

Multi-Objective Tire Design Optimization by Artificial Neural Networks

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Abstract— High performance tire design calls for multi-objective optimization of tire design parameters. This paper discusses the application of artificial neural networks (ANNs) for determination of optimal tire design parameters for simultaneous minimization of strain energy density at belt edge and chafer. Based on finite element (FE) simulation experimental trials, conducted according to full factorial design where three tire design parameters were arranged (belt angle, belt cord spacing and elasticity of tread compound), two ANN models of the same topology were developed. The set of optimal tire design parameter values was obtained by graphical optimization method. The quality of multi-objective optimization solutions was validated by performing additional FE experimental trials.

I. INTRODUCTION

Although at the first glance it may not be evident, pneumatic tire represents a complex structure, comprising of various rubber components and rubber based composites. Designed for tough exploitation conditions, it must perform well considering a number of mutually opposing performance characteristics such as dry/wet handling and traction, endurance, wear resistance, ride comfort, rolling resistance, aquaplaning, weight, noise and vibration etc. [1, 2]. In order to design a high performance tire that meets, to the greatest extent, desired performance characteristics, selection of suitable tire design parameter values is of prime importance. The main difficulty with which design engineers are faced is the fact that optimal combination of tire design parameter values for one performance characteristic may not even be near optimal for another performance characteristic. From these reasons, for the considered performance characteristics, one needs to formulate and solve tire design multi-objective optimization problem so as to determine suitable combination of tire design parameters.

For tire design optimization different methods and approaches were previously proposed and applied including artificial neural networks (ANNs) [Nakajima et al., 1999], conventional satisficing trade-off method (STOM) [3], multi-objective genetic algorithm (MOGA) and self-organizing map (SOM) [2], utility function approach [Serafinska et al., 2013] and regression analysis (RA) and GA [4]. In most cases, tire design optimization is performed as a two-stage approach: mathematical modeling and optimization. Although the use of RA speeds up and simplifies mathematical modeling process, the use of RA may be of limited applicability and reliability in cases where there exist complex non-linear

relationships between dependent and independent variables. As a consequence, the optimization results may not be satisfactory, i.e. there may exist big deviations between experimental and RA model predictions, particularly in the case of multi-objective optimization. In such situations RA polynomial models can be replaced with ANNs, which are based on matrix-vector multiplications combined with nonlinear (activation) functions. Actually, the advantage of the applications of ANNs for empirical modeling of complex non-linearities and interactions in tire design is well documented [2, 5, 6].

Motivated by the lack of studies regarding multi-objective optimization of tire design this paper aims at determination of tire design parameters for multi-objective optimization of strain energy density at belt edge and chafer by the application of ANNs. Determination of the optimal tire design parameter values was performed by graphical optimization method.

II. EXPERIMENTAL PLAN AND FE ANALYSES

As described in detail in [4], objective functions and tire design parameters that were involved in optimization were selected based on two criteria. Those were the significance considering tire design and simple change of tire design parameters inside finite element (FE) model (Fig. 1) used to perform the experiments. Detailed description of the methodology used in finite element modeling and analysis of tires may be found in [7-9].

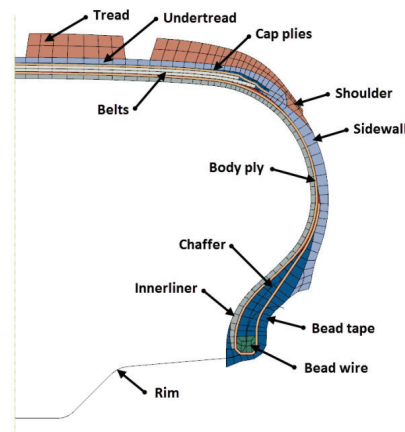


Figure 1. Axisymmetric FE model of an existing tire used to perform the experiments in optimization studies. Structural components of the tire may clearly be distinguished

Three tire design parameters, namely belt angle (A), belt cord spacing (B) and elasticity of tread compound (C) were considered. It should be noted that all tire design parameters are continual variables, i.e. they can take any value within the specified ranges. The tire design parameter ranges were selected based on preliminary FE experimental trials as well as by considering some technically manageable ranges and guidelines from literature. The selected parameters are known to have a significant influence on tire performance, such as maneuverability, durability or rolling resistance. FE experimentation was conducted as per 3³ full factorial experimental plan upon which each tire design parameter was changed at low, middle and high level. Tire design parameters and their levels within the FE experimentation are given in Table 1.

TABLE I.
TIRE DESIGN PARAMETER RANGES AND THEIR LEVELS

Tire design parameter	Unit	Level		
		1	2	3
Belt angle (A)	°	18	22	26
Belt cord spacing (B)	mm	0.65	1.05	1.45
Elasticity of tread compound (C)		0.6	1	1.4

The configuration of the initial tire design is defined as A = 22°, B = 1.05 mm and C = 1. Tread compound was modeled using hyperelastic Yeoh material model. The value of C = 1 corresponds to nominal values of Yeoh coefficients: C₁₀=1.0236 N/mm², C₂₀= -0.4272 N/mm² and C₃₀=0.1732 N/mm². Values of Yeoh coefficients used in various FE models were obtained by multiplication of all the coefficients with the value of elasticity of tread compound (C). Therefore, elasticity of tread compound (C) is dimensionless.

After conducting 27 FE experimental trials with different combinations of tire design parameter values, values of strain energy density at belt edge (f₁) and chafer (f₂) were recorded and used for development of ANN models. As explained in [4], strain energy density is seen to be a good indicator of complex stress-strain state at a given location inside the tire, taking into account material nonlinearities. Belt edge and bead area are known to be critical zones in tire structure, as abrupt stiffness changes and cyclic flexion lead to stress concentration and fatigue, which in turn cause structural failures.

III. ARTIFICIAL NEURAL NETWORK MODELS

A. ANN Basics

ANNs are one of the most powerful artificial intelligence (AI) tools for mathematical modeling of the relationships between a number of inputs and outputs. Universal function approximation capability, resistance to noisy or missing data, good generalization capability, adaptive nature and other useful features of ANNs made them a preferable choice for modeling complex relationships which are difficult to describe using analytical models.

From many developed types of ANNs, the feed-forward ANNs are among the most used ones, because of their simplicity and ease of implementation. Feed-forward ANNs are composed of a number of simple and highly interconnected processors, i.e. neurons, which are grouped

into input, hidden and output layer. Establishment of mathematical relationships between input and outputs is based on input to hidden and hidden to output weights, biases of the hidden and output neurons and the use of transfer (activation) functions in hidden and output layer, which enable non-linear data processing.

B. ANN Models for Optimization of Tire Design

In this study ANN models are aimed at establishing mathematical relationships between inputs, i.e. tire design parameters (belt angle, belt cord spacing and elasticity of tread compound) and outputs, i.e. strain energy density at belt edge (f₁) and strain energy density at chafer (f₂).

FE experimental data, obtained from the full factorial experimental design, were used for development of ANN predictive models. FE experimental data were randomly divided into a data subset for ANN training (22 data) and data subset for testing the prediction accuracy of the developed ANN models (5 data). Given that the number of hidden neurons is dependent on the number of data available for training, two ANN models with four neurons in the hidden layer were designed for the purpose of strain energy density prediction. Since it was assumed that there exist some non-linear relationships between tire design parameters and strain energy density, linear and hyperbolic tangent sigmoid activation functions were used in the output and hidden layer, respectively.

In order to determine near optimal combination of input to hidden and hidden to output weights values and weights of biases of the hidden and output neurons, ANN training resembles a necessary step, which has the predominant influence on the prediction accuracy of developed models. For the purpose of ANN training, Levenberg-Marquardt algorithm was applied due to its fast convergence rate and stability. The ANN training process was monitored via the mean squared error. Fig. 2 shows the variation of mean squared error as a function of the number of iterations.

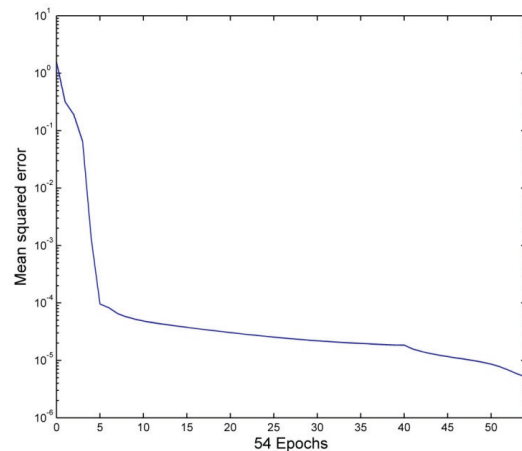


Figure 2. ANN training process

After the ANN training is finished one needs to test the prediction accuracy of the developed models. It is of particular interest to investigate generalization, i.e. ability of ANNs to make accurate predictions when data, which were not used in the training process, are introduced. For the ANN model which related tire design parameters and strain energy density at belt edge (f₁), the mean absolute

percentage errors were found to be 0.03 % and 0.12 % considering training and testing data, respectively. Similarly, for the ANN model which related tire design parameters and strain energy density at chafer (f_2), the mean absolute percentage errors were found to be 0.014 % and 0.034 % considering training and testing data, respectively, which is better than RA modeling as reported in [4]. These statistical results irrefutably confirm excellent agreement between FE experimental data and ANNs predictions as well as high robustness of the developed ANN models. Therefore, these models can be used for the analysis of the effects of tire design parameters on strain energy density as well as to serve as fitness functions for the purpose of tire design optimization.

IV. ANALYSIS AND DISCUSSION

The interaction effects of the tire design parameters on the strain energy density at belt edge and chafer are given in Fig. 3. 3-D response surfaces for strain energy density were generated by changing belt angle (A) and elasticity of tread compound (C) at a time, while belt cord spacing (B) was held at low, center and high level.

From Fig. 3 it can be seen that the increase in belt angle (A) results in increase of the strain energy density at belt edge and at chafer. This is probably due to the fact that with increasing belt angle the angle between carcass and belt cord spacing becomes smaller and thus the stiffness change at belt edges becomes larger [4]. It can be also observed that increase in elasticity of tread compound (C) produces a nonlinear increase in strain energy density at belt edge. On the other hand, elasticity of tread compound (C) has negligible influence on the strain energy density at chafer.

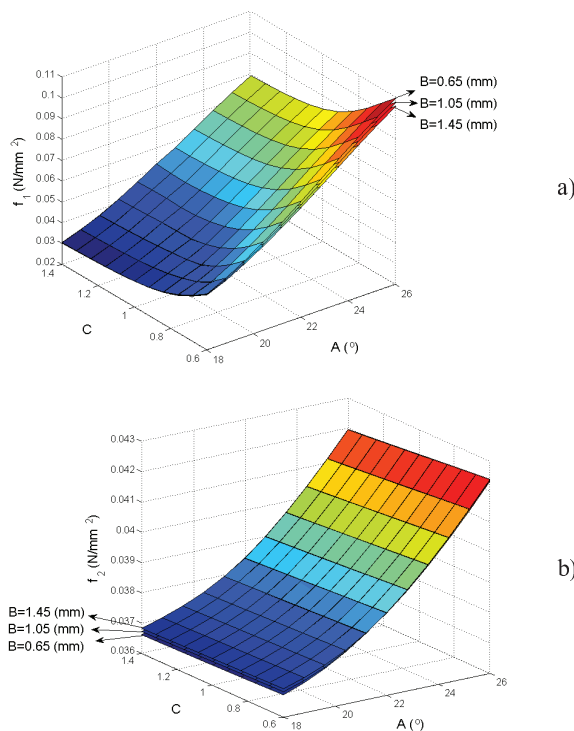


Figure 3. 3-D response surfaces for strain energy density a) at belt edge, b) at chafer

Finally, one can observe that there exists a small decrease in strain energy density at belt edge with increase of belt cord spacing (B). However, regarding the strain energy density at chafer, small decrease in strain energy density comes with decrease of belt cord spacing (B).

From Fig. 3 it is obvious that belt angle (A) has the maximum influence on the strain energy density and that the minimal strain energy density at belt edge and at chafer are obtained when belt angle (A) has minimal value, i.e. $A=18^\circ$.

The optimal selection of tire design parameters should increase tire durability to some extent by minimizing strain energy density at belt edge and chaffer [4]. Therefore, in the context of multi-objective optimization, the goal is to determine suitable combination of tire design parameters so as to minimize strain energy density at belt edge and chaffer simultaneously. The common approach for multi-objective optimization is based on the use of optimization algorithms. However, based on the conducted analyses multi-objective tire design optimization can be reduced to multi-objective problem having only two independent variables, i.e. belt cord spacing (B) and elasticity of tread compound (C), hence the simplest way for performing multi-objective tire design optimization is graphical optimization method. To this aim, two 3-D response surfaces for strain energy density at belt edge and at chafer are given on the same plot (Fig. 4). Fig. 4 was generated by changing belt cord spacing (B) and elasticity of tread compound (C) at a time, while belt angle (A) was kept constant at $A=18^\circ$.

From Fig. 4, it is obvious that response surface for strain energy density at chafer is flat, which means that changing belt cord spacing (B) and elasticity of tread compound (C), when belt angle is $A=18^\circ$, has negligible influence on strain energy density at chafer. Therefore, since the change in strain energy density at chafer is very small, multi-objective tire design parameter optimization problems can be reduced to single objective optimization problem where to goal is to identify tire design parameter values so as to minimize strain energy density at belt edge. The analysis of Fig. 4 reveals that there are different combinations of belt cord spacing (B) and elasticity of tread compound (C) that yield acceptable solutions regarding strain energy density at belt edge. For example, belt cord spacing of $B=0.65$ mm, elasticity of tread compound $C=1.4$ produces minimal strain energy density at belt edge of $f_1=0.0299$ N/mm^2 .

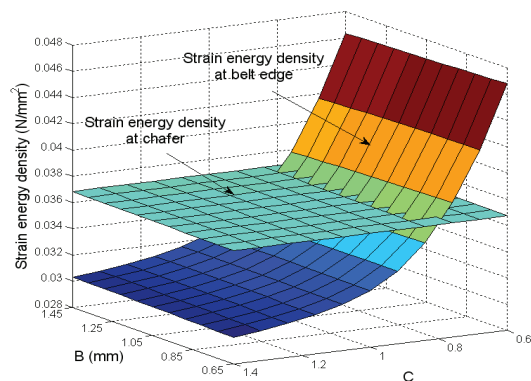


Figure 4. Strain energy density at belt edge and chafer for belt angle $A=18^\circ$

TABLE II.
COMPARISON OF ANN PREDICTIONS AND FE SIMULATION EXPERIMENTAL VALUES FOR STRAIN ENERGY DENSITY

Optimization solution	A (°)	B (mm)	C	ANN predictions		FE simulation	
				f_1 (N/mm ²)	f_2 (N/mm ²)	f_1 (N/mm ²)	f_2 (N/mm ²)
1	18	0.65	1.4	0.0299	0.0366	0.02997	0.03662
2	18	0.97	1.4	0.0301	0.0367	0.03015	0.03671
3	18	0.73	1.4	0.03	0.0366	0.03002	0.03664
4	18	0.83	1.4	0.03	0.0367	0.03008	0.03667
5	18	0.75	1.4	0.03	0.0366	0.03003	0.03665
6	18	0.65	1.23	0.0306	0.0366	0.03093	0.03664
7	18	0.65	1.36	0.0301	0.0366	0.03021	0.03663

Thus, from the point of view of the performed optimization, any pair (B, C) that yield minimal value of strain energy density at belt edge can be selected as optimal one. In practice, other constructive parameters and goal functions would be taken into account, as well as production limitations and standards, and the choice of parameter values would certainly not be so wide.

In order to check the quality of determined optimization solutions, one needs to compare ANN model predictions and FE simulation experimental values for strain energy density at belt edge and chafer. Thus, several FE simulation experimental trials with the combinations of tire design parameters as given in Table 2 were conducted.

As could be observed from Table 2, there exist a perfect match between values of strain energy density at belt edge and chafer predicted by ANN models and obtained by FE simulation. It can be shown that mean absolute percentage errors regarding strain energy density at belt edge (f_1) and chafer (f_2) are less than 0.5%. These results indicate that ANNs can be efficiently used for multi-objective optimization of tire design parameters.

Regarding initial tire design (A=22°, B=1.05 mm and C=1) each optimization solution from Table 2 significantly minimizes strain energy density at belt edge (approximately 42.5%) and strain energy density at chafer (approximately 5%).

V. CONCLUSION

This paper aimed at application of ANNs for determination of tire design parameter values (belt angle, belt cord spacing and elasticity of tread compound) for multi-objective optimization of strain energy density at belt edge and chafer, which are known to influence tire durability. FE simulation based experimental trials, conducted according to full factorial design, provided a set of data for ANNs model development. The conclusions drawn can be summarized by the following points:

- Statistical results indicate excellent agreement between FEM based experimental results and the ANN predictions, which confirms the validity on the use of ANNs for tire design modeling and optimization.
- Quite basic ANN model architecture, trained with Levenberg-Marquardt algorithm using relatively small training data set, outperformed RA based modeling and optimization considering prediction accuracy and generalization capability.

- Belt angle has the most dominant effect on the strain energy density at belt edge and chafer, followed by the elasticity of tread compound and belt cord spacing that have a much smaller influence.

Because of dimension reduction, the optimal tire design parameter values were obtained by graphical optimization method and corresponding strain energy density values were very close to experimentally obtained ones. The determined combinations of tire design parameter values significantly improved initial tire design by simultaneous minimization of strain energy density at belt edge and chafer.

REFERENCES

- [1] A. N. Gent and J. D. Walter, *The pneumatic tire*, Washington D.C., National Highway Traffic Safety Administration, U.S. Department of Transportation, 2006.
- [2] M. Koishi and Z. Shida, "Multi-objective design problem of tire wear and visualization of its Pareto solutions", *Tire Science and Technology*, 34(3), pp. 170-194, 2006.
- [3] J. R. Cho, H. S. Jeong and W. S. Yoo, "Multi-objective optimization of tire carcass contours using a systematic aspiration-level adjustment procedure", *Computational Mechanics*, 29(6), pp. 498-509, 2002.
- [4] N. Korunović, M. Madić, M. Trajanović and M. Radovanović, "A procedure for multi-objective optimization of tire design parameters", *International Journal of Industrial Engineering Computations*, DOI: 10.5267/j.ijiec.2014.11.003.
- [5] Y. Nakajima, H. Kadowaki, T. Kamegawa and K. Ueno, "Application of a neural network for the optimization of tire design", *Tire Science and Technology*, 27(2), pp. 62-83, 1999.
- [6] A. Serafinska, M. Kaliske, C. Zopf and W. Graf, "A multi-objective optimization approach with consideration of fuzzy variables applied to structural tire design", *Computers and Structures*, 116, pp. 7-19, 2013.
- [7] N. Korunović, M. Trajanović and M. Stojković, "Finite element model for steady-state rolling tire analysis", *Journal of the Serbian Society for Computational Mechanics*, 1(1), pp. 63-79, 2007.
- [8] N. Korunović, M. Trajanović, M. Stojković, D. Mišić and J. Milovanović, "Finite element analysis of a tire steady rolling on the drum and comparison with experiment", *Strojniški Vestnik - Journal of Mechanical Engineering*, 57(12), pp. 888-897, 2011.
- [9] N. Korunović, M. Stojković, D. Mišić and M. Trajanović, "FEM based parametric design study of the tire profile using dedicated CAD model and translation code", *Facta universitatis, Series: Mechanical Engineering*, 12(3), pp. 209-222, 2014.