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ROAD PAVEMENT CONDITION INDEX DETERIORATION MODEL FOR NETWORK-LEVEL ANALYSIS OF NATIONAL ROAD NETWORK BASED ON PAVEMENT CONDITION SCANNING DATA

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Abstract. Surveying the condition of the pavement is one of the most important processes in managing the road network. The information collected during these surveys allows for the calculation of the Pavement Condition Index, which is a derivative cumulative qualitative indicator that evaluates various pavement characteristics and defects. Deterioration modelling of these measured indicators and calculated indices is a critical element and its most accurate prediction brings the process of pavement management closer to a higher quality process by more efficiently allocating funds and repair work.

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Many different models – both extremely complex and simple – are used in the world to simulate the condition of individual pavement indicators. However, these models are developed based on the data of a certain country or region and are not suitable in another country due to different requirements for pavement structures and other reasons. In Lithuania, measurements of the quality indicators of road surfaces with new generation survey equipment have been carried out recently but the information stored in the databases about road sections is minimal, and it becomes difficult to adapt the models applied abroad due to the missing information. The aim of this study is to create pavement condition index prediction models by evaluating such quantitative and qualitative indicators as traffic loads, road surface unevenness, type of repair, pavement age, climatic zones, and pavement construction classes.

Keywords: deterioration, IRI, pavement performance, pavement condition index, PCI, panel data analysis, regression analysis, road condition survey.

Introduction

Continuous change in the condition of the road surface is a process during which the road surface deteriorates under the influence of individual factors (road construction properties, environmental factors, and traffic loads). Characteristics of the road structure that influence the deterioration of the pavement are the properties of materials and their aging, the quality of construction works, the age of the pavement, design solutions, etc. Environmental factors are temperature level and change, solar radiation, precipitation, depth of frost, soils, etc. Traffic loads are light and heavy traffic density, number of axles, etc. The condition of the road surface deteriorates over time even in the absence of traffic loads, i.e., road construction characteristics and environmental effects are sufficient.

This continuous process of pavement deterioration is a challenge for road maintenance companies. To manage these challenges, pavement management systems are used, in which one of the most important processes is linked to the prediction of the condition of the analysed road network pavements.

Road maintenance process depends on many factors, such as current road conditions, traffic level and distribution, climatic conditions, construction work quality, local experience. Also, economic indicators influence road maintenance process, e.g., country's level of development, vehicle operating costs, user delay costs, labour costs (Zofka et al., 2014).

Road condition and maintenance management is useful for monitoring and evaluating the current condition of the road network and for planning the maintenance of the road network. This allows for the proper distribution of limited financial resources (Jurkevičius et al., 2020). A well-maintained highway network reflects the country's economic level. However, engineers are constantly looking for simpler and cheaper ways to manage and maintain the condition of the pavement while maintaining an acceptable service level. Pavement management systems enable more efficient and productive maintenance (Dabous et al., 2020).

Project-level modelling is based on predicted future traffic and detailed pavement data (these requirements may be based on condition measurements using stationary or slow-moving equipment, e.g., falling weight deflectometer (FWD) and performing drill cores to determine layer thicknesses, determination of layer materials and granulometric properties). Based on the advanced data, highly accurate decisions can be made regarding the repair strategy. Meanwhile, network-level modelling aims to predict the average deterioration of the road network. Network-level modelling is usually based on predicted different traffic and pavement condition data and historical data, which can only be known from historical records of applied repairs and road network condition measurements. At the project level, the change in the pavement condition of each road section is determined, and at the network level, the average deterioration of the condition of the entire road network is determined. This means that less complex models can be used in network-level simulations, but these models should be calibrated to match the average changes predicted during project-level simulations (Busch & Scar, 2010).

Two main methods of treatment are used to improve the condition of the pavement – routine maintenance and rehabilitation. Maintenance techniques work by slowing the rate of deterioration of the pavement by repairing small defects before they worsen and create larger defects. Rehabilitation methods are used to improve the condition of the pavement of road section by removing relatively large defects (Dabous et al., 2020)a utility approach is proposed for maintenance prioritization purposes based on the condition assessment results of the pavement sections. A pavement network of five sections is considered in this study, and a numerical example is illustrated considering one section to show the implementation of the utility approach for section ranking. The overall assessment of various pavement sections was provided by the inspector as degrees of belief in seven assessment grades, which are: A (Good. AASHTO divides road asset maintenance methods into reactive and proactive. Reactive maintenance is already applied when the road surface needs to be repaired by removing surface defects, while proactive maintenance is preventive and predictive. Preventive maintenance is applied to slow down the deterioration process by delaying the application of complex repairs. Preventive maintenance techniques are planned actions designed to extend the life of an asset. However, predictive methods are based on the results of condition monitoring, based on which the condition is predicted and repair actions are foreseen in the future (AASHTO, 2011; Karimzadeh & Shoghli, 2020).

Proactive maintenance based on condition prediction allows road maintenance companies to manage maintenance actions and improve road conditions by preventing condition deterioration, as opposed to a reactive maintenance model that operates only when deterioration reaches an undesirable threshold. Condition forecasting offers maintenance actions based on the expected condition of the asset so that decision-making is based on maintenance needs, and it allows for more efficient use of the allocated funding. It allows for the allocation of the necessary budget, the allocation of resources, the classification of priorities, and the planning of maintenance work (Karimzadeh & Shoghli, 2020).

Keeping as many roads as possible in better condition while reducing the number of road sections in poor condition must be the goal of a modern and sustainable road maintenance system (Zofka et al., 2014).

In Lithuania, the national road network includes 21 249 km of roads, of which 1750 km are trunk roads, 4926 km are regional roads, and 9010 km are regional roads with an asphalt surface. Of these, 27% of road sections are in good condition, 34% are satisfactory, and 39% are in bad condition. To build and repair this road network, 300 million € was allocated in 2021.

In Lithuania, information about the road network began to be collected after the creation of the first Lithuanian road information system (LAKIS) in 2009. Since 2021, it has been integrated into the road asset management information system (KTVIS). Information on the condition of the surfaces began to be collected in 2007, but the periodicity of the measurements depended on the allocated funding and capacities. Since 2019, when the new generation of research equipment has been used in Lithuania, the condition of roads has been measured annually. Additional design information about the solutions applied in the repaired sections – layer thicknesses and materials – has also begun to be collected, but due to the small scope of work, these data are being accumulated slowly.

For this reason, this study aims to create empirical models of pavement condition index deterioration for network-level analysis. It is impossible to create mechanistic models due to the lack of additional data and their slow accumulation.

1. Fundamentals of pavement condition assessment

The term "asset management" includes the management activities of one or more (generally all) of several assets. It primarily refers to the maintenance and operation of these structures, and only later to the improvement and development of these assets (Deix et al., 2012) road operators, road owners and other affected stakeholders. It is a complex process which needs flexible and adaptable methods, the experience from road owners and operators and a clear definition of the stakeholders' requirements. An innovative approach is the development of optimised procedures for cross asset management of the total road infrastructure (pavements, structures, road furniture etc..

The goal of asset management, as summarised by Gordon, Sharp, and Martin, is to provide current and future road users with the required level of service at the lowest life-cycle cost using a "whole organisation" concept, where the combined activities of different responsibilities create a result in the acquisition and management of assets (Gordon et al., 2018).

In the field of road asset management, the most developed area of road pavement management systems (PMS), appeared 40 years ago. Recently, there has been a strong development in the world of management systems for bridges and tunnels, management systems for water drainage, etc.

Pavement management is a set of processes designed to help decision-makers find the best strategy for maintaining the road network pavement condition in a serviceable condition for a given period at the lowest cost (Kulkarni & Miller, 2003).

Different PMS can have many different modules and procedures, but they can be divided into three main areas: data, analysis, and reporting. Database modules are designed to store data on inventory, condition, geometry, traffic intensity, etc. The data domain could also include modules or procedures for processing and aggregating the data before importing the data into the PMS itself. The area of analysis includes all modules and procedures related to pavement management – pavement condition assessment, pavement deterioration prediction, optimization, etc. The area of reporting results includes modules for presentation and visualization of results (AASHTO, 1990).

To achieve and maintain an effective level of road infrastructure management, it is necessary to accurately predict the degradation of the road surface condition. Road pavement condition prediction is a key component of pavement condition management systems, the accuracy of which depends on the effectiveness of road infrastructure network management (Lin & Madanat, 2002).

Two types of information describing the condition of infrastructure objects can be distinguished: information about the current condition of structures, which is determined by years of inspections or periodic surveys, and information about the future condition, which is determined by condition change models when forecasting it (Madanat, 1993).

Pavement condition prediction involves predicting the condition of the pavement under certain traffic loads and environmental conditions. The first pavement management systems did not have condition prediction capabilities and were designed to assess the current condition of the pavement. Later, the first prediction models were simple and based on engineering expected design life depending on the repair actions applied (Kulkarni & Miller, 2003).

Pavement condition prediction models are a key element of road infrastructure asset management systems or road pavement management systems. Therefore, the successful implementation of these systems is highly dependent on the used pavement condition forecasting models, as the accuracy of the obtained forecasts determines the validity of the decisions made (Erlingsson, 2010).

Models of pavement condition deterioration are important not only for road maintenance companies to manage their road network but also for road pricing and regulatory studies. Both the deterioration of the pavement over time and the relative influence of various factors on the deterioration of the pavement are important data for such studies. With appropriate models, it should be possible to calculate the influence of the most important variables on pavement deterioration. Some of these variables are pavement design (used materials, designed strength properties, construction technologies etc.), traffic (number of axles and axle loads), and environmental conditions (temperature and humidity) (Lin & Madanat, 2002).

Researchers in publication (Gharieb et al., 2022) reviewed pavement deterioration model types found in the literature and summarised to three mostly common groups: deterministic (regression models), probabilistic (Markovian and Bayesian models) and hybrid (Fuzzy Logic, Artificial Neural Network, and Neuro-fuzzy models).

Two levels of analysis and modelling are mostly found in the literature – the network level and the object level. They are the most relevant because the condition of the road network is assessed and planned for maintenance at one of these two levels. At the network and object levels, the tools or models required to perform the analysis differ. At the network level, the goal is to identify and predict the overall condition of the road network and how it will change, e.g., what percentage of road sections are in poor condition now and how many will be five years from now under a given funding plan. Meanwhile, at the object level, all attention is paid to one object, so it is appropriate to use more complex models that require a lot of additional information about materials or their properties, which increases the accuracy of the simulated results. The use of such network-wide information is difficult and expensive to collect (Busch & Scar, 2010; Kulkarni & Miller, 2003).

The road surface deterioration model is a mathematical function whose independent variables – the construction of the road surface, its technical and operational characteristics, age, applied maintenance and repair standards, car traffic intensity, car loads on the surface, road geometric parameters, climatic conditions, etc. – are expressed by physical quantities or factors. These are dynamic models because time is always one of the variables (Braga, 2005; Madanat, 1993).

Deterministic types of condition change prediction models are most commonly encountered in the field of road pavement management: empirical, mechanistic, and mechanistic-empirical. Empirical models were created by applying statistical analysis and taking into account the main factors that contribute to pavement deterioration (e.g., traffic load, and pavement age). The mechanistic type models are made taking into account the mechanical and structural characteristics of the pavements. The combination of these two types – mechanistic-empirical models – are the methods of mechanistic and empirical models (Braga, 2005; Karimzadeh & Shoghli, 2020).

Pavement management systems and their solutions are based on condition assessment. Pavement condition assessment – quantitative determination of the pavement condition level – is performed to determine the serviceability of the pavement condition and compare the road section with other road sections. In the world, different countries or different road management companies use different methods to assess the condition of the pavement. This often depends on the funding provided for monitoring the condition of the pavements, and the management model chosen and applied. All pavement condition assessment methods can be divided into two groups – the visually estimate condition rating and the assessed condition of the pavement measured condition rating by automated devices. Each country or other institution that conducts assessments of the state of the road network chooses which method to apply – it can choose from existing ones or create its method.

Among the already existing methods for visual assessment, the following are often found (Okine & Adarkwa, 2013):

– Pavement Surface Evaluation and Rating System (PASER) – a specialist visually evaluates the condition of the pavement on a

scale from 1 to 10, based on the examples provided in the manual of the evaluation system;
- Condition Rating Survey (CRS) – the condition of the pavement is visually assessed by a specialist on a scale from 1 to 9, based on the examples and descriptions provided in the assessment system manual;
- Present Serviceability Rating (PSR) – based on the ride quality experienced by a group of observers driving the vehicle on a given section of pavement. The rating scale used is from 0 to 5.

Among the existing methods for evaluating the measured pavement condition, the following are often found (Litzka et al., 2008; Okine & Adarkwa, 2013):
- Present Serviceability Index (PSI) – based on physical measurements of pavement characteristics, in addition to observations by trained assessors, using a rating scale from 0 to 5;
- Surface Rating (SR) – two raters categorize the damage by species and measure it, convert it to percentages, and convert it to a surface rating on a scale of 0 to 4, where 4 means very good and 0 means very bad;
- Pavement Condition Index (PCI) – each damage identified on the pavement surface is assigned a value based on its type, size, and degree of deterioration. Summing up all the individual values and subtracting them from 100 points gives an estimate of the condition of the pavement with a rating on a scale of 0 to 100, where 100 means very good and 0 means very bad;
- General (Global) Performance Indicator (GPI) – an indicator proposed by the COST 354 Action (European Cooperation in the field of Scientific and Technical Research) project to assess the condition of the pavement. This indicator is on a five-point scale, where 0 is very good and 5 is very bad. This method is developed after analysing the evaluation methods used in Europe and the USA and uses research equipment to collect information about the road surface. The calculation of the Pavement condition index applied in Lithuania (named DBI) is also based on the principles of the evaluation method.

The surveys (measurements) of the indicators required for the evaluation of the condition of the pavement can be divided into four main types: roughness (ride quality) surveys; defect surveys; bearing capacity surveys; wheel adhesion measurements (Okine & Adarkwa, 2013).

The indicators measured during the studies of the condition of roads can be divided into two groups (Peraka & Biligiri, 2020; Pierce & Weitzel, 2019; Wadalkar et al., 2018):
- *Functional pavement indicators*:

- Road roughness;
  - Rutting;
  - Surface defects (patches, potholes, bleeding, ravelling);
  - Mean profile depth;
  - Skid resistance;
- *Structural pavement indicators*:
  - Deflections;
  - Cracks (fatigue, longitudinal, transverse).

All of these listed indicators can be measured automatically with the help of special research equipment adapted to measure at the speeds of traffic flow.

2. Methodology, research equipment, and sections

2.1. Pavement condition assessment methodology

The research was conducted based on the historical indicators of the condition of road surfaces stored in the Road Asset Management Information System (KTVIS), which were recalculated into the Lithuanian Pavement Condition Index (PCI) used to assess the condition of the asphalt pavement in Lithuania. This index to assess the condition of pavements in Lithuania has been used since 2019. It was compiled taking into account international experience – COST Action 354 Performance Indicators for Road Pavements (Litzka et al., 2008) recommendations by combining individual pavement condition indicators into one global index (LAKD, 2018). Kravcovas et al. (2020) performed a comparison of these two methodologies, and found that when calculating the estimates with both methodologies, the results were close, but in 10 cases out of 15, the methodology developed by LRA provided higher PCI values (worse pavement condition).

The pavement condition index is a cumulative indicator, calculation of which consists of three parts: assessment of individual pavement quality indicators by transposing them into dimensionless quantities – single performance index (PI); combining these indicators into combined performance indices (CPI) and combining combined performance indices into a global (cumulative) pavement condition index (PCI). During the assessment of the condition of the road network, the main characteristics of the condition of the road surface are analysed, the measurements of which were performed automatically on the entire road network. This method makes it possible to determine the level of condition of the road surface of the entire road network, to determine the level of deterioration of individual road sections, and whether the characteristics of the individual road surface under consideration meet the quality requirements set for them, to compare the condition of individual road sections on the scale of the entire network.

During the PCI calculation, the following condition characteristics are evaluated. Road surface condition indicators include: road roughness, rut depth, mean profile depth, cracks, and surface defects. These characteristics are included in the calculation of combined performance indices (comfort, safety, and structural) depending on their characteristics and influence on each CPI. The evaluation of the combined indices of the condition of the road surface (comfort, safety, and structural) is important when analysing the influence of quality indicators of the surface on traffic safety, driving quality, and strength characteristics. The cumulative pavement condition index is a major indicator of road surface condition that evaluates three combined performance indices, and whose value describes the condition of the road surface in a five-point system, where PCI = 0 means very good (newly installed) surface and PCI = 5 means very bad surface condition.

The unevenness of the road surface is also very important in the study. This is a technical parameter that is determined during measurements of the longitudinal road profile and is calculated using the mathematical model of a “quarter car”: It is the sum of car vibrations caused by unevenness of the longitudinal road profile in ruts for a standard type of car. This is the ratio of the sum of the vertical movements of the car suspension and the distance travelled, moving at 80 km/h speed (Paterson, 1990). This ratio is called the International Roughness Index and is abbreviated as – IRI with units of measure – m/km.

Road roughness directly reflects the impact of the road surface on cars and driving comfort and is considered to be affected by all road surface damage – cracks, potholes, patches, structural deformations, ruts, etc. (Braga, 2005). The pavement condition index evaluates the damage sizes separately and aggregates them according to their importance and the weighting factors specified in the methodology. In Lithuania, as in many other countries, the investigation of the unevenness of the road surface after construction works is a mandatory control inspection, which is regulated in regulatory documents.

Since both IRI and PCI are related to damage to the road surface, it can be assumed that there should also be a direct relationship between IRI and PCI. Elhadidy et al. (2019) reviewed several published studies and presented their own, which analysed the relationship between IRI and PCI. All analysed sources, as well as the model presented by the authors, were compiled using data from roads located in the US territory.

2.2. Research equipment

Standard surveys of the condition of road network pavement are usually carried out with the help of multifunctional mobile road survey equipment. The prevalence and popularity of this equipment were determined by the 20th century. In the 1990s, computer and laser equipment became popular, which made it possible to create non-contact research equipment – laser profilometers. These became even more popular in the 21st century, when longitudinal and transverse profile measurement (recording) techniques began to be integrated, allowing for the creation of three-dimensional profiles and the use of video recording cameras (Sjögren, 2015).

The mobile road survey equipment used in Lithuania is the RST63 laser profilometer. It is a multi-component road pavement test equipment, the two main components of which are marked in Figure 1. Two LCMS-2 lasers for road surface surveys (Figure 1A) – capable of scanning a 2 m wide band (4 m in total) – capture about 112 million points per second. LCMS-2 lasers with 28 000 Hz scanning frequency can reach 1 mm longitudinal scanning interval at speeds up to 100 km/h and with 1 mm transverse resolution. It also can reach 0.25 mm vertical accuracy with 0.05 mm vertical resolution. These lasers have extremely accurate depth geometry and create a very detailed image (photo) of the road surface. With the help of mathematical algorithms, technical and geometric characteristics can be calculated from this digital 3D image: rut depth, water depth, various types of cracks and surface defects, and other elements can be identified. Point lasers are mounted on the front of the mobile road survey equipment to measure road surface roughness and mean profile depth (Figure 1B). The equipment used for testing road

Figure 1. Mobile road research equipment RST63 (A – LCMS-2 lasers; B – point type lasers)

roughness meets the requirements of ASTM E950-98 and EN 13036-6. The accuracy of road roughness measurement is less than 0.1 m/km and 0.2 mm for mean profile depth. Road surface roughness (IRI, m/km) is calculated based on the ASTM E1296 standard.

2.3. Sections of research

After using the road roughness measurement protocols collected by Lithuanian Road Administration (LRA) after the construction works, objects were selected for experimental research. The selected road sections were repaired between 2008 and 2016. They have road roughness inspection protocols performed at the time of construction completed and the method of repair applied is known. The choice of the start of this construction period was influenced by the fact that in 2007 and 2008, the RST 28 laser profilometer (the predecessor of the RST 63 research equipment with the same road roughness measurement technology) was put into operation in Lithuania, which was used to measure the road surface roughness after the construction works. The upper limit of the analysed period was chosen in 2016 to have an age period of more than 5 years.

During measurements with the RST63 equipment, the following characteristics were observed: road surface roughness IRI, rut depth,

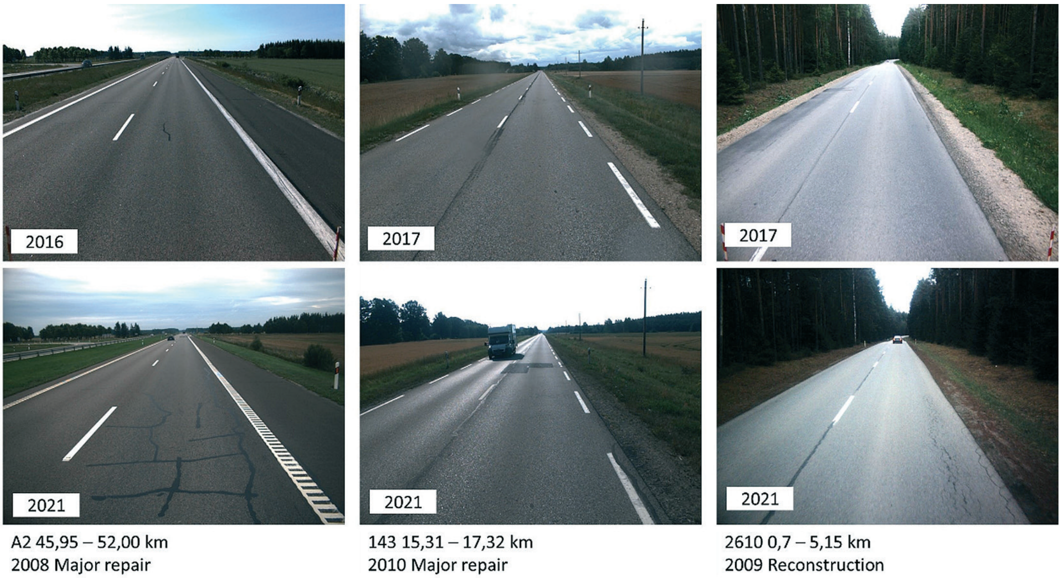

Figure 2. Pavement condition difference

average profile depth, different types of cracks and surface defects. All these indicators are used to calculate the pavement condition index PCI. The resulting changes in the coating are shown in Figure 2.

After evaluating the information on the selected objects, it was found that the objects were located throughout the territory of the country (see Figure 3). A total of 321 road sections were selected for the study (Table 1). There are objects on all types of roads: 65 objects on main roads, 59 objects on national roads, and 197 objects on regional roads.

Table 1. Selected road sections for research

Road type	Quantity of objects, pcs	Length of objects, km	Construction type	Quantity of objects, pcs	Length of objects, km
Main roads	65	353 118	Major repair	109	431 775
National roads	59	269 571	Simple repair of asphalt pavement	31	57 286
Regional roads	197	553 955	Reconstruction	181	687 583
Total	321	1 176 644	Total	321	1 176 644

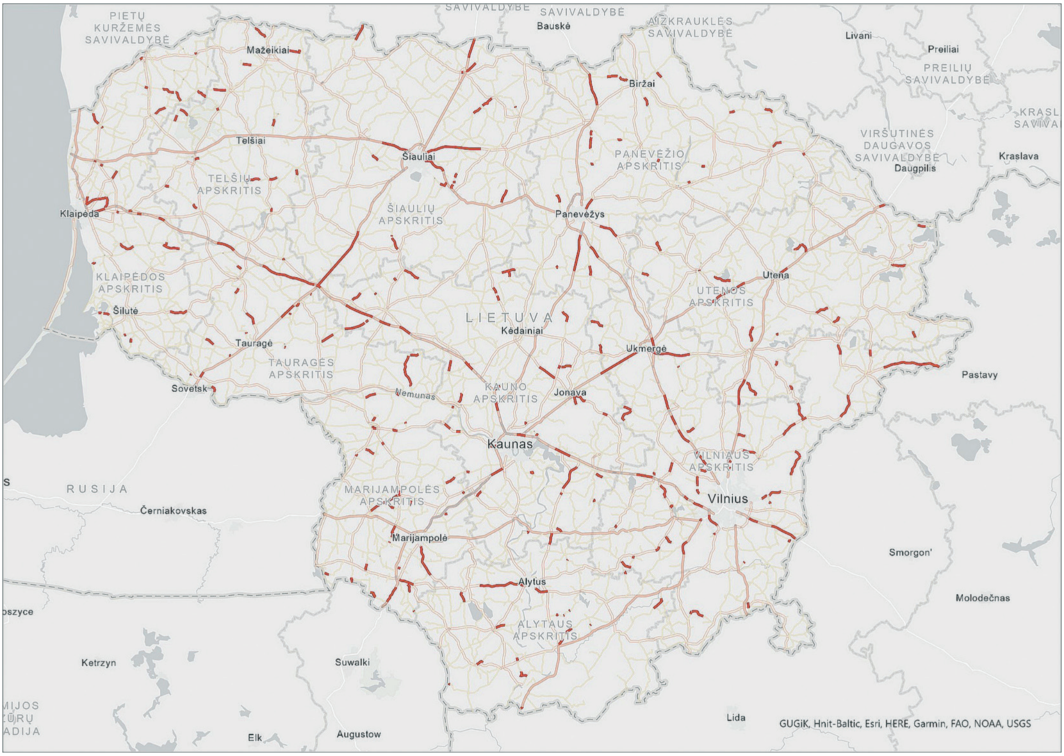

Figure 3. Investigated road sections

The investigated objects were repaired in one of three ways – simple repair of asphalt pavement, major repair, or were reconstructed. The distribution of repairs is presented in Table 1.

Inventory and historical data were collected for each analysed road section: road type; length; type of repair; year of repair; climatic data according to the division of the country's territory (zone affected by frost, zone affected by frost depth, zone affected by temperature); historical traffic load data; road roughness data and PCI values (in 2019, 2020 and 2021).

To properly design the pavement, it is necessary to take climatic factors into account, because the loads caused by environmental factors are inevitable and sometimes decisive. Environmental factors, especially temperature and humidity, affect the performance of the non-rigid pavement. These factors have long been considered in pavement design and practice, as they can influence the deterioration and stiffness of pavement materials, thereby affecting pavement performance. Two main aspects are distinguished: sufficient bearing capacity and sufficient resistance to cold. The second one is especially important in cold climate regions where there are many freeze-thaw cycles and at the same time deep freeze (or freeze).

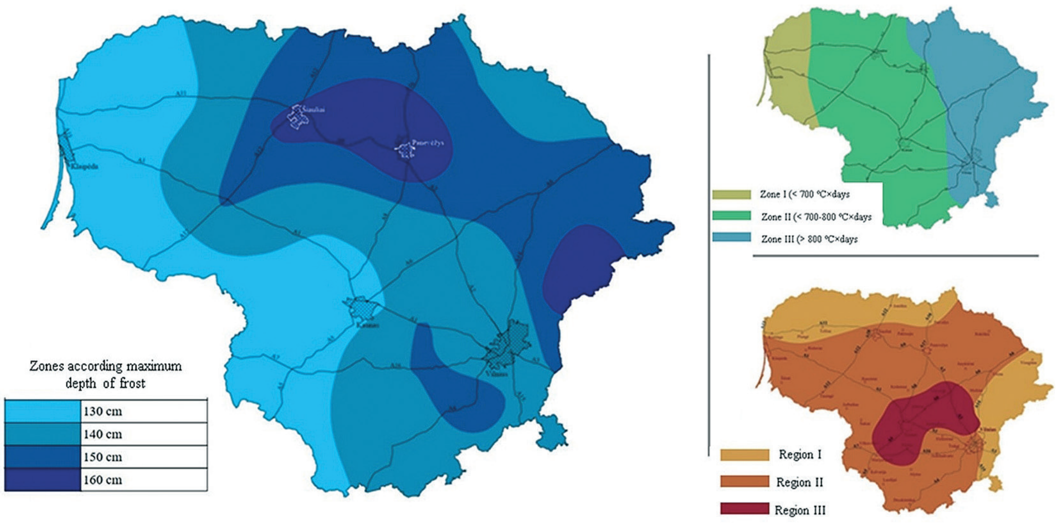

Figure 4. Mapping of the territory of Lithuania according to climatic phenomena (on the left – according to the maximum depth of frost; on the top right – according to the maximum freezing index and on the bottom right – according to the frequency of the surface temperature intervals)

VilnusTech scientists (Vaitkus et al., 2016) performed an analysis of the data collected by Road Weather Stations (RWS) on the Lithuanian road network and compiled a mapping (zoning) of the territory of Lithuania according to the maximum frost depth (Figure 4, left) and according to the maximum freezing index (Figure 4, top right). In another publication, VilniusTech scientists (Kleizienė et al., 2017; Vaitkus et al., 2021) presented the division of the territory of Lithuania into three temperature zones according to the frequencies of the pavement temperature intervals (Figure 4, bottom right). A tendency was observed that the initial thickness of the frost-resistant pavement structure increased with an increasing number of ESALs and with increasing sensitivity of soil to frost.

3. Analysis and results

3.1. Significance test

The research aims to determine the dependence of road surface deterioration on: traffic load, depth of frost, frost-affected zone, the last repair type applied to the road section, road construction class, and road roughness.

$$P = f(T, L, M, K, I, N, P, R), \tag{1}$$

where
T – traffic load;
L – road construction class;
M – frost exposure zone;
K – construction type (repair method);
I – pavement age;
N – cold affected zone;
P – temperature effect zone;
R – road roughness IRI.

The study examined the condition of 319 road sections and data on each object, which were divided into quantitative (pavement condition index DBI (Lithuanian pavement condition index), traffic load, road age, and roughness of the road surface) and qualitative (road construction class, frost exposure zone, construction type, frost exposure zone), temperature effect zone) variables, three and five indicators, respectively.

Descriptive statistics, correlation analysis, and regression analysis were performed to determine the significance of different parameters.

3.2. Descriptive sample statistics and correlation analysis

After evaluating the values of the historical pavement condition estimates in individual years (DBIo – pavement condition index value immediately after the repair; 2019; 2020 and 2021), we can see that every year there are fewer and fewer exceptions in the road pavement deterioration estimate data. The most exceptions are in the data up to 2019, the least in the data of 2021 (Figure 5). We also see that the median road surface deterioration is increasing every year.

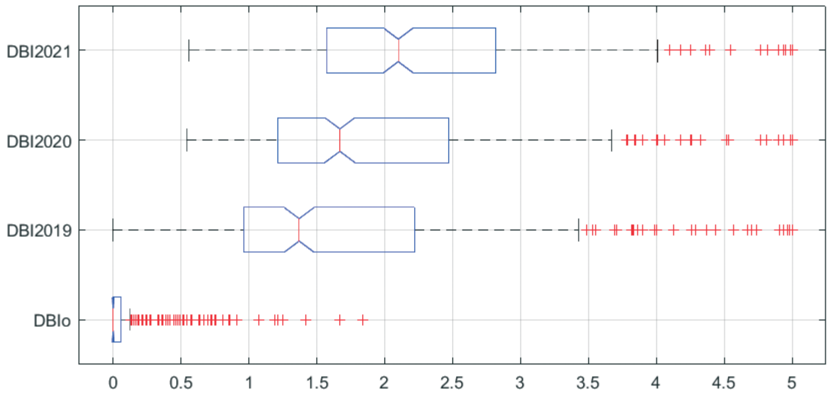

Figure 5. Comparison of numerical characteristics of pavement deterioration

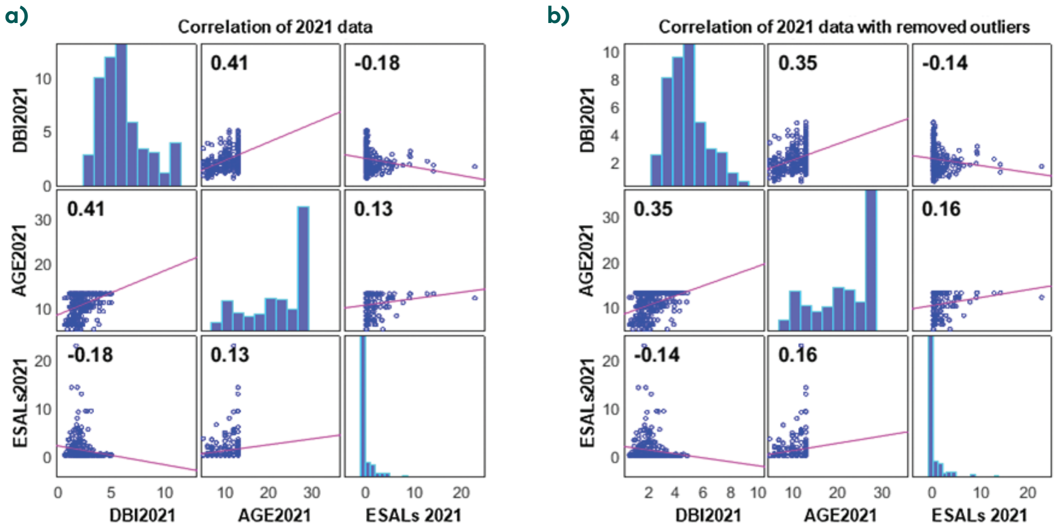

Figure 6. Correlation of 2021 data: a) without removing outliers and b) after removing outliers

Correlation analysis was performed to find out if there was a linear relationship between the quantitative variables: DBI, Traffic load, and road age. Correlational analysis was performed for the data of the individual analysed years: 2019, 2020, and 2021. Chart for correlation of 2021 data (Figure 6) presents correlation coefficients between DBI2021, AGE2021 and ESALs2021.

The performed correlation analysis showed (Figure 6a) that the linear relationship between the studied variables was not strong; therefore, the correlation between these indicators was evaluated after removing the outliers (Figure 6b). Removing outliers reduced the correlation between DBI2021 and AGE2021 and between DBI2021 and ESA2021. Considering the results of the correlation analysis, it was decided to construct the regression models without removing the outliers, because the removal of the outliers reduced the strength of the linear relationship between DBI2021 and other considered variables.

3.3. Regression analysis

The study carried out a regression analysis in three stages:

- The functional relationship between IRI and PCI (the international equivalent of DBI) was analysed using (Elhadidy et al., 2019) a regression model with road roughness IRI data to determine the relationship between DBI and road surface roughness;
- Data regression analysis was performed between DBI values and other known indicators (quantitative and qualitative variables) to determine indicators that might have a significant influence on the change of DBI;
- A regression analysis of panel data was performed to determine DBI dependence models.

3.3.1. Dependence of the pavement condition index on the unevenness of the road surface

A regression model of foreign researchers (Elhadidy et al., 2019) was selected. A regression model is proposed in which PCI depends on the IRI value of road surface roughness (Equation (2)).

$$\log\left(PCI\right) = 2 - 0.436 \times \log\left(\frac{IRI}{0.727}\right), \tag{2}$$

where

IRI – road roughness IRI, m/km;

PCI – pavement condition index, dimensionless index.

By applying the model proposed by the researchers (Equation (2)) to the available data, an analysis was performed with data from different years. The model equations for the respective analysed data for individual years are presented in Table 2.

The coefficients of determination obtained after the regression analysis are presented in Table 2. The compliance of the measured (observed) data of 2021 with the values modelled according to the presented model of 2021 (Table 2) is shown in Figure 7a, and the predicted values according to the model of 2021 (Table 2) and the observed values are shown graphically in Figure 7b.

In Figure 7a, we see a considerable spread of values, while in Figure 7b we see observed PCI values in blue and modelled in orange. For the comparison of the models of different years, the confidence intervals of the obtained coefficients to the unknowns are presented in Table 3.

Table 2. The results of the analysis of the dependence of the PCI on the road roughness

Year	The model equation	The determination coefficient
2019	$\ln(DBI2019+2)=\beta0+\beta1\cdot x1$	0.295
2020	$\ln(DBI2020+0.5)=\beta0+\beta1\cdot x1$	0.361
2021	$\ln(DBI2021+0.1)=\beta0+\beta1\cdot x1$	0.266

Table 3. Confidence intervals of the coefficients to the unknowns

Model	Free member		Coefficient at IRI	
Year 2019	0.9451	1.0545	0.3174	0.4474
Year 2020	0.2784	0.4362	0.5351	0.7187
Year 2021	0.1958	0.3934	0.4919	0.7114

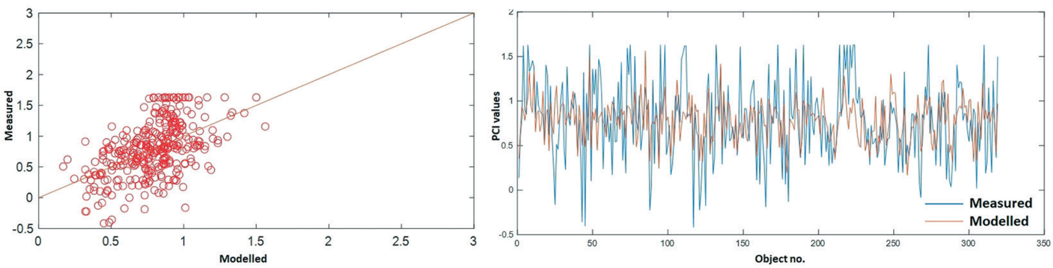

Figure 7. Compliance of the model for the year 2021 with the observed values (a) and forecasted values by the model for the year 2021 and observed values in the year 2021 (b)

From the obtained results, we can see that every year the influence of the free member on the DBI results decreases, while the value of the IRI indicator of road surface roughness increases.

Applying this already established model of foreign researchers would be insufficient for the available data.

3.3.2. Regression analysis of data to determine significant factors

During the regression analysis of the collected data, a linear regression model was initially created including all the considered indicators (with pseudo-variables): road age (X_1), traffic loads (X_2), pavement structures (X_3, X_4, ..., X_9), frost zones (X_{10}, X_{11}, X_{12}), temperature zones (X_{13}, X_{14}), cold zones (X_{15}, X_{16}) and type of construction (X_{17}, X_{18}). A model was created to determine the dependence of road surface deterioration (Y) on the following indicators for each year:

$$Y = \beta_0 + \sum_{j=1}^{18} \beta_j \cdot X_j + \varepsilon. \quad (3)$$

The coefficients of determination for the data of 2019, 2020, and 2021 were obtained. The regression analysis of the 2019 data showed that the linear regression model explained 27% of the data dispersion and that road age and road construction class DK 1 had a statistically significant influence. The regression analysis of the 2020 data showed that the linear regression model explained 28.3% of the data dispersion and the pavement construction classes DK 0.1, DK 0.3, DK 1, and the first temperature effect zone had a statistically significant influence. The regression analysis of the 2021 data showed that the linear regression model explained 27.4% of the data dispersion and the pavement construction classes DK 0.1, DK 0.3, DK 1 and the first temperature effect zone had a statistically significant influence.

Taking into account the obtained results of linear regression and finding the best option, linear regression models were created by logarithmizing those indicator values that showed significance. In this way, linear regression was checked for the data of 2019 by logarithmizing the following indicators: road age (X_1), traffic load (X_2), DK of pavement structures 0.1; DK 0.3 and DK 1 (X_3, X_4, X_5), the 3rd frozen zone (X_6). The following linear regression model was analysed for the described case:

$$y_i = \beta_0 + \beta_1 \cdot x_{1i} + \beta_2 \cdot x_{2i} + \beta_3 \cdot x_{3i} + \beta_4 \cdot x_{4i} + \beta_5 \cdot x_{5i} + \beta_6 \cdot x_{6i} + \varepsilon_i, \left(i = \overline{1, n}\right). \quad (4)$$

For the data of 2020, linear regression was checked by logarithmizing the following indicators: road age (X_1), traffic load (X_2), DK of pavement constructions 0.1; DK 0.3 and DK 1 (X_3, X_4, X_5), 3rd frost zone (X_6) and 1st temperature effect zone (X_7). For the data of 2021, linear regression was checked by logarithming the following indicators: road age (X_1), traffic load (X_2), DK of pavement constructions 0.1; DK 0.3 and DK 1 (X_3, X_4, X_5), 3rd frozen zone (X_6).

The linear regression equation for 2020 and 2021 data:

$$y_i = \beta_0 + \beta_1 \cdot x_{1i} + \beta_2 \cdot x_{2i} + \beta_3 \cdot x_{3i} + \beta_4 \cdot x_{4i} + \beta_5 \cdot x_{5i} + \beta_6 \cdot x_{6i} + \beta_7 \cdot x_{7i} + \varepsilon_i , \quad \left(i = \overline{1, n}\right) \tag{5}$$

According to the value of the coefficient of determination, we can say that the regression model explains (defines) 28.9%; 31.3%, and 29.4% (respectively for the data of 2019, 2020, and 2021) of the change in PCI values through the selected independent variables.

The built-up regression models showed that the road surface deterioration estimate was statistically significantly influenced by road age, traffic load, road construction class DK 0.1; DK 0.3, and DK 1, and level of frost 3rd zone.

In the continuation of the regression analysis, the qualitative parameter of road type (main road, national road, and regional road) was included. The model variables are: road age (X_1), traffic load (X_2), 3rd frost zone (X_3), main road (X_4), and national road (X_5). The model equations for the respective analysed data for individual years are presented in Table 4.

The obtained coefficients of determination are presented in Table 5, which shows how much the data dispersion is described by the linear regression model.

To evaluate the influence of road construction class on pavement deterioration, pseudo-variables of the pavement structure class are included in the regression model. Based on engineering experience, eight classes of road surface structures were divided into three generalized groups according to the design loads acting on them, which are presented in Table 5.

Road sections are divided into roads with pavement structures designed for heavy, medium, and light loads. This division is based on assessment (VĮ Lietuvos automobilių kelių direkcija (LAKD), 2019):

Table 4. Regression models

Year	The model equation	The determination coefficient
2019	$\ln(DBI2019 + 2.0) = \beta 0 + \beta 1 \cdot x1 + \beta 2 \cdot x2 + \beta 3 \cdot x3 + \beta 4 \cdot x4 + \beta 5 \cdot x5$	0.283
2020	$\ln(DBI2020 + 0.5) = \beta 0 + \beta 1 \cdot x1 + \beta 2 \cdot x2 + \beta 3 \cdot x3 + \beta 4 \cdot x4 + \beta 5 \cdot x5$	0.314
2021	$\ln(DBI2021 + 3.0) = \beta 0 + \beta 1 \cdot x1 + \beta 2 \cdot x2 + \beta 3 \cdot x3 + \beta 4 \cdot x4 + \beta 5 \cdot x5$	0.294

- DK0,1 – DK1 are intended for normal traffic load;
- DK2 – DK100 are intended for road sections exposed to heavy traffic load;
- DK2 – DK3 cover a small section of the design load, and until the approval of new design guide (KPT SDK 19) presented one common group;
- Clause 38 of KPT SDK 19 distinguishes DK10, DK32, and DK100 road construction classes and recommends applying additional mechanistic-empirical methods for checking the construction thickness.

Analysing only the road sections whose pavement construction is classified as I GRCC, regression analysis model equations are created for each year of analysed data and are presented in Table 6. The variables of this regression model are: road age (X_1), traffic loads (X_2), and road type (X_4, X_5).

The obtained coefficients of determination are presented in Table 6, which shows how much the data dispersion is described by the linear regression model.

Analysing only the road sections whose pavement construction is classified as III GRCC, the regression analysis model equations for each year of the analysed data are presented in Table 7. Regression model variables: road age (X_1), traffic loads (X_2), frost zone (X_3), road type (X_4, X_5).

Table 7 presents the obtained coefficients of determination for each year data, which show how much the data dispersion is described by the linear regression model.

Analysing only road sections with II GRCC pavement construction, regression analysis model equations for each year of the analysed data provided analogous results – the results were statistically influenced only by the age of the pavement, and the coefficients of determination of the models obtained showed the absence of correlation (according to the obtained value of the coefficient of determination in 2019, we can say that the regression model defines only 9.91% of the variation in the values of the selected independent variables). The model equations for each year of the analysed data evaluated the following variables: road age (X_1), traffic load (X_2), frost zone (X_3), and road type (X_4, X_5).

After performing a regression analysis of the accumulated data in various cross-sections, we can see that significant indicators differ in different years of analysis. In further research, we will consider the grouping of road structure strength, which showed the greatest influence during the regression analysis and the relationship with road surface roughness in IRI.

3.4. Regression analysis of panel data

The data array collected for the study includes 319 individual objects, each of which has 4 times (measurement) points. Panel data analysis is suitable for this type of data.

The fixed-effects regression model was chosen because the observed data (when evaluating individual objects – road sections) are heterogeneous – the confidence intervals of the average of the analysed data fluctuate – in some data groups it is narrower, in others it is wider, both when comparing by year of measurements and when analysing

Table 5. Grouping of pavement structure classes

Road construction class	Design load A (ESALs), mln	Name	GRCC*
DK 100	> 32	Pavement adapted (designed) for high-traffic load	I GRCC
DK 32	> 10–32		
DK 10	> 3.0–10		
DK 3	> 2.0–3.0	Pavement adapted (designed) for medium-traffic loads	II GRCC
DK 2	> 1.0–2.0		
DK 1	> 0.3–1.0	Pavement adapted (designed) for low-traffic load	III GRCC
DK 0.3	> 0.1–0.3		
DK 0.1	≤ 0.1		

* Group of road construction class

Table 6. Regression models for I GRCC incorporating road construction class Clustering

Year	The model equation	The determination coefficient
2019	$\ln(DBI2019+1)=\beta0+\beta1\cdot x1+\beta2\cdot x2+\beta3\cdot x3+\beta4\cdot x4$	0.355
2020	$\ln(DBI2020+1)=\beta0+\beta1\cdot x1+\beta2\cdot x2+\beta4\cdot x4$	0.430
2021	$\ln(DBI2021+1)=\beta0+\beta1\cdot x1+\beta2\cdot x2+\beta4\cdot x4$	0.470

Table 7. Regression models for III GRCC incorporating clustering of road construction classes

Year	The model equation	The determination coefficient
2019	$\ln(DBI2019+1)=\beta0+\beta1\cdot x1+\beta2\cdot x2+\beta3\cdot x3$	0.233
2020	$\ln(DBI2020+1)=\beta0+\beta1\cdot 1+\beta2\cdot x2+\beta3\cdot x3+\beta4\cdot x4+\beta5\cdot x5$	0.223
2021	$\ln(DBI2021+1)=\beta0+\beta1\cdot x1+\beta2\cdot x2+\beta3\cdot x3+\beta4\cdot x4+\beta5\cdot x5$	0.228

each object separately. Since the regressors (of individual road sections) are very different, the analysis was performed by dividing the data into clusters according to groups of pavement construction classes (GRCC), as in the case of regression data analysis by determining significance factors.

Observations (measurements) of one object are shown in Figure 8. The first observation (measurement) of each object was performed immediately after the construction works (all objects were repaired between 2008 and 2016). The next three observations were made during the years of one of the authors' doctoral studies: 2019, 2020, and 2021 as part of the research work.

The heterogeneity of I GRCCs assigned to road sections can be observed for each object separately in Figure 9.

3.4.1. Construction of a fixed-effects regression model for panel data of I GRCC sections

The previous part of the study showed that using PCI logarithmic values for the regression model, the obtained model better described the observed data, i.e., a higher coefficient of determination (Adj. R-Squared) and a lower sum of squares of residual errors (Residual Sum of Squares)

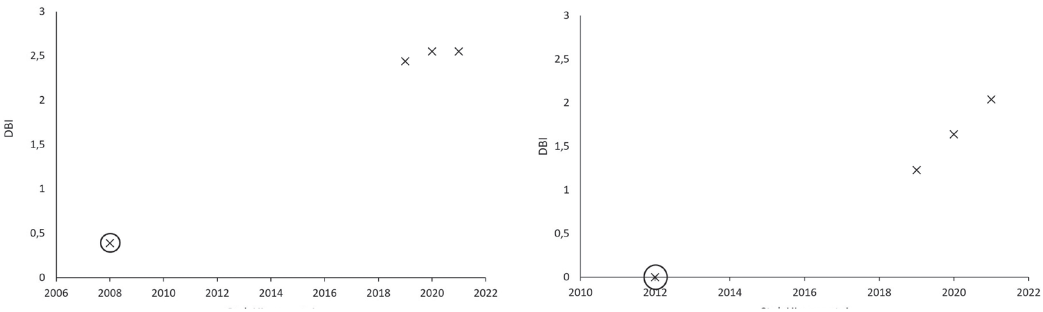

Figure 8. An example of the periodicity of object condition monitoring: year of construction on the left – 2008, on the right – 2012

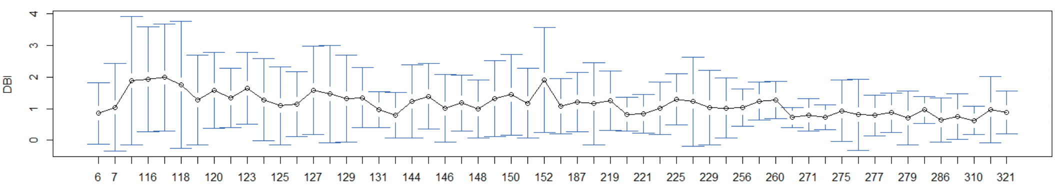

Figure 9. Heterogeneity for I GRCC sections (each object has 4 years of measurement)

were obtained. For analysis, the model includes: traffic loads, age, and road roughness IRI. When constructing the regression model, it was found that observations 9 and 145 were outliers that affected the quality of the regression model. For this reason, these observations were not used to create the regression model, so the final amount of observed data (objects) was 56. Time points – 4. The regression model is created:

$$y_i = \beta_0 + \beta_1 \cdot x_{1i} + \beta_2 \cdot x_{2i} + \beta_3 \cdot x_{3i} + \varepsilon_i, \left(i = \overline{1, n}\right). \qquad (6)$$

To assess the adequacy of the created model, a residual error analysis is performed by checking the normality and independence (autocorrelation) of the residual errors. When evaluating the distribution of residual errors ε_i, $(i = (1,n))$, the histogram of residual errors and the quantile comparison chart (QQ) are drawn in Figure 10. The resulting histogram is not symmetrical, but the quantile values are located close to the line, and the "tails" are not so far away from this line. After carrying out the Anderson and Darling test for normality, it was found that the model errors satisfy (obtained p value = 0.1471) the conditions of normality (p value > 0.05).

Also, there was detected no autocorrelation of the model (p value = 0.9676, which is determined by applying the Durbin-Watson test (threshold p value ≥ 0.05) to determine autocorrelation. According to the value of the coefficient of determination, we can say that the regression model explains (defines) a 79.56% change in PCI values across selected independent variables, showing a strong correlation between modelled values and actual data.

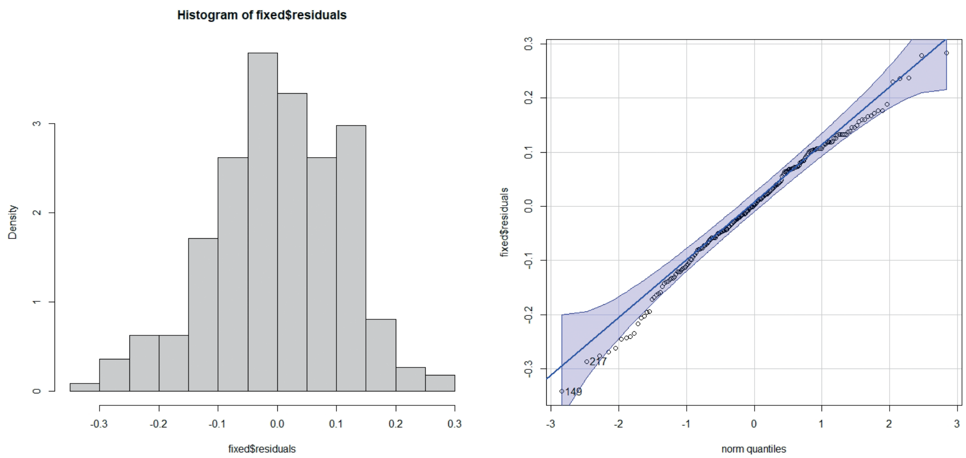

Figure 10. The model (Equation (7) histogram of errors and the quantile comparison chart (QQ)

$$\ln(\widehat{PCI}_{it}+1)=0.209\cdot\ln(ESALs_{it}+1)+0.103\cdot Age_{it}+0.126\cdot IRI_{it},$$
$$\left(i=\overline{1,56},t=\overline{1,4}\right). \tag{7}$$

Based on the analysis, the PCI prediction model of the pavement condition index for road sections classified as I GRCC is presented in Equation (7).

3.4.2. Construction of a fixed-effects regression model for panel data of II GRCC sections

When examining the data assigned to the II GRCC group, it was observed how traffic load, age, and road roughness IRI influenced the pavement condition index PCI. After data analysis, no autocorrelation was detected according to the Durbin-Watson test (p value = 0.9806).

Evaluating the distribution of residual errors, the residual error histogram and quantile comparison plot (QQ) are illustrated in Figure 11. Model errors meet normality conditions (p value = 0.05335) using the Andersen and Darling test. According to the value of the coefficient of determination, we can see that the regression model explains 69.13% of the variation in PCI values through the selected independent variables. This shows a reasonably strong relationship between the simulated values and the real data.

$$\ln(\widehat{PCI}_{it}+0.5)=0.770\cdot\ln(ESALs_{it}+1)+0.149\cdot AGE_{it}+0.560\cdot IRI_{it},$$
$$\left(i=\overline{1,53},t=\overline{1,4}\right). \tag{8}$$

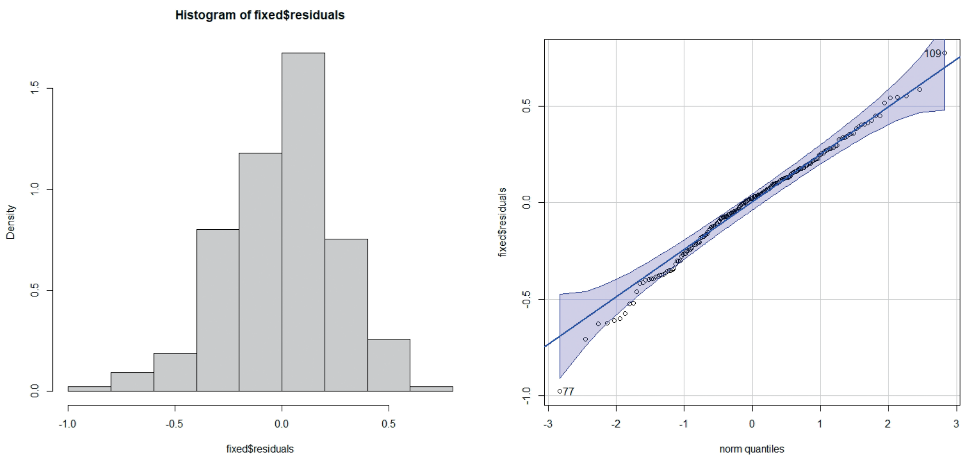

Figure 11. The model (Equation (8)) histogram of errors and the quantile comparison chart (QQ)

Based on the analysis, the pavement condition index PCI forecast model for road sections classified as II GRCC is presented in Equation (8).

3.4.3. Construction of fixed-effects regression model of panel data of III GRCC sections

Analysing the data on the condition of sections assigned to III GRCC, it was observed how the traffic load, age, and unevenness of the road surface (IRI) influenced the variation of the pavement condition index PCI.

According to the coefficient of determination of the model obtained during the study, we can see that the regression model defines 65.69% of the variation in PCI values with the selected independent variables. This shows a reasonably strong correlation between the modelled values and the observed data. The performed data analysis did not identify autocorrelation according to the Durbin-Watson test (p value = 1), but the established model errors did not satisfy (p value = 0.005907) the condition of normality (threshold p value ≥0.05) when applying the Andersen and Darling test. Due to the large sample of objects under investigation, the condition of normality is not very significant, but in the case of weak pavement construction, it was decided to investigate smaller groups by dividing them according to road types: main, national, and regional roads. Since there are only two sections of main roads in III GRCC, these two exceptions were connected to the group of roads of regional importance.

3.4.4. Construction of fixed-effects regression model of panel data of III GRCC sections for national road sections

Examining the data of rural roads classified as III GRCC group, it was observed how traffic load, age, and road roughness IRI influenced the pavement condition index PCI. Evaluating the distribution of residual errors, the residual error histogram and quantile comparison plot (QQ) are illustrated in Figure 12.

The resulting histogram is not symmetrical, but the quantile values are located close to the line, and the “tails” are not so far away from this line. Model errors meet normality conditions (p value = 0.3027) using the Andersen and Darling test. Durbin-Watson test also revealed no autocorrelation (p value = 0.9762). Considering the obtained value of the coefficient of determination, we can say that the regression model explains (defines) 60.56% of the variation in PCI values through the selected independent variables. This indicates a sufficiently strong relationship between the simulated values and the real data.

$$\ln(\widehat{PCI}_{it}+0.1)=2.081\cdot ESALs_{it}+0.302\cdot AGE_{it}+1.701\cdot IRI_{it},$$
$$\left(i=\overline{1,20}, t=\overline{1,4}\right). \tag{9}$$

The designed pavement condition index PCI prediction model for road sections classified as national roads of III GRCC is presented in Equation (9).

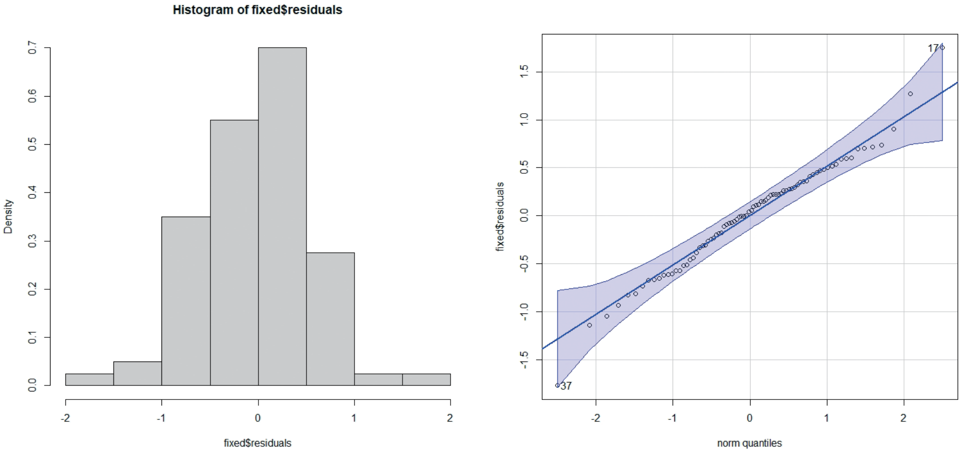

Figure 12. The model (Equation (9)) histogram of errors and the quantile comparison chart (QQ)

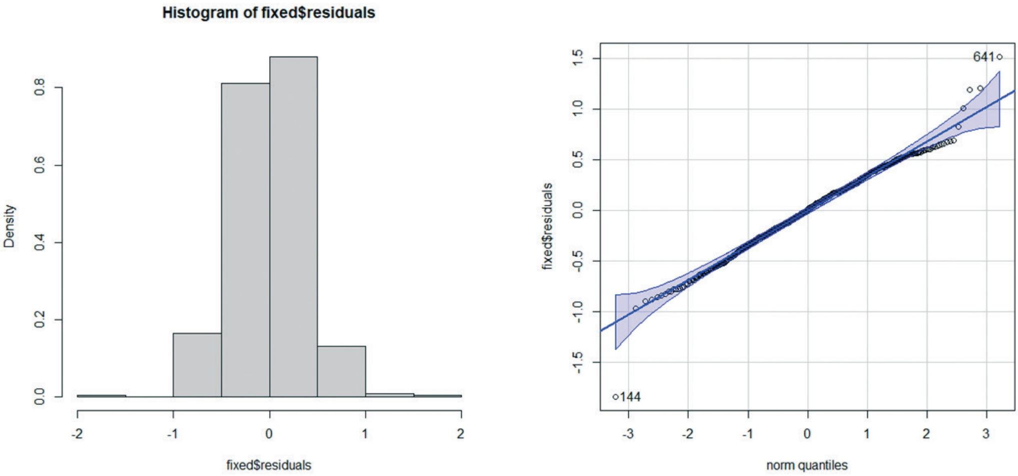

Figure 13. The model (Equation (10)) histogram of errors and the quantile comparison chart (QQ)

3.4.5. Construction of a fixed-effects regression model for panel data of III GRCC for regional and main road sections

No autocorrelation was found according to the Durbin-Watson test (p value = 1.0) after the analysis of the state data of district and main road sections classified as III GRCC. The errors of the obtained model satisfy (p value = 0.05146) the conditions of normality by applying the Andersen and Darling test. The resulting histogram is not symmetrical, but the quantile values are located close to the line, and the "tails" are not so far away from this line.

Evaluating the distribution of residual errors, the residual error histogram and quantile comparison plot (QQ) are illustrated in Figure 13.

According to the obtained value of the coefficient of determination, we can say that the regression model explains 67.36% of the variation in PCI values through the selected independent variables. This shows a reasonably strong relationship between the simulated values and the real data.

The designed pavement condition index PCI prediction model for road sections classified as regionally significant roads of low pavement construction class is presented in Equation (10).

$$\ln(\widehat{PCI}_{it} + 0.55) = 0.762 \cdot \ln\left(ESALs_{it} + 0.35\right) + 0.342 \cdot AGE_{it} + 0.889 \cdot IRI_{it}, \quad \left(i = \overline{1,192}, t = \overline{1,4}\right). \tag{10}$$

Conclusions

The measurement and assessment of road pavement performance indicators is a widespread method in the pavement management process. To achieve the best possible condition management results, it is necessary to assess the condition of the pavement not only in the current time but also to be able to predict the change in the condition of the pavement in a pavement management system.

There are many different techniques and methods for pavement condition modelling used in the world, but they are mostly country or region specific and difficult to apply elsewhere. There are countries, which have medium or large road network, but there is little information collected about it: there is no information about the thickness of the structure, nor about the materials, nor is the history of the repair of the section collected. Adapting the deterioration models used in other countries is difficult not only because of the climatic conditions but also because of the geographic and natural conditions, technologies, and materials used in construction.

For that purpose, in this study a typical situation was analysed, when it was known when the repair was carried out, the level of condition reached after the construction works, and transport loads passed through in a year. Road surface condition indicators were measured and the pavement condition index was calculated for 2019, 2020 and 2021.

This study analysed the various variables that might affect the deterioration of road surfaces and identified those variables that could be used to construct deterioration curves.

The determined heterogeneity shows how the sections are individual and how they can differ from each other. At the same time, the descriptive statistics of the measurement data show that as the age of the pavements increases, the condition becomes similar (range of average DBI increase) and the recorded exceptions decrease, contrary to what was recorded when assessing the condition of the pavement immediately after the construction works (very narrow average range).

In this study, a regression analysis of panel data using a fixed-effects regression model was performed and significant relationships were found between PCI values and pavement construction classes adapted to heavy traffic loads (I GRCC) – DK10 - DK100 and for small traffic loads (III GRCC) – DK0.1 - DK1. A lower correlation was found in the II GRCC group (pavements intended for medium traffic loads).

Also, during the regression analysis, it was found that only the fourth frost depth zone was statistically significant. Interestingly, this fourth zone began to be evaluated when designing structures since 2019. This established relationship shows that the thickness of the frost-resistant road construction structure applied until 2019 was insufficient.

After conducting the study, four deterioration models for predicting the pavement condition index were created, dividing the roads into three groups according to the pavement construction class – pavements adapted for high-traffic loads (one model), medium-traffic loads (two models) and low-traffic loads (one model). These models are the dependence of the pavement condition index on traffic load ESALs, pavement age and pavement roughness.

The models for predicting the deterioration of the pavement condition index make it possible to predict the change in the pavement condition index of each road section, without applying the deterioration forecast of other indicators necessary for the calculation of the pavement condition index, which is very difficult to predict (ruts, cracks and surface defects, etc.).

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