Expert Systems with Applications 37 (2010) 4660–4670

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Prediction of Marshall test results for polypropylene modified dense bituminous mixtures using neural networks

Serkan Tapkın [a,*], Abdulkadir Çevik [b], Ün Uşar [a]

[a] Anadolu University, Civil Engineering Department, Eskişehir 26555, Turkey
[b] University of Gaziantep, Civil Engineering Department, Gaziantep 27310, Turkey

ARTICLE INFO

Keywords:
Neural networks
Polypropylene
Stability
Flow
Marshall Quotient
Parametric study

ABSTRACT

This study presents an application of neural networks (NN) for the prediction of Marshall test results for polypropylene (PP) modified asphalt mixtures. PP fibers are used to modify the bituminous binder in order to improve the physical and mechanical properties of the resulting asphaltic mixture. Marshall stability and flow tests were carried out on specimens fabricated with different type of PP fibers and also waste PP at optimum bitumen content. It has been shown that the addition of polypropylene fibers results in the improved Marshall stabilities and Marshall Quotient values, which is a kind of pseudo stiffness. The proposed NN model uses the physical properties of standard Marshall specimens such as PP type, PP percentage, bitumen percentage, specimen height, unit weight, voids in mineral aggregate, voids filled with asphalt and air voids in order to predict the Marshall stability, flow and Marshall Quotient values obtained at the end of mechanical tests. The explicit formulation of stability, flow and Marshall Quotient based on the proposed NN model is also obtained and presented for further use by researchers. Moreover parametric analyses have been carried out. The results of parametric analyses were used to evaluate mechanical properties of the Marshall specimens in a quite well manner.

1. Introduction

Types of bituminous mixtures are many and varied. They range from simple surface treatments to more expensive hot bituminous mixtures using high quality aggregates. For better type of pavements, dense bituminous concrete is generally produced where carefully proportioned amounts of fines, sand and coarse aggregate are heated and mixed with hot asphalt cement and then carried to the site, placed in the prepared roadbed while still hot (must be at least 125 °C) and rolled to guarantee a dense and relatively permanent bituminous concrete.

Asphalt concrete was originally developed in the USA to meet the need for stiff and strong pavements to carry the heavy loads and high tire pressures of aircrafts. In the UK asphalt concrete is used for airfields and is often termed as Marshall asphalt. Asphalt concrete derives its strength and stability primarily through aggregate interlock and to a lesser extent through the sand/filler/bitumen mortar. The composition of asphalt concrete is determined by the USA Asphalt Institute Marshall mix design procedure (The Asphalt Institute, 1988). The concepts of the Marshall method of designing paving mixtures were formulated by Bruce Marshall, formerly bituminous engineer with the Mississippi State Highway Department. The US Corps of Engineers, through extensive research and correlation studies, improved and added certain features to Marshall's test procedure, and ultimately developed mix design criteria (The Asphalt Institute, 1988). Since 1948, the test has been adopted by organizations and government departments in many countries, sometimes with modifications either to the procedure or to the interpretations of the results.

The Marshall test consists of the manufacture of cylindrical specimens 102 mm in diameter and 64 mm high by the use of a standard compaction hammer and a cylindrical mould. The specimens are compacted using the compactive effort applicable to the loading conditions. For roads and streets with low tire pressures, the materials are compacted on two faces, utilizing fifty blows of a 4.53 kg hammer dropped from a 45.72 cm height. For a 200 psi tire pressure, 75 blows of the hammer on each face is used. The specimens are tested for their resistance to deformation at 60 °C at a constant rate of 50.8 mm/min in a test rig. The jaws of the loading rig confine the majority but not the entire circumference of the specimen. The top and the bottom of the cylinder is unconfined. Because of this fact, the stress distribution in the specimen during testing is extremely complex (Tapkın, 1998).

Two properties are determined from the Marshall test. These are:

* Corresponding author. Tel.: +90 222 3213550/6619; fax: +90 222 3239501.
E-mail addresses: cstapkin@anadolu.edu.tr (S. Tapkın), akcevik@gantep.edu.tr (A. Çevik), uusar@anadolu.edu.tr (Ü. Uşar).

0957-4174/$ - see front matter
doi:10.1016/j.eswa.2009.12.042

(a) The maximum load the specimen will carry before failure, which is known as the Marshall stability.
(b) The amount of deformation of the specimen before failure occurred, which is known as the Marshall flow.

The ratio of stability to flow is known as the Marshall Quotient. Marshall Quotient is a sort of pseudo stiffness which is a measure of the material's resistance to permanent deformation (Tapkın, 1998).

From the Marshall design procedure, the aim is to obtain the optimum bitumen content. In order to find the optimum bitumen content, the designer has to find the below mentioned values from the test property curves.

From these data curves, bitumen contents are determined which yields the following:

(a) Maximum stability.
(b) Maximum unit weight.
(c) The median of limits for percent air voids.
(d) The median of limits for voids filled with asphalt.

The testing procedure in order to determine the optimum bitumen contents is very time consuming and needs skilled workmanship. On the other hand, at the end of the Marshall test only stability and flow values of the specimens can be obtained physically. The specific gravity of mixture, theoretical specific gravity, voids in mineral aggregate (V.M.A.), voids filled with asphalt (V_f) and air voids (V_a) are obtained by carrying out extra calculations. Therefore if the researchers can obtain the stability and flow values of a standard mix by the help of another means, the rest of the calculations will just be mathematical manipulations. Neural networks can be a suitable mean to obtain the stability and flow values obtained at the end of Marshall test procedure.

The first aim of this study was to review available literature on the application of neural networks in pavement engineering researches. Second, the possibilities of improving the mechanical properties of asphalt mixtures by the utilization of polypropylene fibers were explored. Then a short background on neural networks was stated out. Next, the main focus of this study, which is the prediction of stability, flow and Marshall quotient values of asphalt specimens obtained from a series of Marshall test using neural networks based on experimental results was given in the numerical application part. Finally, in order to obtain the main effect plot, a wide range of parametric study has been performed by using the well trained NN model.

2. Historical background of neural network applications in pavement engineering

Very detailed information about the applications of traffic engineering can be found in the relevant literature (Tapkın, 2004). At this point, it is important to state out, one by one, the relevant important neural network applications in the pavement engineering area.

In a study by Ritchie, Kaseko, and Bavarian (1991), a system that integrates three artificial intelligence technologies: computer version, neural networks and knowledge-based system in addition to conventional algorithmic and modeling techniques were presented. Kaseko and Ritchie (1993) used neural network models in image processing and pavement crack detection. Gagarin, Flood, and Albrecht (1994) discuss the use of a radial-Gaussian-based neural network for determining truck attributes such as axle loads, axle spacing and velocity from strain-response readings taken from the bridges over which the truck is traveling. Eldin and Senouci (1995) describe the use of a BP algorithm for condition rating of roadway pavements. They report very low average error when compared with a human expert determination. Cal (1995) uses the backpropagation algorithm for soil classification based on three primary factors: plastic index, liquid limit, water capacity, and clay content. Razaqpur, Abd El Halim, and Mohamed (1996) present a combined dynamic programming and Hopfield neural network bridge-management model for efficient allocation of a limited budget to bridge projects over a given period of time. The time dimension is modeled by dynamic programming, and the bridge network is simulated by the neural network. Roberts and Attoh-Okine (1998) use a combination of supervised and self-organizing neural networks to predict the performance of pavements as defined by the International Roughness Index. Tutumluer and Seyhan investigated neural network modeling of anisotropic aggregate behavior from repeated load triaxial tests (Tutumluer & Seyhan, 1998). The BP algorithm is used by Owusu-Ababia (1998) for predicting flexible pavement cracking and by Alsugair and Al-Qudrah (1998) to develop a pavement-management decision support system for selecting an appropriate maintenance and repair action for a damaged pavement. Kim and Kim (1998) used artificial neural networks for prediction of layer module from falling weight deflectometer (FWD) and surface wave measurements. Shekharan (1998) studied the effect of noisy data on pavement performance prediction by an artificial neural network with genetic algorithm. Attoh-Okine (2001) uses the self-organizing map or competitive unsupervised learning model of Kohonen for grouping of pavement condition variables (such as the thickness and age of pavement, average annual daily traffic, alligator cracking, wide cracking, potholing, and rut depth) to develop a model for evaluation of pavement conditions. Lee and Lee (2004) presents an integrated neural network-based crack imaging system to classify crack types of digital pavement images which includes three types of neural networks: image-based neural network, histogram-based neural network and proximity-based neural network. In an article by Mei, Gunaratne, Lu, and Dietrich (2004), it is presented a computer-based methodology with which one can estimate the actual depths of shallow, surface-initiated fatigue cracks in asphalt pavements based on rapid measurement of their surface characteristics. Ceylan, Guclu, Tutumluer, and Thompson (2005) has investigated the use of artificial neural networks as pavement structural analysis tools for the rapid and accurate prediction of critical responses and deflection profiles of full-depth flexible pavements subjected to typical highway loadings. Bosurgi and Trifiro (2005) has described a procedure that has been defined to make use of the available economic resources in the best way possible for resurfacing interventions on flexible pavements by using artificial neural networks and genetic algorithms. Attoh-Okine (2005), in his paper, presents the application of functional equations and networks to incremental roughness prediction of flexible pavement.

3. Use of polypropylene fibers in asphalt concrete mixtures

The main applications of polymer fiber reinforcement in the modern era have begun in early 1990s. Brown et al. have enriched the development of this kind or research (Brown, Rowlett, & Boucher, 1990). They have stated out the potential of some kind of fibers in improving the tensile and cohesive strength of asphaltic concrete on account of developing greater tensile strength when compared to bitumen. Also some other researchers believe that some type of fibers create physical changes to modifiers which has a preferable effect on drain-down reduction than polymer modifiers do (Maurer & Malasheskie, 1989; Shao-Peng, 2006). In another study, fracture mechanics approach was utilized to assess the effects of fiber reinforced asphalt concrete on resistance to cracking (Jenq, Chwen-Jang, & Pei, 1993). Namely polypropylene and polyester fibers were utilized to modify the asphalt mixtures and these mixtures were tested in order to determine their tensile strengths, modulus of elasticities and fracture energies. The fracture energy in the modified samples were increased by 50–100%. That means toughness values increased considerably but on the other hand tensile strength and elasticity values were not affected in a pronounced manner. Simpson and Kamyar (1994) conducted another study in which polypropylene, polyester fibers and some other polymers were used to modify the bituminous binder. Testing procedures included Marshall stability, indirect tensile strength (IDT), moisture damage susceptibility, freeze/thaw susceptibility, resilient modulus and repeated load deformation. Mixtures containing polypropylene fibers were found to have higher tensile strengths and resistance to cracking. None of the fiber modified mixtures showed resistance to moisture induced, freeze/thaw damage. Fiber modified mixtures showed no improvement in stripping potential. IDT results predict that the control and polypropylene mixtures will not have problems with thermal cracking whereas the mixtures made with polyester fibers and polymers may. Mid-range temperature resilient modulus tests show polypropylene fiber modified mixtures were stiffest, while high temperature resilient modulus testing measured increased stiffness for all mixtures over the control. Rutting potential as measured by repeated load deformation testing was found to decrease only in polypropylene modified samples. In a study carried out by Cleven (2000), fibers (polypropylene, polyester, asbestos and cellulose) appear to increase the stiffness of the asphalt binder resulting in stiffer mixtures with decreased binder drain-down and increased fatigue life. Mixtures containing fibers showed less decrease in void content and increased resistance to permanent deformation. The tensile strength and related properties of mixtures containing fibers was found to improve especially for polypropylene but not all of the fiber types. Ohio Department of Transportation carried out extensive research on the addition of polypropylene fibers to the asphalt mix in a dry basis (ITEM 400HS, 1998). Tapkın (2008) has found out that the addition of polypropylene fibers into the asphalt concrete in a dry basis alters the behavior of the mixture in such a way that, Marshall stability values increase, flow values decrease and the fatigue life increases in a pronounced manner. Finally, Tapkın, Usar, Tuncan, and Tuncan (2009) have also worked on the addition of polypropylene fibers to the asphalt concrete on a wet basis, and have shown that the most polypropylene type was M-03 and the addition of this type of bitumen has increased the Marshall stability values by 20%. Also the stiffness of the Marshall specimens has increased in a considerable manner, which is also supported by the visible increase in the Marshall Quotient values. Carrying out repeated load creep tests under different loading patterns have also shown that the lives of the fiber modified asphalt specimens under repeated creep loading at different loading patterns increased by 5–12 times vs. control specimens, which is a very significant improvement. The repeated creep tests resulted in primary creep stage in case of the modified specimens, while the control specimens reached their tertiary creep stages. This fact is also well supported by the creep stiffness values. While the control specimens are failing, the creep stiffness values in the fiber reinforced specimens have dropped only to 50% of their original values (Tapkın et al., 2009).

In this study, it is aimed to investigate the effect of polypropylene fibers on the mechanical properties of Marshall specimens such as stability, flow and Marshall Quotient. This has been carried out by standard Marshall test, neural networks and parametric study. Therefore this study has three outcomes obtained throughout the extensive analyses that have been carried out.

4. Experimental program

4.1. Material properties

Marshall specimens were fabricated in the laboratory utilizing 50 blows on each face representing medium traffic conditions according to ASTM D1559-76. The standard 50/70 penetration bitumen was modified in the laboratory with polypropylene fibers. Marshall stability and flow tests were done on these modified asphalt samples. These tests were considered to be adequate to clarify the positive effect of polypropylene fibers on asphalt concrete.

In laboratory test program, continuous aggregate gradation has been used to fit the gradation limits for wearing course Type 2 set by Highway Technical Specifications of General Directorate of Turkish Highways (Highway Technical Specifications, 2006). The aggregate was calcareous type crushed stone obtained from a local quarry and 50/70 penetration bitumen obtained from a local refinery was used for preparation of the Marshall specimens. Physical properties of the bitumen samples are given in Table 1. The physical properties of coarse and fine aggregates are given in Tables 2 and 3. The apparent specific gravity of filler is 2790 kg/m^3.

Aggregate gradation for the bituminous mixtures tested in the laboratory has been selected as an average of the wearing course Type 2 gradation limits given by General Directorate of Turkish

Table 1
Physical properties of the reference bitumen.

Property	Test value	Standard
Penetration at 25 °C, 1/10 mm	55.4	ASTM D 5-97
Penetration index	−1.2	–
Ductility at 25 °C (cm)	>100	ASTM D 113-99
Loss on heating (%)	0.057	ASTM D 6-80
Specific gravity at 25 °C (kg/m^3)	1022	ASTM D 70-76
Softening point (°C)	48.0	ASTM D 36-95
Flash point (°C)	327	ASTM D 92-02
Fire point (°C)	376	ASTM D 92-02

Table 2
Physical properties of coarse aggregates.

Property	Test value	Standard
Bulk specific gravity (kg/m^3)	2703	ASTM C 127-04
Apparent specific gravity (kg/m^3)	2730	ASTM C 127-04
Water absorption (%)	0.385	ASTM C 127-04

Table 3
Physical properties of fine aggregates.

Property	Test value	Standard
Bulk specific gravity (kg/m^3)	2610	ASTM C 128-04
Apparent specific gravity (kg/m^3)	2754	ASTM C 128-04
Water absorption (%)	1.994	ASTM C 128-04

Table 4
Type 2 wearing course gradation (Highway Technical Specifications, 2006).

Sieve size (mm)	Gradation limits (%)	Passing (%)	Retained (%)
12.7	100	100	0
9.52	80–100	90	10
4.76	55–72	63.5	26.5
2.00	36–53	44.5	19.0
0.42	16–28	22	22.5
0.177	8–16	12	10.0
0.074	4–10	7	5
Pan	–	–	7

Table 5
Physical properties of the 3‰ M-03 type polypropylene modified bitumen samples.

Property	Test value	Standard
Penetration at 25 °C, 1/10 mm	45.5	ASTM D 5-97
Penetration index	−0.8	–
Ductility at 25 °C (cm)	>100	ASTM D 113-99
Loss on heating (%)	0.025	ASTM D 6-80
Specific gravity at 25 °C (kg/m^3)	1015	ASTM D 70-76
Softening point (°C)	52.05	ASTM D 36-95
Flash point (°C)	292	ASTM D 92-02
Fire point (°C)	345	ASTM D 92-02

Highways (Highway Technical Specifications, 2006). The mixture gradation and gradation limits are given in Table 4.

The physical properties of the polypropylene fibers used in the experimental program are given in the relevant literature (Tapkın, 2008).

4.2. Polypropylene modification of bitumen samples

The standard 50/70 penetration bitumen that was used in the experiments was modified by using polypropylene fibers. The mixing temperature was around 165–170 °C. The fibers were premixed with bitumen using a standard mixer at 500 revolutions per minute. The mixing period was two hours. M-03 type (having fiber length of 3 mm), M-09 type (having fiber length of 9 mm) and waste fibers were utilized in this modification process. For M-03 type fibers, fiber contents of 3‰, 4.5‰ and 6‰ by weight of aggregate were premixed with bitumen and were used for preparation of standard Marshall specimens. For M-09 type and waste fibers only 3‰ fiber content was utilized. According to the workability criteria, M-03 type fibers were found to be the most suitable modifiers and due to the consistency of the Marshall test results, M-03 type fibers with 3‰ fiber content had been determined as the optimal addition amount for standard 50/70 penetration bitumen. The physical properties of the polypropylene modified bitumen samples with 3‰ fiber content are given in Table 5.

When the above Table 5 is examined, it can be clearly seen that the physical properties of the fiber modified bitumen samples were greatly improved vs. reference. For example, penetration, penetration index and softening point values were improved the most. Finally, the addition of 3‰ of M-03 type fibers provides the most significant effect on the properties of asphalt mixtures.

4.3. The proportioning of the bituminous mixture

In order to determine the optimum bitumen content, it is required to perform Marshall stability and flow tests. The relevant Marshall test results are summarized in Tables 6–11. The values stated in these tables are the average values for three different specimens. Therefore, each table represents the test results of 24 different specimens. Table 6 represents the Marshall test results of specimens prepared with reference bitumen.

Tables 7–9 present the Marshall test results of specimens with M-03 fiber contents of 3‰, 4.5‰ and 6‰ (by weight of aggregate).

Table 6
Marshall test results for specimens prepared with reference bitumen.

Bitumen content (%)	V.M.A. (%)	Air void (%)	Unit weight (kg/m^3)	Stability (kg)	Flow (mm)	Marshall Quotient
3.5	16.982	8.847	2369	1399	2.38	587.8
4.0	16.009	6.653	2408	1525	2.57	593.4
4.5	15.339	4.775	2439	1562	2.60	600.8
5.0	15.370	3.675	2450	1395	2.83	492.9
5.5	15.482	2.671	2458	1158	4.47	259.1
6.0	16.402	2.611	2443	981	4.67	210.1
6.5	17.338	2.594	2427	845	5.41	156.2
7.0	18.209	2.524	2413	719	6.90	104.2

Table 7
Marshall test results for specimens modified with 3‰ of M-03 type polypropylene fibers.

Bitumen content (%)	V.M.A. (%)	Air void (%)	Unit weight (kg/m^3)	Stability (kg)	Flow (mm)	Marshall Quotient
3.5	17.519	9.436	2354	1569	2.65	592.0
4.0	16.557	7.263	2393	1858	2.99	621.4
4.5	16.217	5.761	2414	1869	3.20	584.0
5.0	15.812	4.179	2437	1720	3.70	464.9
5.5	15.643	2.856	2454	1408	4.10	343.4
6.0	16.257	2.442	2447	1250	4.50	277.8
6.5	17.047	2.250	2436	1034	5.55	186.3
7.0	17.933	2.195	2421	862	6.85	125.8

Table 8
Marshall test results for specimens modified with 4.5‰ of M-03 type polypropylene fibers.

Bitumen content (%)	V.M.A. (%)	Air void (%)	Unit weight (kg/m^3)	Stability (kg)	Flow (mm)	Marshall Quotient
3.5	17.607	9.533	2351	1629	3.60	452.5
4.0	17.007	7.762	2380	1882	3.04	619.1
4.5	17.097	6.752	2388	1876	3.24	579.0
5.0	16.609	5.086	2414	1967	3.24	607.1
5.5	16.628	3.991	2425	1467	3.87	379.1
6.0	17.250	3.598	2418	1252	3.96	316.2
6.5	17.825	3.167	2413	1146	3.84	298.4
7.0	18.347	2.688	2409	977	4.59	212.9

Table 9
Marshall test results for specimens modified with 6‰ of M-03 type polypropylene fibers.

Bitumen content (%)	V.M.A. (%)	Air void (%)	Unit weight (kg/m^3)	Stability (kg)	Flow (mm)	Marshall Quotient
3.5	18.436	10.443	2327	1622	2.98	544.3
4.0	17.947	8.807	2353	1807	2.68	674.3
4.5	18.864	8.739	2338	1717	3.49	492.0
5.0	19.072	7.889	2343	1721	4.10	419.8
5.5	17.327	4.795	2405	1682	3.24	519.1
6.0	18.543	5.104	2381	1428	3.68	388.0
6.5	18.441	3.893	2395	1380	3.61	382.3
7.0	19.497	4.059	2375	1250	5.04	248.0

Table 10
Marshall test results for specimens modified with 3‰ of M-09 type polypropylene fibers.

Bitumen content (%)	V.M.A. (%)	Air void (%)	Unit weight (kg/m^3)	Stability (kg)	Flow (mm)	Marshall Quotient
3.5	17.178	9.062	2363	1881	2.74	686.5
4.0	16.133	6.791	2405	2036	3.17	642.3
4.5	15.795	5.287	2426	2201	2.83	777.7
5.0	15.572	3.905	2444	2041	3.91	522.0
5.5	17.969	5.534	2386	1223	3.35	365.1
6.0	18.495	5.049	2382	1152	4.92	234.1
6.5	18.928	4.466	2380	1096	3.66	299.5
7.0	19.301	3.826	2381	1023	4.36	234.6

Table 11
Marshall test results for specimens modified with 3‰ of waste polypropylene fibers.

Bitumen content (%)	V.M.A. (%)	Air void (%)	Unit weight (kg/m^3)	Stability (kg)	Flow (mm)	Marshall Quotient
3.5	17.275	9.168	2361	1455	3.44	423.0
4.0	17.029	7.787	2379	1394	3.69	377.8
4.5	16.463	6.038	2407	1492	4.62	323.0
5.0	15.913	4.294	2434	1471	3.61	407.5
5.5	15.634	2.845	2454	1273	3.75	339.5
6.0	16.114	2.275	2452	973	4.53	241.8
6.5	17.105	2.319	2434	829	5.72	144.9
7.0	18.109	2.298	2418	725	7.19	100.8

Table 12
Optimum bitumen contents for different type and amount of polypropylene fibers.

Different PP percentages	Optimum bitumen content (%)
Control	4.81
M-03‰ 3 PP	4.97
M-03‰ 4.5 PP	5.36
M-03‰ 6 PP	5.79
M-09‰ 3 PP	4.6
Waste‰ 3 PP	5.14

Tables 10 and 11 present the Marshall test results of specimens with M-09 type fiber at 3‰ content and waste polypropylene fibers with fiber content 3‰ (by weight of aggregate).

To determine the optimum bitumen content, the bitumen contents corresponding to the mixtures with maximal stability and unit weight, 4% air voids and 70% voids filled with asphalt, were found and averaged according to the limits given by General Directorate of Turkish Highways (Highway Technical Specifications, 2006). These optimum bitumen contents are represented in Table 12.

Based on the performed experiments, the optimum bitumen content varies depending on the type and dosage of fibers (Table 12). However, in addition to optimum bitumen content, the optimal polypropylene amount and type, the homogeneity in the preparation of the Marshall specimens, the ease in the addition of the polypropylene fibers, the ease in the fabrication of the specimens and the fluctuations of the obtained data are very important. For example, Marshall test results for specimens prepared with more than 3‰ M-03 type fibers and all mixtures made with M-09 and waste fibers resulted in increased values of optimum bitumen contents. M-09 and waste fibers also had very little workability. The addition of these fibers into bitumen is very difficult and the high viscosity of the modified bitumen does not allow fabricating dense Marshall specimens. The fluctuations in the stability and flow values and Marshall Quotients support the above mentioned facts. Based on these results, M-03 polypropylene fibers at dosage of 3‰ by the weight of aggregate were selected as optimal.

The maximum average stability value of control mixture was 1562 kg (Table 6). Mixture with 3‰ of M-09 polypropylene fibers had the maximum average stability value of 2201 kg (Table 10). However, the Marshall specimens prepared with 3‰ of M-03 polypropylene fibers had 20% increase in the average Marshall stability and according to the workability criteria, chosen as is. The polypropylene fiber modification aims to increase the service lives by increasing the stiffness of asphalt specimens. This increase arises from modification of bitumen samples resulting in the decrease of penetration values and increase of softening points. This increase is occurring from the stability effect dominantly as it will be explained in detail in the further sections of the study.

Also when air voids are concerned, the noticeable increase is visualized from Tables 6–11. More air voids means more resistance to flushing and bleeding problems (therefore rutting) especially in hot climates. Moreover the increase in Marshall Quotient values, which is a kind of pseudo stiffness, is noticeable. Therefore, the polypropylene modification provides a positive contribution to the overall performance of asphalt pavements. This finding has quite important practical implications for the design of high performance asphalt concrete pavements.

5. Background on neural networks

A neural network is a 'machine' that is designed to model the way in which the brain performs a particular task or function of interest. The network is usually implemented using electronic components or simulated in software on a digital computer. Neural networks are information processing techniques built on processing elements, called neurons that are connected to each other (Hecht-Nielsen, 1990). Haykin (1994) defines a neural network as a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

(a) Knowledge is acquired by the network through a learning process.
(b) Interneuron connection strengths known as synaptic weights are used to store the knowledge.

The basic element of a neural network is the artificial neuron which is actually the mathematical model of a biological neuron. A biological neuron is made up of four main parts: dendrites, synapses, axon and the cell body. The dendrites receive signals from other neurons. The axon of a single neuron serves to form synaptic connections with other neurons. The cell body of a neuron sums the incoming signals from dendrites. If input signals are sufficient to stimulate the neuron to its threshold level, the neuron sends an impulse to its axon. On the other hand, if the inputs do not reach the required level, no impulse will occur.

The artificial neuron consists of three main components namely as weights, bias, and an activation function. Each neuron receives inputs $x_1, x_2, \ldots, x_n$, attached with a weight w_i which shows the connection strength for that input for each connection. Each input is then multiplied by the corresponding weight of the neuron connection. A bias b_i can be defined as a type of connection weight with a constant nonzero value added to the summation of inputs and corresponding weights u, given in Eq. (1).

$$u_i = \sum_{j=1}^{H} w_{ij} x_j + b_i \tag{1}$$

The summation u_i is transformed using a scalar-to-scalar function called an "activation or transfer function", $F(u_i)$ yielding a value called the unit's "activation", given in Eq. (2).

$$Y_i = f(u_i) \tag{2}$$

Neural networks are commonly classified by their network topology, (i.e. feedback, feed forward) and learning or training algorithms (i.e., supervised, unsupervised). For example a multilayer feed forward neural network with back propagation indicates the architecture and learning algorithm of the neural network. Back propagation algorithm is used in this study which is the most widely used supervised training method for training multilayer neural networks due to its simplicity and applicability. It is based on the generalized delta rule and was popularized by Rumelhart, Hinton, and Williams (1986, chap. 8).

5.1. Optimal NN model selection

The performance of a NN model mainly depends on the network architecture and parameter settings. One of the most difficult tasks in NN studies is to find this optimal network architecture which is based on determination of numbers of optimal layers and neurons in the hidden layers by trial and error approach. The assignment of initial weights and other related parameters may also influence the performance of the NN in a great extent. However there is no well defined rule or procedure to have optimal network architecture and parameter settings where trial and error method still remains valid. This process is very time consuming.

In this study Matlab NN toolbox is used for NN applications. Various back propagation training algorithms are used given in Table 13. Matlab NN toolbox randomly assigns the initial weights for each run each time which considerably changes the performance of the trained NN even all parameters and NN architecture are kept constant. This leads to extra difficulties in the selection of optimal network architecture and parameter settings. To overcome this difficulty, a program has been developed in Matlab which handles the trial and error process automatically. The program tries various number of layers and neurons in the hidden layers both for first and second hidden layers for a constant epoch for several times and selects the best NN architecture with the minimum MAPE (Mean Absolute % Error) or RMSE (Root Mean Squared Error) of the testing set, as the training of the testing set is more critical. For instance a NN architecture with 1 hidden layer with 7 nodes is tested 10 times and the best NN is stored where in the second cycle the number of hidden nodes is increased up to 8 and the process is repeated. The best NN for cycle 8 is compared with cycle 7 and the best one is stored as best NN. This process is repeated N times where N denotes the number of hidden nodes for the first hidden layer. This whole process is repeated for changing number of nodes in the second hidden layer. More over this selection process is performed for different back propagation training algorithms such as trainlm, trainscg and trainbfg given in Table 13. The program begins with simplest NN architecture i.e. NN with 1 hidden node for the first and second hidden layers and ends up with optimal NN architecture. Flowchart of optimal NN selection can be found in relevant literature (Çevik & Güzelbey, 2008).

Table 13
Back propagation training algorithms used in NN training.

MATLAB function name	Algorithm
trainbfg	BFGS quasi-Newton back propagation
traincgf	Fletcher–Powell conjugate gradient back propagation
traincgp	Polak–Ribiere conjugate gradient back propagation
traingd	Gradient descent back propagation
traingda	Gradient descent with adaptive linear back propagation
traingdx	Gradient descent w/momentum and adaptive linear back propagation
trainlm	Levenberg–Marquardt back propagation
trainoss	One step secant back propagation
trainrp	Resilient back propagation (Rprop)
trainscg	Scaled conjugate gradient back propagation

6. Numerical application

The main focus of this study is the prediction of stability, flow and Marshall Quotient of asphalt concrete specimens obtained from a series of Marshall test using NNs based on experimental results described above. The testing (20%) and training (80%) sets for NN training procedure are selected randomly from the experimental database. Ranges of variables of the experimental database are given in Table 14. The optimal NN architecture for stability, flow and Marshall Quotient was found to be 8-5-1 (5 hidden neurons). The optimum training algorithm was found to be Levenberg-Marquardt back propagation. Hyperbolic tangent sigmoid and log sigmoid transfer functions were used for the hidden layer and output layer respectively. Statistical parameters of testing and training sets and overall results of NN models are presented in Table 15. NN results are observed to be very close to actual test results.

NN applications are treated as black-box applications in general. However this study opens this black-box and introduces the NN application in a closed form solution. This study aims to present the closed form solutions of proposed NN models for stability, flow and Marshall Quotient based on the trained NN parameters (weights and biases) as a function of PP type, PP%, bitumen%, specimen height (mm), unit weight (kg/m^3), voids in mineral aggregate (V.M.A.)%, voids filled with asphalt (V_f)% and air voids (V_a)%. Using weights and biases of trained NN model, stability can be given as follows:

$$\text{Stability} = \frac{2290}{1 + e^{(9 - 0.386\tanh \text{H1} + 9.7\tanh \text{H2} + 0.55\tanh \text{H3} + 0.285\tanh \text{H4} - 0.92\tanh \text{H5})}} \tag{3}$$

where;

H1 = 4.4PPType + 1.73%PP + 1.47%Bit − 0.41SpecHeight + 0.0135UW − 0.366VMA − 0.237V_f − 0.91V_a − 1.875;
H2 = 2.46PPType − 0.035%PP + 0.58%Bit. + 0.0476SpecHeight + 0.0113UW − 0.22VMA − 0.004V_f + 0.39V_a − 39.5;
H3 = −0.81PPType − 0.165%PP + 4.75%Bit. + 0.012SpecHeight + 0.011UW + 0.73VMA − 0.235V_f − 1.41V_a − 39.9;
H4 = −11.47PPType−0.356%PP − 5.43%Bit. + 0.31SpecHeight + 0.0044UW − 0.34VMA − 0.0048V_f + 2.3V_a − 6.58;
H5 = −0.009PPType + 0.18%PP + 1.0316%Bit. − 0.058SpecHeight + 0.012UW − 0.77VMA + 0.0117V_f + 0.756V_a − 22.9.

Similarly, flow can be found as follows:

$$\text{Flow} = \frac{7.92}{1 + e^{(-5.88 + 5\tanh \text{H1} + 1.32\tanh \text{H2} + 1.39\tanh \text{H3} + 0.25\tanh \text{H4} + 1.06\tanh \text{H5})}} \tag{4}$$

where;

H1 = 7.046PPType − 1.464%PP − 1.699%Bit. − 1.922SpecHeight + 0.012UW + 1.707VMA + 0.358V_f + 2.728V_a + 33.14;
H2 = −0.443PPType − 0.95%PP + 0.482%Bit. + 0.005SpecHeight + 0.004UW − 0.405VMA−0.273V_f − 0.880V_a + 18.37;

Table 14
Ranges of experimental database.

	PolType	PolPerc	Bit. (%)	Spec. height (mm)	UW calc. (kg/m^3)	V.M.A. (%)	V_f (%)	V_a (%)	MQ	Stability	Flow
Max.	3.00	6.00	7.00	62.00	2470.24	19.78	89.45	10.76	886.77	2289.4	7.92
Min.	0.00	0.00	3.50	58.00	2311.26	14.47	40.70	1.48	92.77	689.52	1.85
Mean	1.15	2.78	5.24	59.86	2408.41	16.98	68.62	5.00	412.64	1396.6	3.96
Std. Dev.	1.00	2.05	1.15	1.00	37.63	1.25	14.07	2.51	201.45	387.8	1.38

Table 15
Statistical parameters of neural networks models.

		Mean	COV	R^2
Flow	NN train set	1.00	0.11	0.93
	NN testing set	0.98	0.25	0.71
	NN total set	0.99	0.16	0.81
MQ	NN train set	1.00	0.12	0.94
	NN testing set	0.97	0.24	0.81
	NN total set	0.99	0.17	0.87
Stability	NN train set	1.00	0.03	0.99
	NN testing set	1.02	0.08	0.94
	NN total set	0.99	0.05	0.97

H3 = −1.2PPType + 0.068%PP − 3.637%Bit. + 0.72SpecHeight −0.014 UW − 0.806VMA + 0.39V_f + 2.5V_a − 6.31;
H4 = −9.41PPType + 3.43%PP − 4.078%Bit. + 1.73SpecHeight − 0.005UW − 2.25VMA − 0.39V_f − 3.22V_a + 2.74;
H5 = 2.364PPType + 1.69%PP − 0.764%Bit. − 0.391SpecHeight − 0.002UW + 0.167VMA − 0.033V_f + 0.445V_a + 23.81.

In the same way Marshall Quotient can be derived as:

$$\mathrm{MQ} = \frac{887}{1 + e^{(0.915 - 4.14\tanh \mathrm{H1} - 8.35\tanh \mathrm{H2} - 1.17\tanh \mathrm{H3} + 1.98\tanh \mathrm{H4} + 3.25\tanh \mathrm{H5})}} \quad (5)$$

where;

H1 = 0.809PPType − 0.558%PP + 0.18%Bit. − 0.294SpecHeight + 0.011UW + 0.031VMA − 0.055V_f + 0.068V_a − 7.32;
H2 = −0.503PPType + 0.086%PP + 0.053%Bit. + 0.205SpecHeight − 0.004UW − 0.097VMA − 0.017V_f − 0.2V_a + 1.65;
H3 = −0.47PPType + 0.21%PP − 0.545%Bit. − 0.367SpecHeight + 0.0005UW − 0.34VMA + 0.046V_f − 0.494V_a + 29;
H4 = 0.034PPType − 0.103%PP + 0.38%Bit. + 0.145SpecHeight + 0.005UW − 0.4VMA + 0.001V_f − 0.067V_a − 15.1;
H5 = −1.922PPType + 0.035%PP + 0.3%Bit. + 0.28SpecHeight + 0.006UW + 0.017VMA + 0.041V_f + 0.244V_a − 34.

7. Parametric study

The main effect plot is an important graphical tool to visualize the independent impact of each variable on stability, flow and Marshall Quotient values. This graphical tool enables a better and simple picture of the overall importance of variable effects on the output which is the stability for the first case and will provide a general snapshot. In main effects plot, the mean output is plotted at each factor level which is later connected by a straight line. The slope of the line for each variable is the degree of its effect on the output. To obtain the main effect plot a wide range of parametric study has been performed by using the well trained NN model. To observe the general trend of each variable the mean values of all variables are used. The evaluation of separate interaction effects plot between any two variables is also presented by using the mean values of all variables. The main effects plot will also help further researchers willing to perform experimental studies on stability, flow and Marshall Quotient values for the Marshall design.

7.1. Analysis of results

In this part of the study, analyses of the graphs that have been obtained at the end of parametric study have been given. First of all the results of the stability analyses are stated out.

7.1.1. Stability analyses

In this figure the mean stability values increase in a noticeable manner with increase in voids filled with asphalt (V_f) values. This is an expected increase as more bitumen in the voids of the mixture means more stable mixture. Also the noticeable mean stability differences can be observed in Fig. 1. due to the polypropylene modification of the samples (PolType 0).

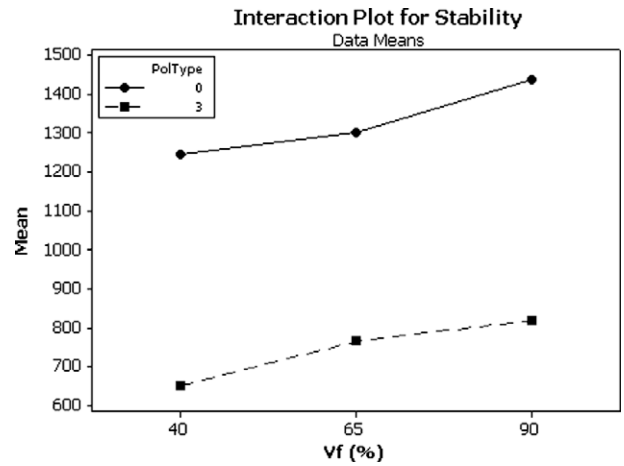

Fig. 1. Polypropylene type vs. voids filled with asphalt (V_f).

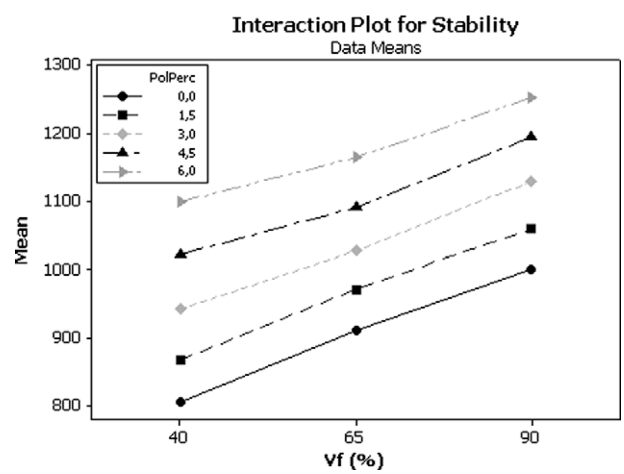

Fig. 2. Polypropylene percentage vs. voids filled with asphalt (V_f).

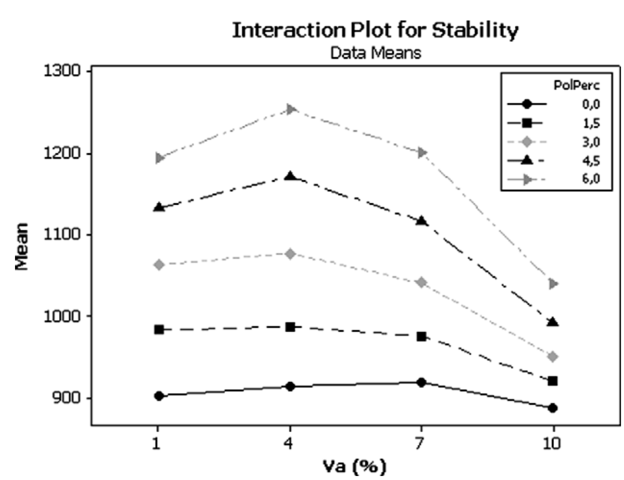

Fig. 3. Polypropylene percentage vs. air voids (V_a).

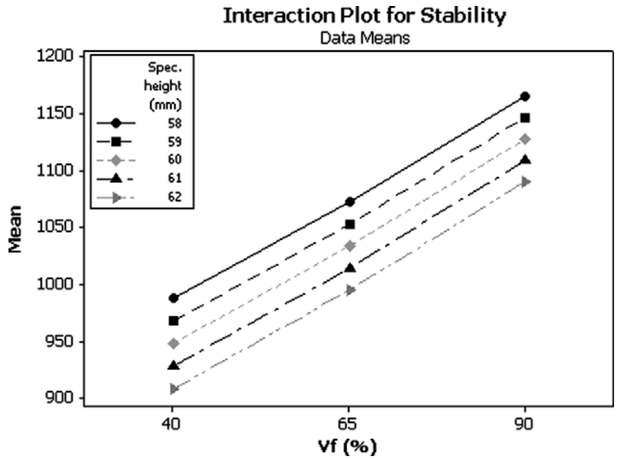

Fig. 4. Specimen height vs. voids filled with asphalt (V_f).

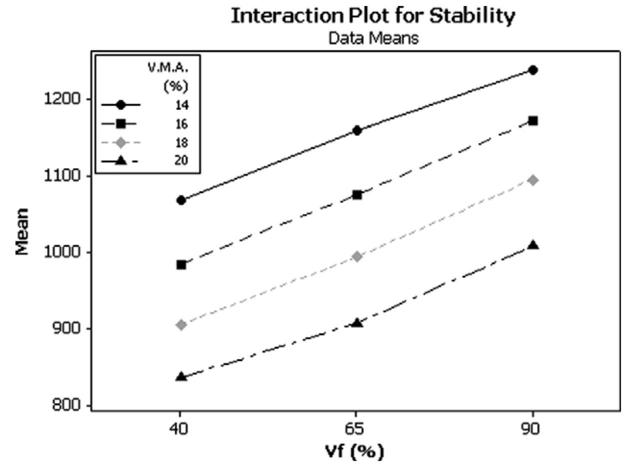

Fig. 6. Voids in mineral aggregate (V.M.A.) vs. voids filled with asphalt (V_f).

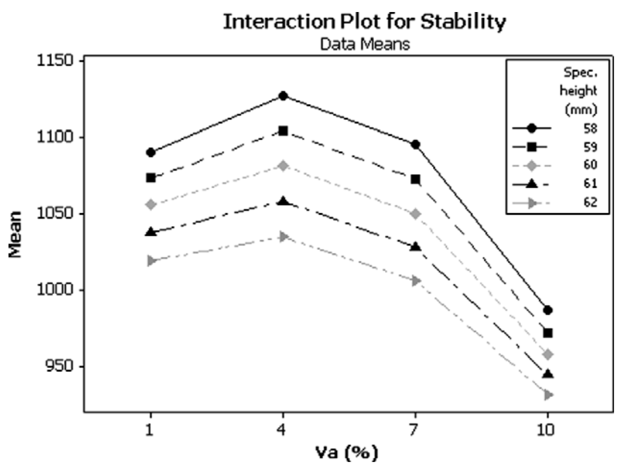

Fig. 5. Specimen height vs. air voids (V_a) values.

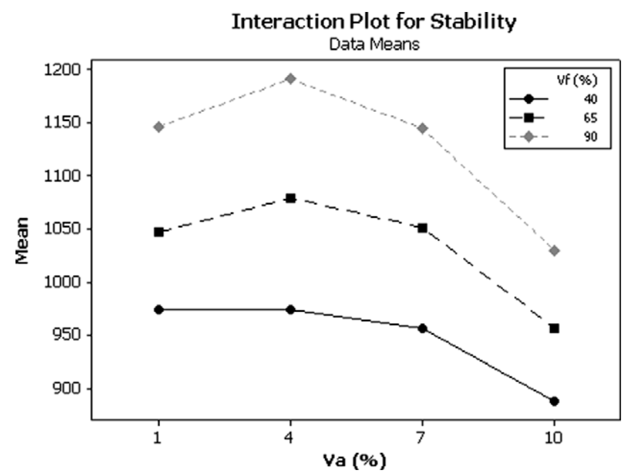

Fig. 7. Voids filled with asphalt (V_f) vs. air voids (V_a).

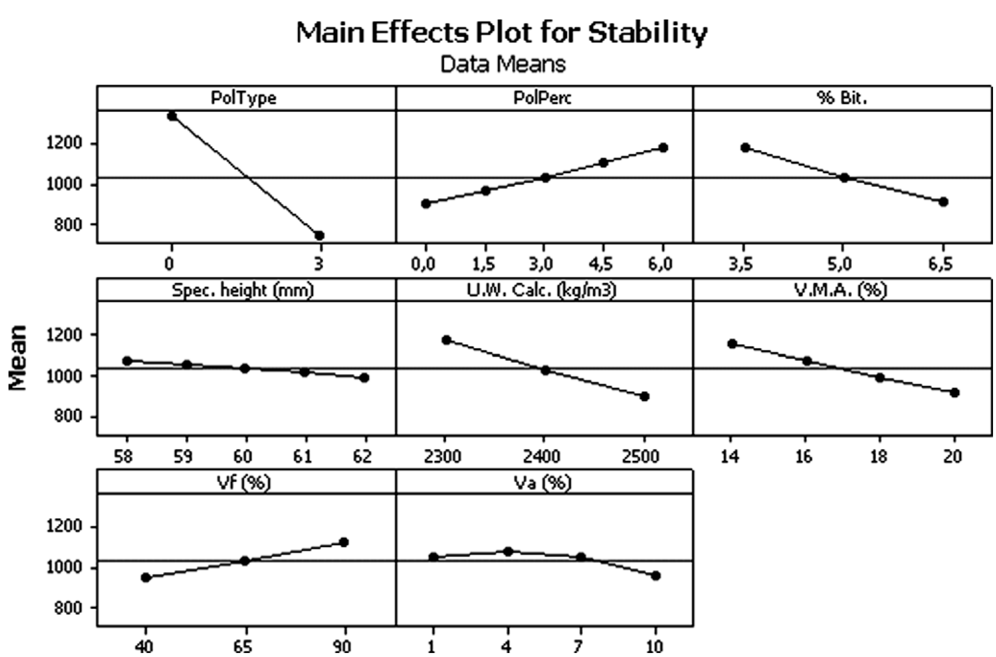

Fig. 8. Whole trends for the parametric study of mean effects of stability analysis.

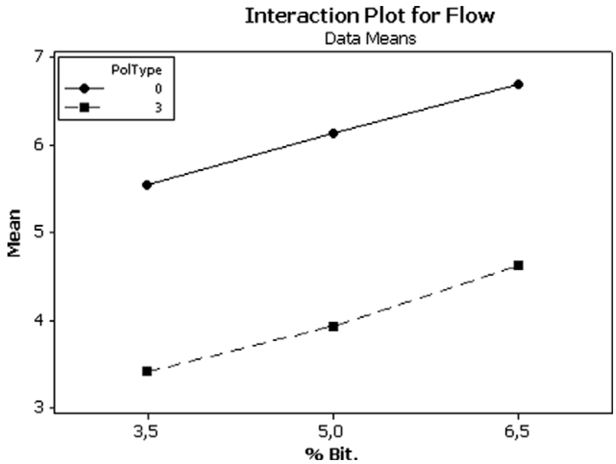

Fig. 9. Polypropylene type vs. bitumen percentage.

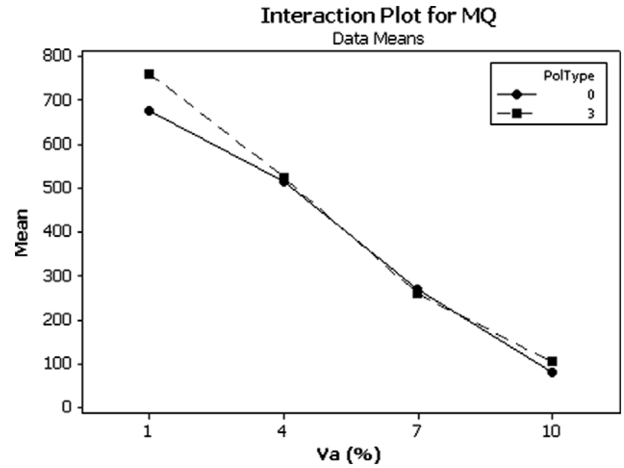

Fig. 12. Polypropylene type vs. air voids (V_a).

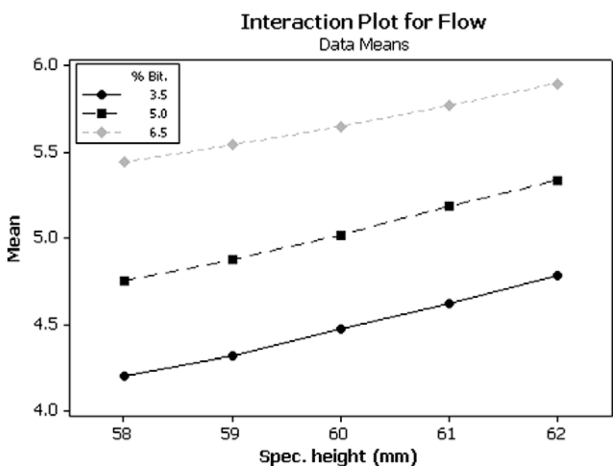

Fig. 10. Percent bitumen vs. specimen height.

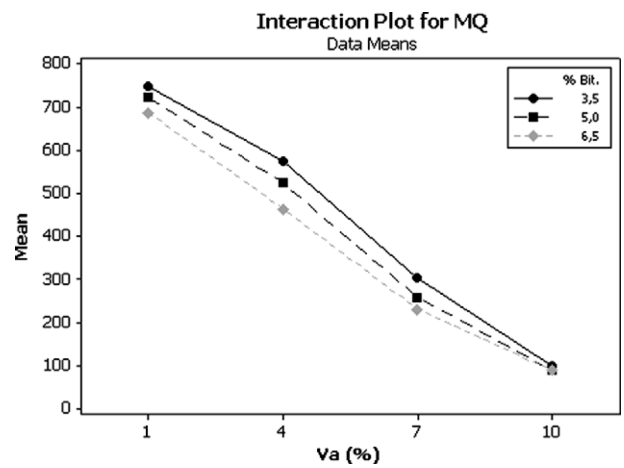

Fig. 13. Bitumen percentage vs. air voids (V_a).

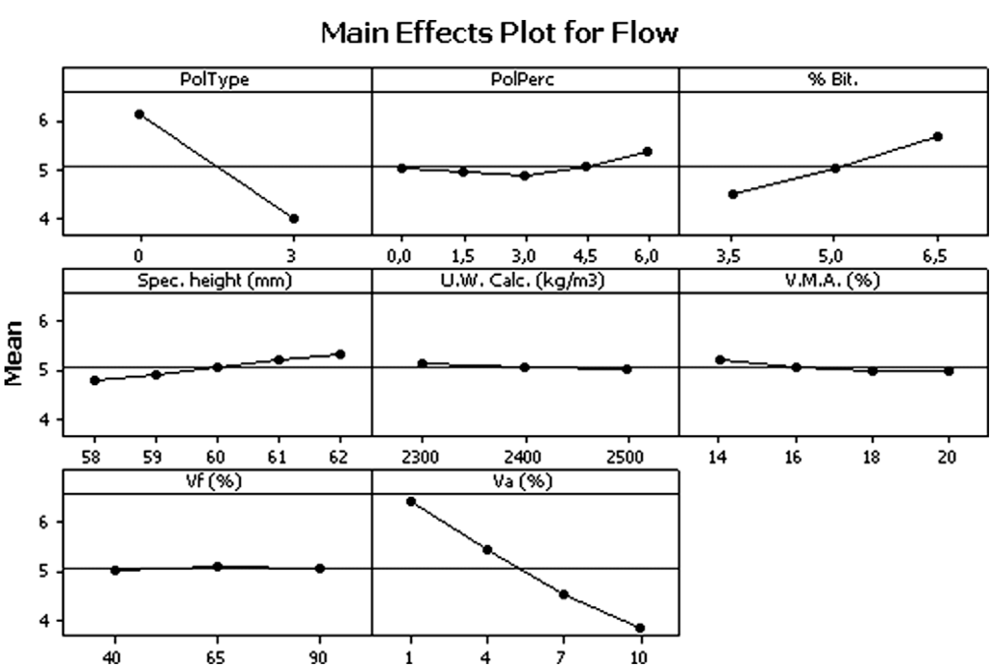

Fig. 11. Whole trends for the parametric study of mean effects of flow analysis.

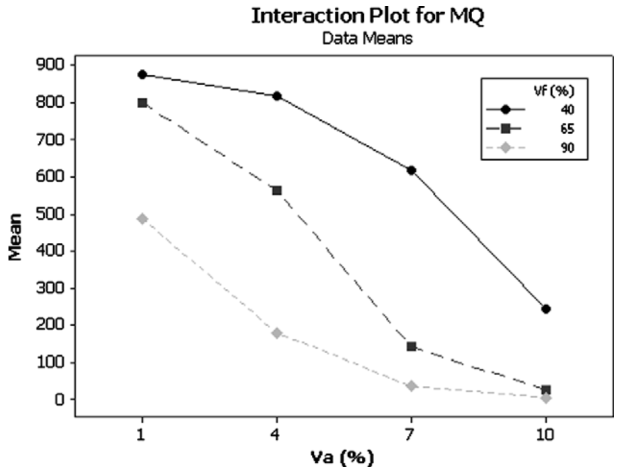

Fig. 14. Voids filled with asphalt (V_f) vs. air voids (V_a).

When Fig. 2 is examined, as voids filled with asphalt (V_f) values increase, it is observed that the mean stability values also increase in a stable manner. Besides, the increase in polypropylene percentage increases the mean Marshall stability values in a noticeable manner. These are expected cases.

When air voids increase, the mean stability values tend to increase first and then they start to decrease in a noticeable manner as in one to one correspondence with stability vs. bitumen content graphs of Marshall design. In addition, the increase in polypropylene percentage increases the mean Marshall stability values as it is evident form Fig. 3.

This time, as specimen height increases, obviously, the values of voids filled with asphalt (V_f) increase (see Fig. 4). This is because of the nature of the asphaltic mixture. Moreover, as the specimen height values increase, the stability values also decrease. This is again an expected case (see Fig. 4).

In Fig. 5, it can be visualized that as the air voids increase, the mean stability values tend to increase first and then decrease as can be expected. Also the mean stability values decrease with increasing specimen heights.

When Fig. 6 is examined, it is clear that when V.M.A. values start to increase, mean stability values tend to decrease in a noticeable manner resulting from material properties. Also when V_f values increase, the mean stability values increase correspondingly.

In Fig. 7, as air void values increase, mean stability values start to increase and then decrease in an expected manner. The mean stability values increase in a noticeable manner again when V_f values increase.

In Fig. 8, the whole trends for the parametric study of mean effects of stability analysis can be visualized.

7.1.2. Flow analyses

As we have polypropylene modification, it is visualized that the mean flow values increase in a noticeable manner (PolType 0). Also as the bitumen percentage increases, the mean flow values start to increase (see Fig. 9).

As specimen height increases, air voids increase therefore mean flow values also increase. In addition, as bitumen percentage increases, mean flow values further increase as can be visualized in Fig. 10.

In Fig. 11, the whole trends for the parametric study of mean effects of flow analysis can be visualized.

7.1.3. Marshall Quotient (MQ) analyses

In the above Fig. 12, it can be seen that as air voids increase, the Marshall Quotient values decrease in a noticeable manner.

As air voids increase, Marshall Quotient values decrease as can be expected. Also at a fixed air voids value, as bitumen percentage increases, Marshall Quotient value decreases. This is also very obvious from the pavement engineering point of view (see Fig. 13).

As increase in air voids results in decrease in Marshall Quotient, for a specific air voids value, increase in voids filled with asphalt means, again, decrease in Marshall Quotient value (see Fig. 14).

In Fig. 15, the whole trends for the parametric study of mean effects of Marshall Quotient analysis can be visualized.

The reader must not forget that the obtained results at the end of this study is valid only for a specific type of aggregate, bitumen, aggregate gradation, mix proportioning, modification technique and laboratory conditions.

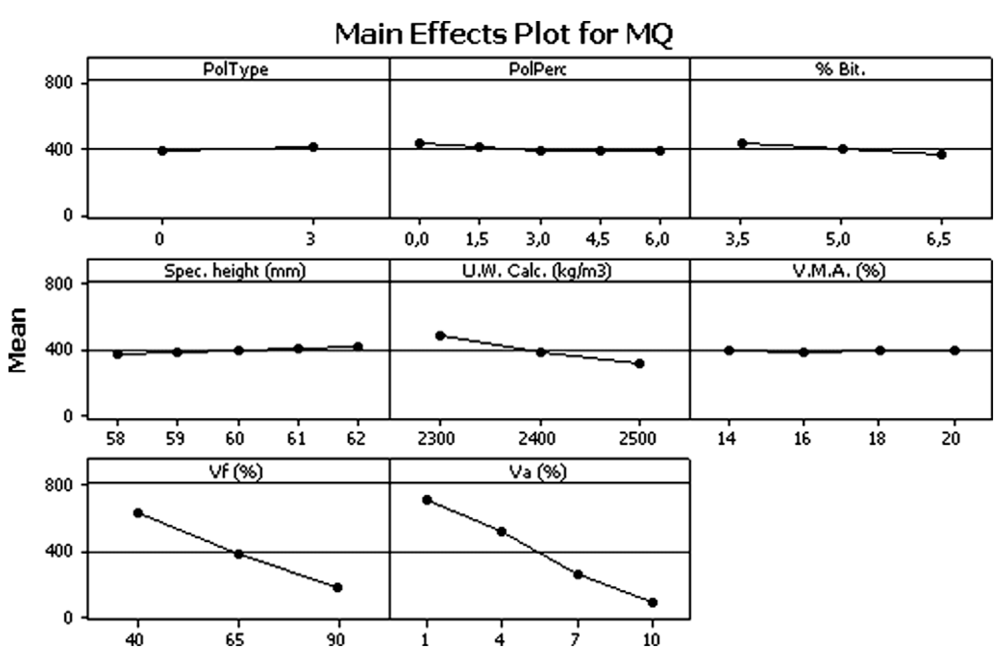

Fig. 15. Whole trends for the parametric study of mean effects of Marshall Quotient analysis.

8. Conclusions

This paper presents a new and efficient approach for the prediction of mechanical properties such as stability, flow and Marshall Quotient obtained from Marshall design tests utilizing neural networks. The increase in the stability values for the polypropylene modification deserves attention. Also when air voids are concerned, the noticeable increase is visualized from the test data. Moreover the increase in Marshall Quotient values, which is a kind of pseudo stiffness, is noticeable. This approach is very important in the sense that for a specific type of asphalt mixture and for predetermined testing conditions, the stability, flow and Marshall Quotient values obtained at the end of Marshall design tests can be estimated without carrying out destructive tests which takes too much time and human effort. Moreover, the polypropylene modification provides a significant contribution to the performance of asphalt pavements. These findings have quite important practical implications for the design of high performance asphalt concrete pavements.

Backpropagation neural networks are used for the NN training process. The proposed neural network models for stability, flow and Marshall Quotient have shown good agreement with experimental results ($R^2 = 0.97, R^2 = 0.81, R^2 = 0.87$). The proposed NN model is valid for the ranges of the experimental database used for NN modeling. The explicit formulation of stability, flow and Marshall Quotient based on the proposed NN model is also obtained and presented for further use by researchers. To obtain the main effects of each variable on stability, flow and Marshall Quotient, a wide range of parametric study has been performed by using the well trained NN model. As a result, the proposed neural network model and formulation of the available stability, flow and Marshall Quotient of asphalt samples is quite accurate, fast and practical for use by other researchers studying in this field.

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