LEAGUE CHAMPIONSHIP ALGORITHM FOR LAYER MODULI ESTIMATION OF FULL-DEPTH ASPHALT PAVEMENTS

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Keywords	Abstract
Flexible Pavement, Backcalculation, League Championship Algorithm, Artificial Neural Network.	This study proposes a backcalculation tool, based on the hybrid use of League Championship Algorithm (LCA) and Artificial Neural Network (ANN), in order to predict the stiffness related layer properties of full-depth asphalt pavements. The proposed algorithm, namely LCA-ANN, is composed of two main parts; (i) an ANN forward response model, which is developed with the nonlinear finite element solution, for computing the surface deflections, and (ii) LCA search algorithm which is employed to search and provide the best set of layer moduli to the ANN model. In order to evaluate the performance of the proposed method, a synthetically generated dataset and real field data are utilized. Moreover, to assess the searching ability of LCA, well-accepted metaheuristic algorithms; Simple Genetic Algorithm (SGA) and Particle Swarm Optimization (PSO) are employed for comparison purposes. Obtained results reveal that the proposed algorithm can predict the layer properties with a low order of error values and enables fast and reliable tool for backcalculation studies.

TAM DERİNLİKLİ ESNEK ÜSTYAPILARIN KATMAN ÖZELLİKLERİNİN TAHMİNİ İÇİN LİG ŞAMPİYONASI ALGORİTMASI

Anahtar Kelimeler	Öz
Esnek Yol Kaplaması, Geri Hesaplama, Lig Şampiyonası Algoritması, Yapay Sinir Ağları.	Bu çalışma tam derinlikli esnek üstyapıların katman özelliklerinin tahmin edilmesinde kullanılacak, Lig Şampiyonası Algoritması (LCA) ve Yapay Sinir Ağları (ANN) tabanlı bir geri hesaplama algoritması önermektedir. LCA-ANN adı verilen bu algoritma iki ana bölümden oluşmaktadır: (i) yol yüzeyindeki deplasmanların hesaplandığı, lineer olmayan sonlu elemanlar çözümleri ile geliştirilen, ANN ileri hesaplama modeli ve (ii) ANN modeline girdi olarak verilecek en uygun katman elastisite modüllerinin belirlenmesinde kullanılan LCA arama algoritmasıdır. Önerilen yönetimin performansını değerlendirmek amacıyla sentetik olarak üretilen veri seti ile gerçek bir veri seti kullanılmıştır. Ayrıca, LCA'nın arama yeteğini değerlendirmek için, kabul görmüş algoritmalar olan Basit Genetik Algoritma (SGA) ve Parçacık Sürü Optimizasyonu (PSO) karşılaştırma amacıyla kullanılmıştır. Elde edilen sonuçlar göstermiştir ki önerilen algoritma düşük hata miktarlarıyla esnek üstyapı katman özellikleri tahmin edebilmekte ve geri hesaplama çalışmalarında hızlı ve güvenilir bir yöntem olarak ortaya çıkmaktadır.

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1. Introduction

The current structural condition of in-service pavements should be monitored routinely to decide about the maintenance and rehabilitation needs of road networks. Falling Weight Deflectometer (FWD), which is nondestructive test equipment, has been used for decades to assess the layer stiffness properties which are associated with pavement structural capacity. FWD is a device that produces an impact on the pavement surface through a falling mass and collects displacement data, named deflection basin, using the sensors placed at load application point and several locations away from it. The prediction process of pavement layer moduli from the measured deflections is called pavement backcalculation. Generally, in this process, a numerical model of the pavement section is generated and deflections are calculated theoretically under the same loading conditions of FWD. After that, the most representative layer moduli of the real pavement section is searched by trying to minimize the error between the experimental deflections and calculated ones.

Since pavement layer backcalculation is an ill-posed inverse engineering problem, its solution is complicated, and therefore, there have been several studies performed to reduce the complexity of the solution. A typical backcalculation method incorporates a theoretical pavement analysis component, namely the forward response model, where the pavement is numerically modeled, and deflections are calculated. In some of the conventional backcalculation studies and commercial computer programs, layered elastic theory (LET) is utilized as the forward response model (Scullion et al., 1990; Zhou et al., 1990; Reddy et al., 2004; Kim and Im, 2005). Since LET assumes that all the layers are linearly elastic, homogeneous and isotropic, it provides calculation simplicity. However, taking into account the linearity for the layers of which present nonlinear behavior actually may produce erroneous deflection computation despite the provided advantages of LET analysis. For this reason, researchers utilized the finite element method (FEM) for response calculations by regarding nonlinearity for the pavement geomaterials, which result in more realistic deflections. On the other hand, time-consuming analysis stages of finite element (FE) analysis make the forward response calculation impractical. Therefore, Artificial Neural Networks (ANNs) emerge as a powerful tool due to their ability to establishing a nonlinear relationship between input and output pairs within a short period. Thanks to these advantages of ANNs, they have been successfully implemented in several studies of different branches in civil engineering (Baltacıoğlu et al., 2010; Keskin and Taylan, 2010; Katanalp et al., 2019). In the pavement backcalculation area, researchers replaced computationally expensive FE forward response models with the ANN models for decades in several studies (Goktepe et al., 2006). Initial backcalculation studies of which estimate layer moduli and thickness proved the high potential of ANNs in the pavement engineering area (Meier and Rix, 1994; Meier, 1995; Saltan et al., 2002). Researchers utilized ANN as the surrogate model for both linear (Rakesh et al., 2006; Saltan et al., 2013) and nonlinear (Ceylan et al., 2005; Li and Wang, 2019) FE based forward analysis of pavement geomaterials to backcalculate the layer properties layer moduli, thickness, and Poisson ratio. In this way, more accurate and faster solutions comparing to the LET and FEM based forward analysis methods would be possible.

Another component of a typical backcalculation algorithm is the optimization algorithm which is utilized to search for the layer stiffness properties. Here, the optimization method tries to minimize the error between experimental deflections and calculated ones with the forward response model by seeking the set of layer properties and providing them to the forward model iteratively. In conventional studies, researchers used database search and least-squares methods as the search approach (Uzan et al., 1988; Sivaneswaran et al., 1991). Since backcalculation problems have stochastic nature, these methods provide limited solutions because of trapping the local optimum solutions and dependence on the initial layer moduli (Sharma and Das, 2008). To overcome such limitations, bio-inspired metaheuristic optimization methods have been successfully utilized as the search approach thanks to their competence for handling complex search spaces and independence to the seed moduli. Among the metaheuristic methods, Genetic Algorithms (GAs) are the widely applied one in all kinds of backcalculation studies such as linear and nonlinear material considerations with static and dynamic analysis of the FWD test (Rakesh et al., 2006; Hu et al., 2007; Sangghaleh et al., 2014). Bio-inspired metaheuristic search techniques mimic the different types of phenomena in nature, and therefore, their approach to solving the problems are distinctive. For this reason, the application of any other method as the search technique can contribute to the accuracy of the solution of the backcalculation problems. Apart from GAs, particle swarm optimization (PSO) (Gopalakrishnan, 2009; Öcal, 2014), differential evolution (DE) (Gopalakrishnan and Khaitan, 2010), gravitational search algorithm (GSA) (Öcal, 2014), shuffled complex evolution (SCE) (Gopalakrishnan, 2009), and levy ant colony optimization (ACO$_{RL}$) (Fileccia Scimemi et al., 2016) have been successfully employed in the searching phase of the backcalculation algorithms.

In this study, a backcalculation model developed with a novel metaheuristic optimization method, league championship algorithm (LCA), and ANN forward response model is proposed. Within the scope of the study, full-depth asphalt pavement (FDP) is taken into account for backcalculation. The performance of the proposed method,

namely LCA-ANN, is investigated against the well-known metaheuristic methods PSO and a simple genetic algorithm (SGA) by analyzing the synthetically generated and field data, respectively.

2. Material and Method

The development stages of the proposed backcalculation algorithm consist of three main stages. In the first one, the FE model of full-depth asphalt pavement is created, and the FWD test is simulated mathematically in order to calculate the surface deflections. In the second part, ANN forward response model is trained through the solutions of the FE mechanical model. By this way, the FE model is replaced with ANN to calculate the deflections with high accuracy and quickly. In the last part, LCA is developed as the searching technique and embedded in the ANN model to supply the input data of ANN. In the following subsections, the details of the proposed LCA-ANN backcalculation algorithm is explained in detail.

2.1. Material Characterization of Full-Depth Asphalt Pavements

Full-depth asphalt pavements are made up of one or more layers of hot mixed asphalt material placed over the subgrade (Huang, 2003). In this study, only the FDP pavements constructed over the fine-grained subgrade is considered. Unlike conventional studies, this study takes into account the nonlinear stress softening behavior of fine-grained geomaterials. To define this behavior in the FE modeling stage, the bilinear or arithmetic model will be utilized (Thompson and Robnett, 1979). In this constitutive model, the resilient modulus of the material is decreased under the condition of increasing stress levels. The mathematical expression of the model is given in Equation 1. According to (Thompson and Robnett, 1979), E_{Ri} referring to the breakpoint resilient modulus is the best indicator of the material behavior comparing to other parameters, and therefore, the parameter is used to characterize subgrade material.

$$M_R = E_{Ri} + K_3(\sigma_{di} - \sigma_d) \text{ when } \sigma_D \leq \sigma_{di}$$
$$M_R = E_{Ri} + K_4(\sigma_d - \sigma_{di}) \text{ when } \sigma_D \geq \sigma_{di} \tag{1}$$

where M_R corresponds to the resilient modulus, K_3 and K_4 are the coefficients calculated from the laboratory experiments, σ_D is the deviator stress, and σ_{di} refers to the breakpoint deviator stress, respectively.

For the ease of calculation, the asphalt layer is assumed as presenting the linear elastic material behavior, and it is characterized by the elastic moduli, E_{AC}. To cover the mostly encountered pavement geomaterial properties in the field, the range of the layer properties considered in the analysis is selected, as presented in Table 1.

Table 1. Range of the Layer Properties

LAYER	THICKNESS RANGE (mm)	MODULI RANGE (MPa)	POISSON'S RATIO
Asphalt	127 - 635	689 - 13780	0.35
Subgrade	7620-t_{AC}	6.9 - 96.5	0.45

2.2. Finite Element Modeling of Full-Depth Asphalt Pavements

FDP sections are modeled with the 2D axisymmetric ILLI-PAVE FE pavement analysis and design software. The total analysis depth of the FDP model is adjusted to 7620 mm (300 in.), and the thickness of the subgrade is calculated by subtracting the thickness of the asphalt layer, t_{AC} from the total depth. Since the deflection data at the exact locations, where the FWD sensors are available, are required to be computed, the horizontal spacing of the FE mesh is arranged according to the FWD sensor coordinates. Selected geometry of the FE domain enables us to calculate the deflections at the FWD impact locations and at the sensors placed 305 mm (12 in.), 610 mm (24 in.), and 914 mm (36 in.) away from the load application. The deflections measured at these locations are depicted with D_0, D_{12}, D_{24}, and D_{36}, respectively. Although the FWD tests can be performed for different load levels, in this study, 40 kN load acting on a circular plate and resulting in 552 kPa uniform pressure over the pavement is defined to the FE model since it simulates an equivalent single axle load.

Through the analysis of the developed FE FDP model, a database is generated with the numerous combinations of material properties given in Table 1. From these analyses, the pairs of t_{AC}, E_{AC}, and E_{Ri} and their corresponded deflections D_0, D_{12}, D_{24}, and D_{36} are incorporated for the generation of ANN forward response model.

2.3. Artificial Neural Network Forward Response Model

ANNs are the soft computing methods that are inspired by the neural system of brains. They are able to learn and mimic the process of a system using its inputs and outputs. In the complex, nonlinear problems, ANNs can successfully establish the relationship between input and output variables. An ANN is composed of interconnected layer groups named input, hidden and output, and each of them includes several neurons (Gurney, 2005). The neurons take and process the information from the previous layer's neurons and transmit them to the consecutive neurons by considering the weight of each neuron and connection that is adjusted throughout the learning process.

In this study, a back-propagation type multilayer feed-forward neural network model is utilized. The dataset generated with the FE model is employed in the training phase of the ANN. Since it is a forward response model, inputs of ANN are t_{AC}, E_{AC}, and E_{Ri}, while the outputs are D_0, D_{12}, D_{24}, and D_{36}. Thus, the input and output layers consist of 3 and 4 neurons, respectively. On the other hand, two hidden layers with 60 neurons at each one are also adjusted. The trained ANN forward response model is depicted in Figure 1.
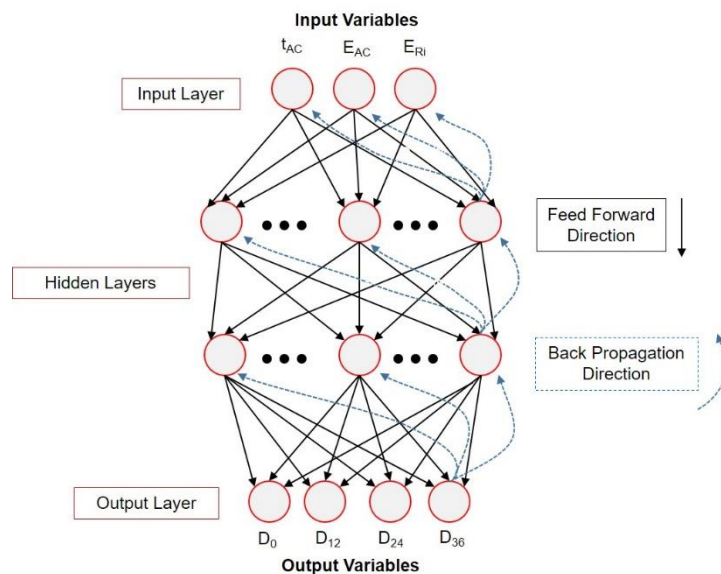

Figure 1. ANN forward response model

2.4. Search Method: League Championship Algorithm (LCA)

LCA is a population-based metaheuristic optimization algorithm proposed in 2009 (Kashan, 2009). As the name of the algorithm implies that LCA is developed by inspiring the competition between teams in a sports league. According to the method, the teams in the league are the individuals or agents in the population. As it is in other population-based metaheuristic techniques, teams are possible solutions of the problem that is being solved, and they are evolved throughout the iterations in order to approach the optimum solution. According to the league schedule, each team competes with the rest of the teams along with the weeks that refer to the number of iterations in the algorithmic implementation. The results of the competition are determined either win or loss based on teams' playing strength of which means to the teams' fitness value. Finally, in conformity with the performance of the teams in the current week, the new formation of each team is arranged through different mutation strategies for the following week's competitions, and the contest continues for previously defined number seasons (Kashan, 2014). The main stages of LCA together with their mathematical representations are explained below.

The number of players in each team, n is determined by the number of variables in the problem. The size of the league is expressed with the L number of teams competing with each other during the $S \times (L-1)$ weeks, where S refers to the number of seasons. LCA starts with the random initialization of the teams. The formation of the ith team at the week t is denoted with the vector X_i^t as in Equation 2.

$$X_i^t = (x_{i1}^t, x_{i2}^t, \dots, x_{in}^t) \tag{2}$$

Following that the playing strength of team i, which is expressed as $f(X_i^t)$, is evaluated through an objective function. On the other hand, the best formation of team i, B_i^t until week t is found by checking the previously experienced playing strength of the team. After that the best value of the playing strength, $\hat{f}$ up to the week for the whole league is determined for a minimization problem as given in Equation 4.

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$$B_i^t = (b_{i1}^t, b_{i2}^t, \dots, b_{in}^t) \tag{3}$$

$$\hat{f} = \min_{i=1,\dots,L} \{f(B_i^t)\} \tag{4}$$

The next stage is the generation of the league schedule, where teams are matched in pairs for the course of the weeks. The algorithm utilizes a single round-robin schedule, which means that only one match is performed between two teams. After that, competition between teams is performed and winner/loser teams are determined. It should be noted that tie conditions are not considered. In order to decide the winning team, firstly, the probability of beating its rival for each team is computed. Within this respect, assuming that team i and j are playing for the week t, the beating probability of team i, p_i^t is calculated with Equation 5. Then, a random number within the interval of [0,1] is generated and if this number is less than or equal to p_i^t, team i is marked as the winner; otherwise, team j becomes the winner of the match.

$$p_i^t = \frac{f(X_j^t) - \hat{f}}{f(X_j^t) + f(X_i^t) - 2\hat{f}} \tag{5}$$

For the following week's matches, each team goes through a revision process by evaluating the previous week's performance of the teams. In order to decide about the revision in a team, both the previous week's performance of the team and its following opponents are analyzed in an artificial manner by simulating the strengths/weaknesses/opportunities/threats of the teams, which is also known as SWOT analysis (Kashan, 2014). Here, strengths and weaknesses are considered the internal performance evaluation of a team, while the opportunities and threats are the external performance evaluation of its opponents. This revision process can be considered the update of an individual for the following iteration of a typical population-based metaheuristic optimization algorithm. Assuming that team i had played against team j at week t and the next opponent of the team i for the week $t+1$ is team l who had competed with team k at week t. Therefore, four different cases are available based on the winner/loser conditions of four teams. The new formation of the teams considering the conditions in week t is determined through the following strategies:

- If both team i and team l were the winners of the week, strength/thread (S/T) strategy is applicable to create new formations with the given equation below:

$$x_{id}^{t+1} = b_{id}^t + y_{id}^t \left(\psi_1 r_{1id}(x_{id}^t - x_{kd}^t) + \psi_1 r_{2id}(x_{id}^t - x_{jd}^t) \right) \tag{6}$$

- If team i was the winner while team l was the loser, strength/opportunity (S/O) strategy is applied to the team i as expressed below:

$$x_{id}^{t+1} = b_{id}^t + y_{id}^t \left(\psi_2 r_{1id}(x_{kd}^t - x_{id}^t) + \psi_1 r_{2id}(x_{id}^t - x_{jd}^t) \right) \tag{7}$$

- If team i was the loser and team l was the winner of the week, weakness/tread (W/T) strategy, given in the below equation, is applied to the team i.

$$x_{id}^{t+1} = b_{id}^t + y_{id}^t \left(\psi_1 r_{1id}(x_{id}^t - x_{kd}^t) + \psi_2 r_{2id}(x_{jd}^t - x_{id}^t) \right) \tag{8}$$

- If both team i and team l were the losers of the week, the new team formations are adjusted according to weakness/opportunity (W/O) strategy as expressed below:

$$x_{id}^{t+1} = b_{id}^t + y_{id}^t \left(\psi_2 r_{1id}(x_{kd}^t - x_{id}^t) + \psi_2 r_{2id}(x_{jd}^t - x_{id}^t) \right) \tag{9}$$

Here, d refers to the dimension of the problem, while r_{1id} and r_{2id} are the uniform random numbers within the interval of [0,1]. ψ_1 and ψ_2 are the algorithm parameters which determine how much strength-weakness and opportunity-thread approaches make contributions. y_{id}^t is a parameter which decides whether the dth variable in the new formation will be changed or not. Therefore, if its value is 1, it means that variable d will be updated according to Equations 6 to 9; otherwise it will remain the same. The number of variables, which will be updated, is also designated by another LCA parameter, q_i^t and it is defined in Equation 10.

$$q_i^t = \left[\frac{\ln(1 - (1 - (1 - p_c)^{n-q_0+1})r)}{\ln(1 - p_c)} \right] + q_0 - 1 \qquad (10)$$

In order to determine the number of changes dynamically, LCA utilizes the truncated geometric probability distribution (Kashan, 2014). In Equation 10, p_c corresponds to the probability of success which is less than one and not equal to zero, r is a random number between [0,1], and q_0 is the least number of changes. Making use of the given equations above, the new team formations are generated, and the algorithm goes on its stages until reaching the termination criteria.

2.5. Backcalculation Algorithm: LCA-ANN

In the current study, the ANN forward response model is combined with the LCA search technique to form the LCA-ANN backcalculation algorithm. In this section, the working scheme of the LCA-ANN backcalculation algorithm is expressed with the steps given below:

1. Control parameters of the LCA; L, S, p_c, q_o, ψ_1, ψ_2 are defined prior to the initialization of the algorithm.
2. Team formations (each team has n dimensions, which refers to the t_{AC}, E_{AC}, and E_{Ri}) are initialized randomly according to their lower and upper bounds given in Table 1. It should be noted that t_{AC} is known, and only layer moduli are being searched.
3. Team formations are transmitted to the ANN model, and each team produces a set of deflections D_0, D_{12}, D_{24}, and D_{36}.
4. Playing strength of the teams is calculated through the fitness function given in Equation 11. In the equation, FWD_i and ANN_i are the measured and calculated deflections at the sensor number i of where 1 refers to D_0 measurement, while 4 corresponds to the D_{36} measurement.

$$fitness = \frac{1}{1 + \sum_{i=1}^{4}(FWD_i - ANN_i)^2} \qquad (11)$$

5. According to Equation 5, winners and losers of the competitions are determined for the current week.
6. Using the winning and losing information, the new team formations are generated on the basis of Equations 6 to 10.
7. The new team formations are provided to the ANN model for the following week.

The processes continue from Step 2 to 7 until reaching the termination criteria.

3. Results

In order to evaluate the performance of the proposed LCA-ANN backcalculation algorithm, two different FWD dataset that the first one is synthetically generated with the FE model and the other one is the field data, which is extracted from the Long Term Pavement Performance (LTPP) Program database, are utilized. To assess the searching capability of LCA, the same ANN forward response model is combined with the well-known optimization algorithms; SGA and PSO (namely SGA-ANN and PSO-ANN), and their moduli estimation and convergence performances are investigated, respectively.

SGA is a population-based evolutionary optimization algorithm that searches the optimum solution of problems by mimicking the survival of the fittest approach in nature (Goldberg, 1989). The algorithm starts with the random generation of the population having individuals called phenotypes in natural selection, and as the result of fitness evaluation of phenotypes, a set of fittest individuals are selected to form the next generation of the population. To perform that, the simulation of crossover and mutation operations are utilized for the purpose of transferring the best individuals' information to the future generations and enabling the population diversity.

PSO, which is also a population-based search algorithm, simulates the social behavior of a bird flock or a fish school (Kennedy and Eberhart, 1995). The aim of the algorithm is to converge all the members of the population around the optimum points. In PSO, the population is randomly initialized and each individual's best location and the global best location of the population are stored to find the optimum solution. Each particle in the population is defined with its position and velocity. The velocity determines how much the individual moves by evaluating the local and global best positions of the population.

3.1. Parameter Settings

To ensure the consistency within the results of LCA-ANN, SGA-ANN and PSO-ANN algorithms, the population is considered to be composed of 50 teams/individuals/phenotypes. While the termination criterion is set as 100 maximum number of iterations for SGA-ANN and PSO-ANN, 5000 number of function evaluations (equal to the 100 iterations x 50 teams) are defined for the LCA-ANN. Each algorithm has its own control parameters that affect the accuracy of the solutions. The control parameters of LCA are determined through the performed parameter tuning studies, SGA and PSO parameters are decided in the light observed better performance and proposed values by the researchers as given in Table 2 (Shi and Eberhart, 1998; Reddy et al., 2004).

Table 2. Parameter Settings of LCA, PSO, and SGA

ALGORITHM	PARAMETERS		
LCA	ψ_1	ψ_2	p_c
	0.2	1	0.1
PSO	w	c_1	c_2
	0.9	0.5	2.2
SGA	p_{cr}	p_m	
	0.74	0.1	

where w, c_1, and c_2 are the inertia weight, cognitive and social scaling factors, and p_{cr} and p_m are the probability of crossover and mutation, respectively.

3.2. Analysis of Synthetic Data

Among the testing dataset, 20 different FDP sections given in Table 3 are randomly selected to evaluate the estimation performance of the backcalculation algorithms. Each pavement section in the dataset is analyzed 5 times, and the results are averaged. To calculate the error between actual and estimated E_{AC} and E_{Ri} data, the mean absolute percentage error (MAPE) function is utilized as given in Equation 12.

$$MAPE = \frac{100\%}{20} \sum_{i=1}^{20} \left| \frac{actual_i - estimated_i}{actual_i} \right| \qquad (12)$$

where $actual_i$ and $estimated_i$ are the actual and backcalculated layer moduli values, respectively.

Table 3. Analyzed FDP Sections

SECTION NO	t_{AC} (mm)	E_{AC} (MPa)	E_{Ri} (MPa)
1	457	10804	14
2	368	2709	24
3	264	5070	45
4	239	12041	30
5	185	6651	57
6	434	13576	67
7	290	3212	16
8	318	3851	73
9	198	756	47
10	422	11922	56
11	163	760	25
12	389	6908	28
13	180	13586	13
14	211	11584	51
15	226	9290	29
16	224	4806	76
17	269	1050	78
18	378	2282	73
19	378	12229	39
20	300	7003	62

Figure 2 shows the E_{AC} prediction capability of the algorithms against the ILLI-PAVE FE solutions. While LCA-ANN estimated the E_{AC} with 1.72% MAPE value, PSO-ANN and SGA-ANN obtained 2.22% and 2.12% error values, respectively. It can be seen that LCA-ANN presents better performance compared to PSO-ANN and SGA-ANN.
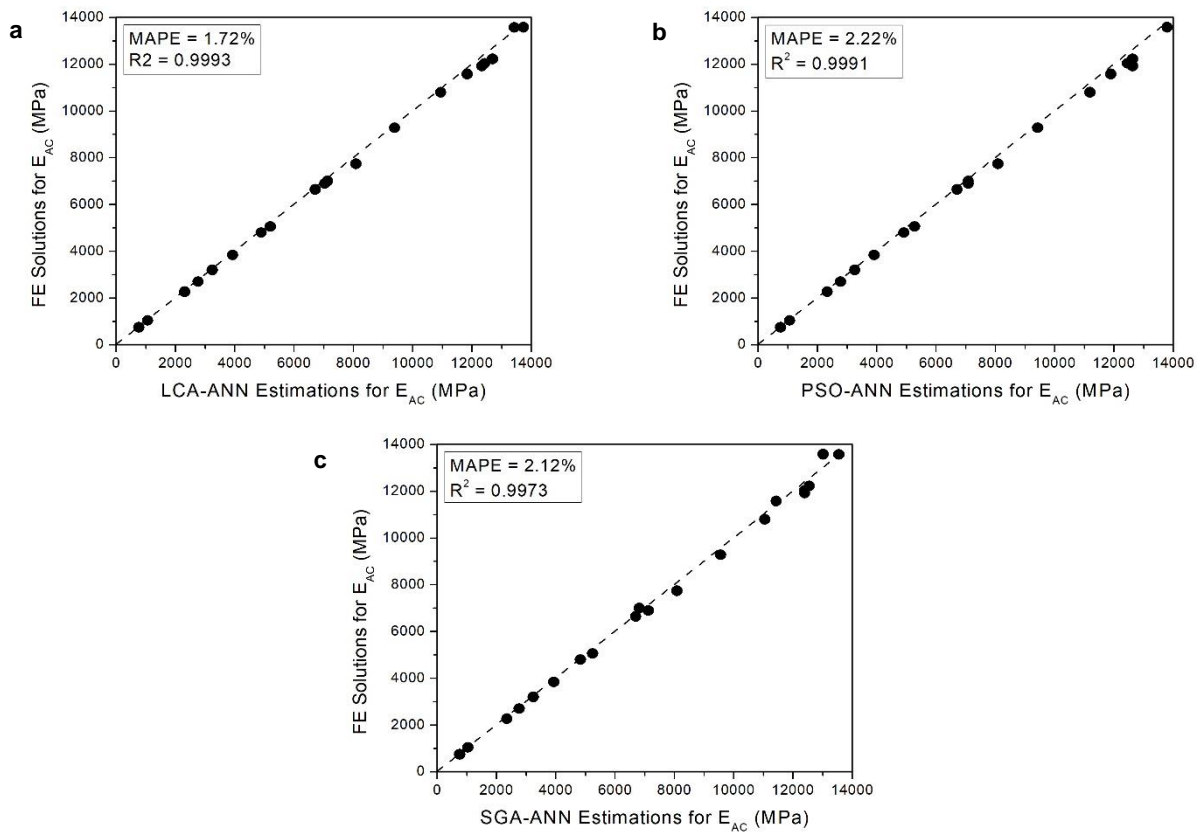
Figure 2. E_{AC} estimation performance of **a)** LCA-ANN, **b)** PSO-ANN, **c)** SGA-ANN

In Figure 3, E_{Ri} estimation performance of the algorithms is presented. It is observed that LCA-ANN shows much better performance compared to the other algorithms. The promising results obtained with the LCA-ANN algorithm gave 1.93% MAPE value. The error values are 2.84% and 3.04% PSO-ANN and SGA-ANN, respectively. According to the results of synthetic data, it is concluded that LCA-ANN is a backcalculation tool capable of estimating layer moduli with smaller order of errors compared to other algorithms through synthetic FE solutions. On the other hand, it is seen that LCA shows better performance on the searching of the best set of layer properties giving the closest deflection basin to the field measurements against the well-known SGA and PSO algorithms.

3.3. Analysis of Field Data

The results obtained in the previous section have to be validated with the field FWD data since the synthetic sections are numerical models, and for this reason, these sections may not actually include all factors affecting the in-service pavement. Therefore, FWD tests data of an FDP section collected from the field throughout the years are extracted from the LTPP Program database, which can be accessed online (FHWA, n.d.).

The selected pavement section with the 18-A350 identification number is located in Indiana, USA. The section was constructed in 1975, and it has been monitored and different types of performance data had been collected between 1987 and 1995. The section is composed of about 390 mm of asphalt layer placed over the lean organic clay. In the study, FWD tests applied in the years of 1990, 1993, 1994, and 1995 are chosen to backcalculate the layer moduli. While selecting the data the same FWD loading conditions (equal to 552 kPa pressure) are taken into consideration and corresponding deflection data is extracted.

Extracted FWD deflection data and layer thickness are utilized by the backcalculation algorithms, and each year's data is run for five individual times, and results are averaged. Figure 5 presents the estimation performance of the algorithms and the readily available backcalculated layer moduli values in the LTPP database. LTPP Program uses Evercalc 5.0 commercial backcalculation software to analyze the collected FWD data. Evercalc 5.0 employs LET based analysis software WESLEA as the forward response engine and Augmented Gauss-Newton algorithm as the search approach (Washington State Department of Transportation, 2005).

As can be seen in Figure 4, each approach estimates E_{AC} close to each other and LTPP value as well. Since Evercalc also takes into account the asphalt layer as presenting linear elastic behavior, obtained results are interpreted as consistent. However, the average estimation of LCA-ANN seems closer to the LTPP calculations. On the other hand,

larger standard deviations are observed in SGA-ANN solutions comparing to other results. When the E_{Ri} is investigated, it is seen that significant differences between algorithms and LTPP solutions are observed. It is thought that the reason for these discrepancies is mainly caused by the considered nonlinear material behavior of subgrade. Therefore, it is concluded that our approaches produce more realistic layer moduli for fine-grained subgrade comparing to the LTPP solutions. Just like the E_{AC} estimations, SGA-ANN estimates the E_{Ri} with larger standard deviations.
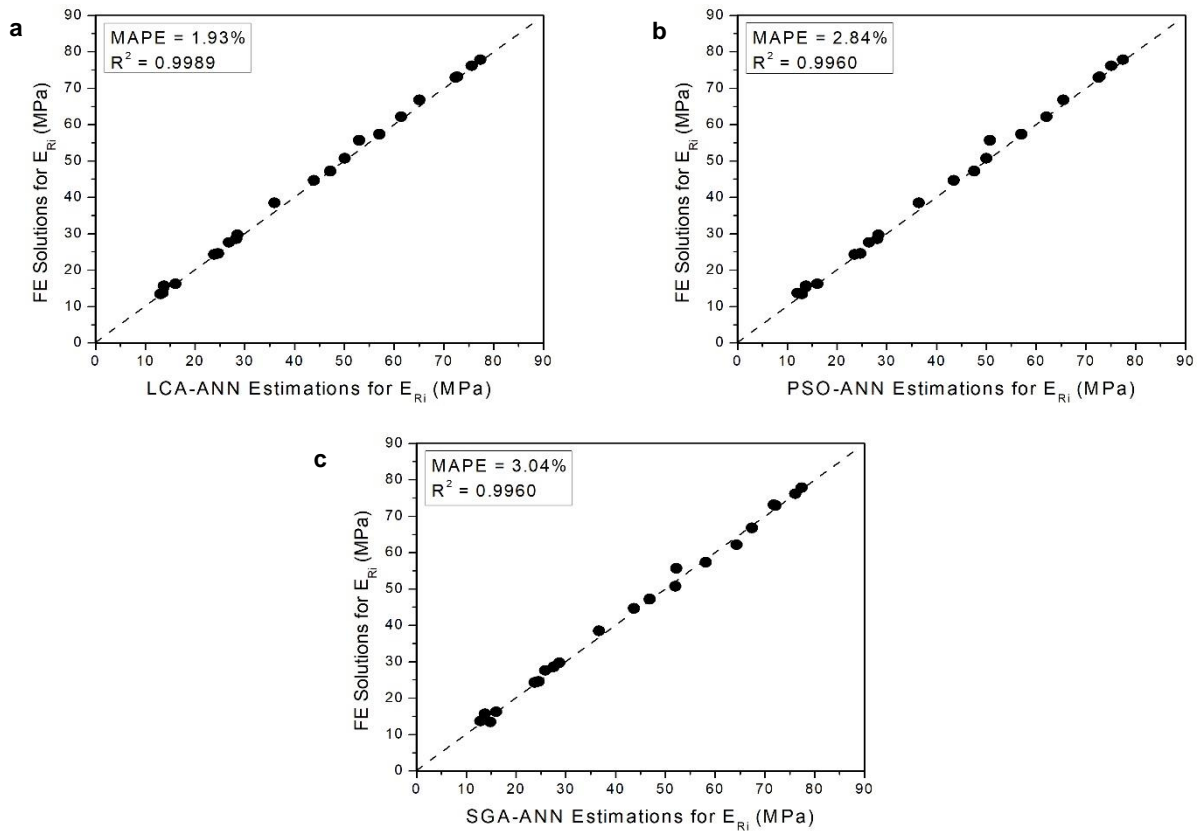

Figure 3. E_{Ri} estimation performance of **a)** LCA-ANN, **b)** PSO-ANN, **c)** SGA-ANN
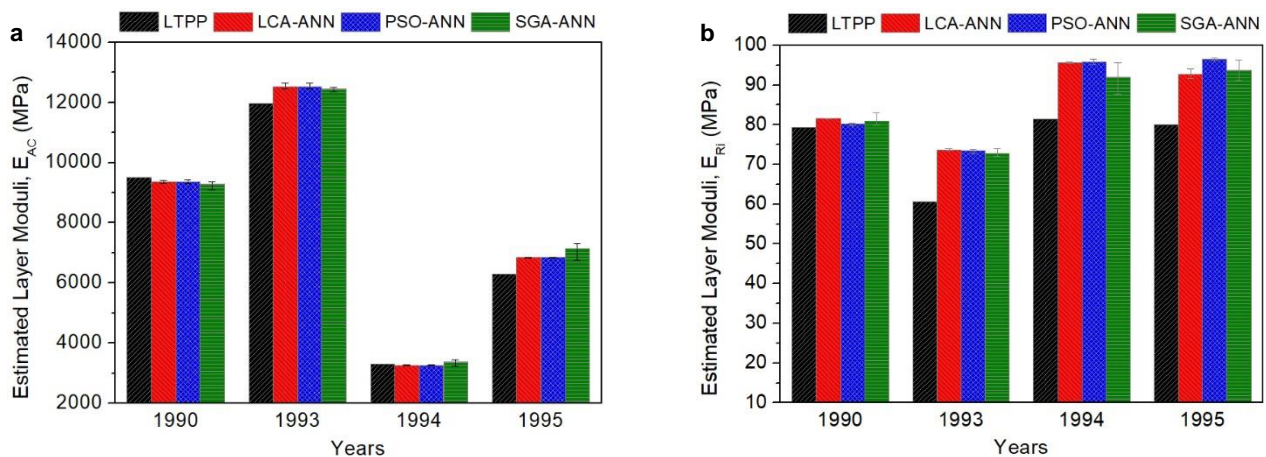

Figure 4. Field data prediction performance of **a)** E_{AC}, **b)** E_{Ri}

3.4. Evaluation of Convergence Performance

In this section, the convergence performance of the metaheuristic search techniques is investigated through the analysis of a randomly selected synthetic test section. The section analyzed five times with each algorithm and obtained best, worst and average fitness curves are plotted as depicted in Figure 5. As can be seen that LCA obtains higher fitness values, which are closer to the maximum fitness, for each of the best, worst, and average curves. On the other hand, SGA and PSO algorithms converge their maximum values gradually after the 2500 function

evaluations while LCA gets closer to the maximum value around the 1000 function evaluations. It is evident that LCA can reach the optimum solution with less number of function evaluations than the other algorithms. Therefore, it is proved that LCA has the capability of handling the complex search space of pavement backcalculation problems without trapping the local optimum points with less efforts.
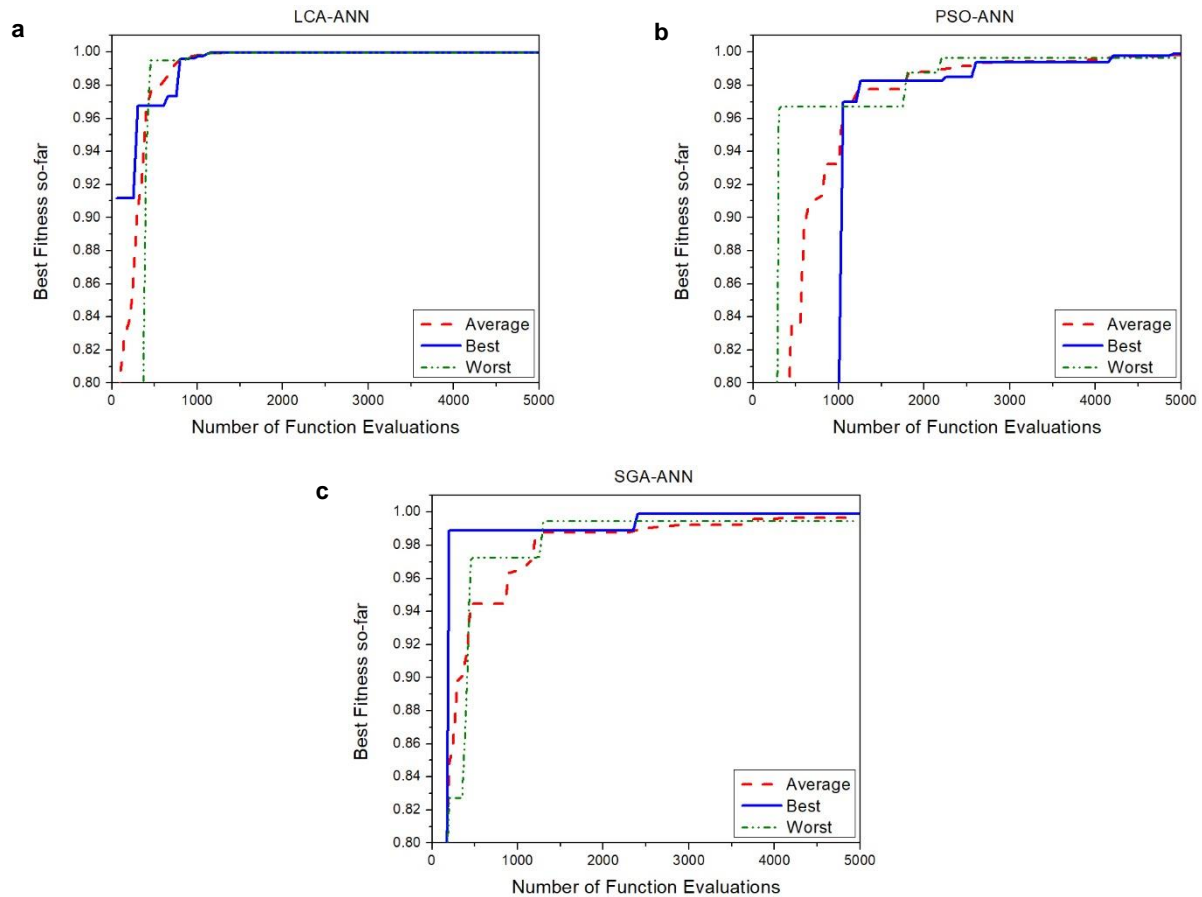

Figure 5. Convergence Performance of **a)** LCA-ANN, **b)** PSO-ANN, **c)** SGA-ANN

4. Discussion and Conclusion

In this study, a backcalculation algorithm, namely LCA-ANN, is proposed to backcalculate the mechanical layer properties of the FDP sections. Since the pavement backcalculation problem has an ill-posed nature and the solution space of the problem is complex and nonlinear, it requires intelligent strategies to tackle these difficulties. Within this respect, ANN forward response model is trained with a large number of solutions of FE analysis where the nonlinear material behavior of fine-grained subgrade soil is considered in order to increase the accuracy of the calculated deflections. In this way, it is aimed to calculate the surface deflections accurately within a short span of time. The other component of the proposed tool is the LCA metaheuristic search approach, which is utilized to effectively search for the set of layer moduli values in the complicated search domain. LCA tries to find the best pair of E_{AC} and E_{Ri} that produces the closest deflection basin to that of measured by FWD. The performance of the proposed LCA-ANN algorithm is investigated with both synthetically generated deflection basins by an FE software and field deflections gathered from the LTPP database. Moreover, to evaluate the search capability of LCA, well-accepted metaheuristic search algorithms SGA and PSO are also combined with the ANN forward model, and the same analyses are performed as well. Obtained results show that the LCA-ANN algorithm provides reasonable solutions with a low order of error values for both E_{AC} and E_{Ri} estimations comparing to the SGA-ANN and PSO-ANN predictions. Also, the results indicated that LCA-ANN gives consistent result to the FE solutions and show fewer variations. When the analysis of field data is examined, it is seen that the solutions of each approach are in agreement with the solutions of commercial backcalculation software Evercalc in the E_{AC} prediction part. Since each approach takes into accounts the same material nature for the asphalt layer, the success of the proposed method can be presented. However, there is a slight variation between E_{Ri} estimations of proposed methods and the Evercalc solutions, due to the considered nonlinear stress softening nature of the subgrade by our forward model. Therefore, the solutions of our approach can be considered more realistic. In the convergence performance comparison of the algorithms, it is seen that LCA performs excellent convergence performance by reaching the best fitness value at earlier stages of the iterations. These results indicate the success of LCA in the exploration and

exploitation of the search space. Since the forward response model is developed with the synthetic data considering linear and nonlinear material models, some conditions encountered in the real conditions may not be taken into account. Therefore, to improve the overall performance of the response model, field data can also be utilized to consider the actual cases over the pavements in future studies. On the other hand, taking into account the viscoelastic material properties of the asphalt layer may also contribute to the accuracy of the forward response calculations by considering the temperature and dynamic FWD loading effects. However, employing real data and viscoelastic material nature can increase the complexity of the problem, and therefore, it is necessary to obtain much data to develop efficient and robust response calculations. Here, it is also proposed to utilize other machine learning approaches to handle the difficulties in the backcalculation problem. Overall, LCA-ANN, which is an efficient and powerful tool that estimates the layer moduli values with high accuracy, is developed in the present study, and it has the potential to be employed in real-time pavement performance investigation applications.

Conflict of Interest

No conflict of interest was declared by the author.

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