrective actions

SUMO Simulator (Simulation of Urban Mobility) is considered for this step given its ability to integrate realistic components of a transport network such as traffic. The popularity of SUMO and the capabilities of its extension made it chosen it in many research and development works.

3.3.2 Methodology of using SUMO at risk zones of the City

3.3.2.1 Configuration of SUMO

The treatment process of each risk zone is based on the search for the best speed limit as action against road safety risks with consequences on the reduction of congestion. According to literature review presented in Section 2, speed limit plays an important role for safety enhancements despite the challenges related to its choice. Based on SUMO capacities, we consider the integration of identified risk zone considering the OpenStreetMap environment as shown in Figure 3.

Figure 3: Integration of Zone 1 with SUMO environment

At the operating level of the simulator, it is possible to generate traffic according to different models and to collect various information relating to the travel time for each vehicle individually or for all the vehicles considered in an area. Table 6 illustrate examples of output information that will be considered in the process of corrective actions to be taken to minimize the risks of the areas in question.

Output of SUMO	Category of information
Summary-output	Provides overall data on vehicle speed and waiting time
Tripinfo-output	Basically gives information on the duration of vehicle trips
Vehroute-output	Provides detailed information on each vehicle

Table 6: Output files of SUMO for traffic and congestion measurements

4.3.2.2 Methodology for risk areas processing

Table 7 describes the processing steps to select the best new speed limit in order to achieve more confident accident risk indexes such as lower traffic density.

Search for safe and ecological conditions for Area Z1
1. Test with the current speed limit: Case 1 1.1 Identify the cruising speed of the area (special periods) 1.2 Evaluate the travel time of specific vehicles with specific departure and arrival points with cruising speed 1.3 Generate different levels of congestion based on segment capacity and vehicle speed parameters during a time period T 1.4 Assess travel time delays for each level of Traffic 1.5 Associate congestion levels with observed delays
2. Analysis of new speed limits in area Z1
For each acceptable speed limit for area Z1 a. Repeat steps 1.1 to 1.5 b. Calculate the AADT of Z1 area with the new speed limit c. Calculate a risk index for Z1 area based on the new AADT
3.**Choosing the best speed limit to maintain** **1.** Compare the levels of congestion between Case 1 and each case based on a new speed limit that becomes safe by its new AADT 2. Choose the new speed limit that provides the lowest level of congestion among the speed limits tested.

Table 7: Process for selecting the best speed limit for risk areas

A series of SUMO environment configurations are underway to generate the required information such as sensor-based count information whose installation will be simulated at the risk intersections of the study areas. The validation of step 1 may lead to real tests at risk zones in order to anticipate more incidents in the road network and also to increase ecological mobility in these areas.

4.Conclusions et future direction

Despite the availability of massive data from emerging ITS technologies, many questions are raised regarding the relevance of collected data. With respect to road network accident prediction algorithms, the relevant data are those necessary for the accuracy of the prediction results.

An empirical study based on data from the City of Gatineau has identified parameters whose correlation increases the accuracy of accident predictions. Prediction methods based on AI techniques are considered.

The new approach presented in this paper lies in identifying potentially risky areas of the city through some risk index adaptations. A methodology is defined regarding a decision-making process on the measures to be taken regarding risk zones. The choice of speed limit is the subject of a second empirical study, the results of which will allow an integrated solution to deal with the risks of road safety and at the same time increasing a green mobility of the considered zones of the city.

For future work, a real test bench will be considered according to the results of the current experiments based on urban mobility simulator.

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5.References

[1] L. Thakali, L. Fu and T. Chen. Comparing Crash Estimation Techniques for Ranking of Sites in a Network Screening Process, TRA-946-1, Annual Conference of Canadian Society for Civil Engineering, Resilient Infrastructure, London, 2016, p. 12.
[2] V. Rosolinoa et al. "Road safety performance assessment: a new road network Risk Index for info mobility" - Social and Behavioral Sciences 111 (2014) 624 – 633
[3] Using Safety Analyses for Planning- https://safety.fhwa.dot.gov/tsp/fhwasa15089/chap5.cfm
[5] [Abdel-Aty, M. et al., "Crash Risk Assessment Using Intelligent Transportation Systems Data and Real-Time Intervention Strategies to Improve Safety on Freeways", Journal of Intelligent Transportation Systems, 11(3):107–120, (2007).
[6] Chengcheng Xu, Wei Wang, and Pan Liu, "A Genetic Programming Model for Real-Time Crash Prediction on Freeways", IEEE Transactions on Intelligent Transportation Systems, pp 1-13, Issue, 99, (2012).

[7] llham Benyahia, Giancarlo Colmenares, François Bellavance, "From Highways Risk Monitoring Process to Intelligent System for Highways Safety Calibration for Autonomous Vehicles", Revue Routes et Transports, Volume 46, no 2, pp 52-57, 2017.
[8] G. Ali & A. Tayfour, "Characteristics and Prediction of Traffic Accident Casualties In Sudan Using Statistical Modeling and Artificial Neural Networks", International Journal of Transportation Science and Technology · vol. 1 · no. 4 · 2012 – pages 305 – 317
[9] S. Khair et al., "Prediction of Road Traffic Accidents in Jordan using Artificial Neural Network (ANN)", Journal of Traffic and Logistics Engineering Vol. 2, No. 2, pp 92-94, June 2014
[10] F. N. Ogwueleka *et al*, "An Artificial Neural Network Model for Road Accident Prediction: A Case Study of a Developing Country", Acta Polytechnica Hungarica- Journal of Applied Sciences, Vol. 11, No5, 2014, pp 177-197.
[11] M. Madireddy et al., "Assessment of the impact of speed limit reduction and traffic signal coordination on vehicle emissions using an integrated approach". Transportation Research Part D: Transport and Environment, Volume 16, Issue 7, October 2011, Pages 504-508
[12] G. Bel et al., "The environmental effects of changing speed limits: A quantile regression approach", Transportation Research Part D, Vol 36 (2015) pp 76–85
[13] M. Hadji et al., "Determining optimal speed limits in traffic networks ", IATSS Research, Vol 39 (2015) 36–41
[14] M. Grote, "Including congestion effects in urban road traffic CO2 emissions modelling: Do Local Government Authorities have the right options?", Transportation Research Part D 43 (2016) 95–106
[15] S. Bharadwaj et al., "Impact of congestion on greenhouse gas emissions for road transport in Mumbai metropolitan region", Transportation Research Procedia 25 (2017) 3538–3551