

Article

Utilizing Selected Machine Learning Methods for Conicity Prediction in the Process of Producing Radial Tires for Passenger Cars

Wojciech Majewski ¹, Ewa Dostatni ¹, Jacek Diakun ¹, Dariusz Mikołajewski ² and Izabela Rojek ^{2,*}

¹ Faculty of Mechanical Engineering, Poznań University of Technology, Marii Skłodowskiej-Curie 5, 60-965 Poznań, Poland; wojciech.majewski@doctorate.put.poznan.pl (W.M.); ewa.dostatni@put.poznan.pl (E.D.); jacek.diakun@put.poznan.pl (J.D.)

² Faculty of Computer Science, Kazimierz Wielki University, Chodkiewicza 30, 85-064 Bydgoszcz, Poland; dariusz.mikolajewski@ukw.edu.pl

* Correspondence: irojek@ukw.edu.pl

Abstract: This article presents the current state and development directions of the tire industry. One of the main requirements that a tire must meet before it can leave the factory is achieving values of quantities describing uniformity at a defined level. Of particular importance are conicity and the components of the tire with the greatest impact on its value. This research is based on the possibility of using an ANN to meet contemporary challenges faced by tire manufacturers. In order to achieve a satisfactory level of prediction, we compared the use of a multi-layer perceptron and decision trees XGBoost, LightGbmRegression, and FastTreeRegression. Based on data analysis and similar examples from the literature, metrics were selected to evaluate the models' ability to solve regression problems in relation to the described problem. We selected the best possible solution, standing at the top of the features covered by the criterion analysis. The proposed solutions can be the basis for acquiring new knowledge and contributions in the field of the computational analysis of industrial data in tire production. These solutions are characterized by the required accuracy and efficiency for online work, and they also contribute to the creation of the best fit elements of complex systems (including computational models). The results of this study will contribute to reducing the volume of waste in the tire industry by eliminating defective tire parts in the early stages of the production process.

Keywords: radial tire; tire uniformity; conicity; real data; machine learning; quality control



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1. Introduction

Regardless of the industry branch in question, reducing costs and increasing productivity is highly important to all companies. With regard to tire manufacturers, it is necessary to develop solutions that reduce the amount of production scraps and allow the company to meet modern standards. As the part of a vehicle that is directly responsible for safety during travel, a tire should be reliable. In the high-volume production of tires, environmental protection aspects should also be taken into account. Rubber waste, which is used as an alternative fuel (energy recovery), is responsible for 6% of the global CO₂ emissions [1]. Thus, the constantly developing strategies for dealing with used tires through material [2,3] and product [4] recycling are not by themselves sufficient to maximize the use of rubber as a raw material.

The existing driving systems and fuels that are based on alternative energy sources create numerous challenges for the tire industry in terms of achieving ever lower tire rolling resistance [5,6]. Moreover, thanks to EU-standardized labels [7] that help compare performances in areas such as wet grip, fuel efficiency, and noise, informed users can easily choose the safest and most economical and comfortable tires. The intensification of the development of electric cars, which is related to decisions made by the European Parliament

that are motivated by zero emissions transport [8], has also generated new tire construction methods that are more difficult to carry out. This translates into minimizing the weight of the tire by constantly reducing its cross-sectional area. This leads to significant problems in terms of meeting tire physical uniformity limits, which are constantly being narrowed by car manufacturers.

Physical uniformity is one of the qualitative aspects that proves the homogenous structure of the tire, which is also a measure of its ability to run smoothly without vibrations [9]. It consists of a package of physical quantities that are measured for each tire before it leaves the factory. There are radial phenomena, including RFV (radial force variation), static balance, dynamic balance, and RRO (radial runout), and lateral phenomena, such as the LFV (lateral force variation), LRO (lateral runout), LRP (the highest and the lowest points measured in the tire's shoulder area), and CON (conicity). They describe factors including equal weight distribution on the circumference of the tire [10], which directly translates into the mechanism of its wear [11]. In addition to the influence of the tread pattern [12], this is another one of the factors that affects the tire's noise emission during its rolling motion. Ensuring the uniformity of tires at the assumed level therefore contributes to increasing their durability and predictable behaviors in road traffic for the duration of their usage.

Regarding quantities describing uniformity, it is worth paying attention to conicity, which is also called the "cone effect". Specifically, this is the tendency of a tire to pull the vehicle (left or right) out of its intended trajectory. It is associated with the lack of symmetry and off-centeredness of the tire's components relative to its axle. The inability to measure the dimensional symmetry of the materials used in an already vulcanized tire makes it necessary to determine its conicity, which can be said to be the result of the symmetry of the tire components.

Conicity describes a tire's ability to maintain the track set by the vehicle's suspension system. Depending on the market (country) for which a given tire is designed, an appropriate belt application sequence is used (Figure 1). In radial passenger car tires, there is usually a 10–20 mm width difference between tread ply 1 and tread ply 2; the difference at the top of this scale may be used to compensate for the impact of the asymmetric tread pattern. The purpose of this procedure is to force the vehicle to always pull towards the roadside, for example, in cases where the driver lets go of the steering wheel or falls asleep while driving. Therefore, the steel cord of the wider tread ply 1 is always directed towards the roadside. For the proper functioning of this assumption, and to guarantee safety during travel, conicity must be ensured at a certain level. Moreover, a tire with too high a conicity value will wear irregularly (i.e., greater weight loss of the rubber tread compound on the left side compared to the right side of the tire or vice versa), so conicity determines the correct wear mechanism of the tire during its exploitation [13]. Therefore, a tire that is within the limit of this output variable will exhibit predictable and safe behavior when in use. For this reason, every tire leaving the factory is subjected to conicity measurements, which are required and verified by car manufacturers. It can therefore be concluded that conicity is one of the key determinants of tire reliability.

In order to meet the above-mentioned requirements, automatic machines that allow for the online registration of process input data are increasingly used for tire production. This fits into the Industry 4.0 paradigm, assuming technical control at every stage of the product's life cycle. The measurements for tire uniformity recorded so far, as well as the possibility of registering the input data, are conducive to finding new dependencies between the aforementioned data. Due to the high level of complexity of the tire production process, this article proposes the application of artificial neural networks (ANNs) to find relationships that directly affect the elimination of tire defects, which will directly translate into the production of more uniform tires.

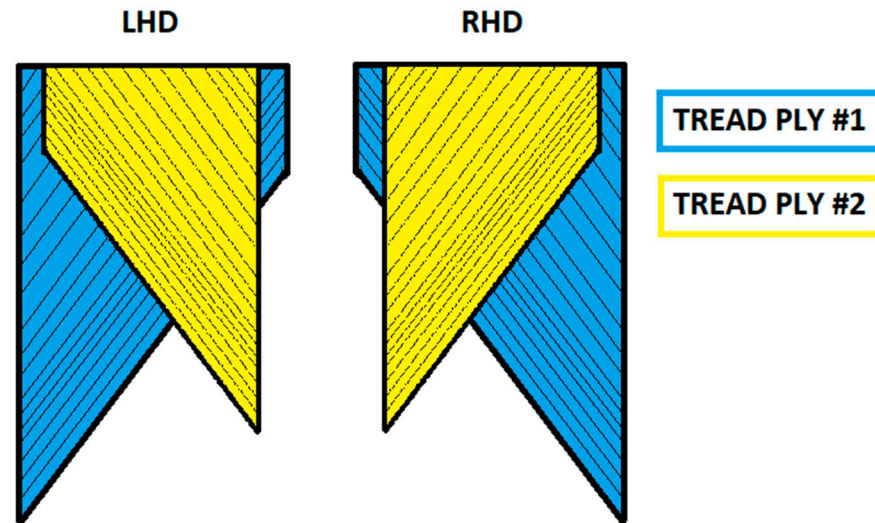


Figure 1. Tread ply 1 and tread ply 2 layout for right-side traffic (LHD—left-hand drive) and left-side traffic (RHD—right-hand drive).

The idea itself is not new; until now, artificial neural networks and decision trees have mainly been used to identify the parameters of a tire model [14] and the influence that the conditions of pressure, load, and speed have on tire uniformity measurements [15]. These techniques have also already been used for the estimation of tire–road interactions [16] and to model tires for vehicle system dynamics and control prediction [17] or to analyze the forces acting on the tire [18,19]. The system of suspension–brakes–tire–surface is responsible for maintaining the vehicle’s safe and stable trajectory [20]. ANNs are currently also used to approximate the parameters describing the vehicle’s braking process in the diagnostics of the braking system [21]. Another interesting application of ANN involved building a prediction model for tire tread pattern noise, where the input data were the tread pattern noise and pattern images [22]. However, during the literature review, no research was found describing the use of ANN and decision trees to predict conicity during the tire production stage; this article fills this research gap. The aforementioned studies mainly focused on examining the tire’s behavior during its operation. It should be noted here that visual tire inspection systems based on convolutional neural networks are currently being intensively developed [23,24]. Methods based on deep learning, unsupervised learning, and supervised learning will successfully replace humans during this stage of tire quality control, which is an indispensable part of the tire production process. The use of artificial intelligence in the context explored in this work demonstrates the broad possibilities in this area; this study represents a new approach that will be further developed in future research.

The aim of this article is to compare, assess, and identify the best available machine learning-based approach and to use it for predicting conicity in the process of producing radial tires for passenger cars. As we demonstrate here, prediction means forecasting the statistical features of random events, which can be measured. The main scientific contribution of this work is to find ML-supported solutions for the automation of a difficult aspect of technical control in Industry 4.0/5.0, i.e., tire production. Our conclusions show which activities, models, and tools are the most effective at a given stage, thus guiding their further development towards increasing the technology readiness level (TRL). This article is the result of work focused on implementing and using the ML model in a real production enterprise. The obtained dependencies and data collected in real time make it possible to react quickly in a production environment, e.g., by immediately withdrawing from using the material causing defects or by introducing corrections to the process, which has a significant impact on reducing production costs by eliminating time loss, minimizing material losses, and reducing the amount of scrap. The use of the described model will increase the flexibility in the short-term planning of producing materials and tires thanks

to quick feedback regarding the occurrence of incorrect prefabricated elements or defective final products.

2. Materials and Methods

This research focused on real data recorded during the process of producing radial tires. The measurements of the dimensions of tire components from the assembly stage (performed on a VMI MAXX tire assembly machine) and the results of the tire uniformity measurements taken during the final inspection stage (performed on a TUO machine) were recorded in dedicated databases. The authors emphasize that the examined relationships are non-linear; this is a conclusion drawn from the previously conducted EDA (exploratory data analysis), which is an analytical process focused on understanding the structure, patterns, properties, and hidden information in the collected data. This allowed for a better understanding of the essence of the data, identifying trends, detecting anomalies, and preparing the data for further analysis. The quality of the analyzed data was improved to make it easier to extract useful knowledge from them. Inaccuracies in the data were corrected (data cleaning), normalization was performed, and the size of the feature vector was reduced, leaving the most important ones (originally, the number of features was 396, which was reduced to 5). Data related to the production of one tire size were integrated and selected; they consisted of 6987 records for which 5 input variables were combined with 1 output variable for a given tire barcode. The data obtained were initially audited using Statistica 13 (StatSoft, Tulsa, OK, USA) software to detect and exclude uncertain, incomplete, or outlier data; in the case of data of debatable value, the decision to fix/remove the record was made by a panel of experts based on a statistical analysis. For all tested methods, the data (each attribute of the input and output vectors) were scaled to the range $<0; 1>$, because they should be in the same order of magnitude for a reliable comparison of the results. In this study, the data were divided into three sets: learning (70%), testing (15%), and validating (15%). A flow diagram of the registration and data preparation in the context of the tire production process is presented in Figure 2.

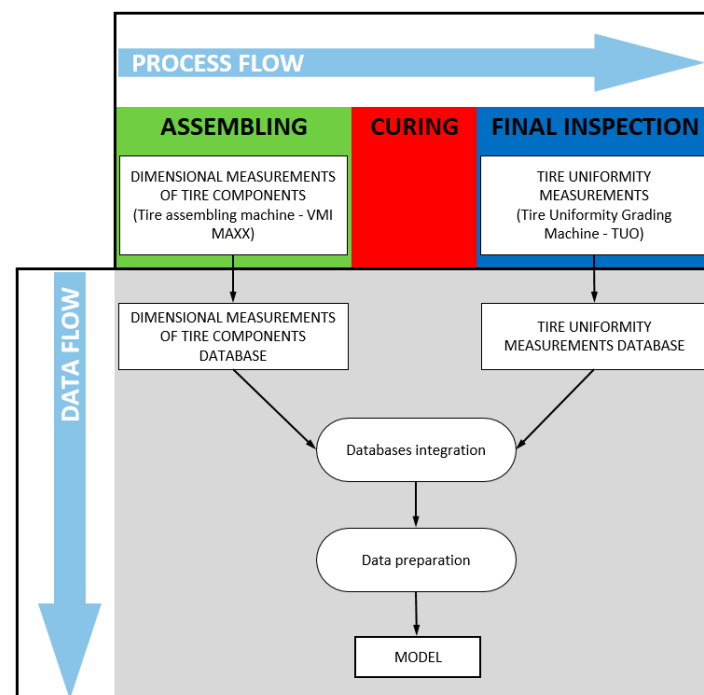


Figure 2. Flow diagram of the registration and data preparation in the context of the tire production process.

The tire components and features that most influence the model's prediction efficiency were selected due to the nature of the tire's operation and the specificity of the tire conicity phenomenon [9]. When in motion, the top tread (ensuring contact with the ground) and tread plies (ensuring the tire's stiffness) are mainly responsible for maintaining the set driving path in modern tire constructions [10]. Disturbing the symmetry of the aforementioned materials relative to the tire axis and failure to maintain the specification of their width are the main reasons why the conicity limit is exceeded. On this basis, the feature vector was reduced (396 features were reduced to 5). Moreover, this statement was further confirmed by the enterprise's years of experience in eliminating defects in a large number of tire sizes. Finally, the reasons described above (the physical properties of the tire and the company's experts' opinions) led to the selection of the following features (input variables):

- BR1_WIDTH_MEASURED: tread ply 1's average total width;
- 1BAP_BODY_AVG_OFF_CENTER: tread ply 1's average off-centeredness relative to the BT (band transfer) drum center line;
- BR2_WIDTH_MEASURED: tread ply 2's average total width;
- 2BAP_BODY_AVG_OFF_CENTER: tread ply 2's average off-centeredness relative to the BT drum center line;
- TD_WIDTH_MEASURED: top tread average total width.

One output variable was measured in compliance with [25] using a TUO (tire uniformity grading machine):

- CON, conicity: This must be within the limit of $X \pm 40$ N, where X is a value (generally close to 0 N) determined on the basis of the average measurement from the first production batch of a new tire size. The volume of this population is determined by the customer's requirements (usually 1000–5000 tires). The specific components of the tire that most significantly affect its conicity are shown in Figure 3.

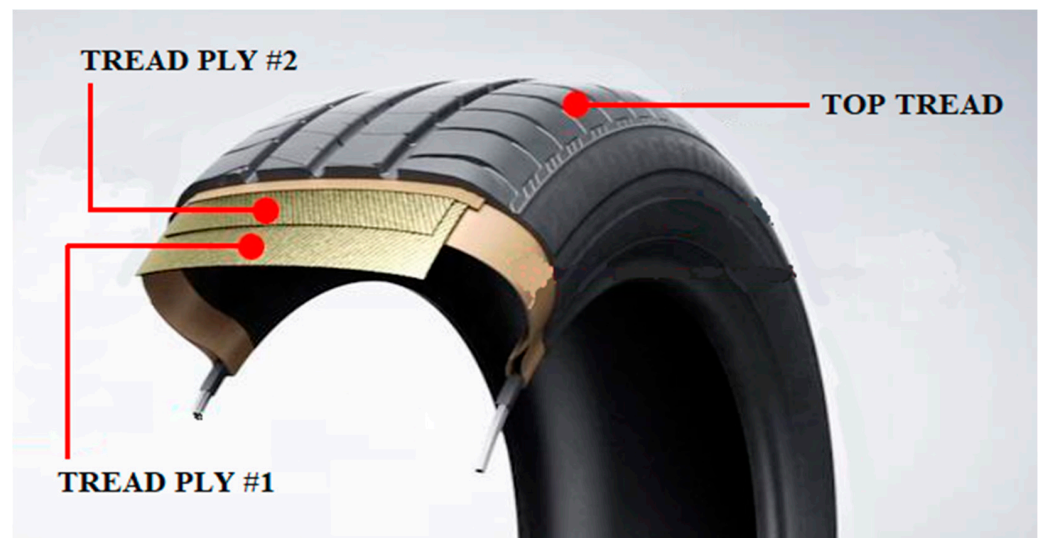


Figure 3. Tire components that most significantly influence the conicity.

The methods presented in the three groups of models described below are proprietary, proven in other studies on both mass production data and small datasets, which have been developed by team members since 2015.

2.1. Models Based on Data Miner Statistica

These are basic models built using the scientific Data Miner Statistica 13 software, which are automatically optimized to obtain the best possible result in terms of accuracy, the minimization of the RMSE, and the speed of the algorithms' convergence (ultimately, with a computation time that is as short as possible and a semi-automatic opinion given by the models/system). The MLP (multi-layer perceptron) allows non-linear models to

be taught almost in real time (online learning). The authors decided to use MLP-based models due to their universality. We successfully propose solutions, e.g., for maintaining the production rate [26] and continuity [27] and for forecasting the quality and efficiency of the operation of motor vehicles in the transport service system [28].

In this research, the Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) optimization algorithm was applied; it converges faster for small datasets than the Stochastic Gradient Descent (SGD), which requires at least 10,000 samples. This study used a back-propagation algorithm. The structure of a MLP network with five inputs, various numbers of neurons in the hidden layer, and one output is shown in Figure 4. The number of hidden layer neurons and network parameters were selected experimentally. This involved testing 30 MLP neural network models using a different number of neurons in the hidden layer (in the range of 5–20, but increasing the number of neurons did not improve the quality of the models), various combinations of activation functions in the hidden and output layers, and different training times for the MLP network.

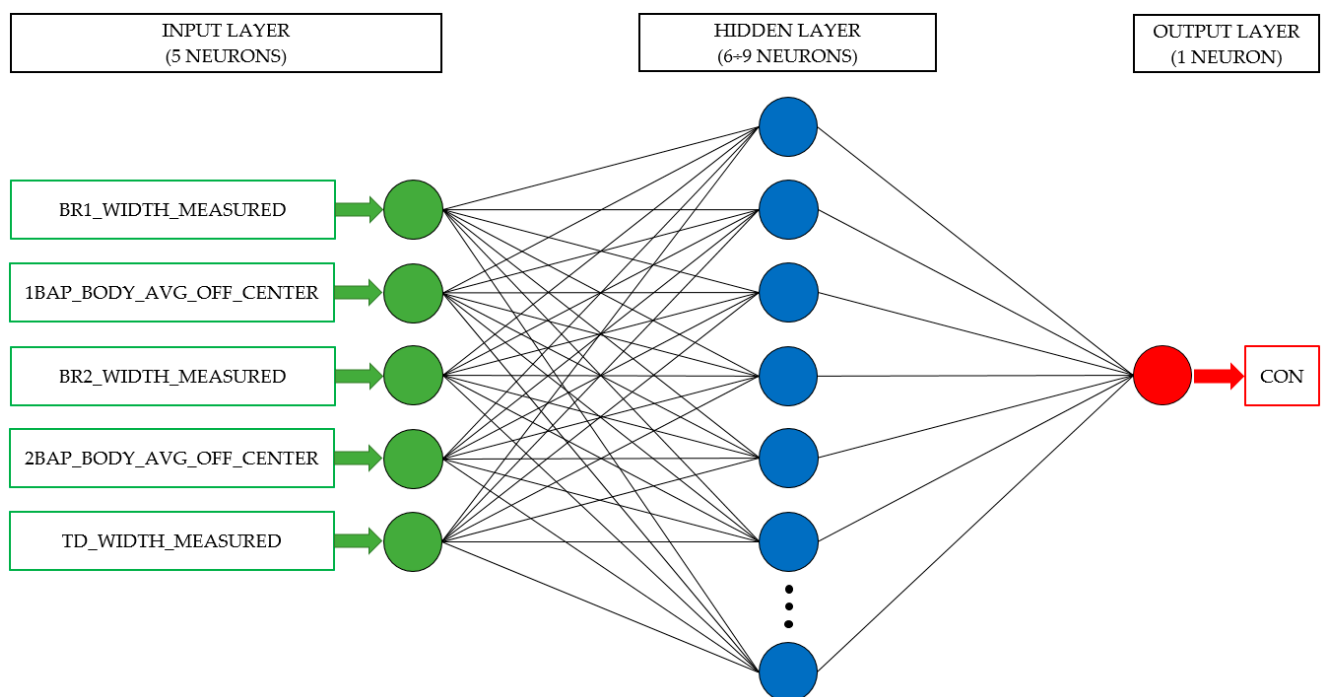


Figure 4. Structure of the MLP network developed in research with five inputs, various numbers of neurons in the hidden layer, and one output.

2.2. Models Based on Decision Trees XGBoost, LightGbmRegression, and FastTreeRegression

XGBoost is an advanced model with commercial applications working in the Python and R environments. It based on the possible use of XGBoost 1.7.6., which is an intermediate solution between the approaches describes in this paper in terms of both accuracy and calculation time. XGBoost is a scalable end-to-end boosting system, which is widely used to achieve state-of-the-art results in many machine learning challenges. It is characterized by parallelization; that is, it uses a parallel implementation to run a sequential tree-building process. This is possible due to the interchangeable characteristics of the loops used to create the underlying learners. The inner loop counts features, while the outer loop acquires the leaf nodes of the tree. Loop nesting limits parallelization, because it is impossible to run the outer loop without terminating the inner loop. Parallel and distributed computing makes learning faster, which enables quicker model exploration. XGBoost has implemented regularization, i.e., a kind of “penalty” imposed on the model if there are too many final observation segments or leaves in the decision tree. The complexity of the model is controlled here using the Ridge and LASSO techniques. The general form of the XGBoost

algorithm consists of two parts. The first component is responsible for minimizing the error, which is called the loss function or cost function. The second part, regularization, helps prevent overfitting and controls the complexity of the model. The XGBoost machine learning algorithm has a cross-validation method implemented in each iteration. This eliminates the need for extensive programming and determining the exact number of stimulation iterations needed to perform one run. Additionally, it has other improvements, e.g., “out of core” calculations, which use disk space and handle data frames that do not fit in the computer’s main memory.

For the purposes of this paper, the XGBoost model was trained for different values of the maximum depth (in the range of 2–15); it was found that the best results were obtained for a maximum depth equal to 8 (Table 1, Figure 5). The part of the example tree generated by the XGBoost model is shown in Figure 6.

Table 1. Results of the XGBoost model according to the maximum depth parameter. The tree with the best performance is shown in bold.

	Maximum Depth											
Measure	2	3	4	5	6	7	8	9	10	11	12	15
RMSE	0.1266	0.1214	0.1209	0.1199	0.1189	0.1176	0.1156	0.1160	0.1159	0.1177	0.1187	0.1225
R ²	0.4225	0.4690	0.4730	0.4818	0.4903	0.5014	0.5182	0.5151	0.5161	0.5007	0.4924	0.4588

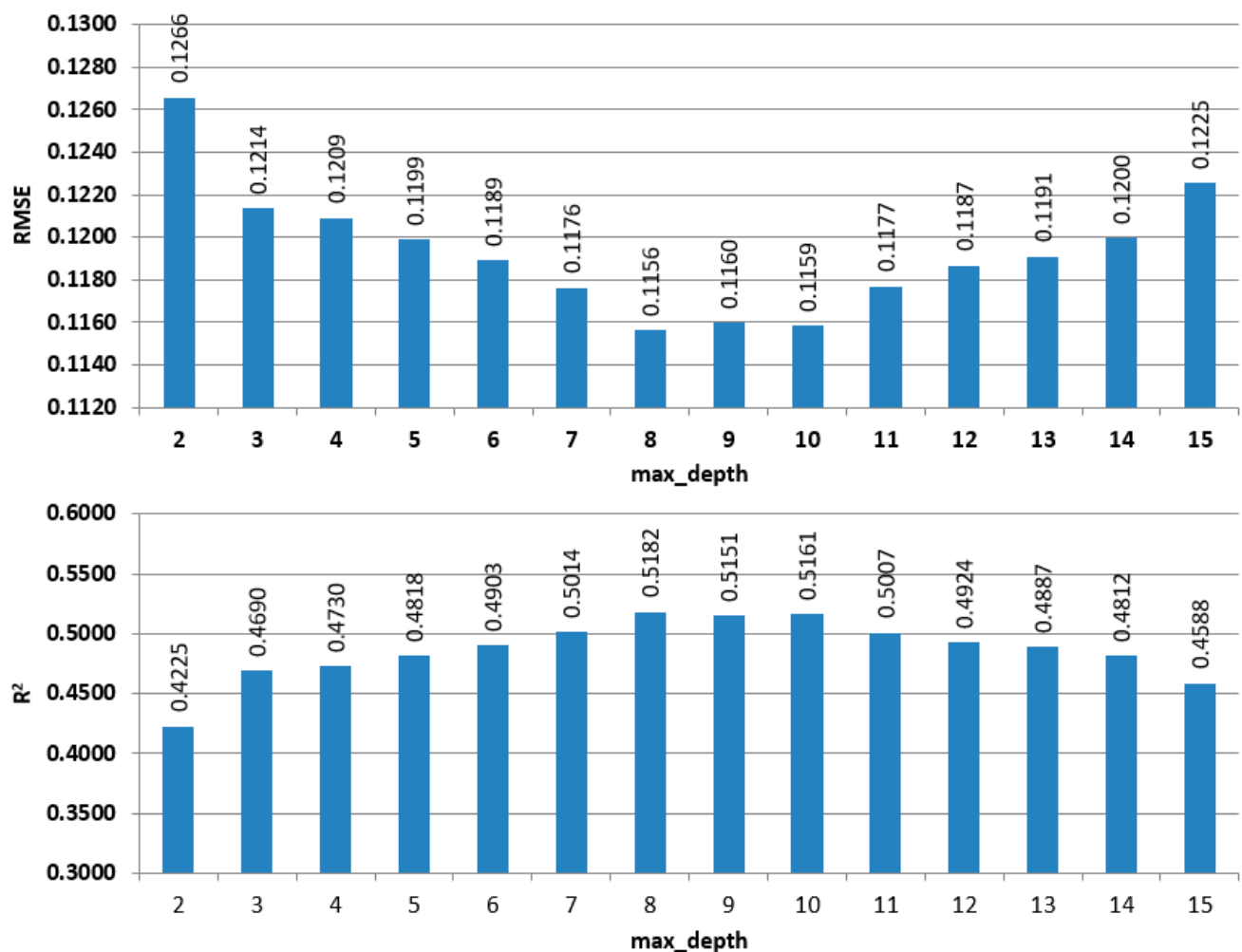


Figure 5. XGBoost model RMSE and R² results for the depth parameter tuned in the range of 2–15.

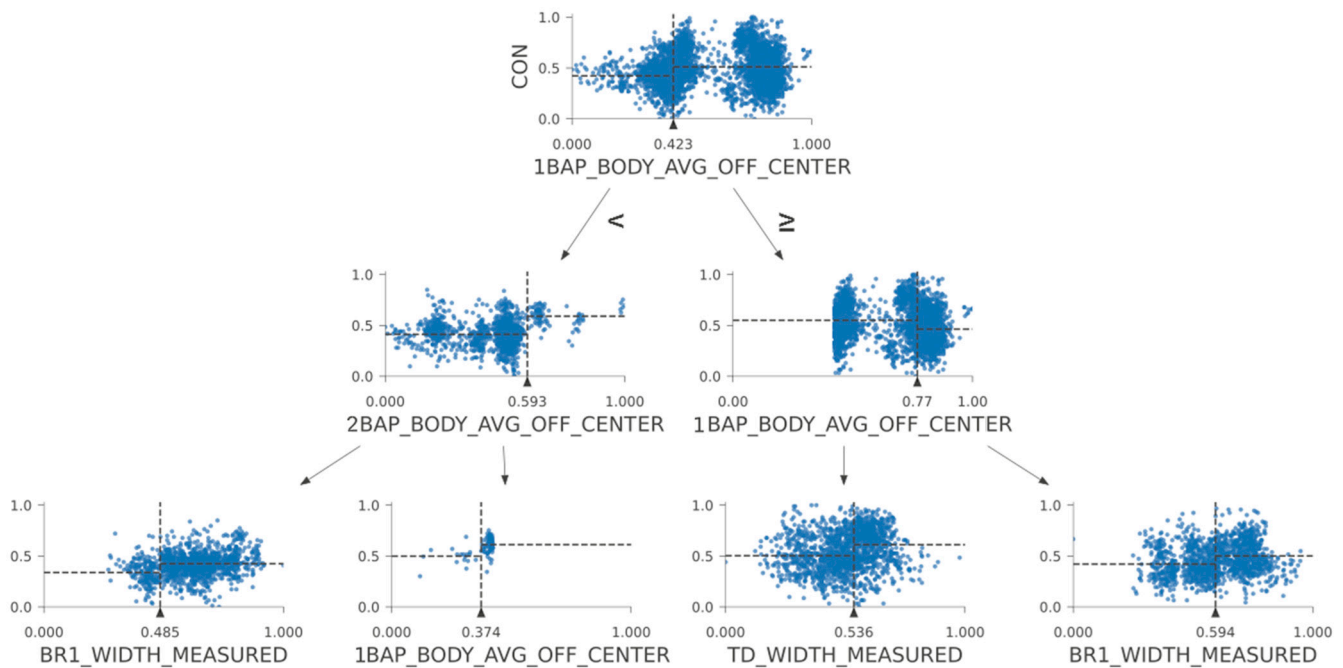


Figure 6. Part of the example tree generated by the XGBoost model.

The next proposed methods are advanced automated self-learning models, based on ML.NET working in the Visual Studio 2022 environment. For the acquired data, solutions can be selected from more than 120 algorithms (learning time: up to 1000 s); these models yield an API (application programming interface) and code in C# for later use in the system. Each of the available ML algorithms has a set of unique parameters, so-called “hyperparameters” that allow it to tune its operation to a dedicated application. Focusing on FastTreeRegression, an efficient implementation of the Multiple Additive Regression Trees (MART) gradient boosting algorithm, this research produced the following exemplary hyperparameters:

- Bias: a value added to the weighted sum of the scores of all trees.
- Trees: the i-th RegressionTreeBase (container base class) in Trees.
- TreeWeights: the weight of the i-th RegressionTreeBase in Trees.

Changing these parameters leads to an increase in the effectiveness or efficiency of the model being built. The ML.NET framework uses the AutoML tool, which supports work with machine learning by automatically selecting the best algorithms and hyperparameters for the examined dataset. This solution is useful for achieving high levels of model effectiveness and for saving time on the manual tuning of the created models. After running the experiment for a given time, AutoML creates models with various combinations of algorithms and hyperparameters to obtain the best possible result for the indicated metric (the proposal for each such combination is a single trial). One of the strongest features of the library is its high efficiency level; this may be an important criterion when deciding on the choice of a machine learning tool in a production environment. It is worth noting that it is a relatively young tool (first released in 2018) and still does not have some of the functionalities available in the Python ecosystem. When using ML.NET, two types of gradient boosting decision trees (GBDTs) have been suggested: LightGbmRegression and FastTreeRegression. These algorithms use two new techniques [29]:

- Gradient-based one-side sampling (GOSS): This retains occurrences with large gradients (i.e., larger than a predefined threshold) or selects among the highest percentiles and randomly removes only occurrences with small gradients to maintain the accuracy of the information gain estimation. This is connected to the fact that different occurrences of the data play different roles in the calculation of the information gain,

i.e., instances with larger gradients (undertrained instances) contribute more to the information gain. This results in a more accurate estimate of gain than uniform random sampling.

- Exclusive feature bundling (EFB): This causes exclusionary features to be safely combined into a single feature, i.e., a set of exclusionary features. The complexity of the histogram construction then decreases, and the speed of the training structure improves without compromising the accuracy of the data. This is due to the fact that high-dimensional data are infrequent, which creates the possibility of an almost lossless reduction in the number of features, particularly when multiple features are mutually exclusive.

3. Results and Discussion

3.1. Models Based on Data Miner Statistica

When working with a problem formulated in this way, the learned ANN directly transforms the input data into output data by extracting the rules linking the output data to the input data during the learning process. This network does not calculate the outputs but estimates them in one pass, hence the more complex data structure. A network with a more complex hidden layer is needed for the estimation of the results.

The best MLP network structure for solving the present task turned out to be a 5-8-1 MLP network, i.e., one with eight neurons in the hidden layer, with all activation functions in the hidden layer (Tanh), and the output layer being exponential (Table 2). This may indicate a significant non-linearity in the relationship between the input and output variables.

Table 2. Activation functions of the best MLP networks for the task described in the paper. The network with the best performance is shown in bold.

Network Structure	Activation Function Type (Hidden Layer)	Activation Function Type (Output Layer)
MLP 5-9-1	logistics	Tanh
MLP 5-9-1	Tanh	Tanh
MLP 5-6-1	Tanh	linear
MLP 5-9-1	logistics	linear
MLP 5-8-1	Tanh	exponential

The correlation coefficient r determined for the MLP network (Table 3) is calculated between the output variable and its prediction conducted by the network. It is a measure of whether the predicted values are consistent with the actual values of the dependent variable. It takes values in the range $<-1; 1>$, where “1” means perfect compliance. The data used in the research are measurement results; they therefore contain a certain amount of metrological noise (also called “dynamic noise”). As such, the correlation coefficient calculated correctly for training cases should not be close to 1 (unless the noise is very weak). In the case of a very high r , one may suspect that the network has been overfitted. This is a basic means of verifying the correct operation of the network. The predictions of an overtrained network will have an inflated correlation coefficient, compared to the values in the training sample. In this case, the network’s prediction for data that it “had not seen before” during training was poor. Therefore, when choosing a network, its quality for the test and validation sets must be taken into account. A low (but not negative) correlation coefficient does not necessarily indicate the poor quality of the network, but it may reflect high noise levels in the data, which the network copes with as well as possible. The correlation coefficient r , which, in this study, oscillates around the values presented in Table 3, indicates that the network has been trained correctly.

Table 3. The MLP network correlation coefficient r for different network structures. The network with the best performance is shown in bold.

Network Structure	Correlation Coefficient r (Learning)	Correlation Coefficient r (Testing)	Correlation Coefficient r (Validation)
MLP 5-9-1	0.537	0.532	0.570
MLP 5-9-1	0.569	0.542	0.567
MLP 5-6-1	0.522	0.505	0.519
MLP 5-9-1	0.528	0.544	0.568
MLP 5-8-1	0.545	0.550	0.555

In order to reliably assess the performance of the models, additional indicators describing their quality should be considered. For regression models, a commonly used measure is R^2 , which is the percentage of variance in the dependent variable explained by the independent variables. R^2 takes values in the range $<0; 1>$, where 1 is the best-fitting value. In some calculation systems, R^2 may be negative, e.g., when the network does not reflect the trend of changes. The R^2 and RMSE values for the best MLP neural networks in the research are presented in Table 4.

Table 4. RMSE and R^2 values for the best MLP neural networks considered in this study. The best solution is bolded.

Network Structure	RMSE	R^2
MLP 5-9-1	1.266	0.298
MLP 5-9-1	1.074	0.312
MLP 5-6-1	0.411	0.265
MLP 5-9-1	0.953	0.298
MLP 5-8-1	0.176	0.302

The root mean square error (RMSE) (also called the root mean square deviation or RMSD) measures the difference between the values predicted by the model and the values observed in the modeled environment. The RMSE is the square root of the squared loss, but it gives greater weight to larger differences. The mean square error is commonly used in forecasting and regression analysis to verify experimental results. It is always non-negative, and the closer its value is to 0, the higher the model's quality. The RMSE is a measure of accuracy used to compare the prediction errors of different models for a given dataset but not between datasets, because it is dependent on scale (order of magnitude). It can therefore be said that it hyperbolizes the errors of the developed models.

The use of a relatively simple and fast MLP artificial neural network is one way of solving the problem with little computational effort and avoiding defining the rules themselves. This can be important in the case of incomplete knowledge of the rules. However, obtaining very good results comes at the price of a long time being spent on the manual tuning of the network; this is because there are more than 60 parameters that can be adjusted for use. Moreover, this process requires considerable experience in adjusting the network parameters to the characteristics of the data. Thus, it is a solution that requires the tire company to have its own IT support department with an experienced engineer who is familiar with AI methods and techniques; this is a rarity on the current job market.

3.2. Models Based on Decision Trees XGBOOST, LightGbmRegression, and FastTreeRegression

The best XGBoost model for the problem discussed in this paper was built with use of the hyperparameters [30] listed below:

- max_depth = 8;
- learning_rate = 0.1;
- n_estimators = 1000;

- objective = “reg:squarederror”;
- booster = “gbtree”.

The values of the metrics assessing the quality of the model obtained in this way are presented in Table 5.

Table 5. Results for the best XGBoost model.

RMSE	R ²
0.1156	0.5182

A key advantage of decision trees is their ability to quickly determine the importance of a given feature for the developed model. XGBoost identified the features’ importance (Figure 7), indicating that the factor with the greatest influence on the conicity prediction (and, indeed, on the value of this quantity describing the uniformity of tires) was the width of TP1. The impact of the other independent variables is approximately 30–45% lower. Moreover, its advantage over the ML.NET library is its ability to precisely analyze the course of calculations in a “step-by-step” manner (similar to MLP) due to the environment it uses. This translates into a better understanding of the principle of operation of the built model.

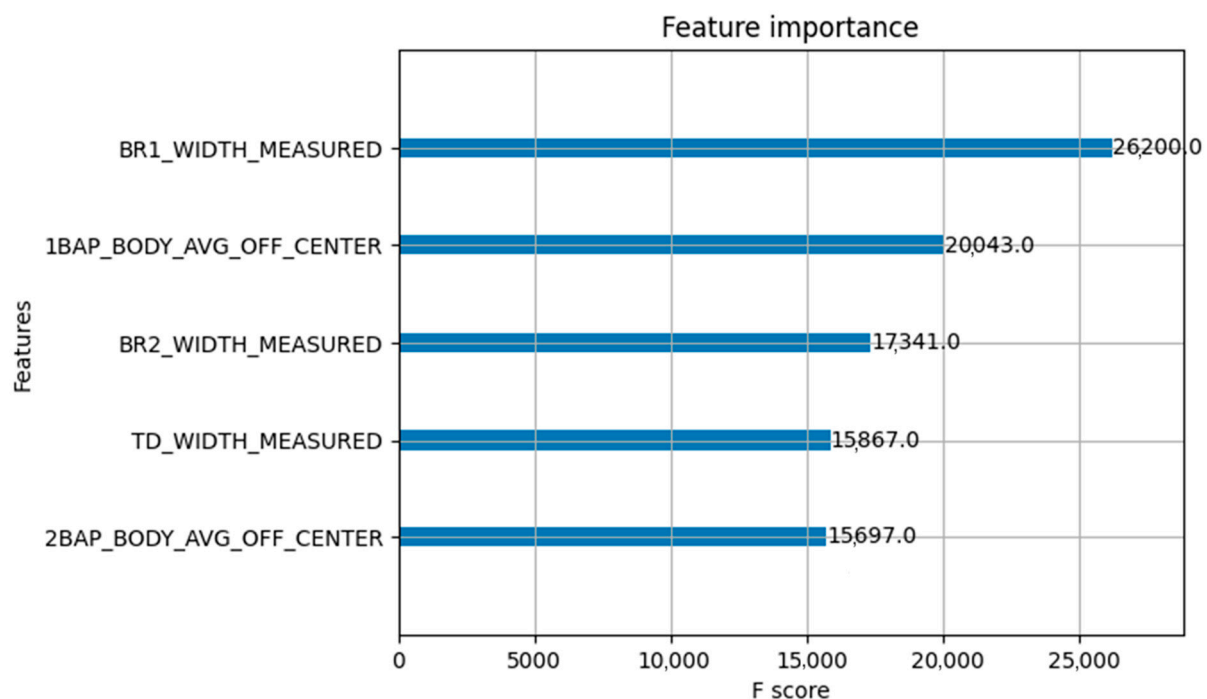


Figure 7. Feature importance of the XGBoost model.

Based on 132 conducted trials, ML.NET identified the two best models for the problem, which are shown in Table 6.

Table 6. Results for the best models explored by ML.NET.

Trial	Trainer	R ²	RMSE
26	FastTreeRegression	0.7163	0.085
24	LightGbmRegression	0.7070	0.086

When selecting the best possible model to solve a given production problem, the possibility of implementing it into the existing IT infrastructure should be considered. It is important to match the required computing power to the hardware used in the enterprise

in question. The expected implementation costs are also important. It is crucial to define the term “accuracy” for each individual case in order to determine the algorithm that will be most suitable for the nature of the problem. Moreover, the response time of the model based on the data received online should guarantee a smooth production process.

In order to effectively predict the length of gas turbine fatigue cracks, the authors of [31] compared multiple linear and polynomial regression, random forest, kernel-based methods, AdaBoost, XGBoost, and artificial neural networks in the context of a small dataset (approximately 30 observations). It transpired that the polynomial regression model was the best model, considering the cross-validation score and the normalized RMSE evaluated against the test set. Nevertheless, it was not sufficiently sensitive to changes in the input parameters. It also underestimated the longest observations, which is a common drawback with the created models. The AdaBoost regression model predicted these cracks with the lowest normalized RMSE. A study discussing the dimensional control of welded stamped steel arms [32] came to similar conclusions. The smallest mean absolute percentage error (MAPE) was achieved for the ANN, and it was noticed that the accuracy of the model increased as the size of the training dataset increased; meanwhile, increasing the number of data has the opposite effect for linear regression. In [33], regression algorithms and neural networks were selected to determine the value of information flow in the production chain model; the comparative criteria were MAE, MSE, RMSE, and R^2 . However, it was noted that the size and nature of the company’s production had a significant impact on the selection of the evaluation factors for the comparative analysis. Another study [34] focused on hybrid forecasting models for manufacturing systems—specifically, in terms of the three manufacturing system areas of production planning, maintenance, and quality control; it confirmed that manufacturing companies are willing to select the right forecasting method for their particular needs. The assessment of the accuracy of the analyzed forecasting methods was based on the average R^2 , which was calculated for each case study separately. Another study, dealing with the reliability prediction of diesel engines [35], compared random forest and MLP; the RMSE is a metric commonly used for the cross-validation procedure.

The results from the models discussed in this paper were compared and contrasted based on the criteria in terms of the performance of the final system. Regarding the different mechanisms of action of the methods used in this study, it was difficult to bring the results to a “common denominator” in order to reliably compare the effectiveness of their operations (the possibility of solving the described problem) and the outcomes obtained. Based on the literature analysis and the authors’ experience in building models based on ANNs, two comparative measures were selected: R^2 and RMSE. The authors emphasized that the selected measures were used to evaluate the generalization abilities of the model. It was decided that the selection of the best possible ML for solving the non-linear regression problem in this case should not be rigidly based only on one metric.

Based on the above-mentioned criteria, it was found that the best solution was the FastTreeRegression model (Table 7), which was characterized by the lowest RMSE (error assessment) and the highest R^2 value (prediction quality assessment). Additionally, this algorithm exhibited significant opportunities for improvement both in terms of functioning and in improving the achieved metric values [36,37].

Table 7. Comparison of the solutions in the research based on the selected criteria.

Model	RMSE	R^2
MLP 5-8-1	0.177	0.3024
XGBoost	0.116	0.5182
LightGbmRegression	0.086	0.7070
FastTreeRegression	0.085	0.7163

In real-world applications, as in our study, R^2 values exceeding 0.7 indicate a strong influence on the dependent variable. We tested various model solutions, and none of them resulted in a significant improvement in this respect; this means that intervention is

required in the data rather than in the model itself. Admittedly, R^2 can be increased by, for example, adding appropriate variables to the model, as additional variables introduce more flexibility into the model; this allows it to capture noise and random fluctuations in the data. However, R^2 can also be increased by improving the quality of the data, which we intend to test in the further development stages of our system. However, this is difficult in real-time systems, as the preprocessing and initial data selection take up valuable computational time. As such, compromises often have to be made.

4. Conclusions

This research was a continuation of the work started in [38]. The developments presented in this article are the basis for new knowledge in the field of the computational analysis of industrial data in the tire industry (both big data and small datasets) with the required accuracy and efficiency, creating the best fit components of complex systems (including computational models). These findings will be used in the further stages of our research, including building and testing prototypes of algorithms and systems in laboratory conditions and making improvements and corrections to them, maximizing the end result in industrial conditions. In the context of an industrial, commercialized solution, this will allow for an effective transition from TRL = 2–3 to TRL = 6. It will also allow for better harmonization and the interoperability of the proposed solutions with those already available on the market.

In regression networks, the RMSE should not be automatically chosen as the only cost function, because the results may not be the most beneficial from a business, risk management, or other relevant perspective. A custom cost function (or a group of metrics) better reflects the requirements of the specific enterprise and may favor certain solutions. The structure of an error/accuracy interpretation (benchmarking) drives the form and capabilities of the model.

The analyzed dataset was not obtained during an experiment; instead, it was generated from components that are used in the industrial environment under variable operating conditions. The main challenge when implementing the described model in factory settings involves defining the criteria used to verify the quality of its prediction abilities, because this will be the main basis for making decisions about rejecting a defective green tire. Every single incorrect decision in this case is equivalent to the loss of the cost of producing one tire. Therefore, it will be necessary to constantly adjust the hyperparameters and train the obtained model. In order to implement the best possible tool supporting the mass production of tires, our future research will focus on assessing the work of the model in various (local) weather conditions, considering factors such as the air temperature and humidity in the production hall and the temperature of tire components applied on a TAM (tire assembly machine). Measurements of these parameters are now recorded during mass production and will be correlated with the dependent variable (CON) in further research. The literature analysis shows that it is necessary to conduct research on a broader dataset for the best possible fitting of the model in the business environment. This will minimize the error (RMSE) and improve the prediction skill (R^2) of the developed model. The expansion of the research will include the analysis of historical data on more tire sizes. This will verify the quality of the model's operations, which will likely affect the final structure of the model and the values of its parameters.

A further advantage of the developed model, which makes it suitable for use in the mass production of tires, is its immediate response to the (out of range) values of the input variables. This feature can facilitate the immediate withdrawal of batches of faulty tire components, minimize material losses, and speed up the investigation of root causes of faults arising during the production process (leading to the elimination of time loss). The modifications of the machine settings suggested by the model in conjunction with expert verification can therefore stop a defective product (e.g., a green tire) from progressing to the next stages of the production process, facilitating the elimination of scrap. The developed solution will contribute to reducing the amount of tire waste by eliminating

pieces of products that do not meet the quality requirements during the earlier stages of the production process. It will be possible to carry out the appropriate tire disposal measures immediately after the tire assembly process (i.e., a defective raw tire will not be subjected to the vulcanization process), reducing the costs associated with scrap. Furthermore, the described solution can potentially be implemented in any company that produces radial tires for passenger cars, provided that it has the ability to register the input and output variables described in this article.

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