Civil Engineering Infrastructures Journal 2022, 55(1): 89-108
DOI: 10.22059/CEIJ.2021.310767.1710

RESEARCH PAPER

Developing a Hybrid ANN-Jaya Procedure for Backcalculation of Flexible Pavements Moduli

Ghanizadeh, A.R.[1*], Heidarabadizadeh, N.[2] and Khalifeh, V.[3]

[1] Associate Professor, Department of Civil Engineering, Sirjan University of Technology, Sirjan, Iran.
[2] Research Assistant, Department of Civil Engineering, Sirjan University of Technology, Sirjan, Iran.
[3] Assistant Professor, Department of Civil Engineering, Sirjan University of Technology, Sirjan, Iran.

Received: 05 Oct. 2020; Revised: 19 Jul. 2021; Accepted: 19 Jul. 2021

ABSTRACT: This research aim is to develop a procedure for backcalculation of flexible pavements moduli based on the hybridization of the Artificial Neural Network (ANN) and the Jaya optimization algorithm. The ANN was applied to predict the pavement deflection basin, and the Jaya was employed for moduli backcalculation. The comparison of hybrid ANN-Jaya procedure with some backcalculation software indicates the high ability of the developed method to perform backcalculation of flexible pavements moduli. The comparison of the computational speed and accuracy of hybrid ANN-Jaya with ANN-PSO and ANN-GA indicates the superior performance of ANN-Jaya compared to other methods.

Keywords: Artificial Neural Network (ANN), Backcalculation, Falling Weight Deflectometer (FWD), Flexible Pavements, Jaya Optimization Algorithm.

1. Introduction

In the pavement engineering, the Falling Weight Deflectometer (FWD) device, is commonly applied to estimate the pavement stiffness modulus and the structural properties of the layers in a non-destructive manner (Saltan and Terzi, 2008; Gopalakrishnan and Papadopoulos, 2011; Li et al., 2018). The structural analysis of pavements has a key role in estimating the pavements life and determination of the optimal maintenance activities. As a part of FWD results interpretation process, the accurate measuring the pavement moduli provides a reliable basis for the road management department to formulate pavement maintenance plans and rationally arrange funds., Utilizing the several sensors called geophones in the FWD test procedure, the deflection basin (deformations) of the pavement surface in response to the applied dynamic load pulse was measured at different radial distances from the center of rubber plate (the loading center). The dynamic load pulse simulates the moving wheel load and is produced by dropping a heavyweight on the pavement through a circular rubber plate. Moreover, the measured deflections can be employed

* Corresponding author E-mail: ghanizadeh@sirjantech.ac.ir

to evaluate the pavement life and estimate the pavement layers stiffness through backcalculation analysis.

The backcalculation of pavement layers moduli consists of comparing the deflections measured by the FWD and the calculated ones through an iterative process (using a pavement response model). Usually, in most backcalculation software, the multilayered elastic theory was employed for forward analysis of pavement structure. In this process, the modulus of each layer is initialized, and the pavement surface deflections will be calculated by forward analysis. In the subsequent iterations, the moduli of different layers are adjusted, and then the computed deviations are compared with the measured ones, until the difference is within the acceptable range. Over the years, different methods of intelligence computing and deep learning was emerged and developed to solve complicated problems (Vasant et al., 2019). Several static, dynamic and artificial intelligence methods have been implemented to the flexible pavement moduli backcalculation including dataset search, least squares, and soft computing such as genetic algorithm, neural network and, fuzzy logic system (Saric and Pozder, 2017; Guzzarlapudi et al., 2017; Aubdulnibe, 2019; Zhang et al., 2021). In recent years, advanced computational intelligence methods have been proposed with higher computational speed and accuracy.

Saltan et al. (2002) used a backcalculation process to predict the thickness of layers affecting the pavement service life. They used the Artificial Neural Network (ANN) to eliminate the time-consuming calculations based on linear elastic theory and Finite Element. They obtained a value of $R^2 = 0.94$ and $R^2 = 0.88$ based on the training and testing data, respectively (Saltan et al., 2002).

Gopalakrishna and Thompson (2004) used the ANN to predict the moduli of the three-layer pavement based on FWD measurements. They modeled the asphalt layer as linear and base and subgrade as nonlinear layers. The Coefficient of Determination (R^2) for predicting the asphalt and subgrade moduli was obtained 0.98 and 0.97, respectively (Gopalakrishnan and Thompson, 2004). Ceylan et al. (2005) used the ANN for the pavement structural analysis and determined the deflection basin of full-depth asphalt pavements. They were able to estimate the asphalt layer modulus based on the FWD measurements and increase the speed of backcalculation process (Ceylan et al., 2005). Rakesh et al. (2006) used the ANN method to calculate the surface deflections of four pavement systems, including pavement with 2, 3, 4 and 5 layers, and compared the results with actual data. The value of R^2 for these systems was 0.997, 0.996, 0.997, and 0.997, respectively. Saltan and Terzi (2008) modeled the deflection basin of the flexible pavement using ANN with a cross-validation technique by applying a backcalculation process (Saltan and Terzi, 2008).

Gopalakrishnan (2010) proposed a new intelligent system for back-calculating the stress-dependent modulus of the layers using pavement deflection data. For this purpose, the integration of three methods, including Finite Element, ANN, and Particle Swarm Optimization (PSO) as a hybrid backcalculation tool, was used to develop a robust system for predicting the nonlinear modulus of granular base and subgrade layers. The values of R^2 obtained from the calculated modulus, and the actual data for the asphalt and subgrade layer were 0.996 and 0.984, respectively. In this research, the developed model has validated with BACKFAA and WESDEF software in the six different airport pavement sections (Gopalakrishnan, 2010).

Saltan et al. (2013) used the ANN approach to evaluate the structural properties of a typical flexible pavement, including the layers thickness, the Poisson's ratio, and the resilient modulus (Saltan et al., 2013). Ocal (2014) presented an artificial intelligence algorithm to backcalculate the asphalt pavements moduli based on FWD results. For this purpose, a novel hybrid Gravitational Search Algorithm (GSA)-ANN method was proposed (Öcal, 2014). The Ant Colony Optimization algorithm was applied by Scimemi et al. (2016) to back-calculate the airport pavement moduli based on the surface deflection data. They evaluated back-calculated moduli in comparison with the field data utilizing the BACKGA software, and found that the maximum error is equal to 0.66%. Li and Wang (2019) used ANN and Genetic Algorithm (GA) to back-calculate the flexible pavement layers moduli.

You et al. (2020) utilized two ANN based back-calculation models to evaluate the interlayer conditions and predicting the layers moduli of four types of pavements. Moreover, the ANSYS software was applied to build the corresponding database. The results of two proposed ANN models compared to the results of two multiple regression models have shown that, there are no significant differences between them.

Fu et al. (2020) estimated the dynamic surface deflections of asphalt pavement subjected to the FWD and evaluate the static backcalculation of layer moduli using the MODULUS and EVERCALC software. They found that the static backcalculation process caused considerable errors due to regardless of the dynamic effects of FWD loading.

Wang et al. (2020) evaluated the traditional backcalculation method based on the finite element and the multilayer elastic theory compared to a new one without backcalculation based on the ANN to predict pavement surface deflections using Heavy Weight Deflectometer (HWD). They showed that the traditional approach overestimated tensile strain in a thin asphalt layer and concluded that the accuracy of the ANN was better than others.

The represented background for application of Computational Intelligence (CI) methods to back-calculate the pavement layer properties, reveals that a comprehensive comparison of results obtained by these methods with actual field data as well as existing backcalculation software has not been performed. The limitations of the dataset for the development of ANN and the lack of developed software to implement the developed CI method are two other shortcomings. Also, the Jaya algorithm has not been used to perform backcalculation of flexible pavements moduli. Unlike other population-based optimization algorithm, lack of specific control parameters is the most important advantage of Jaya algorithm. Furthermore, better performance and faster convergence capability are two other reasons that this algorithm is employed in this research work.

In this paper, a hybrid optimization model (ANN-Jaya) is proposed for performing backcalculation of flexible pavements moduli, and an applied software is developed to implement it. Furthermore, the performance of the developed model is evaluated based on the field data as well as different backcalculation software, including ISSEM4, MODCOMP, MODULUS, WESDEF, and BACKFAA. Besides, the ability of the Jaya algorithm in terms of robustness, convergence rate and run time is compared with other optimization methods including the GA and the PSO algorithm.

2. Falling Weight Deflectometer (FWD)

The Falling Weight Deflectometer (FWD) is a testing device that was firstly introduced in France to estimate the structural capacity and physical properties of pavements (Ullidtz, 1987). In this device, an impact load is applied on a loading plate, and then the surface deflection can be measured at different radial distances using several geophones. In the LTPP program, the geophones distance from the loading center was assumed to be 0, 203, 305, 457, 610, 915, and 1525 mm (Von et al., 2002). The impact load can be altered by changing the falling weight height. The load pulse is applied through a series of springs in a short time to the pavement surface (about 28 milliseconds). The falling load of the FWD device is not enough to evaluate the airport pavements that have a higher thickness and load capacity. In such a situation, the Heavy Falling Weight Deflectometer (HFWD) can simulate a Boeing 747-wheel load with a maximum dynamic pressure of 250 KN and loading time between 20 and 25 milliseconds. The schematic image of the FWD device is demonstrated in Figure 1. Some of the variables which affect the shape and dimension of the deflection basin include the Poisson's ratio, the thickness, the layers modulus, the load applied by the FWD, and the subgrade depth (Bendana et al., 1994). Having these values and deflections in different radial distances, the modulus of different layers can be obtained through backcalculation process.

3. Artificial Neural Network (ANN)

An artificial neural network (ANN) adapted from the behavior of the neurons of the brain nervous mechanism. The ANN consists of the artificial neurons which be connected (Gurney, 2005). Each connection has a specific weight that increases or decreases the strength of the transmitted signal at a link. The ANN can determine nonlinear relationships between input and output variables. Since solving complex problems with traditional methods is very difficult, ANN is widely being used in various Civil Engineering fields. The feed-forward neural network is one of the most applicable types of ANN for modeling of engineering problems. It consists of several the processing units (the neuron, cell, or node) placed in the layers that connected the inputs to the output set. A multilayer feed-forward neural network includes input, hidden, and output layers which are composed of connected neurons.

For developing a multilayer feed-forward neural network, a learning rule should be used. One of the most popular tools for learning is the error back-propagation algorithm. The general architecture of this algorithm is shown in Figure 2. In this figure L: is the number of neurons in the hidden layer and x_{p1} to x_{pN}: are the input and y_{p1} to y_{pM}: are the output variables. The elements as well as the computational process for a typical artificial neuron is shown in Figure 3.

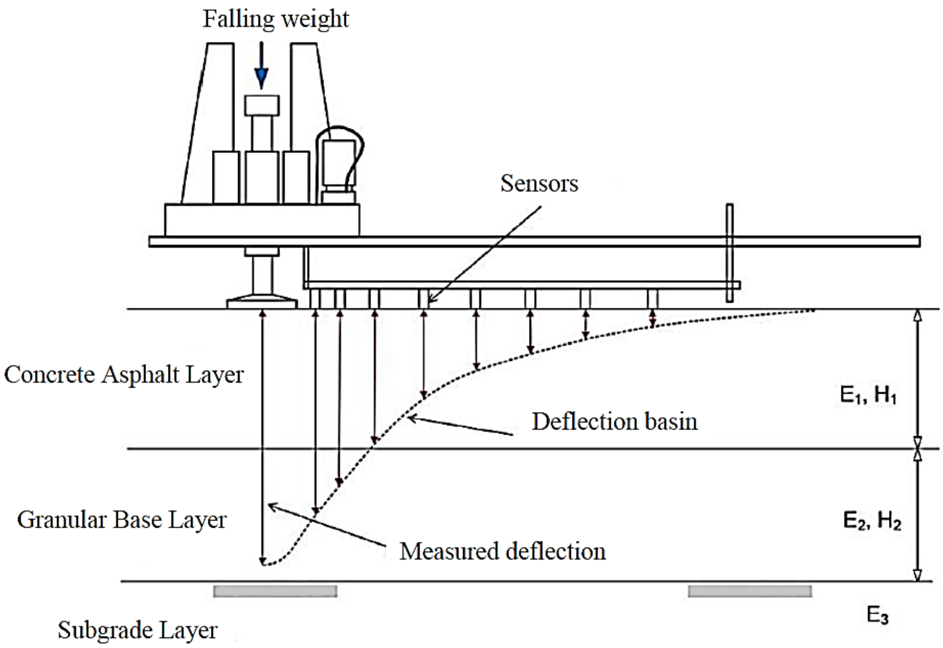


Fig. 1. Schematic image of the FWD and measuring the deflection basin for a flexible pavement

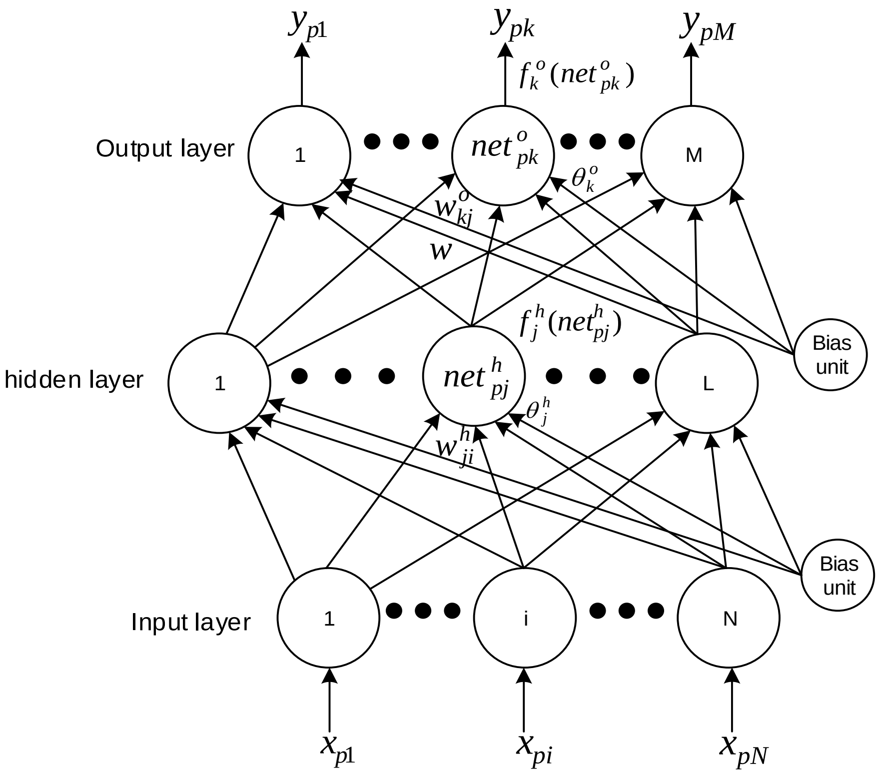
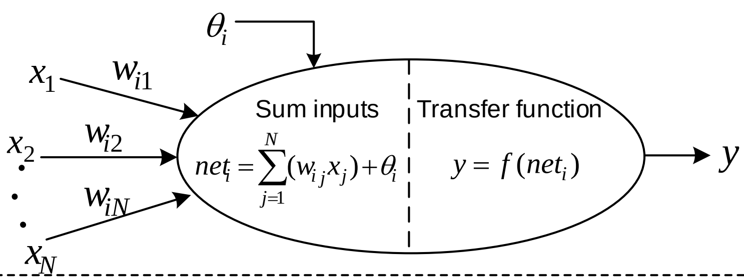


Fig. 2. Architecture of feed-forward neural network structure



$xi(i = 1,2,..., N)$: *Set of inputs*
wij : *Connection weights*
θ_i : *Bias term*
Net_i : *Net input signal*
Transfer function: tan*gent sigmoid function* $f(x) = \left[\frac{2}{1+e^{-2x}} - 1\right]$ *or linear function* $f(x) = x$

Fig. 3. Structure of a typical artificial neuron

where y_i: is the output signal. Other variables are described in the figure. To propagate the activation, the input signals are assessed using their connection weights and enters into the activation function as input. The input signal of the neuron is obtained using Eq. (1):

$$net_i = \sum_{j=1}^{N} (w_{ij} X_j) - \theta_i \quad (1)$$

The output signal can also be computed utilizing the Eq. (2):

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

in which f: is the transfer function (activation function) and can be classified as a linear, sigmoid, and tangent sigmoid function. The tangent sigmoid transfer function can be acted as real neurons. The value of the output signal (y_i) for tangent sigmoid activation function varies between 0 and 1. The tangent sigmoid function can be calculated by Eq. (3):

$$f(x) = \frac{2}{(1 + e^{-2x})} - 1 \quad (3)$$

Using the input and output data set, the recursive algorithm modifies the weights and biases for successive iterations. The recursive learning rule is based on minimizing the difference between the calculated and desired output values (error). The learning process is randomly started by assigning connection weights, and then the values of weights and biases are updated according to the error value in the successive iterations. The error back-propagation E^k: is determined utilizing the Eq. (4) at the end of each stage:

$$E^k = \frac{1}{2}\sum_i \left[t_i^k - y_i^k\right] \quad (4)$$

where t_i^k: is the real output for the i^{th} neuron and the k^{th} data in the training set. After completing the activation phase, the connection weights are adjusted and the backpropagation phase will begin. In this case, the output of the activation path is converted to the return path toward inputs, and the new connection weight of the neurons i and j are updated using Eq. (5):

$$w_{ij}(it+1) = w_{ij}(it) + \eta \sum_k \delta_i^k X_j^k + \alpha\left[w_{ij}(it) - w_{ij}(it-1)\right] \quad (5)$$

where α: is the momentum factor that affects the weight in consecutive iterations to prevent the algorithm from falling down in the local optima and oscillation. The bias values are also updated as follows:

$$\theta_i(it+1) = \theta_i(it) + \eta \sum_k \delta_i^k + \alpha[\theta_i(it) - \theta_i(it-1)] \quad (6)$$

This process is repeated for each of the training data, while the difference between the calculated and the desired outputs is minimized (Pekcan et al., 2008). Thereafter, two criteria including coefficient of determination (R^2 and Root Mean Square Error (RMSE) were employed to evaluate the neural network performance using the following equations.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d_i - y_i)^2} \quad (7)$$

$$R^2 = \frac{\left(N\sum_{i=1}^{N}(d_i y_i) - \sum_{i=1}^{N} d_i \sum_{i=1}^{N} y_i\right)}{\left(N\sum_{i=1}^{N} d_i^2 - \left(\sum_{i=1}^{N} d_i\right)^2\right)\left(N\sum_{i=1}^{N} y_i^2 - \left(\sum_{i=1}^{N} y_i\right)^2\right)} \quad (8)$$

where d_i: is the actual value, and y_i: is the predicted value for the i^{th} data from the neural network and N: is the number of data points.

4. Jaya Algorithm

Metaheuristic algorithms have been utilized to many complicated Civil Engineering problems (Kaveh and Dadras, 2017; Hajiazizi et al., 2021; Samadi et al., 2021; Sonmez et al., 2017; Ghanizadeh and Heidarabadizadeh, 2018; Ghanizadeh et al., 2020).

Most of the metaheuristic algorithms such as the Particle Swarm Optimization (PSO) (Eberhart and Kennedy, 1995), the Genetic Algorithm (GA) (Holland, 1975), the Teaching Learning-Based Optimization (TLBO) (Rao et al., 2011), and the Firefly Algorithm (FFA) (Yang, 2009) have several internal tuning parameters, and the tuning stage is necessary to determine these parameters. The internal tuning parameters are usually set for a specific problem, and there is no guarantee that these values will lead to a globally optimal solution in case of other issues.

Rao (2016) proposed a simple Jaya (a Sanskrit word meaning victory) algorithm that does not have any internal tuning parameter. The initial solutions of the Jaya, P candidates, are randomly generated. Then, the variables of the solution are stochastically updated.

Suppose 'j' is the design variable, 'k' is the candidate solutions, and 'i' is the iteration number. The value of the jth variable for the kth candidate in the ith iteration is called $X_{j,k,i}$ and calculated from Eq. (9).

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\left(X_{j,best,i} - \left|X_{j,k,i}\right|\right) - r_{2,j,i}\left(X_{j,worst,i} - \left|X_{j,k,i}\right|\right) \quad (9)$$

where $X_{j,best,i}$ and $X_{j,worst,i}$: are the values of "j" for the best and worst solution, respectively. Also $r_{1,j,i}$ and $r_{2,j,i}$: are the two random numbers in the range of 0 to 1. The term "$r_{1,j,i}$ (($X_{j,best,i}$- $|X_{j,k,i}|$)": shows the tendency to the optimal solution and the term "-$r_{2,j,i}$ ($X_{j,worst,i}$- $|X_{j,k,i}|$)": defines the avoidance to the worst solution. The updated value of $X_{j,k,i}$ ($X'_{j,k,i}$) is accepted only when the corresponding value of objective function is improved. All the acceptable values are maintained as the inputs of the next iteration.

The Jaya algorithm updates the costs of the solutions so that the cost of their objective function converges to the optimal solution. After updating the solutions, with comparing the updated and corresponding old values, only one of them is selected for the next iteration, which will be the better value of objective function.

It should be noted that, the optimal solution is found in every iteration, and the worst one will be removed, simultaneously. Thereby, this algorithm provides both useful intensification and diversification of the search process in an appropriate way.

In this way, the algorithm always tries to get closer to the optimal solutions and to avoid diverging from the optimal solutions. The general procedure for the Jaya algorithm is presented in Figure 4 (Rao, 2016).

As can be seen, the Jaya algorithm need to the usual control variables (population size and number of generations), while, the other optimization algorithms such as PSO, GA, FA, FFA, etc. require the tuning of respective algorithm-specific parameters. The proper implementation of this procedure has positive effects on the performance of the algorithms, otherwise, either the calculations will increase or it will get stuck at the local optimal solution.

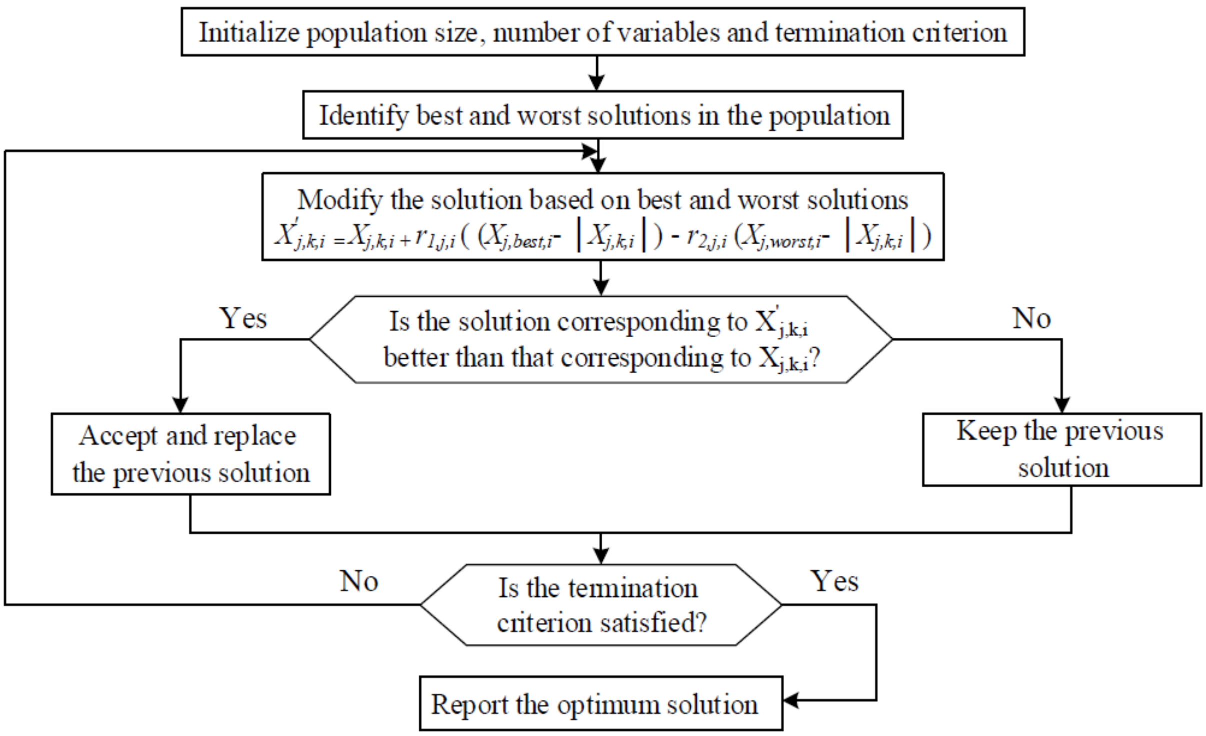


Fig. 4. The Jaya algorithm Flowchart (Rao, 2016)

5. Developing Feed-Forward Neural Network

5.1. Artificial Dataset

In this study, 10000 different flexible pavement sections, consisting of asphalt concrete, granular base, and subgrade soil, were analyzed to create a comprehensive dataset for training and testing artificial neural networks. The deflection of the pavement section surface was calculated in seven different radial distances (0, 203, 305, 457, 610, 915, and 1525 mm). The load was applied as a circular contact area with uniform vertical stress of 552 kPa and a contact radius of 152 mm. Table 1 shows the statistical characteristics of the analyzed pavement sections. The Poisson's ratio of the subgrade soil, granular base, and asphalt concrete were assumed to be 0.40, 0.35, and 0.35, respectively, which is commonly used in the literature (Maher and Bennert, 2008).

Previous studies have also shown slight changes in the pavement response due to changes in the Poisson ratio (Huang, 2004). The NonPAS program has been applied, which provide the possibility of linear and nonlinear analysis of pavements subjected to 10 circular contact loads using multilayered elastic theory. The NonPAS verification process showed that the NonPAS results compared to other applications such as KENLAYER and JULEA are very consistent (Ghanizadeh and Ziaie, 2015). The Statistical characteristics of the deflections obtained for different radial distances are shown in Table 2.

5.2. Optimal Architecture

The training and testing procedure was conducted using a developed program in MATLAB which is developed by MathWorks. In each run of the program, the MATLAB toolbox assigns random values to the initial neural network weights and biases. Despite the consistency of the neurons and architecture of each layer, the random assignment of weights and biases strongly affects the ANN performance. To address this issue, another MATLAB-based program was developed to obtain the optimal number of neurons in the hidden layer of ANN. The number of neurons was considered to be between 5 and 100. With regards to the random values of weights, and the architecture with the least error was considered as the optimum architecture. In this study, the training, validating, and testing procedure were applied based on the 65% (6500 data points), 10% (1000 data points) and 25% (2500 data points) of the data, respectively. Moreover, the transfer function of the hidden and output layers was assumed as the tangent sigmoid and the linear, respectively.

The results showed that increasing the number of neurons up to 90 improves the performance of artificial neural networks. Therefore, the neural network with a hidden layer and with an architecture of 7-90-5 has sufficient accuracy for predicting the pavement surface deflections at different radial distances. The architecture of the selected neural network is shown in Figure 5.

5.3. Evaluation of ANN Performance

The ANN performance for prediction of surface deflections at different radial distances for the training and testing sets is shown in Figures 6 and 7, respectively. As can be seen, the coefficient of determination in all cases is more than 0.9999, which indicates the high accuracy of the developed model in predicting the surface deflections of flexible pavements.

Table 1. Statistical characteristics of the inputs used for dataset development

Statistical parameter	H_1 (mm)	H_2 (mm)	E_1 (MPa)	E_2 (MPa)	E_3 (MPa)
Maximum	309	500	10000	2000	400
Minimum	50	100	500	100	20
Median	300	181	4319	728	100
Mean	178.38	282.55	4703	847	148
Standard deviation	79.42	119	2682	560	112

Table 2. Statistical characteristics of the outputs used for dataset development

Statistical parameter	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Maximum	3.0721	2.0286	1.494	1.0439	0.8883	0.6476	0.3793
Minimum	0.0567	0.0454	0.0414	0.0371	0.0334	0.0275	0.0169
Median	0.2657	0.2137	0.1893	0.1667	0.1481	0.1182	0.0743
Mean	0.3673	0.2982	0.2601	0.2224	0.1931	0.1502	0.0993
Standard deviation	0.3081	0.2466	0.2153	0.1827	0.1588	0.1254	0.0859

Deflection in mm.

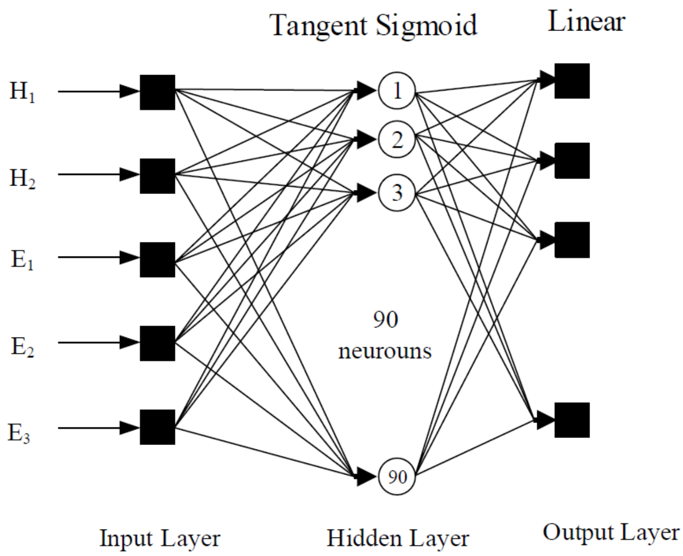
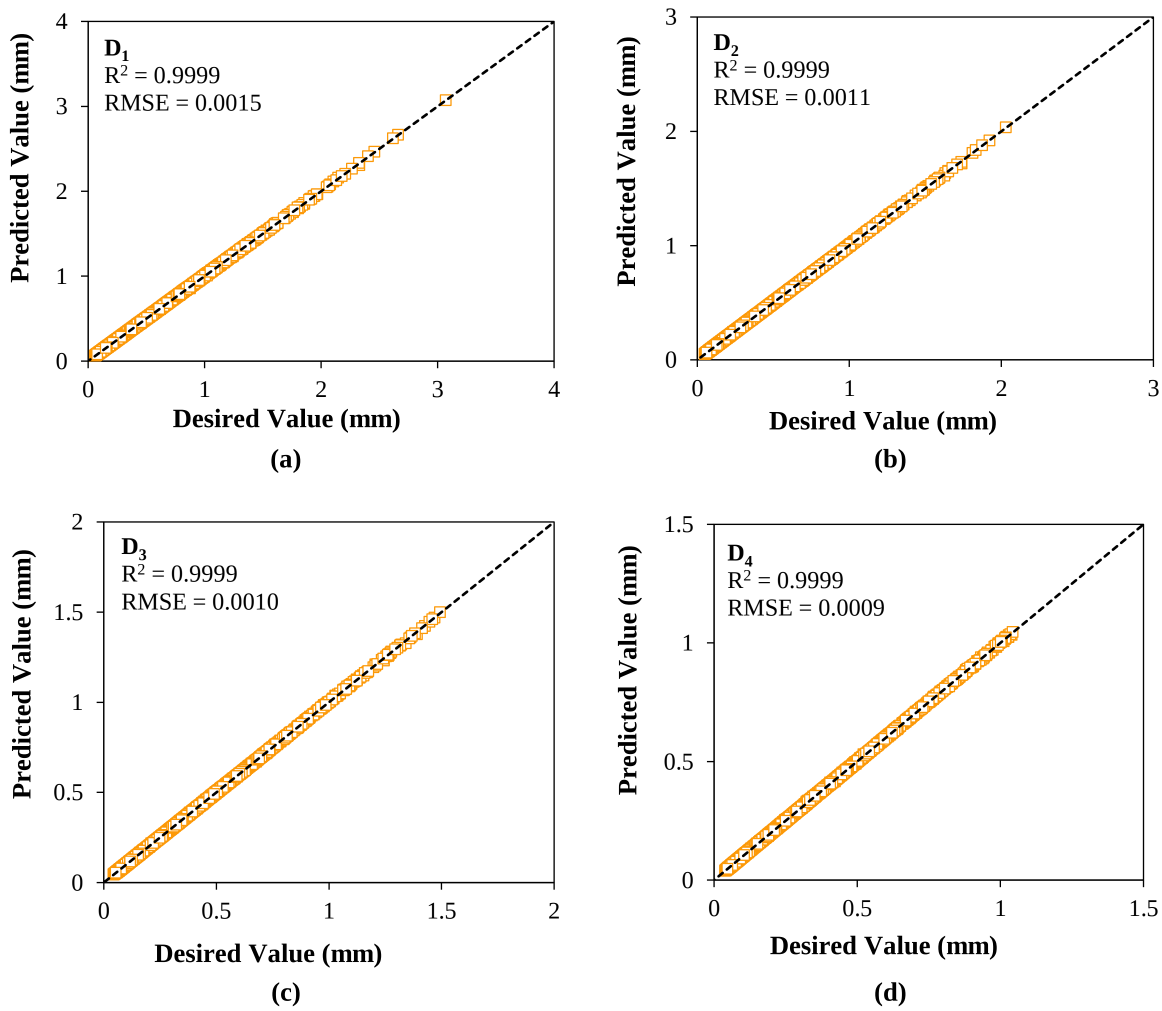


Fig. 5. Optimal ANN architecture



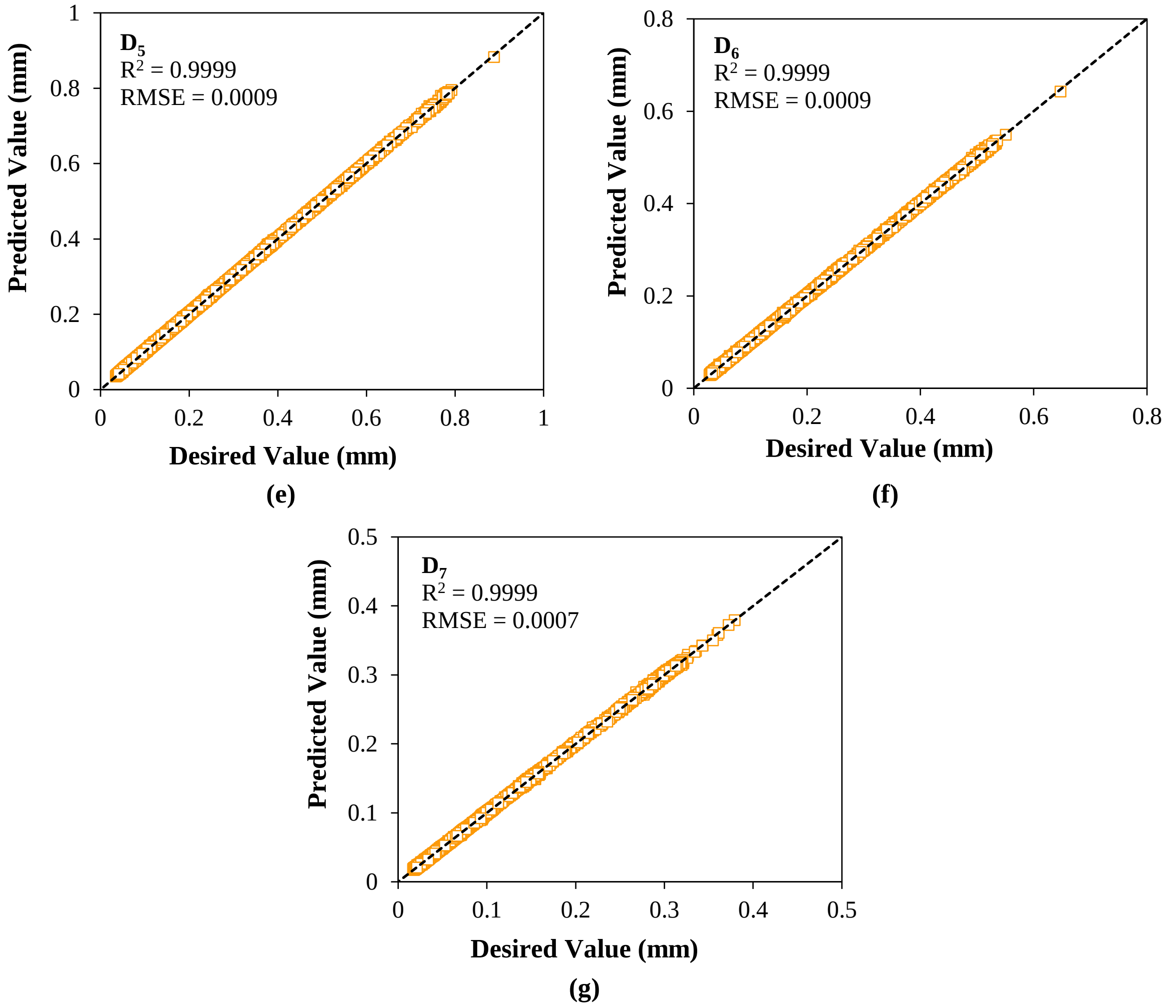
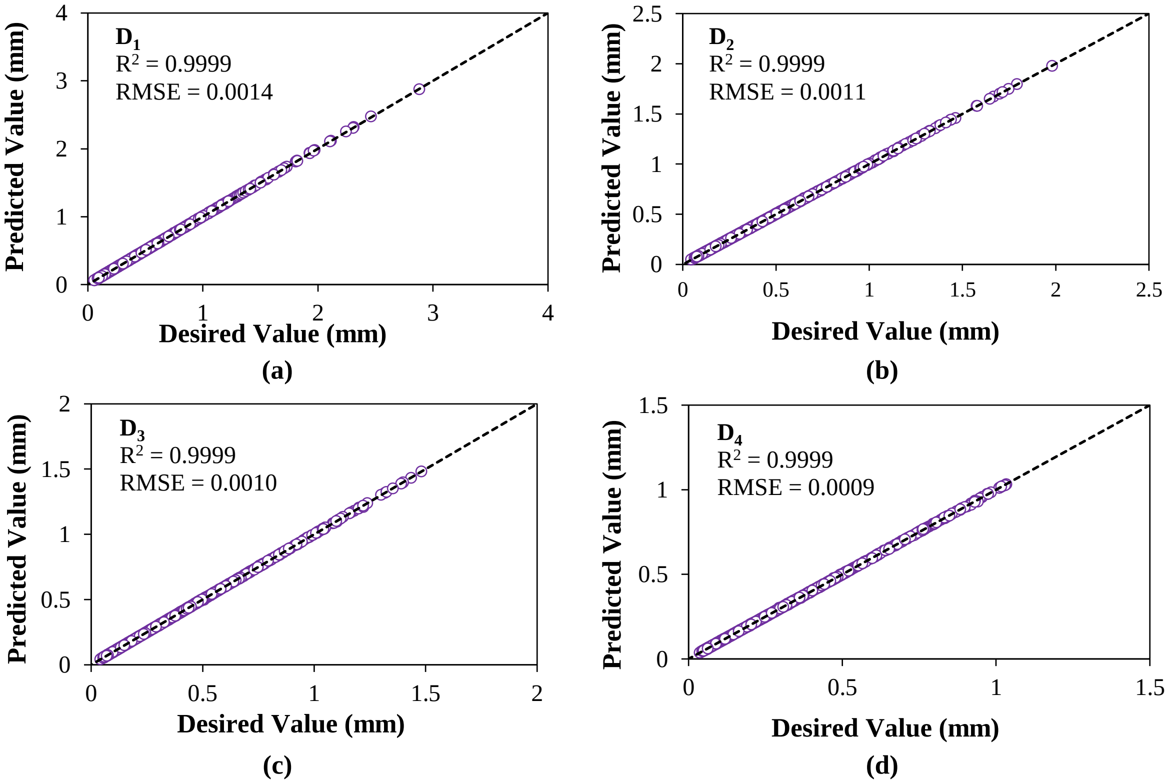


Fig. 6. ANN performance to predict the pavement surface deflections at different radial distances based on the training set



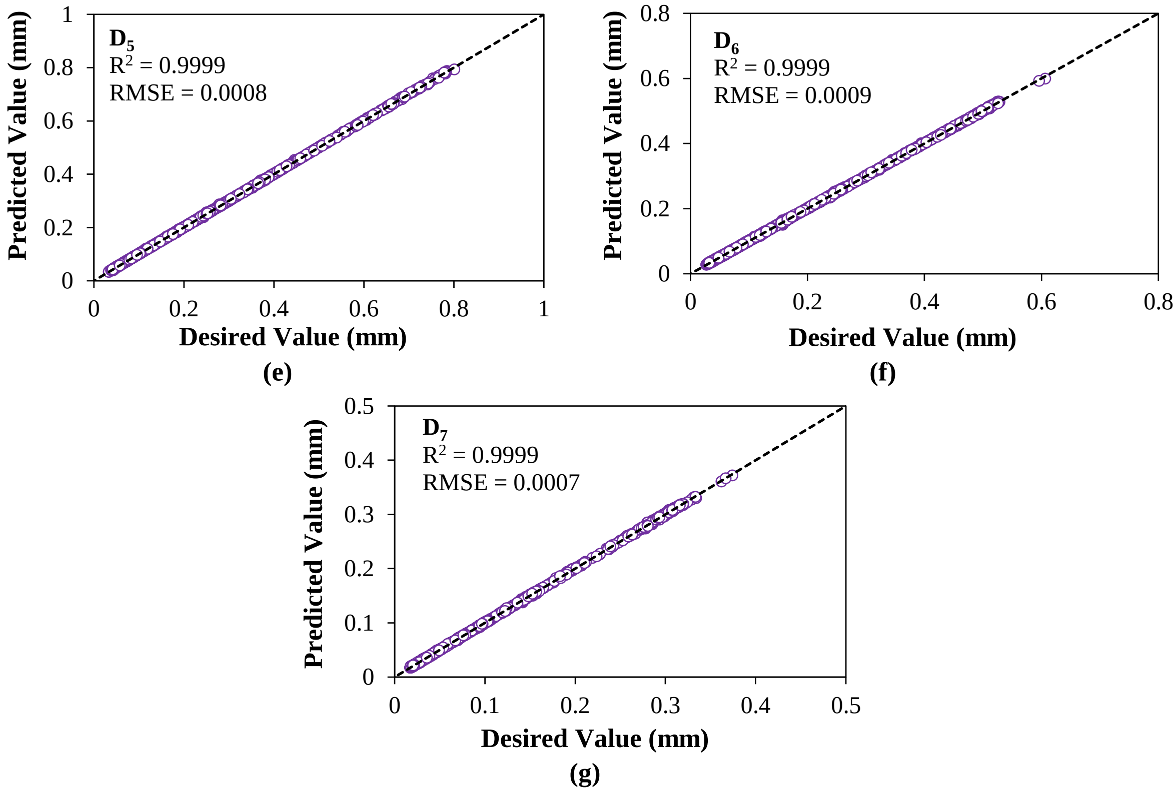


Fig. 7. ANN performance to predict the pavement surface deflections at different radial distances based on the testing set

6. Hybrid ANN-Jaya

6.1. Backcalculation Procedure Using Hybrid ANN-Jaya

In this paper, a procedure based on the hybridization of ANN (forward calculations) and Jaya (determining the modulus of layers) has been proposed for the moduli backcalculation of flexible pavements. The schematic diagram of this procedure is represented in Figure 8. The calculation of deflections is conducted using the ANN, and the Jaya applied to determine the optimum values of the neural network inputs so that the deflections calculated through the ANN are as close as possible to the FWD measured deflections. In other words, the difference between both measured and calculated deflection values should be minimized. Therefore, the objective function can be expressed according to Eq. (10).

$$f = \sum_{i=1}^{n} |D_i^m - D_i^c| \qquad (10)$$

where D_i^m and D_i^c: are the deflections measured by the FWD and calculated by ANN for i^{th} geophone, respectively, and n is the number of geophones (n = 7).

6.2. Implementation of Hybrid ANN-Jaya

To implement the hybrid ANN-Jaya, the JayaBack (a MATLAB-based program) which provides the possibility of fast and reliable backcalculation of the pavement layers moduli was developed. This program gets the inputs including the asphalt thickness and granular base layers (cm), the granular base and subgrade soil moduli (MPa), upper and lower range of the asphalt, deflection values at seven radial distances (mm), contact pressure of FWD device (MPa), the maximum number of iterations and the number of moduli generated per iteration and then determine the asphalt, granular base and subgrade soil moduli (MPa) using the algorithm represented in Figure 8. The graphical user interface (GUI) of JayaBack is shown in Figure 9.

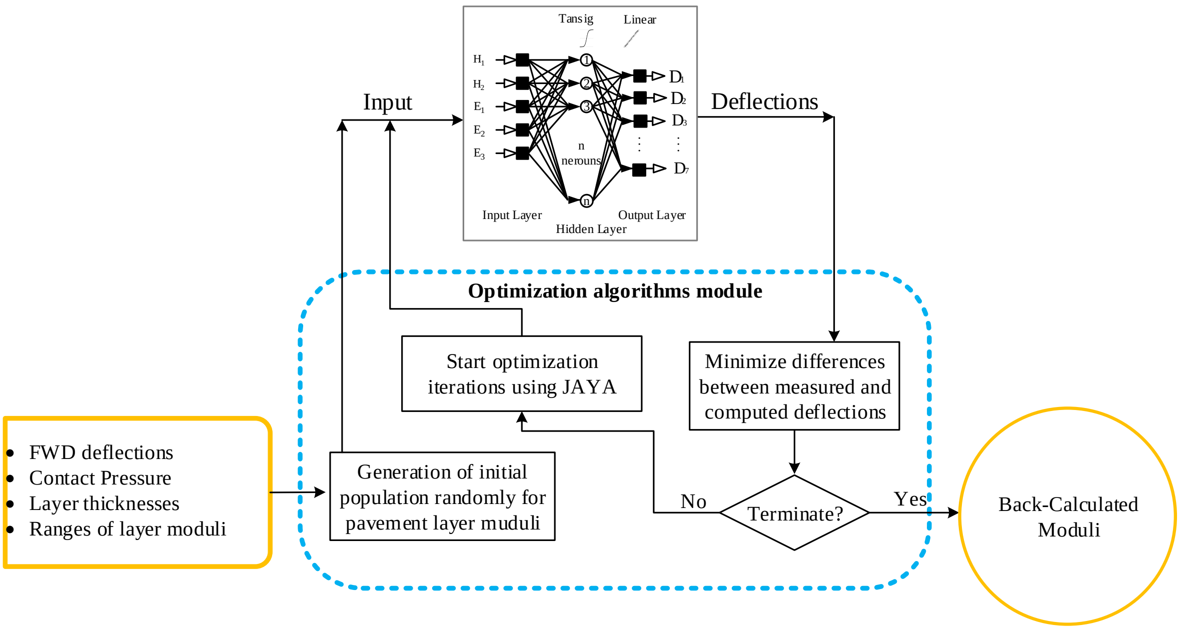


Fig. 8. Implementation of a hybrid ANN-Jaya approach for pavement layer backcalculation

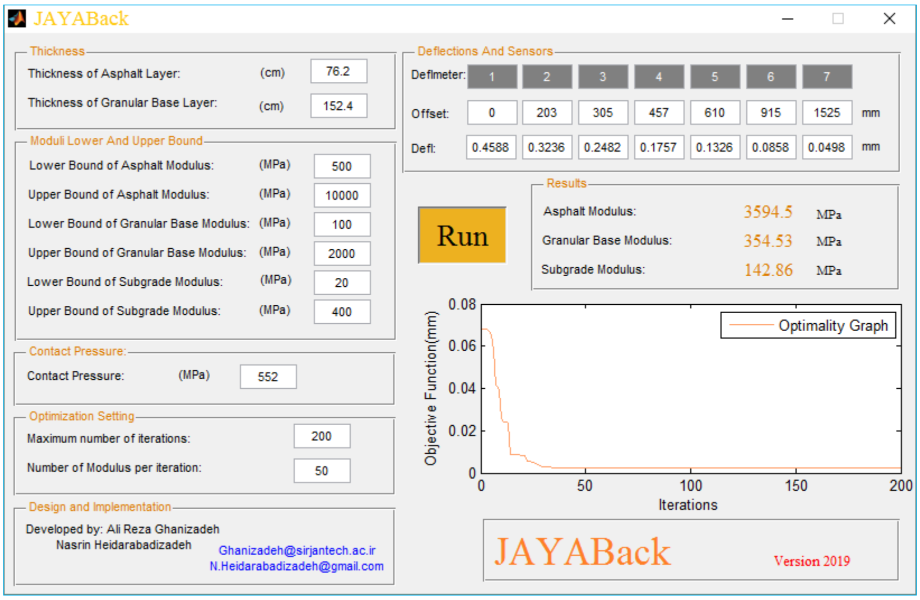


Fig. 9. The JayaBack program GUI

6.3. Validation of the ANN-Jaya Method

6.3.1. JayaBack Validation Using Field Data

To access the performance of the hybrid ANN-Jaya method, the deflection values measured by FWD measured for six different pavement sections were used (Table 3). These values have been adapted from the SHRP-P-651 report (SHRP, 1991).

Table 3. Surface deflection values measured by the FWD (SHRP, 1991)

Section	Layer thickness (mm)		Radial distances (mm)						
	AC	Base	0	203	305	457	610	915	1525
1	106.5	127	0.2936	0.2290	0.1845	0.1361	0.1012	0.0615	0.0342
2	106.5	127	0.2839	0.2193	0.1779	0.0133	0.1005	0.0609	0.0316
3	106.5	127	0.2664	0.2079	0.1697	0.1284	0.0975	0.0597	0.0315
4	106.5	127	0.2573	0.2003	0.1645	0.1256	0.0960	0.0592	0.0318
5	76.2	152	0.4588	0.3236	0.2482	0.1757	0.1326	0.0858	0.0498
6	152.4	304.8	0.4198	0.3417	0.3026	0.2580	0.2218	0.1701	0.1078

To validate and evaluate the accuracy of the proposed procedure, the FWD measured deflections, the contact pressure and the thickness of Asphalt Concrete (AC) and granular base were given to the MODCOMP, ISSEM4, MODULUS, BACKFA, WESDEF, and JayaBack programs and the moduli for asphalt, granular base, and subgrade soil was backcalculated.

ISSEM4 program which has been developed by Dynatest Company, is based on the layered elastic theory (ELSYM 5) and employs an iterative procedure to match the measured deflections with the theoretical deflections calculated at the pavement surface (Bush and Baladi, 1989). MODCOMP was developed for the U.S. Army Cold Regions Research and Engineering Laboratory by Irwin and Szebenyi (1983). It uses the layered elastic theory for the forward computation of surface deflections and an iterative process for backcalculation of moduli. The program first calculates the modulus of the deeper layers, and then calculates the modulus of the upper layers. It can estimate the moduli for a pavement system having 2 to 15 layers and assumes that the lowest layer is as infinite half-space. It can also handle 6 different loads, each with 10 deflections. MODCOMP considers material behavior as linear elastic or nonlinear elastic for to estimate layers modulus (Irwin, 1983; William, 1999).

MODULUS program which has been developed at the Texas Transportation Institute, uses WESLEA's forward analysis program to create the deflection database, and employed the Pattern Search Algorithm for inverse calculation (Alexander et al., 1989; Richardson and Lusher, 2015; Van et al., 1989). The WESDEF uses the WESLEA program as forward analysis tool and to backcaulate the layers moduli that results in the best fit between a computed and a measured deflection basin (Hassan, 2003). The BAKFAA, was developed by Federal Aviation Administration (FAA) and uses the LEAF, a layered elastic theory program, for forward analysis (Brill and Hughes, 2007; Gopalakrishnan, 2012).

The value of the moduli calculated by the JayaBack program and other programs are represented in Figure 10. Table 4 shows the percentage of the difference between the predicted modulus of the JayaBack and other programs.

As can be seen in Table 4, maximum difference between the predicted modulus of the JayaBack and the other programs for the asphalt layer, base, and subgrade was found to be 22.5, 33.7, and 19.9 percent, respectively. To evaluate the accuracy of the JayaBack, the backcalculated moduli by the ISSEM4, MODCOMP, MODULUS, WESDEF, BACKFA, and JayaBack program were given to the KENLAYER program, and the surface deflections in case of each pavement section was computed. Then, the deflection basin resulted from the KENLAYER program based on the backcalculated moduli of each program was compared to the deflection basin measured by the FWD device.

The values of R^2 and RMSE obtained from the comparison of the deflection basin measured by the FWD device and calculated by the KENLAYER program based on the backcalculted moduli using different software are given in Table 5. according to this table, the JayaBack deflection results, in comparison with the other programs, have more compatibility with the FWD results. Therefore, it can be concluded that the backcalculted modules obtained from the JayaBack are reliable. Figure 11 shows the deflection basins calculated based on the moduli backcalculated using the JayaBack and ones measured by the FWD device for six different sections.

6.3.2. Hybrid ANN-Jaya Method in Comparison with other Optimization Methods

To investigate the ability of the Jaya with the GA and PSO, the hybrid ANN-GA and ANN-PSO were developed, and their results were compared with ANN-Jaya. The speed and accuracy of these three methods were investigated for the different pavement sections mentioned in the previous article.

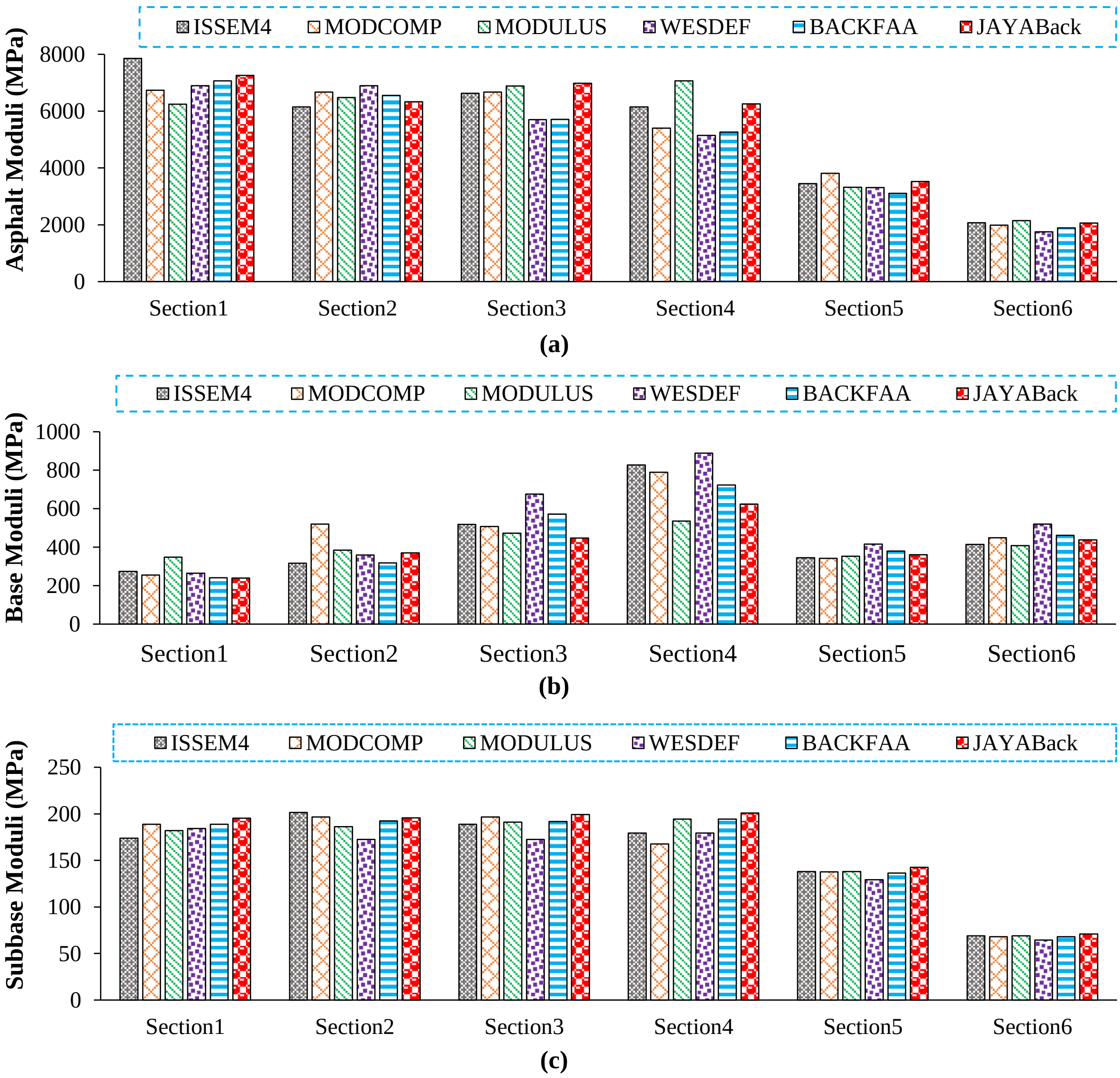


Fig. 10. Backcalculated moduli by JayaBack and other programs

Table 4. Difference between the moduli backcalculated by the JayaBack and other programs

		ISSEM4	MODCOMP	MODULUS	WESDEF	BACKFAA
Section 1	E_1	7.7	7.7	16.2	5.2	2.7
	E_2	12.7	6.1	31.1	9.3	0.7
	E_3	12.4	3.4	7.3	6.1	3.4
Section 2	E_1	2.9	5.2	2.4	8.2	3.4
	E_2	17.1	28.6	3.5	3.4	16.6
	E_3	2.8	0.4	5.1	13.5	1.7
Section 3	E_1	5.3	4.6	1.3	22.5	22.1
	E_2	13.5	11.6	5.3	33.7	21.7
	E_3	5.5	1.4	4.4	15.6	4.0
Section 4	E_1	1.8	15.8	11.5	21.4	18.9
	E_2	24.5	20.8	16.4	29.8	13.8
	E_3	12.0	19.9	3.3	12.0	3.3
Section 5	E_1	3.1	4.6	3.1	10.1	4.3
	E_2	6.0	2.5	7.6	15.7	5.1
	E_3	0.4	3.4	3.9	17.3	8.9
Section 6	E_1	3.3	3.5	3.3	10.4	4.4
	E_2	4.5	5.5	2.2	13.5	5.0
	E_3	2.3	7.5	6.2	6.5	13.4

Table 5. Evaluation of deflection basin, measured by the FWD, and calculated by the KENLAYER

		ISSEM4	MODCOMP	MODULUS	WESDEF	BACKFAA	JayaBack
Section 1	R^2	0.99928	0.99983	0.99942	0.99977	0.99985	0.99986
	RMSE	0.01093	0.00499	0.00526	0.00689	0.00488	0.00103
Section 2	R^2	0.99681	0.99572	0.99608	0.99929	0.99916	0.99946
	RMSE	0.00709	0.00776	0.04308	0.02281	0.00536	0.00208
Section 3	R^2	0.99862	0.99932	0.99536	0.99623	0.99956	0.99958
	RMSE	0.00532	0.00202	0.04159	0.01442	0.00440	0.00176
Section 4	R^2	0.99954	0.99976	0.99357	0.99985	0.99961	0.99967
	RMSE	0.00945	0.02045	0.04342	0.01027	0.00407	0.00173
Section 5	R^2	1.00000	0.99992	1.00000	0.99935	0.99998	1.00000
	RMSE	0.00695	0.00552	0.00670	0.01224	0.00628	0.00175
Section 6	R^2	0.99999	0.99996	0.99999	0.99964	0.99999	0.99997
	RMSE	0.00862	0.00746	0.00843	0.01311	0.00694	0.00089

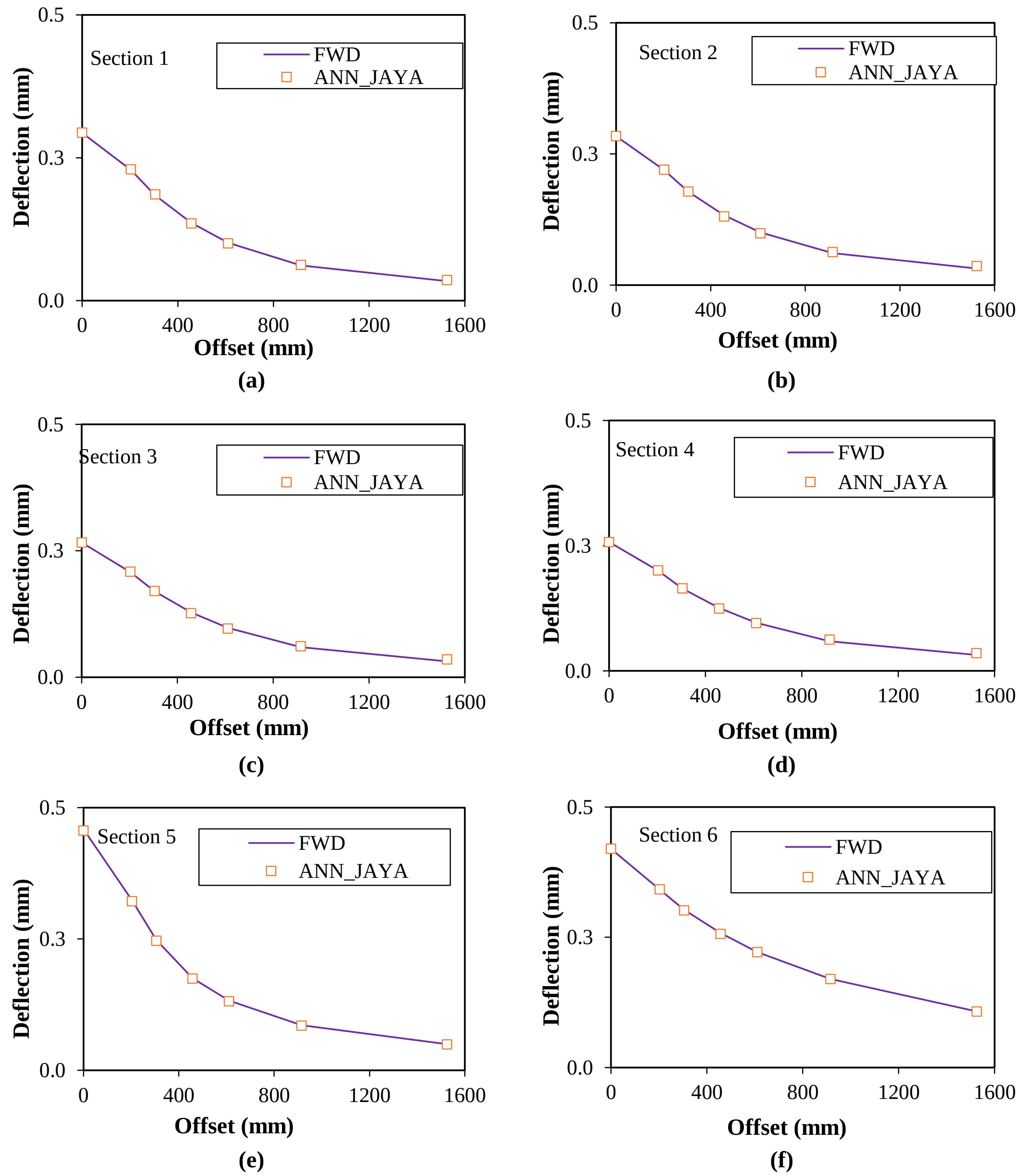


Fig. 11. Deflection basins calculated based on the JayaBack backcalculated moduli and ones measured by the FWD device; a) Section 1; b) Section 2; c) Section 3; d) Section 4; e) Section 5; and f) Section 6

Before the backcalculation, the tuning parameters of the optimization algorithms should be determined. The Jaya algorithm needs no tuning parameter. The PSO algorithm has two tuning parameters of c_1 and c_2, which vary between 1 and 2. The Genetic Algorithm consists of two parameters, including the intersection probability and the probability of mutation, and the range of variations of these two parameters was considered to be [0.7-1] and [0.1-0.4], respectively (Yang, 2010). The optimal values were determined while the objective function was evaluated based on 50 particles and 1000 iterations. The optimal value of the c_1 and c_2 in the PSO algorithm was equal to 2. Moreover, the best value for crossover and mutation probability parameters were found to be 0.9 and 0.4, respectively.

The optimal values of the objective function can be seen for ANN-Jaya, ANN-PSO, and ANN-GA methods for six different pavement sections in Table 6. It is clear from this table that the optimal value of the objective function for the ANN-Jaya and ANN-PSO is approximately equal, although the ANN-Jaya has achieved a more accurate value. It can be also seen that the ANN-GA method has been trapped into the local optima, and in most cases, it is not able to find global optima. Figure 12 shows the convergence diagram of each method for six pavement sections. According to the figure, the convergence rate of the Jaya algorithm to the global optima is faster than the PSO and notably greater than the GA algorithm.

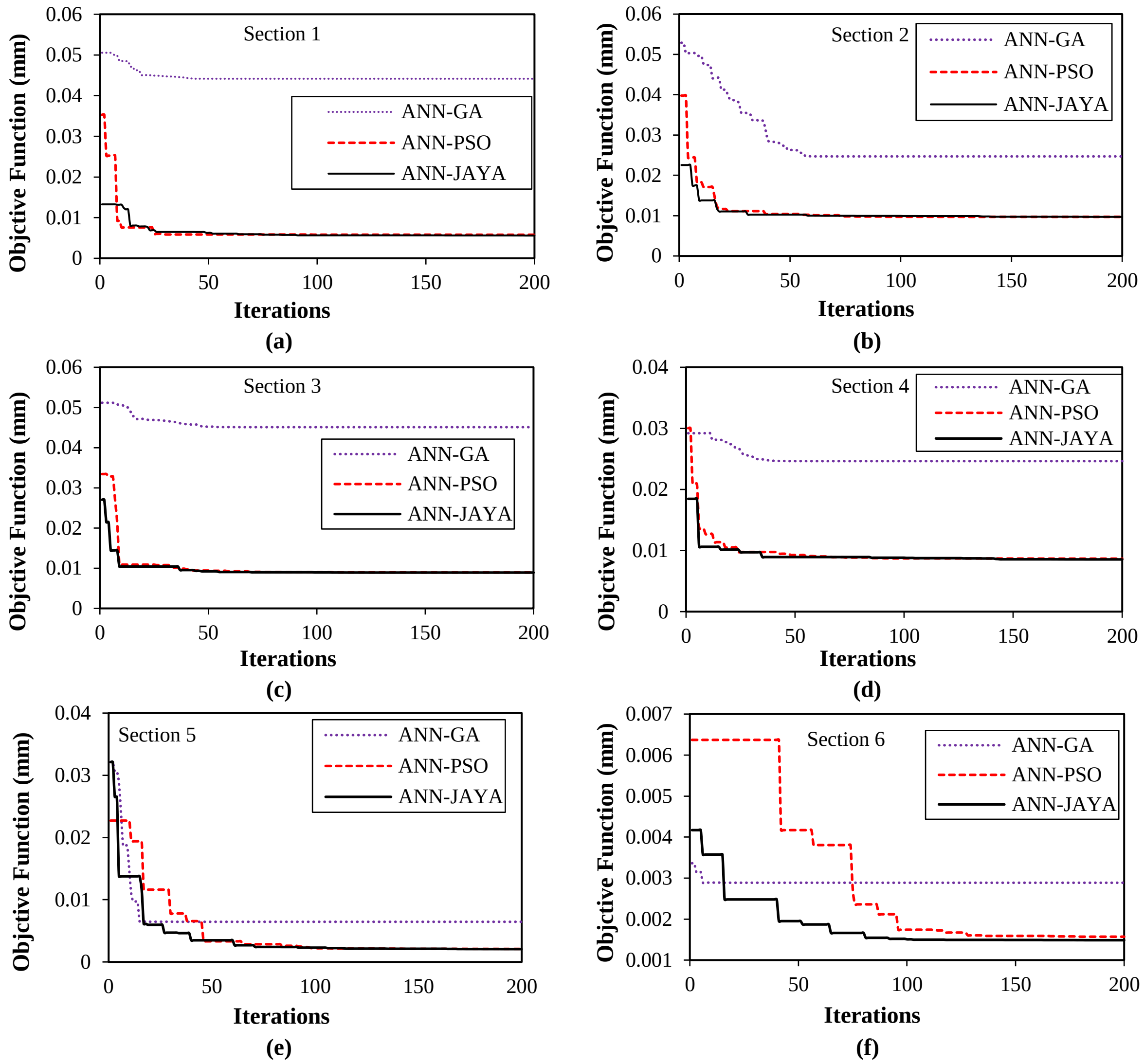


Fig. 12. The convergence diagram of ANN-GA, ANN-PSO and ANN-Jaya for different pavement sections; a) Section 1; b) Section 2; c) Section 3; d) Section 4; e) Section 5; and f) Section 6

Table 6. Optimal values of the objective function derived from backcalculation using different methods

Section	ANN-GA	ANN-PSO	ANN-Jaya
1	0.044151	0.005788	0.005586
2	0.024705	0.009703	0.009701
3	0.045097	0.008931	0.008909
4	0.024637	0.008672	0.008546
5	0.006453	0.002098	0.002068
6	0.002886	0.001571	0.001486

6.4. Experimental Results

The proposed method was implemented in the MTLAB program. All computations were solved on an Intel Core i5-3210 M CPU 2.5 GHz with 4 GB of RAM. The developed program gets the input parameters including the asphalt and granular base layers thicknesses (cm), the granular base and subgrade soil moduli (MPa), asphalt content, the contact pressure of FWD device (MPa), the deflection values at seven radial distances (mm), the number of moduli generated per iteration and the maximum number of iterations. The software determines the asphalt, granular base and subgrade soil moduli (MPa) as the output.

In order to compare the robustness, stability, reliability and convergence of different optimization algorithms including the Jaya, PSO, and GA, each field data was run as much as 10 times by means of each optimization algorithms. To evaluate the robustness, stability, reliability and convergence of the developed model, each field data was run as much as 10 times. At each implementation, five hundred iterations are run and, fifty modulus is considered at each iteration, and the objective function is RMSE value of predicted values of deflections with desired deflections. The thickness of asphalt concrete and granular base layers for each pavement section along with the measured deflections are given in Table 3. The lower and upper band of the resilient modulus were also considered for asphalt concrete layer, granular base layer, and subgrade soil layer as 500 to 10,000 MPa, 100 to 2000 MPa and 20 to 400 MPa, respectively.

Tables 7-9 indicate the statistical parameters of the optimal objective function value, the last optimization iteration, and the run time for the Jaya, PSO, and GA algorithms, respectively. In this study, the maximum number of iterations as well as the minimum RMSE have been used as the stopping criteria. As can be seen, the Jaya algorithm indicates the high robustness and superior convergence in comparison with the GA and PSO algorithms.

Table 7. The statistical parameters to evaluate of the Jaya algorithm

		Section 1	Section 2	Section 3	Section 4	Section 5	Section 6
Optimal objective function value (mm)	Min	0.001237	0.001886	0.001731	0.001714	0.000652	0.000980
	Max	0.001989	0.001980	0.001978	0.001990	0.001872	0.001990
	Average	0.001653	0.001940	0.001879	0.001852	0.001519	0.001637
	Sta. Dev	0.000248	0.000029	0.000079	0.000089	0.000337	0.000230
Total time (sec)	Min	0.61	0.87	0.72	0.70	0.67	0.85
	Max	0.97	1.21	1.10	0.84	0.96	1.03
	Average	0.79	1.01	0.85	0.78	0.80	0.91
	Sta. Dev	0.10	0.10	0.09	0.05	0.09	0.06
The latest iterations of optimality	Min	3	28	9	7	2	23
	Max	33	56	38	23	31	38
	Average	17.4	37.1	19.8	18.4	19	28.1
	Sta. Dev	8.80	8.37	7.21	2.87	6.65	4.91

Table 8. The statistical parameters to evaluate of the PSO algorithm

		Section 1	Section 2	Section 3	Section 4	Section 5	Section 6
Optimal objective function value (mm)	Min	0.001461	0.001900	0.001782	0.001796	0.001125	0.001152
	Max	0.001996	0.001994	0.001987	0.001996	0.001925	0.001991
	Average	0.001702	0.001953	0.001904	0.001916	0.001570	0.001648
	Sta. Dev	0.000165	0.000029	0.000062	0.000054	0.000279	0.000338
Total time (sec)	Min	0.66	5.36	1.54	1.02	0.17	5.17
	Max	7.05	9.56	9.04	7.19	11.11	10.18
	Average	3.22	6.91	5.39	3.11	4.59	7.79
	Sta. Dev	1.72	1.29	2.09	1.60	3.34	1.61
The latest iterations of optimality	Min	5	34	13	14	8	28
	Max	41	52	48	45	67	54
	Average	19.7	41.5	29	19.8	28.4	41.5
	Sta. Dev	10.20	5.48	10.86	9.85	20.02	8.33

Table 9. The statistical parameters to evaluate of the GA algorithm

		Section 1	Section 2	Section 3	Section 4	Section 5	Section 6
Optimal objective function value (mm)	Min	0.003789	0.002363	0.002248	0.002320	0.001765	0.001634
	Max	0.015410	0.010474	0.013726	0.008998	0.021849	0.001874
	Average	0.008279	0.005942	0.005759	0.004917	0.010778	0.001715
	Sta. Dev	0.003149	0.002791	0.003260	0.001803	0.007063	0.000087
Total time (sec)	Min	370.77	367.24	368.21	369.57	284.44	0.46
	Max	416.56	374.35	399.72	420.18	417.61	4.98
	Average	383.99	369.40	375.94	410.13	396.06	2.13
	Sta. Dev	15.13	2.67	10.97	15.46	39.98	1.24
The latest iterations of optimality	Min	500	500	500	500	500	2
	Max	500	500	500	500	500	17
	Average	500	500	500	500	500	8.2
	Sta. Dev	0	0	0	0	0	4.24

7. Conclusions

The goal of this study was development of a moduli backcalculation method for the flexible pavements using the hybridization of the ANN and Jaya. The ANN was employed as the forward model to predict the pavement deflection basin, and the Jaya was applied to find the modulus of the layers based on the minimizing the difference between measured and calculated deflections. The results of this research can be concluded as follows:

- The developed ANN can predict the pavement deflections with high accuracy such that the coefficient of determination (R^2) in all cases is more than 0.9999.
- Comparison of results obtained by the hybrid ANN-Jaya method with other programs such as ISSEM4, MODCOMP, WESDEF, MODULUS and BACKFAA showed that the hybrid ANN-Jaya method can predict the pavement layers moduli with high accuracy.
- The deflection basins computed by the KENLAYER program based on the backcalculated moduli resulted from different programs as well as ANN-Jaya procedure were compared to the deflection basin measured by the FWD device and results confirm that the ANN-Jaya procedure can be used as a reliable method for backcalculation of flexible pavements.
- Comparison of ANN-Jaya results with ANN-GA and ANN-PSO showed that the ANN-Jaya has a higher capability to find the optimum solutions in terms of convergence speed and finding global optima. It was also observed that, the ANN-GA was not able to find the global optima in most cases.
- The developed method was implemented in a computer program called JayaBack to facilitate the use of this method for moduli backcalculation of flexible pavements and further researches.
- The method (ANN-Jaya) and software (JayaBack) developed in this research can be used more accurately than the previous methods to predict the resilient modulus based on the FWD test results.

8. References

Alexander, D.R., Kohn, S.D. and Grogan, W.P. (1989). "Nondestructive testing techniques and evaluation procedures for airfield pavements", *In Nondestructive Testing of Pavements and Backcalculation of Moduli*, ASTM International, West Conshohocken, 502-524.

Aubdulnibe, F.F. (2019). "An application of Artificial Neural Networks (ANNs) to the backcalculation of flexible pavement moduli", *Journal of Physics: Conference Series*, 1362(1), 012146.

Bendana, L., Yang, W. and Lu, J. (1994). "Interpreting data from the falling weight deflectometer", Engineering Research and Development Bureau, New York State Department of Transportation, Research Report, 160.

Brill, D.R. and Hughes, W.J. (2007). "New FAA pavement design software", *International Airport Review*, 11(2), 17-20.

Bush, A.J. and Baladi, G.Y. (1989). *Nondestructive testing of pavements and backcalculation of moduli*, ASTM International, West Conshohocke.

Ceylan, H., Guclu, A., Tutumluer, E. and Thompson, M. R. (2005). "Backcalculation of full-depth asphalt pavement layer moduli considering nonlinear stress-dependent subgrade behavior", *International Journal of Pavement Engineering*, 6(3), 171-182.

Eberhart, R. and Kennedy, J. (1995). "A new optimizer using particle swarm theory", *Proceedings of the 6th International Symposium on Micro Machine and Human Science*, Nagoya.

Fu, G., Xue, C., Zhao, Y., Cao, D. and Alae, M. (2020). "Accuracy evaluation of statically backcalculated layer properties of asphalt pavements from falling weight deflectometer data", *Canadian Journal of Civil Engineering*, 47(3), 317-325.

Ghanizadeh, A.R. and Ziaie, A. (2015). "NonPAS: A program for nonlinear analysis of flexible pavements", *International Journal of Integrated Engineering*, 7(1), 21-28.

Ghanizadeh, A.R., Heidarabadizadeh, N. and Mahmoodabadi, M.J. (2020). "Effect of objective function on the optimization of highway vertical alignment by means of metaheuristic algorithms", *Civil Engineering Infrastructures Journal*, 53(1), 115-136.

Ghanizadeh, A.R. and Heidarabadizadeh, N. (2018). "Optimization of vertical alignment of highways in terms of earthwork cost using colliding bodies optimization algorithm", *International Journal of Optimization in Civil Engineering*, 8, 657-674.

Gopalakrishnan, K. (2010). "Neural network-swarm intelligence hybrid nonlinear optimization algorithm for pavement moduli back-calculation", *Journal of Transportation Engineering*, 136(6), 528-536.

Gopalakrishnan, K. (2012). "Instantaneous pavement condition evaluation using non-destructive neuro-evolutionary approach", *Structure and Infrastructure Engineering*, 8(9), 857-872.

Gopalakrishnan, K. and Papadopoulos, H. (2011). "Reliable pavement backcalculation with confidence estimation", *Scientia Iranica*, 18(6), 1214-1221.

Gopalakrishnan, K. and Thompson, M.R. (2004). "Backcalculation of airport flexible pavement non-linear moduli using Artificial Neural Networks", *Proceedings of the FLAIRS Conference*, Florida.

Gurney, K. (2005). *An introduction to neural networks*, CRC Press, London.

Guzzarlapudi, S.D., Kumar Adigopula, V. and Kumar, R. (2017). "Comparative study of flexible pavement layers moduli backcalculation using approximate and static approach", *Materials Today: Proceedings*, 4(9), 9812-9816.

Hajiazizi, M., Taban, M.H. and Ghobadian, R. (2021). "Prediction of Q-value by multi-variable regression and novel Genetic Algorithm based on the most influential parameters", *Civil Engineering Infrastructures Journal*, 54(2), 267-280.

Hassan, H. and Mousa, R. (2003). "Evaluation of nondestructive testing data using AASHTO and WESDEF backcalculation approaches", *Journal of Engineering and Applied Science*, 50(1), 75-93.

Holland, J. (1975). *Adaptation in natural and artificial systems*, Michigan Press, Ann Arbor.

Huang, Y.H. (2004). *Pavement analysis and design*, Pearson Education, New Jersey.

Irwin, L. (1983). *User's guide to Modcomp2, Version 3.2*, Local Roads Program, Cornell University, Ithaca, NY.

Kaveh, A. and Dadras, A. (2017). "A guided tabu search for profile optimization of Finite Element models", *International Journal of Optimization in Civil Engineering*, 7(4), 527-537.

Li, M. and Wang, H. (2019). "Development of ANN-GA program for backcalculation of pavement moduli under FWD testing with viscoelastic and nonlinear parameters", *International Journal of Pavement Engineering*, 20(4), 490-498.

Li, Y., Ma, D., Zhu, M., Zeng, Z. and Wang, Y. (2018). "Identification of significant factors in fatal-injury highway crashes using Genetic Algorithm and Neural Network", *Accident Analysis and Prevention*, 111, 354-363.

Maher, A. and Bennert, T.A. (2008). "Evaluation of Poisson's ratio for use in the mechanistic empirical pavement design guide (MEPDG)", Transportation Resaerch Board, No. FHWA-NJ-2008-004.

Öcal, A. (2014). "Backcalculation of pavement layer properties using artificial neural network based gravitational search algorithm", Ph.D. Thesis, Middle East Technical University, Ankara, Turkey.

Pekcan, O., Tutumluer, E. and Thompson, M. (2008). "Artificial Neural Network based backcalculation of conventional flexible pavements on lime stabilized soils", *Proceedings of the 12th International Conference of Iinternational Association for Computer Methods And Advances in Geomechanics (IACMAG),* Goa, India.

Rakesh, N., Jain, A., Reddy, M.A. and Reddy, K.S. (2006). "Artificial Neural Networks-Genetic Algorithm based model for backcalculation of pavement layer moduli", *International Journal of Pavement Engineering,* 7(3), 221-230.

Rao, R. (2016). "Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems". *International Journal of Industrial Engineering Computations,* 7(1), 19-34.

Rao, R.V., Savsani, V.J. and Vakharia, D. (2011). "Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems", *Computer-Aided Design,* 43(3), 303-315.

Richardson, D.N. and Lusher, M. (2015). "MoDOT pavement preservation research program volume III, development of pavement family and treatment performance models", Division of Construction and Materials, Final Report Prepared for Missouri Department of Transportation.

Saltan, M. and Terzi, S. (2008). "Modeling deflection basin using artificial neural networks with cross-validation technique in backcalculating flexible pavement layer moduli", *Advances in Engineering Software,* 39(7), 588-592.

Saltan, M., Tigdemir, M. and Karasahin, M. (2002). "Artificial Neural Network application for flexible pavement thickness modeling", *Turkish Journal of Engineering and Environmental Sciences,* 26(3), 243-248.

Saltan, M., Uz, V.E. and Aktas, B. (2013). "Artificial Neural Networks-based backcalculation of the structural properties of a typical flexible pavement", *Neural Computing and Applications,* 23(6), 1703-1710.

Samadi, D., Taghaddos, H., Nili, M.H. and Noghabaei, M. (2021). "Development of a bridge maintenance system using bridge information modeling", *Civil Engineering Infrastructures Journal*, 54(2), 351-364.

Saric, A. and Pozder, M. (2017). "Artificial Neural Networks application in the backcalculation process of flexible pavement layers elasticity modulus", In: *International Symposium on Innovative and Interdisciplinary Applications of Advanced Technologies*, 549-559, Springer, Cham.

Scimemi, G.F., Turetta, T. and Celauro, C. (2016). "Backcalculation of airport pavement moduli and thickness using the Lévy Ant Colony Optimization algorithm", *Construction and Building Materials,* 119, 288-295.

Sonmez, M., Akgüngör, A.P. and Bektaş, S. (2017). "Estimating transportation energy demand in Turkey using the Artificial Bee Colony Algorithm", *Energy*, 122, 301-310.

Strategic Highway Research Program (SHRP). (1991). "SHRP layer moduli backcalculation procedure software selection", SHRP Technical Report, Washington D.C.

Ullidtz, P. (1987). *Pavement analysis, developments in Civil Engineering,* Elsevier, Netherlands.

Van Cauwelaert, F.J., Alexander, D.R., White, T.D. and Barker, W.R. (1989). "Multilayer elastic program for backcalculating layer moduli in pavement evaluation", *1st International Symposium on Nondestructive Testing of Pavements and Backcalculation of Moduli*, Baltimore, Maryland, USA.

Vasant, P., Zelinka, I. and Weber, G. (2019). *Intelligent computing and optimization*, Springer, Turkey.

Von Quintus, H.L. and Simpson, A.L. (2002). *Back-calculation of layer parameters for LTPP test sections, Volume II: Layered elastic analysis for flexible and rigid pavements*, FHWA-RD-01-113, United States.

Wang, H., Xie, P., Ji, R. and Gagnon, J. (2020). "Prediction of airfield pavement responses from surface deflections: Comparison between the traditional backcalculation approach and the ANN model", *Road Materials and Pavement Design*, 22(9), 1930-1945.

William, G.W. (1999). "Backcalculation of pavement layers moduli using 3D nonlinear explicit finite element analysis", Ph.D. Thesis, West Virginia University Libraries.

Yang, X.-S. (2009). *Firefly algorithms for multimodal optimization,* Springer, Cambridge.

Yang, X.-S. (2010). *Nature-inspired metaheuristic algorithms,* Luniver press, UK.

You, L., Yan, K. and Liu, N. (2020). "Assessing Artificial Neural Network performance for predicting interlayer conditions and layer modulus of multi-layered flexible pavement", *Frontiers of Structural and Civil Engineering*, 14(2), 487-500.

Zhang, X., Otto, F. and Oeser, M. (2021). "Pavement moduli back-calculation using Artificial Neural Network and Genetic Algorithms", *Construction and Building Materials,* 287, 123026.