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Determination of asphalt layer temperature in FWD and TSD measurements using machine learning

Abstract: The paper presents the application of machine learning techniques in estimating the temperature of asphalt layers during measurements using FWD (Falling Weight Deflectometer) and TSD devices (Traffic Speed Deflection). The problem of accurate determination of temperature is crucial for analysing the durability of road pavements. Traditional methods such as the BELLS3 model, although widely used, have limitations in forecast accuracy. The work presents the implementation of advanced algorithms such as multivariate adaptive regression spline (MARS), support vector machines (SVM), artificial neural networks (ANN), random forest (RF) and boosted trees (BT), among others, to optimise a model for estimating the temperature of asphalt layers T_d. The BELLS3 model, used as the baseline in the optimisation process, was evaluated for prediction effectiveness. The results showed moderate effectiveness of this model (R^2 = 82%, $RMSE$ = 2.3°C), which triggered a need for further improvements. The use of machine learning techniques, particularly boosted gradient trees (BTs), has made it possible to significantly improve the precision of predictions. The BT model achieved the greatest fit for the dependent variable T_d (R^2 = 99% and $RMSE$ = 0.61°C), indicating its clear advantage over other models, including the baseline BELLS3 model. Finally, the authors highlight the potential of integrating traditional approaches with advanced data analysis methods to further improve the accuracy of forecasting bituminous mixture layer temperature and effective management of road infrastructure.

Keywords: BELLS3, data mining, deflections, FWD, temperature, pavement, TSD, validation.

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1. INTRODUCTION

Reliable pavement condition data is a cornerstone of road infrastructure management. Regularly collected and properly processed, it enables not only current condition assessment but also forecasting future deterioration. One key aspect is the evaluation of pavement durability, which traditionally relies on point-based methods like the Falling Weight Deflectometer (FWD). In recent years, however, continuous deflection measurement systems such as the Traffic Speed Deflectometer (TSD) and RAPTOR [1, 2] have gained traction due to their ability to collect data at traffic speeds, enhancing both efficiency and safety.

Despite their advantages, both FWD and TSD have limitations, particularly in accurately determining asphalt layer temperature during measurements. In routine measurements using FWD, the applied procedures provide for direct measurement at the mid-thickness of the layers using a probe inserted into a pre-made hole. In Poland, among others, the procedure provides for measurement before and after the deflection measurement along a given stretch and every 4 hours, as well as whenever the air temperature changes by more than 5°C [3]. The result is that, despite fairly frequent temperature measurements, the recorded deflections are corrected against a single temperature over long stretches, while this temperature can change drastically over a relatively short period of time, by as much as 20°C in a day [4].

In TSD-based surveys, temperature measurements are limited to air and surface measurements as direct subsurface temperature sensing would compromise the measurement process over the typical 70 km test range. Therefore, the estimation of pavement temperature in this context requires predictive modelling based on on-board sensor data and external meteorological inputs.

Traditionally, empirical models have been used for this task, using historical data sets to form equations relating air temperature, surface temperature and solar radiation to the asphalt layer temperature [5, 6]. However, these models are often constrained by the range of data from which they were developed, limiting their generalisability. In contrast, numerical approaches such as the Finite Volume Method (FVM) allow detailed simulation of thermal behaviour in pavement layers, capturing effects such as solar radiation and wind [7, 8], but at the cost of computational complexity.

Modern alternatives use data mining (DM) and machine learning techniques. These methods can identify complex, non-linear relationships in large data sets that are often missed by linear models. DM tools integrate concepts from statistics, artificial intelligence and database systems to derive meaningful insights from raw data. Machine learning involves "training" models on historical inputs and outputs to learn underlying patterns. Crucially, the effectiveness of such models depends not only on the nature of the relationships between variables, but also on the representativeness and volume of the data [9].

Examples of the implementation of artificial intelligence and machine learning methods in road engineering can be found in many works. The paper [10] developed and evaluated the effectiveness of two machine learning methods, the random forest (RF) and the gradient boosting algorithm XGBoost (eXtreme Gradient Boosting), for predicting the structural condition of pavements based on annual average daily traffic (AADT), changes in the proportion of heavy vehicles, and traffic slowdowns, among other factors. The RF technique was also used in the work [11] to predict potential damage to asphalt pavements through analysing such factors as moisture, temperature, and pavement texture. Other studies have used the Support Vector Machines (SVM) method to classify the effects of moisture and temperature on asphalt pavements, which allowed the identification of critical conditions in which the pavement was particularly vulnerable to degradation [12]. Due of their ability to recognise non-linear relationships, ANNs (Artificial Neural Networks) are particularly useful in analyses where data is characterised by high variability. In the work [13], ANNs were successfully applied to evaluate the effect of climatic conditions on the durability of bituminous mixture layers, allowing for more precise results compared to classical analytical methods. The use of hybrid models, such as the combination of empirical predictive models with machine learning algorithms, seems particularly promising. The work [14] showed that this approach allows for better representation of complex phenomena occurring in asphalt layers, thus making it more effective compared to single methods.

In road engineering, machine learning techniques are widely used in evaluating other pavement parameters, such as longitudinal evenness *IRI*, rut depth, surface damage (e.g., cracks) and roughness. In the paper [15], the authors used various machine learning algorithms, including

Ordinary Least Squares (OLS), Decision Trees (DTs), and Random Forests (RF) to model the degradation of flexible pavements based on IRI. In [16], support vector machines (SVM) were used to predict the susceptibility of asphalt pavements to rutting. In [17], on the other hand, the authors used Convolutional Neural Networks (CNNs) to automatically detect and classify cracks on road pavements. The CNN model has achieved high precision and sensitivity in identifying different types of cracks based on pavement images. In publication [18], the authors used RF and ANN algorithms to evaluate pavement roughness based on data collected from sensors. These models made it possible to accurately predict the anti-slip properties of the pavement under various operating conditions. In the paper [19], C&RT (Classification and Regression Trees), XGBoost, RF, ANNs and SVMs were used to predict the luminance ratio of aggregates used in road pavements, finding that the XGBoost gradient boost algorithm proved most effective in this application. On the other hand, the use of ANNs and SVMs allowed the authors of works [20, 21] to develop a model that allows inverse calculation of layer modules based on real-time FWD measurements. As shown, the dynamics of implementing machine learning methods in road engineering is very high, especially in climatic data analysis and pavement condition assessment. In this context, methods that allow for even higher accuracy in evaluating pavement parameters are gaining in importance. The paper [22] showed that BELLS3 can be optimised to local conditions using linear regression methods. However, the results obtained as part of this optimisation are not sufficient especially in the light of the possibilities offered by applying machine learning. The ability to develop an effective DM model for determining the asphalt layer temperature will help improve the precision of pavement fatigue life calculations. With this approach, the results of the optimisation of the BELLS3 model served as a starting point for further analyses aimed at evaluating the relationship between surface and air temperatures at the time of measurement, the previous day's average daily air temperature, and the time of day.

2. ANALYSIS OF THE INPUT DATA SET AND BASE MODEL

The analysis was based on deflection data acquired using a FWD between 2021 and 2023 on selected road sections in Poland. While specific measurement locations were excluded from further processing, their diversity ensured a random character of the input data. In addition to the primary measurement values as $T_{(1\text{-}day)}$ (previous day's average daily temperature), IR (Infrared Surface Temperature), supplementary variable T_{Air} represents the ambient temperature at that time were included in the dataset (Table 1): To support calculations, two auxiliary variables $sSin15.5$ and $sSin13.5$ were also introduced. As defined in the BELLS3 model framework, they are derived from the auxiliary variable $hr18$ and represent the values of $sin(hr18 - 15.5)$ and $sin(hr18 - 13.5)$, respectively.

Table 1. Input data set quality evaluation

Variable	% N valid	Number of outliers	Variable quality	Average	Standard deviation	Min.	Max.	Kurtosis	Skewness
$T_{(1\text{–}day)}$ [°C]	100	0	OK	12.5	5.1	1.3	25.7	–0.710	–0.090
T_d [°C]	100	0	OK	16.9	5.0	3	26.6	–0.838	–0.278
IR [°C]	100	0	redundant	18.2	7.5	1.6	38.4	–0.497	0.261
T_{Air} [°C]	100	0	redundant	14.9	5.1	2.5	29.5	–0.540	0.102
d [mm]	100	0	constant	120	0	120	120	0	0
$sSin15.5$ [rad]	100	0	OK	–0.005	0.814	–1	0.999	–1.731	–0.071
$sSin13.5$ [rad]	100	0	OK	–0.071	0.737	–1	0.999	–1.523	0.118

As the road structures tested were of similar composition and the asphalt layer thicknesses relevant for temperature assessment exceeded 20 cm, all direct temperature measurements (denoted as T_d) were taken at a standard depth of 120 mm. In the dataset, T_d served as the dependent variable, while other variables such as $sSin15.5$, $sSin13.5$, $T_{(1\text{-}day)}$, IR and T_{Air} which were only collected for records where in-situ temperature was measured, served as predictors. The two calculated sinusoidal variables were also treated as predictors in the subsequent modelling.

A noteworthy observation was a high correlation ($r = 0.88$) between IR and T_{Air}, with their respective Variance Inflation Factors (VIF) reaching 32 and 69. Such high collinearity (well above the threshold of 10) undermines the robustness of additive models by inflating the variance of coefficient estimates. While the variable *d* (depth) remained constant at 120 mm, it was retained in the model, and its role was captured through experimental coefficients. Outlier analysis using the standard interquartile range method $< Q1 - 1.5 \cdot IQR; Q3 + 1.5 \cdot IQR >$ confirmed that the dataset was free of anomalies. The correlation matrix under consideration is presented in Fig. 1.

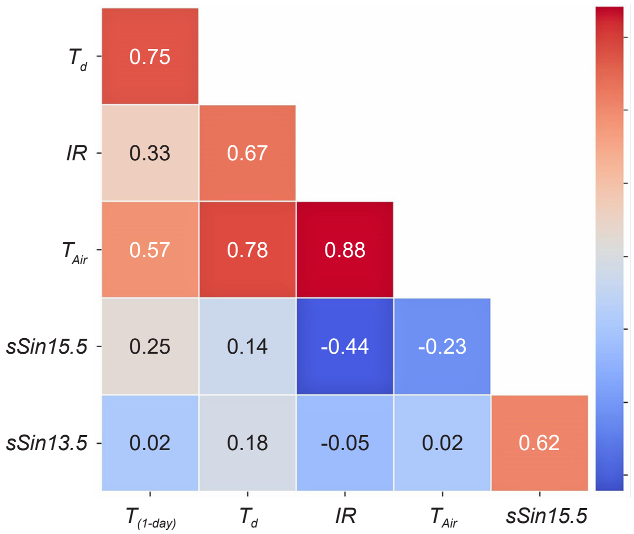

Fig. 1. Correlation matric of features used for determination of asphalt layer temperature

The distribution of the sine-derived functions (*sSin*15.5 and *sSin*13.5) deviated significantly from normality, with an apparent bimodal behaviour (peaks at –1 and 1). Other predictors such as *IR*, T_{Air} and $T_{(1\text{-}day)}$ were approximately normally distributed, with only slight skewness. The dependent variable T_d showed a slightly left skewed distribution and potential bimodality. Overall, the dataset was complete and consistent and did not require further pre-processing.

As mentioned in the introduction, the BELLS3 model, as one of the most widely used in road engineering, was adopted as the starting point for analysis using DM. A preliminary analysis of the existing BELLS3 model conducted in the paper [22] indicated a coefficient of determination of $R^2 = 82\%$ and an estimation error of $RMSE = 2.3°C$. It was also confirmed that the distribution of normality of the residuals was not fully preserved, which may have been the result of insufficient representativeness of the thermal parameters of the materials in the dataset. The same work also featured the process of optimising the model using the OLS method with cross-validation (5-fold), which, however, was not spectacularly successful. The quality of the model optimised in this way increased by only 1% compared to the reference model, while the RMSE estimation error decreased by 0.18°C.

3. DATA MINING (DM) TECHNIQUES USED

3.1. GENERAL REMARKS

This chapter presents techniques for analysing a dataset using machine learning. Chosen were the techniques that allow obtaining the model in explicit form, such as the nonparametric statistical regression method (MARS), quasi-explicit form, such as additive models (GAM), and implicit form, such as support vector machines (SVM), random trees (RF), gradient-boosted random trees (BT), and artificial neural network (ANN). All models derived from machine learning require tuning of learning parameters. To this end, the robust caret library within the R programming language was employed based on theoretical assumptions [23]. During the modelling and tuning process using the caret library, common assumptions were adopted to ensure reproducibility:

language/libraries - R 4.3.3; caret = 6.0-94, earth = 5.3.2, e1071 = 1.7-14, mgcv = 1.9-0, nnet = 7.3-19, randomForest = 4.7-1.1, xgboost = 1.7.6; Randomness - fixed seed set.seed(1) in each invocation of the train block; 10-fold cross-validation (CV) with stratified division based on the variable T_d*; Primary metric: RMSE and secondary* R^2*; Scaling - Predictors standardized (center = TRUE, scale = TRUE) within the preProcess function of the caret package; Division - Train/Test 70% training + 30% testing.*

A set of learning parameters, specific to a given technique, provides basis for reconstructing the numerical model in the situation where it is necessary to repeat the learning process by another user who does not have access to the model recorded in the form of an exchange file such as: *.R, *.XML. It is also important to note that later in the paper, when building models using machine learning techniques, the T_{Air} feature was also introduced into the analysis as an associated variable entered in the input file.

3.2. MARS METHOD

The Multivariate Adaptive Regression Splines (MARS) method is a non-parametric regression technique commonly used in data mining tasks. It is well suited to modelling complex, non-linear relationships involving many independent variables [23]. One of the key advantages of MARS is that it produces an explicit mathematical model – a valuable feature for engineering applications where many machine learning techniques only return a black box solution represented by a set of weights.

Another strength of MARS is its robustness to non-normally distributed inputs and its built-in mechanism for automatic variable selection. The algorithm prunes non-significant predictors by applying a predefined threshold, aiming to minimise the generalised cross-validation error GCV while maximising the coefficient of determination R^2 [23]. The MARS algorithm approximates an unknown target function in a linear form using hinge basis functions (truncated functions) as expressed in equation (1):

$$y(x) = \beta_o + \sum_{m-1}^{M} \beta_m B_m(x), \qquad (1)$$

where:

$y(x)$ – dependent variable,

B_m – basis function, defined as the product of up to degree hinge functions representing interactions between predictor variables,

β_m – coefficient for the hinge function $B_m(x)$,

β_o – intercept.

The summation is executed across all M component functions of the model. The learning process commences with an initiation phase wherein only the intercept term is present. β_o. Then, for each current base B_m and each variable x is tested node t. In the next steps, more bases are added B_m so as to reduce the residual error of the regression as much as possible. Upon attaining an excessive representation of the model max(M), the subsequent step involves a "back-pruning" process where those bases are successively removed which least adversely affect the *GCV* estimator, as set forth by the formula (2) provided below:

$$GCV = MSE \frac{1}{(1 - \frac{C}{N})^2}, \qquad (2)$$

where: *GCV* refers to the Generalized Cross-Validation error, *MSE* pertains to the mean squared error of estimation, C represents the complexity measure of the model proportional to its components, and N denotes the number of cases.

The complexity of the model is contingent upon the measure of parameter C, which necessitates that the *GCV* estimator attains its minimum. Subsequently, for a given family of basis functions, the model parameters β_I are determined classically using the method of least squares [22]. The tuning was performed using the validation method in the form of 10-fold cross-validation according to the adopted hyperparameter grid:

degree: *1, 2, 3*; *nprune*: *10, 20, ..., 60, 80*.

In the tuning process, the model yielded the following learning parameters:

degree = 2; *npruned = 60*; *RMSE = 1.84*°C;
R^2 *= 0.87*; *GCV = 3.48*°C.

The final model obtained the form (3):

$$\begin{aligned} T_d = {} & 15.2987497 + 5.1899496 \cdot (T_{(1\text{-}day)} - 6.7) + \\ & - 0.8981118 \cdot (6.7 - T_{(1\text{-}day)}) + 1.3814614 \cdot \\ & \cdot (sSin15.5 + 0.656425) - 9.8854435 \cdot \\ & \cdot (-0.656425 - sSin15.5) + 0.3002118 \cdot (IR - 16.4) + \\ & - 0.8129789 \cdot (16.4 - IR) - 0.0114712 \cdot \\ & \cdot (T_{(1\text{-}day)} - 6.7) \cdot (IR - 15.2) - 0.0330287h \cdot \\ & \cdot (T_{(1\text{-}day)} - 6.7) \cdot (15.2 - IR) - 0.7156053h \cdot \\ & \cdot (T_{(1\text{-}day)} - 12.6) - 0.1105460 \cdot (T_{(1\text{-}day)} - 12.6) \cdot \\ & \cdot h(17.1 - IR) - 0.4835894 \cdot (IR - 18.5) \cdot \\ & \cdot (-0.656425 - sSin15.5) + 1.1658962 \cdot (18.5 - IR) \cdot \\ & \cdot (-0.656425 - sSin15.5) + 0.3804224 \cdot (10.3 - IR) \cdot \\ & \cdot (sSin15.5 + 0.656425) - 4.2201232 \cdot (T_{(1\text{-}day)} - 6.2). \end{aligned} \qquad (3)$$

The model achieved a good fit to the experimental data with an R^2 of 87%, an improvement of 6% over the original BELLS3 model. It also provided a reduction in prediction error of about 0.4°C. Certain terms, such as $5.1899496 \cdot (T_{(1\text{-}day)} - 6.7) - 0.8981118 \cdot (6.7 - T_{(1\text{-}day)})$, clearly illustrate how the MARS model handles non-linearities through piecewise functions, providing greater flexibility than traditional linear approaches. The final model contains 16 different expressions, reflecting the diversity of thermal responses in the input data. This level of detail, visible in the number of fitted coefficients, suggests that the dataset captures significant variation in pavement thermal behaviour that linear models cannot effectively account for.

The distribution of residuals delivered by the BELLS3_MARS model (Fig. 2) indicates that the systematic effect was significantly reduced in the >20°C value range. The trend line (red line) has a horizontal course. This also indicates that the BELLS3_MARS model significantly increased the quality of the T_d feature forecast. This can be observed best by comparing the results predicted against the forecasted T_d feature between the BELLS3_MARS and BELL3 models (Fig. 3).

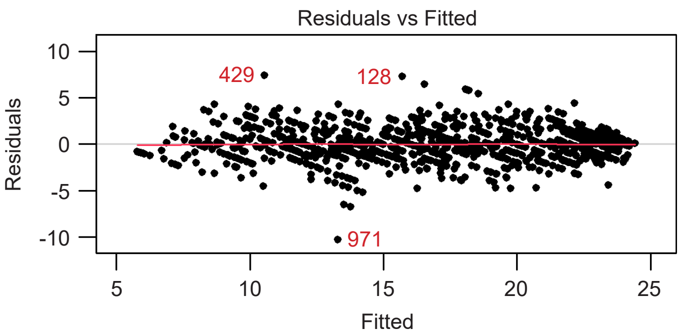

Fig. 2. Scatter of residuals as a function of predicted values of the BELLS3_MARS model

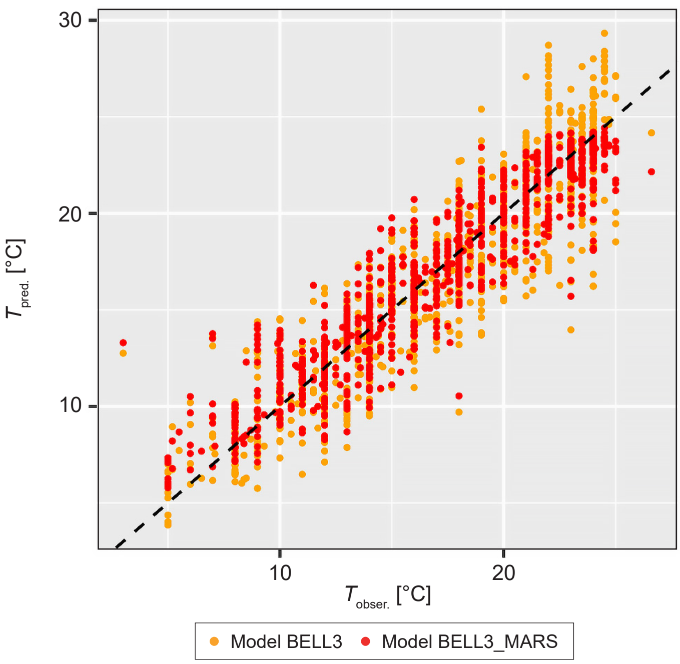

Fig. 3. Comparison of the BELLS3_MARS model with the BELLS3 reference model

As already mentioned, the BELLS3_MARS model handles data prediction in the >20°C range significantly better, and managed to achieve higher convergence against the equivalent line than the BELLS3 model. The machine learning technique used also made it possible to assess the validity of a given predictor in terms of its impact on the prediction of a given dependent variable. Based on the calculations, it can be concluded that the BELLS3_MARS model was sensitive to changes in the $T_{(1\text{-}day)}$ ($CGV = 100$) and IR ($CGV = 54$) features, and to a lesser extent in the $sSin155$ ($CGV = 35$). Their correct estimation affects the quality of the forecast of the variable T_d. The validity of other predictors will not trigger as much importance as the three mentioned earlier. Of course, this does not mean that they are insignificant, but their impact on the quality of the forecast beyond the daily range of the experiment will not play such an important role.

3.3. SVM METHOD

The Support Vector Machines (SVM) method is based on partitioning the decision-making space with hyperplanes, enabling both classification and regression. In the case of regression (SVR), the model adjusts errors to a specified tolerance interval, rather than minimising the difference between predicted and actual values. A key element of SVM is the selection of kernel functions, such as linear, polynomial, radial basis functions (RBF), or sigmoidal [24].

The SVM model stores the tuned parameters in a data file, requiring a numerical machine for calculations. Alternatively, you can declare learning parameters, which allows you to reproduce the model at a given seed, in the study set to 1. In the tuning process using the caret library, parameters were optimised, thus creating a model that is best suited to the data. The SVM algorithm approximates the unknown objective function of the character (4):

$$f(x) = K\langle x, x'\rangle + b\,, \tag{4}$$

where:

$K\langle x, x'\rangle = \exp(-\gamma\|x - x'\|^2)$ – kernel function (RBF),

x – input feature vector of first sample,

x' – input feature vector of another sample,

γ – constant controlling the width of the Gaussian distribution.

The tuning was performed using the validation method in the form of 10-fold cross-validation according to the adopted hyperparameter grid:

C – parameter: *1*, *10*, *100*, *1000*;
γ – parameter: *1e-4*, *1e-3*, *1e-2*;
ε – parameter: *0.05*, *0.1*, *0.2*;
Nprune: *10*, *20*, *…*, *60*, *80*.

The results of the learning process of the BELLS3_SVM model are as follows:

$$C = 100;\ \gamma = 0.01;\ Kernel = Radial\ (RBF)\ function;$$
$$RMSE = 2.01°C;\ R^2 = 0.84.$$

When choosing an RBF-type function kernel, its parameter γ and the overall model parameter C should be determined. The most significant parameter γ determines the range of influence of the support vectors: the larger it is, the smaller the range (the Gauss curve becomes narrower), and consequently the decision-making boundary will be more jagged. If the model is overlearned, decrease γ, and increase it if underlearned. In consequence of the tuning process, the resulting fit quality metrics in the BELLS3_SVM model indicate a non-significant improvement in the ability to predict the T_d trait compared to the BELLS3 model.

Based on the calculations, it can be concluded that the BELLS3_SVM model was sensitive to changes in the T_{Air} (CGV = 100) and $T_{(1\text{-}day)}$ (CGV = 87) features and, to a lesser extent, in the IR (CGV = 76).

When using the SVM technique, the relevance of the predictors was quite different from that of the MARS technique, so their validity depends on the algorithms of the learning process, rather than their actual mutual correlation. However, the $T_{(1\text{-}day)}$ feature still ranks high in terms of its importance in the model. In summary, this type of technique was not able, despite the tuning process, to increase the predictive ability of the T_d feature.

3.4. GAM METHOD

A very interesting machine learning technique is the generalised additive model (GAM) technique. This type of technique is a good alternative to the non-linear least squares method. It allows taking into account non-linear effects using certain functional transformations of the predictors [25].

Parameter fitting to the model follows a course similar to that of linear generalised models (GLMs). An activity that requires the computing power of a numerical machine is the selection of appropriate parameters of the smoothing functions *s( )* that are used to transform the predictors. The approximation model of the regression function of the GAM model has the formula (5):

$$g(E\,|\,Y) = \beta_o + \sum_{j-1}^{p} f_j(X_j)\,, \tag{5}$$

where:

$g(E\,|\,Y)$ – connecting function (identical function used in the work),

f_j – unknown, smooth single predictor function X_j as a series of cubic spline functions.

As a result, the tuning process consisted of the coordination of the hyperparameter λ_j by means of REML (Restricted / Residual Maximum Likelihood). The tuning of the GAM model was performed according to the adopted grid of hyperparameters:

number of spline nodes (5 selected): *5*, *7*, *9*;
selection criterion: minimum GCV; *automatic selection of* λ_j *including cross-validation (mgcv package).*

As a result of the process of fitting the parameters of the spline smoothing functions and weights to the expressions of the transformed predictors in the BELLS3_GAM model, a formula in quasi-explicit form was obtained (6):

$$\begin{aligned} T_d = {} & 16.99537 + 3.924 \cdot s(T_{(1\text{-}day)}) + 7.809 \cdot s(IR) + \\ & + 3.686 \cdot s(T_{Air}) + 2.242 \cdot s(sSin155) + \\ & + 2.269 \cdot s(sSin135). \end{aligned} \tag{6}$$

In Equation (6), $s(x)$ denotes a smoothing spline function of the predictor x, as estimated by the GAM algorithm. This allows the model to capture nonlinear effects of predictors such as IR (infrared radiation) on the target variable T_d.

The diametrical increase in estimation error ($RMSE$ = 3.7°C with R^2 = 0.85) indicates that the BELLS3_GAM model has definitely reduced the quality of precision in predicting the T_d feature.

Using the model, results in the >20°C range showed real improvements in prediction quality, while in the rest of the range the GAM technique led to erroneous conclusions. The likely reason for this result was the inability of the spline function in quadratic form to describe the strongly non-linear relationship between the predictors and the dependent variable.

3.5. ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network (ANN) is a mathematical model that learns to optimise a function based on input data. The learning process involves tuning the weights of the neurons by minimising the estimation error, with each neuron having an activation function that processes the data. The choice of network structure (number of neurons and layers) and other parameters (e.g., learning speed) is crucial to avoid overlearning [26]. The learning rate of a neural network is a parameter that determines the extent to which the update step affects the current value of the weights. Weight decay in the learning process of a neural network is a regularisation parameter introduced to avoid overlearning the network, and it is of relevance for the learning process. The approximation model, resulting from the propagation equation of ANNs (single-layer MLP network), has the formula (7):

$$h_k = \sigma\left(\sum_{j-1}^{p} w_{kj}^{1} x_j + b_k^{1}\right), k = 1 \ldots H$$
$$y = \sum_{k-1}^{H} w_k^{2} h_k + b^{2}\ , \tag{7}$$

where:

h_k – output of the k-th neuron in the hidden layer,

$\sigma(.)$ – activation function (ReLU),

b^i, w^i – network tuning parameters.

The ANN model tuning was performed according to the adopted grid of hyperparameters:

grid dimension: *from 5 to 20*; *decay*: *from 10-4 to 0.5*;
activation functions: *tan h*, *linear*.

The optimal topology of the BELLS3_ANN network was achieved by tuning the parameters to minimise the RMSE metric. This process took into account the analysis of the number of layers and neurons in the hidden layer (1 hidden layer was established), which led to an effective network configuration. The layer's activation function was linear, which enabled effective modelling of the data in the analysed set (Fig. 4).

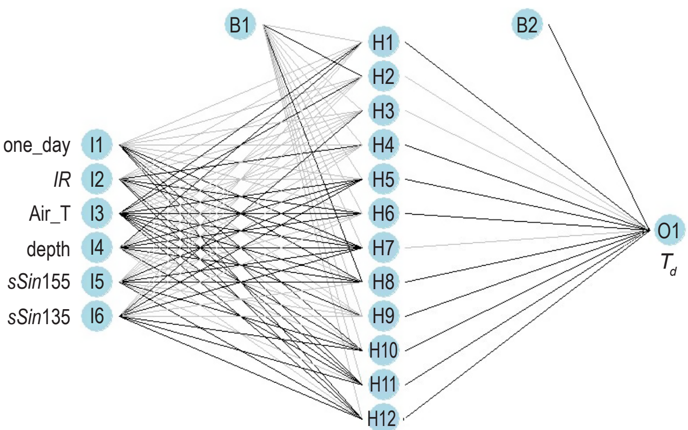

Fig. 4. Neural network topology for the BELLS3_ANN model (B1 and B2 are bias neurons)

Weights were determined for each of the neural connections, of which there were 97. The optimal topology of the neural network was 6-12-1 (6 inputs – 12 neurons in the hidden layer – 1 output). The results of fitting the BELLS3_ANN model to experimental data and learning parameters with cross-validation are as follows:

size = 12; *weight decay = 0.1*;
RMSE = 1.93°C; R^2 = *0.85*.

In the analysis of the results of comparing the convergence of the BELLS3_ANN model with the BELLS3 model, it was noted that the optimal neural network did not introduce a significantly new quality in terms of improving the prediction accuracy of the T_d variable. The convergence of the results with experimental results is comparable to previous models, such as the classical linear, SVM or MARS.

3.6. RF RANDOM FOREST METHOD

Forest regression is believed to handle a variety of non-linear tasks and relationships well [25]. Random forests are a set of decision trees generated from samples derived from a learning set. The model averages the results of multiple trees, which improves prediction accuracy and reduces the risk of overtraining. Randomness lowers the variance of the estimator, which sets it apart from individual trees, which have a high variance and tend to overgeneralise [27]. The learning process, which additionally includes a cross-validation step, uses two learning parameters: *mtry* (the number of variables randomly selected as candidates in each split) and *ntree* (the number of trees to grow). The approximation model for regression of the RF technique is based on the formula (8):

$$y(x) = \frac{1}{B} \sum_{b=1}^{B} T_b(x)\ , \tag{8}$$

where:

x – new observation (vector of all feature inputs),

T_b – single tree B prediction (the tree assigns X to a single leaf and returns the average of the Y values in that leaf),

B – number of trees in the "forest".

The RF model tuning was performed according to the adopted hyperparameter grid:

ntree: *from 100 to 1000*; *mtry*: *50*, *100*, *200*;
nodesize: *1*, *3*, *5*, *10*.

Note that the best convergence of the BELLS3_RF model can be obtained already with a value of *ntree* = 100. In contrast, increasing the number of variable draws did not improve the quality of the fit. The best result was already obtained with a parameter value of *mtry* = 100. The results of the learning process and quality metrics for fitting the BELLS3_RF model to the experimental data are as follows:

$$ntree = 100;\ mtry = 100;\ nodesize = 5,$$
$$RMSE = 1.77°\text{C};\ R^2 = 0.88.$$

The BELLS3_RF model next to the BELLS3_MARS model proved to be the most effective technique for this stage of the analysis. It is worth noting that the BELLS3_RF model took into account the strong relationships between the predictors and the dependent variable as in the BELLS3_ANN model. In addition, the BELLS3_RF model also took into account numerous interactions (including of order greater than 2). As a result, this type of technique has definitely improved the quality of T_d feature prediction. The complexity of the interaction effects is also a result of the random forest technique's definition of the hidden relationships that apply to the set. It should be added that the present relations have their explanation in the structure of the set, in which the temperature T_d was determined for different road structures.

3.7. BOOSTED TREES (BT) METHOD

The technique of gradient-boosted random trees, in addition to the technique of deep learning (convolutional networks), is among the most effective methods for learning and mapping very complex phenomena. The amplified tree algorithm evolved from applying boosting methods to regression trees. The main idea is to create a sequence of (very) simple trees, each successive one built to predict the residuals generated by the previous one. The model is widely used for classification and regression tasks because it offers many advantages, such as high efficiency, simplicity, and interpretability [28, 29].

The process of building the BELLS3_BT model consisted of two stages. The first stage was related, as before, to the process of tuning a populous set of parameters taking into account cross-validation. The second stage consisted of verifying the model, using the tuned parameters, making use of two sets: a learning set and a test set. The action plan so constructed was to create a model distinguished by minimum aberration effect. The regression approximation model employing the BT technique initiates with the construction of a basic forecast, such as the average of the dataset. Subsequently, in each iteration, additional small trees are incrementally integrated. Each new tree addresses the errors made by its predecessors. Upon the computation of forecasts, the residual errors undergo evaluation. In the ensuing steps, the algorithm focuses exclusively on these errors, endeavoring to rectify areas where the regression prediction exhibited minimal strength and attempting to target deficiencies identified in previous models. Consequently, the learning process is articulated by the following formula (7), which represents the summation over T trees (9):

$$y(x) = f_0(x) + \eta \sum_{t=1}^{T} f_t(x)\,, \tag{9}$$

where:

$y(x)$ – Forecast value after t-th iteration,

$f_t(x)$ – a new, small tree (its "leaves" return constant values),

η – learning-rate from 0 to 1 specifying the contribution of a given tree to the explanation of the dependent feature.

The tuning of the BT model was made according to the adopted grid of hyperparameters:

η: *from 0.01 to 0.3*; *max depth*: *from 4 to 12*;
min_child_weight: *1*, *3*, *10*; *subsample*: *from 0.5 to 1.0*;
colsample_bytree: *from 0.5 to 1.0*; *γ*: *from 0 to 5*;
λ: *from 0 to 5*; *α*: *from 0 to 5*; *nrounds*: *35*.

In the learning process encompassing cross-validation and optimization the early-stopping options were used. The results of the process of tuning the BELLS3_BT model to the experimental data, along with the quality assessment, are as follows:

eta = 0.05; *max_depth = 10*; *gamma = 0*;
colsample_bytree = 0.90; *min_child_weight = 3*;
subsample = 0.80; *nrounds = 200*;
$RMSE = 1.32°\text{C};\ R^2 = 0.90.$

The results of the tuning indicated that the use of the BT technique is promising. The resulting convergence of model results against experimental results is 90%. Meanwhile, the estimation error result $RMSE = 1.32°\text{C}$ is the best result that was obtained compared to other techniques used in the study. Making use of the previous tuning results, the model was re-built using the advanced algorithms of the XGBoost library containing the xgb.cv function, which in the params option included the learning parameters vector provided earlier. The validation process required performing a 5-fold cross-validation on two sets:

the teaching (*train*) and validation (*test*). The learning set consisted of randomly selected cases at 70% of the total input set. In contrast, the test collection consisted of 30% of other cases. As part of the cross-validation averaging of responses from k-1 models was performed, so the result was a random variable. The result of the approximate, optimal required number of iterations to avoid overlearning is shown in Fig. 5.

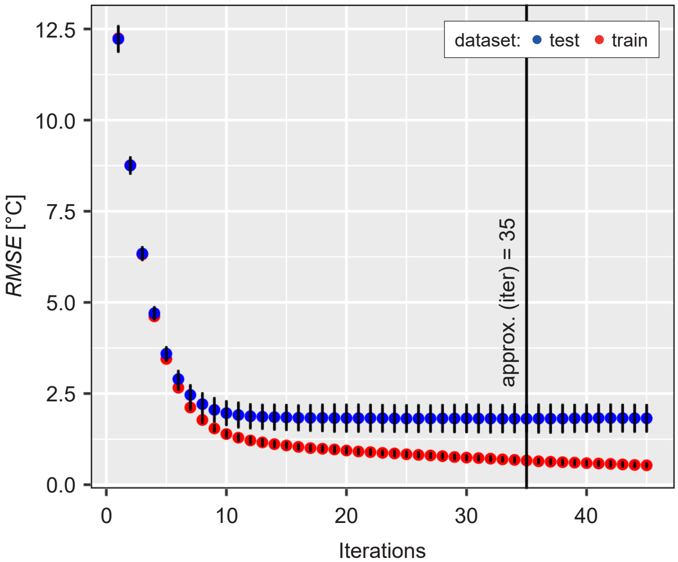

Fig. 5. Evaluation of approximate number of iterations by means of cross-validation

The results of the learning process of the BELLS3_BT model, taking into account the cross-validation, also include a confidence interval of ±2σ. Based on the evaluation of the relationship between the error of the test set and the learning set, it was determined that the approximate optimal number of iterations is around 35. The culmination of the entire analysis was the formulation of the final BELLS3_BT model, which will be used to calculate the predicted temperature in the pavement T_d at a depth of 120 mm. For this purpose, based on the previously performed evaluation of the initial number of iterations, the *early_stopping_rounds* parameter, which is responsible for implementing the procedure for stopping further learning, was set accordingly.

The obtained results (Table 2) revealed a definite advantage of the BELLS3_BT gradient-boosted tree model over other regression techniques. Its fit to the experimental data amounted to 96%, and the prediction error of a single result reached 0.61°C.

Table 2. Final fit metrics of the BELLS3_BT model

Iteration	*RMSE* (teaching) [°C]	*RMSE* (test) [°C]	R^2 (teaching + test)	*RMSE* (teaching + test) [°C]
51	0.58	1.45	0.96	0.61

Compared with the BELL3 model, it can be observed that the results of the new model align very close to the line representing perfect model convergence (Fig. 6).

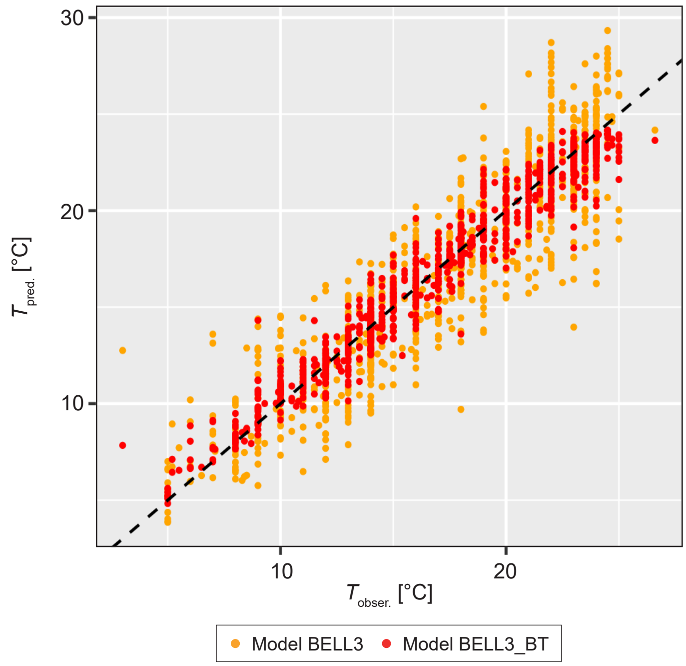

Fig. 6. Consistency of BELLS3_BT model results with those of the current BELLS3 model

For features: *IR* and T_{Air} their effect on the predicted value of T_d has the greatest power when the temperature exceeds 10°C. In contrast, the $T_{(1\text{-}day)}$ feature significantly affects the model as early as at 5°C (Fig. 7). Below this temperature, the characteristics of *sSin*155 and, to a lesser extent, *sSin*135 play a significant role. It can also be noted that above 25°C the characteristics: T_{Air} and $T_{(1\text{-}day)}$ do not introduce a new quality in the explanation of the T_d feature.

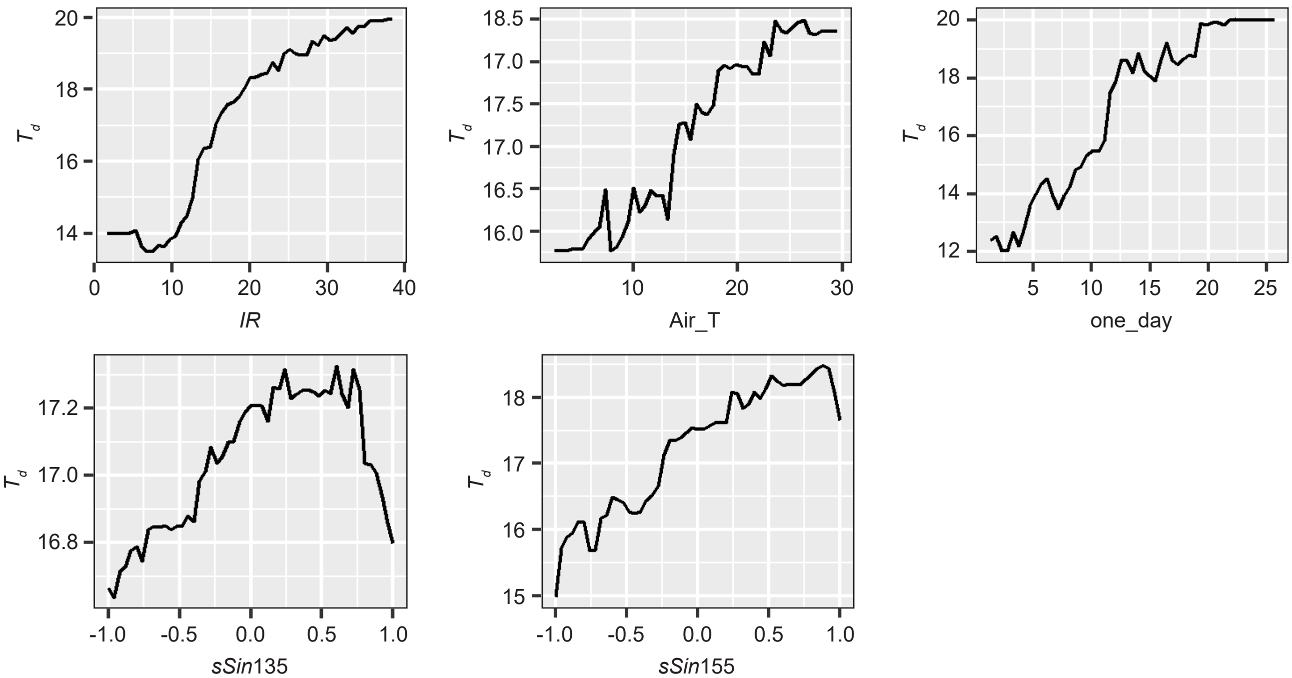

Fig. 7. Individual effect of predictors on feature T_d

4. DISCUSSION OF RESULTS

4.1. GENERAL REMARKS

Nine different modelling techniques were used in the search for the most effective regression model to refine and enhance the existing BELLS3 approach. This task proved challenging, mainly due to the inherent correlation of input variables in the BELLS3 dataset, which is based solely on temperature measurements and their transformations.

As highlighted in [22], ideally detailed data on the thermal properties of pavement materials would be required to achieve greater model accuracy. However, obtaining such data on a large scale is both logistically difficult and cost prohibitive. With this in mind, the study used machine learning methods to derive functional relationships that indirectly reflect these material properties based solely on available temperature-related inputs.

The results of all modelling approaches were benchmarked in terms of their predictive performance and visually summarised in Fig. 8, which illustrates the level of agreement between observed and predicted values. In addition, key statistical indicators such as root mean square error *RMSE* and coefficient of determination R^2 were compiled and presented in Fig. 9 to allow quantitative comparison between models.

Analysing the obtained results (Fig. 9), it should be noted that among the techniques that allow obtaining an implicit model, the best result was yielded by the BELLS3_BT model based on the gradient-boosted tree technique. Its fit was R^2 = 96%. However, in terms of the machine learning technique that provides the explicit form of the model, the most noteworthy is the BELLS3_MARS model, whose fit is R^2 = 87% (Fig. 9). Therefore, for engineering purposes, the BELLS3_MARS model can be used alternatively, allowing a precision of 1.84°C. Based on the fact that the trained BELLS3_BT model can be flexibly used in digital form with *.JSON and *.XML extensions (provided as attachments), its selection is recommended as it showed the precision of 0.55°C. It can be implemented (after possibly adjusting the header) to well-known programs like: Statistica, R or SAS. Another important feature that distinguishes the BELLS3_BT model is that all the final objects (leaves) are a set of rules that have a relationship to the actual features assigned to the construction layers. Thus, it can be assumed that the rule of each end leaf can be the characteristic thermal properties of the asphalt pavement, such as the thermal conductivity coefficient as well as their specific heat.

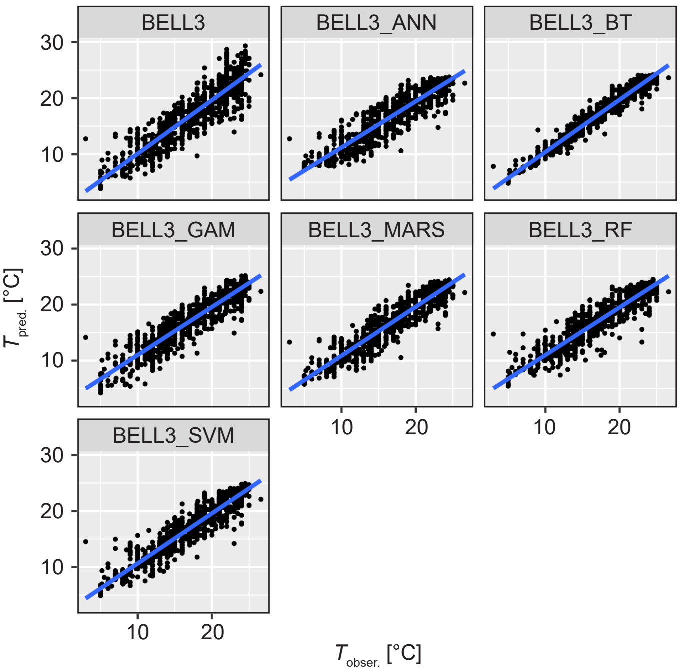

Fig. 8. Evaluation of the convergence of the tested machine learning techniques

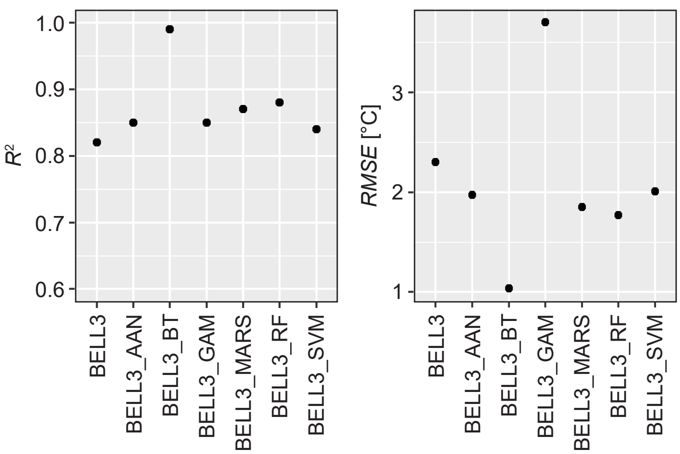

Fig. 9. Evaluation of the fit metrics of the tested machine learning techniques

At the same time, it is important to point out the scope of this model, in particular BELLS3_BT and BELLS3_MARS. Performing extrapolations is limited and should be done with caution. Therefore, it is worth remembering the range in which the effectiveness of these models has been confirmed by advanced validation techniques. This range is determined by the minimum and maximum values (Table 3), which is consistent with the temperature range at which pavement deflection measurements should be made in Poland.

As the BELLS3_BT model proved to be the best in terms of fit in predicting pavement temperature, its digital record was exported to *.R, *.json and *.XML files. An execution script was also developed to predict the pavement temperature T_d at a depth of 120 mm with set predictor values according to the header of the provided data file.

Table 3. Scope of applicability of the BELLS3_BT and BELLS3_MARS model

Variable	Relevant descriptive statistics				
	intermediate	min.	max.	standard deviation	common variable
$T_{(1\text{-}day)}$	12.50	1.30	25.70	5.09	40.7
T_d	16.99	3.00	26.60	5.05	29.7
IR	18.20	1.60	38.40	7.52	41.3
T_{Air}	14.89	2.50	29.50	5.17	34.7
d	120.00	120.00	120.00	0.00	0.0
*sSin*155	–0.0058	–1.00	1.00	0.81	–13955.4

4.2. ASSESSMENT OF THE EFFECTIVENESS OF THE MODEL USING THE WDSN MEASUREMENT QUALITY CONTROL PROCEDURE AS AN EXAMPLE

In order to verify the accuracy of determining the temperature of the asphalt layer, an analysis of the results of two approaches – the BELLS model and the BELLS3_BT model – was carried out on data from control measurements made as part of road network measurement campaigns in the 2019-2024 period. The inspection procedure is described in the WDSN [30], which in brief involves assessing repeatability by comparing the mean value *r* and standard deviation σ of the differences D0 and SCI300 from routine and control measurements with specified tolerances.

Table 4. Statistics of temperatures determined by the BELLS3 and BELLS3_BT model

Statistical measure	BELLS3 _routine	BELLS3 _control	BELLS3_BT _routine	BELLS3_BT _control
Average	21.43	22.13	19.52	20.00
Median	21.43	22.93	19.71	20.39
Standard deviation	5.03	5.24	3.24	3.65
Meter	3,900	3,900	3,900	3,900

A comparison of the calculated BELLS3 routine and control model's temperatures with the corresponding BELLS_BT values (Table 4) shows that the average temperatures obtained for the BELLS_BT model are slightly lower compared to the values from the BELLS model (e.g., 19.52°C vs. 21.43°C in routine measurements). At the same time, the difference between the average routine and control temperatures is smaller for BELLS_BT (about 0.48°C) than for BELLS (about 0.70°C), suggesting greater stability of BELLS_BT prediction under different measurement conditions. The standard deviations of BELLS_BT temperatures (3.24°C routine, 3.65°C control) are smaller than those of the BELLS method (5.03°C and 5.24°C, respectively), confirming the higher repeatability of predictions. Statistical analysis suggests that the BELLS_BT model has slightly higher stability, which affects both the accuracy of predicting the temperature itself and the resulting parameters (such as D0 deflection). At the same time, both approaches show a certain level of variability, reflecting the complexity of the measurement process and the diversity of field conditions.

On this occasion, a comparison was made between the *r* and σ resulting from the analysed dataset and the threshold values (marked as I_present in the chart) currently adopted in the WDSN control procedure (Fig. 10). An analysis of the position of *r* and σ currently used against the actual distribution of data shows that they do not match the observed differences both in terms of averages and standard deviations. On the one hand, they may allow results that are very different from typical conditions, and on the other hand, they may unfairly eliminate measurements that are within the limits of reasonable variability. The lack of clear reliance on field statistics indicates that these thresholds are rather arbitrary and do not guarantee a fully accurate assessment of pavement quality.

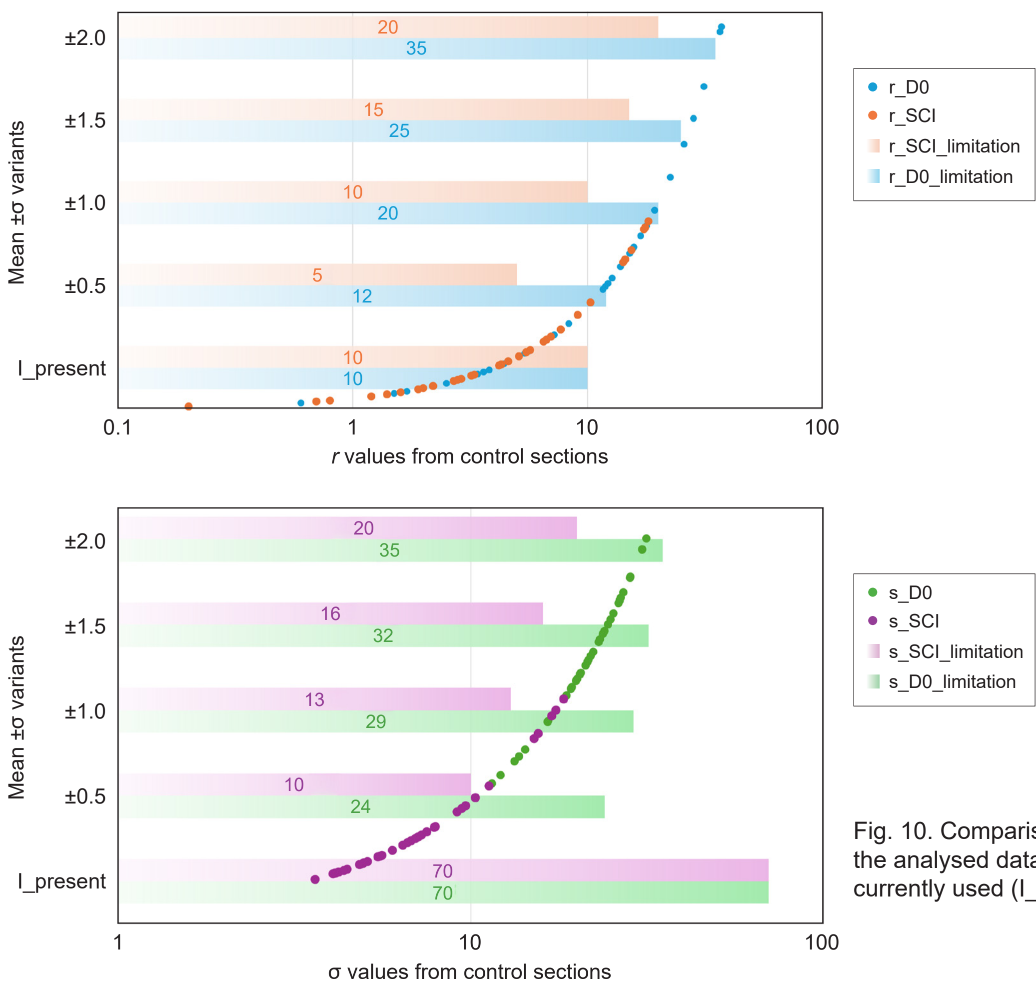

Fig. 10. Comparison of *r* and σ resulting from the analysed dataset with the threshold values currently used (I_present)

In the context of the above conclusions, it is proposed that a "mean ±1.5σ" threshold be introduced in the future as a new criterion for accepting differences between routine and control measurements. This solution draws on the distribution of data from actual surveyed sections, so it takes into account the specifics of field measurements to a greater degree. As a result, it makes it possible to isolate measurements fraught with significant irregularities, without leading to an excessive narrowing of the range of results considered correct.

5. CONCLUSIONS

Based on the analysis carried out in this article, the following conclusions can be drawn:

1. The analysis showed that, despite its popularity in engineering practice, the BELLS3 model used to date has limited precision in estimating the temperature of asphalt layers. The achieved fit indices ($R^2 = 82\%$, $RMSE = 2.3°C$) do not meet modern requirements for the accuracy of forecasting thermal parameters of the pavement. The use of modern data mining methods, particularly machine learning, has made it possible to significantly improve the accuracy of predictive models. The model based on boosted gradient trees (BT) showed the highest performance, achieving a fit of $R^2 = 96\%$ and a prediction error of $RMSE = 0.61°C$.
2. An analysis of the impact of the variables showed that the air temperature at the time of measurement T_{Air}, the temperature of the previous day $T_{(1\text{-}day)}$ and the surface temperature IR had the most significant impact on the predicted temperature of the asphalt layer T_d. At the same time, the need to apply the model within the range of learning data was emphasised. Extrapolation of results beyond the range of input values (temperature, time, surface temperature) should be done carefully and always with consideration of possible reduction in the quality of the forecast.
3. In the light of the results obtained from the analysis of the quality control data carried out based on WDSN, among others, it seems reasonable to introduce a new threshold for the acceptability of measurement differences in the form of "mean ±1.5σ." This approach better reflects the actual field variability and can improve the efficiency of eliminating erroneous measurements without unnecessarily limiting the data scope.
4. Despite achieving high accuracy in predicting asphalt layer temperature using the gradient-boosted trees (BT) model, several limitations of this study should be acknowledged. First, all models were trained and validated on a single dataset derived from FWD and TSD measurements conducted on selected road sections in Poland, which may limit the generalisability of the results to other climatic or structural conditions. Second, the absence of direct data on the thermal properties of pavement materials (e.g., thermal conductivity, specific heat capacity) necessitated their indirect representation through correlations with surface and air temperatures. Third, the effectiveness of the models has been confirmed only within the range of the training data (Table 3), meaning that extrapolation beyond the input temperature, time, and surface conditions may result in a significant decrease in prediction accuracy.

This study builds upon earlier work on calibrating the BELLS3 model to local conditions [22], in which the use of linear regression resulted in only marginal improvements in prediction accuracy. The present paper demonstrates that data mining techniques, such as MARS, RF, and BT, can significantly enhance the precision of predictive models while offering new opportunities for integrating classical engineering methods with modern data analysis tools. Future research should focus on expanding the dataset to include more diverse pavement structures and climatic conditions, as well as incorporating material-specific thermal data to further improve the generalisability of the developed models.

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Wyznaczanie temperatury warstw asfaltowych w pomiarach FWD i TSD z wykorzystaniem uczenia maszynowego

Streszczenie: W pracy przedstawiono zastosowanie technik uczenia maszynowego w szacowaniu temperatury warstw asfaltowych podczas pomiarów urządzeniami FWD i TSD. Problem precyzyjnego określenia temperatury jest kluczowy dla analizy trwałości nawierzchni drogowych. Tradycyjne metody, takie jak model BELLS3, choć szeroko stosowane, mają ograniczenia w dokładności prognoz. Praca prezentuje implementację zaawansowanych algorytmów, między innymi takich jak regresja adaptacyjna (MARS), wektory nośne (SVM), sieci neuronowe (ANN), drzewa losowe (RF) i drzewa wzmacniane (BT), w celu optymalizacji modelu szacowania temperatury warstw asfaltowych T_d. Model BELLS3, wykorzystany jako bazowy w procesie optymalizacji, został oceniony pod kątem skuteczności predykcji. Wyniki wykazały umiarkowaną skuteczność tego modelu (R^2 = 82%, *RMSE* = 2,3°C), co stanowiło potrzebę dalszych udoskonaleń. Zastosowanie technik uczenia maszynowego, w szczególności wzmacnianych drzew gradientowych (BT), pozwoliło na znaczne zwiększenie precyzji prognoz. Model BT osiągnął najwyższe dopasowanie do zmiennej zależnej T_d (R^2 = 99% oraz *RMSE* = 0,61°C), co wskazuje na jego wyraźną przewagę nad innymi modelami, w tym nad bazowym modelem BELLS3. Na koniec autorzy podkreślają potencjał integracji tradycyjnych podejść z zaawansowanymi metodami analizy danych w celu dalszej poprawy dokładności prognozowania temperatur warstw mieszanek mineralno-asfaltowych i efektywnego zarządzania infrastrukturą drogową.

Słowa kluczowe: BELLS3, eksploracja danych, FWD, nawierzchnia, temperatura, TSD, ugięcia, walidacja.