Analytical Model for Winter Road Maintenance Efficiency Determination

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Abstract: Analytical model to increase the Winter Road Maintenance (WRM) cost-efficiency has been developed. It supports the planned WRM decision-support system and is a crucial element to plan, develop and maintain a cost-efficient WRM system. The model emphasizes the indirect costs of WRM, and the importance level of data sources used to define winter road conditions in a certain area. Multiple measurements of data provided by data sources are carried out and are used as the main WRM cost-influencing factor. The model determines steps and guidelines for the calculation of the WRM costs and the impact of data sources used to define road and driving conditions.

1 INTRODUCTION

A decision support system for winter road maintenance (WRM) is crucial to determine road and driving conditions through data retrieval from real-time sources. The use of Intelligent Transportation Systems (ITS) in WRM has been adopted globally, with various application methods being employed (Deksne et al., 2021, October). To ensure valuable information is provided, a capability-based WRM data ecosystem has been designed (Deksne et al., 2021), connecting both standard and non-standard data sources from different stakeholders.

The decision-making process in WRM is heavily reliant on the data obtained from sources, which makes the sufficiency and reliability of the data critical factors. Improper determination of road conditions can lead to an increase in WRM costs due to inefficient operations, and an analytical model of winter road maintenance efficiency has been designed to consider the impact of data sources based on parameters such as data completeness, availability, and variety (Deksne et al., 2021).

The objective of this paper is to develop an analytical cost-efficiency model that evaluates the importance of data sources in WRM decision-making and assesses their reliability.

2 BACKGROUND

This research is part of an industry-sponsored project aimed at developing an integrated decision-support ERP system for WRM. The proposed system is based on a data ecosystem that allows for data sharing between parties to form valuable information. The capability-based ecosystem model (Grabis et al., 2022) is used to design the system's capabilities, ensuring that business goals are met (Deksne et al., 2021, September). The availability of timely information is critical to WRM operations, and a decision-support system that retrieves data from various sources can increase WRM efficiency.

The architecture and technology selection of the proposed system have been described in Deksne et al. (2021, October). The main components of the architecture include a data ingest framework, a decision-making and interpretation module, and an adjustment module. Additional services such as data sharing, archiving, visualization, performance indicator measurement, and knowledge management will also be provided.

A rules engine, developed in close collaboration with WRM field experts in Latvia (Jokste et al., 2022), will be used to determine the road and weather condition rules that trigger necessary WRM actions based on retrieved data. The analytical cost-efficiency model is a part of the proposed decision-support

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system, enabling the evaluation of data sources used in WRM decision-making and the assessment of potential risks to increase cost-efficiency.

3 MODEL

3.1 Road Maintenance Costs

The direct costs of WRM are incurred from various factors such as anti-slip material use and snow removal activities, and are often calculated based on the road distance traveled. However, direct WRM expenses should not be considered the only measure of total WRM expenses, as public interests and macroeconomic goals must be considered in increasing cost-efficiency of WRM services. Ratkevicius et al. (2017) designed an economic effect model of WRM that compares direct expenses with societal expenses such as vehicle expenses, road accidents, and travel time expenses, as well as environmental expenses affecting the economic effect.

The main goal of WRM is to provide safe driving conditions by reducing the risks of inappropriate road conditions caused by snow and ice. These risks should be considered as indirect costs of WRM in determining overall cost-effectiveness.

The relationship between weather conditions and road accidents has been widely studied, with Bergel-Hayat et al. (2013) reporting a correlation between temperature and the number of injury accidents and Malin et al. (2019) reporting a relative accident risk more than two times higher in the case of snowfall compared to weather conditions such us rain, sleet, and no precipitation. Theofilatos et al. (2014) have investigated more studies that have discovered a link between traffic, weather conditions, and road safety. Considering accident and speed reduction risks as risks that correlate with weather and road conditions, costs of these risks need to be included in the total cost equation for a specific road section (1).

$$C_{MN} = (AC_{MN} + SRC_{MN} + DMC_{MN}) \quad (1)$$

where C_{MN} – road section MN costs, where M is the road section start point, and N – the endpoint,
AC_{MN} – accident costs of the road section MN,
SRC_{MN} – speed reduction costs of the road section MN,
DMC_{MN} - direct maintenance costs of the road section MN.

The total cost of WRM for a given road section (1) is influenced by several factors, including the number of accidents, traffic volume, and availability of data sources. The availability of timely information on weather and road conditions is crucial for WRM service providers, as it enables them to make informed decisions that can minimize the number of accidents and reduce speed reduction costs. A prompt response time and appropriate selection of WRM activities are critical for ensuring an efficient maintenance process. As a result, it is necessary to evaluate the data sources used to assess their impact on cost-effectiveness.

The accuracy of information obtained about the WRM actions required is influenced by the attributes related to data source evaluation. Inaccurate information can result in repeated maintenance work for the same road section and inefficient decision-making regarding driving routes, leading to increased total travel distance for the service vehicle and thus higher maintenance costs.

3.2 Road Accident Costs

The costs of road accidents have been widely analyzed in previous studies. Salli et al. (2008) studied the impact of different winter road conditions on accident risk in passenger car traffic and found that the accident risk for accidents resulting in physical damage or injuries was 4.1 times greater on snowy or icy roads compared to bare roads. Norrman et al. (2000) established quantitative relationships between road slipperiness, accident risk, and WRM activities. Authors have reported accident risk for each type of classified slipperiness level (2). The accident rate was divided by the expected number of accidents, assuming that all accidents in a month occurred evenly.

$$A_{riskT} = \frac{1}{N} \sum_{m-first\ month}^{last\ month} A_{t,m} h_m \left(A_m h_{t,m}\right)^{-1} \quad (2)$$

where A_{riskT} – accident risk for the road slipperiness type,
$A_{t,m}$ – the number of accidents slipperiness type t, month m,
h – number of hours,
N – number of months.

Minimizing accident risk during winter by reducing road slipperiness requires timely and accurate information on weather and road conditions. Accident costs, which are used as input in the cost-efficiency model, are influenced by the available information from data sources. The potential accident costs increase when information on road conditions is not available and decrease when it is available in a timely manner. Other factors such as road pavement type, driving speed, and tire quality can also contribute to road accidents, but they are not analyzed in this research with a focus on the WRM domain.

As reported by Partheeban et al. (2008), accident costs can be used to calculate the expenditure on road safety management and assess the impact of road safety improvements in an economic manner. Different methods have been applied in previous studies to calculate accident costs, which range from 0.5% to 5.7% of the gross national product, as reported by Elvik (2000). Silcock et al. (2003) defined cost components for calculating the cost of road crashes, and Bougna et al. (2021) and the World Bank (2021) described the main methodologies used to calculate road accident costs, including restitution costs, human capital, and willingness to pay.

Wijnen et al. (2016) analyzed the estimates of social costs of road crashes in several countries, where costs are calculated as a proportion of the gross domestic product (GDP). Direct and indirect accident costs have been studied, with total accident costs defined by Partheeban et al. (2008) as the sum of hospital expenses, future consumption costs in the case of a fatal accident, gross loss of future output, vehicle damage costs, and others. Accident costs are mainly calculated as losses for the economy, as in the case of fatal road accidents, those individuals cannot contribute to the state's economy. Direct costs include those incurred by vehicle owners, road exploitation services, medical institutions, and the cost of road accident investigation, while indirect costs cause a subsequent negative impact but cannot be directly calculated.

Wijnen et al. (2017) found that the total costs of crashes vary between 0.4% and 4.1% of GDP due to the different methodologies used and cost components calculated for different countries that may not be in accordance with international guidelines. The Latvian Road Safety Directorate performed a cost-benefit analysis to evaluate the effectiveness of road safety improvement measures and found that the average costs of road accidents without victims were 2215.78 EUR, while in the case of fatal road accidents, they were 40457.29 EUR (2021). Most accidents in Latvia occurred in cities or on main roads connecting cities. (CAIS)

3.3 Impact of Data Sources

The proposed WRM decision-support system aims to process various types of data from multiple sources in order to enhance the efficiency of WRM operations. The quality of each data source is assessed based on indicators such as accuracy, timeliness, credibility, and accessibility. These indicators are used to measure the quality of each data source and thus determine its importance. Not all data sources are equally important when calculating necessary weather and road conditions to generate tasks for WRM (Jokste et al., 2022). Poor usage of data sources and low-quality levels of data can increase maintenance costs because necessary information will not be available in order to perform WRM, which will result in inefficient WRM service and can increase accident risks (Fig. 1).

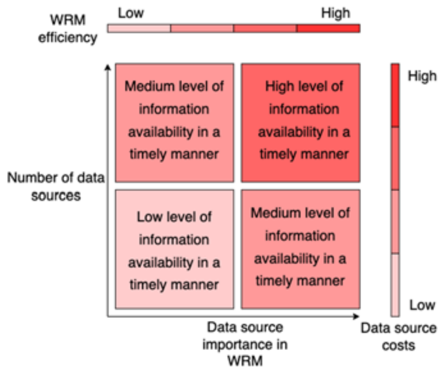

Figure 1: Impact of data sources and their importance.

The number and importance of data sources in terms of their ability to describe relevant weather and road conditions play a crucial role in determining overall WRM efficiency (Fig. 1). The use of open data and semi-open data sources, which are owned by third-party companies, may increase the cost of data sources.

It is necessary to evaluate the importance and impact of data sources by considering road and weather conditions to minimize data costs. Furthermore, defining the importance of data sources can assist WRM decision-makers in making informed decisions regarding their usage and increasing the number of data sources in areas where the risk of poor quality or insufficient data is high.

The availability, completeness, and variety of data are factors that affect the total maintenance costs and WRM efficiency. Timeliness of road and weather information is essential for effective WRM operations and reducing accident risks. Data quality needs to be evaluated to determine the reliability and importance of each data source (Fig. 2).

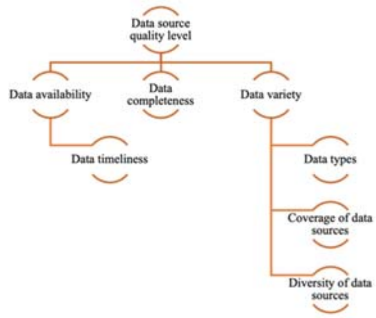

Figure 2: Data quality and its indicators.

Data availability is determined by the time interval after which necessary data is received and ready for use. Given that road and weather conditions can change rapidly, it is crucial to have timely access to data to perform WRM activities effectively. Data completeness refers to the validity of collected data and its ability to provide reliable information to decision-makers. Data variety is evaluated based on the types of data, coverage of data sources, and diversity of data sources. The importance of different data types is determined by assigning weights to their relevance in setting defined rules and context elements. The coverage of data sources describes their availability in a specific geographical location, while the diversity of data sources minimizes the risk of data unavailability or insufficiency and enhances accuracy.

4 APPLICATION

A specific section of road has been selected for the purpose of calculating the costs associated with WRM. This calculation involves determining the direct maintenance costs, potential accident costs, and the significance of data sources. The data used for this calculation is obtained from meteorological and video cameras operated by the Latvian State Road. The significance of the data sources and the level of road slipperiness are calculated based on the data received from the two available meteorological stations. The data period for this calculation is one month, specifically December 2021. The chosen road section has been precisely defined and the data from both meteorological stations, provided by the Latvian State Roads, is utilized to calculate the level of slipperiness in the road and to determine the potential risk of an accident.

4.1 Direct maintenance

The direct road maintenance costs are determined by WRM service companies based on the extent of cleared roads and the distance traveled. Therefore, these costs are not included in the present study. However, the planned WRM decision-support system will enable the analysis of direct costs and ensure their efficiency. Additionally, the analytical model will facilitate the reduction of direct costs as outlined in Section 3.

4.2 Accident Costs

Accident costs are considered as one of the metrics to calculate the total WRM costs (1). There are numerous factors that influence the number of accidents, including road conditions and human behavior. However, in this study, only the type of road slipperiness is used to determine the weather-related accident costs. The primary objective of calculating the accident costs is to evaluate the cost-benefit in the event that the accident risk is reduced. The type of slipperiness is the main variable. The road slipperiness types, the cost per road accident, and the location of the road section are attributes that affect the outcome (Fig. 3).

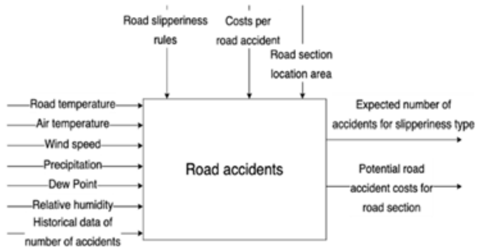

Figure 3: Inputs and outputs calculating potential road accident costs and expected number of slipperiness type.

Table 1: Expected accident costs per slipperiness type for the given case.

Slipperiness type	Accident risk	Slipperiness hours, h	Expected number of accidents	Expected accident costs, EUR
Type 1	11,6	0	0,00	0,00
Type 2	6,1	114	10,62	13997,17
Type 3	3,4	14	0,72	958,10
Type 4	6,4	0	0,00	0,00
Type 5	1,5	22	0,50	664,23
Type 6	3,2	20	0,97	1288,21
Type 7	2,5	0	0,00	0,00
Type 8	4,5	0	0,00	0,00
Non-slippery	0,7	573	6,1	8073,43

To calculate the road accident costs, the following steps are defined:

Step 1 – The accident risk defined by Norrman et al. (2000) is employed to describe the number of times the average number of accidents is expected in T-slipperiness conditions in comparison to the average number of accidents estimated for all types of slipperiness.

Step 2: Historical accident data (CAIS) is used to calculate the average number of accidents per hour.

Step 3: The average number of fixed T-slipperiness hours per month is calculated based on the rules defined by Norrman et al. (2000).

Step 4: The average number of accidents per month in T-slipperiness conditions on the road section MN is calculated.
Step 5: The average accident costs, based on research conducted by the Latvian Road Safety Directorate, are used to determine the average accident costs.
Step 6: The expected average road accident costs for the road section due to the road slipperiness are calculated (Table 1).

4.3 Impact of Data Sources

Multiple methods are employed to assign data importance weights, which serve to determine the quality of the data and its source. The expert evaluation method is utilized to assign categories of importance and weights for Data Availability, Data Completeness, Coverage of Data Sources, and Diversity of Data Sources. Field experts with extensive experience in WRM decision-making and operations planning in Latvia participated in this evaluation. The machine learning method is utilized to assign weights for data variety, while the best scenario method is employed to determine the necessary conditions for minimizing data risk and to inform decision-making related to road, driving, and weather conditions.

The importance weights are used to identify the ideal scenario for utilizing data sources to produce valuable information for a specific road section. If the data is not readily available, or if its quality is low, the risk of inaccurate information increases, leading to inefficient WRM decision-making. The determination of data risk levels provides opportunities to identify strategies for reducing risk by improving data quality.

Data availability importance weights reflect the accessibility of a specific data source and the importance of its timeliness. For example, a higher weight is assigned to data that is updated less frequently than every 10 minutes, as this is considered the most suitable frequency for accurately defining weather and road conditions in close to real-time. The availability levels of data sources are calculated for each road section and determined by WRM field experts. Data is considered highly available if its timeliness is less than 10 minutes, medium-high if it falls between 10 and 20 minutes, medium-low if it falls between 20 and 60 minutes, and low if its timeliness exceeds 60 minutes.

The machine learning method is utilized to determine the importance of each data type for creating a context element based on predefined rules (Jokste et al., 2022). The data ecosystem model (Deksne et al, 2021, September) includes measurable properties that are used to generate valuable information about road conditions, and historical data is necessary to train the model and determine the importance of these properties. Measurable properties are included in the model to establish the confidence level for each cascade (Fig. 4). The maximum confidence level identifies the best scenario for utilizing measurable properties to determine the context element.

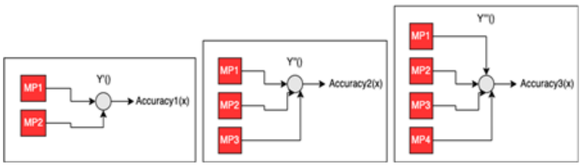

Figure 4: Machine learning cascade to define the importance of measurable properties setting context element.

The objective of the machine learning model cascades is to identify the set of measurable properties that offer the greatest accuracy level. This serves as the best case scenario for determining if the data types used in the calculation of the context element for a specific road section are of sufficient quality to reduce the risk of data insufficiency. The machine learning approach is used to assign importance weights to different data types, allowing for the evaluation of the significance of the data sources used. The model is trained using a training data set provided by the Latvian State Roads data ecosystem party, utilizing the XGBoost machine learning algorithm.

Two model cascades are implemented, the first of which is trained using meteorological station data. The variables included in the model are selected based on the rules established by the Rules Engine (Jokste et al. (2022)). The second cascade encompasses the same variables as well as video data.

The importance weights and accuracy levels generated by the model are utilized as constants in the algorithm, although further calibration may be necessary when more training data becomes available. Furthermore, as new data sources become available in the future stages of the platform's implementation, additional cascades may be established to accommodate the expanded data availability.

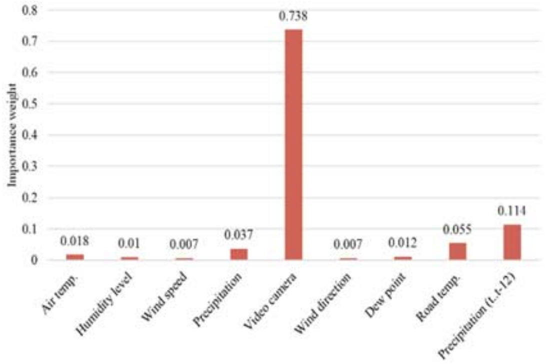

Figure 5: Importance weights set by machine learning model.

The results of the machine learning model when using meteorological station data and video camera data (Fig. 5) indicate that video cameras are the most critical data source in determining road conditions. Additionally, the importance weights were calculated in the scenario where only meteorological station data is used (Fig. 6), and in this case, the actual precipitation and precipitation from the previous 12 periods were found to have the highest impact on road condition determination.

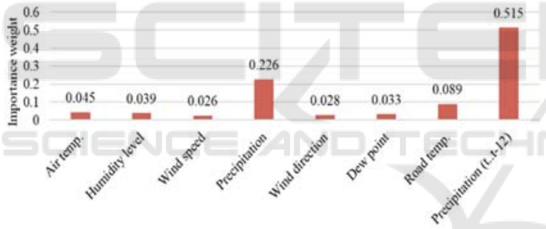

Figure 6: Importance weights set by machine learning model.

The accuracy level for various attribute combinations was calculated using a machine learning model. A total of 511 combinations were formed, with the highest accuracy achieved by combining the following attributes: air temperature, air humidity level, wind speed, video camera, dew point, road temperature, and precipitation (t-1 to t-12). To determine the importance and accuracy levels of the specific data sources used to assess road conditions for a given road section, they are compared to the best-case scenario, which is the maximum output of the machine learning model.

The level of data completeness is calculated by evaluating the data obtained from sources used to create context elements for a specific road section. Incomplete data, anomalies, and errors can affect the data reliability of a data source.

The coverage area defines the maximum region in which data sources are deemed appropriate for determining road and weather conditions for a specific road section. To calculate the road area without coverage (Fig. 7), the WRM experts first define the reliable information coverage radius of the data source, then the coverage is calculated.

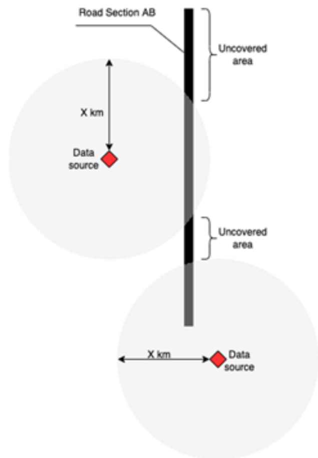

Figure 7: Road area data coverage for the given road section.

The coverage area is simulated for all data sources within a designated area and is contingent on the distance between the road section and the data sources. This information can be used to measure the length of the uncovered road section and identify the risk level, indicating if additional data sources should be taken into consideration to determine road conditions for a given road section. Additional coverage levels, defined by WRM experts, indicate the extent to which the data obtained from available sources covers the necessary road section area (Table 2).

Table 2: Coverage levels of data sources.

Coverage of data sources	Coverage level
70 - 100%	High coverage level
50 – 70%	Medium high coverage level
30 – 70%	Medium low coverage level
Less than 30%	Low coverage level

The coverage of data sources for a particular road section is calculated based on the maximum distance of 10 km from the data source to the road section which is deemed a reliable source for weather and road condition data by WRM experts.

The diversity of data sources is assessed through a best-case scenario where data from meteorological stations, video cameras, and crowd-sourced applications is used to determine the road and weather conditions for a specific road segment. The three main data source types are distinguished due to their differing methods of processing and data capture: meteorological stations use sensor-based data capture, video cameras employ visual data capture for image recognition road condition evaluation, and crowd-sourced applications provide real-time data from dynamic locations regarding road conditions.

5 RESULTS AND CONCLUSION

An analytical cost-efficiency model has been developed to assess the data source availability and the associated risks due to data insufficiency. The emphasis on data availability as a crucial factor in minimizing risk and maintenance costs has been established as the main objective in increasing the cost-efficiency of the WRM. The calculation of accident risks based on road slipperiness types also serves as an evaluation factor in WRM efficiency.

In collaboration with WRM field experts in Latvia, various levels of data source-specific attribute values have been established to enable the assessment of data sources from the WRM perspective. This information can be utilized to determine the need for additional data sources to minimize data insufficiency risks and potential accident risks and maintenance costs for a specific road section.

The specific case was used to calculate the different aspects of data insufficiency and accident risks, with the results presented in Table 3.

Table 3: Calculation results of the given case.

Measure	The given case results
Potential accident risk level	(Table 1)
Potential accident costs	16 907,22 EUR
Data availability	Medium-low level of data availability
Data types	Medium level of data type accuracy High level of data type importance
Data completeness	83,33%
Data source coverage	High coverage level
Diversity of data sources	Low level of diversity

Both expert evaluation and machine learning were employed to set the output levels for the data source evaluation criteria, with the latter determining the weights of data type accuracy and importance. However, the machine learning model requires further training and data collection to increase its accuracy.

The results provide the option to evaluate the available information for a given road section and prioritize maintenance processes based on potential accident costs. The quality of available data and data sources is significant in WRM as decisions strongly rely on timely accessible information. The introduced model allows the determination of data source impact to reduce WRM risks and costs. WRM expert assessment is utilized to set the expected levels of different data sufficiency measurements from the WRM viewpoint, with calibrations made as necessary when actual data is used over an extended period.

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REFERENCES

Bergel-Hayat, R., Debbarh, M., Antoniou, C., Yannis, G. (2013). Explaining the road accident risk: Weather effects, Accident Analysis & Prevention, vol. 60, pp. 456-465, ISSN 0001-4575, doi: https://doi.org/10.1016/j.aap.2013.03.006. https://www.sciencedirect.com/science/article/pii/S0001457513000948

Bougna, T., Hundal, G., & Taniform, P. (2021). Quantitative analysis of the social costs of road traffic crashes literature. Accident Analysis & Prevention, 106282. doi: https://doi.org/10.1016/j.aap.2021.106282

CAIS, A tool for the analysis of the scene of traffic accidents, violations and crimes in the field of traffic. Ministry of Internal Affairs of Latvia. Available: http://gis.ic.iem.gov.lv/giswebcais/

Deksne, L., Grabis, J., & Žeiris, E. (2021, September). Towards Data Ecosystem Based Winter Road Maintenance ERP System. In International Conference on Business Informatics Research (pp. 69-83). Springer, Cham.

Deksne, L., Vempers, J., & Kampars, J. (2021, October). Technology Selection for Development of Intellectual Road Maintenance Platform. In 2021 62nd International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS) (pp. 1-9). IEEE.

Elvik, R. (2000). How much do road accidents cost the national economy?. Accident Analysis & Prevention, 32(6), 849-851.

Grabis, J., Deksne, L., Roponena, E., & Stirna, J. (2022). A Capability-Based Method for Modeling Resilient Data

Ecosystems. In Domain-Specific Conceptual Modeling (pp. 339-363). Springer, Cham.

Jokste, L., Jeļisevs, B., Dosbergs, D., Zviedris, M. (2022) Formalization and Automated Enactment of Winter Road Maintenance Regulatory Requirements.

Latvian Road Safety Directorate. Road Traffic Accidents. Damage caused to the state as a result of road traffic accidents [Online]. Available: https://www.csdd.lv/celu-satiksmes-negadijumi/celu-satiksmes-negadijumu-rezultata-valstij-raditie-zaudejumi

Malin, F., Norros, I., Innamaa, S. (2019). Accident risk of road and weather conditions on different road types. Accident Analysis & Prevention, vol. 122, pp. 181-188, ISSN 0001-4575, doi: https://doi.org/10.1016/j.aap.2018.10.014.https://www.sciencedirect.com/science/article/pii/S0001457518308455

Norrman, J. (2000). Slipperiness on roads – an expert system classification. *Meteorological application*, 7(1), 27 – 36.

Norrman, J., Erikkson, M., Lindqvist, S. (2000). Relationships between road slipperiness, traffic accident risk and winter road maintenance activity. *Climate Research*, 15(3), 185-193. https://www.int-res.com/abstracts/cr/v15/n3/p185-193/

Partheeban, P., Arunbabu, E., & Hemamalini, R. R. (2008). Road accident cost prediction model using systems dynamics approach. Transport, 23(1), 59-66.

Ratkevicius, T., Laurinavicius, A. (2017). Assessment model of levels for winter road maintenance. The Baltic Journal of Road and Bridge Engineering. https://bjrbe-journals.rtu.lv/article/download/bjrbe.2017.15/1783

Salli, R., Lintusaari, M., Tiikkaja, H., & Pöllänen, M. (2008). Wintertime road conditions and accident risks in passenger car traffic. TUTKIMUSRAPORTTI, RESEARCH REPORT, (68).

Silcock, R., TRL (2003). Guidelines for estimating the cost of road crashes in developing countries. *London: Department for International Development*. The World Bank

The World Bank (2021). Socio-Economic Costs and Human Impacts of Road Accidents in Azerbaijan. URI: http://hdl.handle.net/10986/35986

Theofilatos, A., Yannis, G. (2014). A review of the effect of traffic and weather characteristics on road safety. Accident Analysis & Prevention, vol. 72, pp. 244-256, ISSN 0001-4575, doi: https://doi.org/10.1016/j.aap.2014.06.017.

Wijnen, W., & Stipdonk, H. (2016). Social costs of road crashes: An international analysis. Accident Analysis & Prevention, 94, 97-106. doi: http://dx.doi.org/10.1016/j.aap.2016.05.005