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Bayesian and neural network models for risk assessment of traffic-induced vibrations in residential buildings

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ABSTRACT

The operation of buildings aims to ensure their safe and economical use throughout their lifespan. However, the importance of operational management in building facilities is sometimes underestimated. Cases of damage or deterioration often indicate unresolved maintenance issues or the absence of effective forecasting, especially in environments exposed to dynamic external influences. These shortcomings can lead to management decisions that fail to account for critical factors influencing the long-term structural and operational performance of a building. One significant challenge, closely linked to these considerations, is the impact of traffic-induced vibrations on buildings located near roads. Traffic-induced vibrations can challenge building operations, causing plaster scratching and cracking, plaster detachment, structural damage, or even building collapse. Measuring dynamic actions on real structures is labor-intensive, costly, and not always justified. Therefore, the primary objective of this research was to develop a predictive algorithm for assessing the risk of adverse dynamic impact on residential buildings. Artificial Neural Networks and Bayesian Networks were employed to forecast the effects of traffic-induced vibrations. This paper presented a detailed performance analysis of these systems and the validation of the proposed assessment model. The verification process involved in situ measurements on the structures identified as being at risk from paraseismic effects. This study introduced an integrated approach combining Bayesian networks and artificial neural networks in an iterative mutual-learning process, in which both models correct their internal parameters based on correct and incorrect classifications, thereby enhancing the stability of predictions and demonstrating its practical applicability through validation using real in situ measurements of traffic-induced vibrations. Experimental results confirmed that the proposed methodology serves as an effective predictive tool in civil engineering. To mitigate the effects of vibrations on buildings, the study explored both active and passive protection methods. The choice of protection method depends on several factors, including whether the building and road are existing or planned, and the specific conditions for implementing vibration impact protection.

Keywords: building operation, traffic-induced vibrations, artificial intelligence, Bayesian networks, artificial neural networks.

INTRODUCTION

Vibrational comfort in building structures has become a key aspect of modern civil engineering due to rising living standards and user demands. In the previous decade, structures with high mass and stiffness dominated, rarely resonating under everyday loads, such as the vibrations induced by traffic. Contemporary engineers strive to create lighter, more flexible structures, which leads to lowering the natural frequency of buildings and bringing it closer to the external vibration frequency. Previous engineering approaches focused primarily on structural safety, often neglecting the feelings of building occupants. Today, the vibrations induced by intensive vehicle traffic are a common cause of occupant discomfort and a challenge in preventing structural damage [1].

Artificial intelligence (AI) is becoming common in various fields of science and industry. The use of AI may affect the efficiency and speed of actions, but the most important thing seems to be the ability to adapt to specific cases. Algorithms must be adaptable because the context in which they are applied will never be the same twice. Even if building facilities were replicated in some way, the needs of managers and decision makers would be different, because the priorities, goals, knowledge, influence of different stakeholders, and available information about the history of a building are always unique. Thus, the question arises: what tools can effectively address problems in this challenging field? Currently, numerous methods are available for predicting phenomena in civil engineering. Therefore, the aim of this paper was to apply AI algorithms, specifically those based on artificial neural networks (ANN) and learning Bayesian networks (LBN), in the diagnostics of buildings. The use of AI algorithms in making choices related to construction issues can bring many benefits to decision-makers, because it reduces the risk of making wrong decisions, and therefore also reduces operating costs. This paper focused on the impact of traffic-induced vibrations on residential buildings. The main aim was to create a model supporting decisions whether a given object is exposed to vibrations caused by traffic. The primary benefit of the proposed methodology is that the model serves as an integrating tool, utilizing both historical and current data about building operations and surrounding conditions to evaluate the probability of impact vibrations.

AI is very widely used in civil engineering. LBNs are potent instruments for vibration diagnostics, providing comprehensive methodologies for performing inference, as detailed in [2]. An exemplary instance of the practical application of this methodology, meriting attention, can be observed in article [3], which explores the application of Bayesian neural networks in monitoring the structural health of bridges. It presents a two-step strategy for detecting and assessing damage in long-span bridges under ambient vibrations, emphasizing the advantages of Bayesian methods in handling uncertainties and enhancing the accuracy of damage identification. In the subsequent article [4], the authors delved into the utilization of Bayesian Belief networks (BBNs) for risk assessment and management during the construction of a road tunnel under the Dead Vistula River in Gdansk, Poland. They illustrate how BBNs can be employed to evaluate uncertainties and make informed decisions throughout the implementation phase of this large-scale construction project. The study emphasized the effectiveness of BBNs in identifying potential risks, predicting their impacts, and selecting optimal response strategies. Consideration should also be given to the application of Bayesian networks for constructing the model of cross passages between tunnel tubes in soft soils [5]. To ameliorate the problem related to the scarcity of risks information, often encountered in construction projects, the authors employed BBNs and expert knowledge to enhance the available data. A review of the literature indicates that the use of this methodology in the context of making complex decisions in construction is appropriate.

Another methodology is ANNs. They have found wide application in civil and seismic engineering. Chudyba and Kuźniar employed neural networks to predict the impact of mining-induced vibrations on structures [6, 7]. Another instance of utilizing this kind of algorithm is detailed in [8], where a network was applied to rank bridge constructions. The objective was to develop a system that could assess, based on various criteria, whether a bridge required immediate refurbishment. The authors achieved a commendable outcome, and the system is currently being adopted by the General Directorate for National Roads and Motorways. In the context of applying neural networks in civil engineering, it is pertinent to highlight article [9]. In this study, the authors explored the use of neural networks to predict driver behavior in accepting gaps at stop-controlled intersections. The study focused on assessing the safety of merging into traffic at low-volume rural intersections. The ANN algorithm was additionally utilized to evaluate the extent of technical deterioration in historic structures [10].

Recent research has also demonstrated that the artificial intelligence methods are increasingly applied in broader aspects of the built environment, including energy-efficient residential construction, sustainable urban development and intelligent mobility systems. For example, Nath et al. [11] used machine-learning-supported optimization to evaluate PCM–CLT wall systems across different climatic zones, highlighting the potential of AI-based tools for improving building performance. Zumaya et al. [12] applied data-driven methods to analyze sustainable urban placemaking strategies, while Halawani [13] demonstrated the effectiveness of AI-supported smart roundabout coordination systems for improving traffic flow and urban mobility. These studies underscore the versatility of AI approaches and support the rationale for applying machine-learning methods in vibration diagnostics.

Building on the substantial findings reported in authors' earlier studies [14,15], in which the effective use of artificial neural networks and Bayesian networks for analyzing vibration effects in buildings was described, the present work further advances in this research direction by introducing an integrated methodological framework. In contrast to previous studies, in which Bayesian networks and artificial neural networks were treated as two independent predictive modules, this work presents a fully integrated approach that enables iterative mutual learning between the models. The proposed framework combines the capacity of Bayesian networks for probabilistic interpretation of processes with the sensitivity of artificial neural networks to complex data patterns. In the presented method, the information derived from correct classifications obtained by the neural networks is used to update the conditional probability tables in the Bayesian networks, allowing for their dynamic adjustment in response to new observational data. Conversely, the cases misclassified by the neural network but correctly recognized by the Bayesian network are employed to modify selected parameters of the neural models, thereby enhancing their generalization capability. Together, these mechanisms create a bidirectional information-exchange process that leads to gradual stabilization and mutual reinforcement of predictions. The use of real in situ measurements enabled not only the verification of prediction quality but also the assessment of the model's practical applicability in the context of managing the operation of buildings exposed to traffic-induced vibrations.

A review of the literature indicates that the aforementioned methods can be effectively applied across diverse domains. Their implementation not only fosters technological advancement but also contributes to cost reduction and mitigates the potential for negative outcomes.

RESEARCH PROBLEM AND METODOLOGY

In recent years, there has been a growing interest in the use of artificial intelligence (AI) methods to predict the effects of dynamic loads, as traditional analytical and empirical approaches do not always allow for an adequate representation of the complex relationships between soil parameters, structural characteristics, and vibration sources. The aim of this article was to evaluate the effectiveness of selected AI techniques in forecasting and assessing the impact of traffic-induced vibrations on buildings and their occupants. By integrating the AI algorithms within situ measurements, the study sought to enhance building safety and occupant comfort while gaining a more comprehensive understanding of the correlation between vibration parameters and structural response. The analysis also encompasses the strategies for mitigating potential damage and improving the resilience of building structures.

Previous studies have demonstrated that the models based on Bayesian networks and artificial neural networks can effectively assess the risk of dynamic effects on residential buildings, achieving accuracies exceeding 80% (see [14, 15]). These findings confirm the relevance of AI techniques in the analysis and prediction of traffic-induced vibration impacts. Decision-support systems and AI algorithms further offer cost-effective and efficient solutions, enabling satisfactory handling of engineering problems despite their approximate nature [16, 17]. For this reason, LBN and artificial neural networks (ANN) were selected in this study due to their demonstrated effectiveness in performing such tasks.

The dataset used to develop the models consisted of 140 cases collected from 60 residential structures located near roads with varying traffic intensities. For each case, the following input variables were recorded: building technical condition (BTC), distance from the road edge (DBR), soil absorption (SA), road surface technical condition (RSTC) and prevailing vehicle type (V). The cases covered a broad range of conditions, with DBR varying from 1.9 to 15.0 m, BTC including categories from "poor" to "good" condition, and soil absorption spanning from low to high damping capacity. For model development, the dataset was randomly divided into three subsets: 70% of the cases were used for training, 15% for validation and 15% for testing. Each subset contained both safe and at-risk cases, ensuring a balanced representation of the output classes.

Learning Bayesian network (LBN)

Bayesian probabilistic networks, also known as causal networks or BBNs, constitute an advanced framework for representing knowledge and performing inference under uncertainty. They model probabilistic dependencies among a set of random variables using a directed acyclic graph, where edges encode conditional relationships or causal influences.

A central feature of Bayesian networks is the process of belief updating in response to newly observed evidence. The introduction of new information triggers probabilistic inference throughout the network, resulting in adjustments to the values in the conditional probability tables. This mechanism reduces uncertainty and aligns the model with current observations. Consequently, Bayesian networks enable dynamic, efficient, and internally consistent updating of knowledge, leading to more accurate inference and improved decision-making. An example of using the Bayesian network is shown in Figure 1.

Traditional BBNs require an expert to manually define the network structure and input values into the conditional probability tables. This process can be quite cumbersome and time-consuming. Therefore, the proposed project advocates the use of LBNs, which have been seldom utilized in the construction field.

LBNs involves two primary components: the network structure and the parameters. The network structure is represented by a directed acyclic graph (DAG), where each node corresponds to a variable, and the absence of an edge signifies a conditional independence statement. The parameters consist of a set of conditional probability distributions (CPDs). Each node (Xi) in the graph is associated with a CPD, (P(Xi|Parents(Xi))), where (Parents(Xi)) denotes the parents of (Xi) in (DAG). The learning process involves determining both the structure of the network and the values of the parameters (P(Xi|Parents(Xi))). Parameter learning involves fitting the probability distributions to the data. This is typically achieved by maximizing the likelihood function of the data, expressed as Equation 1:

$$P(Data|Model) = \\ = \prod_{i=1}^{n} P(X_i|Parents\ (X_i)) \tag{1}$$

where: (*Data*) represents the set of observations, and (*Model*) denotes the network structure and its parameters [18, 19].

In this study, the initial structure of the Bayesian network was defined based on expert knowledge of the causal relationships between the considered variables, with directed edges reflecting physically justified influence paths (e.g., from soil absorption and distance from the road to the vibration impact node). Building on the substantial results of authors' previous studies [14,15], in which Bayesian-network and artificial-neural-network models for vibration assessment were developed and evaluated, the preliminary Bayesian network structure derived in those works was further refined in the present study by incorporating additional observational data and by adjusting the network in accordance with the patterns identified by the artificial neural networks, thereby enhancing the coherence and reliability of the resulting model.

Parameter learning was performed using maximum likelihood estimation, assuming multinomial conditional probability distributions for the discrete variables. The learning process consisted in iteratively updating the conditional probability tables to maximize the likelihood of the observed dataset, as expressed in Equation 1. To avoid overfitting, the model complexity was monitored and excessively detailed discretization of input variables was avoided.

LBNs, utilizing available source data, can automatically generate network structures and incorporate a formalized mechanism for learning conditional probability values. Research indicated that this approach not only alleviates the burden on experts but also mitigates the widely discussed and criticized subjectivity inherent in BN, which can lead to distortions in the estimation process.

Artificial neural network (ANN)

The functioning of an artificial network mirrors the principles of a human neural network. Information is transmitted to the cells, processed, and stored for future use. Artificial systems operate similarly, where data is input, processed, stored, and even adjusted by the system [20]. Like a biological neural network, the cells in an ANN can communicate with each other, forming a multilayered structure that enhances the computational capabilities of the algorithm. Building the network involves three fundamental steps. In the first stage, the input data is multiplied by the user's assumed weights. The next step was to assign an activation function, i.e., an input-output

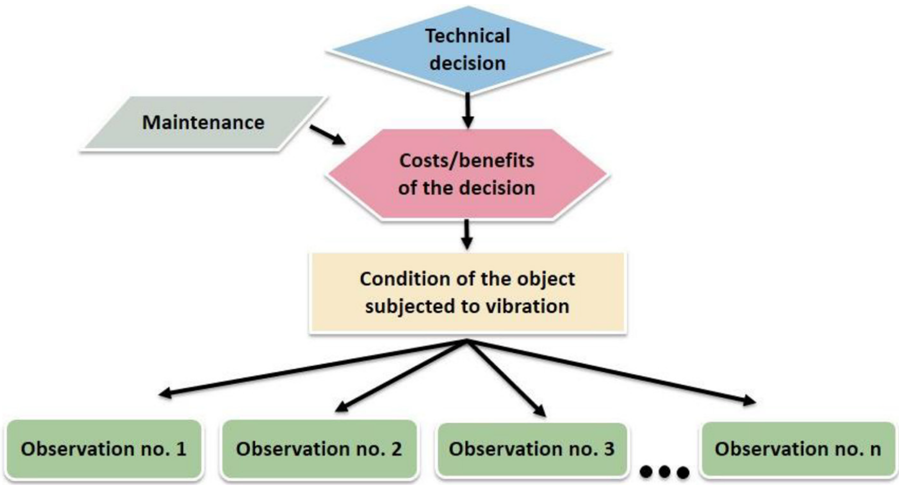

Figure 1. Example model of Bayesian network

function. The basic activation functions in ANNs are a linear function, a unit step function, a sigmoid function, and a hyperbolic tangent function. Finally, the output signal for a single neuron is obtained from the relationship (2–4) [21]:

$$\boldsymbol{x} = [x_1, x_2, \ldots, x_n]^T \tag{2}$$

$$\boldsymbol{e} = f(x, w) = \sum_{i=0}^{n} x_i w_i \tag{3}$$

$$\boldsymbol{w} = [w_1, w_2, \ldots, w_n]^T \tag{4}$$

where: x – vector of input signals, e – internal processing function, w – vector of weights, n – the number of inputs to the neuron.

In the present study, a feed-forward multilayer perceptron architecture was adopted. The optimal network configuration, selected after preliminary experiments, consisted of an input layer with five neurons (corresponding to BTC, DBR, SA, RSTC and V), 3–12 hidden layer(s), and a single output neuron representing the binary classification of the vibration impact ("safe" vs "at risk"). The hidden neurons employed the sigmoid activation function, while a logistic activation was used in the output layer.

All input variables were normalized to the [0,1] range prior to training to improve numerical stability. The networks were trained using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization algorithm, with a maximum of 300 training epochs and an early stopping criterion based on the validation error. The loss function was defined as the cross-entropy between predicted and true class labels. Hyperparameters such as the number of hidden neurons and the learning rate were tuned using a trial-and-error procedure guided by the performance on the validation set.

The first phase is dedicated to learning, where some samples (cases) are selected and processed using an algorithm, see Equation 2. The second phase focuses on verification, where another set of data is applied to the model, and the results are compared with actual measurements. The network is refined to minimize the discrepancy between the algorithm's output and experimental results. The final, third phase involves testing the network with a set of cases not used during the development of the algorithm (Equation 3). This phase allows for the determination of the network accuracy and the percentage of correct output signal predictions (see Figure 2). In this article, the Broyden-Fletcher-Goldfarb-Shanno function was used. It is a Quasi-Newton method a type of second-order optimization algorithm, The BFGS algorithm is arguably one of the most widely used second order algorithms in numerical optimization and is commonly used to tune machine learning algorithms, such as logistic regression (Equation 4).

This chapter presents the idea of using ANN and LBN algorithms to predict the risk of damage occurrence in residential buildings located near vehicular roads. Figure 3 shows the flowchart that leads to the determination of the risk in question. The model is applicable to both current and planned buildings.

According to the diagram in Figure 3, the risk management process is divided into 3 stages. In the first stage, the parameters and situational factors must be established. The second stage is

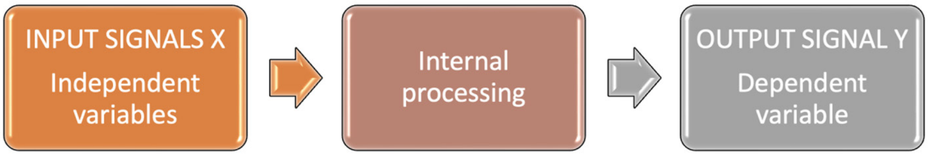

Figure 2. The general model of ANNs

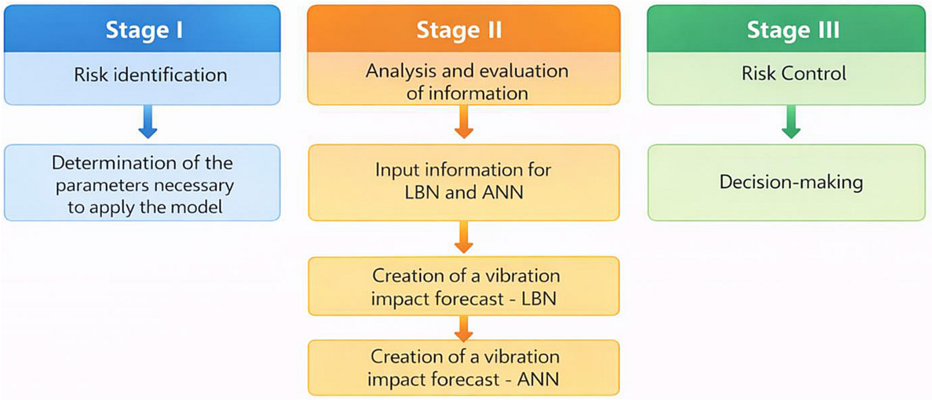

Figure 3. Schematic representation of the procedure for predicting the risk of damage caused by traffic-induced vibrations

to feed the collected data (about the building, its location, road parameters) into the algorithms of artificial neural networks and learning Bayes networks. In the third stage, on the basis of the results obtained through these two independent methods, a decision should be made on the further course of action.

The model had been created based on two methods: Bayesian networks and artificial neural networks. The following factors had been taken into account when building the model (described in more detail in [14] and [15]): condition of the building (BTC), distance from the edge of the road (DBR), soil absorption (SA), road condition (RSTC) and type of moving vehicles (V).

The selection of input variables was guided by engineering judgment, relevant standards [22] and previous studies on vibration transmission from traffic to buildings [14, 15]. Building technical condition (BTC) reflects the global stiffness and presence of pre-existing damage, both of which influence the structural response to dynamic loads. The distance from the road edge (DBR) is a primary geometric parameter controlling attenuation of ground-borne vibrations. Soil absorption (SA) accounts for the damping properties of the subsoil, while road surface technical condition (RSTC) determines the level of excitation generated by vehicle–pavement interaction. Finally, the dominant vehicle type (V) represents the mass and dynamic characteristics of traffic loads.

Several additional parameters, such as traffic volume or vehicle speed, were initially considered; however, they were not included in the final model due to limited data availability and the need to maintain a compact and practically measurable set of input variables. Nevertheless, their influence is partly captured indirectly through the adopted categories of vehicle type and road condition.

The building analyzed in this paper is a residential house belonging to dynamic influence scale II (DIS II) according to the [22] standard. The building is in good technical condition, the distance is less than 11 m. The surface is in poor condition, and the type '3' vehicles travel on it (encompasses all other vehicles traveling on the road, including trucks, buses, and waste collection trucks). The influence of the type of soil on vibration absorption was also taken into account, and by analyzing the central geological database portal [23] and adopting the criteria contained in [24], an approximate absorption was established as the average vibration absorption.

Figure 4 illustrates the outcome of the previously developed learning Bayesian network for a specific scenario, considering the assumed parameters of the building and the passage of the heaviest vehicle. The analysis indicates a 92.4% probability that is possible the building will be affected by vibrations. Consequently, a decision with an effect value of 9.39322 suggests that the risk of vibration impact is high, necessitating appropriate action.

Then, an analysis has been performed based on the previously created neural networks. Artificial neural networks were created with a division into learning (70%), validation (15%) and test (15%) sets. The Broyden-Fletcher-Goldfarb-Shanno learning algorithm was used in all networks.

Each of these sets included both safe and at-risk cases. It can be concluded that the networks predict the possible impact of vibrations with a reliability of 89.4% for the learning samples and 85% for the testing samples. Beyond this overall performance, the artificial neural network was further evaluated using detailed classification metrics. On the test set, the model achieved an overall accuracy of 89.0%, with a precision of 88.2% and a recall of 89.0% for the "at risk" class.

In order to assess the reliability of the Bayesian model's predictions, the confidence margin, defined as the difference between the two highest posterior probabilities produced by the Bayesian network, was employed. For the obtained results, the most probable class reached a posterior value of p_1=0.924, while the second most probable class was assigned p_2=0.076, yielding a confidence margin of M=0.848. Such a substantial margin indicates a clear and dominant preference for a single hypothesis, thereby reflecting high predictive reliability and low decision uncertainty. This result demonstrates that the model exhibits strong decisional stability, with its inference being largely robust to minor perturbations in the input data – an important indicator of the quality and consistency of Bayesian reasoning within adaptive or self-learning architectures.

The combined use of both models thus yields a robust decision-support framework, where the neural network supplies strong predictive performance and the Bayesian network facilitates explanation and sensitivity analysis.

Given that both completely separate methods creating a mutually validating algorithm produced the same prediction, it is recommended performing experimental measurements in situ using specialized equipment, which is the next chapter.

IN-SITU MEASUREMENT TESTS

In order to conduct a proper on-site inspection, it is necessary to understand what affects the vibration level in the building. The level of vibrations generated by moving vehicles is affected by several factors [22]:

- proximity of the structure to the vibration source (road);
- vehicle-related factors: weight, speed, number of vehicles passing simultaneously, starting, and stopping;
- surface-related factors: type, condition, irregularities, and protruding manholes that alter the vehicle trajectory, thereby increasing the emission of waves propagating through the ground;
- factors related to the ground: geotechnical cross-section, groundwater, partitions, wells – the speed of wave propagation depends on the type of ground and the presence of groundwater;

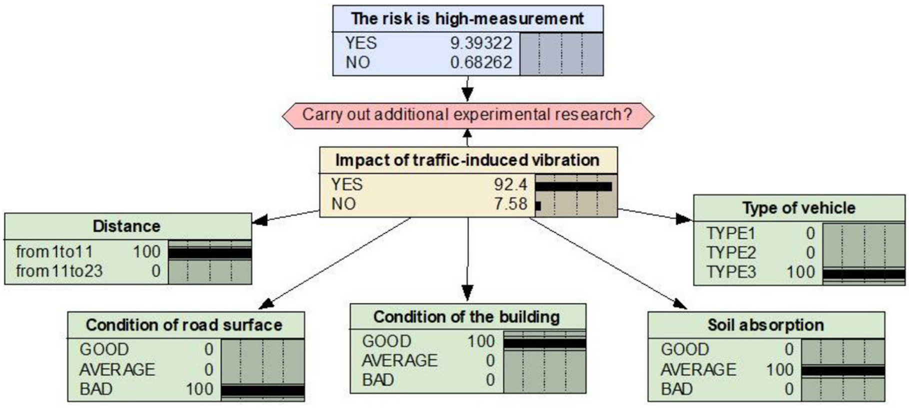

Figure 4. Visualization of results loaded into the LBN algorithm

- factors related to the building: type, structure, method of foundation, technical condition, damping – the above-mentioned factors affect the way waves are transmitted through the foundation to the remaining structure, it is also important whether the building is in good condition or has the damage that affects its stiffness.

The durability of the impacts is also important: in the standard [22], vibrations are divided into permanent vibrations, i.e. occurring more than 30 minutes a day, long-term vibrations – occurring a minimum of 3 minutes, a maximum of 30 minutes a day, and short-term vibrations, which occur – less than 3 minutes a day.

The intensity of vibrations transmitted to the building depends on the above-mentioned factors. The more vibrations from vehicular traffic are transmitted to a building and the more it is exposed to these vibrations, the more damage can occur. There may be a local failure of the structure, but it may also result in more serious damage.

In order to make measurements according to the standard, a series of measurements must be made while vehicles are passing by using specialized equipment, then frequency analysis must be performed and the results plotted on a DIS chart. From the chart, it should be read in which danger zone the object is located. The procedure is described in detail in [25].

On the basis of the preliminary predictions described for the example of the building in the previous chapter, it was determined that a measured analysis would be performed on the building. Figure 5 shows the measurement result. The case-study building analyzed in this work is a residential house belonging to Dynamic Influence Scale II (DIS II) according to PN-B-02170:2016-12 [22]. The building is in good technical condition and is located less than 11 m from the road edge, with a pavement in poor condition and traffic dominated by heavy vehicles (vehicle type "3", including trucks, buses, and garbage trucks). The measurement campaign lasted approximately 6 hours and recorded 20 vehicle passages under favorable weather conditions. The recorded data were subsequently processed in accordance with the procedure. The graph refers to the second scale of dynamic influences. The highest speed values were selected and plotted on a graph. The boundary lines indicate the degree of vibration impact on the building – the higher the line, the greater the impact. Exceeding the lowest line already indicates an impact, albeit minor (peeling paint, plaster).

The result of the measurements clearly shows that the created algorithm based on artificial intelligence is a good tool for predicting the impact of vibrations. The results of the maximum values were plotted on the DIS II scale. Bars in the graph

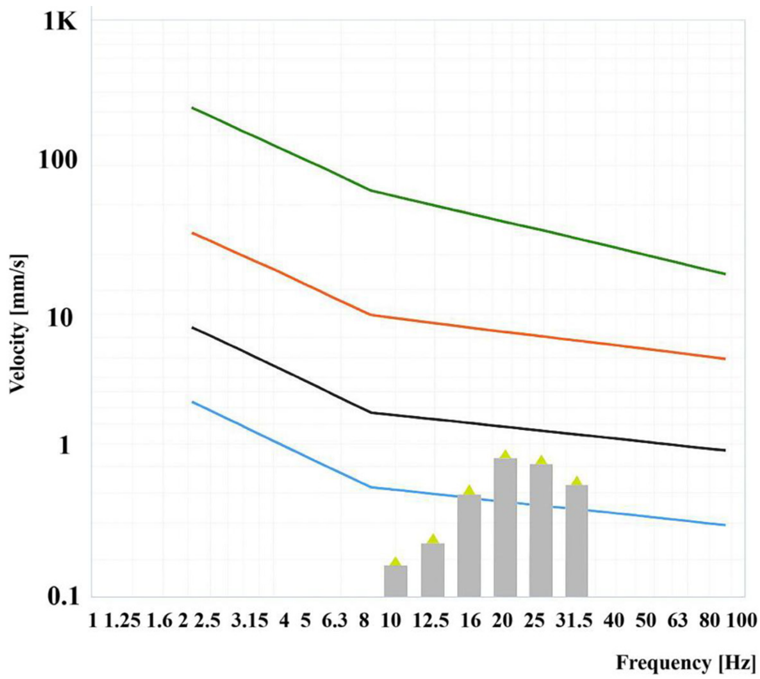

Figure 5. Resulting analysis according to the standard [22]

exceeding the ‘A’ boundary line indicate that the impact of vibrations caused by vehicles on a nearby road may be felt by the building. There is, therefore, a legitimate path for the measurements made by an accredited laboratory for further mediation with the road manager. It should also be emphasized that the standard allows for raising the main line A if the building is in good condition, and then it may turn out that the chart is entirely on the safe side. The options for dealing with and managing such risk are described in detail in chapter 4.

Additionally, there are ISO standards [26, 27] that also describe the guidelines for the design and diagnosis of building vibrations. For example, ISO 4866:2010 provides the guidelines for the measurement of vibrations and evaluation of their effects on structures, and ISO 10137:2007 outlines the serviceability of buildings and walkways against vibrations.

VIBRATION MITIGATION METHODS

Vibrations, particularly those acting over extended periods, may lead to significant structural degradation. Consequently, it is essential to identify the objects susceptible to such dynamic influences and to implement appropriate countermeasures that effectively reduce their adverse effects [28]. Available engineering solutions may be classified into two principal categories: active protection, focused on interventions at the vibration source or along the propagation path, and passive protection, applied within the structure exposed to vibrations. The selection of a suitable approach depends on whether the intervention concerns an existing or a designed road, or an existing or a newly planned building.

In the case of existing road infrastructure, active protection primarily involves the modifications that reduce the intensity of vibrations generated by vehicle traffic. The measures related to traffic management, such as lowering permissible speed limits or reducing allowable axle loads, serve to decrease the dynamic forces induced by vehicle movement. Improvements in the technical condition of the pavement constitute another essential aspect of active protection. Eliminating surface defects, repairing cracks, correcting the positioning of rainwater inlets and utility covers, sealing joints, or resurfacing the pavement all contribute to reducing the dynamic impulse transmitted from vehicles to the subgrade. The application of vibration barriers or screens, located as close as possible to the protected structure, further supports the attenuation of wave propagation [28]. Simple solutions, such as trenches formed along the wave path and filled with materials exhibiting low wave propagation velocity and high damping capacity, can significantly weaken vibrations before they reach nearby buildings.

In the design phase of a new road, the range of available preventive actions is considerably broader. The geometry of the route may be optimized to limit dynamic excitation, while the pavement structure may be engineered to enhance surface continuity and vibration-damping properties. Infrastructure elements, such as drainage inlets or inspection covers can be strategically positioned to avoid direct wheel loads. The intentional incorporation of anti-vibration screens or subsurface barriers into the design enables pre-emptive mitigation that would be more challenging to implement once the road is completed.

Passive protection becomes necessary when active measures are either infeasible or insufficient to provide satisfactory mitigation. For existing buildings, passive solutions involve interventions that modify the structural system or its interaction with the subsoil. Structural stiffening, localized strengthening of load-bearing elements, or improving the foundation system – through ground replacement, underpinning, or the use of micropiles – can enhance the resistance of a building to dynamic effects. Vibration isolation techniques, including the installation of resilient mats, elastomeric layers, or tuned damping elements, reduce the transmission of vibrations into the structural framework [29, 30]. Additional actions may address non-structural components, such as partition walls, window frames, or sensitive equipment, ensuring that they remain stable under vibration exposure.

For buildings at the design stage, passive protection can be implemented more comprehensively and with greater effectiveness. The building may be situated at an increased distance from the vibration source or oriented in a manner that reduces the exposure to dynamic loads. Foundation design may incorporate damping layers, elastic bedding, or specific types of foundations that alter dynamic interaction with the soil [31]. Complete structural separation of the building from the ground, for instance, through elastic layers placed beneath the slab above the basement level, can provide substantial isolation from ground-borne vibrations [32]. Furthermore, the dynamic properties of the structure – such as stiffness, mass distribution, and inherent damping – may be shaped during the design process to limit susceptibility to resonant effects.

Overall, the choice of vibration mitigation techniques depends on the state of both the road and the building, as well as the feasibility of applying active or passive measures. Active protection focuses on modifying the vibration source, particularly in road infrastructure, while passive protection aims to enhance the resistance or isolation of the structure subjected to vibrations. The design stage of both roads and buildings offers the greatest opportunity to implement effective and integrated solutions, whereas interventions in existing structures typically demand a more constrained and adaptive approach (see, for example, [33]).

CONCLUSIONS

The algorithm developed in this study supported informed decision-making regarding the siting of proposed investments and provided a reliable basis for assessing vibration-related risks in existing structures. It established a consistent framework for identifying potential hazards and determining whether further diagnostic measurements were necessary. The application of artificial intelligence significantly enhanced the accuracy of identifying structures exposed to traffic-induced vibrations. The AI methods enabled precise forecasting of vibration impacts and delivered effective classification of risk levels, thereby strengthening the overall reliability of the analytical process and improving the interpretation of building response. The results generated by the LBN and ANN models formed a solid basis for selecting actions appropriate to the predicted vibration effects. The situations with negligible impact were identified as not requiring additional measures. The cases involving elevated vibration influence were linked to interventions aimed at reducing external excitation. When the predicted effects indicated that structural performance was affected, the models supported the decision to conduct specialized accredited measurements to verify the influence of traffic-induced vibrations. These outcomes confirm the robustness of the proposed methodology and demonstrate its effectiveness in ensuring reliable assessment of vibration impacts on buildings.

It should be emphasized that the present models were calibrated using the data collected from a specific set of residential buildings and local geotechnical conditions. As a result, the direct transfer of the trained LBN and ANN models to other regions or building typologies may require additional calibration or retraining using local data. Nevertheless, the proposed modeling framework and the selected input variables are general in nature and can be adapted to different contexts, provided that appropriate datasets and diagnostic measurements are available.

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