A Neural Model of Automotive Cold Brake Performance

Dragan Aleksendrić
Teaching Assistant

Čedomir Duboka
Professor
University of Belgrade
Faculty of Mechanical Engineering

The automotive brake's performance results from the complex interrelated phenomena occurring in the contact of the friction pair. These complex braking phenomena are mostly affected by the physicochemical properties of friction materials' ingredients, its manufacturing conditions, and brake's operation regimes. Analytical models of brakes performance are difficult, even impossible to obtain due to complex and highly nonlinear phenomena involved during braking. That is why in this paper all relevant influences on the cold brake performance have been integrated by means of artificial neural networks. The influences of 26 input parameters defined by the friction material composition (18 ingredients) its manufacturing conditions (5 parametars) and brake's operation regimes (3 parameters) have been modelled versus changes of the brake factor C. The neural model of the cold brake performance has been developed by training and testing of 90 neural models. These neural models have been obtained by training of 18 different architectures of neural networks with the five learning algorithms.

Keywords: *neural model, cold brake, brake performance*

1. INTRODUCTION

The demands imposed to the braking system, under wide range of operating conditions, are high and manifold. It is expected that the friction coefficient should be relatively high but also stable friction force, reliable strength, and good wear resistance are needed irrespective of temperature, humidity, age, degree of wear and corrosion, presence of dirt and water spraying from the road, etc. The braking system performance is mostly determined by brakes performance. The basic requirements imposed to the automotive brakes are related to the values and stability of the friction coefficient versus different brake's operation conditions defined by changing of pressure application and/or sliding speed and/or temperature. These demands are increasing due to different vehicle's weights, four-wheel drive vehicles, different vehicles' maximum speeds, and introduction of electronically controlled systems (ABS, ESP, BAS, and ROP etc.) whose functions are realized by braking system. That is why, braking systems capabilities are deteremined by the brakes' operation i.e. friction pair performance.

The automotive brake's performance results from the complex interrelated phenomena occurring in the contact of the friction pair during braking. These complex braking phenomena are mostly affected by the physicochemical properties of friction materials' ingredients and brake's operation regimes. The brake's performance is primarily influenced by contact situation between a cast iron brake disc and friction materials. The contact situation is additionally complicated by the fact that friction materials are complex composites and may contain over to 20 different ingredients. That is why, the contact situation can be differently affected by wide diversity in mechanical properties of the friction material's ingredients [1,2,3,4]. Synergetic effects of all these ingredients determine the final friction material characteristics and accordingly affecting the final brake's performance.

Improvement of automotive brakes performance, under different operating conditions, is complicated by the fact that braking process has stochastic nature affected by changing of real contact area size, transfer layer existence between friction pair, changing pressure, temperature, speed, deformation and wear. The size of the area of real contact between the pad and the disc is far from constant [5], very small compared to the total contact area [6], and highly dependent to changes of pressure, temperatures, deformation and wear. Taking into consideration that very complex and highly nonlinear phenomena are involved into braking process [7], analytical models of brake operation are difficult, even impossible to obtain. In contrast to classical approaches, neural modelling can be used to model complex non-linear, multidimensional functional relationships between the brake's inputs and outputs.

In order to improve the control of brake operation, prediction of effects influenced by friction material composition and/or its manufacturing conditions together with the conditions of brake operation, should be provided [8,9,10]. In this paper, artificial neural networks have been used for neural modelling of the cold brake performance by integrating influences of the complete friction material composition, its manufacturing parameters, and brake's operation conditions. Based on developed neural models of the cold brake performance, the braking system performance can be precisely predicted providing

Received: January 2007, Accepted: April 2007
Correspondence to: Dragan Aleksendric,
Faculty of Mechanical Engineering,
Kraljice Marije 16, 11120 Belgrade 35, Serbia
E-mail: daleksendric@mas.bg.ac.yu

preconditions for improving the brake and accordingly braking system performance.

2. EXPERIMENT

In order to be learned about the brake performance versus different types of friction materials and brake's operation conditions, the artificial neural networks have to be trained with corresponding data. The process of neural modelling of brakes operation is not trivial and many critical issues have to be resolved. The following issues have to be considered: (i) select data generator, (ii) data generation (define the range and distribution of the training data set), (iii) perform data generation (iv) data pre-processing, (v) selection of neural networks architectures, (vi) selection of training algorithms, (vii) training of the neural networks (viii) validation accuracy evaluation, and (ix) testing of the artificial neural networks.

Therefore, the preliminary step in a neural model development is the identification of the model inputs and outputs. Input/output identification depends on model objectives and choice of the data generator. According to the objectives of this paper, the input parameters are defined by the friction material composition, its manufacturing conditions, and brake operating conditions. The brake factor C has been taken as an output parameter, representing the brake performance. The type of data generator depends on application and the availability. In this case, as a data generator, single-end full scale inertia dynamometer has been used (fig. 1), developed at laboratory for friction mechanism and braking systems-FRIMEKS (Automotive Department, Faculty of Mechanical Engineering, University of Belgrade).

The role of data generator is important from the point of view of repeatability of the testing conditions. That is why, it has been decided to perform testing of the brake together with the different types of friction materials under strictly controlled conditions related to changes of pressure application, initial speed, initial temperature, and inertia of revolving masses. These testing conditions are chosen in order to simulate the real operating regimes by full-scale inertia dynamometer shown (figure 1). The DC motor (1) drives, via coupling (2), a set of six flywheels (3) providing in such way different inertia from 10 to 200 kgm^2 independently mounted on the driving shaft (4). The flange (5) firmly jointed to the shaft (4), bears rotating part of the tested brake (disc) while immobile flange (6), being firmly connected to the foundation (7) is used for mounting stationary parts of the tested brake (calliper) [12]. The full-scale inertia dynamometer is equipped by PC –based automatic control and data acquisition system of pressure, speed, temperature, and braking torque at a sampling rate of 50Hz. The brake factor C is calculated from the average values of friction coefficient in the range of speed changing between 0.8v and 0.1v. Therefore, the brake has been tested according to the adopted testing methodology. Obviously, testing methodology needs to be chosen according to the range and distribution of data that are going to be collected. From table 1, it can be seen the testing methodology used for output data generating. The brake testing conditions, after burnishing procedure, have been chosen in order to identify the influences of pressure applications, initial speed, and temperatures on the final brake's performance for the specific type of friction material [11,13]. These data have been used for training of the neural networks in order to establish the functional relationship between brake operation conditions, type of friction material, and the brake factor C.

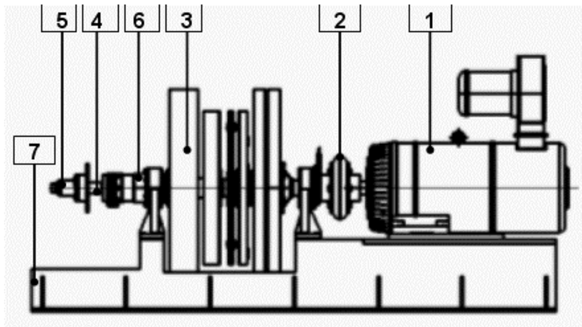

Figure 1. Single-end full-scale inertia dynamometer

It is mentioned that the range and distribution of the data for training, validation, and testing have to be predefined. Furthermore, neural modelling of brake performance takes into consideration the three groups of inputs data: (i) friction material composition, (ii) friction material manufacturing conditions, and (iii) the brake's operation conditions. The range and distribution of data related to the brake's operation conditions is defined by testing methodology (table 1). On the other hand, choice of the range and distribution of the manufacturing and especially composition parameters of the friction materials is a much more difficult task. For the purpose of the training and validation data set forming, each ingredient in the composition of friction material and manufacturing parameters are selected and ranged (F1-F9), as shown in tables 2 and 3.

Table 1. Testing methodology

Test No.	Test	Pressure [bar]	Initial speed [km/h]	Temp. [°C]	No. braking
1.	Burnishing	40	90	<100	100
2.	Cold performance	20-100	20-100	<100	25

Regarding tables 2 and 3, it can be seen that 11 different types of the friction materials, as a disc pad assembly, were produced, mounted, and tested in the brake assembly. Disc pads were designed to be mounted on the brake for the front axle of passenger car (Yugo Florida 1.4) with static load of 730 kg, effective disc radius of 101 mm, floating calliper (piston diameter 48 mm), friction surface area of 32.4 cm^2, and thickness of 16.8 mm. The composition and manufacturing parameters for the each type of the friction material, shown in tables 2 and 3, were completely different from others. Results obtained during brake testing with the friction materials F1-F8 have been used for training of the neural networks, while results of brake testing with the friction material F9 have been used for validating the generalization capabilities of the artificial neural networks. Furthermore, the capabilities of the trained neural networks (neural models) for predicting the brake performance have been tested by input/output data stored in the test data set related to the two different types of friction materials (F_{T1} and F_{T2}).

Table 2. The selection and ranges of raw materials (% vol.)

Raw materials	F1-F9 (training and validation data set)	F_{T1} (test data set)	F_{T2} (test data set)
Phenolic resin	17-25	25	17
Iron oxide	3-5	5	3
Barites	26-15	15	26
Calcium Carbonate	1-3	3	1
Brass chips	1-3	3	1
Aramid	2-6	6	2
Mineral fiber	10-16	10	9
Vermiculite	4-8	8	4
Steel fiber	4-1	1	4
Glass fiber	2-4	4	2
Brass powder	1-2	2	1
Copper powder	1-3	3	1
Graphite	7-3	3	7
Friction dust	5-2	2	5
Molybdenum Disulphide	1-3	3	1
Aluminium oxide	2-3	3	2
Silica	1-2	2	1
Magnesium oxide	8-2	2	8

Table 3. Manufacturing parameters

Manufacturing parameters	F1-F9 (training and validation data set)	F_{T1} (test data set)	F_{T2} (test data set)
Specific moulding pressure [kg/cm^2]	450-650	400	700
Moulding temperature [°C]	155-170	170	155
Moulding time [min]	6-11	11	6
Heat treatment temperature [°C]	200-250	200	250
Heat treatment time [h]	12-5	12	5

Due to unknown interrelated influences between ingredients during braking, for the specific manufacturing conditions and different brake's working regimes, random distribution was used over to the selected ranges. In order to evaluate generalization capabilities of the selected artificial neural networks, the test data set was sampled by brake testing with the new types of friction materials whose compositions and manufacturing conditions correspond to the upper and lower limit of the training and validation data set (tables 2 and 3). The data stored into test data set are completely unknown for the trained neural networks.

The composition and manufacturing conditions of the friction materials F_{T1} and F_{T2} have been chosen to represent the upper and lower limit of the prescribed ranges for composition and manufacturing parameters changing. Based on tables 1, 2 and 3, neural modelling of brake performance has been performed between 26 input parameters (18 parameters related to the friction materials composition, 5 parameters related to the manufacturing conditions, and 3 parameters related to the brake testing conditions), and one output parameter (brake factor C).

Neural modelling of the brake performance is a complex task, besides all, the appropriate architecture of neural network as well as the learning algorithm need to be properly determined. The architecture of artificial neural network consists of a description of how many layers a network has, the number of neurons in each layer, each layer's transfer function and how the layers are connected to each other. The best architecture to use depends on the kind of problem to be represented by the network. The best neural network set is affected by representational power of the network and learning algorithm [14,15]. Neural network learning ability to extend its prediction power on data out of the training data set is essential in implementation of artificial neural networks for predicting the brake performance.

It is clear that sufficient input/target pairs have to be stored into training data set. Input/output parameters obtained by formulation, manufacturing, and testing 11 types of the friction materials representing data set that can be used for training, validation, and testing. The total number of output results, collected by friction material testing according to adopted testing methodology is 25 (table 1). It means that 275 input/output pairs are available for the neural networks training, validation, and testing. The total number of 275 input/output pairs has been divided into three sets, 200 pairs for the neural networks training, 25 for validation, and 50 pairs for the neural networks testing. Thus, the best neural network architecture and learning algorithm are unknown in advance, the trial and error method during training process has been employed to find out the network characteristics (number of hidden layers, number of processing units-neurons and values of connections-weights between neurons, learning algorithms) for matching the particular input/output relationship. Based on MatLab 6.5 Rel. 13 the following networks architectures have been investigated in this case: (i) one-layered structures 26 $[1]_1$ 1, 26 $[2]_1$ 1, 26 $[3]_1$ 1, 26 $[5]_1$ 1, 26 $[8]_1$ 1, (ii) two-layered structures 26 $[1\text{-}1]_2$ 1, 26 $[2\text{-}2]_2$ 1, 26 $[3\text{-}2]_2$ 1, 26 $[5\text{-}2]_2$ 1, 26 $[8\text{-}2]_2$ 1, 26 [8-4]$_2$ 1, 26 [10-5]$_2$ 1 and (iii) three-layered structures 26 [3-2-2]$_3$ 1, 26 [4-3-2]$_3$ 1, 26 [4-2-2]$_3$ 1, 26 [5-2-2]$_3$ 1, 26 [8-2-2]$_3$ 1, 26 [8-4-2]$_3$ 1. These network architectures have been trained by the following training algorithms: Levenberg-Marquardt, Bayesian Regulation, Resilient Backpropagation, Scaled Conjugate Gradient, and Gradient Decent. Sigmoid activation function has been used between the input and hidden layers (see expression (1)).

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

Pre-processing of the input parameters have been done before the neural networks training. Thus, 18 parameters related to the friction materials formulations were presented to the network in percent by volume, 5 manufacturing parameters and 3 testing parameters were scaled in the range of 0 to 1 according to expression (2). On the other hand, output parameter has been linearized by expression (3). A linear activation function ($f(x) = 1\,x$) has been employed between the hidden and output layer.

$$I_{Scal} = 1 + \frac{(I_{Curr} - I_{Max})}{(I_{Max} - I_{Min})} \tag{2}$$

where:

I_{Curr} - current input value, I_{Max} – maximum input value, and I_{Min} – minimum input value.

$$O_{Lin} = 0,75 + 0,2\frac{(O_{Curr} - O_{Max})}{(O_{Max} - O_{Min})} \tag{3}$$

where:

O_{Curr} - current output value, O_{Max} – maximum output value, and O_{Min} – minimum output value.

3. RESULTS AND DISCUSSION

The analysed networks and learning algorithms, after processes of their training and validation, have been employed for predicting the performance of the brake with the friction materials F_{T1} and F_{T2} (test data set). The total of 90 different neural models have been tested (18 different neural networks with the five learning algorithms) in order to evaluate their capabilities for generalizing the brake performance. The quality of prediction has been evaluated by difference (in percents) between predicted and real values of the brake factor C. Accordingly, the sixth error intervals have been established (0-5%; 5-10%, 10-15%; 15-20 %; 20-25 %; 25-30 %). Based on the calculated errors between predicted and real values, the number of the predicted results, which belong to each of these error intervals, has been calculated and expressed as a fraction of the test data set (in percent). The influences of different architectures and learning algorithms of the artificial neural networks on the final "performance" of the neural models have been demonstrated in [1].

The best results of predicting the cold brake performance have been reached by the neural model BR 26 8 4 1, based on the two-layered neural network with 8 neurons in the first and four neurons in the second hidden layer, trained by Bayesian Regulation learning algorithm. In order to illustrate the ability of this neural model, its predictions abilities of the brake factor C, under specified brake's operation conditions, have been shown on fig. 2, 3, and 4. The abilities of the neural model for predicting the cold brake performance ($T \leq 100°C$) have been tested in the specified ranges of pressure applications and initial speeds changing (table 1) for the two types of friction materials F_{T1} and F_{T2} (tables 2 and 3).

The complex interrelated influences of the cold brake's operation regimes on the brake's performance, for the specific type of friction material, has been shown in fig.2. From fig. 2 it can be seen 3-D plot of the real cold brake performance, with the friction material F_{T1}. It is evident that cold brake performance is strongly affected by different brake's operation conditions. That is why, it was very important to develop the neural model able to predict these complex influences. The neural model (BR 26 8 4 1) abilities to generalize influences of the friction material's (F_{T1}) composition and manufacturing parameters on the cold brake performance, under specified pressure application and initial speed changes, have been shown in fig. 3. It can be seen (fig. 3) that the neural model has well predicted very complex changes of the brake factor C versus different brake's operation regimes and the friction material characteristics unknown to the neural model.

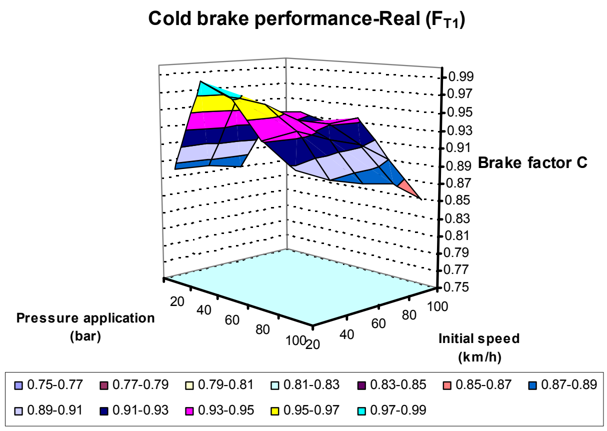

Figure 2. 3-D plot of the real cold brake performance (friction material F_{T1})

Furthermore, the neural model of cold brake performance has been also employed for predicting the influences of the new type of friction material (F_{T2}) on the cold brake performance together with the brake's operation regimes changes (fig. 4, and 5). The real cold brake performance has been shown in fig. 4. Regarding figures 2 and 4, it is evident that the friction materials, whose composition and manufacturing parameters corresponding those shown in table 3 and 4, differently influence the cold brake performance. The neural model of cold brake performance (BR 26 8 4 1) has well predicted the cold brake performance represented by the brake factor C (fig. 3 and 5).

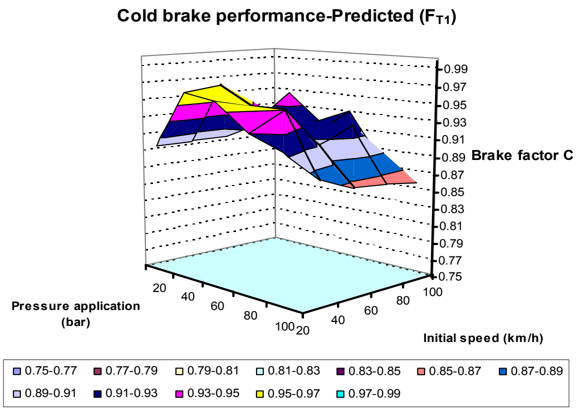

Figure 3. 3-D plot of the cold brake performance –predicted by BR 26 8 4 1 (friction material F_{T1})

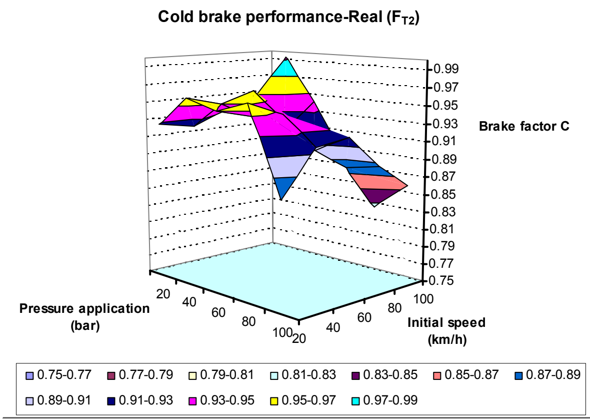

Figure 4. 3-D plot of the real cold brake performance (friction material F_{T2})

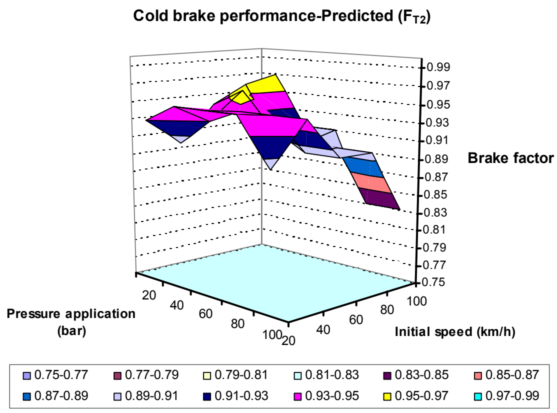

Figure 5. 3-D plot of the cold brake performance –predicted by BR 26 8 4 1 (friction material F_{T2})

4. CONCLUSION

The results show that the artificial neural networks can be used for neural modelling of complex nonlinear phenomena influenced by different friction material compositions, their manufacturing conditions, and the brake's operation regimes. The influences of the whole friction materials composition with 18 different ingredients, 5 the most important manufacturing conditions, and 3 brake's testing conditions have been modelled versus changes of the brake factor C. Based on training of 18 different neural networks' architectures with the five learning algorithms, the total of 90 neural models have been investigated in this paper regarding their abilities for predicting the cold brake performance.

The capabilities of the neural models to predict cold brake performance have been tested against unknown data stored into test data set. The neural model BR 26 8 4 1 has shown the best prediction abilities of the cold brake performance regarding test data set. Based on results shown in this paper, the technique of neural modelling can be used for modelling of cold brake performance regarding synergistic influences of the friction materials' composition, its manufacturing conditions, and brake's operation regimes. Accordingly, the control of the brakes operation can be substantially improved providing preconditions for intelligent controlling of braking system performance. The neural model of the cold brake performance well predicted the brake's responses (brake factor C changes) versus different types of friction materials and brake's operation regimes. Accordingly, the appropriate pressures can be selected for the brakes application in order to achieve high and stable value of the brake factor C.

REFERENCES

[1] Aleksendrić D., Duboka Č.: Automotive friction material development by means of neural computation, Braking 2006, 7-9 May, York, United Kingdom, pp. 167-176, 2006.

[2] Cho M. H., Kim S. J., Basch R.H., Fash J.W., Jang H.: Tribological study of cast iron with automotive brake linings: The effect of rotor microstructure, Tribology International 36, pp. 537-545, 2003.

[3] Eggleston D.: *Automotive friction materials, Technical bulletin*, 00010433, 2000.

[4] Talib R.J., Muchtar A., Azhari C.H.: Microstructural characteristics on the surface and subsurface of semi metallic automotive friction materials during braking process, Journal of Materials Processing Technology 140, pp. 694–699, 2003.

[5] Eriksson M., Jacobson S.: Tribological surfaces of organic brake pads, Tribology International Vol. 33, pp. 817-827, 2000.

[6] Eriksson M.: Friction and contact phenomena of disc brakes related to squeal, Ph. D. Thesis, Faculty of Science and Technology, University Uppsala 2000.

[7] Aleksendrić D., Duboka Č., P.F.Gotowicki, G.V.Mariotti, V. Nigrelli: Braking procedure analysis of a pegs-wing ventilated disk brake rotor, Int. J. Vehicle Systems Modelling and Testing, Vol. 1, No. 4, pp.233–252., 2006.

[8] Aleksendrić D., Duboka Č: Prediction of automotive friction material characteristics using artificial neural networks-cold performance, Wear Vol. 261, Issues 3-4, pp. 269-282, 2006.

[9] Aleksendrić D., Duboka Č.: Fade performance prediction of automotive friction materials by

means of artificial neural networks, Wear 262, Issues 7-8, pp. 778-790, 2007.

[10] Aleksendrić D., Duboka Č.: A Neural Model of Friction Material Behavior, 24th Annual Brake Qolloquium 2006, October 8-11, Texas, USA. SAE Paper 2006-01-3200, 2006.

[11] Aleksendrić D., Duboka Č: Artificial technologies in the design of braking systems, Innovative Automotive Technology – IAT'05, Bled, 21st-22stApril, Slovenia, pp. 41-48, 2005.

[12] Duboka Č., Todorović J., Arsenić Ž.: Application of an inertia dynamometer to check braking performance against theoretical predictions, 6th International Heavy Vehicles Seminar, Christchurch, New Zealand, 1996.

[13] Aleksendrić D., Duboka Č: Friction material development using artificial intelligence, 10th EAEC European Automotive Congress, 30th May-1stJune, Belgrade, Serbia & Montenegro, EAEC05-AD09, 2005.

[14] Liu, T.S. Chang, Y. Zhang: A constructive algorithm for feddforward neural networks with incremental Training, IEEE Tran. on Circuits and Systems, Vol. 49, No.12, pp. 1876 – 1879, December 2002.

[15] Fonseca D., Navaresse D.O., Moynihan G.P.: Simulation metamodeling through artificial neural networks, Engineering Application of Artificial Intelligence 16, 177-183, 2003.

НЕУРОНСКИ МОДЕЛ ПЕРФОРМАНСИ ХЛАДНЕ КОЧНИЦЕ МОТОРНИХ ВОЗИЛА

Драган Александрић, Чедомир Дубока

Перформансе кочница моторних возила су резултат сложених медјусобно повезаних феномена који се јављају у контакту фрикционог пара. Ови сложени кочни феномени су углавном одредјени физичко-механичким особинама сировина фрикционог материјала, условима његове производње и радним условима кочнице. Успостављање аналитичких модела кочних перформанси је врло тешко, готово немогуће, услед сложених и изражено нелинеарних феномена који се јављају у току процеса кочења. Због тога су у овом раду обухваћени сви релевантни утицаји на перформансе хладне кочнице помоћу вештачких неуронских мрежа. Утицаји 26 улазних параметара одредјени саставом фрикционог материјала (18 сировина), његовим производним условима (5 параметара) и радним условима кочнице (3 параметра) су моделирани у односу на промену Ц карактеристике кочнице. Неуронски модел перформанси хладне кочнице је развијен на основу обуке и тестирања 90 различитих неуронских модела. Ови неуронски модели су добијени обуком 18 различитих архитектура неуронских мрежа које су обучаване са пет алгоритама учења.