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CONDITION MONITORING OF OFF-HIGHWAY TRUCK TIRES AT SUNGUN COPPER MINE USING NEURAL NETWORKS

MONITOROWANIE STANU TECHNICZNEGO OPON W CIĘŻKICH POJAZDACH TERENOWYCH EKSPLOATOWANYCH W KOPALNI MIEDZI SUNGUN, PRZY UŻYCIU SIECI NEURONOWYCH

Maintenance cost of the equipment is one of the most important portions of the operating expenditures in mines; therefore, any change in the equipment productivity can lead to major changes in the unit cost of the production. This clearly shows the importance and necessity of using novel maintenance methods instead of traditional approaches, in order to reach the minimum sudden occurrence of the equipment failure. For instance, the tires are costly components in maintenance which should be regularly inspected and replaced among different axles. The paper investigates the current condition of equipment tires at Sungun Copper Mine and uses neural networks to estimate the wear of the tires. The Input parameters of the network composed of initial tread depth, time of inspection and consumed tread depth by the time of inspection. The output of the network is considered as the residual service time ratio of the tires. The network trained by the feed-forward back propagation learning algorithm. Results revealed a good coincidence between the real and estimated values as 96.6% of correlation coefficient. Hence, better decisions could be made about the tires to reduce the sudden failures and equipment breakdowns.

Keywords: Maintenance, Cost Optimization, Truck Tire, Artificial Neural Networks.

Koszty użytkowania sprzętu stanowią jedną z najpoważniejszych pozycji w zestawieniu kosztów eksploatacyjnych kopalni, dlatego też każda poprawa wydajności sprzętu powoduje w efekcie zmianę jednostkowego kosztu produkcji. Wyraźnie pokazuje to wagę i konieczność stosowania nowoczesnych metod eksploatacji w miejsce podejścia tradycyjnego w celu minimalizacji ryzyka wystąpienia awarii sprzętu. Przykładowo, opony są elementami kosztownymi w eksploatacji, wymagają regularnego przeglądu i ponownego mocowania na osi. W artykule przebadano stan techniczny opon w maszynach i urządzeniach eksploatowanych w kopalni miedzi Sungun. Przy zastosowaniu metod wykorzystujących sieci neuronowe określano zużycie opon. Parametry wejściowe sieci to początkowa głębokość bieżnika, okres pomiędzy przeglądami, zużycie bieżnika do czasu przeglądu. Parametr wyjściowy to współczynnik określający

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czas serwisowania opon. Sieć uczono przy użyciu algorytmu propagacji wstecznej z wyprzedzeniem (feedforward back-propagation algorithm). Uzyskane wyniki wskazują wysoką zbieżność pomiędzy wartościami rzeczywistymi a estymowanymi, współczynnik korelacji kształtuje się na poziomie 96.6%. Umożliwia to podejmowanie lepszych decyzji w odniesieniu do eksploatacji opon, tak by zapobiec nagłym uszkodzeniom i awariom sprzętu.

Słowa kluczowe: eksploatacja, optymalizacja kosztów, opona ciężarówki, sztuczne sieci neuronowe

1. Introduction

The level of mine production extremely relates to mechanization of the equipment. The mechanization leads to higher production rate, lower mining costs and higher safety, (Hoseinie et al., 2011). Improvement of the equipment productivity needs to proper planning and applicable of the novel methods. The cost of tires would be considered as one of the most noticeable elements of the operating costs in any surface mining project. It is also important from safety point of view due to the fact that the tires are the main medium of the contact between the road and the machine, (Adetan et al., 2008). Additionally, it affects the fuel consumption rate. Hence a proper maintenance of the tires would lead to longer service life time of the tires and subsequently the higher safety and lower cost levels, (Michelin & Zingraff, 1996).

This paper describes an intelligent method which has been developed for calculation of the residual life time of the tires of the mining dump trucks based on the wear rate of their treads. Following introduces the general features and structure of the tires as well as the effective factors on the wear rate of the tires. Then, section 3 describes the artificial neural networks (ANN) and its performance procedure. Afterward a case study describing the condition monitoring of the tires of the dump trucks at Sungun Copper Mine and its results is presented in section 4. Finally, section 5 concludes the research.

2. Typical tire structure

Tires could be classified into Bias and Radial categories depending on the contact surface with the road and its thermal behavior. A typical tire structure has been shown in Fig. 1. Accordingly the major components could be considered as:

- Tread: Provides the primary traction and wear resistance and protects the carcass underneath.
- Belt: Multiple, low angle, steel cord layers provide strength to the tire, stabilize the tread and prevent penetrations into the carcass.
- Sidewall: Provides protection for the ply and withstands flexing and weathering.
- Ply: The radial (90˚) ply transmits all loads, braking and steering forces between the wheel and the road and withstands the burst loads of the tire under operating pressure.
- Inner liner: A layer of rubber in tubeless tires specially compounded to prevent loss of air.
- Bead bundle: The steel bead bundle properly seats and seals the tire on the rim and maintains it in position.
- Apex: Rubber filler in the bead and lower sidewall area to provide progressive transition from the stiff bead area into the flexible sidewall.
- Chafer: A layer of hard rubber that resists erosion of the bead zone by the rim flange.

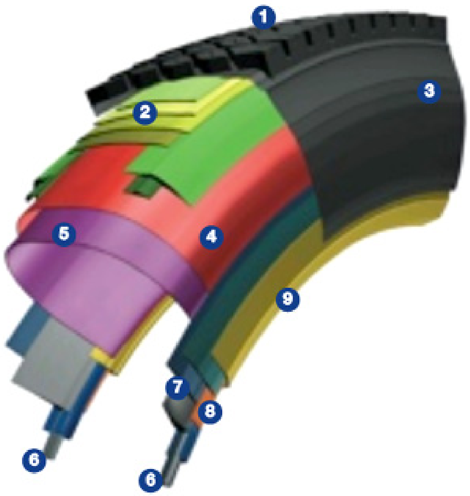

Fig. 1. A typical tire structure (Goodyear, 1996)

In fact, the treads are the main components of the tires that are always in a direct contact with the ground and designed in various size and configurations in order to provide proper traction under certain conditions, (Goodyear OFF-THE-ROAD TIERS 1996). Hence, the height of the remaining treads of the tires have been considered in this research as an appropriate parameter in estimation of the residual service life of the tires, (Michelin & Zingraff, 1996).

2.1. Effective factors on the wear rate of the tires

Effective factors on the wear rate of the tires are as following:

- Quality of the raw materials and production process: Tire manufacturing is a complicated process by using of more than 80 different raw ingredients, (Abou-Ali & Khamis, 2003). Therefore, quality and service lifetime of tires highly depend on the raw materials quality and the processing variables.
- Operating condition: Unfavorable climate conditions such as sunlight, water, heat etc. can lead to cracks in surface of the tire. Additionally, quality of the road surface is another effective factor in service lifetime of the tire, (Goodyear OFF-THE-ROAD TIERS, 1996). Similarly, the existing particles (soils and sediments) can also lead to more tire wear, (Wik & Dave, 2009).
- Inflation pressure of the tire: Proper inflation pressure of the tires is a critical and essential factor in the optimization of the tire performance, safety and fuel consumption. Pressure gages should be used for measurement of the inflation pressure of the cool tires, (Dunlop, 2005). Normally tires are designed for a particular pressure and load which can be associated with the standard of the tire, air temperature and maximum load on the axle, (Goodyear OFF-THE-ROAD TIERS, 1996). Over-inflation can lead to the crack creation in the grooves; irregularly wear on the tire surface and increases the wear in the central part of the tire. Conversely, under-inflation affects the safety and service lifetime of the

tire as well as the increase in fuel consumption due to the more contact surface and friction with road. At the same time the risk of the blowout and unexpected losses in under-inflated tires increases as the result of more contact surface with ground and cutting of the sidewalls of the tires. However, the tread wear will be lower in the central parts. Fig. 2 shows the different conditions of the tire inflation, (Coast Tire & Auto Service, 2004).

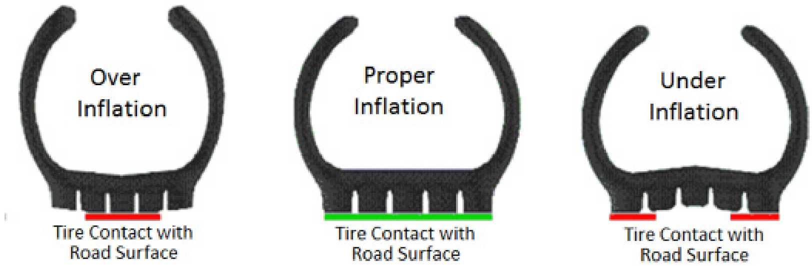

Fig. 2. Comparison of the tires at the over-inflation, proper inflation and under-inflation conditions, (Coast Tire & Auto Service, 2004)

- Other elements: Consist of the improper implementation of the wheel balancing and wheel alignment, (Coast Tire & Auto Service, 2004). Finally, the operator and her style of driving such as speed and acceleration can affect the wear rate of the treads, (Wik & Dave, 2009). To conclude, in order to decrease break downs and increasing of the service life time a regularly inspection of the tires should be accomplished by controlling of the inflation pressure and distinguishing of the defects.

3. Artificial neural networks

Neural networks (McCulloch & Pitts, 1943), are a branch of artificial intelligence and inspired by the biological structure of the neural cells of the human brain for interconnecting of the basic components. It mimics the function of the neurons as the logic processing unit of the human brain. A typical biological neuron consisted of a cell body, a tubular axon and a multitude of hair-as dendrites in the human brain neural network, (Mehrotra et al., 1997).

The typical artificial network is usually composed of an input layer, one or more hidden layer, and an output layer. The multi-layer networks are extremely powerful. A good example is the multi-layer perceptron networks known as feed-forward back propagation (FFBP) networks with two layers (a sigmoidal initial layer is with Logsig transfer function and another linear layer with purelin transfer function). These networks can estimate any arbitrary function with the finite number of discontinuous points. Fig. 3 shows a typical artificial neural network composed of the input layer; 3 layers with the neurons, weights, bias and transfer functions and finally output of each layer, (Demuth, Beale et al. 2009).

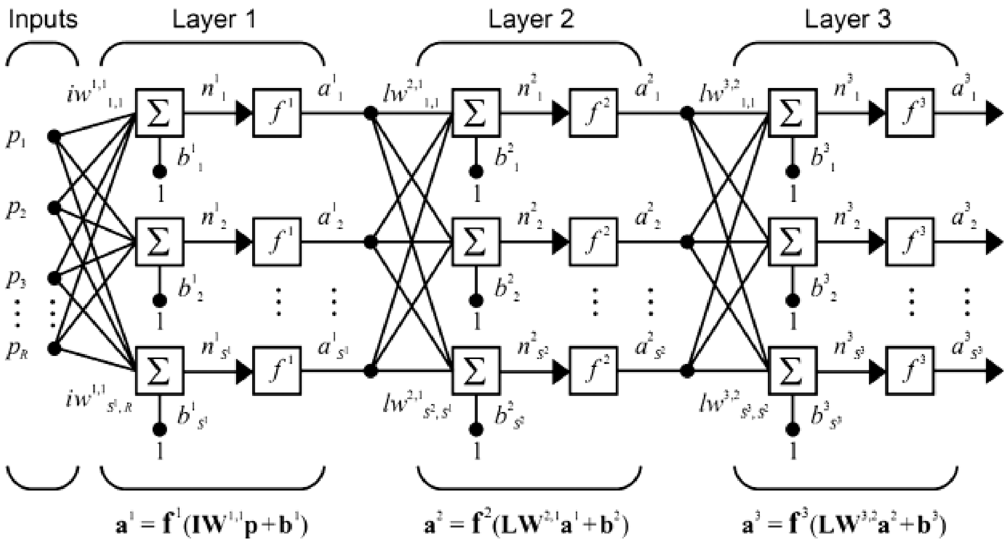

Fig. 3. A typical ANN structure (Demuth, Beale et al. 2009)

3.1. Transfer functions

There are different types of transfer function which are usually chosen based on the required purposes. The non-linear transfer functions are composed of the Tansig and Logsig whereas linear transfer functions are composed of the Purlin and Poslin. Generally, the non-linear transfer functions are used in the hidden layers and the linear transfer functions are utilized in the network output. Fig. 4 shows a non-linear transfer function, (Demuth et al., 2009). In general, the vector of output layer would be written as:

$$\underline{a} = f(\underline{W}\,\underline{P} + \underline{b}) \tag{1}$$

where $\underline{a}$ is the network output matrix; f is the transfer function; $\underline{W}$ is the weight matrix; $\underline{P}$ is the input data matrix and $\underline{b}$ is the bias matrix, (Demuth et al., 2009).

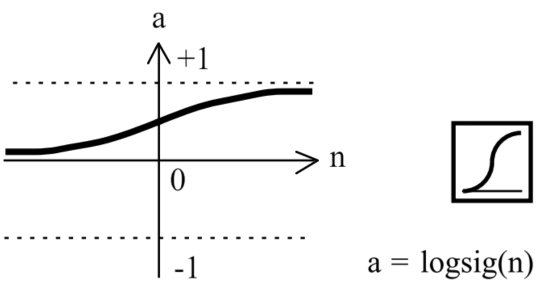

Fig. 4. Sigmoidal non-linear transfer function (Demuth, Beale et al. 2009)

3.2. Training and validation of the model

Different algorithms have been proposed for training of the neural networks. However, the back propagation (BP) algorithm is the most widely used learning procedure for the neural networks (Rumelhart et al., 1986; Werbos, 1990; Zhu & Qi, 1997; De Jesus & Hagan, 2001; Wang et al., 2004; Al-Garni et al., 2006). In this algorithm, the network weights and biases are determined in steepest descent direction of the performance function using the mean squared error (MSE), (Demuth et al., 2009). This technique provides the most efficient learning results for multi-layer perceptron (MLP) neural networks, (Tawadrous & Katsabanis, 2007). Fig. 5 shows a typical performance procedure of a neural network.

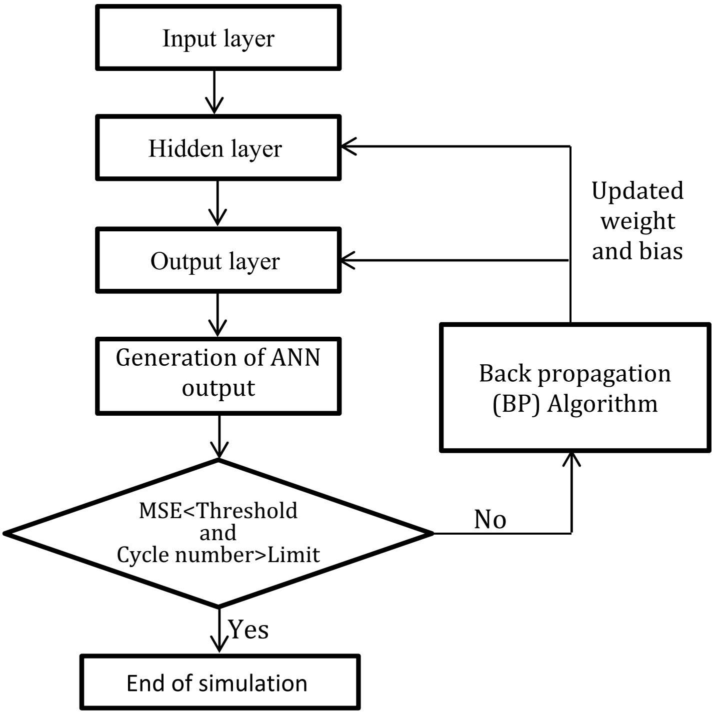

Fig. 5. Flowchart of neural network Algorithm that shows the typical performance procedure of a neural network

4. Case study

4.1. Sungun Mine

Sungun copper deposit is the second largest copper mine in Iran. It is located on a hillside of a steep mountain between Sungun and Pakhir rivers in North-West of the country in East Azerbaijan province near to the border of Azerbaijan and Armenia and 130 km distance from

Tabriz, the capital of the province (Fig. 6). Geological reserve of the deposit is estimated as 828 million tons with average copper grade of 0.62 percent.

The first phase of the processing plant has been started the production in 2006 with the annual capacity of 7 million tons and planned to be expanded to 14 million tons in 2013. The mine has been designed in four push backs and it is planned to remove 50 million tons of rocks annually (ore plus waste) during the first 10 years of the mine life. Special circumstances have made the National Iranian Copper Company (NICICO) to deliver the mining operation to the domestic contractors. Currently two contractors are active in the mine site by employing a fleet of 20 Komatsu 100 ton trucks, 52 Komatsu 32 ton trucks, 11 Caterpillar 988 loader, 1 Liebherr 17 cubic meter shovels, 8 Komatsu PC800 excavators and 9 drilling rigs.

Fig. 6. Location of Sungun mine (Google maps)

4.2. Data collection

Selection of the effective input parameters for estimation of the tire condition is very challenging, because most of the involving factors such as road condition, operator performance, inflation pressure etc. are very hard to quantify. However simplified modeling could be accomplished by assuming uniform operating condition, constant wear rate of the treads and continuous inspection of the inflation pressures. Therefore, three input parameters including initial tread depth, consumed tread depth by the time of inspection and life time of the tire by the time of inspection are selected as input parameters. The output of the network is considered as the residual service life time ratio of the tires. Study started by collecting of data and creation of a database for tire information of mining dump trucks of Sungun mine.

The data is collected from the performance of mining dump trucks during 2006 and 2009. Available data was limited to 56 tires from three different brands because of missing information in the other tires and types. Then 47 data has been selected out of the mentioned 56 for training and validation of the network and 9 others have been separated for testing of the network (Table 1 and Table 2 respectively). The work started with random categorization of the 47 data set into two subsets for training (80%) and validation (20%) purposes. Training of the network continued as long as the network's error to validation data is reduced. Testing data of the network has been done using simulation.

4.3. Network architecture

A feed-forward back propagation network has been selected for the study. It contains three input parameters, two hidden layers having 7 and 9 neurons respectively and an output layer having a single neuron. Transfer functions for the hidden and output layers have been chosen as Logsig (logarithmic sigmoidal transfer function) and Purelin (purely linear transfer function) respectively. Training of the network has been implemented by Levenberg-Marquardt algorithm which is the fastest method for training of the moderate sized feed-forward back propagation networks, (Gholamnejad & Tayarani, 2010).

TABLE 1

Dataset used for training and validation of the network

Initial tread, (mm)	Inspection time (Hr)	Consumed tread at the inspection time, (mm)	Residual life time ratio	Initial tread, (mm)	Inspection time, (Hr)	Consumed tread at the inspection time, (mm)	Residual life time ratio
66.5	8173	59.5	0.002	55	4374	39	0.278
54	2169	25	0.571	66.5	5534	41.5	0.325
66.5	4269	34.5	0.419	66.5	5377	44.5	0.250
66.5	4857	48.5	0.291	54	2169	27	0.575
49	4150	29	0.383	55	3931	37	0.235
55	3819	35	0.355	66.5	4275	39.5	0.409
55	4058	34	0.318	55	3931	41	0.184
49	3583	29	0.362	66.5	4814	35.5	0.333
72	5641	55	0.306	55	3950	36	0.212
66.5	4925	41.5	0.271	66.5	4725	34.5	0.353
54	3289	34	0.361	54	3158	34	0.425
66.5	4946	44.5	0.242	55	3921	37	0.258
66.5	4269	41.5	0.318	55	3921	41	0.169
55	4413	36	0.272	66.5	4241	35.5	0.414
54	1221	14	0.773	54	1809	22	0.680
66.5	5657	42.5	0.303	66.5	5399	37.5	0.382
55	4176	34	0.318	54	2205	25	0.626
55	4823	40	0.185	66.5	5534	43.5	0.258
55	4807	43	0.206	55	4886	33	0.238
66.5	4913	39.5	0.308	55	5129	41	0.162
55	4413	36	0.272	66.5	4455	40.5	0.321
49	4150	32	0.362	54	2413	24	0.571
54	3158	32	0.394	66.5	4872	41.5	0.334
54	2495	26	0.510	-	-	-	-

TABLE 2

Dataset used for simulation

Initial tread, (mm)	Inspection time, (Hr)	Consumed tread at the inspection time, (mm)	Residual life time ratio
54	1777	24	0.639
54	3118	27	0.139
54	2206	25	0.562
49	2206	19	0.526
54	2149	31	0.344
49	2211	21	0.386
54	1563	22	0.535
55	2140	22	0.561
55	661	12	0.778

4.4. Test and validation

Training as well as Testing and validation are accomplished by the mean squared error of the network output and target data as following:

$$MSE = \frac{1}{N}\sum_{N}\left(\underline{t} - \underline{a}\right)^2 \tag{2}$$

where N is the number of data, $\underline{t}$ is the target values and $\underline{a}$ is the network output, (Demuth et al., 2009).

Results could be evaluated after generation of the network and its training and validation. There were 20 iterations to reach convergence and the 14th iteration was the last improved iteration for which the values of mean squared errors were 0.00039, 0.0008 for training and validation respectively. The values of the coefficient of correlation for these stages were as 98.94, 98.8 percentage respectively, (Fig. 7).

Various neuron and layer numbers have been analyzed to evaluate the selected network architecture. Table 3 shows the best results obtained by different neuron and layer numbers.

TABLE 3

Best results of different layer and neuron numbers

Best training performance	Best validation performance	Number of neuron in layers	Training correlation %	Validation correlation %	Test correlation %	Best epoch
0.00096	0.0027	5,7	97.3	97.24	91.26	3
0.00086	0.0024	4,9	97.87	93.94	82.63	7
0.00092	0.00097	7,9,13	97.87	97.31	86.34	5
0.0014	0.0011	5,9,17	98.16	97.58	75.36	10
0.0007	0.0005	3,8,5,14	98.35	98.49	57.24	21

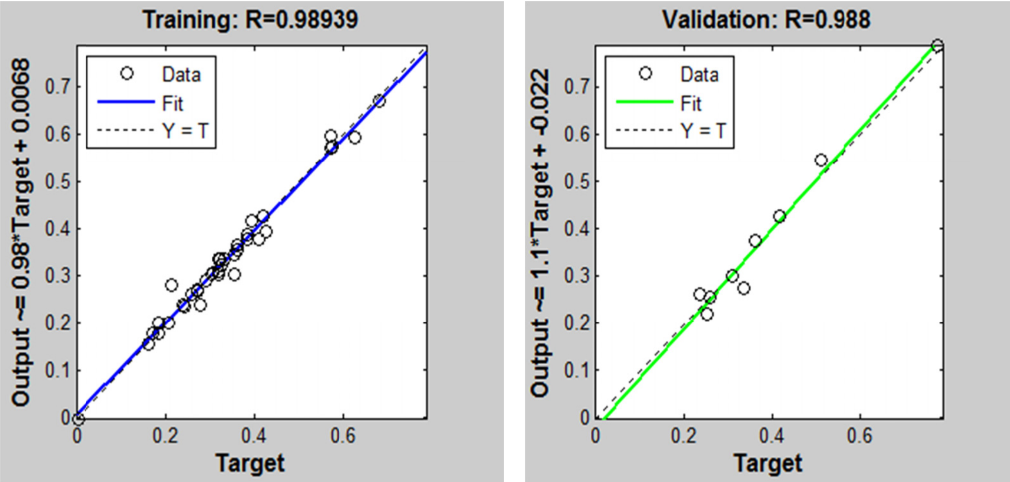

Fig. 7. Correlation of the target and outputs during training and validation

Trained network simulation could be utilized for estimation of the residual service lifetime ratio of the tires. Trained network has been validated by comparison of the estimated and actual values of 9 independent data, Fig. 8. Fig. 9 shows their correlation which indicates some 96.6% of correlation between two values.

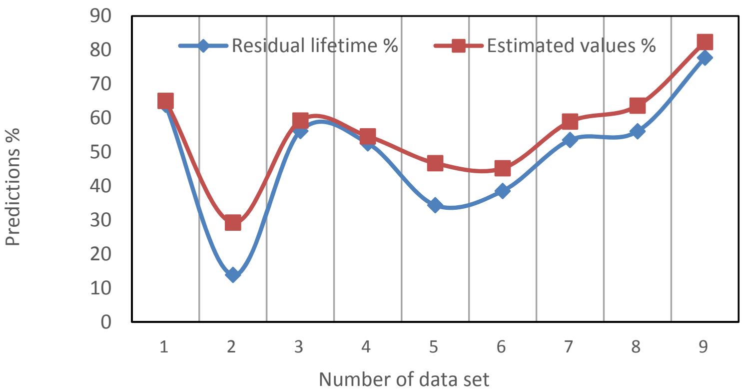

Fig. 8. Comparison of the estimated and actual values

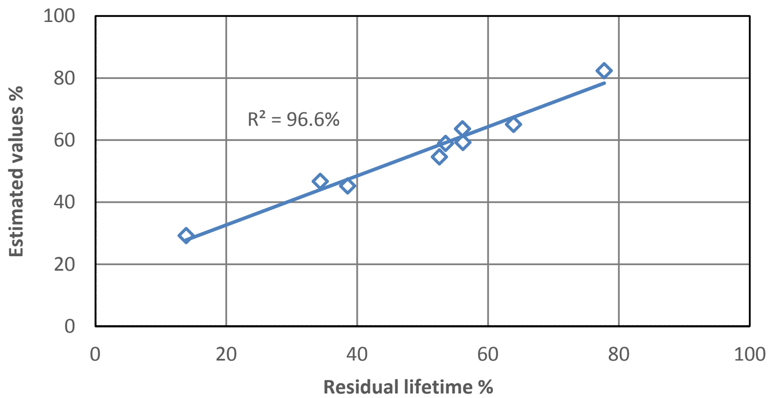

Fig. 9. Correlation of the estimated and actual values

5. Conclusion

Considering the importance of the reliability of the tires in proper operation of the mining trucks and its effects on availability of the machine as well as the related costs, current study conducted on investigation of the condition of the haulage machines' tires at Sungun Copper Mine. Study aimed to estimate of the service life time of the tires in order to prevent sudden failures. Results revealed that artificial neural networks could be effectively applied to the condition monitoring and life time estimation of the tires. For simplicity three input parameters including initial tread, inspection time and the consumed tread at the time of inspection have been considered for the network. Study showed that the lowest mean squared error occurs by considering of two hidden layers containing 7 and 9 neurons. The value of training mean squared error was equal to 3.9×10^{-4} in this case. Historical data has been used for training of the network and its efficiency has been validated by simulation of some other mutually independent data. Trained network could be used as a tool for estimation of the possible down time of tires and their required substitution time before the final failure.

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