

STUDYING THE ABRASION BEHAVIOR OF RUBBERY MATERIALS WITH COMBINED DESIGN OF EXPERIMENT-ARTIFICIAL NEURAL NETWORK

Mehdi Shiva^{a*}, Hossein Atashi^b and Mahtab Hassanpourfard^c

^a Research and Development Department of Kavir Tire Company, P.O. Box 518, Birjand, Iran

^b Department of Chemical Engineering, Sistan and Baluchestan University, P.O. Box 98-164161, Zahedan, Iran

^c Department of Chemical Engineering, Amirkabir University of Technology, Tehran, Iran

Abstract In this study, an application of artificial neural network (ANN) has been presented in modeling and studying the effect of compounding variables on abrasion behavior of rubber formulations. Three case studies were carried out in which the experiment data were collected according to classical response surface designs. Besides developing the ANN models, we developed response surface methodology (RSM) to confirm the ANN predictions. A simple relation was employed for determination of relative importance of each variable according to ANN models. It was shown through these case studies that ANN models delivered very good data fitting and their simulating curves could help the researchers to better understand the abrasion behavior.

Keywords: Abrasion; Feed forward neural networks; Rubber compounding; Central composite design.

INTRODUCTION

Identification of compounding variables that control abrasion behavior of rubbery materials is very important and it is essential to know the relations between compounding ingredients and abrasion behavior. These relations maybe investigated using artificial neural network, which is widely used in various fields of science and technology as well as polymer studies^[1, 2]. An ANN is a massively interconnected network structure consisting of many simple processing elements that incrementally learn from their environment (data) to capture essential linear and nonlinear trends in complex data. In effect, ANN can handle multiple independent and dependent variables simultaneously without having prior knowledge about the functional relationship^[3].

Neurons are the basic computing units that perform local data processing inside a network. The neurons are connected to each other by links with their own weight factors or “weights”. Usually neural networks are trained by adjusting the values of the weights of the links between neurons, so that the network will fit its outputs as closely as possible to the represented experimental data.

Analysis of controlling factors leading to the identification of primary factors is important in rubber compounding studies. However, the artificial neural networks have also been labeled as “black box” because they are believed to provide little explanatory insight into the contributions of the independent variables in the prediction process. Therefore, beyond the predictive realm of ANNs, focus has now switched to the development methods for quantifying the explanatory contributions of the predictor variables in the network^[3–5]. The methods such as sensitivity analysis, partial derivatives, input perturbation and “weights” methods are widely used in ANN literatures, and it seems to be helpful in rubber compounding studies.

* Corresponding author: Mehdi Shiva, E-mail: Mehdi.shiva@gmail.com

Received September 2, 2011; Revised November 18, 2011; Accepted November 29, 2011
doi: 10.1007/s10118-012-1154-y

The other aspect of ANN is that it usually requires a large set of experimental data to build an efficient model and ensure the model generalizes well. Non-generalization of the network is due to the weights growing too large. The experimental data usually divide into three parts; training set, validation set and testing set.

In the absence of sufficient experimental data, here we proposed the alternative procedure:

(1) Collecting the data according to experimental design methodology^[6] to ensure the optimum distribution of the data through understudy domain.

(2) Using Bayesian regularization algorithm for network training to ensure the weights not to grow too large values and networks generalize well.

(3) Demonstration of the results through simulated graphs and validation of the results with the other methodology such as response surface procedures.

In this study we have constructed simple ANN models based on data which were gathered by experiential designs to study the effect of compounding variables on abrasion behavior of rubber vulcanizates. The capability of ANN models in prediction and also identification of the behaviors has been highlighted *via* simple case studies.

ARTIFICIAL NEURAL NETWORKS

There are various types of ANNs. For our purposes we employed multilayer feed forward neural networks which are commonly used in science and engineering studies, because they are suggested to be universal approximation of any continuous function. The architecture of this network consists of input, hidden and output layers, with each layer containing one or more neurons, in addition to bias neurons connected to the hidden and output layers. Number of the neuron in the input layer equals to the number of data to be given to ANN. Number of neuron at the output layer equals to the number of knowledge that will be taken from ANN. Neuron number of the hidden layer is found experimentally.

Each neuron in hidden layer accepts a weighted set of inputs with a bias given by:

$$n_i = \sum_{i=1}^p a_{ii}x_i + \beta_i \quad (1)$$

where p is the number of elements, a_{ii} is interconnections weights between inputs and hidden neurons, and β_i is the bias for the hidden neuron. Then the output of each neuron in the hidden layer is obtained by

$$y_i = f(n_i) \quad (2)$$

where, f is an activation function.

Similarly, the output layer is calculated:

$$n_k = \sum_{i=1}^s (y_i b_{ik} + \beta_k) \quad (3)$$

$$o_k = f(n_k) \quad (4)$$

o_k : output of each neuron in output layer, b_{ik} : interconnections weights of hidden neurons and output neurons, k : number of output neurons, s : number of hidden neurons.

Using a suitable learning method, ANN can be trained to perform a particular function by adjusting the values of connections *i.e.* weighting coefficients, between the processing neurons. The training process continues until the network output matches the target. The error between the output of the network and the desired (experimental) output is minimized by modifying the weights and biases. When the error falls below a predetermined value for maximum number of epochs is exceeded, the training process is terminated. This trained network can be used for simulating the system outputs for the inputs that have not been introduced before.

A neural network derives its computing power through its massively parallel-distributed structure and its ability to learn and therefore generalize. The generalization is an important aspect and refers to the neural network producing reasonable outputs for inputs not encountered during training. If the network over fit the data, it can not generalize well.

Overfitting is a result of weights growing too large. There are several aspects for over fit elimination; trials and errors approaches, adding random noises to inputs, leave one-out test and early stopping. In our studies we have employed a Bayesian regulation backpropagation algorithm to ensure model generalization. In this method the weight and bias values are updated according to Levenberg-Marquardt optimization that minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well^[3].

$$W = \text{MSE} + \delta \sum_{j=1}^m a_j^2 \quad (5)$$

Where MSE is mean sum of error, the second term in the equation is a regularization term, a_j is a weight in the total set of m weights in the network and δ is a regularization parameter.

DETERMINING THE SIGNIFICANCE OF EACH VARIABLE

Although the interpretation of neural networks will obviously never be as straightforward as simple regression models, it is now apparent that a select of robust methodologies is available for illuminating the “black box”^[6].

In the present study, the following simple equation proposed by Hattori^[7] was used to calculate a contribution of i th input data to k th output data (C_{ik}), which is expected to represent the relative importance of each input data, from the set of weightings.

$$C_{ik} = \left| \sum_j a_{ij} \times b_{jk} \right| \quad (6)$$

where, a_{ij} and b_{jk} are the weightings of connecting links between i th input unit and j th hidden unit and between j th hidden unit and k th output unit.

EXPERIMENTAL

Design of Experiments

The experimental data of this study for neural network modeling purposes were obtained by performing the series of designed experiments through three case studies.

In experiment 1, an NR/BR (75/25) based truck tire tread compound was selected. A central composite design with two variables was chosen to study the simultaneous effect of *cis* butadiene rubber/natural rubber ratio (material variable) and rotor speed of mixer (process variable) on abrasion of vulcanizates. The levels of N330, sulfur and accelerator were kept constant at 50, 1.34 and 0.82 phr, respectively. The butadiene rubber ranged from 2 phr to 60 phr (or natural rubber range from 98 phr to 40 phr). The mixer rotor speed ranged from 28 r/min to 70 r/min. 8 compounds were prepared according to the central composite design. The center point was repeated 5 times (total 13 runs).

In experiment 2, a Box-Behnken design was employed to study the effect of partial substitution of based rubber (SBR) with BR, partial substitution of base carbon black (N234) with silica (and 10% silane) and addition of carbon black N330 to a passenger tire tread compound. The other ingredients were kept constant. The amount of base carbon black (N234) in reference formulation was 70 phr. According to the Box-Behnken design 15 formulations were planed (3 variables at 3 levels with 3 replications).

In experiment 3, an SBR based tire tread compound with 40 phr carbon black N234 was selected. 20 formulations were designed according to a central composite plan in which the levels of N330, aromatic oil and

accelerator CBS were changed in following ranges: N330, 23–37 phr (addition to base carbon black N234); oil, 5–11 phr; CBS, 1–2 phr.

All experiments were conducted randomly and parallel tests were done to avoid random error.

Compound Preparation, Curing and Test

A laboratory-sized internal mixer (POMINI MIX32) was employed to prepare the master rubber compounds. The mixing conditions were set as follows, initial chamber temperature: 50°C, rotor speed: 28–70 r/min for case study 1, 40 r/min for case study 2 and 3. After master preparation, the compounds were finalized on two roll mills (MCCIN 152 X 305 R-E).

The prepared compounds were cured in a curing press in abrasion moulds according to the optimum curing time as determined by ODR measurements. The curing temperature was selected as 151°C for the compounds of experiment 1 and 145°C for the compounds of experiments 2 and 3. The cured samples were tested with an abrasion machine tester according to ISO standards. The average volume loss of samples was recorded.

Development of ANN Models

Based on the experimental data presented in Tables 1–3, three ANN models were developed for three case studies. The details of the networks and their predictions are also shown in Tables 1–3. All three networks have one hidden layer. The Bayesian regulation algorithm was used to train the network and adjusting the weights. The training dataset was the experimental design points of each study. The MSE was selected as performance function. In each experiment, the network was trained with different number of neurons in hidden layer as well as different activation functions. The activation function of hidden layer was selected Log-sigmoid transfer function, Tan-sigmoid transfer function and hyperbolic tangent sigmoid transfer function were selected as the activation function of hidden layer for experiment 1, experiment 2 and experiment 3, respectively to achieve the best fit. It was observed that optimum number of neurons in hidden layer was 4 for all the three experiments under above conditions. The calculated weights after training are presented in Table 4. Significance of each variable was calculated according to the Eq. (6) and is presented in Table 4.

Table 1. Experimental and predicted values of case study 1, studying the effect of NR/BR ratio and mixing rotor speed on abrasion behavior of NR/BR based truck tire tread compound

Run	Variables		Responses (abrasion)	
	BR	RPM	Experimental value of Exp. 1	Predicted by ANN
1	2	50	142.7	138.8491
2	30	50	89.7	80.9993
3	10	35	115.6	118.8210
4	30	50	84.9	80.9993
5	30	50	78.9	80.9993
6	60	50	51.8	52.2755
7	30	50	80.5	80.9993
8	30	30	85.0	79.1821
9	30	70	82.2	82.9203
10	30	50	72.9	80.9993
11	50	65	51.7	58.2297
12	50	35	57.8	57.0339
13	10	65	121.4	122.5163
R^2				0.9850

ANN architect: number of neurons in hidden layer, 4; activation function of hidden layer, log-sigmoid transfer function; activation function of output layer, linear transfer function; training algorithm, Bayesian regulation

Table 2. Experimental and predicted values of case study 2, studying the effect of BR, silica and carbon black N330 on abrasion behavior of SBR based passenger tire tread compound

Run	Variables			Responses (abrasion)	
	BR	Silica	N330	Experimental value of Exp. 2	Predicted by ANN
1	0	0	7	148.2	141.1818
2	30	0	7	108.4	107.3600
3	15	20	0	108.4	110.3205
4	30	10	14	111.8	112.8856
5	0	10	14	127.2	133.2100
6	15	0	0	106	107.1607
7	0	10	0	131	128.7692
8	30	10	0	96.5	96.3988
9	15	10	7	125	124.1724
10	15	10	7	124.2	124.1724
11	15	0	14	124.5	126.4093
12	0	20	7	132	130.7227
13	30	20	7	102	103.6339
14	15	20	14	126.9	128.8577
15	15	10	7	129	124.1724
R^2					0.9770

ANN architect: number of neurons in hidden layer, 4; activation function of hidden layer, tan-sigmoid transfer function; activation function of output layer, linear transfer function; training algorithm; Bayesian regulation

Table 3. Experimental and predicted values of case study 3, studying the of N330, oil and CBS on abrasion behavior of SBR/BR based passenger tire tread compound

Run	Variables			Responses (abrasion)	
	N330	Oil	CBS	Experimental value of Exp. 3	Predicted by ANN
1	30	5	1.5	105.05	103.6149
2	23	8	1.5	100.67	101.4673
3	30	8	1.5	104	102.3352
4	34.2	9.8	1.2	112	112.6570
5	34.2	6.2	1.2	111.8	112.1216
6	34.2	9.8	1.8	107.34	108.4924
7	30	8	1.5	105	102.3352
8	30	8	1.5	99.66	102.3352
9	25.8	6.2	1.2	93.06	95.2297
10	30	8	1.5	105	102.3352
11	30	8	1.5	99.66	102.3352
12	25.8	6.2	1.8	101.6	101.1516
13	30	8	1	108.7	107.0927
14	37	8	1.5	107	106.7006
15	30	8	2	109.4	108.8734
16	30	11	1.5	128.64	127.9318
17	30	8	1.5	102.21	102.3352
18	25.8	9.8	1.8	121.9	121.4932
19	25.8	9.8	1.2	114.5	114.9451
20	34.2	6.2	1.8	101.6	103.0529
R^2					0.9815

ANN architect: number of neurons in hidden layer, 4; activation function of hidden layer, hyperbolic tangent sigmoid transfer function; activation function of output layer, linear transfer function; training algorithm, Bayesian regulation

Table 4. Value of weights and calculated relative importance (RI) and C_{ik} (Eq. (6))

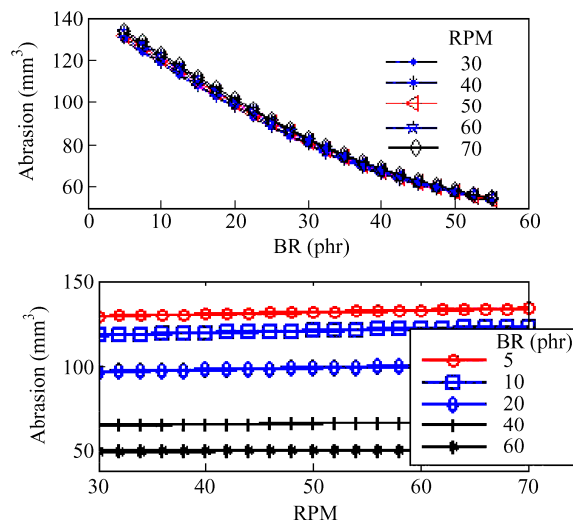
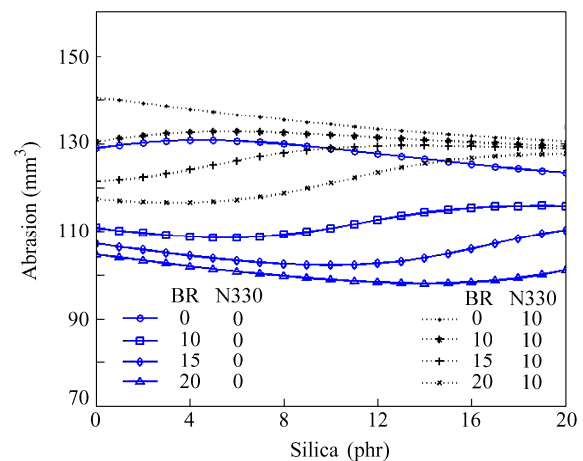
	Experiment 1		Experiment 2			Experiment 3		
Weights of hidden layer in trained neural network	-0.0507	0.0012	0.0189	0.0500	0.0276	0.2888	-0.2910	0.3205
	0.0589	-0.0060	-0.0223	-0.0491	-0.0286	0.2800	-1.1350	1.5148
	-0.0507	0.0008	-0.0759	-0.0061	0.3142	-0.2616	0.4203	2.5630
	0.0582	-0.0056	-0.1940	0.1720	0.2056	-0.1541	0.2960	2.4344
Weights of output layer	1.0506, -0.7482, 1.0533, -0.7587		-0.3037, 0.3037, 0.3343, 0.3472			3.9441, -2.2808, 2.2763, -1.9387		
C_{BR} (RI)	0.1950 (0.95)							
C_{RPM} (RI)	0.0108 (0.05)							
C_{BR} (RI)			0.1052 (0.36)					
C_{silica} (RI)			0.0276 (0.09)					
C_{N330} (RI)			0.1593 (0.54)					
C_{N330} (RI)						0.2037 (0.06)		
C_{oil} (RI)						1.8239 (0.59)		
C_{CBS} (RI)						1.0766 (0.35)		

Response Surface Methodology to Validate the Predicted ANN Behaviors

The significance of each variable and also significance of interaction and quadratic terms were calculated according to response surface methodology, the details of the procedure have been described elsewhere^[8].

RESULTS AND DISCUSSION

The predicted values of abrasion and the R^2 coefficient of each model are presented in Tables 1–3. All the three studies show the high value of R^2 for ANN models. To ensure the generalization capability of models, we simulated the abrasion behavior with several data of input variables in the range of study. The simulated curves are shown in Fig. 1 (for the first study), Figures 2 and 3 (for the second study) and Figs. 4 and 5 (for the third study).

**Fig. 1** Experiment 1, effects of NR substitution by BR and also mixer rotor speed on abrasion of final vulcanizates**Fig. 2** Experiment 2, effects of silica introducing at different BR and N330 levels on abrasion behavior of passenger tire tread formulations

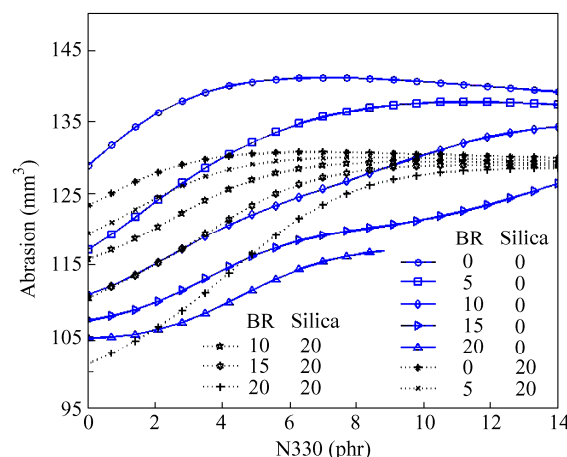


Fig. 3 Experiment 2, effects of N330 addition at different BR and silica values on abrasion behavior of passenger tire tread formulations

The results of response surface calculations are also given in Table 5 for better investigation of ANN prediction capabilities. The calculated R^2 and also the Anova statistics clearly show that the response surface models fit the results well and their results can be used to check the ANN predictions.

Table 5. Calculated regression coefficient of abrasion quadratic equation and their significance (Case study 1)

Term	Coefficient	T	P
Constant	81.38	34.829	0.000
BR	-45.26	-17.326	0.000
RPM	-0.75	-0.288	0.782
BR*BR	13.97	3.525	0.010
RPM*RPM	0.32	0.080	0.939
BR*RPM	-5.95	-1.139	0.292
$R^2 = 97.8\%$			
Analysis of variance			
Source	Degree of freedom	F	P
Regression	5	62.83	0.000
Lack-of-Fit	3	0.26	0.855

In experiment 1, the effects of rotor speed and BR/NR ratio on abrasion behavior of filled rubber vulcanizates were studied. The ANN simulated curves of this simple case study are given in Fig. 1. The graphs clearly show that the substitution of NR with BR rubber (increase of BR contribution in rubber formulation) would decrease (*i.e.* improve) the abrasion of rubber. This is in agreement with our previous knowledge that the butadiene has super abrasion among the rubbers. The calculated coefficient for BR is also very high (-45.26 in Table 5) according to the response surface calculations, that verified the ANN curves. Dependency of abrasion on BR is not linear as shown in Fig. 1, this behavior has been confirmed by response surface results because the calculated coefficient of BR*BR is high (13.07) and statistically significant ($P = 0.01$).

Little effect of mixer rotor speed on abrasion behavior can also be observed, according to Fig. 1. The response surface methodology shows the same results, the effect of rotor speed (RPM) on abrasion behavior is statistically insignificant, because the P -value of t-statistics of RPM coefficient is higher than 0.05 (Confidence level of 0.95) *i.e.* 0.782.

The other important result from Fig. 1 is that when NR content is high (BR content is low), RPM has a little effect on abrasion behavior. This behavior may be attributed to the effect of RPM on the filler dispersion. The dispersion of filler in high viscosity domain of natural rubber (NR) is more difficult than that in butadiene

rubber (BR) and hence is influenced by mixer rotor and has an effect on abrasion of vulcanizates. Although this phenomenon is small, it can be detected by ANN curves.

The calculated relative importance (RI) of BR and RPM from network weighs according to Eq. (6) is presented in Table 4. The $RI_{BR} = 95\%$ and $RI_{RPM} = 5\%$ accurately demonstrated the relative importance of each variable which is in agreement with the above discussion.

In experiment 2, the effect of butadiene rubber, silica/silane and N330 on abrasion behavior of SBR based tire tread compound was investigated. The calculated regression coefficients according to regression/statistical analysis (Table 6) clearly shows that butadiene rubber has a significant improving effect, silica has statistically no significant effect and N330 has a significant effect on abrasion.

ANN simulated curves in Fig. 2 also indicate that generally silica has no significant effect on abrasion behavior. The calculated regression coefficient of silica is -2.22 which is statistically insignificant (calculated P -value is 0.403 which is greater than 0.05), that shows the silica has a statistically insignificant negative effect on abrasion behavior (to 20 phr substantiation). It can be concluded that very high surface area (silane modified) silica aggregates distribute well in rubber domains and deliver high filler-rubber interactions similar to N234 carbon blacks at least in relatively low substitutions.

However, Fig. 2 clearly shows that although, substituting of SBR with BR leads to better abrasion in all cases, when the amount of silica gradually increases the BR improving effect falls and the BR curves approach to each other. This effect is more obvious when the amount of N330 is high. ANN curves also show that in the absence of BR (SBR = 100 phr) silica introducing has an improving effect on abrasion to some extent. However in SBR/BR blends the silica substituting has a little harmful effect. This behavior is in agreement with surface energy studies that confirm the SBR chains interact better to silica rather than BR chains due to their more polarity^[9]. We can see that ANN simulates well this behavior.

The effect of adding N330 (not substituting) on abrasion behavior is introduced in Fig. 3. The addition of N330 (= addition of total filler) increases the abrasion amount and has a harmful effect. The regression/statistical analysis (Table 2) illustrates that the effect of N330 on abrasion is statistically significant and a high positive regression coefficient (6.06) has been calculated. Also, a high negative regression coefficient for quadratic term ($N330*N330$) has been calculated in agreement with the shape of predicted ANN curves (Fig. 3). The addition of total filler touses the optimum level of filler-rubber interaction for optimum of abrasion and is harmful. However, it seems that the curves approach to a constant, especially in the presence of silica, *i.e.* when the total filler increases the improving effect of butadiene rubber substitution becomes insignificant. This behavior clearly demonstrated the very important effect of total filler on abrasion behavior.

The relative significance of these variables according to the ANN predictions are $RI_{BR} = 36\%$, $RI_{silica} = 9\%$ and $RI_{N330} = 54\%$ in qualitative agreement with our observations.

In experiment 3, the effect of N330 carbon black, oil and accelerator CBS on abrasion behavior of SBR/BR based tire tread compound was studied. The simulated ANN curves of this study are presented in Figs. 4 and 5. The regression and statistical analysis of Table 7 shows that only oil has significant influence on abrasion, However, quadratic term of CBS ($CBS*CBS$) has high and statistically significant value. The strong interaction between N330 and oil and between N330 and CBS is also observable. Therefore it is clear the complicated dependency presents between abrasion and the variables in this study.

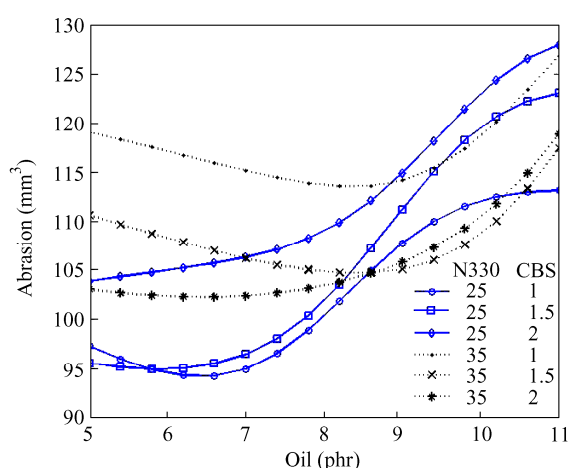
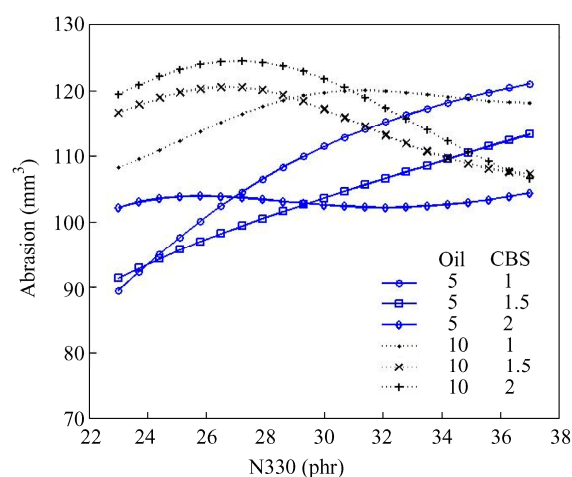
Effects of aromatic oil level on abrasion behavior of rubber vulcanizates in different CBS and N330 levels are illustrated in Fig. 4. In agreement with the statistical analysis (RSM) results, the abrasion increases with increase of oil contents. However, there are exceptions when N330 content is high; in these cases increasing of oil level would decrease abrasion then subsequent addition of oil would increase it. Oil would weaken the rubber-filler interaction and has a harmful effect on abrasion. However, in high filler levels, where the filler-rubber interaction is too high (not optimum), addition of oil would decrease the interactions and has a useful effect.

Table 6. Calculated regression coefficient of abrasion quadratic equation and their significance (Case study 2)

Term	Coefficient	<i>T</i>	<i>P</i>
Constant	126.07	31.659	0.000
BR	−14.96	−6.136	0.002
Silica	−2.22	−0.912	0.403
N330	6.06	0.000	0.055
BR*BR	−1.62	−0.452	0.670
Silica*Silica	−1.80	−0.500	0.638
N330*N330	−7.82	−2.179	0.081
BR*Silica	2.45	0.710	0.509
BR*N330	4.78	1.385	0.225
Silica*N330	0.00	2.486	1.000
$R^2 = 91.2\%$			
Analysis of Variance			
Source	Degree of freedom	<i>F</i>	<i>P</i>
Regression	9	5.78	0.034
Lack-of-Fit	3	11.32	0.082

Table 7. Calculated regression coefficient of abrasion quadratic equation and their significance (Case study 3)

Term	Coefficient	<i>T</i>	<i>P</i>
Constant	102.69	95.380	0.000
N330	1.50	1.257	0.237
Oil	10.70	8.945	0.000
CBS	0.28	0.231	0.822
N330*N330	−0.27	−0.140	0.892
Oil*Oil	12.74	6.501	0.000
CBS*CBS	4.94	2.522	0.030
N330*Oil	−12.43	−4.791	0.001
N330*CBS	−10.69	−4.122	0.002
Oil*CBS	1.53	0.589	0.569
$R^2 = 94.4\%$			
Analysis of Variance			
Source	Degree of freedom	<i>F</i>	<i>P</i>
Regression	9	18.75	0.000
Lack-of-Fit	5	1.26	0.404

**Fig. 4** Experiment 3, effect of oil introducing at different N330 and CBS levels on abrasion behavior of passenger tire tread formulations**Fig. 5** Experiment 3, effects of N330 adding at different oil and CBS levels on abrasion behavior of passenger tire tread formulations

The interaction of rubber-filler and also rubber-rubber is influenced by the accelerator CBS level. From Fig. 4 and also Fig. 5 we can conclude that in high carbon black levels, increase of CBS would decrease (improve) abrasion, while in low carbon black, increase of CBS would increase abrasion. This observed behavior is in agreement with statistical analysis that shows N330*CBS is statistically significant.

The relative significance of these variables according to the ANN predictions are $RI_{N330} = 6\%$, $RI_{oil} = 56\%$ and $RI_{CBS} = 35\%$ in qualitative agreement with our observations.

CONCLUSIONS

The complex relation of abrasion behavior with the compounding variables and the excellent capability of artificial neural networks in modeling and demonstration of the behaviors have been studied here through three case studies. It was shown that employment of experimental designs (such as box-behnken or central-composite design which is standard designs of response surface methodology) was helpful for data gathering and model construction. Employment of Bayesian regulation algorithm for training feed forward one hidden layer neural network would prevent weight gowning and ensure network generalization. Effects of compounding variables on abrasion behavior were demonstrated very well with simulated ANN curves. The R^2 value of the models was high for all cases. Also a suitable relation for determination of the relative importance of each variable on response (abrasion) was proposed and was tested in three cases. The accuracy of the predictions was investigated with the standard procedure, RSM, and in almost all cases a very good agreement was observed. From case studies and ANN/RSM analysis, it is clear that derivation of decisive rules which control the abrasion behavior is very hard and this behavior completely depends on the compounding variables, for example from experiment 2 we can see that even famous substitution of SBR with BR may not improve the abrasion. The filler-rubber interaction has a critical role on abrasion and is influenced by filler type and its level and also the oil and curing agent levels. The rubber-rubber interaction *via* crosslinks is the other important aspect which is affected by curing agent levels, filler and to some extent oil level. The abrasion behavior becomes optimum when the filler-rubber and rubber-rubber interactions approach to an optimum level. Therefore, employment of efficient experimental approaches such as we carried out in this study would help efficiently the better understanding and modeling of the behaviors.

ACKNOWLEDGEMENTS The authors gratefully acknowledge the support from Kavir Tire Company.

REFERENCES

- 1 Zhang, Z. and Friedrich, K., *Compos. Sci. Technol.*, 2003, 63: 2029
- 2 Kadi, H.E., *Compo. Struct.*, 2006, 73: 1
- 3 Samarasinghe, S., "Neural networks for applied sciences and engineering", Auerbach Publications, Boston, 2006
- 4 Gevrey, M., Dimopoulos, I. and Lek, S., *Ecol. Model.*, 2003, 160: 249
- 5 Proust, M., "Design of Experiments", SAS Institute Inc., Cary, NC, USA, 2005
- 6 Olden, J.D., Joy, M.K. and Death, R.G., *Ecol. Model.*, 2004, 178: 389
- 7 Hattori, T. and Kito, S., *Catal. Today*, 2006, 111: 328
- 8 Atashi, H. and Shiva, M., *Asia. J. Chem.*, 2010, 22(8): 6451
- 9 Wang, M.J. and Wolf, S., *Rubber Chem. Technol.*, 1991, 64: 559