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PAVEMENT DIAGNOSIS ACCURACY WITH CONTROLLED APPLICATION OF ARTIFICIAL NEURAL NETWORK

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Abstract. Results of research studies, the amount of input data available in pavement management system databases, and artificial intelligence methods serve as versatile tools, well-suited for the analysis conducted as a part of pavement management system. The key source of new and to be employed knowledge is provided. In terms of e.g. assessing thickness of bituminous pavement layers, the default solution is pavement drilling, but for the purposes of pavement management it is prohibitively expensive. This paper attempts to test the original concept of employing an empirical relationship in an algorithm verifying results produced by the artificial neural network method. The assumed multi-stage asphalt pavement layer thickness identification control process boils down to evaluating test results of the road section built using both, reinforced and non-reinforced pavement structure. By default, the artificial neural network training set has not included the reinforced pavement sections. Hence, it has been possible to identify "perturbations" in assumptions underlying the training set. Pavement test section points' results are indicated in the automated manner, which, in line with implemented methods, is not generated by perturbations caused by divergence between actual pavement structure and assumptions taken for purposes of building pavement management system database, and the artificial neural network learning dataset is based on.

Keywords: fatigue life assessment of pavement, perturbations of data set in ANN methods, PMS databases, thickness identification by ANN.

1. Introduction

In order to comply with level two and level three standards of analysis accuracy as per *NCHRP Project 1-37A:2004 Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures*, the major proportion of computations, related to pavements, starts with the preparation of large inputs datasets (Zeghal, El Hussein 2008). Highway engineering requires advances in computer science (Koch *et al.* 2015), thus, sources for datasets is a critical starting point for modelling road pavements using the theory of artificial neural networks (Kim *et al.* 2009) or another theories which make possible to analyse the incomplete data (Luo 2011).

The artificial neural network (ANN) is increasingly popular in successful identifying of pavement layers moduli of elasticity (Saltan *et al.* 2011). ANN analysis is also well-suited for unbound layers (Gopalakrishnan *et al.* 2009; Park *et al.* 2009), which, often for purposes of back calculation and nonlinear material characteristic, is easily considered. One of the key accomplishments in ANN regarding back calculation procedures, is the elimination of seed parameters, thus, making identification of algorithms is less prone to finding local minima. The possibility of using artificial intelligence (AI) in analysing risk profile of building pavement structures (Ceylan, Gopalakrishnan 2011) facilitates building hybrid models, which take into account both, stochastic processes concerning time-varying pavement parameters and uncertainty, related to poor build quality of pavement structure. AI looks like a promising supplement tool for risk assessment among another available techniques of multiple criteria decision making modelling (Tamošaitienė *et al.* 2013).

The application of interval-based uncertainty techniques to ANN regression model (Pierce *et al.* 2008), the Bayesian-trained networks as a superior fit to training data (Er *et al.* 2012), selective combination techniques as reported in (Ahmad, Zhang 2009), and, finally, the algorithms that reduce the error of prediction by subsequently inserting connections and neurons (Dieterle *et al.* 2003), are the examples of few research directions which are the attempts of quantifying and controlling the ANN results.

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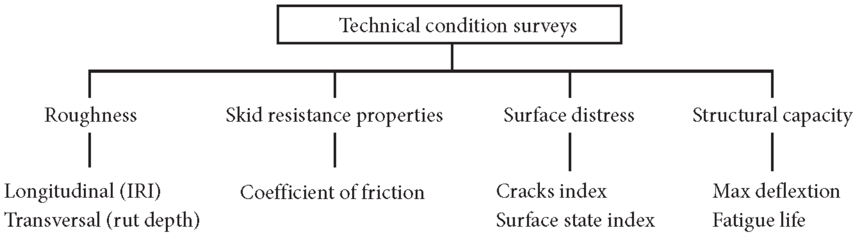


Fig. 1. Sample diagram of properties that are usually considered to assess the technical condition of pavement in PMS

Regarding the situation when a pavement fatigue life is determined and based on classic fatigue criteria (Yu *et al.* 2012; Yu, Zou 2013), the priority is an accurate diagnosis of pavement parameters. The varying pavement thickness directly affects a pavement fatigue life and it is critical for a pavement behaviour over time.

The workload, required by pavement management system (PMS) mountainous tasks, constrains empirical data collection stage. Therefore, it is critical to efficient use of that data in every instance (Jorge, Ferreira 2012; Zhang, Gao 2012). Research studies of maximising utilisation of "inputs" have to be the priority. There are many other authors (Bilodeau, Doré 2014; Pasquini *et al.* 2013) who discuss the methods of using different range of information (compared to many PMS standard procedures), concerning falling weight deflectometer (FWD), based on bearing capacity of pavement analysis.

2. Inventory data in PMS diagnosis

The efficient throughout of the entire lifecycle maintenance of a pavement structure requires rational support of making the rehabilitation decisions. The robust solutions which are developed around the PMS is the complex maintaining tool in a road infrastructure engineering. However, a key element of PMS identifies the technical condition of the pavement. The structure of this identification in the PMS has a different character but, in most cases, the manager will be interested in features that are illustrated in Fig. 1.

Taking into consideration only the method of assessing the structural capacity, there is a large group of road authorities in Poland, who control this feature limiting themselves only to the verification of maximum pavement deflection. It is assumed that by increasing the scope of the analysis of the results already stored in PMS databases, compared to the most frequently used standards, a better quality model of road maintenance programs, as the degradation of pavement models (which are based on the mechanistic approach, Fig. 1 – fatigue life estimation), is achieved.

Table 1. Statistical values of training set elements

Statistics	Thickness AC	Thickness Subbase	Temperature	Deflection
	h, cm		T, °C	d_0, μm
Mean	23.6	30.4	+13.5	208
Median	23.6	30.0	+15.6	196
Standard deviation	5.0	8.1	+5.7	73
Minimum	14.8	10.0	+1.0	54
Maximum	37.0	56.0	+19.6	1026

3. The aim of the study

Due to the sheer scale of PMS, the pavement structure identification is limited to selected sections, and collection of this type of data is forsaken. A large obstacle in the development of advanced models of PMS in Poland is a wider range of parameters that are usually needed to estimate quantities as fatigue life or residual pavement strength. Therefore, in this work, the main attention was paid to the usage of numerical methods that effectively complement this gap. Firstly, ANN which is in the case of PMS databases, is a natural choice because the enormous input data resources are available for the training sets. Secondly, using a hybrid of ANN capabilities with routine pavement evaluation under PMS substantially expands the range of possible pavement evaluations. When it is decided to use ANN for purposes of pavement layer identification, it should be taken into consideration that these methods are problematic due to the uncertainty caused by potential "perturbations", which occur (under actual PMS conditions they do) in assumptions underlying the training set. This paper attempts to use a certain empirical relationship which is employed with success of verifying diagnostic accuracy of ANN method. The following hypothesis is tested, from ANN result set comprising identified asphalt layer thickness information on pavement test section, it is possible to automatically exclude the majority of those values which further down the line generate of highly erroneous values of pavement fatigue life.

4. Elements of ANN training set structure

4.1. Characteristics of created PMS based database

All research study results (for ANN training set) come from the routine pavement evaluations carried for purposes of a pavement management system. Considering that their format is not dictated by strict requirements relevant to certain databases, using those datasets with ANN has required building a database. The general statistics of used results set is presented in Table 1.

Thickness and structure of pavement layers have been identified and based on specimens from pavement coring in both, bituminous layers and another courses (Fig. 2).

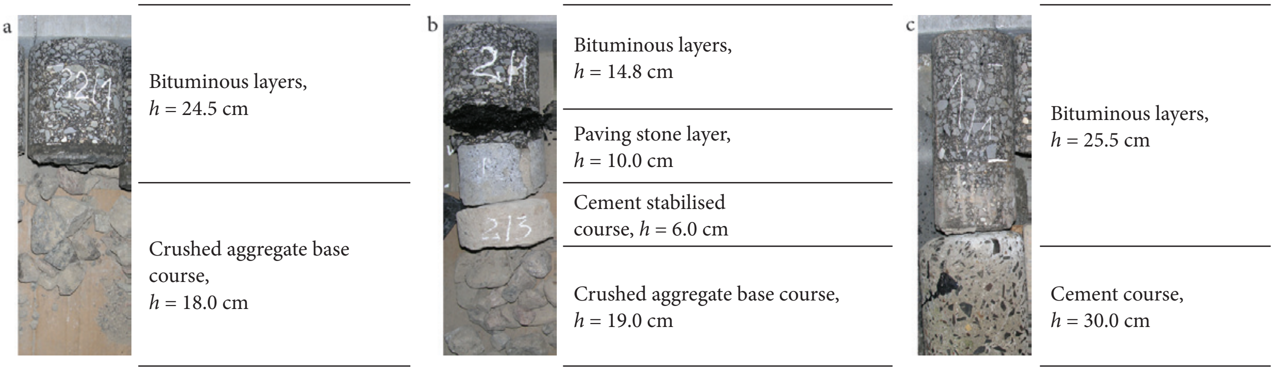


Fig. 2. Example specimen of: a – flexible pavement; b – "mixed pavement"; c – semi-flexible pavement

The database has been built using pavement evaluation datasets from Polish road sections. It holds 4078 records, among which are pavement deflection, temperature data and location data. There are 209 instances of locations with known pavement structure. Those locations match places where falling weight deflectometer (FWD) testing was carried out. The frequency of impulse loading applied by FWD deflectometer has been taken as approx $1/(2{\cdot}t) \approx 18$ Hz, where t stands for rise-time force. It has been assumed a constant across the databases for all deflection datasets.

The entire pavement cross-section has been surveyed by ground-penetrating radar in places, where boreholes were made. The additional information on pavement layer structure has been obtained by means of non-destructive testing.

4.2. ANN training set structure details

4.2.1. Architecture selection

Following a multi-stage process, the architecture of neural network (NN) has been designed and based on multilayer perceptron (MLP) network and radial basis function (RBF) network. The dataset has been divided into three subsets: training, testing and validation – 70%, 15% and 15% respectively. MLP network has proved most usefully for the training process, since their correlation coefficient was almost 1. The correlation coefficient was calculated according to the Eq (1):

$$r_{XY} = \frac{\operatorname{cov}(X,Y)}{SD_X SD_Y}, \tag{1}$$

where r_{XY} – dimensionless correlation coefficient of training set and result set from ANN calculations; cov(X,Y) – covariance of training set X and result set from ANN calculations Y; SD_X and SD_Y – standard deviation of training data sets respectively X and Y.

Neural networks have been trained only for structures with single hidden layer. Measurements, captured by geophones mounted on the FWD deflectometer in two configurations, have been used as inputs. All deflection data has been utilised in first configuration. In second configuration deflection data captured only by the first three geophones has been used (distance from loading axis 0 mm, 300 mm, 600 mm), because values of deflections, measured by first three geophones, mainly depended on pavement layer stiffness properties. The input data also consisted of bituminous pavement layer temperatures and loading, applied by FWD deflectometer's loading plate. The qualitative variable with values 0, 1, 2 has been introduced to analysis. Those values have been assigned to pavement designs: rigid pavement, flexible pavement and "mixed" pavement respectively (Fig. 2). In total, 4 different input and output datasets have been used as training sets for ANN (Table 2).

4.2.2. Optimisation of ANN architecture

The optimisation routine for SSN architecture has been set from 1 to 30 input neurons in hidden layer. Each of the four configurations of the training set has been tested on 10 000 epochs. The standard mean square error measure has been used as an error function. For preliminary weight optimisation, the conjugate gradient method has been employed with reduction factor 0.001 for the hidden layer and output layer. The following activation functions have been tested: linear, logistic, hyperbolic tangent, exponential, sine, standard exponential function. Eligible for further analysis have been networks which correlation coefficient satisfied the condition r_{XY}~1 (details are given in point 4.2.3).

4.2.3. Optimisation of ANN weights, network training

MLP network architectures 5–9–1, 5–7–1, 9–11–1, 5–12–1, 9–10–1 have been selected for further analysis. The weights have been selected through multiple sampling. Knowing architecture and activation function, used for network training, has been algorithm Broyden–Fletcher–Goldfarb–Shanno (Gopalakrishnan 2010). Weight initialisation has

Table 2. Configurations of input and output layers tested with ANN structure

State	Input layer	Output layer
1	T, σ, d_0, d_1, d_2	h
2	T, σ, d_0, d_1, d_2, type of structure	h
3	T, σ, d_0, d_1, d_2, d_3, d_4, d_5, d_6	h
4	T, σ, d_0, d_1, d_2, d_3, d_4, d_5, d_6, type of structure	h

Note: T – temperature, °C; σ – applied stress, MPa; d_n – value of deflection (n^{th} geophone), mm; h – total bituminous layer thickness (or bitumen-binder bases) of the pavement in built database, cm.

been pseudorandom, using the following breakpoint condition: number of epochs ≤10 000 and $\Delta\varepsilon < 0.000001$ after 20 epochs. In case of MLP networks, the correlation coefficient for hidden layer has been assumed 0.0001 and for output layer 0.001. The best results, in terms of maximum value of Pearson correlation coefficient, have been obtained for MLP 5–9–1 network architecture (Table 3).

Best choice network has been set to 5 input neurons (d_0, d_1, d_2, T and σ) and 9 hidden layer neurons. Ultimately, based on analysed results, obtained for tested activation functions, the logistic and linear function has been selected to normalise input and output dataset respectively (MLP 5–9–1 *log-lin*).

Table 3. Values of selected statistics – ANN testing

ANN	Correlation	Covariance	MAPE*
For training set containing research results pertaining to flexible pavement, mixed pavement and semi-flexible pavement			
MLP 5–9–1 logistic-linear (log-lin)	0.688	12.81	13.87%
MLP 5–9–1 logistic-logistic (log-log)	0.696	13.23	15.52%
For training set containing flexible pavement research results			
MLP 5–9–1 logistic-linear (log-lin)	0.675	11.70	12.20%
MLP 5–9–1 logistic-logistic (log-log)	0.675	11.82	12.15%

Note: * – mean absolute percentage error.

5. Empirical testing of the independent road sections

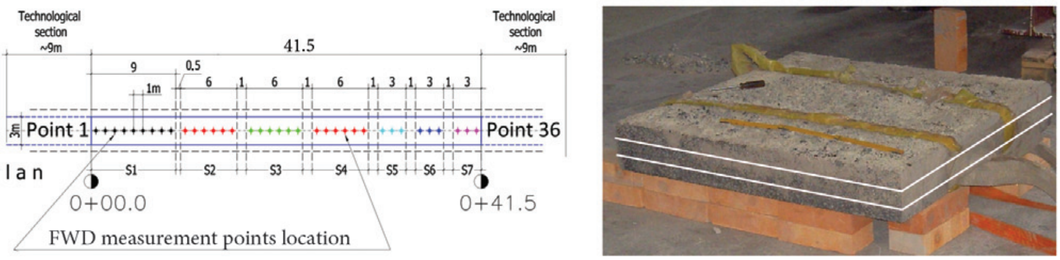
5.1. Test section S1

The data, selected to verify trained neuron network, has come from studies investigating test sections with both, non-reinforced and geosynthetics-reinforced flexible pavement structures. The test section S1 (Fig. 3) has been built using standard non-reinforced, flexible pavement. The remaining sections have different types of reinforcement. For purposes of this study, those remaining sections (S2–S7) have been reduced to sections with "perturbation" pavement structures, compared to ones providing ANN training set. The test section pavement has consisted of the following three asphalt concrete (AC) layers:

- 5 cm surface course with a maximum nominal aggregate size of 12.8 mm,
- 6 cm wearing course with a maximum nominal aggregate size of 16 mm,
- 7 cm base course with a maximum nominal aggregate size of 22 mm.

AC layers have been spread on the mechanically stabilised base course of 20 cm thick with a maximum nominal aggregate size of 31.5 mm. Test section pavement layer thickness has been measured every 1 m by pavement cut-outs.

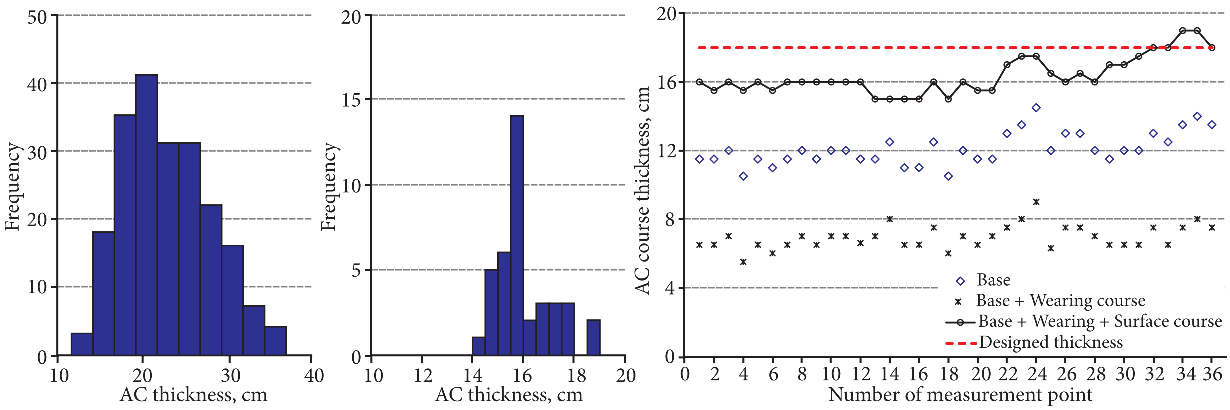
Total asphalt layer thickness (Fig. 4) as per the analysis ranged is between $14.0 \le h_{AC} \le 18.4$ cm. The mean value of total bituminous layer thickness (or including tar-bitumen binder, historically laid underlying bases) of the training set satisfies the condition $14.8 \le h_{AC} \le 37.0$ cm. It is noticed that measurements of asphalt pavement layer thickness of



Pavement test section used for verification of ANN

Photo of example 1×1 m specimen cut-out from pavement

Fig. 3. View of the Section 1



Histogram of total thicknesses from training set

Histogram of total thicknesses for pavement test section S1

Thickness from measurements of pavement test section S1

Fig. 4. Thickness of bituminous layers

actual pavement testing sections, considerable thickness variations have been recorded at individual test points (numbers from 1 to 36) and compared to values assumed in the project. The maximum thickness deficit, identified at several test points of the test section, has been 3.0 cm.

Bituminous layers' complex stiffness moduli of the test section (histograms are shown in the Fig. 5) have been determined experimentally by employing the Four Point Bending Beam (4PBB) testing methodology. Test beam specimens compliant with *EN 12697-26: 2012 Bituminous Mixtures – Test Methods for Hot Mix Asphalt – Part 26: Stiffness,* have been cut out from layers of asphalt plate specimens (Fig. 3b). Experiments have taken place in temperature 15 °C and frequency 10 Hz.

Bituminous-aggregate mixture composition has been identified from specimens taken in-situ. Physical properties factored in further analysis are given in the Table 4.

The base course and subgrade mechanical properties of pavement test section have been determined by deflection testing of mechanically stabilised aggregate base course. Benkelman Beam (BB) and lorry with axle load of 80 kN have also been used for the experiment (Fig. 6a). The base course and subgrade of considered pavement have been modelled by elastic half-space. The moduli of elasticity have been determined for the following boundary conditions:

– no horizontal forces acting at $z = 0 \rightarrow \tau = 0$;
– flexible plate loading

$$\sigma(z=0) = -aq\int_0^{\infty} J_0(kr)J_1(ka)dk, \tag{2}$$

where σ – stress, Pa; z – vertical ordinate, m; r – distance from loaded axis, m; a – plate radius, m; q – load, Pa; k – integral coefficient, J_n – n^{th} Bessel function.

Using the general form of the integral of vertical displacements of elastic material:

$$w = \frac{1+\nu}{E}\left[(2-2\nu)\nabla^2\Phi - \frac{\partial^2\Phi}{\partial z^2}\right], \tag{3}$$

where w – vertical displacement, m; ν – Poisson coefficient, ∇ – Laplacian, Φ – stress function, E – modulus of elasticity, Pa.

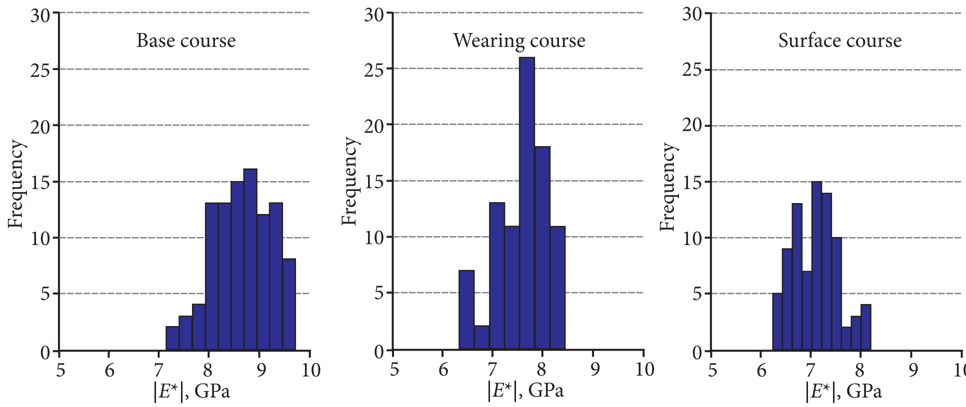
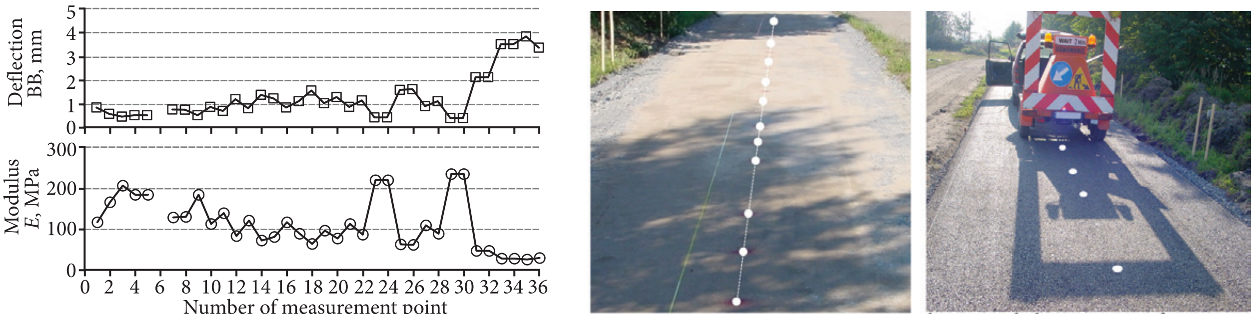


Fig. 5. Complex modulus value distribution $|E^*|$ (T = 10 °C, f =10 Hz) determined experimentally (4PBBT) for beams cut-out from pavement test section asphalt layers

Table 4. Selected AC physical properties factored into fatigue life analysis

HMA	Bitumen content V_b,		Air volume content V_a,	Density ρ,
	% by volume	% by weight	% by volume	g/cm^3
Surface course	13.4	5.1	3.4	2.766
Wearing course	12.0	4.6	4.4	2.740
Base course	9.2	3.8	7.2	2.558



a – deflections obtained by using BB results on an aggregate base course (with corresponding values of moduli of elasticity at subsequent test points located on its surface

b – an asphalt concrete surface course prepared for deflection tests

Fig. 6. Testing conditions

Modulus of elasticity for a base course with underlying subgrade has been computed using the relationship:

$$E(r=0)=\frac{qD\left(1-v^2\right)}{w}, \tag{4}$$

where D – a flexible plate diameter, m.

Test points on the surface course have been located where values of elastic deflections of test section base course and subgrade have been known (Fig. 6b). One FWD test run has consisted of six vertical loadings with the target value of 50 kN.

5.2. Test section S2

An appropriate dataset for testing deflections' basin parameters (DBPs) (Bilodeau, Doré 2012), and especially, Surface Curvature Index (SCI), Base Damage Index (BDI) and Base Curvature Index (BCI) has also been prepared. This dataset comprises of FWD deflection data and parameters of pavement cores, and borehole specimens (Fig. 7a). Coring and drilling have been carried out each 500 m. The subject to testing was the road section with a diversified flexible pavement. The analysed test section has been 30 km long. FWD deflection basin parameters SCI, BDI and BCI have been determined. The following relationship has been a subject to in-depth visual examination:

$$d_0=f\left(h_{AC}, SCI, BDI, BCI\right), \tag{5}$$

where d_0 – deflection from first FWD geophone, μm; h_{AC} – total thickness of pavement bituminous layers, m; *SCI, BDI, BCI* – deflection basin parameters, mm.

Further, the regression curve was produced which was then used to study "perturbations" with a relation to the training set. A sufficient coefficient of the determination ($r^2 \geq 0.95$) is displayed in Fig. 7b. It is obtained for the power function as given by (6):

$$d_0=a\frac{1}{\left(\dfrac{h_{AC}}{SCI\cdot BDI\cdot BCI}\right)^{0.1}}, \tag{6}$$

where a – regression parameter.

The obtained data has been generated by FWD testing in temperature range of mid-depth AC layers (or tar-bitumen binder layers) from 15 °C to 30 °C.

Further analysis shows that the regression curve has properties useful for investigating perturbations, occurring in analyses using ANN identification data.

6. Verification of trained ANN structure

At the next stage, the MLP 5–9–1 model has been verified. The data underlying verification has been:

– results of in-situ and laboratory study, carried out for an independent (in relation to ANN training set) flexible pavement test section (Fig. 3);

– FWD deflection data and pavement structure data independent of ANN training set (test section S2);

– current Polish fatigue life criteria.

6.1. AC thickness control

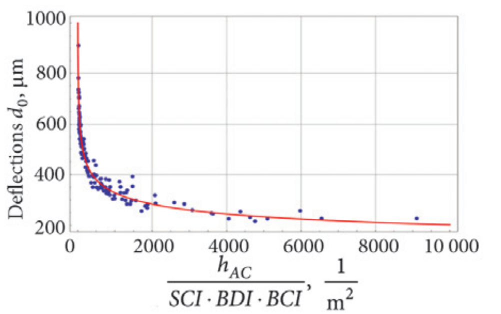
The confrontation concerns the thickness have estimated on the basis of a trained network and independently measured thicknesses in test section S1. The values of a root mean square error (RMSE) and MAPE errors (Table 5) have been computed by:

– sections with "perturbations" and

– sections consistent with assumptions underlying the training set (through the same flexible pavement structure).

In order to use the maximum number of real data from experimental and in-situ tests, it has been assumed that the equivalent modulus for a base course and

a – example of a road section used in paper (circles mark places were pavement was drilled)



b – regression curve describing the relationship between deflections from first FWD geophone, and total bituminous layer thickness and FWD deflection basin parameters

Fig. 7. FWD deflection basin parameters testing

Table 5. Errors when evaluating by ANN the total bituminous layer thickness from testing section S1

ANN	Test points along test section			
	1–9	10–36	1–9	10–36
	RMSE, %		MAPE, %	
MLP 5–9–1 logistic-logistic (*log-lin*)	1.84	9.5	1.50	7.68

subgrade is known across all 36 test points, throughout the analysed section (based on BB measurements calculation).

6.2. Fatigue life comparison

6.2.1. Fatigue file criteria used in the paper

A range of fatigue criteria has been used for purposes of this paper to describe:

– limit state related to cracks on a surface course (acc. to well-known relationship of Asphalt Institute):

$$N_1 = 18.7^{4.84\left(\frac{V_b}{V_a+V_b}-0.69\right)} \cdot 6.167 \cdot 10^{-5} \cdot \varepsilon_1^{-3.291} \left|E^*\right|^{-0.854}, \quad (7)$$

where N_1 – total repeated applications of loads before 20% cracked road pavement or 50% decrease in modulus of stiffness, 100 kN equivalent single axle load (ESAL); V_a – volumetric air void content in AC, %; V_b –volumetric bitumen content in AC, %; ε_1 – value of horizontal tensile strain; $|E^*|$ – complex modulus of AC, MPa.

– limit state related to structural deformations (Asphalt Institute):

$$N_2 = \left(\frac{\varepsilon_c}{k}\right)^{\frac{1}{m}} = \frac{1.365 \cdot 10^{-9}}{\varepsilon_c^{4.447}}, \quad (8)$$

where N_2 – total repeated applications of loads before the critical structural deformation in pavement structure of 12.5 mm, 100 kN ESAL; k and m – experimental coefficients respectively equal k = 0.0105 and m = 0.223; ε_c – value of vertical compressive strain on subgrade surface.

6.2.2. Result of calculations

The fatigue life N for pavement test section has been calculated using MLP network, based on identification of bituminous layer thickness. The following configurations have been considered:

1) N (*h*_36), a fatigue life analysis based on bituminous layer thickness, measured at all 36 test points along test section (reference configuration);

2) N (*h*_Mean), a fatigue life analysis, assuming mean bituminous layer thickness, is known (reference configuration);

3) N (*h*_MLP *log-lin*), a fatigue life based on analytical bituminous layer thickness of pavement test section – ANN employed (MLP 5–9–1 *log-lin*).

The fatigue life results of calculations are presented in Fig. 8. Pearson correlation coefficient has been used to measure the correlation between fatigue life calculated and based on actual thickness and identified using MLP (Table 6). The strength of correlation between each set and reference configuration has been assessed both, for non-reinforced test section (test points from 1 to 9) and reinforced sections (test points from 10 to 36).

Having the reviewed results of calculations and research studies presented in this paper, the conclusion is the biggest drawback of ANN, a limited possibility to verify the data is produces. This problem is particularly evident in PMS, due to a sheer scale of workloads required to carry out all necessary measurements and road maintenance. The possibility to use the aforementioned Eq (5) for control purposes is presented further on.

6.3. Controlling the results of ANN application, perturbed section

Seeing the general Eq (5), constant for independent flexible pavement test sections, the formula where h_{AC} is replaced by an identified value of h_{AC}ANN i.e. total thickness identified by ANN is also correct. The regression curve (Fig. 9a) is included in the analysis, in an attempt to obtain some information on the pavement sections, which ought to be skipped due to potential "perturbations" to assumptions underlying the training set. Consequently, it is the decreasing diagnosis of accuracy of estimated pavement remaining life for potential purposes of PMS. Analysing the differences between individual values of both sets is critical. The first set z_1 contains maximum values of deflections d_{0i} i.e. $z_1 = (d_{01}, d_{02}, ..., d_{0i}, d_{0(n-1)}, d_{0n})$ and the second set z_2 contains maximum values of deflections calculated for h_{AC}ANN, where for both cases „i" have the values within range from 1 to n = 36 (n is the number of test points along test section). The last stage involves

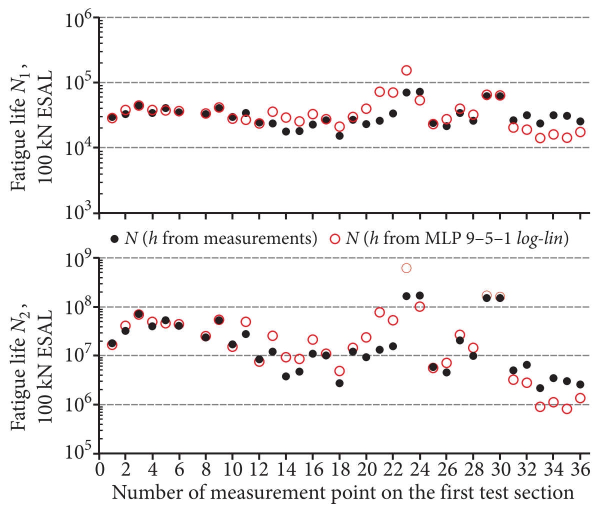


Fig. 8. Analytical fatigue life data for a pavement structure test section (N_1, N_2 – fatigue life of asphalt layers and subgrade respectively)

Table 6. Values of the correlation coefficient between sets of a fatigue life data calculated for considered configurations

Fatigue life correlation set	Pearson correlation coefficient			
	AC		Subgrade	
	fatigue life criteria,			
	N_1		N_2	
	Test points along test section			
	1–9	10–36	1–9	10–36
N (*h*_36) N(*h*_MLP *log-lin*)	85	69	95	75
N (*h*_Mean) N (*h*_MLP *log-lin*)	91	56	98	70

calculating differences Δz, while comparing them against the assumed specification limit of error ε, as given by (9):

$$\Delta z_1^i - \Delta z_2^i \leq \varepsilon. \quad (9)$$

Automating this procedure by a computer code causes some bituminous layer thickness, identified by ANN on test section S1 (for an assumed normalised value ε = 30) to be removed (Fig. 9b).

The data displayed in Fig. 9b shows that the majority of test points is set in conditions significantly deviating from assumptions underlying the training set (they are located on different configurations of reinforced pavement, i.e. the "perturbations" zone). Hence, conclusions formulated on the back of RMSE and MAPE error analysis, match the perturbation verification algorithm discussed in this paper.

7. Results and discussion

The study results concerning flexible, "mixed" and semi-rigid pavements (Fig. 2) have been used to create the database for purposes of dataset training neuron networks. An independently selected flexible pavement test section has been used to verify the built model. A road section has been selected to introduce "perturbation" into results produced by neuron networks, which individual pavement sections (as opposed to results in the ANN set training) have been built using both, non-reinforced and geo-synthetics reinforced pavement.

It is noticed that values of bituminous layer thickness identification error concerning test section S1 (RMSE and MAPE) have been ranging from 2% to 10%. The values of errors regarding test points from 1 to 9 are considerably lower compared to errors in remaining test points, and they do not exceed 2%. Natural tendency to accept ANN identified thickness occurs provided that 10% errors are acceptable. The results of fatigue life calculations are alerting.

The conclusion that RMSE and MAPE errors are greater than about 2% decrease diagnostic accuracy of pavement fatigue life is drawn from analysing the correlation strength between ANN identified fatigue life and fatigue life as per measured thickness. The results are different in an order of magnitude, thus, practically disqualifying such identification. The value analysis of correlation coefficient shows that most correlated ($r \geq 0.85$) are value sets of fatigue life calculated by MLP 5-9-1 *log-lin* neuron network for pavement test section at test points numbered from 1 to 9 (flexible pavement without geosynthetics, no "perturbations"). At test points numbered from 10 to 36 (reinforced pavement, referred to as "with perturbations"), correlation was significantly weaker ($0.75 \geq r \geq 0.56$). It is assumed that fatigue life was calculated and based on such thickness values, RMSE and MAPE errors that are greater than 5% and indicative of highly inaccurate bituminous layer thickness identification.

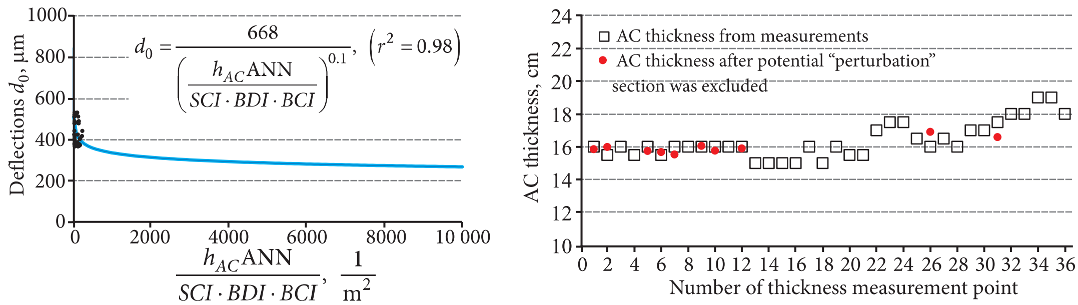
Furthermore, it was attempted to find the empirical relationship for improving pavement diagnostic accuracy by eliminating erroneous results produced by ANN. High uncertainty, caused by numerous "perturbations" affecting assumptions underlying training set, is inherent to soft computer techniques employed to identify pavement layer thickness. The paper suggests to develop a hybrid methodology using the empirical relationship between maximum deflection, bituminous layer thickness and deflection basin parameters (SCI, BDI and BCI). This methodology enabled elimination of most values from the result set of bituminous layer thickness identified by MLP 5-9-1 *log-lin*, which potentially generated highly erroneous values of the fatigue life for analysed pavement test section.

8. Conclusions

This paper proved that the research study data, collected by pavement management system on a cyclical basis, is a source of additional and unused knowledge. Motivated by cost-based optimization of empirical data collection, the tools for verifying and controlling of artificial values, identified in neural network, have to be developed.

The accuracy of interpreting routine pavement evaluation data, gathered under pavement management system, was substantially improved by using the presented methodology in combination with artificial neural networks. Based on a conducted experiment, the following conclusions were drawn:

1. The research study results concerning independent flexible pavements were the part of an artificial neural network training set, in line with assumptions to the experiment. The value of a fatigue life correlation coefficient calculated for non-reinforced flexible pavement sections ("no perturbations flexible pavement structure") is ≥0.85, and both, root mean square and mean absolute percentage



a – regression curve for the pavement of test section S1

b – identified bituminous layer thickness of test section automatically narrowed down to points which with probabality satisfy the assumptions of the ANN training set

Fig. 9. ANN application

errors are <2%. Hence, the identification of bituminous layer thickness of independent pavement test section using artificial neural network is credible.

2. An assumption was made not to include reinforced pavement data in the training set database containing test results for independent pavements. Then, the value of a fatigue life correlation coefficient for reinforced pavement test section is ≤0.75, and root mean square and mean absolute percentage errors are >7%. Those parameters prove that the identification of an artificial neural network pertains to road section inconsistently with assumptions underlying the training set.

3. The fatigue life calculations, based on artificial neural network identified thickness, proved that, in case, when a root means square error exceeds 7%, the value of an analytical fatigue life is greater than an actual fatigue life by order of magnitude. Hence, in order to efficiently use the artificial neural network, since in practice, in-depth monitoring, all pavement parameters, in pavement management system databases they are virtually impossible methods, have to be used.

4. Based on the study of "perturbations" affecting neural network training sets, as per pavement management system practice, it was observed that proposed methodology, using deflection basin parameters, is the key element of an artificial neural network-based identification results verification procedure, which does not generate extra costs of additional empirical data.

5. Geosynthetics pavement reinforcement affects deflection data in case of inferior subgrades. It is also proven by the result set for a reinforced pavement, which was not included in neural network training set. This means that the artificial neural network is not satisfactorily accurate to precisely identify geosynthetics-reinforced, bituminous layer thickness solely based on falling weight deflectometer data for the same type pavement, without the reinforcement. Mechanistic calculations using that thickness data are inaccurate.

6. The study of experiment results also revealed that the best configuration for purposes of determining bituminous layer thickness of an artificial neural network was a multilayer perceptron neural network set to architecture. The form was: input data layer which consisted of temperature, applied stress and deflections at distances of 0 mm, 300 mm and 600 mm from the centre of the load, hidden layer with nine neurons and thickness as an output data. The set of input-output activation functions was correctly configured respectively as the logistic function and the linear function.

In summary, the condition necessary to improve interpretation of bituminous layer thickness determination data by a hybrid of artificial neural network and routine pavement evaluation data generated by pavement management system, is the monitoring of potential perturbations to training set. This methodology requires additional control mechanisms, which standard approach leads to pavement drilling, what is prohibitively expensive to the sheer scale of a pavement management system. Instead of this, an original control methodology, based on the empirical relationship between bituminous layer thickness, pavement deflection and basin deflection parameters available from deflection measurement data, is proposed. Consequently, the additional information was obtained, indicating the need to exclude from the mechanistic analysis of pavement thickness identification data for the sections that are inconsistent with assumptions underlying the artificial neural network training set.

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