Tyre Model Review

OXFORD BROOKES UNIVERSITY

Introduction, Aims and Objectives

Tyre performance is one of the key factors for track-use vehicles, as tyres are the only contact point between the vehicle and the road surface. The understanding of tyre characteristics and its performance limits are essential in optimizing grip, contact patch surface, longitudinal and lateral stiffness, wear, cornering speed, braking and acceleration performance and, ultimately, overall lap time.

Tyre performance data can be acquired through tests on track, or via simulations using different tyre models, being the latter the most accessible and cost-effective of the two. This data allows the teams to make informed decisions on setup changes, tyre pressures and strategies to improve the vehicle overall performance.

This research aims to show different tyre models available, highlight each of the model characteristics, advantages and disadvantages of each model, compare them between each other, and determine which model needs to be used to obtain the most valuable information for track-oriented tyres.

Tyre model selection and review

For this research, 3 different non-linear tyre models have been used. Linear tyre models are often used when the tyre operates in conditions far from its limits. As this research treats track-use tyres, it is important to achieve the most accurate data possible.

Empirical model

- The Magic Formula, derived from the wider Pacejka tyre model and widely used for passenger vehicle applications, vehicle simulators, or real-time applications, is less complex than other models, allowing for faster computational speeds (Blundell et al., 2015).
- This model is based on information retrieved from experimental data, representing tyre forces (Figures 1 and 3) and moments (Figure 2) based on slip ratios and angles. However, being an empirical model, it does not account for the underlying physical characteristics of tyre behaviour, such as tyre deformation, tyre temperature, camber, material composition, or tyre tread wear, limiting its accuracy when simulating tyre performance under extreme conditions.

Physical model

- FTire is a 3D non-linear tyre model designed to simulate tyre behaviour under dynamic conditions. It consists of both a structural model, used to describe the damping, stiffness, and inertia characteristics of the tyre, and a tread model, which determines the contact pressure and friction distribution on the contact patch (Figures 5, 6 and 7) (Gipser, M., 2007; Cosin Software, 2022).
- This model is based on a Finite Element 3D representation of the tyre (Figure 4) and requires a large amount of data to function, such as information on tyre structure, composition, operating temperature, pressure, tyre wear, and road characteristics (Wei, C., Olatunbosun, O. A., Yang, X., 2016).
- However, this model does not consider possible changes that occur in the tyre environment, such as changes in ambient air pressure.
- If the dataset provided is accurate enough, the simulations can obtain data under extreme conditions of use, admitting frequencies between 200 and 300 Hz, making it computationally expensive and requiring precise calibration and setup, which makes it difficult to operate and unsuitable for real-time applications (Gipser, M., 2011).

Machine Learning model

- Artificial Neural Network (ANN) models mimic the behaviour of biological neural networks by using perceptrons, multiple algorithms, and extensive data sets to predict tyre behaviour (Rondelli, M., 2022).
- Perceptrons consist of artificial neurons called TLU, used as the layers for different algorithms, with the input and output layers being the most relevant, containing shadow layers in between (Figure 8).
- Additionally, TLUs allow the use of numbers instead of binary inputs. ANN models employ algorithms such as Feedforward, where data flows in one direction from input to output without looping back, or Backpropagation, where data loops back to adjust each layer and minimize error (Marotta, R. et al., 2024).
- ANNs can predict tyre friction coefficients and forces (Figures 9 and 10), excelling in characterising non-linear and high-frequency behaviour under varying conditions (Furlan, M., Mavros, G., 2022).
- Once trained, the computational cost of the model can be significantly reduced, as it does not need physical models or mathematical equations, allowing for real-time monitoring and anomaly detection in tyre performance (Sousa, L.C., Hultmann, H. V., 2022)
- Although recently introduced to the industry, ANN models are already being used for tyre monitoring, optimization, and race strategy selection.

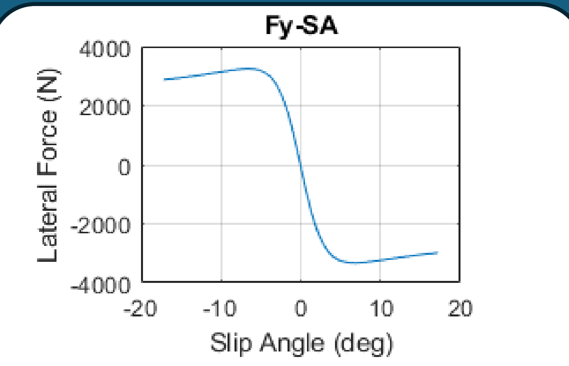

Figure 1. Lateral force graph retrieved from MFeval (MATLAB, 2018)

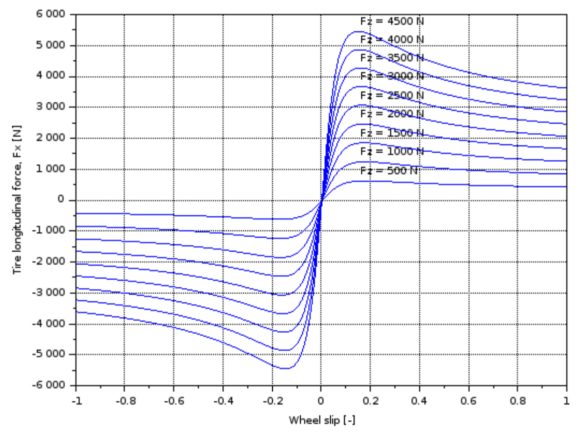

Figure 2. Tire longitudinal force – load dependent coefficients with Scilab (X-Engineer, n.d.)

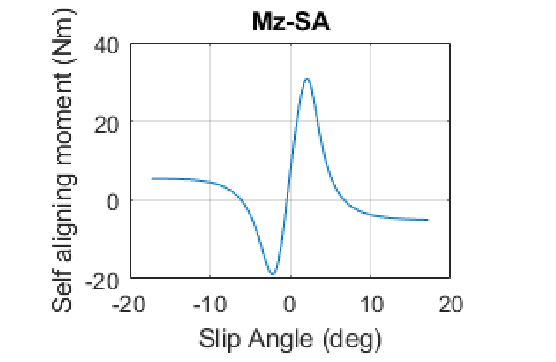

Figure 3. Self-aligning moment graph retrieved from MFeval (MATLAB, 2018)

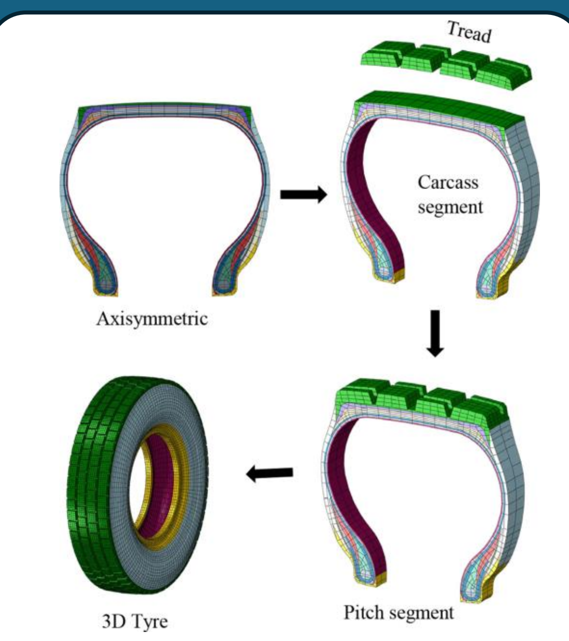

Figure 4. Finite element tyre modelling sequence (Bedi, V. K., et al., 2024)

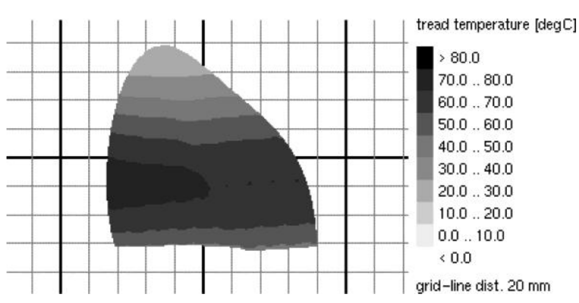

Figure 5. Temperature distribution in the contact patch during cornering at a 6° camber angle (Gipser, M., 2011)

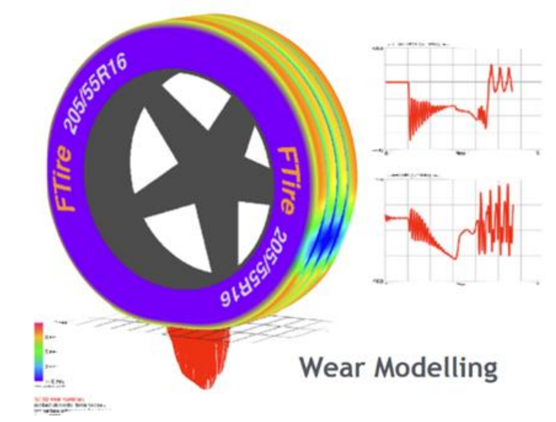

Figure 6. Tyre wear modelling example on FTire brochure (Cosin Software, 2021)

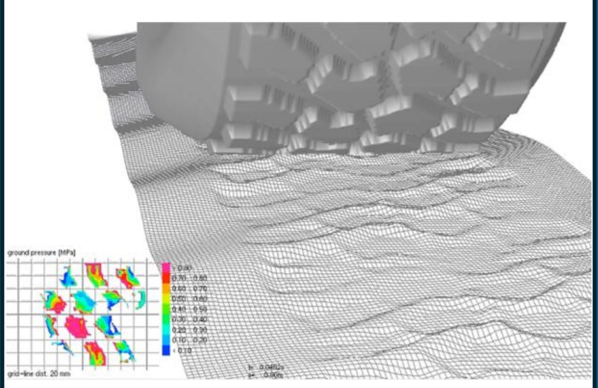

Figure 7. Contact patch modelling example on FTire-soil (Cosin Software, 2021)

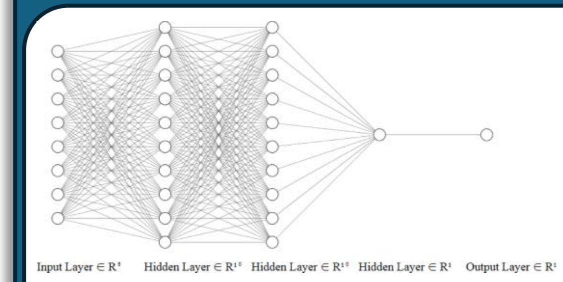

Figure 8. Neural Network Structure for friction estimation using Persson's flash temperature model (Furlan, M., 2022)

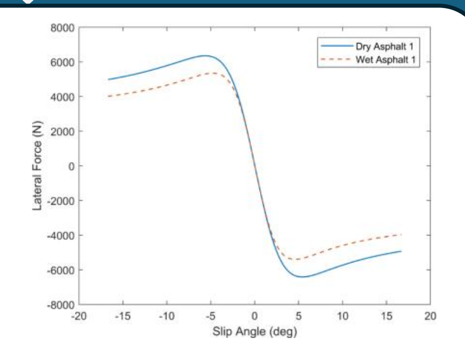

Figure 9. Lateral force simulation on different terrains (Furlan, M., 2022)

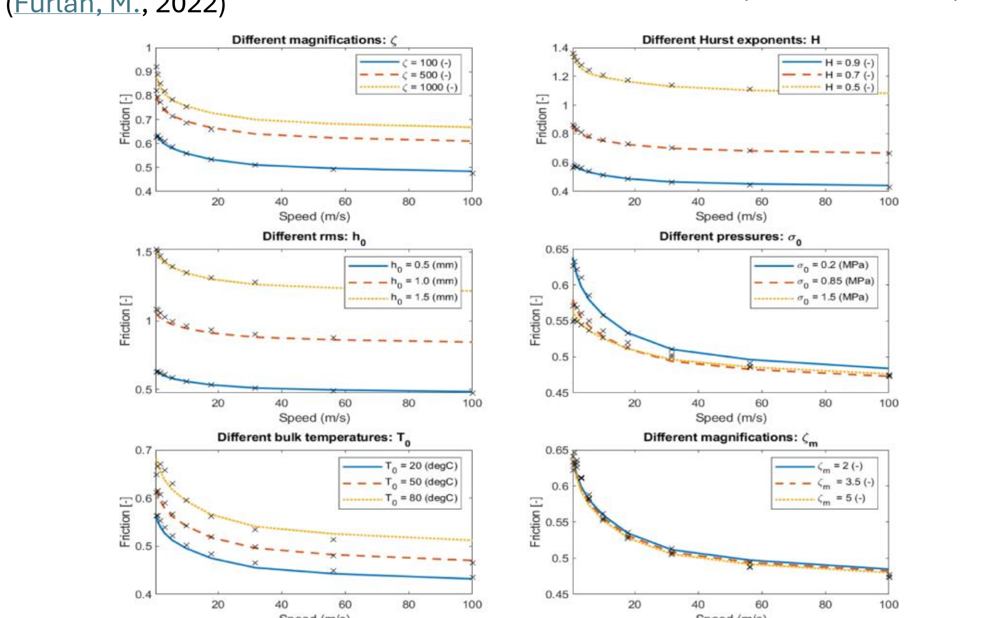

Figure 10. Validation of the neural network (lines) against Persson's model (crosses) at different conditions (Furlan, M., 2022)

Tyre model comparison

	Magic Formula	FTire	ANNs
Tyre model use case	Real-time simulations and monitoring	Real-time simulations and lap time simulations, with detailed tyre-road interactions	Predictive modelling, allowing for real-time decision making and tyre anomaly detection
Non-linearity Handling	Non-linear, but simplified	Fully non-linear, high complexity	Excellent at characterising non-linear behaviour
Real-time suitability	High (fast computation)	Low (computationally expensive)	Moderate (Final computational cost varies depending on the training of the model)
Frequency range	Low frequencies	High frequencies	Can handle high frequencies if trained properly
Data requirements	Moderate (experimental tyre data required)	High (detailed tyre structural and thread data required)	Very high (large amounts of training data required)
Setup Complexity	Relatively simple to calibrate	Complex, requires detailed physical parameters	Moderate, requires significant data preparation and training
Response to High Frequency Events	Poor, as the frequency range for the model only allows low to moderate frequencies	Excellent, the model allows to simulate high frequencies	Response can vary from moderate to excellent response, depending on the network training and complexity
Physical characteristics	No physical characteristic is applied, as it is fully based on mathematical equations	Full tyre structure, thread, tyre deformation, thermodynamical characteristics and road characteristics	Not applied directly, dependant on the origin of the training data set given to the model
Adaptability to new conditions	Poor, as it is limited to the data range provided from the experiments	Good, as it models physical properties of the tyre	Can adapt exceptionally well if the model is trained with diverse data sets and has a good network complexity

Purpose and usefulness

- The magic formula model is extensively used in vehicle simulators, as it is a simple model, consisting only of mathematical equations, and does not have large computational costs, allowing for real-time use. This model can aid in driver training before a real-world session, test new components on a vehicle before their real-world implementation, obtain longitudinal, lateral, acceleration and braking forces, and acquire an initial suspension set-up for the vehicle. The implementation of this model can provide a beginner in tyre performance engineering with the first insights into tyre performance. However, as it does not consider the physical characteristics of either the tyre or the road, it is unable to simulate accurately the tyre on its performance limits, failing in providing tyre performance data.
- FTire tyre model can be implemented on driving simulators, as well as data-driven simulators, such as lap time simulators, where precise and high-fidelity simulations are mandatory, and computational costs are not relevant. This model simulates tyre deformation, temperature effects, tyre wear and road interactions, allowing for precise data collection on changing track conditions, or different amounts of tyre wear. The data obtained can be used to formulate set-ups for the vehicle, as well as predict tyre wear, allowing for race strategies to be made. However, its high computational cost makes it less usable for smaller motorsport teams, as well as needing an experienced tyre performance engineer for its use, as its calibration and input data needed are complex.
- ANNs tyre model can be implemented in data-driven simulations, such as lap time simulators, allowing for race strategy optimization, and driver performance analysis, comparing its optimal tyre data with the telemetry obtained from the driver. This model excels in adapting to new track conditions, predictions on tyre performance for new input data, and noticing anomalies on tyre performance data. However, for this model to excel in these tasks, the model needs a large data set feed into it, has a very large computational cost before it is optimized by its training, and its lack of mathematical and physical bases may cause distrust and confusion to some.

Conclusions

- Magic formula model: although lacking a physical model for the tyre, has the lowest computational cost, simplest setup and the smallest data set needed for its use, being a perfect candidate for smaller teams, who may not be able to do as much real-world testing, only obtaining small data sets from the tyres. This model also can provide a perfect entry point into tyre performance engineering.
- FTire model: Excels in giving insights into tyre behaviour under any circumstance the tyre may be on, providing possibilities for race strategies and vehicle set-up optimization, while also allowing for lap time simulations to be made, making possible the use of its data to coach and improve the driver performance comparing the lap time simulation data with the driver telemetry. While this model has great benefits over the magic formula model, it also has a high computational cost and requires a larger data set and very precise calibration, making it much more expensive to use and less accessible.
- ANNs model: Excels in tyre behaviour prediction, lap time simulation under changing circumstances and driver telemetry comparison, the characteristics of this model may seem similar to those offered by the physical model, but they differ in that this model, it has a great computational capacity, with adequate training and a sufficiently large data set, can predict the characteristics of a tyre without needing a physical model or such extensive data as in other models, obtaining a versatility unequalled by other models.

During this research, we can conclude that, for most motorsport teams, the FTire model is ideal due to its detailed insights into tyre behaviour. Larger teams, like those in F1 or WEC, could benefit from combining FTire with ANNs for enhanced adaptability and precision, while teams running small categories may find the Magic Formula model sufficient.

References

1. Blundell, M. et al., 2015. The Multibody Systems Approach to Vehicle Dynamics. 2nd ed.
2. Gipser, M., 2007. FTire – the tire simulation model for all applications related to vehicle dynamics. Vehicle System Dynamics, 45(sup1), pp. 139–151. Available at: https://doi.org/10.1080/00423110801899960
3. Gipser, M., 2011. FTire: a physically based application-oriented tyre model for use with detailed MBS and finite-element suspension models. Vehicle System Dynamics, 43(sup1), pp. 76–91. Available at: https://doi.org/10.1080/00423110500139940
4. Cosin software, 2022. FTire Model. Available at: https://www.cosin.eu/wp-content/uploads/ftire_model.pdf
5. Wei, C., Olatunbosun, O. A., Yang, X., 2016. A finite-element-based approach to characterising FTire model for extended range of operation conditions. Vehicle System Dynamics, 55(3), pp. 295–312. Available at: https://doi.org/10.1080/00423114.2016.1264613
6. Rondelli, M., 2022. The Future of Formula 1 Racing: Neural Networks to Predict Tyre Strategy. Available at: https://amslaurea.unibo.it/27922/1/Tesi_Massimo_Rondelli.pdf
7. Marotta, R., et al., 2024. Multi-output physically analysed neural network for the prediction of tire–road interaction forces. SAE International Journal of Vehicle Dynamics, Stability, and NVH, 8(2), pp. 285–308. Available at: https://doi.org/10.4271/10-08-02-0016
8. Furlan, M., Mavros, G., 2022. A neural network approach for roughness-dependent update of tyre friction. Simulation Modelling Practice and Theory, 116, p. 102484. Available at: https://doi.org/10.1016/j.simpat.2021.102484
9. Sousa, L.C., Hultmann, H. V., 2022. Nonlinear tire model approximation using machine learning for efficient model predictive control. IEEE Access, 10, pp. 107549–107562. Available at: https://doi.org/10.1109/ACCESS.2022.3212420