

## Effectiveness of computer-based tyre modelling tools based on an embedded telemetry controller

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**Abstract.** This study aimed to analyse key aspects of wheeled vehicle dynamics and to assess the effectiveness of modern computer modelling techniques in the vehicle design process. The research focused on the main parameters influencing tyre performance, including forces, moments, slip angle, vertical load, and their interrelations. The use of modelling was justified as a means of ensuring the required levels of grip, handling, and ride comfort during vehicle operation. Existing tyre models were classified into empirical, semi-empirical, and physical types, with a comparative analysis presented to highlight the advantages and limitations of each. Particular attention was given to the Magic Formula tyre model, which is widely used to characterise tyre behaviour. The study outlined the application of this formula in developing approximate mathematical models through curve-fitting methods, enabling accurate representation of tyre performance under various operating conditions. The research also examined current trends in tyre model development involving machine learning techniques, which facilitate parameter optimisation and improve modelling accuracy. It was demonstrated that the integrated use of machine learning and computer modelling methods can enhance tyre product development and support the creation of innovative solutions in the field of wheeled vehicles. The practical value of the research lies in the potential application of the proposed approaches to improve the dynamic characteristics of vehicles and other wheeled machinery, thereby reducing the need for costly field testing

**Keywords:** computer modelling; wheeled vehicle dynamics; tyre models; Magic Formula tyre model; machine learning

### Introduction

The rapid development of the automotive industry and the growing demands for tyre safety and performance necessitate the use of advanced research methods. Computer modelling significantly reduces the cost of experimental testing, accelerates the development process, and improves the accuracy of tyre performance analysis. The advancement of precise heuristic models enables the simulation of vehicle behaviour in response to driver actions, particularly in preparation for racing or when driving under extreme conditions. Tyres represent one of the most critical components of wheeled vehicles, as they provide the essential contact between the vehicle and the road surface, directly influencing safety and handling.

Modern research in computer modelling and wheeled vehicle dynamics has seen the active integration of machine learning and deep learning methods for modelling tasks, wear prediction, and the enhancement of vehicle control efficiency. A review of scientific publications reveals growing interest in the application of artificial intelligence in the tyre industry. In a study by J.L. Olazagoitia *et al.* (2020), artificial neural networks were proposed for determining the parameters of tyre models. The authors demonstrated that neural networks can accurately approximate complex non-linear relationships between input data (e.g. load, slip angle) and tyre output characteristics, such as friction

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force and resisting torque. This approach considerably reduces the need for experimental testing.

D. Stocco *et al.* (2024) proposed a physically grounded yet simplified tyre model suitable for realtime application. The main advantage of this model lies in its ability to maintain a balance between accuracy and computational speed, making it particularly useful for interactive simulations in transport systems. K. Singh *et al.* (2019) conducted a comprehensive review of machine learning (ML) applications in the tyre industry. Key areas identified include tyre wear prediction, quality control, and the development of intelligent systems. The authors emphasised the importance of processing large volumes of data to improve decision-making efficiency.

In the study by L.C. Sousa & V. Hultmann (2022), the authors explored the substitution of a complex non-linear physical model with an ML-based approximation to predict vehicle behaviour. The proposed solution proved effective in real-time scenarios without significant loss of accuracy, paving the way for the implementation of ML in autonomous control systems. N. Xu *et al.* (2020) introduced an intelligent tyre system equipped with embedded accelerometers to collect data on the contact patch dynamics. Machine learning was employed to evaluate acting forces in real time, enabling the development of highly accurate adaptive control systems. It is also worth noting the development of a comprehensive ML-based system for predicting the remaining service life of commercial vehicle tyres (Karkaria *et al.*, 2024). The model is based on telemetry data and simulations, allowing for process optimisation and reduced maintenance costs.

Advancements in machine learning have opened up new opportunities for optimising tyre models. The use of artificial intelligence algorithms enables the analysis of large volumes of data, the adaptation of models to real-world operating conditions, and the prediction of tyre behaviour in complex scenarios. To ensure accurate correlation between model data and physical tyres, test data obtained from real-world trials are essential. Therefore, the use of specialised computer-based tools for collecting information on tyre behaviour is crucial in the development of tyre models. This research aimed to analyse modern computer-based tools for tyre modelling, assess their capabilities and areas of application, identify the advantages and limitations of these tools, and evaluate their effectiveness and future prospects for improving tyre performance and optimising production processes.

This was a theoretical study based on the analysis of published test results and experiments dedicated to the selection of parameters for automotive tyre models. The research involved a systematic review of scientific publications in the fields of wheeled vehicle dynamics and computer engineering, containing data on tyre characteristics, testing conditions, as well as the outcomes of modelling and practical testing. The sources included peer-reviewed journal articles, conference proceedings, and open-access scientific databases (MDPI, Scopus), published up to 2024. The study was conducted in several stages. Initially,

relevant sources containing detailed information on the physical and mechanical properties of tyres and their testing conditions were selected. The collected data were classified according to the types of tyre models used in wheeled vehicle dynamics, specifically distinguishing between empirical, semi-empirical, and physically based models. A comparative table of tyre models was compiled to provide a visual summary of the findings. This analysis made it possible to understand the advantages and limitations of each model type in relation to requirements for accuracy, computational speed, and application domain. An analysis was carried out on the machine learning methods employed in the reviewed studies to model tyre behaviour. The review of heuristic model parameter selection methods focused on techniques for adjusting parameters through the approximation of experimental data. Particular attention was given to methods that demonstrated high accuracy in modelling parameters such as braking distance, grip coefficient, wear rate, and energy efficiency. The strengths and weaknesses of linear and non-linear models, ensemble methods, and neural networks were also evaluated.

Additionally, the study examined devices used for recording and reading vehicle telemetry data, along with methods for collecting dynamic information from the vehicle. This included the analysis of telemetry packet structures, data exchange formats, techniques for data acquisition using appropriate equipment, and the subsequent application of the collected data in analysis, modelling, and algorithm training processes. In summary, the research was based on a synthesis of existing scientific and practical knowledge, aiming to establish a unified approach to modelling tyre efficiency using machine learning methods.

### **Key aspects and parameters of wheeled vehicle dynamics for modelling**

Computer modelling is an essential tool in the development and optimisation of vehicles, particularly in addressing critical aspects such as traction and handling. Its relevance lies in the ability to test various design solutions and operating modes without the need to produce costly physical prototypes. This enables engineers to iteratively refine vehicle characteristics, predicting performance across a wide range of conditions – from everyday driving to extreme scenarios. Modelling allows for the analysis of tyre-road interaction, optimisation of suspension and steering systems, and evaluation of the influence of different factors (such as speed, load, and road surface conditions). This approach significantly accelerates the development process, reduces costs, and enhances vehicle safety and efficiency before the vehicle is ever driven on the road.

Vehicle dynamics is an engineering discipline concerned with the movement of vehicles in response to driver inputs and environmental conditions such as air temperature, humidity, and wind direction. As the broader field of dynamics includes not only motorised wheeled vehicles but also aircraft and watercraft, the term “wheeled vehicle dynamics” is used here to specifically refer to vehicles that

maintain contact with the ground through rubber tyres. Wheeled vehicle dynamics explores the effects of numerous physical phenomena associated with vehicle motion and encompasses a wide range of aspects – from mechanical systems to advanced safety and performance technologies.

The following key aspects are identified:

1. Handling, which defines how the vehicle responds to driver commands to change direction and how stable the wheelbase remains while cornering. Handling is directly influenced by suspension settings, wheel geometry, weight distribution, and the mechanical grip of the tyres on the road surface.

2. Traction characteristics, which are defined by the grip of the tyres on the road, are measured through the coefficient of friction depending on the road surface type and weather conditions.

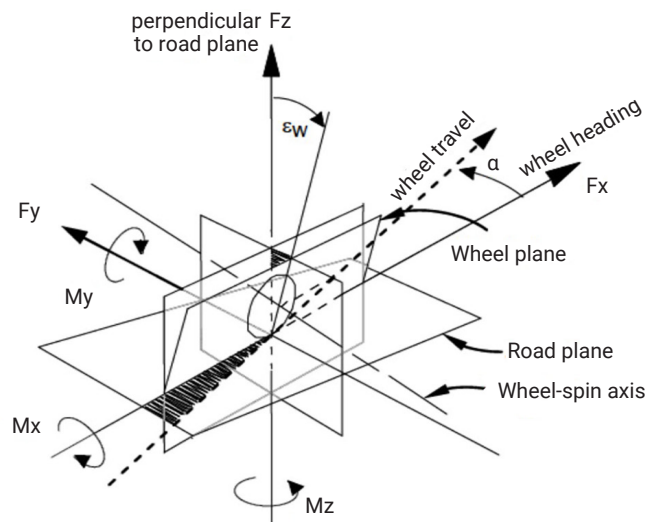
3. Suspension performance, determined by the operation of the suspension system that connects the wheels to the vehicle body and ensures stability when driving over uneven surfaces. Suspension settings can be adjusted by altering the stiffness of the springs.

4. Braking system, which primarily determines the vehicle's ability to stop, but also affects handling and stability

due to weight transfer during braking. The distribution of braking force between the front and rear wheels directly impacts tyre grip on the road surface.

5. Wheel mechanics, which define the geometry of the wheels in relation to the road surface (camber) and to the vehicle (toe angle). The combination of these settings significantly affects the tyre-road contact patch, which in turn influences mechanical grip, tyre temperature, and the rate of rubber wear.

As the grip between tyres and the road surface is the primary force enabling vehicle movement and manoeuvring, accurately representing traction in models is a key priority. Other aspects of wheeled vehicle dynamics influence tyre performance and must therefore be taken into account to ensure high accuracy in computer simulations. The interaction between a vehicle and the road – including handling, stability, comfort, and safety – largely depends on tyre behaviour, which is the main focus of modelling. A vehicle tyre is most effectively described using its own coordinate system, illustrated in Figure 1. The wheel is subjected to three forces and three moments. Additional variables, such as slip angle  $\alpha$  and camber angle  $\epsilon_w$ , also influence vehicle behaviour.



**Figure 1.** Tyre coordinate system, forces, and torques

**Note:**  $F_x$  – longitudinal forces,  $F_y$  – lateral forces,  $F_z$  – vertical force,  $M_x$  – rolling moment,  $M_y$  – rolling resistance moment,  $M_z$  – aligning torque,  $\alpha$  – slip angle,  $\epsilon_w$  – camber angle

**Source:** B. Jacobson *et al.* (2016)

From the perspective of vehicle motion, tyres are responsible for carrying vertical loads, generating longitudinal (braking and traction) and lateral (steering) forces, enabling movement with minimal energy loss, minimising tyre wear and particulate emissions, and maintaining a moderate noise level.

### Modelling and simulation

#### in wheeled vehicle dynamics: Tyre model architecture

As testing all possible parameter combinations would require considerable time and resources, engineers rely on

mathematical models and computer simulations to predict vehicle behaviour under a variety of conditions. This approach enables the precise calibration of all systems without the need for additional on-road testing sessions. Figure 2 shows a tyre model for each wheel and its integration into a broader model of the vehicle, driver, and environment. It is important to distinguish between parameters and variables in the model, as tyre modelling involves the use of dynamic models to simulate processes. Within each simulation, parameters remain constant, while variables change over time (Jacobson *et al.*, 2016).

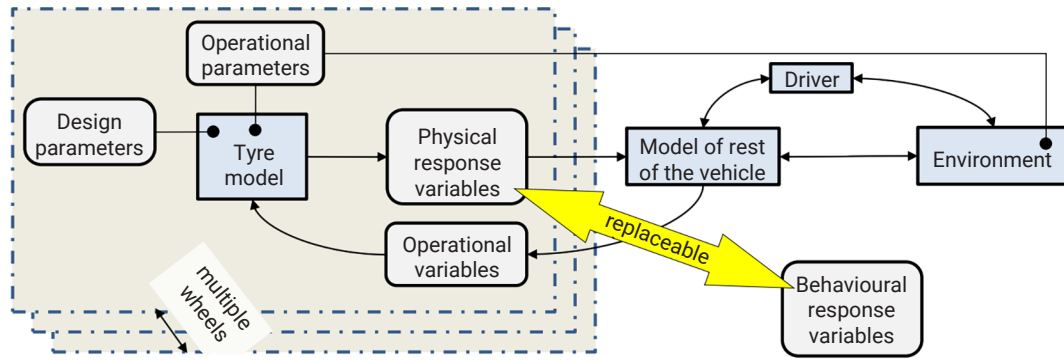


Figure 2. Tyre model architecture

Source: B. Jacobson *et al.* (2016)

Operating variables are the changing operating conditions illustrated in Figure 2 that vary throughout a single driving cycle. Examples of operating variables include longitudinal speed, tyre slip ratio, camber and toe angles, and the vertical load acting on the tyre, as shown in Figure 1. The vertical force on the tyre can either be modelled as a time-dependent function or as a displacement amplitude across different frequencies, where displacement refers to the deviation from the mean value. In the latter case, the mean value would be considered a parameter rather than a variable. The latter approach may be more efficient when simulating extended driving cycles, where tracking every wave-like fluctuation would be computationally inefficient. The physical response variables are transmitted from the tyre model to the vehicle model and consist of forces and moments, as illustrated in Figure 1. These include longitudinal  $F_x$  and lateral forces  $F_y$ , rolling moment  $M_x$ , rolling resistance moment  $M_y$ , and aligning torque  $M_z$ .

Design parameters, selected by engineers during the tyre development process, include the properties of the rubber compound, the number of rubber layers, and the tyre dimensions – such as the outer radius, width, and aspect ratio (width-to-height). Tyre pressure is also a key parameter. Design parameters additionally encompass tread pattern, tread depth, and groove design. Tread-related parameters are particularly important for understanding tyre behaviour under challenging conditions such as rain or snow. Operational parameters change relatively slowly and are therefore considered constant throughout a single driving cycle. These include the type of road surface (e.g. asphalt or gravel), its condition (dry, wet, snowy, or icy), the degree of tyre wear, the tyre’s service age, as well as environmental temperature and humidity.

Behavioural response variables may be modelled as behavioural rather than physical variables. The choice depends on the purpose of the simulation and the type of model being used. Such variables include slip characteristics, rolling resistance coefficient, vertical stiffness, and damping coefficients. When using behavioural rather than physical variables, the variables act as model coefficients rather than measurable physical quantities. A model

coefficient requires a consistent model for correct interpretation, whereas a physical quantity does not.

Slip angle is a key indicator of tyre orientation in vehicle dynamics. It is shown in Figure 3 and defined as the angle between the velocity vector  $v$  and the  $x$ -axis, measured around the  $z$ -axis. From a tyre modelling perspective, the slip angle is a variable that determines the magnitude of the forces acting on the wheel.

The set of forces generated through tyre–road contact is considered to act at the centre of the contact patch. The interaction between the tyre and the road surface generates a system of forces comprising three forces and three moments, as illustrated in Figure 3:

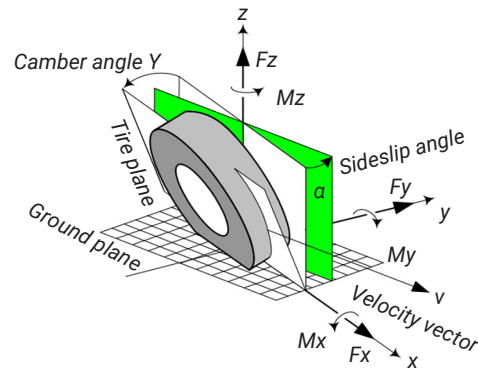


Figure 3. Slip angle in the tyre coordinate system

Note:  $F_x$  – longitudinal forces,  $F_y$  – lateral forces,  $F_z$  – vertical force,  $M_x$  – rolling moment,  $M_y$  – rolling resistance moment,  $M_z$  – aligning torque,  $\alpha$  – slip angle,  $\gamma$  – camber angle

Source: B. Jacobson *et al.* (2016)

1. Longitudinal force  $F_x$  – the force acting along the  $x$ -axis.  $F_x > 0$  when the vehicle is accelerating, and  $F_x < 0$  when braking.
2. Normal force  $F_z$  – the vertical force. The resulting normal force  $F_z > 0$  when directed upwards. This force is also referred to as the wheel load.
3. Lateral force  $F_y$  – the force tangent to the road surface and orthogonal to both  $F_x$  and  $F_z$ . The resulting lateral force  $F_y > 0$  when directed along the  $y$ -axis.

Thus, at the tyre-road contact point, a system of forces and moments arises that defines the vehicle’s dynamic

behaviour. The longitudinal force governs acceleration and braking, the normal force represents the vertical load response and determines potential grip, while the lateral force resists sideways slip. The interaction among these three forces is essential for understanding how forces are transmitted between the wheel and the road, and for further modelling of vehicle motion.

**Main approaches to tyre behaviour modelling**

Historically, most tyre models have been developed for specific purposes, with varying levels of complexity and accuracy. This has led to the emergence of different modelling approaches. A model may be designed either for use in real-world experiments or based on the theoretical understanding of the tyre’s physical structure. Some models are relatively simple but less accurate (Gillespie, 1994). In general, existing tyre models can be categorised into four groups: 1) empirical, 2) semi-empirical, 3) based on simplified physical models, and 4) based on complex physical models.

Empirical models are mathematical representations of tyres that describe measured tyre characteristics using look-up tables, mathematical formulas, and interpolation schemes. These formulas follow a defined structure and contain parameters typically estimated through regression procedures to best fit the measured data. A well-known empirical model is the Magic Formula Tyre Model. Semi-empirical models, such as those developed using the method of similarity, rely on a set of characteristics usually derived from experimental data. By applying deformation, scaling, and multiplication, new relationships are generated to describe specific conditions. This approach is particularly useful for implementation in simulation models of wheeled vehicles where rapid computation is required.

The relatively simple physical models of the third category, such as the brush model, are particularly valuable for gaining a clearer understanding of tyre behaviour. These models offer a simplified yet effective means of analysing tyre-road interaction, allowing for the rapid assessment of key dynamic characteristics without excessive computational complexity. They serve as a foundation for basic simulations and are especially suitable during the early stages of model development. The final category includes models aimed primarily at a more detailed analysis of tyre behaviour. For instance, complex models based on the finite element method fall into this group. These models enable highly accurate simulation of the tyre’s internal structure, stress and strain distribution, and the complex nonlinear effects that arise during operation. They allow for in-depth investigation of thermal conditions, wear resistance, and other physical phenomena that are critical for optimising tyre characteristics at the micro level.

**Empirical tyre models.** Developing physical models that accurately reflect the principles by which forces act on tyres is a complex and time-consuming task. This process can be optimised by employing empirical models. To reduce the number of parameters requiring calibration, curve-fitting techniques are often used, applying trigonometric and

exponential functions. Such models can be applied to various types of data with similar properties, and therefore are useful for describing tyre behaviour under load.

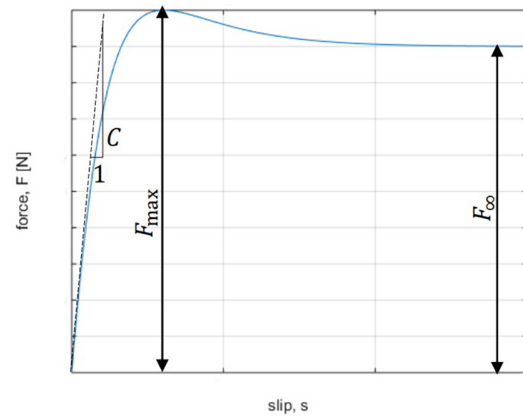
There are numerous heuristic models with varying degrees of curve approximation to experimental data. The simplest option is a linear approximation:

$$F_x = C_x \cdot s_x, \tag{1}$$

where  $F_x$  is the longitudinal force generated in the tyre-road contact area,  $C_x$  is the stiffness coefficient, and  $s_x$  is the degree of longitudinal slip.

This model assumes that the force  $F_x$  is proportional to the slip ratio, and the proportionality coefficient  $C_x$  reflects the tyre’s resistance to deformation under slip. This type of approximation is linear and suitable for small values of  $s_x$ , where tyre behaviour remains within the linear range.

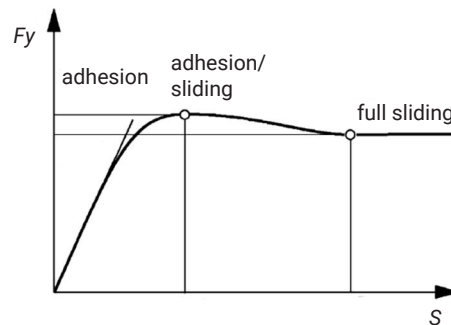
TMsimple and TMeasy are two heuristic curve approximation models. The TMsimple model is shown in Figure 4, and the TMeasy model in Figure 5. TMsimple is a simplified version of TMeasy. For example, TMsimple does not allow the specification of a maximum force at a given slip level. Additionally, TMsimple considers only forces and does not account for moments acting on the tyre. The TMeasy model is described in the study by W. Hirschberg *et al.* (2007).



**Figure 4.** TMsimple model

**Note:**  $C_x$  is the stiffness coefficient,  $F_{max}$  is the force at the onset of slip,  $F_{\infty}$  is the force at loss of grip

**Source:** C. Lex (2015)



**Figure 5.** TMeasy model

**Note:**  $F_y$  is the lateral force,  $s$  is the slip value

**Source:** W. Hirschberg *et al.*(2007)

The choice between TMsimple and TMeasy depends on the trade-off between required modelling accuracy and computational efficiency. TMsimple is generally used for preliminary analysis or when computation speed is a priority, whereas TMeasy offers higher accuracy at the cost of increased computational demand. The selection of a particular model is guided by task requirements, available resources, and the acceptable level of error in the results.

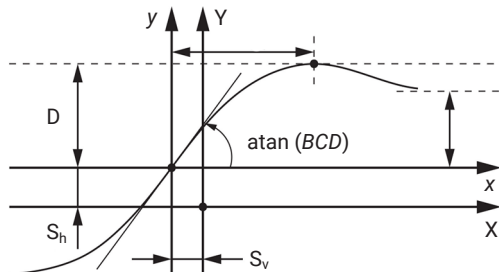
The most well-known empirical model is the Magic Formula, proposed by H.B. Pacejka (2007). This approach uses trigonometric functions to fit experimental data. The formula can be expressed as follows:

$$F = y(x) = D \cdot \sin(C \cdot \arctan(B \cdot x - E \cdot (B \cdot x - \arctan(B \cdot x)))) \tag{2}$$

$$Y(x) = y(x) + S_v \tag{3}$$

$$\text{Slip} = x = X + X_{H_p} \tag{4}$$

where  $B$  is the stiffness factor,  $C$  is the shape factor,  $D$  is the peak value factor, and  $E$  is the curvature factor describing the shape of the curve. The variable  $x$  is the slip angle (or longitudinal slip ratio).  $F$  is the longitudinal or lateral force, depending on the tyre's orientation. Additional parameters,  $S_v$  and  $S_{H_p}$  are used to shift the curve horizontally and vertically, ensuring that it passes through the origin. The relationship between these parameters and the slip/friction characteristics of the tyre is illustrated in Figure 6.



**Figure 6.** The Magic Formula tyre model in the coordinate plane

**Note:** X-axis is the slip angle, Y-axis is the normalised lateral force,  $B, C, D$  are the stiffness, shape, and peak value parameters, respectively,  $S_v$  is the horizontal shift,  $S_H$  is the vertical shift

**Source:** H.B. Pacejka (2007)

The name Magic Formula reflects the fact that the model has no direct physical derivation. Instead, it is the result of carefully selected mathematical expressions that best approximate the tyre's experimentally observed behaviour. The key idea behind the formula is to represent the longitudinal force  $F_x$ , lateral force  $F_y$ , and aligning moment  $M_z$  as functions of longitudinal slip  $s_x$ , slip angle  $\alpha$ , vertical load, and other parameters that capture the specific characteristics of the tyre. Each of the three output quantities –  $F_x, F_y, M_z$  – is calculated using a similar core formula, but with a distinct set of coefficients that are themselves functions of the vertical load.

The approximation of tyre characteristics using the Magic Formula begins with experimental measurements. Tyres are tested on specialised rigs under various slip conditions – both longitudinal and lateral – and at different levels of vertical load. During these tests, the corresponding longitudinal and lateral forces are recorded. For each characteristic, a baseline functional relationship is selected. The values of the coefficients  $B, C, D, E, V$ , along with their dependence on vertical load, are then adjusted so that the curve generated by the Magic Formula tyre model closely matches the experimental data. This process employs a range of curve-fitting techniques. One commonly used method is the least squares method, which minimises the sum of squared differences between the measured values and those calculated using the Magic Formula. In addition, optimisation algorithms, such as genetic algorithms, are often applied. These iteratively modify the coefficients to achieve the best possible alignment with the empirical data.

After determining the optimal coefficient values for various fixed vertical load values, approximating functions are constructed to describe the dependence of each coefficient on  $F_z$ . This enables the model to predict tyre behaviour across a continuous range of vertical loads within the tested interval. The final model, with its defined coefficients, is then validated by comparing its predictions with experimental data not used during the approximation stage. This ensures that the model's accuracy is assessed using independent data sets.

The use of the Magic Formula in tyre modelling offers both advantages and limitations. One of its key strengths lies in its high approximation accuracy, as it aligns closely with experimentally measured tyre characteristics across a broad range of operating conditions. The model is defined by a relatively small set of coefficients, which makes it convenient for use in computer simulations. Although the formula lacks a direct physical derivation, its empirical nature allows it to effectively capture the complex, nonlinear behaviour of tyres – something that is difficult to achieve through purely theoretical methods. However, the absence of physical meaning behind the model's coefficients also presents a drawback: it complicates the prediction of these parameters when simulating new tyres that have not been previously tested. In practice, this limitation is often mitigated by design inheritance, as manufacturers typically build on earlier developments when designing new tyres. Another disadvantage is the difficulty in extrapolating the model's predictions beyond the range of the original test conditions.

**Semi-empirical tyre models.** This category includes models specifically developed to represent the tyre as a component of wheeled vehicles within vehicle simulation environments. The modelling approach is termed semi-empirical because, although the models are based on measured data, they may incorporate structures that are rooted in physical modelling. Prior to the development of semi-empirical models, various types of mathematical functions were used to describe lateral grip force characteristics. However, these often yielded only coarse approximations

of the data. To improve accuracy, tables of measured data points were employed alongside interpolation schemes.

Significant progress in tyre modelling has been achieved through the introduction of the similarity method. This approach, proposed by E. Bakker *et al.* (1987), is used to simplify and model tyre behaviour under various conditions by relying on the concept of similarity to known (reference) conditions. The method employs empirical data from tyre testing to construct a reference model, which is then adjusted to simulate a range of real-world scenarios. This enables the application of simple mathematical operations to modify tyre characteristics according to different loading parameters.

Tyre models have been applied across various fields. Their most widespread use is in the automotive industry, particularly in the development of new tyres. Tyre manufacturers use these models to test prototypes, while vehicle manufacturers rely on them to predict vehicle behaviour, traction, stability, and durability. Crash testing and safety studies also depend on tyre models to analyse vehicle response during emergency braking or cornering situations (Rajamani, 2006). Motorsport represents a segment of the automotive industry that provides opportunities to experiment with tyre models under more predictable conditions, such as fixed track layouts and known weather patterns (Beckman, 1991). Although models developed for racing applications may not always be suitable for conventional road use, innovations in tyre design introduced through motorsport can often be transferred to commercial vehicles.

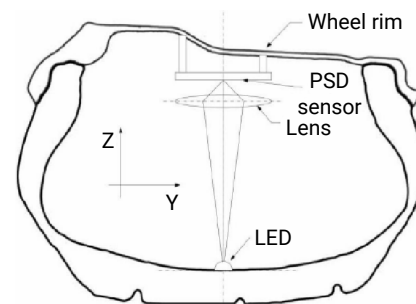
Another promising area for the application of tyre models is the simulation of various road conditions and the behaviour of wheeled vehicles. This involves the use of a virtual environment designed in accordance with the simulation objectives. Examples of such environments include automotive and racing simulators, which are used both to improve driving skills and to predict vehicle performance under specific driving strategies. For instance, when completing a racing lap, a balance must be maintained between cornering speed and tyre temperature, as excessive heating can degrade the vehicle's dynamic performance. Given the high costs associated with motorsport, simulator testing using realistic tyre models significantly reduces the risk of dangerous situations. Tyre wear models for heavy-duty vehicles also play an important role in the logistics sector, helping to forecast tyre condition and estimate maintenance costs for commercial fleets.

### Specialised computer tools for obtaining test data

The development of a tyre model requires a substantial volume of test data, which can be collected from vehicles operating under real-world conditions. The task of acquiring test data on the forces acting on a tyre can be divided into two components: data collection from the tyre itself and the storage of this information for further analysis. To measure the forces acting on a tyre in real time, strain gauge sensors are used. These sensors are embedded into the tyre or wheel to record deformations occurring during motion, allowing

accurate determination of the forces affecting the tyre under actual operating conditions. A strain gauge sensor operates on the principle of changes in the electrical resistance of a conductor under mechanical deformation. When a force is applied to a tyre, it alters its shape, as does the attached strain gauge sensor, which deforms accordingly. The sensor's strain-resistive element consists of a thin wire or foil, whose resistance varies under tension or compression (Tuononen, 2009). This change in resistance is registered by an electronic circuit, such as a Wheatstone bridge (Wheatstone, 1843), which converts it into a voltage signal. The signal is then processed by a microprocessor to determine the force responsible for the deformation. In this way, strain gauge sensors make it possible to measure the mechanical loads acting on the tyre during motion.

Optical deformation sensors, which monitor changes in tyre shape under load, are also commonly used. The operating principle of an optical sensor is illustrated in Figure 7. A light-emitting diode (LED) is affixed to the tyre's inner liner. A lens focuses the infrared light emitted by the LED and directs it onto a position-sensitive detector (PSD). The position of the light spot on the PSD, relative to its current state, is used to determine the measured data (Tuononen, 2009).

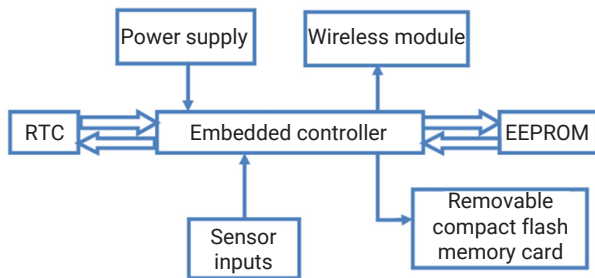


**Figure 7.** Operating principle of an optical sensor  
Source: A.J. Tuononen (2008)

A common issue when processing data from physical sensors on a moving vehicle is the presence of vibrations, which introduce noise into the signal. The measurement of forces acting on the tyre is no exception. Interference resistance of measuring instruments during vehicle motion is critically important, as vibrations, impacts, and electromagnetic disturbances can significantly affect measurement accuracy. The simplest way to mitigate interference is mechanical vibration filtering through the use of damping materials within the sensors. However, electronic filtering using low-pass filters to suppress signal oscillations and calculate average signal values over a set time interval is a more versatile solution, as it does not require modifications to the measuring instruments. Electronic filtering can be implemented either at the hardware level or applied post-ride during data processing.

The collected data are stored using specialised computer systems. These systems are developed separately, taking into account the requirements of the testing

environment, such as data frequency and volume. Figure 8 shows a diagram of the interaction between components in a standard automotive telemetry system.



**Figure 8.** Standard automotive telemetry system

Source: J.R. Chandiramani *et al.* (2014)

In the diagram above, sensors transmit data to an embedded controller, which is designed to process signals and convert analogue inputs into digital form. A Real-Time Clock (RTC) module is used to timestamp the data for recording into a log file, which is stored on a removable data carrier (Chandiramani *et al.*, 2014). The log file format is predetermined according to the requirements for data storage. Existing formats are generally classified as either text-based or binary. Comma-Separated Values (CSV), Controller Area Network (CAN), and Data Logging Configuration (DLC) formats enable data analysis without the need for additional software, as they are stored in plain text. However, they require the recording of additional service information (such as delimiters, keys, and time stamps). In contrast, binary formats, such as Measurement Data Format (MDF), require dedicated reading tools but support the creation of hierarchical multi-channel systems. Since tyre sensors may operate at different frequencies, data from each sensor are recorded as a separate data channel with individual attributes, which are stored as channel metadata. As the most widely used format in the automotive industry, MDF provides lossless data compression and indexing, enabling efficient file access and rapid search capabilities.

However, saving to an MDF file is most effective when handling large volumes of data. Its complex multi-channel structure increases the likelihood of errors during the writing or reading processes. Therefore, alternative log file formats – less common in the automotive sector – should be considered for tyre data collection. One such format is European Data Format (EDF). This is a binary file format designed for storing multi-channel biosignals such as electroencephalogram (EEG), electrocardiogram (ECG), and other physiological signals (Kemp & Olivan, 2003).

The structure of an EDF file is considerably simpler than that of an MDF. Metadata such as the date and time of the recording start, the number of channels, signal names, data sampling frequency, and scaling coefficients are written first. This is followed by signal data recorded in binary format, with the selected sampling rate applied individually to each data channel. The extended version, EDF+, allows for the insertion of annotations at any point

during the recording, as well as support for variable-length records. A significant limitation of both EDF and EDF+ formats is the inability to append data once the file has been closed. Since this format is predominantly used in the medical field – where the recording duration is usually known in advance – this constraint has not posed a serious issue. However, in applications involving wheeled vehicle dynamics, the duration of a test drive cannot always be predicted beforehand.

Modifying the EDF+ format to allow data to be appended after the file has been closed could address this issue and broaden its range of applications. This would enable a one-to-one correspondence between a vehicle test session and a single generated log file, eliminating the need to later merge multiple files. Such a modification would simplify the data collection process while also reducing the risk of errors during post-processing.

### The evolution of modelling methods and machine learning approaches for parameter identification

Empirical and semi-empirical models can be considered relatively simple compared to physical tyre models, which require numerous parameters that vary over time at high frequency. However, the task of identifying the parameters of an empirical model is not trivial. For example, when using the Magic Formula tyre model (2), the modelling parameters  $B$ ,  $C$ ,  $D$ , and  $E$  must be selected in such a way that the correlation between the model's outputs and the values obtained from physical experiments does not exceed the acceptable margin of error. Parameter selection is critical to successful model construction. The task of determining the parameters of an empirical tyre model is complex and may depend on several factors, including the number of model parameters, the computational speed, and the accuracy of data correlation.

Historically, the process of selecting parameters for empirical tyre models has undergone several stages of development, in parallel with advances in the computational power of computer systems. In the early stages of computer modelling, parameters were selected by engineers based on their experience and through iterative trial and error, visually assessing the fit between approximated curves and experimental data. Later, simple optimisation algorithms such as the Gauss-Newton method (Gratton *et al.*, 2007) or the least squares method were introduced. These required the engineer to provide initial parameter estimates. With the advancement of computational technologies, more sophisticated and efficient optimisation algorithms became widely used, including the Levenberg-Marquardt algorithm, the conjugate gradient method, and evolutionary approaches such as genetic algorithms. These methods enabled the automation of the parameter selection process by minimising the error between modelled and experimental data, while significantly reducing dependence on the initial parameter estimates.

A current trend in tyre model parameter selection is the application of multi-objective optimisation (Li, 2025).

In real-world parameter fitting tasks, it is often necessary to simultaneously optimise several criteria – for instance, longitudinal and lateral force accuracy, computational speed, and the robustness of parameters to noise in experimental data. Multi-objective optimisation methods make it possible to identify compromise solutions that best satisfy all these requirements. There is also increasing reliance on technologies for storing, transmitting and processing large volumes of data. As the amount of experimental data collected by tyre manufacturers and research organisations grows, it becomes possible to apply big data analysis techniques to identify patterns and develop more generalised and accurate models.

Physics-informed machine learning (Karniadakis *et al.*, 2021) combines the strengths of machine learning with existing physical knowledge about tyre behaviour. Instead of relying entirely on empirical data, physical constraints and equations can be integrated into the machine learning training process. This enables the development of models that are more physically grounded and generalisable. In practice, the task can be formulated as the identification of model parameters that minimise computational error.

These characteristics of parameter identification highlight the relevance and suitability of machine learning methods for tyre modelling. The advantages of using machine learning methods include:

- ✔ the ability to process large volumes of data (i.e. real tyre characteristics on which the model is based);
- ✔ automatic identification of optimal parameters, provided the tools are appropriately configured;
- ✔ flexibility in the choice of optimisation methods;
- ✔ robustness to data noise through the application of regularisation techniques, which enhance model generalisation;
- ✔ an iterative training approach, gradually improving parameters at each step.

Since the identification of tyre model parameters depends directly on the quality and quantity of available experimental data, as well as on the experience of the engineer responsible for parameter selection, recent decades have seen growing interest in applying machine learning as either an alternative or complementary approach to tyre modelling. This offers the potential for significant improvements in the accuracy and efficiency of parameter identification, as well as in the generalisability of the resulting models. One of the most promising trends is the use of machine learning methods to enhance both the accuracy and efficiency of the parameter identification process. In contrast to traditional optimisation algorithms, which may become trapped in local minima or require substantial computational resources, machine learning methods offer greater flexibility.

Neural networks, owing to their ability to approximate complex nonlinear functions, have become a powerful tool for directly predicting tyre model parameters based on measured characteristics. In this approach, a neural network is trained on a large set of experimental data, where

the input consists of measured tyre forces and moments under varying slip and load conditions, and the output comprises the corresponding parameters of the selected tyre model. Once trained, the neural network can process new sets of experimental data and quickly predict a set of tyre model parameters that best describes the data. This can significantly reduce the time required for parameter identification, particularly when dealing with a wide range of tyre types or when the model needs to be rapidly adapted to new experimental data.

The study by J. Wang *et al.* (2018) demonstrates the capabilities of multilayer neural networks for directly predicting the parameters of empirical tyre models – specifically, the parameters of the Magic Formula tyre model – based on measured longitudinal and lateral forces, vertical load, and slip angle. A key advantage of neural networks lies in their universal approximation ability, which enables them to model complex nonlinear relationships without the need to predefine the exact functional form of these dependencies. After successful training on a sufficiently large and representative experimental dataset, the trained network can quickly and efficiently generate parameter sets for new tyre types or under varying operating conditions. However, one significant drawback of neural networks remains their “black-box” nature, which makes it difficult to interpret the predicted parameter values in terms of the physical properties of the tyre materials and construction. Moreover, the performance of the network is highly dependent on the quality and volume of training data, while the training process itself can be resource-intensive and requires careful tuning of numerous parameters to achieve optimal performance and avoid overfitting.

The Support Vector Machine (SVM) method is another machine learning tool that can be applied both to classification tasks and to the identification of necessary tyre parameters, as demonstrated by J.H. Lee *et al.* (2023). Based on measured tyre characteristics, SVM can classify tyres into specific categories, such as tread type or intended use. This classification can assist in selecting an initial tyre model or in defining a range of expected parameter values. Using SVM, it is possible to train a model to predict a range of potential parameter values for a specific tyre type based on its general characteristics. This is useful for identifying intervals of tyre performance, such as the optimal temperature range for rubber operation. When comparing SVMs with neural networks, SVMs often exhibit better generalisation capability with smaller datasets and are less prone to overfitting. However, neural networks are typically more effective at approximating highly complex nonlinear relationships, particularly when large volumes of data are available.

Regression trees, which include Random Forest and Gradient Boosting, are ensemble machine learning methods that construct multiple decision trees and combine their predictions to achieve more accurate results. These methods are particularly well-suited for identifying complex nonlinear relationships between measured tyre characteristics and their corresponding model parameters. Random

Forest builds a large number of independent decision trees using random subsets of data and features, then averages their predictions. Gradient Boosting, in contrast, builds trees sequentially, with each new tree aiming to correct the errors made by the previous ones. Regression trees can effectively capture complex interactions between various measured tyre characteristics and their influence on model parameters, which can lead to more accurate parameter estimation, especially when the relationships are nonlinear.

The study by M.A. Jabbar *et al.* (2024) introduced a novel machine learning algorithm, EDTSTACK, which combines multiple decision tree methods using stacking

techniques. The model achieves 99% accuracy in classifying tyre condition based on tread depth. Similarly, the study by H. Song *et al.* (2024) highlights the effectiveness of using regression trees to predict tyre parameters during the manufacturing process. Despite their high performance, interpreting complex ensemble models can be less straightforward compared to individual decision trees or some linear models. Furthermore, training these models – particularly large ensembles – can require substantial computational resources. The advantages and disadvantages of the discussed machine learning methods are summarised in Table 1.

**Table 1.** Comparison of machine learning methods for tyre modelling

Method	Model type	Data types	Advantages	Disadvantages
Linear regression	Statistical	Numerical	Simple to implement and interpret	Limited to linear relationships
Neural networks	Deep learning	Numerical, image-based	Capable of modelling complex nonlinear relationships	Requires large volumes of highquality data; difficult to interpret
Support Vector Machines	Classification / Regression	Numerical	Performs well with a large number of features	Poor scalability; complex parameter tuning
Random forest	Ensemble	Numerical, categorical	High accuracy; less prone to overfitting	Lower interpretability
Gradient boosting	Ensemble	Various	High accuracy; compatible with different data types	Requires extensive tuning

**Source:** developed by the authors

In summary, neural networks are a versatile tool for modelling complex nonlinear dependencies between tyre characteristics and their corresponding model parameters. However, they require large volumes of high-quality data and substantial computational resources, and they often lack interpretability. The support vector machine method is effective for classification tasks and can be useful for preliminary analysis and model selection, particularly when data availability is limited. Ensemble methods offer high predictive accuracy and robustness against overfitting, efficiently handling complex dependencies, although their interpretation may be more challenging.

Models trained on large and diverse datasets are better equipped to predict tyre behaviour under conditions not explicitly represented in the training data. Certain machine learning methods (e.g. neural networks with automatic architecture selection) can assist in identifying the most suitable functional form for describing tyre characteristics. Machine learning techniques also tend to be more robust to noise and errors in experimental data and can yield acceptable results even in the presence of incomplete information. Therefore, integrating machine learning methods into the process of tyre model parameter selection represents a promising direction that may lead to significant advances in the accuracy, efficiency, and versatility of vehicle dynamics simulation.

**Conclusions**

The present study focused on analysing current trends in the development of computational modelling in the context

of tyre model parameter selection and identifying opportunities to improve existing approaches through the application of machine learning methods such as neural networks, support vector machines, and ensemble techniques. Their advantages and limitations in tyre modelling and parameter identification tasks were also examined. The analysis demonstrated that each of the methods considered possesses unique strengths and constraints, and their suitability depends on specific requirements for accuracy, the volume of available data, and the need for interpretability. Therefore, the aim of the study can be considered achieved, as a comparative analysis of key machine learning methods in the context of tyre modelling has been conducted.

The study involved a review and analysis of the application of neural networks for determining tyre model parameters, highlighting their ability to approximate complex nonlinear relationships and their rapid prediction performance after training. The use of the support vector machine method for classifying tyre characteristics and providing preliminary estimates of parameter ranges was also examined, with its effectiveness noted in scenarios involving limited data and its strong generalisation capability. Particular attention was given to ensemble methods, which demonstrated high accuracy and robustness in parameter identification tasks.

The findings underscore the importance of machine learning methods in enhancing the tyre modelling process. The application of these methods improves the accuracy of tyre characteristic approximation, reduces the time

required for parameter selection, and enhances the generalisation ability of the models. Conceptually, the study confirms the growing trend towards integrating intelligent algorithms into traditional engineering approaches, opening new possibilities for developing more realistic and efficient virtual models of vehicles. The significance of these findings lies in providing a clear understanding of the current capabilities and limitations of various machine learning methods in the context of tyre modelling, which is essential for the further advancement of this field.

Obtaining test data for machine learning requires the use of specialised computer systems capable of collecting data from different sensors independently, in order to avoid conflicts between various data types, and storing them on a recording device. This ensures the accuracy and consistency of the information used to train the models.

Future prospects in this area include the development of hybrid approaches that integrate the strengths of different machine learning methods, as well as active research into physics-informed machine learning techniques, which combine empirical data with existing physical knowledge of tyre behaviour to create more accurate, interpretable, and generalisable models.

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### Conflict of Interest

None.

## References

- [1] Olazagoitia, J.L., Perez, J.A., & Badea, F. (2020). Identification of tire model parameters with artificial neural networks. *Applied Sciences*, 10(24), article number 9110. doi: 10.3390/app10249110.
- [2] Stocco, D., Biral, F., & Bertolazzi, E. (2024). A physical tire model for real-time simulations. *Mathematics and Computers in Simulation*, 223, 654-676. doi: 10.1016/j.matcom.2024.04.020.
- [3] Singh, K., Sarvari, P., Petry, F., & Khadraoui, D. (2019). Application of machine learning & deep learning techniques in the context of use cases relevant for the tire industry. In *Reifen – Fahrwerk – Fahrbahn* (pp. 241-268). Düsseldorf: VDI Verlag. doi: 10.51202/9783181023563-241.
- [4] Sousa, L.C., & Hultmann, V. (2022). Nonlinear tire model approximation using machine learning for efficient model predictive control. *IEEE Access*, 10, 107549-107562. doi: 10.1109/access.2022.3212420
- [5] Xu, N., Askari, H., Huang, Y., Zhou, J., & Khajepour, A. (2022). Tire force estimation in intelligent tires using machine learning. *IEEE Transactions on Intelligent Transportation Systems*, 23(4), 3565-3574. doi: 10.1109/TITS.2020.3038155.
- [6] Karkaria, V., Chen, J., Luey, C., Siuta, C., Lim, D., Radulescu, R., & Chen, W. (2024). A digital twin framework utilizing machine learning for robust predictive maintenance: Enhancing tire health monitoring. *ArXiv*. doi: 10.48550/arXiv.2408.06220.
- [7] Jacobson, B., et al. (2016). *Vehicle dynamics compendium for course MMF062*. Göteborg: Chalmers University of Technology.
- [8] Gillespie, T.D. (1994). *Fundamentals of vehicle dynamics*. Warrendale: Society of Automotive Engineers.
- [9] Hirschberg, W., Rill, G., & Weinfurter, H. (2007). Tire model TMeasy. *Vehicle System Dynamics*, 45(sup1), 101-119. doi: 10.1080/00423110701776284.
- [10] Lex, C. (2015). *Estimation of the maximum coefficient of friction between tire and road based on vehicle state measurements*. (Doctoral dissertation, Graz University of Technology, Graz, Austria).
- [11] Bakker, E., Nyborg, L., & Pacejka, H.B. (1987). *Tire modelling for use in vehicle dynamics studies*. *SAE Transactions*, 96, 190-204.
- [12] Pacejka, H.B. (2007). *Tyre and vehicle dynamics* (2nd ed.). Butterworth-Heinemann: Elsevier.
- [13] Tuononen, A.J. (2009). Vehicle lateral state estimation based on measured tyre forces. *Sensors*, 9(11), 8761-8775. doi: 10.3390/s91108761.
- [14] Chandiramani, J.R., Bhandari, S., & Hariprasad, S.A. (2014). Vehicle data acquisition and telemetry. In *Proceedings of the 2014 fifth international conference on signal and image processing* (pp. 187-191). Bangalore: IEEE. doi: 10.1109/ICSIP.2014.35.
- [15] Kemp, B., & Oliven, J. (2003). European data format "plus" (EDF+), an EDF alike standard format for the exchange of physiological data. *Clinical Neurophysiology*, 114(9), 1755-1761. doi: 10.1016/S1388-2457(03)00123-8.
- [16] Beckman, B. (1991). *The physics of racing: Part 1*. Retrieved from [http://autoxer.skiblack.com/phys\\_racing/contents.htm](http://autoxer.skiblack.com/phys_racing/contents.htm).
- [17] Rajamani, R. (2006). *Vehicle dynamics and control* (1st ed.). Heidelberg: Springer. <https://doi.org/10.1007/0-387-28823-6>.
- [18] Wheatstone, C. (1843). XIII. The Bakerian lecture. An account of several new instruments and processes for determining the constants of a voltaic circuit. *Philosophical Transactions of the Royal Society of London*, 133, 303-327. doi: 10.1098/rstl.1843.0014.
- [19] Tuononen, A.J. (2008). Optical position detection to measure tyre carcass deflections. *Vehicle System Dynamics*, 46, 471-481. doi: 10.1080/00423110701485043.

- [20] Gratton, S., Lawless, A., & Nichols, N. (2007). Approximate Gauss-Newton methods for nonlinear least squares problems. *SIAM Journal on Optimization*, 18(1), 106-132. doi: [10.1137/050624935](https://doi.org/10.1137/050624935).
- [21] Li, J.-Y., Zhan, Z.-H., Li, Y., & Zhang, J. (2025). Multiple tasks for multiple objectives: A new multiobjective optimization method via multitask optimization. *IEEE Transactions on Evolutionary Computation*, 29(1), 172-186. doi: [10.1109/TEVC.2023.3294307](https://doi.org/10.1109/TEVC.2023.3294307).
- [22] Karniadakis, G.E., Kevrekidis, I.G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, 3, 422-440. doi: [10.1038/s42254-021-00314-5](https://doi.org/10.1038/s42254-021-00314-5).
- [23] Wang, J., Liu, Y., Ding, L., Li, J., Gao, H., & Sun, T. (2018). Neural network identification of a racing car tire model. *Journal of Engineering*, 2018, article number 4143794. doi: [10.1155/2018/4143794](https://doi.org/10.1155/2018/4143794).
- [24] Lee, J.-H., Lee, J.-H., Yun, K.-S., Bae, H.B., Kim, S.Y., Jeong, J.-H., & Kim, J.-P. (2023). A Study on Wheel member condition recognition using machine learning (support vector machine). *Sensors*, 23(20), article number 8455. doi: [10.3390/s23208455](https://doi.org/10.3390/s23208455).
- [25] Jabbar, M.A., Basheer, S., & Alshudukhi, J. (2024). EDT-STACK: An ensemble of decision tree-based stacking model for classifying tire tread status. *Results in Engineering*, 22, article number 102218. doi: [10.1016/j.rineng.2024.102218](https://doi.org/10.1016/j.rineng.2024.102218).
- [26] Song, H., Gao, L., Lu, Y., & Li, H. (2024). Application of selected machine learning methods for prediction of conicity in radial tire production. *Applied Sciences*, 14(15), article number 6393. doi: [10.3390/app14156393](https://doi.org/10.3390/app14156393).

## Ефективність комп'ютерних засобів моделювання роботи шин на базі вбудованого контролера телеметрії

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**Анотація.** Метою дослідження був аналіз ключових аспектів динаміки колісної техніки та оцінка ефективності застосування сучасних методів комп'ютерного моделювання в процесі проектування транспортних засобів. У роботі розглядалися основні параметри, що впливали на роботу шин, зокрема сили, моменти, кут ковзання, вертикальне навантаження та взаємозв'язки між ними. Було обґрунтовано доцільність використання моделювання для забезпечення необхідного рівня зчеплення, керованості та комфортності під час керування транспортними засобами. Здійснено класифікацію існуючих моделей шин з поділом на емпіричні, напівемпіричні та фізичні моделі, наведено їх порівняльний аналіз, визначено переваги та обмеження кожного типу. Особливу увагу приділено «магічній формулі» моделі шин, яка використовується для визначення характеристик шин. В межах дослідження описано застосування цієї формули для створення наближених математичних моделей з використанням методу апроксимації кривих, що дозволяє точно описувати поведінку шин у різних умовах експлуатації. Окремо проаналізовано сучасні тенденції розвитку шинних моделей із залученням методів машинного навчання, які дають змогу автоматизувати процес підбору параметрів і підвищити точність моделювання. Показано, що комплексне використання методів машинного навчання й комп'ютерного моделювання здатне підвищити ефективність розробки шинної продукції та сприяти створенню інноваційних рішень у сфері колісної техніки. Практична цінність дослідження полягає у можливості впровадження запропонованих підходів для вдосконалення динамічних характеристик транспортних засобів та іншої колісної техніки, що потенційно призведе до зменшення кількості дорожовартісних польових випробувань

**Ключові слова:** комп'ютерне моделювання; динаміка колісної техніки; моделі шин; «магічна формула» моделі шин; машинне навчання