REPUBLIC OF TURKEY

ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

DEPARTMENT OF NANOTECHNOLOGY AND ENGINEERING SCIENCES

PREDICTION OF A FURTHER TIRE LIFE BY USING ANN

ENGİN ALTUNSÜZER

MASTER OF SCIENCE

SUPERVISOR

ASSOC. PROF. DR. GÖKHAN TÜCCAR

ADANA 2019

REPUBLIC OF TURKEY

ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

DEPARTMENT OF NANOTECHNOLOGY AND ENGINEERING SCIENCES

PREDICTION OF A FURTHER TIRE LIFE BY USING ANN

ENGİN ALTUNSÜZER

MASTER OF SCIENCE

SUPERVISOR

ASSOC. PROF. DR. GÖKHAN TÜCCAR

ADANA 2019

PREDICTION OF A FURTHER TIRE LIFE BY USING ANN

Submitted by **Engin ALTUNSÜZER** in partial fulfilment of the requirements for the degree of **Master of Science in Department of Nanotechnology and Engineering Sciences, Adana Alparslan Türkeş Science and Technology University** by,

Assoc. Prof. Dr. Gözde BAYDEMİR PEŞİNT
Graduate School Director

Prof. Dr. Hatice İmge OKTAY BAŞEĞMEZ
Department Chair

Assoc. Prof. Dr. Gökhan TÜCCAR
Supervisor

Thesis Committee

Assoc. Prof. Dr. Gökhan TÜCCAR
Adana Alparslan Türkeş Science and Technology University

Prof. Dr. Mehmet BİLGİLİ
Çukurova University

Assist.Prof. Dr. Erinç ULUDAMAR
Adana Alparslan Türkeş Science and Technology University

Thesis Defense Date

10.06.2019

I hereby declare that all information in this thesis has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all information that is not original to this work.

[Signature]

Engin ALTUNSÜZER

ABSTRACT

PREDICTION OF A FURTHER TIRE LIFE BY USING ANN

Engin ALTUNSÜZER

Department of Nanotechnology and Engineering Sciences

Supervisor: Assoc. Prof. Dr Gökhan TÜCCAR

Year: 2019, Pages:50

1. ÇALIŞMANIN ÖNEMİ VE AMACI (Importance and objective of the study)

Tires are essential components of the automotive industry; In our modern world, it is inevitable to see every current vehicle equipped with some sets of tires. Depending on the nature of the business, there are lots of applications that are using tires like; Commercial, Industrial, Aerospace Etc. The needs always change by technology and the requests of business type. Thus, tire producers must develop new, modern tires which could provide the requirements and compete with their competitors.

All these requests must be covered in an efficient way, including price, technology, research & development, and these activities must be parallel to partner industries.

Tires mostly produced of natural or synthetic rubber, fillers (Carbon black), oil, steel, and textile. Because rubber is a highly elastic, almost incompressible material, depending on its composition, it can be stretched five times without showing signs of cracking or permanent deformation.

In daily usage of tires, the tread part and tread materials contacts with different kinds of surfaces like asphalt, gravel, sand, etc. Due to friction forces and forces applied on the tire, the tire starts to lose volume from the tread part this is a known physical and chemical reaction caused by friction between the tire and road surface. Some other vital factors affect these results like tire compound, speed, the load on the tire, driving behaviour, tire pressure, tire contour, etc.

All these effects could seem as tread volume loss, mini cuts, and chipping rubber parts on the tread surface. Thus results in mileage performance problems and visual mini cut and chipping issues that could be one of the critical factors of consumers in the tire using industries.

This study aims to identify these phenomena before production or early mileage of tires and implement these results in the production line to select the right material, the method to save investment costs.

Keywords (Artificial neural network, estimation of tire life, tire measurements, tire tread depth)

ÖZET

PREDICTION OF A FURTHER TIRE LIFE BY USING ANN

Engin ALTUNSÜZER

Nanoteknoloji ve Mühendislik Bilimleri

Danışman: Doç. Dr Gökhan TÜCCAR

Yıl: 2019, Sayfa:50

1. ÇALIŞMANIN ÖNEMİ VE AMACI (Importance and objective of the study)

Lastik otomotiv endüstrisinin temel bileşenidir. Modern dünyada, mevcut her aracın lastik kullanması kaçınılmazdır. İşletmenin,işin niteliğine bağlı olarak lastiğin kullanıldığı çok sayıda uygulama mevcuttur. Ticari, Endüstriyel, Havacılık vb. İhtiyaçlar, teknolojiye ve işletme türünün istekleri doğrultusunda farklılık gösterebilmektedir. Bu nedenle lastik üreticileri, gereksinimleri karşılayacak ve rakipleriyle rekabet edebilecek yeni ve modern lastikler geliştirmelidir. Tüm bu talepler fiyat, teknoloji, araştırma ve geliştirme dahil olmak üzere etkin bir şekilde karşılanmalıdır.

Lastikler çoğunlukla doğal veya sentetik kauçuk (oldukça elastik, neredeyse sıkıştırılamaz bir malzeme), dolgu maddeleri (Karbon siyahı), yağ, çelik ve tekstil malzemelerinden üretilirler. Kauçuk; bileşimine bağlı olarak, çatlama veya kalıcı deformasyon belirtileri göstermeden beş defa kullanılabilmektedir. Bu özelliği onu lastik üretiminde oldukça önemli bir malzeme yapmaktadır.

Lastiklerin günlük kullanımında, lastik üzerinde mevcut bulunan sırt kısmı asfalt, çakıl, kum vb. Farklı yüzey türleri ile temas edebilir. Bu temas neticesinde lastik üzerinde oluşan kuvvetler nedeniyle, lastik sırt kısmı hacmini kaybetmeye başlar. Bu, lastik ile yol yüzeyi arasındaki sürtünmeden kaynaklanan fiziksel ve kimyasal bir reaksiyondur. Lastiğin bileşiği , hız, lastik yükü, sürüş davranışı, lastik basıncı , lastik pozisyonu vb. Gibi diğer önemli faktörlerde aşınma sonuçlarına etki etmektedir.

Tüm bu etkiler, lastik sırt yüzeyinde malzeme kaybı, minik kesikler vb. Olarak görülebilmektedir. Böylece, kilometre performansı problemleri yanında tüketiciler için kritik önem arz edebilecek görsel minik kesikler, ufalanma sorunları ile karşılaşılabilir.

Bu çalışma, üretimden önce veya lastiklerin erken kilometresinde bu etkileri tanımlamayı ve sonuçlar yardımıyla yatırım maliyetlerinden tasarruf etme yöntemini seçmek için üretim hattında erken tahmin çalışması olarak uygulamayı amaçlamaktadır.

Anahtar Kelimeler(Artificial neural network, estimation of tire life, tire measurements, tire tread depth)

ACKNOWLEDGEMENTS

First of all, I would like to thank the supervisor, Assoc. Prof. Dr Gökhan TÜCCAR for necessary guidance and support. I am very indebted for his patience and self-abnegation in this thesis study.

I want to thank Assist. Prof. Dr. Kerimcan ÇELEBİ for his support, guidance and encouragement.

I want to thank Prof. Dr. Mehmet BILGILI for his beneficial support, help and valuable comments during the study.

I want to thank Research. Assist Prof Dr. Erinç ULUDAMAR for the support and knowledge share during the study.

A special thanks to my family, my two sons for activating my energy.

Finally, I would like to thank my wife for her patient and support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

ANN:	Artificial Neural Network
SCG:	Scaled Conjugate Gradient
LM:	Levenberg-Marquart
MLR:	Multiple Linear Regression
RPE:	Root Mean Squared Error
MAE:	Mean Absolute Error
MATLAB:	Matrix Laboratories
p:	Total input number
y:	Input signals
w:	Synaptic weights
u:	Linear combiner output
θ:	Threshold
θ(.)	Function of activation
f(x):	Transfer function
n:	Iteration number
d(n):	Desired response or target output
R:	Correlation Coefficient
RMSE:	Mean Absolute Percentage Error
MAPE:	Mean Absolute Error
$W_{k:}$	K. weight in iteration
I:	Unit matrix
μ:	Marquardt parameter
δ:	Derivative symbol

1. INTRODUCTION

1.1. BASIC INFORMATION ABOUT TIRES

A tire is a pressurised cap insists steel cords and some chemical and natural components, helps the vehicle contact with road surface by using the air pressure uniformity inside. It is thus resulting in the vehicle load transported for the movement.

Tires perform two primary functions; Acts as a soft cushion between the road and metal wheel and Provide adequate traction with the road surface.

The primary function of a tire and wheel is to carry the standard load. Additionally, a tire must handle lateral and radial forces safely under driving conditions. Casing must serve the comfort that road conditions should not be passed into the vehicle like vibration, noise etc.

Demands additionally include long life, high endurance, economical and environmentally friendly solution.

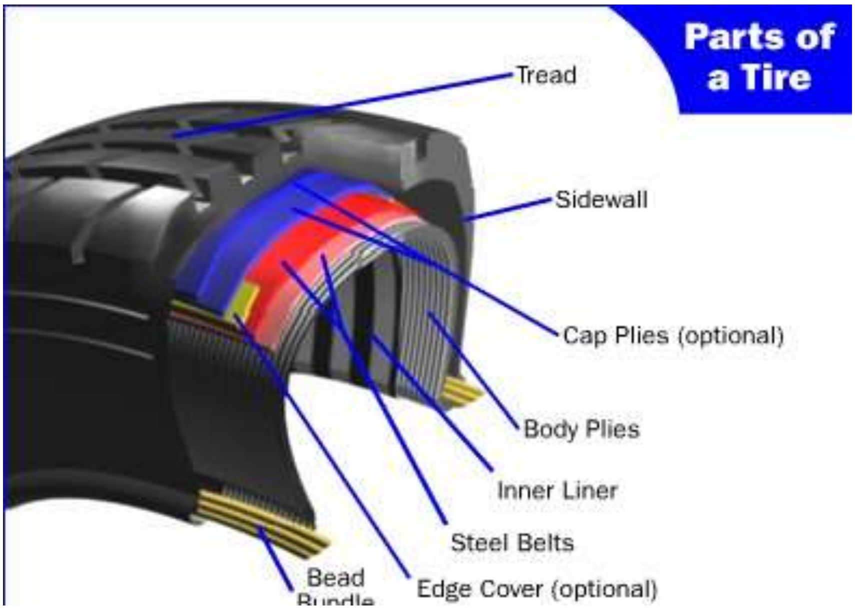


Figure 1.1. Parts of a tire (how stuff works 2000.)

A tire is built up by several materials and components. The bead part of the tire is a high strength loop of cables from steel and components coated with rubber.

1.1.1. Bead: Bead gives the tire strength to be stable enough on the wheel rim and handle the forces during tire work and mounting of tire operations. Bead consists of two rings made of steel wires, and they hold tire sidewall easily on the rim.

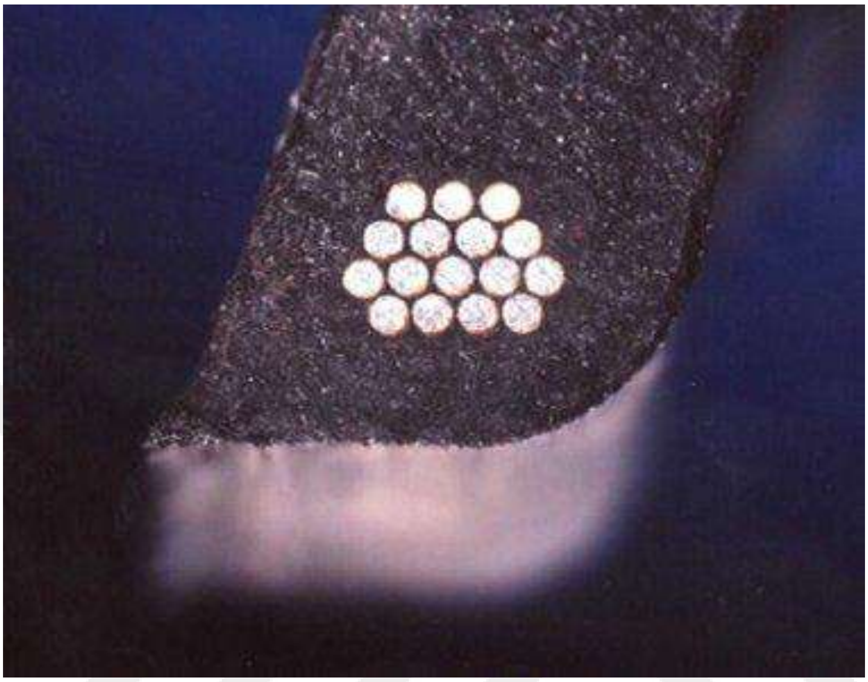


Figure 1.2. Bead (Continental AG.)

1.1.2. Sidewall: The sidewall provides stability of tire in the lateral direction. Sidewall protects the body plies and keeps the air inside the tube-shaped tire. Additional components are used for sidewall production to increase the stability of tire.

Figure 1.3. Sidewall (how stuff works, 2000.)

1.1.3. Tread: Tread is produced from a mixture of many different natural and synthetic rubbers. The tread is the part of the tire contacts with the road. Tread is the part of the tire which directly effects from the forces from the way, vehicle etc. Tread is a thick rubber or composite compound which handles traction. In a tread part of a tire, it could be found, description of grooves, sipes, tie bars, lugs, tread wear indicator, carbon beam centre which technically produced during the production of the tire via tire moulds. All these have a particular effect on driving parameters.

Figure 1.4. Tread

1.2. MISSION OF TIRE

The tire is one of the critical components to fulfil some requirements for vehicle transportation. These could align as;

Providing the capacity of load carrying;

Transmitting driving torque;

Transmitting braking torque;

Keeping the stability;

Ensure durability trough unexpected situations; (Structural endurance in steady use, at maximum allowed speed, puncture resistance, burst pressure

Generating the steering movements;

Ensure driving stability; (Straight ahead balance: Flat/uneven road conditions, pulling to one side, pulling to one side during braking/acceleration)

Ensure driving stability; (Stability in curves: Load transfer, lane change, slalom

Ensure the endurance; (Structural endurance in steady use, puncture resistance, burst pressure)

1.3. TIRE IDENTIFICATIONS

A tire in figure 1.5. With the size of 225 50 R16 92V is given here to describe the meaning of lettering in a tire sidewall.

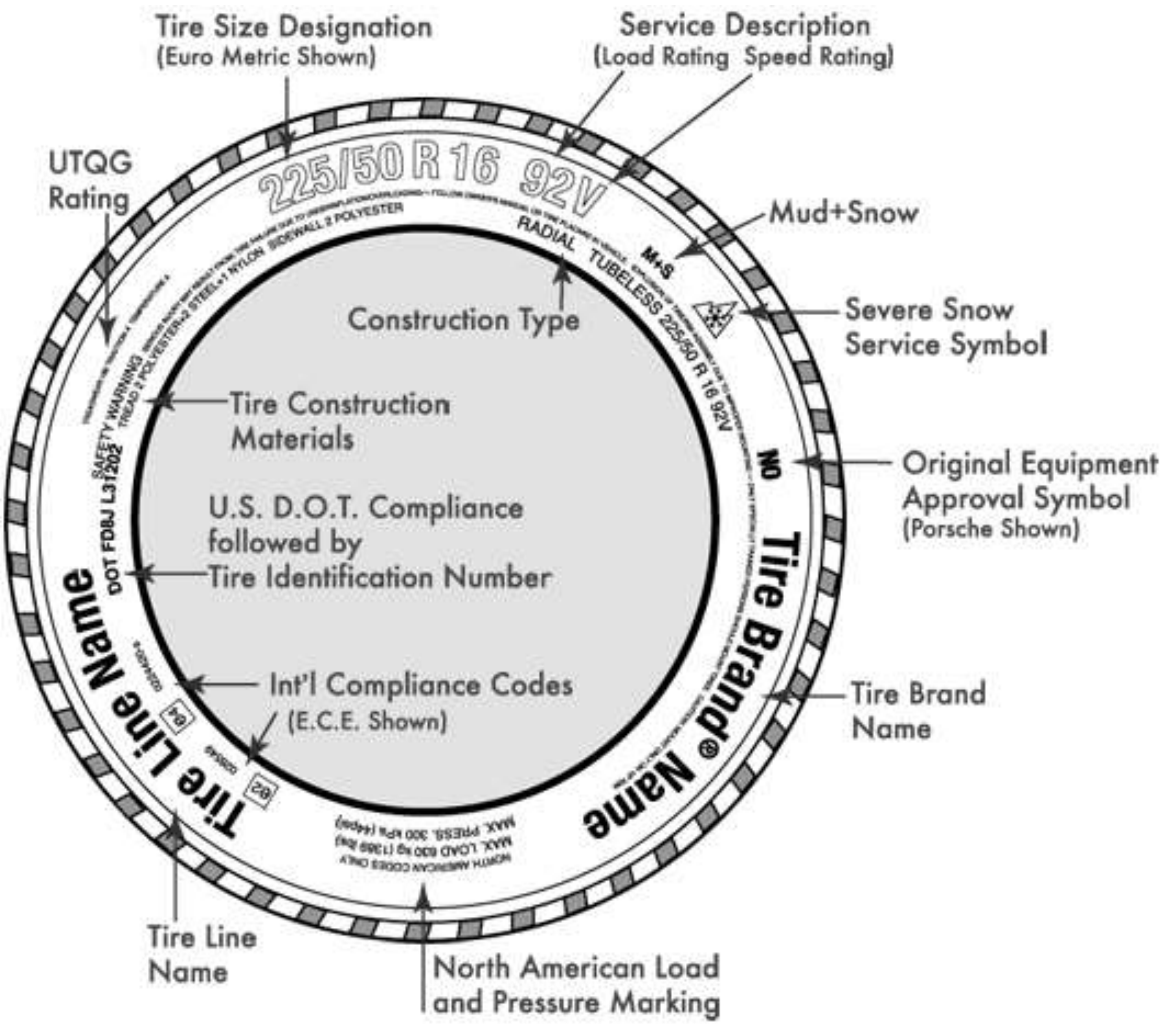


Figure 1.5. Tire identifications (Continental AG diagram.)

Tires branded trough their sidewall with significant information. This information insists on the purpose of the tire, speed and temperature durability knowledge, load capacity, etc.

1. Name of the manufacturer (Tire brand name)
2. Tire size (225/50 R16)
3. Construction type (Radial)
4. Operating conditions (Load Index for single and double fitment 150/146 V)
5. U.S. D.O.T Compliance Tire identification number
6. Tire construction materials (Tread 2 polyester+2steel+1nylon Sidewall 2 polyester)
7. Service symbol
8. Mud+Snow (M+S) for winter tires
9. Load capacity and air pressure details
10. A speed symbol (SI) is used to designate the speed rating of the tire
11. Traction

Figure 1.6. Traction (how stuff works, 2000.)

12. Temperature

This letter indicates a tire's ability to stop on wet pavement. A higher graded tire allows stopping a vehicle on a slippery surface in a shorter distance than a tire with a lower grade. Traction is ranked from highest to lowest as `´AA´´, ´´A´´, ´´B´´, and ´´C´´.

Figure1.7. Temperature (how stuff works, 2000.)

Letters on a tire indicate a tire's resistance to heat. A tire's resistance to heat graded as ´´Á´´, ´´B´´, ´´C´´ . (A=Hot Area, B= Normal Temperature area, C= Cold Area)

13. Load And Speed Index

The usage of LI(Load Index) and SI(Speed Index) was prompted by the introduction of ECE*) regulation no.54 and the EU tire directive for Europe (in force as of January 1, 1993), according to which pneumatic tires intended for road use at speed in excess of 80 km/h must carry an operational designation comprising LI (single/dual) and SI.

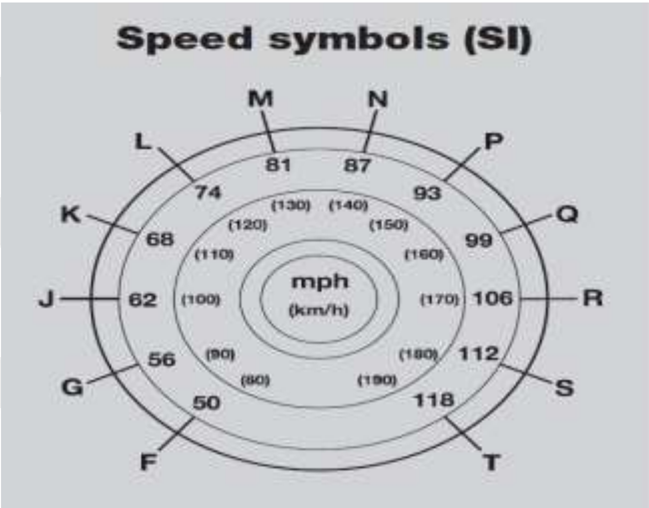
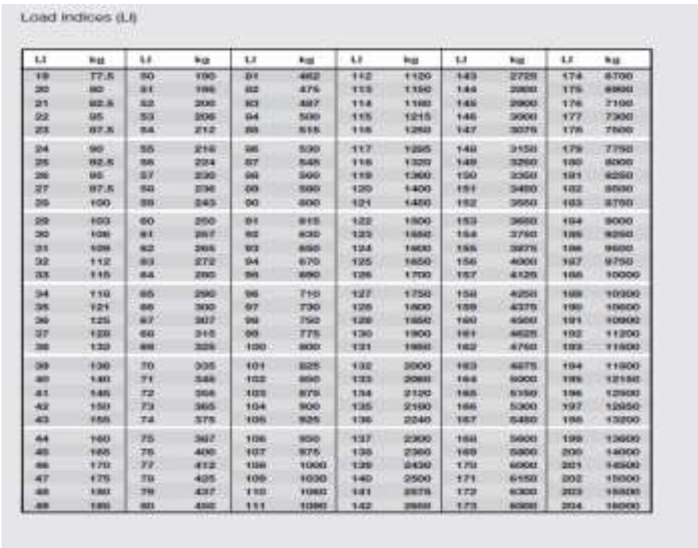


Figure 1.8. Speed symbols (SI) (Continental AG diagram)


Load indices (LI)

LI	kg	LI	kg	LI	kg	LI	kg	LI	kg	LI	kg
19	77.5	50	190	81	462	112	1120	143	2725	174	6700
20	80	51	195	82	475	113	1150	144	2800	175	6900
21	82.5	52	200	83	487	114	1180	145	2900	176	7100
22	85	53	206	84	500	115	1215	146	3000	177	7300
23	87.5	54	212	85	515	116	1250	147	3075	178	7500
24	90	55	218	86	530	117	1285	148	3150	179	7750
25	92.5	56	224	87	545	118	1320	149	3250	180	8000
26	95	57	230	88	560	119	1360	150	3350	181	8250
27	97.5	58	236	89	580	120	1400	151	3450	182	8500
28	100	59	243	90	600	121	1450	152	3550	183	8750
29	103	60	250	91	615	122	1500	153	3650	184	9000
30	106	61	257	92	630	123	1550	154	3750	185	9250
31	109	62	265	93	650	124	1600	155	3875	186	9500
32	112	63	272	94	670	125	1650	156	4000	187	9750
33	115	64	280	95	690	126	1700	157	4125	188	10000
34	118	65	290	96	710	127	1750	158	4250	189	10300
35	121	66	300	97	730	128	1800	159	4375	190	10600
36	125	67	307	98	750	129	1850	160	4500	191	10900
37	128	68	315	99	775	130	1900	161	4625	192	11200
38	132	69	325	100	800	131	1950	162	4750	193	11500
39	136	70	335	101	825	132	2000	163	4875	194	11800
40	140	71	345	102	850	133	2060	164	5000	195	12150
41	145	72	355	103	875	134	2120	165	5150	196	12500
42	150	73	365	104	900	135	2180	166	5300	197	12850
43	155	74	375	105	925	136	2240	167	5450	198	13200
44	160	75	387	106	950	137	2300	168	5600	199	13600
45	165	76	400	107	975	138	2360	169	5800	200	14000
46	170	77	412	108	1000	139	2430	170	6000	201	14500
47	175	78	425	109	1030	140	2500	171	6150	202	15000
48	180	79	437	110	1060	141	2575	172	6300	203	15500
49	185	80	450	111	1090	142	2650	173	6500	204	16000

Figure1.9. Load indices (LI) (Continental AG diagram.)

14. LITERATURE REVIEW

Artificial Neural Networks (ANNs) can offer an inclusive framing for performing non-linear mappings from input variables to output variables, and they can be counted as an expansion of the many conventional mapping techniques (Alba and Marti et al., 2006)

Two algorithms Particle Swarm Optimization (PSO) and Differential Evolution (DE) used to train ANN where the applicability of PSO and DE on finding the best weights for ANN were explained and how PSO and DE are usable for training ANN to solve different nonlinear problems were studied (Garro et al., 2011b).

Recently, Artificial Neural Network (ANN) was the most preferred technique for artificial intelligence applications, and the reason is the powerful ability to solve classification or prediction problems. Most studies on ANN aim to develop a model that learns ideally and to behave correctly according to the given data. Although ANN is a powerful technique, training a network can be a difficult task, and the more complex problems are, the more difficult the training of the network becomes. The most critical studies on training algorithm and parameter optimization as these are the most critical factors which affect the success of the process of ANN modelling. There are several metaheuristic optimization algorithms used to train ANN. Particle Swarm Optimization (PSO) is one of the most common algorithms of these. Artificial Algae Algorithm (AAA) is an optimization algorithm which has been newly developed and showed high success in different types of problems.

A.A.A was suggested as an ANN training algorithm instead of backpropagation. ANN-PSO is improved in the same conditions with the proposed ANN-AAA to compare the performances of algorithms. Two benchmark datasets obtained from UCI KDD Machine Learning Repository were used for this aim. Also, the experiments with MLP-PSO and MLP-AAA were performed to investigate both the effects of class target values and different attribute combinations. The class target values were selected as (0, 1), (0.1, 0.9), (0.2, 0.8) and (0.2, 0.6). The results showed that ANN-PSO performed slightly better than ANN-AAA. However, the performance of ANN-AAA is very effective and a competitor to ANN-PSO, which showed good accuracy. The strong accuracy values were obtained for both datasets with the (0.2, 0.6) target values. (SAEED SHAKIR MAHMOOD MAHMOD et al.,2019)

Meteorology is a science that tries to determine the effects on living and universe by following the occurrences of the events occurring in the atmosphere until the end of the events. There are many sub-branches such as climatology, aerology, dynamic meteorology, synoptic meteorology, agricultural meteorology. In the last century, industrialization, population growth, increase in agricultural production, increased the need for energy, climate change, etc. have attracted attention to the events occurring in the atmosphere due to their positive and negative effects. The parameters measured in meteorology are affected by a variety of factors, such as the Earth's Shapes, latitude and altitude, and are difficult to predict. Our country has the potential of both plant and animal production potential as well as wind and solar energy potential.

For this reason, it is vital to measure and correctly estimate meteorological parameters for use in these sectors. With statistical models, the estimation provides benefit both in terms of cost and time. In this study, using the meteorological data measured in Karaman, where agricultural production is intense, the maximum and minimum temperature estimation was made by using regression model, and artificial neural network model and the consistency was compared. (KAV, R et al., 2019)

ALKAN, V (2008) Prediction of dynamic force characteristics of radial tires using the finite element method. Predict its dynamic force characteristics; a detailed finite element model is constructed. In the finite element analysis of the tire, the nonlinear stress-strain relationship of rubber, the reinforcements of the tire and contact between the tire and ground are modelled. First, a static tire model is constructed. Its vertical force-deflection characteristics on a surface with and without cleat and the pressure distribution over the cross-section are obtained. Then, the dynamic force characteristics of the tire are predicted. In the dynamic analysis of the tire, lateral and vertical force characteristics are examined, tire enveloping characteristics at low speed.
Experimental studies are performed to validate the finite element model results. All experiments are conducted using the Flat-bed Tire Test Machine at the University of Michigan Transportation Research Institute (UMTRI). Model and experimental results are compared to each other, and it is concluded that to some extent, there is a good correlation between them. Error tables are also given to show the accuracy range of the proposed model. (ALKAN, V et al.,.2008) Prediction of dynamic force characteristics of radial tires using finite element and experimental techniques.

15. MATERIAL AND METHOD

3.1. Artificial Neural Networks

At ınput and output mappings artificial neural networks are reliable algorithms which can perform functional input and output. Their computing speed and parallel, multiparametric characters are making them a powerful computational tool, especially for complicated physical-mathematical models. ANNs are called as estimators. Information processed in a non-algorithmic way. We could acquire the knowledge through learning, which means that ANNs can be used used to model complex systems for which mathematical descriptions are not available. (Rajpal et al., 2006)

A neural network works as a brain performing some particular tasks; the system is usually implemented using electronic components or simulated in software on a digital computer (Haykin, 1994). In Science, it is possible to see ANNs are applied successfully in various fields (Kalogirou, 2001). They have been used in a wide range of applications like optimisation, pattern classification, prediction, and automatic control and many other engineering problems (Mohandes et al., 2004). The method takes the information given and learns from the provided examples and constructs input-output mapping to perform predictions. Input data and output values are necessary to make a training and testing model of a neural network (Cam et al., 2005). ANNs can be trained to solve complex problems which are difficult to model analytically. (Sözen et al., 2005).

Inspired by the human brain, a neural network consists of highly connected networks of neurons that relate the inputs to the desired outputs. The network is trained by iteratively modifying the strengths of connections so that given inputs map to correct response.

3.1.1. Biological and Artificial Neurons

Figure 3.1 presents a biological neuron (Kalogirou, 2001). The brain flows coded information by (neurotransmitters) from the synapse towards the axon. The axon of each neuron transmits data to the number of neurons. Estimation is that each neuron may receive stimuli from as many as 10000 other neurons. Groups of neurons organised into subsystems, and the integration of these subsystems forms the brain.

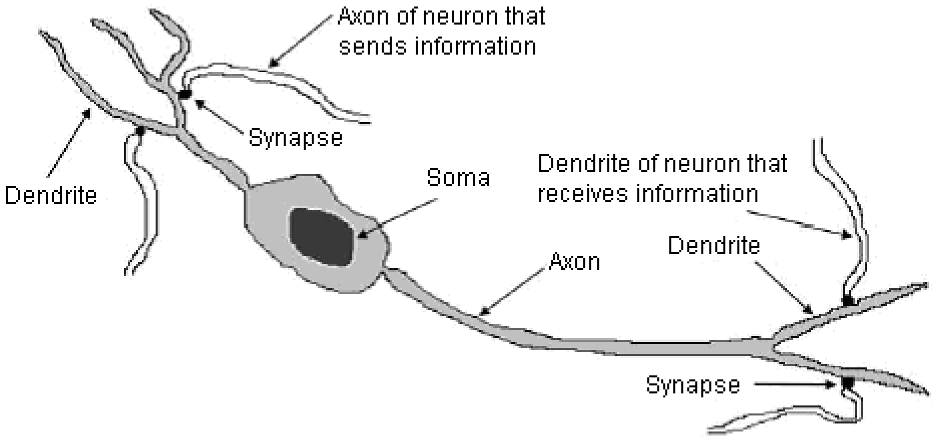


Figure 3.1. A simplified model of a biological neuron (Bilgili., M 2007).

Figure 3.2. Shows an artificial neuron. This artificial neuron could be used for simulating the aspects of a biological neuron (Kalogirou., 2001).

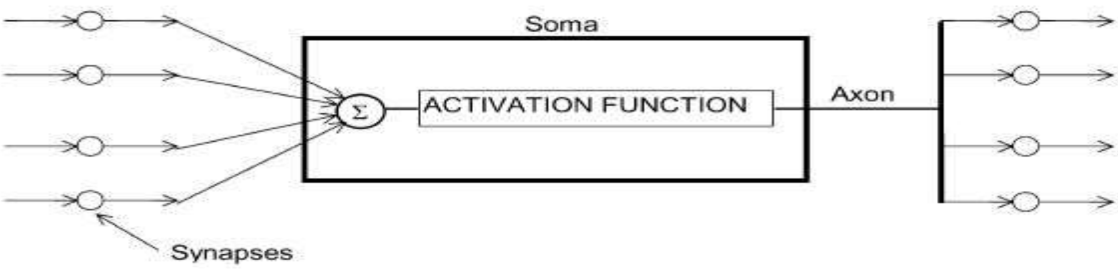


Figure 3.2. A simplified model of an artificial neuron (Bilgili., M 2007).

3.1.1.1. Classification

Classification is the identification of an object in a group. ANN can perform a future classification by using a set of data and can recognize which group the data belongs.

3.1.1.2. Clustering

Besides classification, clustering is done unrelated to a border. There is no need for any data before the operation. Condensation is done by applying similar data to the same group.

3.1.1.3. Prediction

Prediction is the area that neural networks regularly uses. Depending on previous data, future data is produced. ANN provides an essential advantage in using variables for estimating them.

3.1.1.4. Pattern Recognition

Incomplete and defected patterns can be introduced to ANN to obtain the pattern line. This method likes to retinal and facial recognition. Authentication for these processes is possible too.

3.1.1.5. Function Approach

There are many calculation models that the mathematical phrase is not known. Even the input and output knew there are some cases that it is not possible to describe the function between. The function approach is the description of creating the same output as the same input.

3.1.1.6. Optimization

In engineering, optimization is regularly used at the design stage. The optimization can be separated into two parts. The first one is traditional optimization based on analytical data, called traditional optimization. The second one is the optimization method, which is created by using artificial intelligence. This method is used for complex models which cannot be identified as a mathematical function. ANN also use this method.

3.1.1.7. Features of ANN

The property of artificial neural network is that can model; nonlinear problems, calculation and data processing power, to be able to work with missing data, to have fault tolerance, to be able to learn and generalize. This ability gives extreme opportunities to ANN for solving complex problems.

3.1.1.8. Learning

Ann, which uses the processing system of the human nervous system, uses the data to solve the problems to define hidden relations at the process. This process is called as network learning the function process.

3.1.1.9. Adaptability

Artificial neural networks can be adapted up to problems that can be faced and could be trained again to change their weight. With this feature artificial neural network system recognition is used effectively in areas such as audit, adaptive sample recognition.

3.1.2. Models of Neuron

Ann consists of artificial neurons which are connected with similar behaviours. In systems uses ANN stimulation applied as input. After suitable processes, we receive an output. There is a similar behaviour potential of synapses that the artificial neurons modelled as connection weight. Based on proper learning rules, the masses are always modified.

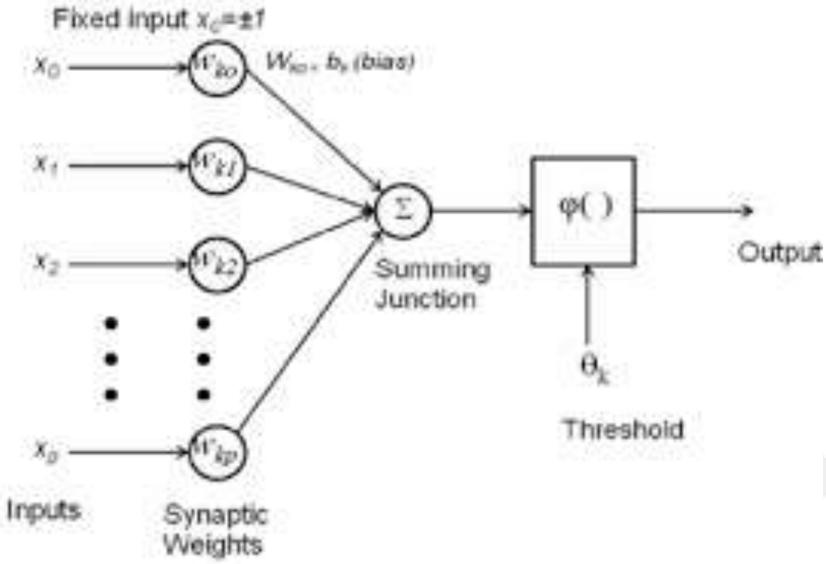


Figure 3.3. A nonlinear model of a neuron (Bilgili, M 2007.)

(Haykin. 1994); mathematically describes a neuron j with the following equation

$$\boldsymbol{Uj = \sum_{i=o}^{p} \mathrm{WjiYi}} \tag{3.1.}$$

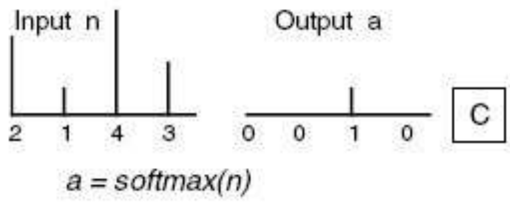
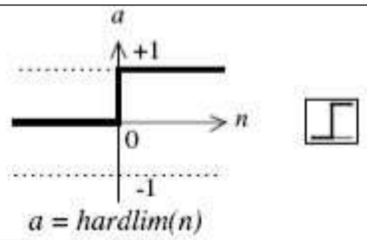
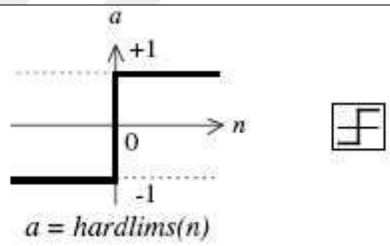
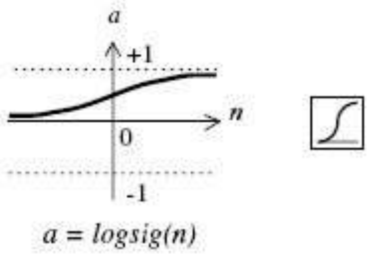
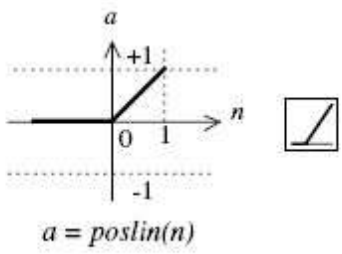
And

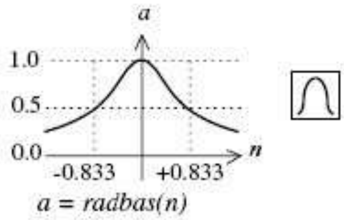
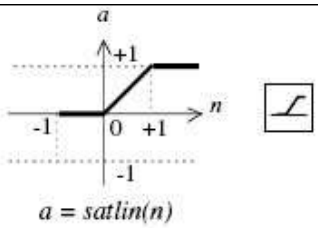
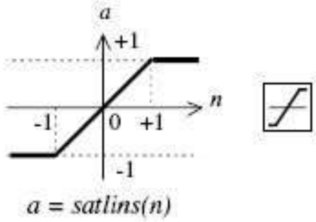
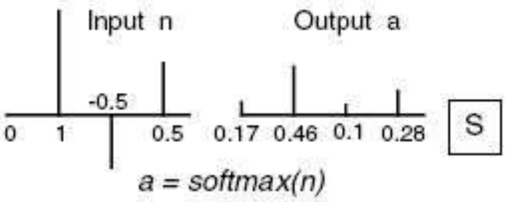
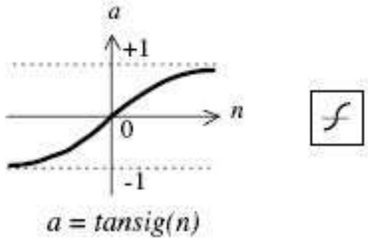
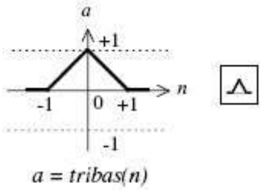
$$\mathbf{Y_j = \varphi\,(U_j\text{-}\theta_j)} \tag{3.2.}$$

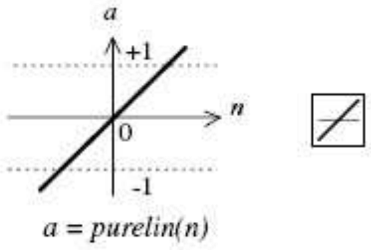
P is the total number of given inputs to neuron **J: $y_1,y_2,y_3,\ldots\ldots y_p$** are the signals of data

$w_{j1},w_{j2},w_{j3},\ldots\ldots w_{jp}$ called as neurons synaptic weights. The linear combiner of the output is u_j and θ_j is the brink. θ(.) =The activation function y_j is the output signal of the neuron.

Table 3.1. Transfer functions and graphs (Bilgili 2007.)

Functions	Graphic
Competitive	
Hard-Limit	
Symmetric Hard-Limit	
Log-sigmoid	
Positive Linear	

Transfer Function	Graphic
Radial Basis	
Satlin	
Satlins	
SoftMax	
Tan-Sigmoid	
Triangular Basis	

Linear	

3.1.3 Training Algorithms

There are several kinds of training algorithms uses backpropagation. All these algorithms have different storage and calculation styles. None of the mentioned algorithms suits to all locations.

Table 3.2. Summarizes the training algorithms included in MATLAB software (Demuth and Beale, 2004).

Table 3.2. Training algorithms

Function	Description
traingd	Basic gradient descent. Slow response, can be used in incremental mode training.
traingdm	Gradient descent with momentum. Generally faster than traingd. Can be used in incremental mode training.
traingdx	Adaptive learning rate. Faster training than traingd, but can only be used in batch mode training.
trainrp	Resilient back-propagation. Simple batch mode training algorithm with fast convergence and minimal storage requirements.
traincgf	Fletcher-Reeves conjugate gradient algorithm. Has smallest storage requirements of the conjugate gradient algorithms.
traincgp	Polak-Ribiere conjugate gradient algorithm. Slightly larger storage requirements than traincgf. Faster convergence on some problems.
traincgb	Powell- Beale conjugate gradient algorithm. Slightly larger storage requirements than traincgp. Generally faster convergence.
trainscg	Scaled conjugate gradient algorithm. The only conjugate gradient algorithm that requires no line search. A very good general purpose training algorithm.
trainbfg	BFGS quasi-Newton method. Requires storage of approximate Hessian matrix and has more computation in each iteration than conjugate gradient algorithms, but usually converges in fewer iterations.
trainoss	One step secant method. Compromise between conjugate gradient methods and quasi-Newton methods.
trainlm	Levenberg-Marquardt algorithm. Fastest training algorithm for networks of moderate size. Has memory reduction feature for use when the training set is large.
trainbr	Bayesian regularization. Modification of the Levenberg-Marquardt training algorithm to produce networks that generalizes well. Reduces the difficulty of determining the optimum network architecture.

3.1.4. Learning Rules The most used learning rules in ANN are Hebb rule, Hopfield rule, Kohonen rule, delta rule, Levenberg-Marquart algorithm and back release algorithm.

3.1.4.1. Hebb rule: it was the first produced learning rule. The rule was developed in 1949 by Canadian psychologist Donald Hebb depending on biological bases. In Hebb rule, if two neurons are gathering information from each other and two of them are active, the connection link between these two neurons must be powered. Means that the active neuron will try to activate the other related neuron. Hebb rule is an uneducated learning rule.

3.1.4.2. Hopfield rule: Presents similarities to Hebb rule. If all of the expected inputs and outputs are active or passive, the connection between the cells could be powered or weakened correlated to learning coefficient. The learning coefficient does not have a specific value; the user assigns the coefficient.

3.1.4.3. Kohonen rule: It is an algorithm developed by Kohonen. This algorithm can rank the cells which are covering the biggest range cell. The rule only regulates the largest weight cell and neighbour cells.

3.1.4.4. Delta rule: It is the modified form of Hebb rule. Delta rule is one of the most used learning rules. The rule is also called Widrof-Hoff rule. The basic idea of the rule is to reduce the difference between the expected value and the produced values by changing the weights. It shows similarities to the least square's method. Aim of delta rule is, to minimize the average of the square difference of results and real values.

3.1.4.5. Levenberg-Marquart algorithm: Levenberg-Marquart algorithm (LM) is an approach to the Newton method. LM method is researching the minimum method. It approaches parabolically in each iteration step and creates the solution for the parabola. LM learning rule uses the Hessian matrix in the equation

$$H=J^T J \tag{3.3.}$$

In the equation J, symbolize Jacobian matrix is the first derivative of network errors according to their weights.

$$J(n) = \frac{\delta e(n)}{\delta w(n-1)} \tag{3.4.}$$

Here;

n: iteration number

δ: Derivative Symbol

e: Vector of network errors

w: Connection weights

The gradient can be found with the equation,

$$g = J^T e \tag{3.5.}$$

moreover, the connection range between neurons could be obtained from equation

$$W_{k+1} = W_k \ [J^T J + \mu I]^{-1} J^T \tag{3.6.}$$

Here;

$W_{k:}$ K. weight in iteration

I: Unit matrix

μ: Marquardt parameter

Marquart parameter is a scalar value. When Marquart parameter is zero LM rule takes the name as Newton algorithm. Levenberg-Marquart algorithm produces faster results compared to other algorithms (Rojas, 1996).

3.1.4.6. Back release algorithm: Called as generalized delta rule. It is the most used learning rule. Rumelhart produced the algorithm (1986) the algorithm powered up the neural networks quite fast after its creation. In the method of the algorithm, the error propagates backwards. Back release algorithm changes the weight of the errors between the actual outputs and the calculated outputs.

In this study, by using ANN; a definition of selected and measured tires was done. A pilot city (Adana/Turkey) was chosen to have more reliable and comparable data. Tires were measured at a period consisting two years, all measurements made was insisting; Tread depths at specific mileages, Minimum tread depth, mini cuts on tires at each measurement, chipping on tires at each measurement, Shore A, temperature, tire pressure, tire position on the axle and date of the measurement. Model 1 in this study is configured up on to these five input values.

Table 3.3. Data inputs first groove

Tread Depth (mm)	Tread Depth (mm)2	Minimum Tread Depth(mm)	Shore A	Temprature Tread	Temprature Air	City	Vehicle Power(PS)	Tire Size	Pressure(Psi)	Measurement Date
96	93	2	70	28	26	Adana	160	235/65 R16	60	20130801
89	85	2	71	22	21	Adana	160	235/65 R16	61	20131111
87	83	2	71	33	32	Adana	160	235/65 R16	52	20140613
78	78	2	72	27	25	Adana	160	235/65 R16	62	20150113
76	75	2	73	30	28	Adana	160	235/65 R16	60	20150113
70	69	2	74	23	35	Adana	160	235/65 R16	61	20150113
70	69	2	75	24	26	Adana	160	235/65 R16	58	20150113
96	93	2	70	28	26	Adana	160	235/65 R16	60	20130801
89	86	2	72	29	30	Adana	160	235/65 R16	60	20131111
86	82	2	72	22	21	Adana	160	235/65 R16	50	20140613
81	78	2	73	34	28	Adana	160	235/65 R16	62	20150113
78	77	2	73	30	28	Adana	160	235/65 R16	65	20150113
75	73	2	74	34	29	Adana	160	235/65 R16	62	20150113
65	65	2	73	24	23	Adana	160	235/65 R16	60	20150113
96	93	2	70	28	26	Adana	160	235/65 R16	60	20130801
86	85	2	71	29	28	Adana	160	235/65 R16	63	20131111
76	76	2	71	20	21	Adana	160	235/65 R16	60	20140613
74	75	2	72	18	17	Adana	160	235/65 R16	66	20150113
69	71	2	73	27	25	Adana	160	235/65 R16	65	20150113
65	67	2	75	29	30	Adana	160	235/65 R16	60	20150113
62	61	2	75	25	26	Adana	160	235/65 R16	61	20150113
96	93	2	71	28	26	Adana	160	235/65 R16	60	20130801
85	84	2	68	29	30	Adana	160	235/65 R16	63	20131111
74	75	2	70	23	21	Adana	160	235/65 R16	60	20140613
72	71	2	71	16	17	Adana	160	235/65 R16	68	20150113
67	66	2	72	33	27	Adana	160	235/65 R16	69	20150113
60	61	2	73	34	29	Adana	160	235/65 R16	62	20150113
74	75	2	74	24	25	Adana	160	235/65 R16	62	20150113
96	93	2	67	28	26	Adana	110	235/65 R16	60	20130801
88	87	2	67	34	33	Adana	110	235/65 R16	65	20131118
88	87	2	70	25	26	Adana	110	235/65 R16	61	20131118
83	82	2	71	22	24	Adana	110	235/65 R16	59	20131118
83	82	2	72	30	31	Adana	110	235/65 R16	66	20131118
83	82	2	72	25	25	Adana	110	235/65 R16	59	20131118
78	76	2	73	25	23	Adana	110	235/65 R16	59	20131118
77	75	2	75	18	15	Adana	110	235/65 R16	64	20131118
96	94	2	68	27	26	Adana	110	235/65 R16	60	20130801
88	88	2	67	34	33	Adana	110	235/65 R16	59	20131118
86	85	2	69	28	29	Adana	110	235/65 R16	64	20131118
85	84	2	70	25	24	Adana	110	235/65 R16	61	20131118
85	84	2	71	32	31	Adana	110	235/65 R16	60	20131118
83	82	2	72	24	23	Adana	110	235/65 R16	64	20131118
79	78	2	73	24	23	Adana	110	235/65 R16	61	20131118
76	73	2	74	19	19	Adana	110	235/65 R16	60	20131118
96	93	2	69	25	26	Adana	110	235/65 R16	60	20130801
85	86	2	67	35	33	Adana	110	235/65 R16	43	20131118
83	82	2	70	28	29	Adana	110	235/65 R16	68	20131118
81	79	2	71	27	27	Adana	110	235/65 R16	69	20131118
80	78	2	72	30	31	Adana	110	235/65 R16	73	20131118
78	77	2	72	24	23	Adana	110	235/65 R16	61	20131118
77	73	2	73	22	23	Adana	110	235/65 R16	65	20131118
72	71	2	74	18	19	Adana	110	235/65 R16	64	20131118
96	93	2	68	24	25	Adana	110	235/65 R16	60	20130801
86	86	2	67	34	32	Adana	110	235/65 R16	64	20131118
83	82	2	69	28	26	Adana	110	235/65 R16	71	20131118
80	80	2	70	26	25	Adana	110	235/65 R16	67	20131118
80	79	2	71	22	23	Adana	110	235/65 R16	70	20131118
78	77	2	72	23	23	Adana	110	235/65 R16	63	20131118
74	74	2	73	22	23	Adana	110	235/65 R16	63	20131118
70	70	2	74	17	18	Adana	110	235/65 R16	63	20131118

The constants like vehicle power, tire sizes are applied to the model as well. These collected data were used as our inputs.

Entirely 1561 measurement inputs were used for 68 different vehicles of different tires, including different brands in this study.

Table 3.4. Data matrix table

Tire size	Tire Series	Tire Number	Vehicle	Vehicle Power (HP)	Tire Working Days	Wear %	Tire Mileage	Groove1 (mm)	Groove2 (mm)	Groove3 (mm)	Groove4 (mm)
205/55 R 16	1	10	07BPF40	80	0	71	0	7.27	7.93	7.93	7.07
205/55 R 16	1	10	07BPF40	80	58	71	9472	6.37	6.7	6.7	6.43
205/55 R 16	1	10	07BPF40	80	122	71	18685	5.7	5.8	5.87	5.83
205/55 R 16	1	10	07BPF40	80	203	71	33434	4.83	5.08	5.08	5.09
205/55 R 16	1	10	07BPF40	80	619	71	105273	3.48	3.46	3.52	3.52
205/55 R 16	1	11	07DR553	139	0	67	0	7.33	7.93	7.93	7.07
205/55 R 16	3	38	07CBB47	100	0	40	0	7.5	8.2	8.2	7.5
205/55 R 16	3	38	07CBB47	100	282	40	11335	6.75	7.52	7.44	6.8
205/55 R 16	3	38	07CBB47	100	607	40	23609	5.7	6.77	6.67	6.1
205/55 R 16	3	38	07CBB47	100	683	40	29163	5.2	6	6.1	5.77
205/55 R 16	3	38	07CBB47	100	993	40	36276	5.12	6.16	6.24	5.82
205/55 R 16	3	39	07KR839	125	0	19	0	7.5	8.2	8.2	7.5
205/55 R 16	3	39	07KR839	125	102	19	2899	7.3	7.93	7.87	7.27
205/55 R 16	3	39	07KR839	125	927	19	20583	6.47	7.1	7	6.37
205/55 R 16	3	40	07BPR23	100	0	37	0	7.5	8.2	8.2	7.5
205/55 R 16	3	40	07BPR23	100	41	37	3373	7.37	7.93	7.77	7.3
205/55 R 16	3	40	07BPR23	100	106	37	11274	6.69	7.41	7.19	6.86
205/55 R 16	3	40	07BPR23	100	188	37	20182	6.35	7.01	6.95	6.53
205/55 R 16	5	11	07ASL39	109	99	49	3378	7.23	7.93	7.83	7.13
205/55 R 16	5	11	07ASL39	109	182	49	9849	6.45	7.22	7.14	6.7
205/55 R 16	5	12	07T1721	74	92	44	11293	6.93	7.67	7.61	7.01
205/55 R 16	5	12	07T1721	74	143	44	22648	6.54	7.49	7.35	6.76
205/55 R 16	7	54	07HS225	109	58	29	5772	6.95	7.5	7.5	7.2
205/55 R 16	7	54	07HS225	109	123	29	13183	6.55	6.93	7.03	6.7
205/55 R 16	7	54	07HS225	109	204	29	21430	5.8	6.38	6.33	6.02

All the tires which were selected to create a model were produced with four grooves on the tread area. For each group, the data was calculated by using the ANN. It was defined as selecting the most significant difference of the phenomena on each specific group. Then 1254 measurement data record was used to train the ANN. 307 input data were used together with the training data to test the results. The inputs used for the calculations were (Vehicle Power, Tire working days, Axle position, Tire mileage (km) & Measurement position).

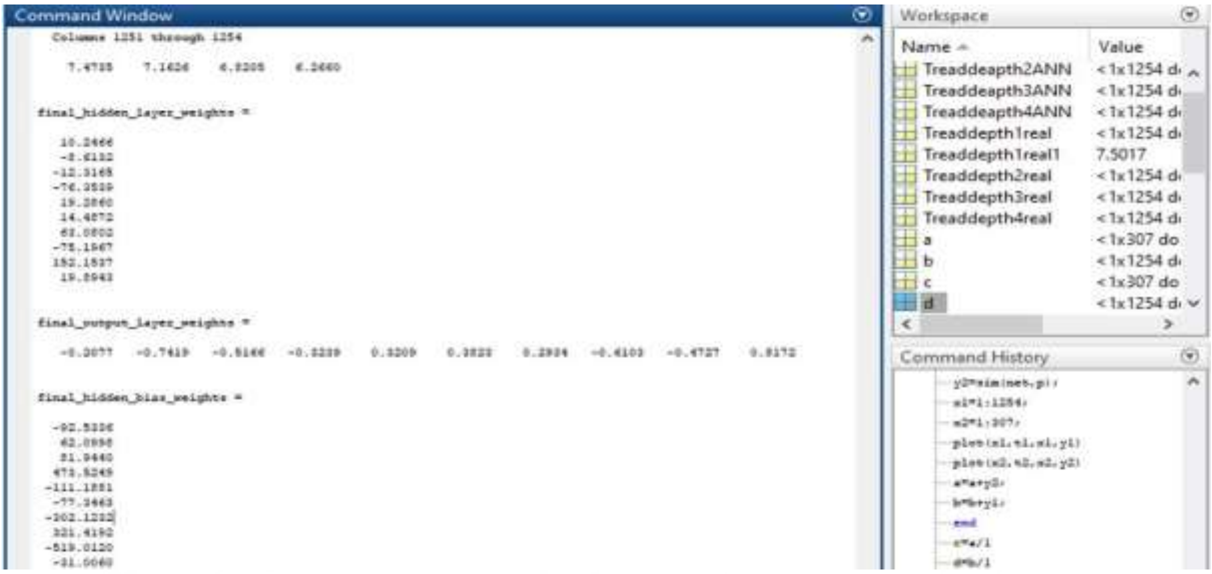


Figure 3.4. Command history

For defining the correlations between the phenomena in the inputs, it was observed that the higher positive interest is between tire mileage and tire working days is 0.696 So, the prediction study was done to the comparison of these two inputs. The values are presented in Table 3.5.

Table 3.5 Correlation relations between inputs

	Vehicle Power (Hp)	Vehicle Axle	Column3	Column4	Tire Mileage	Column6
	Vehicle Power (Hp)	Vehicle Axle	Tire Measurement Position	Tire Working Days	Tire Mileage	Input Number
Vehicle Power (Hp)	1.000	0.009	0.027	0.029	-0.189	0.166
Vehicle Axle	0.009	1.000	0.596	0.034	0.010	0.091
Tire Measurement P	0.027	0.596	1.000	0.008	-0.003	0.113
Tire Working Days	0.029	0.034	0.008	1.000	0.696	-0.756
Tire Mileage	-0.189	0.010	-0.003	0.696	1.000	-0.835
Input Number	0.166	0.091	0.113	-0.756	-0.835	1.000

Figure 3.5. ANN training section screen print

The training formula used in MATLAB for this operation was as given below.

Three hundred iterations applied to collected data by ANN.

Trainlm: Levenberg-Marquart algorithm was used for being one of the fastest algorithms for networks of moderate size. At the same time, the algorithm has a memory reduction feature for use when the training set is large.

Figure 3.6. Shows the training formula of MATLAB in Trainlm algorithm.

```
a=0
b=0
for i=1:1;
p=ogren;
t1=hedef;
net = newff(minmax(p),[5 1],{'logsig' 'purelin'},'trainlm');
net.trainParam.epochs = 300;
net.trainParam.goal = 0.000000000000000000000005;
net = train(net,p,t1);
y1 = sim(net,p);
p=test;
t2=gercek;
y2=sim(net,p);
x1=1:1254;
x2=1:307;
plot(x1,t1,x1,y1)
plot(x2,t2,x2,y2)
a=a+y2;
b=b+y1;
end
c=a/1
d=b/1
final_hidden_layer_weights=net.iw{1,1}
final_output_layer_weights=net.lw{2,1}
final_hidden_bias_weights=net.b{1}
final_output_bias_weights=net.b{2}
```

Figure 3.6. MATLAB formulization screen print

3.1.5. MATLAB operations

It is one of the most used programmes which is used to measure the magnitude of the relations between variables. MATLAB can be performed by using a single variable. In multivariate cases, other variables affecting the dependent variable are considered as fixed. In the study.

In Figure 3.7. A screen view of MATLAB calculations is visible.

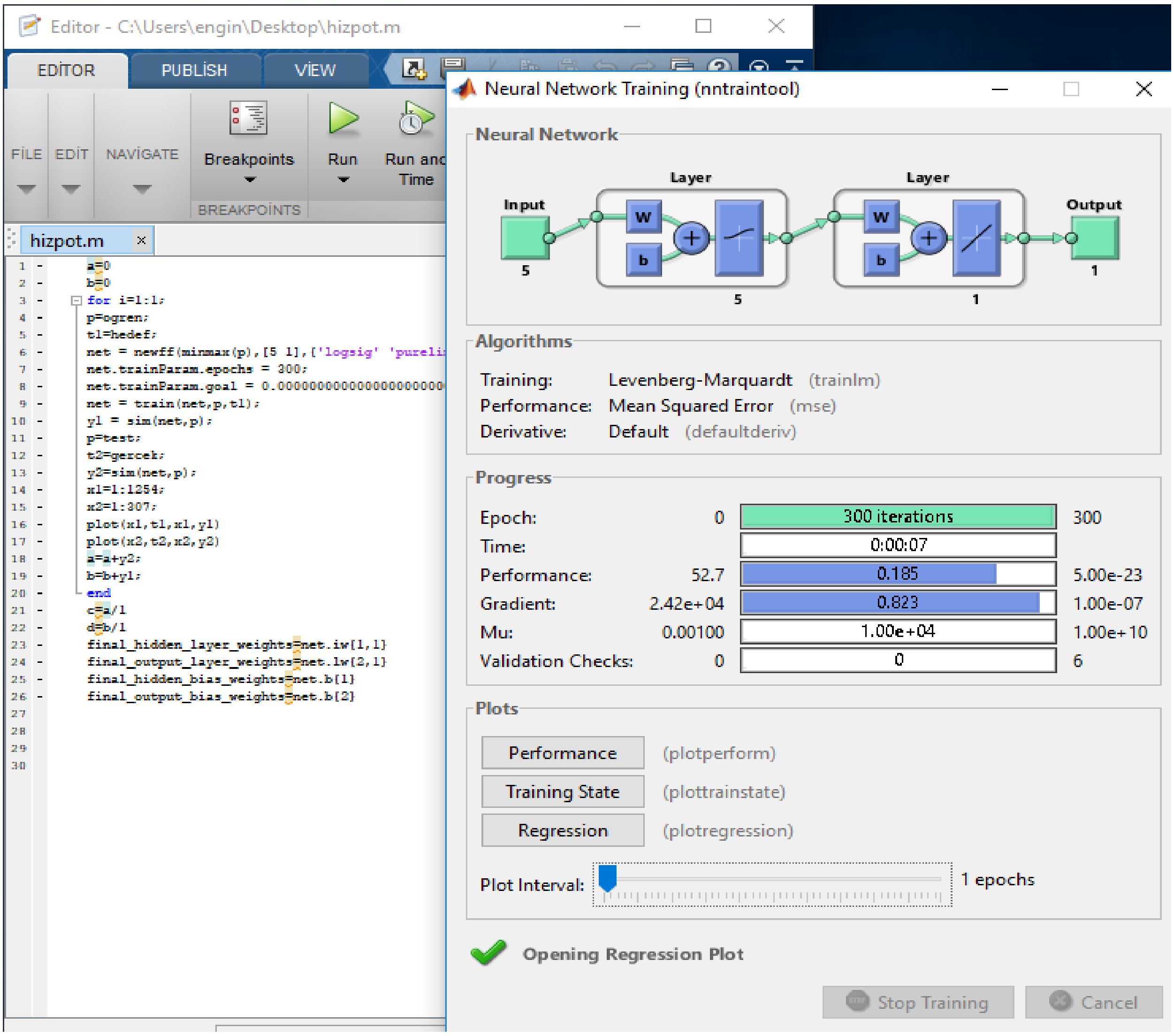


Figure 3.7. ANN operations screen view

Depending on this data, calculations were done at MATLAB

For each tire groove, results taken from ANN were compared to real measurement results.

4. RESULTS AND DISCUSSION

In this study, (RMSE) Root Mean Square Error and (R) coefficient calculation were used as statistical metrics for evaluating the performance of ANN models. RMSE is an estimator one of many ways to quantify the difference between values implied by an estimator and the actual values of the quantity being estimated.

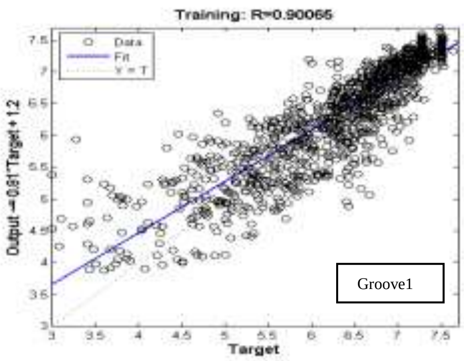
RMSE can be calculated as;

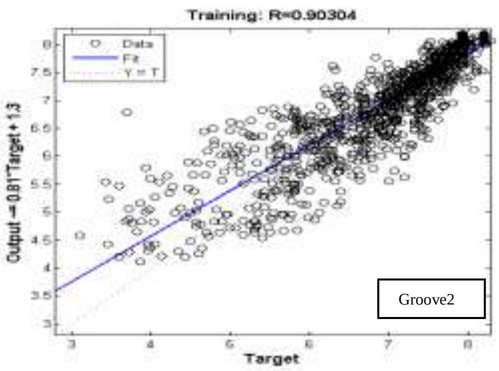
$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{n}(\text{Ymeasured}\, j - \text{Zmodelled}\, j)^2} \qquad \text{(Inyurt\&Sertekin, 2019)}$$

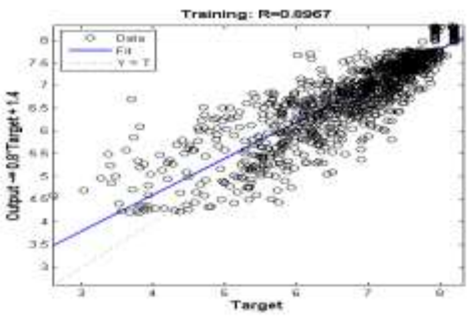
Correlation Coefficient R can be calculated as;

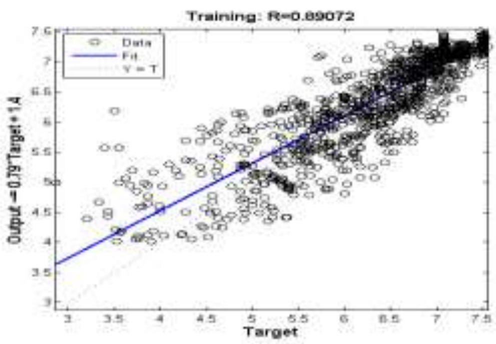
$$R = \frac{\sum(Y_{\text{measured } j} - \overline{Y}_{\text{measured } j})(Y_{\text{modeled } j} - \overline{Y}_{\text{modeled } j})}{\sqrt{\sum(Y_{\text{measured } j} - \overline{Y}_{\text{measured } j})^2 \sum(Y_{\text{modeled } j} - \overline{Y}_{\text{modeled } j})^2}}$$

Where N is the number of the data set, and $\boldsymbol{Y}_{\mathbf{measured}j}$ and $\boldsymbol{R}_{\boldsymbol{modelled}j}$ are measured and modelled tread depth values, respectively. Besides, $Y_{\text{measured } j}$, and $Y_{\text{modelled}}\, j$ represents the mean value of measured and modelled tread depth values, respectively.









Groove3

Groove4

Figure 4.1. Coefficient calculation (R) results.

(RMSE) Value is an essential value for judging mathematical models. Lower (RMSE) results represent a better fitting model. (RMSE) Measures how much error there is between two data sets. It compares a predicted value, an observed or known value. It is one of the most widely used statistics. https://gisgeography.com/root-mean-square-error-rmse-gis/

(R) The correlation coefficient is a mathematical formula that measures the strength between variables and relationships. This coefficient must be found to determine how strong the relationship is between two variables. The value of (R) can range between (-1.00 and 1.00). https://study.com/academy/lesson/pearson-correlation-coefficient-formula-example-significance.html

RMSE&R Calculated results training, testing and prediction results

Table 4.1. RMSE,MAPE&R, calculated results training, testing and prediction results

	1st. groove	2nd. groove	3rd. groove	4th.groove
RMSE	0.38	0.46	0.46	0.38
MAPE	4.61	4.63	4.84	4.64
R	0.90	0.90	0.89	0.89

Table 4.2. in next page shows the weights used in equations for the calculations of input data. The formulas are generated depending on to these calculated.weights. In Model1 all 5 inputs are calculated to get the comparison results and up on to these results all weights are calculeted and the formulations are generated.

Table 4.2. weights used in equations

Groove 1 weights used in equations							
final hidden layer weights					final output layer weights	final hidden bias weights	final output bias weights
w1i	w2i	w3i	w4i	w5i		bias	
-0.0257	-0.526	-0.146	-0.002	-0.0002	1.674	3.524	6
0.0158	0.261	0.062	0.002	-0.00003	4.181	-3.292	
0.002	-0.2076	-0.142	0.004	0.0000021	-2.308	-2.214	
0.08	1.715	0.169	-0.002	0.00022	-0.469	-14.705	
0.211	2.131	-1.581	0.194	-0.004	-0.265	-7.881	

Groove 2 weights used in equations							
final hidden layer weights					final output layer weights	final hidden bias weights	final output bias weights
w1i	w2i	w3i	w4i	w5i		bias	
-0.252	-0.482	0.241	0.027	-0.0154	-0.207	9.591	9
-0.42	-8.38	-1.121	0.04	0.0002	-0.405	11.492	
0.011	0.416	0.304	-0.001	-0.00001	3.458	-1.853	
0.009	0.319	0.201	-0.00005	0.003	-4.789	-1.065	
-0.091	-0.087	-0.365	-0.082		0.003	-0.174	

Groove 3 weights used in equations							
final hidden layer weights					final output layer weights	final hidden bias weights	final output bias weights
w1i	w2i	w3i	w4i	w5i		bias	
0.192	-4.123	-1.463	0.029	-0.001	0.354	-1.569	5
0.68	5.783	0.875	-0.005	-0.093	0.494	-17.559	
1.653	-4.812	1.291	-0.234	-0.008	0.169	-1.121	
0.213	3.909	-3.873	0.094	-0.0003	1.261	-1.816	
0.002	0.367	0.281	-0.001	-0.00003	3.259	0.951	

Groove 4 weights used in equations							
final hidden layer weights					final output layer weights	final hidden bias weights	final output bias weights
w1i	w2i	w3i	w4i	w5i		bias	
0.171	-0.335	-0.947	-0.014	0.002	0.46	3.504	6
0.002	-3.227	0.174	-0.001	-0.00003	2.134	5.317	
-0.166	3.83	-2.617	-0.214	0.004	-0.171	-10.401	
-0.001	-3.753	0.011	0.001	-0.00003	-2.159	4.105	
1.686	-3.788	2.326	0.161	-0.011	0.192	1.581	

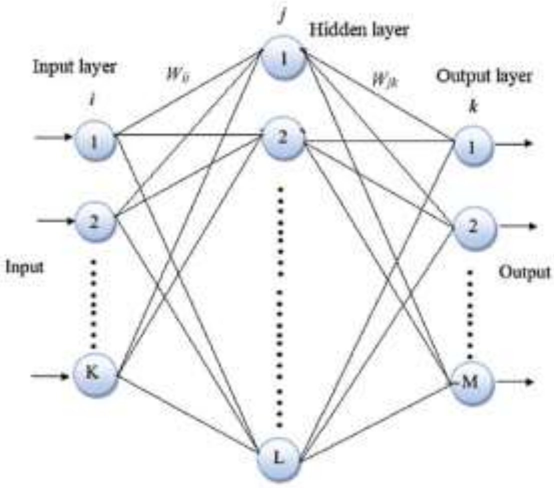


Figure 4.2. A three-layered ANN structure (Mansouri et al. 2016)

<u>Model 1</u> <u>Equations</u>

Groove1 $X_i = w_{1i}$ *(Vehicle Power)* + w_{2i}*(Axle Position)* + w_{3i}*(Measurement Position)* + w_{4i} *(Tire working days)*+ W_{5i}*(Tire Mileage)*+W_6

$$y_i = \frac{1}{1+e^{-x_i}} \tag{4.1.}$$

Groove2 $X_i = w_{1i}$ *(Vehicle Power)* + w_{2i}*(Axle Position)* + w_{3i}*(Measurement Position)* + w_{4i} *(Tire working days)*+ W_{5i}*(Tire Mileage)*+W_{6i}

$$y_i = \frac{1}{1+e^{-x_i}} \tag{4.2.}$$

Groove3 $X_i = w_{1i}$ *(Vehicle Power)* + w_{2i}*(Axle Position)* + w_{3i}*(Measurement Position)* + w_{4i} *(Tire working days)*+ W_{5i}*(Tire Mileage)*+W_{6i}

$$y_i = \frac{1}{1+e^{-x_i}} \tag{4.3.}$$

Groove4 $X_i = w_{1i}$ *(Vehicle Power)* + w_{2i}*(Axle Position)* + w_{3i}*(Measurement Position)* + w_{4i} *(Tire working days)*+ W_{5i}*(Tire Mileage)*+W_{6i}

$$y_i = \frac{1}{1+e^{-x_i}} \tag{4.4.}$$

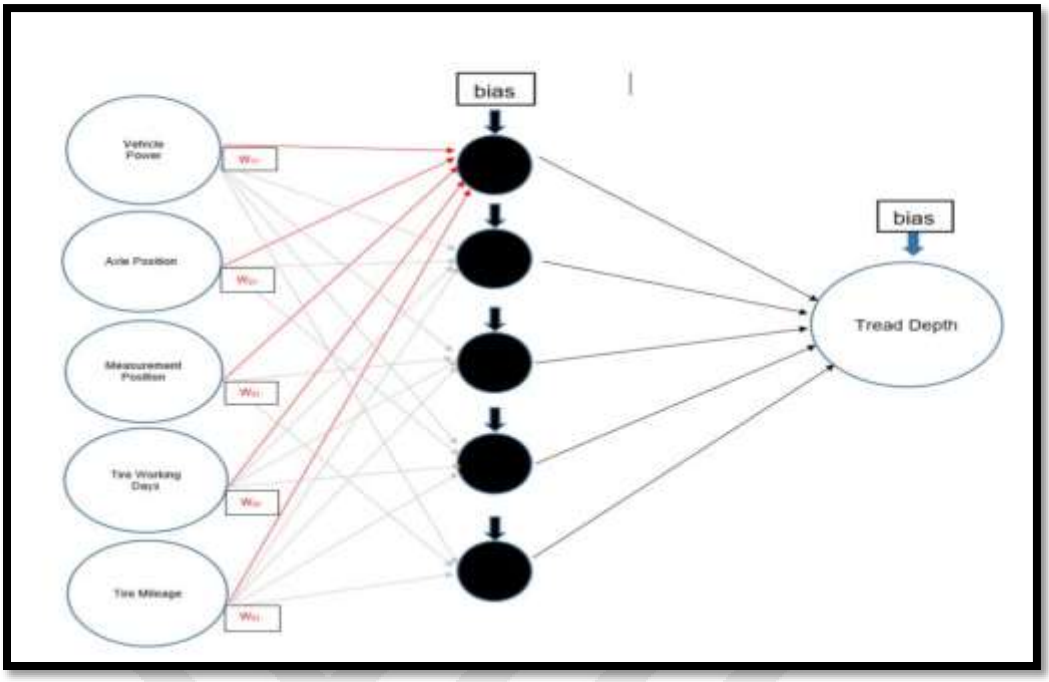


Figure 4.3. Structure of used ANN method (Model1)

The network structure settings have a high impact on the performance of ANN. Tread depth results mainly affected by tire life circle. In this study, an ANN model is constructed with five input layers and five hidden layers to model tread depth measurement results. Input parameters were defined as vehicle power, axle position, measurement position, tire working days, tire mileage to implement our ANN method, training, testing and prediction of data sets.

Data list used for first groove calculations is as shown in table 4.3.

The average of ANN results for the first groove is 4.46 %, and the correlation of ANN results to real measured results are 0.92, which is good enough to use as an output.

The results of the real measurements and ANN is on an expected level.

Table 4.3. First groove calculation input table

Tire	Vehicle Power (HP)	Vehicle Axle	Axle Position	Tire working Days	Tire Mileage	Input Number	1st. Groove
10	80	1	2	0	0	1	7.27
10	80	1	2	58	9472	2	6.37
10	80	1	2	122	18685	3	5.7
10	80	1	2	203	33434	4	4.83
10	80	1	2	619	105273	5	3.48
11	139	1	3	0	0	6	7.33
11	139	1	3	106	7935	7	6
12	139	1	4	0	0	8	7.27
12	139	1	4	106	7935	9	5.97
13	109	2	4	0	0	10	7.27
13	109	2	4	63	11500	11	6.59
13	109	2	4	122	18535	12	6.23
13	109	2	4	189	25658	13	6.03
14	100	2	3	0	0	14	7.27
14	100	2	3	64	7150	15	6.82
14	100	2	3	209	34528	16	5.22
15	100	1	1	0	0	17	7.27
1	66	1	1	0	0		3
63	163	2	4	1042	145366		7.63
28	125	1	2	0	0	1	7.5
28	125	1	2	87	6114	2	7.09
28	125	1	2	146	9715	3	6.91
28	125	1	2	212	12927	4	6.79
29	125	1	1	0	0	5	7.5
29	125	1	1	87	6114	6	7.15
29	125	1	1	146	9715	7	6.83
29	125	1	1	212	12927	8	6.64
30	90	1	1	0	0	9	7.5
30	90	1	1	89	8729	10	6.97
31	109	2	4	0	0	11	7.5
31	109	2	4	61	10763	12	7.02
31	109	2	4	120	15993	13	7.03
31	109	2	4	186	21755	14	6.58
31	109	2	4	269	32155	15	6.4
31	109	2	4	342	38528	16	6.31
31	109	2	4	593	51168	17	5.73
31	109	2	4	654	58850	18	5.42
32	90	1	2	0	0	19	7.5
32	90	1	2	89	8729	20	6.73
33	90	2	2	0	0	21	7.5
33	90	2	2	152	13563	22	6.71
33	90	2	2	313	17733	23	6.5
33	90	2	2	463	28912	24	6.25
34	80	2	4	0	0	25	7.5
34	80	2	4	31	3685	26	7.26
34	80	2	4	126	14789	27	6.57
34	80	2	4	218	26498	28	6.06
34	80	2	4	484	61083	29	4.72
35	90	2	1	0	0	30	7.5
54	109	1	2	58	5772	305	6.95
54	109	1	2	123	13183	306	6.55
54	109	1	2	204	21430	307	5.8

In Table 4.4. Real measurement results were compared to output results of ANN. At early mileage of the tires, it is observed that ANN is showing results which are near to real measurement results. Correlated to tires demounted in two years period, the number of tires(inputs) decreased.

Table 4.4. First groove, tread depth graphics comparison

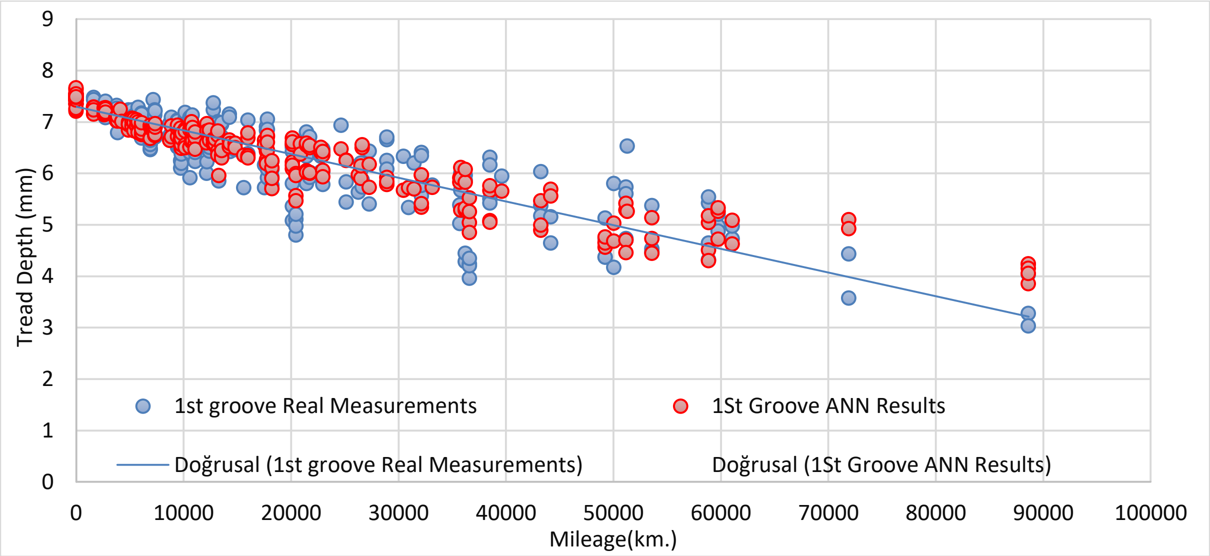
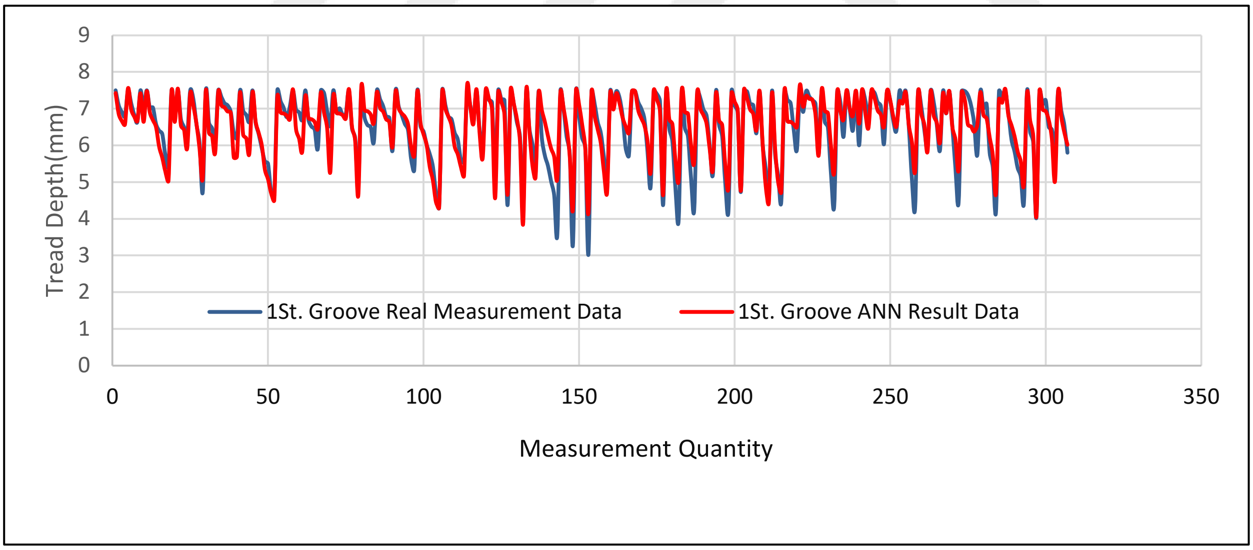


Table 4.5. presents different measurements as inputs at different mileage.

Mileage Km.	Real Measurements	ANN Results
0	7.5	7.425206555
0	7.5	7.559766385
0	7.5	7.420623763
0	7.5	7.478204038
0	7.5	7.494528595
0	7.5	7.547689604
0	7.5	7.423953361
0	7.5	7.498162102
0	7.5	7.467174135
0	7.5	7.447358921
0	7.5	7.450153865
0	7.5	7.335987963
0	7.5	7.527887555
0	7.5	7.346756406
1637	7.3	7.151162076
1637	7.47	7.285358438
1637	7.43	7.280495361
1637	7.23	7.23097581
2603	7.33	7.26697898
2603	7.2	7.137919449
5639	7.15	7.03550588
5639	7.07	6.921964689
5772	7.13	6.806953112
5772	7.18	6.96175419
5772	7.28	6.999007901
5772	6.95	6.789063088

Table 4.5. First groove measurement results summary

Table 4.6. First groove tread depth graphics comparison



Data List used for following groove calculations is as shown below in Table 4.7. similar method is used for the calculations as mentioned up.

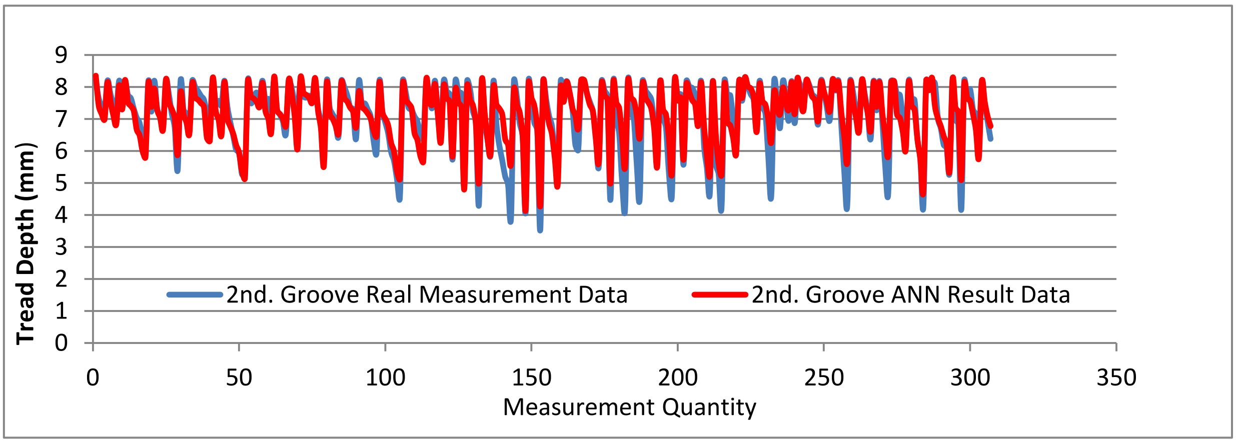
Table 4.7. Groove calculation inputs

	Vehicle Power (HP)	Vehicle Axle	Tire Measurement Position	Tire working Days	Tire Mileage	Input Number	1st. Groove	ANN
10	80	1	2	0	0	1	7.27	7.50166261
10	80	1	2	58	9472	2	6.37	6.75836813
10	80	1	2	122	18685	3	5.7	6.30852361
10	80	1	2	203	33434	4	4.83	5.6644752
10	80	1	2	619	105273	5	3.48	4.04776519
11	139	1	3	0	0	6	7.33	7.2669395
11	139	1	3	106	7935	7	6	6.70424089
12	139	1	4	0	0	8	7.27	7.38361077
12	139	1	4	106	7935	9	5.97	6.81361468
13	109	2	4	0	0	10	7.27	7.47820404
13	109	2	4	63	11500	11	6.59	6.88823591
13	109	2	4	122	18535	12	6.23	6.63566781
1	66	1	1	0	0		3	
63	163	2	4	1042	145366		7.63	
28	125	1	2	0	0	1	7.5	7.42520656
28	125	1	2	87	6114	2	7.09	6.85704765
28	125	1	2	146	9715	3	6.91	6.6653687
54	109	1	2	58	5772	305	6.95	6.78906309
54	109	1	2	123	13183	306	6.55	6.35140252
54	109	1	2	204	21430	307	5.8	6.01638393

The same method is used for the second groove in Table 4.8 and defined the most significant difference between the inputs to give ANN, and then1259 measurement data record was used to train the ANN and for the data input 303 data were used together with the test data to test the results.

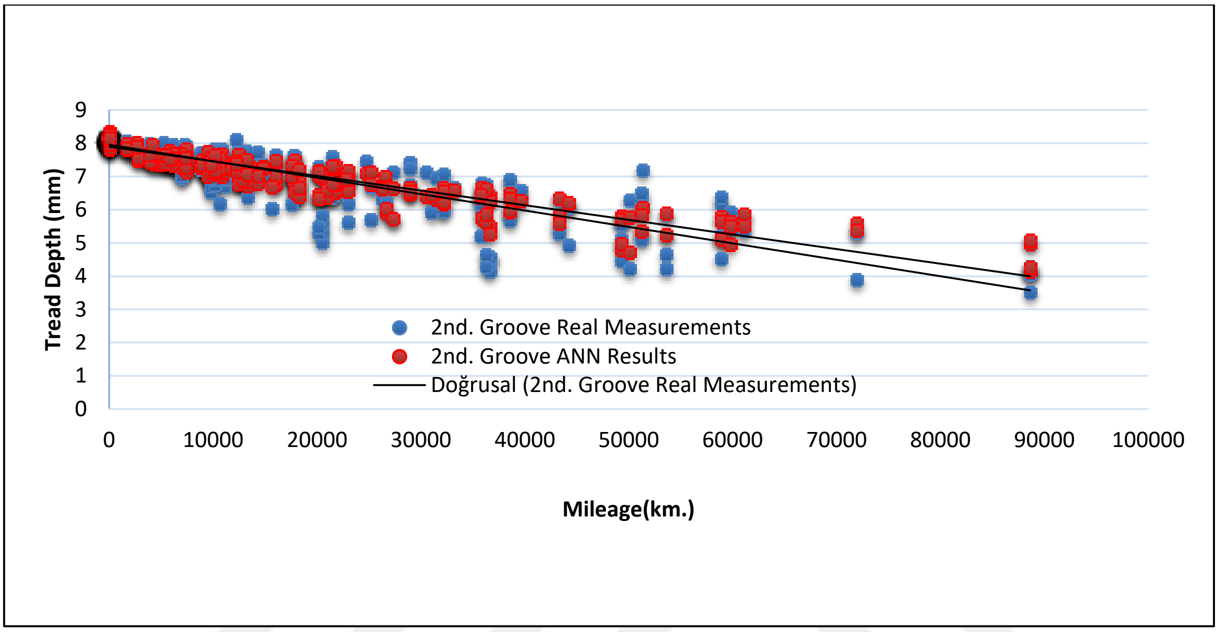
The average of ANN results for the first groove is 4.73 %, and the correlation of ANN results to real measured results are 0.91 which is good enough to use as an output.

Table 4.8. Second groove real tread depth measurements & ANN results



In Table 4.9. Real measurement results were compared to output results of ANN. It is observed as expected that ANN is showing results which are near to real measurement results.

Table 4.9. Second groove tread depth graphics comparison

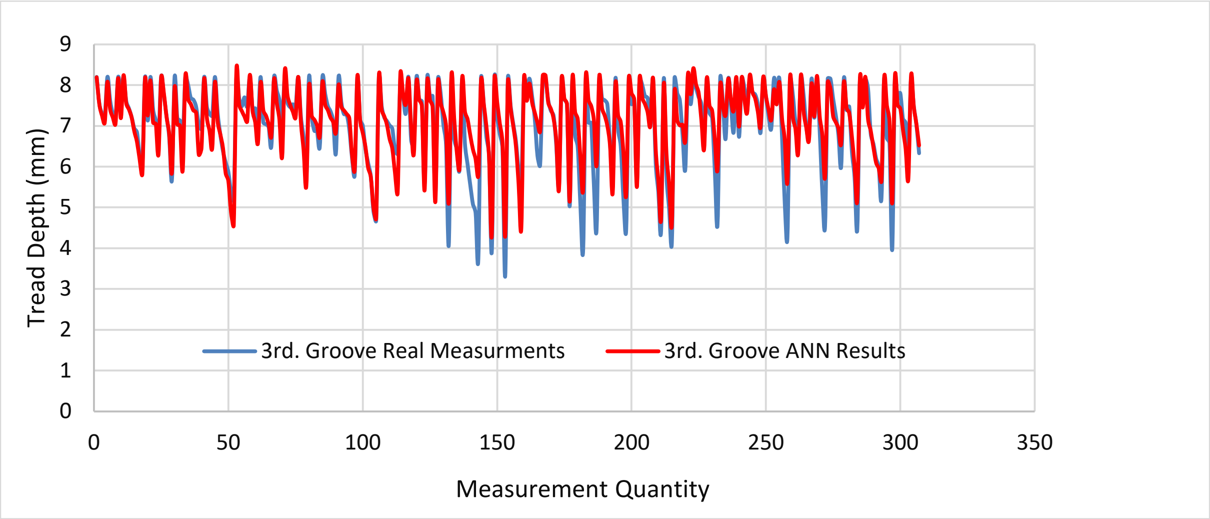


Same data input method was used for third groove calculations as well.

The average of ANN results for the third groove is 4.8 %, and the correlation of ANN results to real measured results are 0.91 which is good enough to use as an output.

Correlated to tires demounted in two years, it is observed that the measurement quantity decreased at the end of the measuring period and decreasing input quantity presents a little far away results at higher mileages. Results are visible below in Table 4.10.

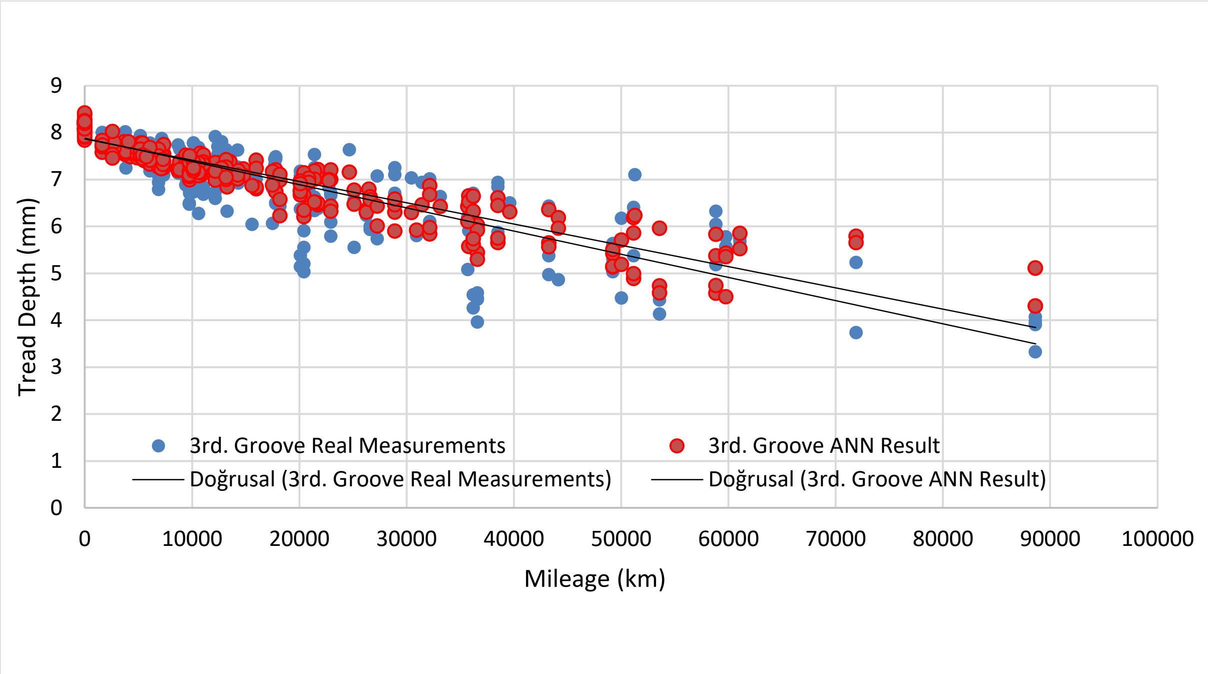
Table 4.10. Third groove real tread depth measurements & ANN results



In Table 4.11. Real measurement results were compared to output results of ANN. It is observed that ANN is showing results which are near to real measurement results. Same data input method was used for fourth. Groove calculations as well.

The average of ANN results for the first groove is 4.77 %, and the correlation of ANN results to real measured results are 0.91 which is good enough to use as an output.

Table 4.11. Third groove tread depth graphics comparison



In Table 4.12. Real measurement results were compared to output results of ANN. It is observed that ANN is showing results which are near to real measurement results.

Table 4.12. Fourth groove real tread depth measurements & ANN results

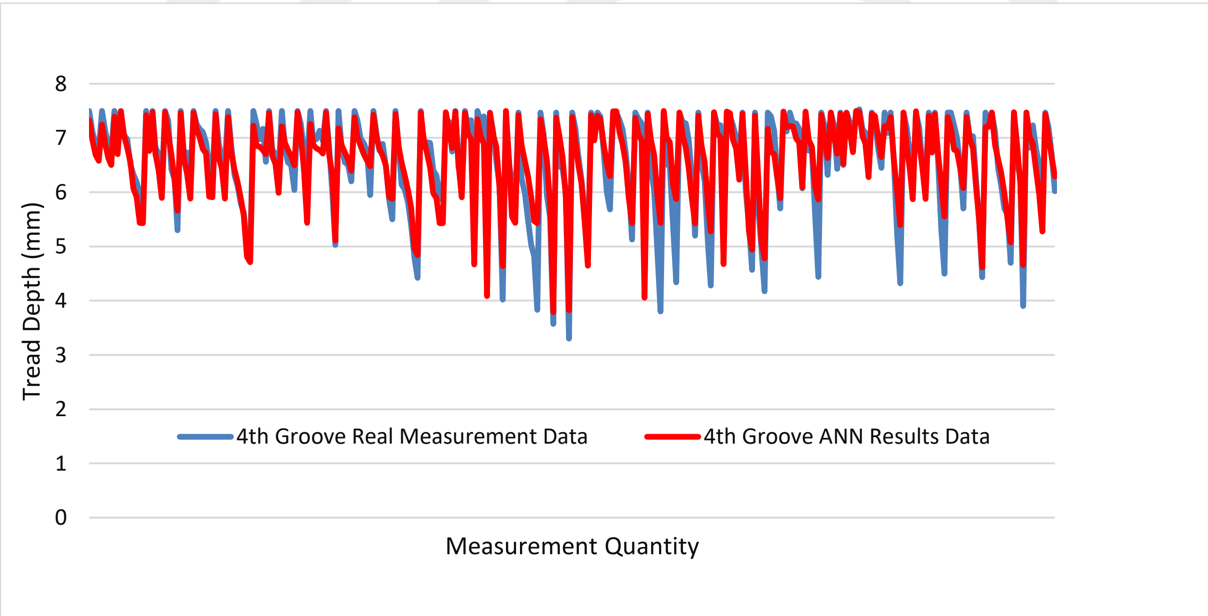
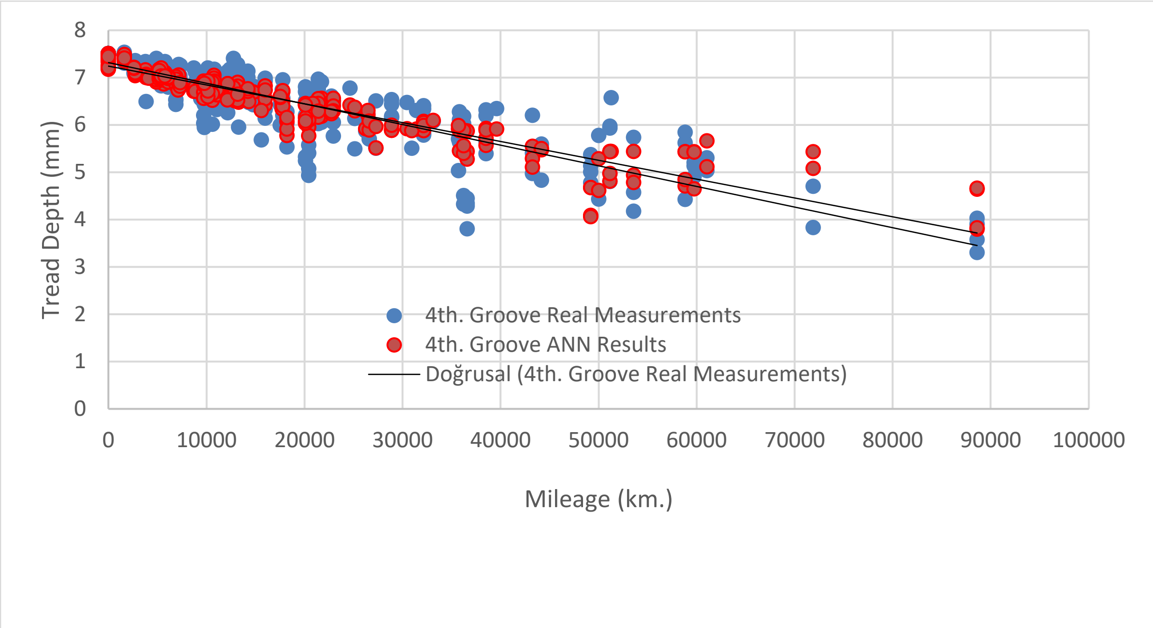


Table 4.13. Fourth groove tread depth graphics comparison


8
7
6
5
4
3
2
1
0
Tread Depth (mm)
0
10000
20000
30000
40000
50000
60000
70000
80000
90000
100000
Mileage (km.)
4th. Groove Real Measurements
4th. Groove ANN Results
Doğrusal (4th. Groove Real Measurements)

Model 2: In this study another model Model 2 is presented at further pages. The aim of presenting the second model is by using by 2 data inputs from the previous 5 inputs we could obtain more reliable results. In this model tire working days and tire milege are used as our inputs. As we applied the calculations on the previous pages, 1254 data input was used to train ANN and 307 data input was used as training results. All results obtained from the calculations are represented in next pages for all 4 grooves of the tires. Attached figure represents the Structure of used ANN method as Model 2. the correlation of ANN results to real measured results are 0.97 which is good enough and more reliable in comparision to previous 5 inputs as an output.

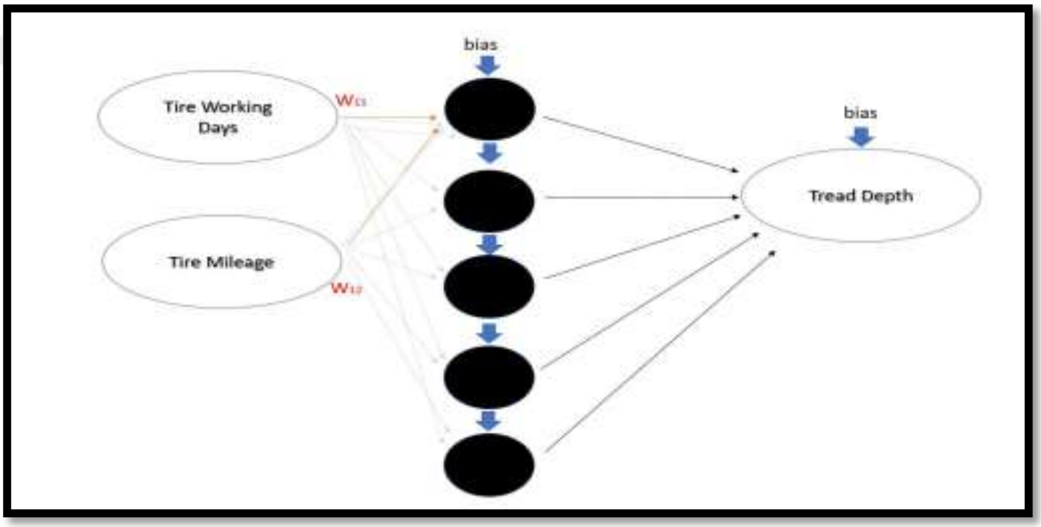


Figure 4.4. Structure of used ANN method (Model 2)

In Figure 4.5 it is possible to see the MATLAB operations of the created model (Model 2)

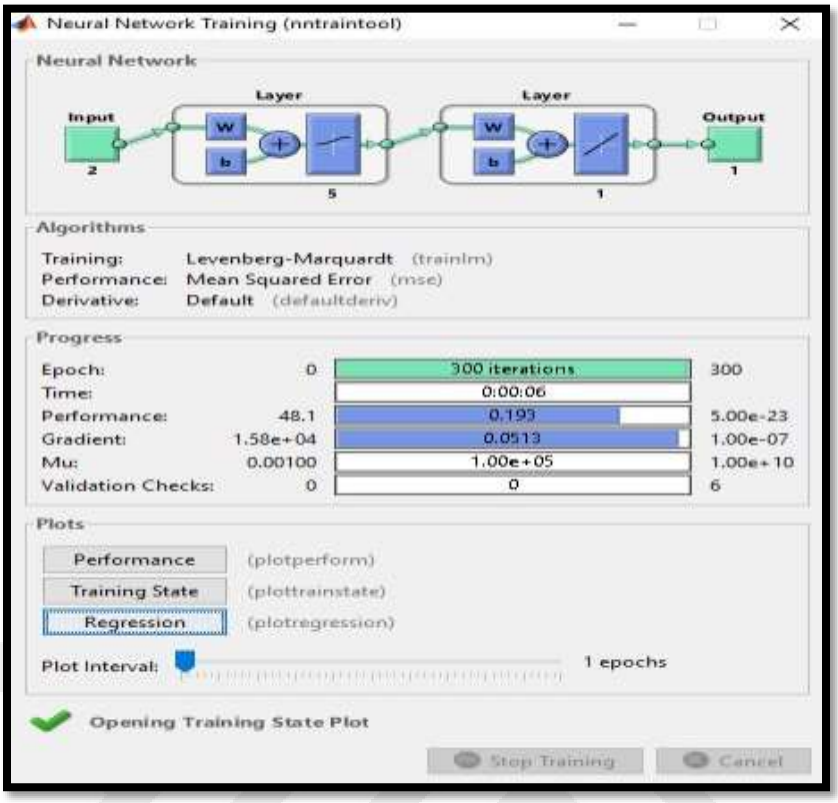


Figure 4.5. ANN operations screen view model 2.

```
final_hidden_layer_weights =

  -0.8414    0.0047
  -0.0018   -0.0595
   0.5476   -0.1961
  -0.0006   -0.0000
  -0.0244    0.0013


final_output_layer_weights =

   0.2164    0.0129    0.0188    4.0607   -0.3233


final_hidden_bias_weights =

  12.2880
 -11.9273
  -8.9303
   1.1002
  -6.6113


final_output_bias_weights =

   4.2087
```


Figure 4.6. Weights used in equations groove 1

Depending to calculations the coefficient (R) is obtained as shown in Figure 4.7. below

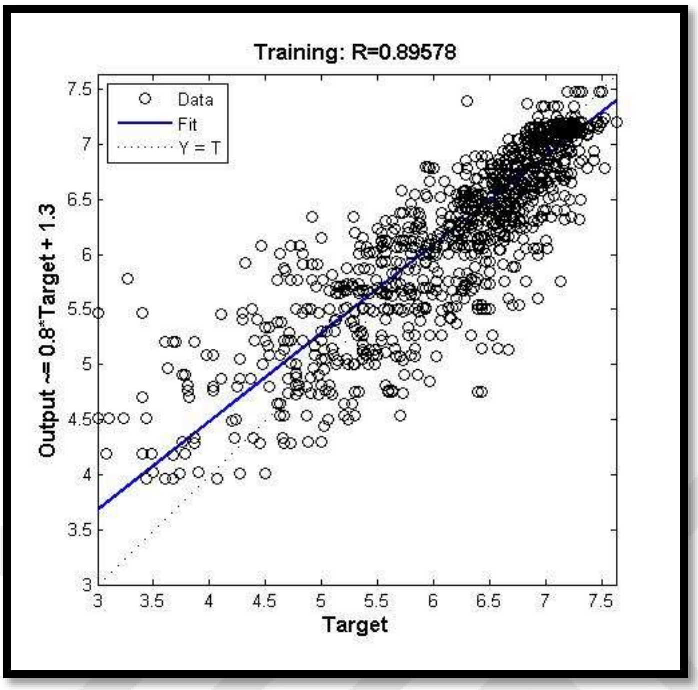


Figure 4.7. Coefficient calculation (R) results groove 1

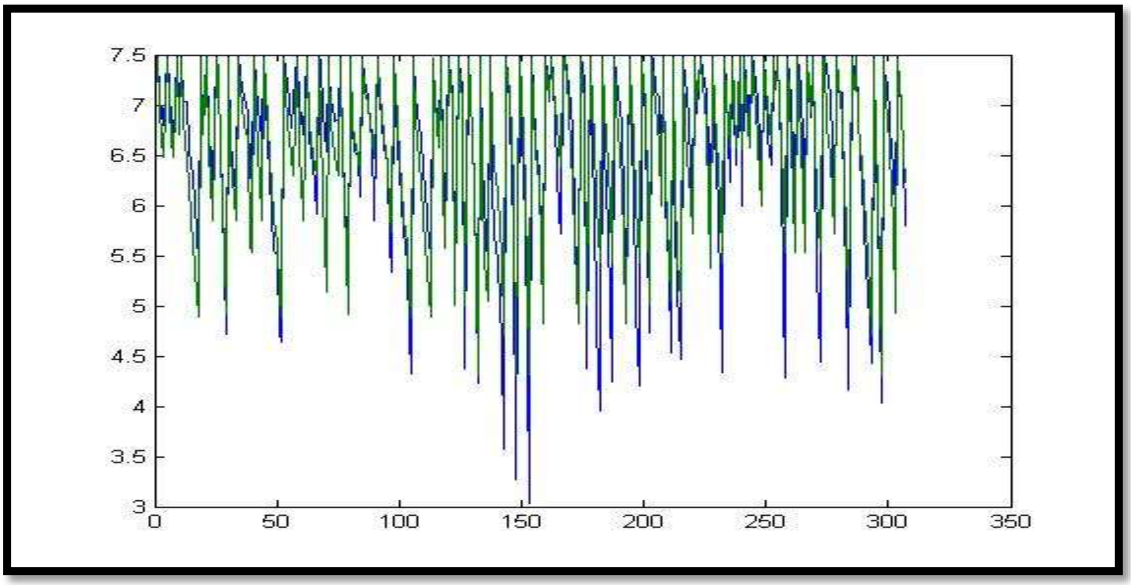


Figure 4.8. Groove 1 real measurements, ANN results comparison MATLAB screen view

Figure 4.9. shows the results of weights in MATLAB calculations for the 2^{nd} groove.

```
final_hidden_layer_weights =

    0.0725    0.0036
   -0.0114    0.0003
   -0.0013   -0.0000
   -0.0294    0.0013
    0.0110   -0.0001


final_output_layer_weights =

   -0.1772   -0.7352    3.2994   -0.4457   -0.4875


final_hidden_bias_weights =

   -4.9350
   -5.1256
    2.0542
   -5.6235
   -0.5301


final_output_bias_weights =

    5.4253
```

Figure 4.9. Weights used in equations groove 2

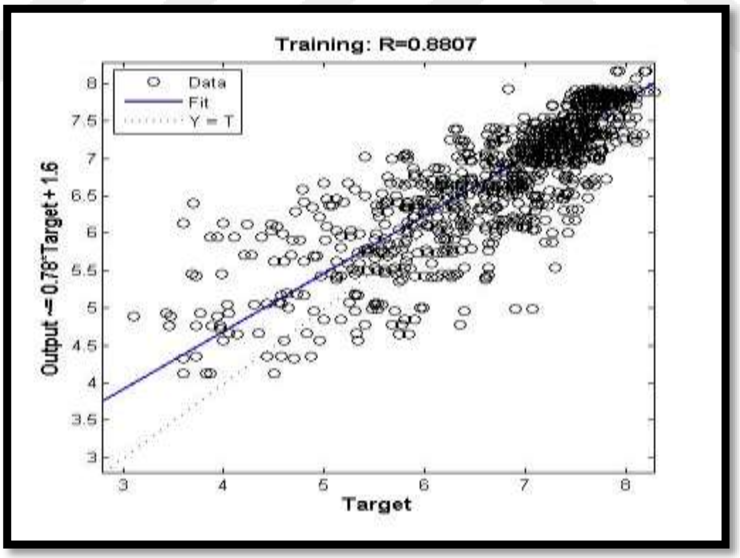


Figure 4.10. Coefficient calculation (R) results groove 2

In Figure 4.11 Real measurements and ANN results are compared. Here the x axes present the measurement quantity and the y axes represents the tread depth values as (mm)

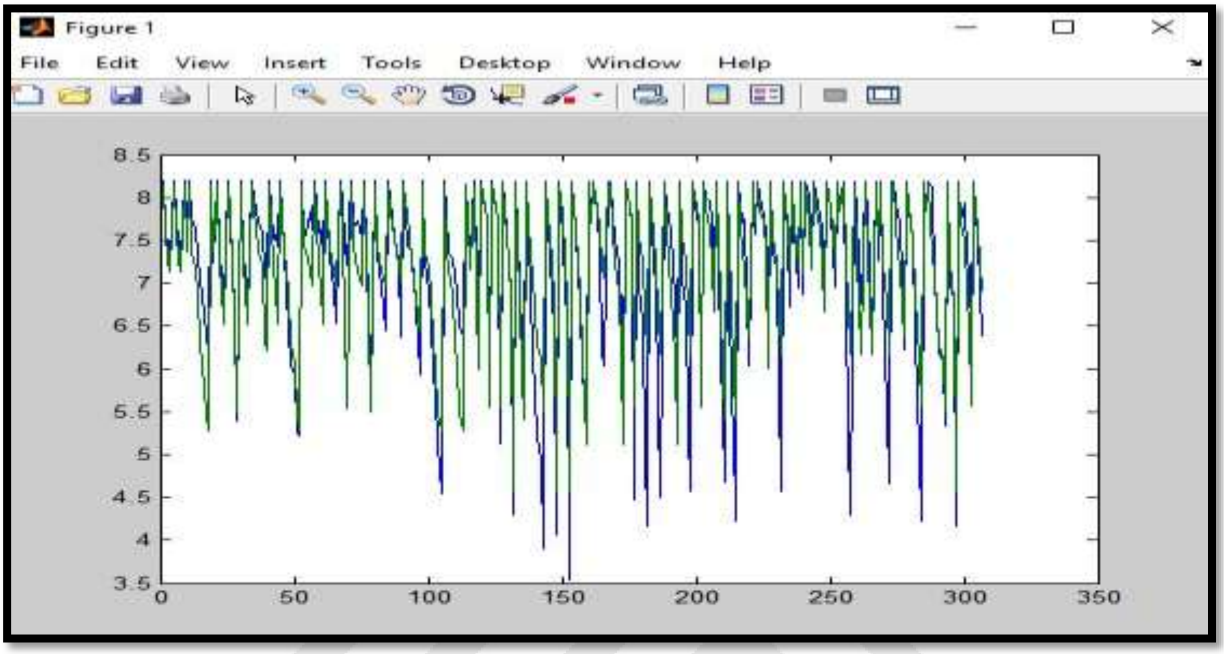


Figure 4.11 Groove 2 real measurements, ANN results comparison MATLAB screen view

R coefficient result is represented in figure 4.12 for the 3rd groove. The results are calculated for the 2nd Model that are using tire working days and tire mileage as inputs.

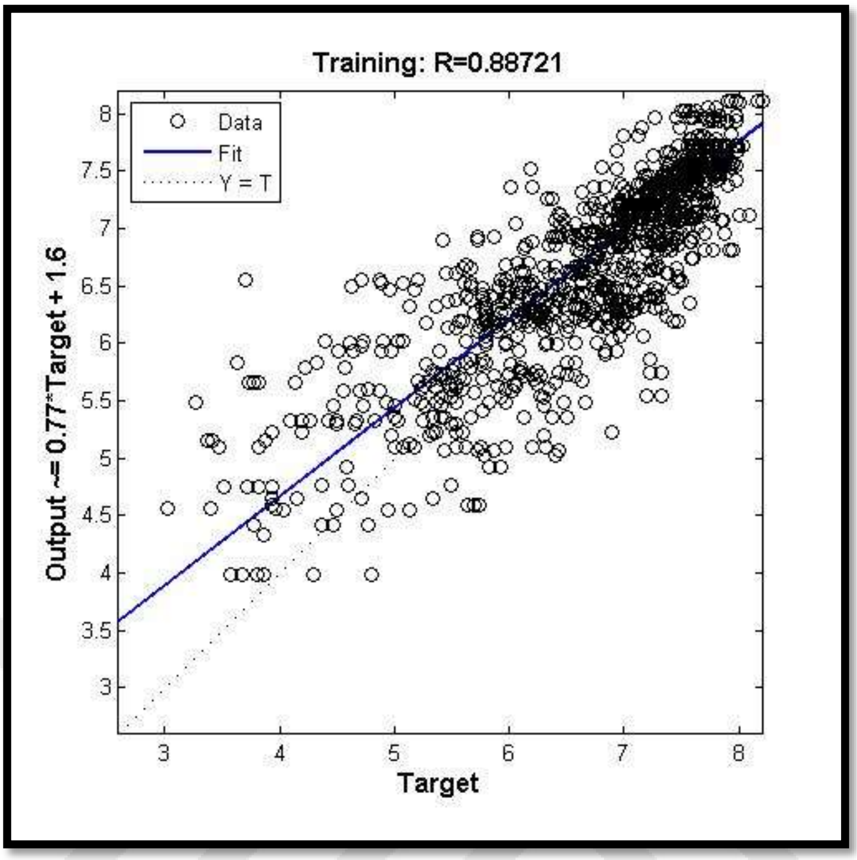


Figure 4.12. Coefficient calculation (R) results groove 3

In Figure 4.13 Real measurements and ANN results are compared. Here the x axes present the measurement quantity and the y axes represents the tread depth values as (mm)

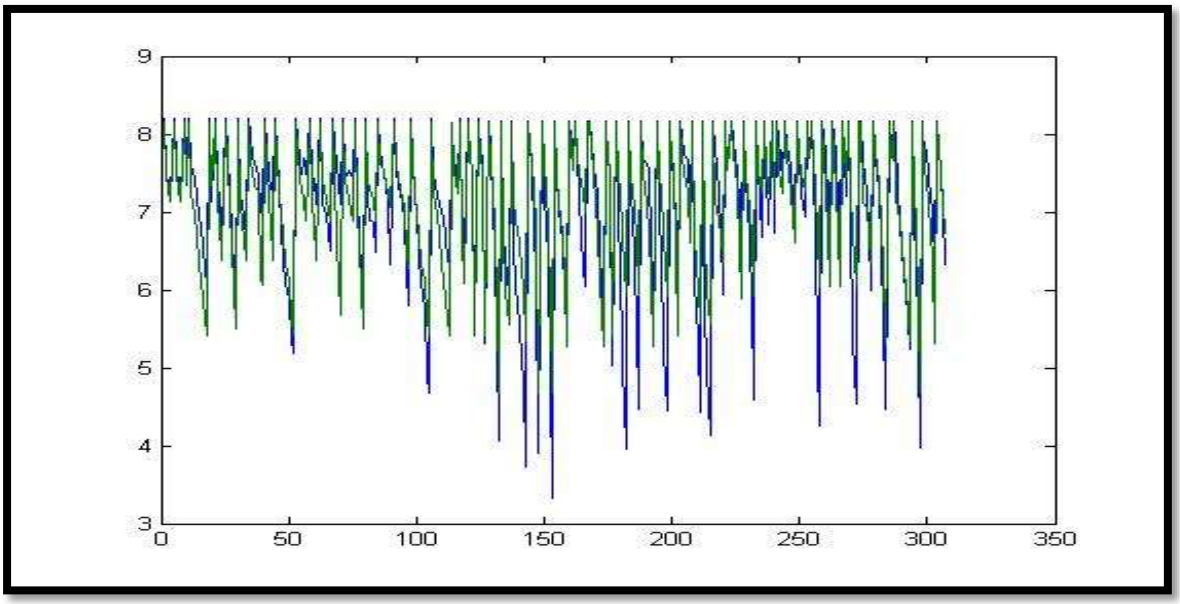


Figure 4.13. Groove 3 real measurements, ANN results comparison MATLAB screen view

Figure 4.14 shows the coefficient calculation results for the 4th groove. As mentioned before same method (Model2) was used for the calculations.

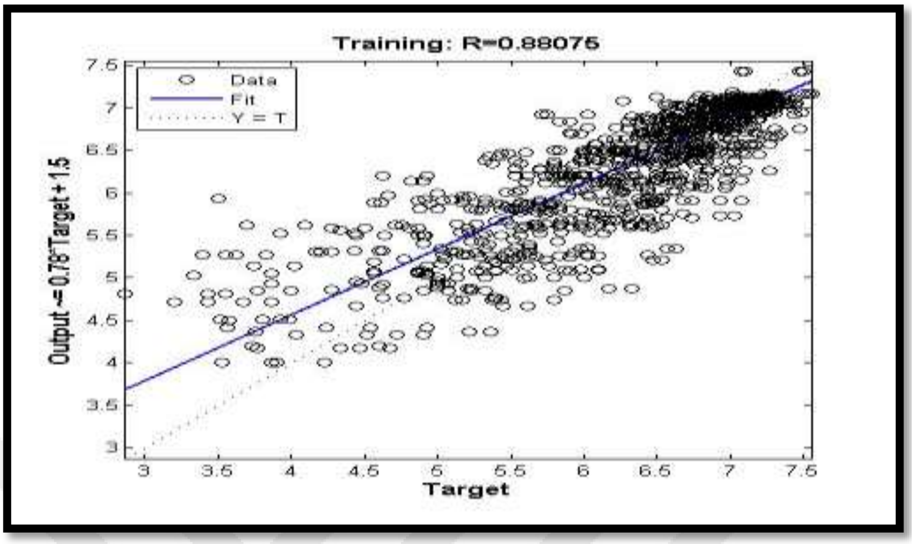


Figure 4.14. Coefficient calculation (R) results groove 4

Figure 4.15. shows the results for real tread depth compared to ANN results. For the calculations tire working days and tire mileage is used as input data to train the ANN. Real measurements and ANN results are compared. Here the x axes present the measurement quantity and the y axes represents the tread depth values as (mm)

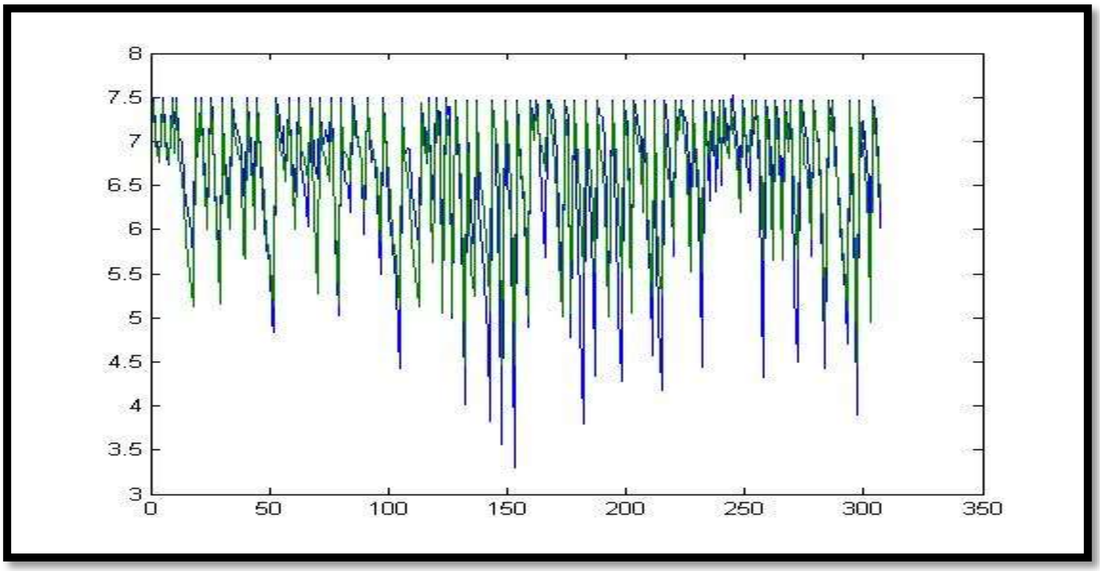


Figure 4.15. Groove 3 real measurements, ANN results comparison MATLAB screen view

In Table 4.14 RMSE&R results calculated in MATLAB for the tire grooves is visible.

Table 4.14. RMSE,MAPE &R calculated results training, testing and prediction results model 2

	1st. groove	2nd. groove	3rd. groove	4th.groove
RMSE	0.41	0.48	0.48	0.42
MAPE	3,83	3,92	3,97	3,84
R	0.89	0.88	0.89	0.89

It is visible that the results obtained from 2nd Model has better reliability as 0.92 and the average ANN tread depth result is 6.39 which is better than the 1st model's result and quite good enough to use as an output. Below the same tables are presented for the first groove with the outputs of the 2nd model as the metdod used previously.

Table 4.15 Model2 first groove real tread depth measurements & ANN results

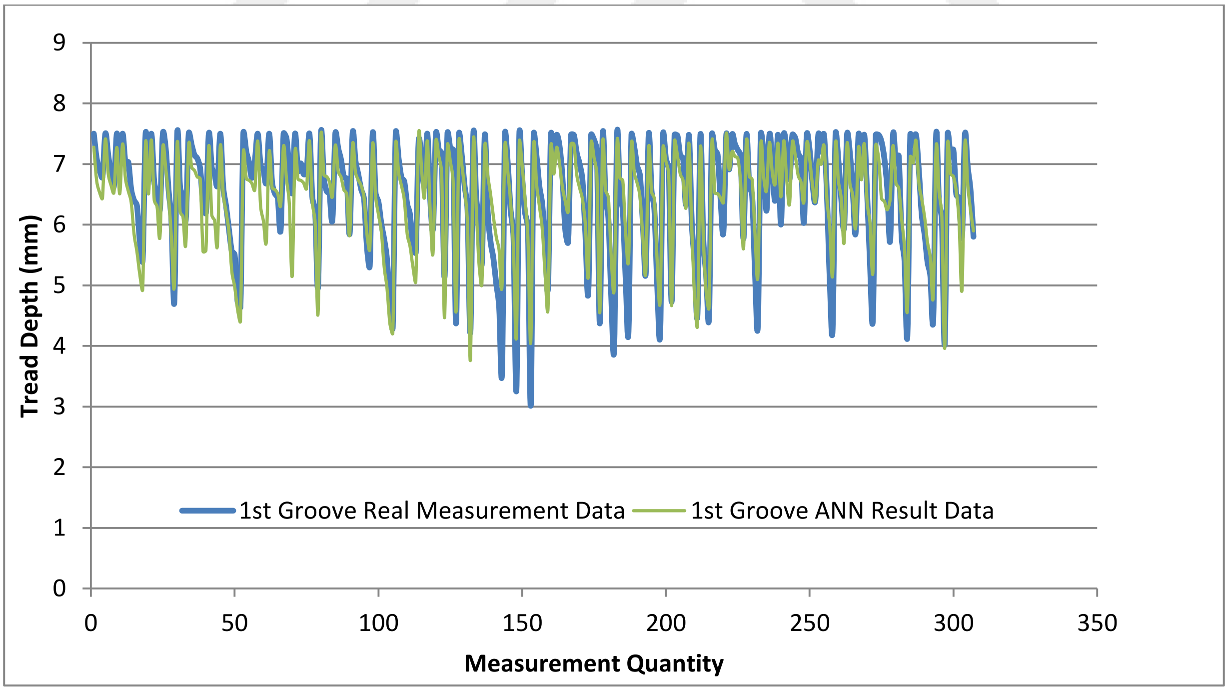
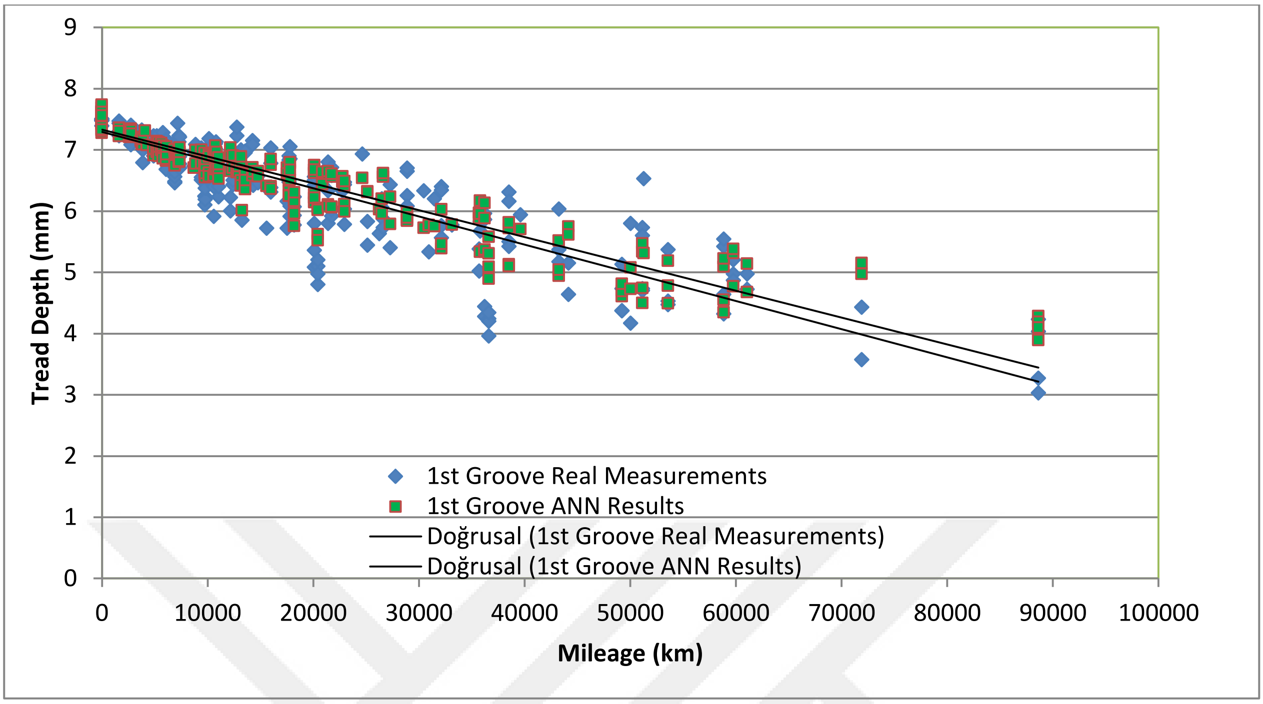


Table 4.16. Model2 first groove tread depth graphics comparison



<u>Model 2</u>   <u>Equations</u>

Groove1 $\quad x_i = w_{1i}\,(Tire\ working\ days) + w_{2i}(Tire\ mileage) + w_3$ (4.5.)

$$y_i = \frac{1}{1+e^{-x_i}}$$

Groove2 $\quad x_i = w_{1i}\,(Tire\ working\ days) + w_{2i}(Tire\ mileage) + w_3$ (4.6.)

$$y_i = \frac{1}{1+e^{-x_i}}$$

Groove3 $\quad x_i = w_{1i}\,(Tire\ working\ days) + w_{2i}(Tire\ mileage) + w_3$ (4.7.)

$$y_i = \frac{1}{1+e^{-x_i}}$$

Groove4 $\quad x_i = w_{1i}\,(Tire\ working\ days) + w_{2i}(Tire\ mileage) + w_3$ (4.8.)

$$y_i = \frac{1}{1+e^{-x_i}}$$

5.CONCLUSIONS AND RECOMMENDATIONS

The objective of the presented study is to define a model from tire measurements and transform this data into a model that can predict a complete life cycle of a tire. In this study, the pilot model created in Adana city had the measurement potential for passenger cars. The potential of data sources has a considerable variety in other cities too.

The results indicate us; it is possible to make predictions using artificial neural networks for the life cycle of a tire. One important outcome from the study is for getting more reliable results; the input quantity and quantity is essential.

The physical work of the input data took a time of two years. It is shown here that if the correct inputs are used for training ANN, the obtained results are very fast and at a decent level. Improvement of this method could bring opportunities to tire producers like a time consuming on their new product development activities by using the previous records of data sets which were obtained and the know-how information they have.

Application of ANN increases in the engineering problems. In the present study, measurement of tires for different ribs are compared, and the obtained results were compared to real results. A formula which can assume the further measurements were created.

It can be seen from the study that the ANN method can be applied to predict to a tire's future life estimation that the previous year measurements used as the input value for the learning and testing process.

Entering data like Tread depths at specific mileages, Minimum tread depth, mini cuts on tires at each measurement, chipping on tires at each measurement, Shore A, temperature, tire pressure, tire position on the axle, date of measurement, it is possible to get results depending on to correlation relations for each input.

REFERENCES

Bilgili, M., Şahin, B. and Kahraman, A., (2004). Wind energy potential in Antakya and İskenderun regions, Turkey. Renewable Energy, 29: 1733-45.

Bilgili, M., Şahin, B. and Kahraman, A., (2007). Application of artificial neural networks for the wind speed prediction of target station using reference stations data. Renewable Energy, 32: 2350-2360.

Chapra, S.C., Canale, R. P. (1985). Numerical methods for engineers. Singapore, McGraw-Hill, Inc., pp. 351-352.

Caudill, M., (1988). Neural Networks Primer Part III, *AI Expert*, 53-59.

C, Fyfe., R, Baddeley. Non-linear data structure extraction using simple Hebbian networks. Biological Cybernetics, 72(6):533–541, 1995.

C, Fyfe. (2000). Artificial Neural Networks and Information Theory.

Daniel, Graupe. (2007). Principles of Artificial Neural Networks.

Habarulema, J.B., McKinnell, L.A., Cilliers, P.J. (2007). Prediction of global positioning

Hamzaçebi, C. (2011). Yapay Sinir Ağları: Tahmin amaçlı kullanımı, MatLab ve Neurosolutions uygulamalı, 107-115.

Hertz, J., Krogh, A. and Palmer, R. G. (1991). Introduction to the Theory of Neural Computation, Addison-Wesley, Reading, MA.

Karaytuğ, Bülent. (2009). Footprint Analyses of Radial Passenger Tire Adana.

Li, T., Burdisso, R., and Sandu, C. (2017). ‘’An Artificial Neural Network Model to Predict Tread Pattern Related Tire Noise,’’ SAE Technical Paper 2017-01-1904.

Öztemel, E. (2003). Yapay Sinir Ağları, Birinci Baskı, İstanbul, 31-36.

System total electron content using neural networks over South Africa. J. Atmos. Sol.-Terr.

Schlammach, A., Groch, K. (1994).Tire Traction and Wear, In Clark, S. K: Mechanics of Pneumatic Tires, DOT ETRTO: Engineering Design information,

Svozil, D., Kvasnicka, V., Pospichal, J. (1997). Introduction to multi-layer feedforward neural networks, Chemometrics and Intelligent Laboratory.*Systems*, *39*, 43-62.

Taylor, Brian J. (2006). Methods and Procedures for the Verification and Validation of Artificial Neural Networks.2,247-270.

White, James. (1995). Rubber Processing, Technology, Materials and Principles, Hanser/Gardner. Phys.69(15), 1842–1850.

Inyurt, S., Sekertekin, A. (2019). Modeling and predicting seasonal ionospheric variations in Turkey using artificial neural network (ANN), https://doi.org/10.1007/s10509-019-3545-9

Anderson, D., and McNeil, G., 1992. Artificial Neural Networks Technology.Rome Laboratory, http://www.dacs.dtic.mil/techs/neural/neural1.html.

CURRICULUM VITAE

Engin ALTUNSÜZER was born in Turkey’s Adana province on 19 Nov. 1976. He completed high school education at Adana Borsa Lisesi in 1994. He graduated from BSc degree of Mechanical Engineering Department at the University of Çukurova in 2000. In 2007, he completed his MSc degree in Çukurova University Engineering and Technology Management. Currently, he is studying MSc education at Alparslan Türkeş Adana Science and Technology University, Nanotechnology and Engineering Sciences and working as Field Intelligence Manager ME at Continental Reifen Deutschland.