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Research Article

Decision-making model based multilayer perceptrons for estimation of optimum design properties for truss structure

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ABSTRACT

Many branches of the structural engineering discipline have many problems, which require the generating an optimum model for beam-column junction area reinforcement, weight lightening for members such a beam, column, slab, footing formed as reinforced concrete, steel, composite, and so on, cost arrangement for any construction, etc. With this direction, in the current study, a structural model as a 5-bar truss is handled to provide an optimum design by determining the fittest areas of bar sections. It is aimed that the total bar length is minimized through population-based metaheuristic algorithm as teaching-learning-based optimization (TLBO). Following, the decision-making model is developed via multilayer perceptrons (MLPs) by performing an estimation application to enable directly foreseen of the optimal section areas and total length of bars, besides, the approximation and correlation success are evaluated via some metrics. Thus, determination of the real optimal results of unknown and not-tested designs can be realized with this model in a short and effective time.

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1. Introduction

Optimization is the process that is carried out to determine the most proper solution ways while reaching the results belonging to a problem, model, event, or case, or displaying the best performance intended for such elements. For this reason, the optimization concept can be accepted as betterment in a sense.

On the other side, in the optimum solution of any problem, reaching the determined aim or target function is necessitated various phases through fulfilling some conditions seen as required. However, the complexity of the problem precludes to search all kinds of possible solutions or solution combinations, and so, intended for the problem, to find good and proper solutions in an acceptable period, turns into the essential purpose. Nevertheless, in the designs consisted of numerous members, the mentioned optimization process may take long periods. In this regard, randomness and probabilistic situations in behaviors of heuristic and also metaheuristic approaches, which are a more advanced and differentiated version of heuristic ones, that one of the frequently used methods for optimization applications, can be a solution in terms of various applications and problems. If it is needed to give some examples to such design models, there are so many types of optimization processes realized to generate the most convenient and effective solutions with the help of various metaheuristics. For example, social spider optimization (SSO), enhanced colliding bodies optimization (ECBO), enhanced vibrating particles system (EVPS), particle swarm optimization (PSO), artificial bee colony (ABC), cuckoo search (CS), a hybrid version of butterfly optimization algorithm (BOA) and symbiosis organism search (SOS) algorithm, harmony search (HS), teaching-learning based optimization (TLBO), bat algorithm (BA) were used to find out the optimal structural design with minimizing the cost, weight, energy, CO_2 from greenhouse gases, etc. (Cakiroglu et al., 2021; Kaveh et al., 2020; Moayyeri et al., 2019; Öztürk, 2018; Sharma et al., 2021; Ulusoy et al., 2018; Ulusoy et al., 2020; Yucel et al., 2020). On the other hand, to create the best design and provide the suitable damping performance for vibration controlling systems such as base isolators, tuned mass dampers, active control mechanisms, etc., different

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methodologies among the mentioned algorithms were evaluated (Çerçevik et al., 2020; Hosseinaei et al., 2021; Lavasani and Doroudi, 2020; Nigdeli and Bekdaş, 2019; Vellar et al., 2019).

The fact remains, in time, it is clear that smart/intelligent techniques, which can reach the desired design criteria and solutions faster, and also have a measurable performance besides perform these actions in a short time and sensitively, replace these methods. The usage of these techniques avails in the sense of both time and spent effort, and thus, early intervention can come into question against negations arising in the designs.

The mentioned methods express the machine learning techniques taken place in artificial intelligence (AI) technology, and for any model, which has numerous design members, it can find out the results wished to be reached and determined, within an extremely short time. For example, in any city network line, pre-calculating how much the amount of water will give to occupants (Brentan et al., 2017; Lertpalangsunti et al., 1999; Msiza et al., 2008; Zubaidi et al., 2020); previously determination of the possibility of vehicular traffic accidents to may occur in any street, road, highway, urban area, etc. (Hu et al., 2004; Sikka, 2014; Wenqi et al., 2017); detection of the most proper dose of medicine for the treatment of any disease (Grossi et al., 2014; Huang et al., 2008; Huang et al., 2017; McDonald et al., 2015); foreseen of how much total construction cost of a structure, which will be made newly (Chakraborty et al., 2020; Koo et al., 2011; Magdum and Adamuthe, 2017; Shuitan et al., 2017), etc. In this regard, generation a combination of both techniques as optimization and machine learning, allow to users about some issues such as expediting of work wished to make, to be not required iteratively performing of intensive analyses, which necessitate long processes, to see quickly some results desired to forecast.

In the present study, a structural design as an optimization problem towards the determination of total bar length within a 5-bar truss model is tried to be solved by benefiting from teaching-learning-based optimization (TLBO). In this regard, optimum section areas of each bar are determined intended for achieving the minimum total length. Here, there is a case as different from classical optimization processes that some design parameters were handled in a specific range without a constant value to be used in the generation of decision-making model via multilayer perceptrons (MLPs), which is a kind of ANNs. Thanks to this, it becomes possible that target values are learned by the MLPs model via the generation of different design combinations intended for the truss model. Even, by this means, various controlling combinations, which are not handled and unknown previously, can be evaluated and directly detected through a developed learning model.

2. Background of Structural Optimization

Structural optimization is a highly important design problem for any engineer, analyzer, designer, etc. reposed in the civil engineering area, at the same time, it is accepted as a scientific discipline that is also studied by numerous researchers. The biggest reason for this importance is to may shine out numerous design combinations having different features, which can be acquired in the direction of factors such as used materials, labor applications, and especially, the defined design targets, etc. In this sense, the significant point is that the most optimum choice, which is a single one, is found to be discovered of design from among these many designs that it can perform the wished aim, and provides the required design conditions together with needs.

Furthermore, it is an important subject that in question determination of the most optimum option, namely what is tried to optimize in the process of optimization of parameters belonging to the design model. The most considerable issue is to be realized of the defined purpose. For instance, minimizing of the displacement values, which can occur in the design of a beam, column, retaining wall etc., establishment of a base isolation system exposing the cost in minimum level, modeling of a retaining wall, which has optimum design properties in the way of keeping CO^2 emission at the lowest degree, can be the major purpose of the designer. However, there is an important second issue that is analysis time and effort amount spent, and addition to these, also usually outlays, in the most proper level while trying to reach to basic purpose in the optimization process. Forwhy, optimization analyses conducted for some design problems take so long times, even a few weeks, and these causes to be not obtained of the desired results immediately in the awaited period. In this sense, it is extremely clear that new and advanced techniques are needed that they can be equal to optimization methods or work collaboratively with these, and thus make sensitive observations and give results in a short time comparing the usage of only optimization. The techniques, which can remove the mentioned disadvantages and provide these effects, are artificial intelligence and machine learning methods.

Accordingly, in structural engineering problems, it is seen that the mentioned methods, which have optimizing capability for such analyses and designs in the context of time, required exertion, are frequently utilized nowadays in terms of supporting optimization processes. For the sake of example to one of these; in the year 2017, a combination of particle swarm optimization (PSO) and bat algorithm (BA) metaheuristics is generated to create a seismically-optimized design for steel frame structures resisted to moment effects, and a model called as wavelet back-propagation neural networks were used for estimating of responses to control the limit state constraints (Gholizadeh and Mohammadi, 2017). Besides, by Xia et al. (2017), the support vector regression (SVR) technique is trained with the usage of genetic algorithm (GA) to detect the optimal parameters specific to SVR to determine damping ratios of cantilever beams by using this generated model. As to the other study, Torkan and Naderi Dehkordi (2018) carried out a study that consists of generation of several combinations, which are based on adaptive neuro-fuzzy inference system (ANFIS), SVR, and ANNs with PSO, to be able to determine the optimal algorithm parameters to estimate of concrete compressive strengths. Yaseen et al. (2018) predicted the shear strength values of steel fiber reinforced concrete beams by considering SVR, and also ANNs, which are utilized with PSO. Also, the applied study is related to optimization of section sizes of steel tubular column model in the direction of achievement to the minimum cost. In this regard, one of the metaheuristic algorithms as flower pollination algorithm (FPA) is combined with multilayer artificial neural networks (ANNs) (Yucel et al., 2018). Additionally, values of dynamic increase factor parameter are determined via an ensemble algorithm as random forest hybridized with firefly algorithm (FA) intended to concrete structures reinforced with steel fiber material (Yang et al., 2019). Zhang et al. (2020) generated a combination for modeling optimum mixture proportions of concretes in the direction of that several machine learning techniques such as random forest, SVR, back-propagation ANNs are collaborated with PSO, respect to arranging of parameters of them. On the other hand, by Yücel et al. (2020a), the evaluation of generalized formulations developed for optimum tuned mass damper (TMD) parameters (f and ξ) is made, that they were proposed previously by using artificial neural networks (ANNs), which were combined with FPA to generate an optimum design of TMD to reduce of the floor responses as displacement and acceleration. Esfandiari and Urgessa (2020) proposed a hybrid model, which is comprised of decision-maker technique and PSO to generate an optimized model for reinforced concrete frames under the case of progressive collapse, too. Moreover, Ly et al. (2020) proposed two different models to estimate the ultimate shear capacities of steel fiber reinforced concrete beam structures. Here, the first and second analysis models are created depending on ANNs, which were arranged with GA and FA, respectively. Except all of these studies, several different optimized structural models are seen where various metaheuristic algorithms as FPA, harmony search (HS), and Jaya algorithm (JA) are benefited and combined via several machine learning techniques containing ANNs, bagging as an ensemble model, and random tree (Yücel et al., 2020b, 2020c).

3. Optimum Structural Design of 5-bar Truss Model

The optimum design model is based on a truss structure, which was consisted of five bar members, and can be seen in Fig. 1(a-b) together with a half-symmetric form belonging to this model. Due to the system is symmetrical, the truss structure can be analyzed and solved with the situation expressed in Fig. 1(b) as a half system.

Material elastic modulus (E) defined for each bar member of truss is 200000 MPa. As to the section areas (A) that belong to bars, is described as 100 mm^2, too. Also, loads, which are applied on the 1st and 2nd nodes taken place in the system, are 100 kN (P_2) and 50 kN (P_2), respectively, besides that the length of the span between supports (L) is 1000 mm.

The principal target in the problem is to find optimum namely the most convenient θ_1 and θ_2 design variable values that enable to minimize the total length of bars within the system. As a mathematical expression of the objective function of the problem, which is based on the mentioned design variables, is denoted via Eq. (1).

$$Min\,Total\ Length = Min\, f\,(\theta_1, \theta_2) = \textstyle\sum_{i=1}^{3} L_i \tag{1}$$

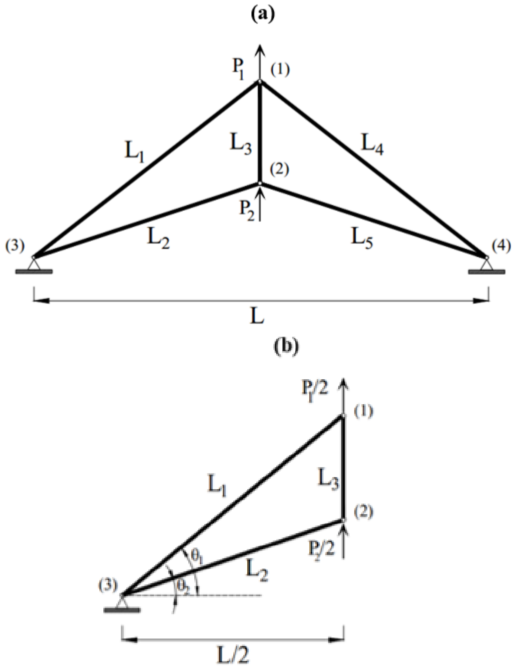

Fig. 1. 5-bar truss model: (a) schema of classical system; (b) half symmetric system (Majid, 1974).

Lengths of L_1, L_2 and L_3 bars that indicated as L_i in the equation, can be obtained by utilizing over geometric relations taken place in Eqs. (2-4), respectively.

$$L_1 = \frac{L}{2\cos(\theta_1)} \tag{2}$$

$$L_2 = \frac{L}{2\cos(\theta_2)} \tag{3}$$

$$L_3 = \frac{L_1}{\cos(\theta_2)} \sqrt{\cos^2(\theta_1) + cos^2(\theta_2) - 2\cos(\theta_1)\cos(\theta_2)\cos(\theta_1 - \theta_2)} \tag{4}$$

For design variables (θ) within the problem, lower ($\theta_{\min}$) and upper ($\theta_{\max}$) limit values determined in literature, can be expressed with Eq. (5).

$$0 < \theta < \frac{\pi}{3} \tag{5}$$

Additionally, in optimization application, which will be performed between these limits, vertical displacements that may occur on the 1st and 2nd nodes of the system (Δ_1 and Δ_2), are describes as design constraints, besides that these values can be provided via Eqs. (6) and (7), respectively. The upper bound of displacements (MaxΔ), which may emerge, is designated as 5 mm.

$$|\varDelta_1(\theta_1, \theta_2)| \le \max\varDelta \tag{6}$$

$$|\varDelta_2(\theta_1, \theta_2)| \le \max\varDelta \tag{7}$$

To define the problem in this stage, according to the maximum vertical displacement condition, which may occur in nodal points, optimization is the operation that finds of combination belonging to the most proper values of θ_1 and θ_2 angles, which remains in between 0 and

$\pi/3$ limits and will make a minimum of total length of bars within the system. Displacements of the mentioned nodal points can be detected by utilizing $K\Delta = P$ expression as static equilibrium equation. In the equation, K, Δ and P correspond to stiffness matrix, displacement vector and load vector in global coordinates, respectively. Here, K can be found via $B^T kB$ in the offing that B is transformation matrix (Eq. (8)) and k is stiffness matrix in local coordinates (Eq. (9)), where, B^T expresses the transpose of the transformation matrix.

$$B = \begin{bmatrix} \sin(\theta_1) & 0 \\ 0 & \sin(\theta_2) \\ 1 & -1 \end{bmatrix} \tag{8}$$

$$k = \begin{bmatrix} \frac{EA}{L_1} & 0 & 0 \\ 0 & \frac{EA}{L_2} & 0 \\ 0 & 0 & \frac{EA}{L_3} \end{bmatrix} \tag{9}$$

Eq. (10) is obtained for K when Eqs. (8) and (9) are substituted in the static equilibrium equation. And following, unknown displacement terms also can be found easily from $K\Delta = P$ equilibrium via Eq. (11).

$$K = EA \begin{bmatrix} \frac{\sin^2(\theta_1)}{L_1} + \frac{1}{2L_3} & -\frac{1}{2L_3} \\ -\frac{1}{2L_3} & \frac{\sin^2(\theta_2)}{L_2} + \frac{1}{2L_3} \end{bmatrix} \tag{10}$$

$$EA \begin{bmatrix} \frac{\sin^2(\theta_1)}{L_1} + \frac{1}{2L_3} & -\frac{1}{2L_3} \\ -\frac{1}{2L_3} & \frac{\sin^2(\theta_2)}{L_2} + \frac{1}{2L_3} \end{bmatrix} \begin{bmatrix} \Delta_1 \\ \Delta_2 \end{bmatrix} = \begin{bmatrix} \frac{P_1}{2} \\ \frac{P_2}{2} \end{bmatrix} \tag{11}$$

As additional information in these structural optimization processes, the number of population as a class comprised of students is handled as 20, besides that iteration number, in other words, total cycles or termination criteria performed for achieving to the optimum design is accepted as 10000.

4. Teaching-Learning Based Optimization (TLBO)

In the year 2011, teaching-learning based optimization (TLBO), which is a population-based metaheuristic algorithm, is improved by Rao et al. (2011) based on the teaching effect of a teacher on students within the class, and interaction together with the transfer of knowledge between students each other as the resultant of this learning. In this algorithm, which is proposed in the direction of consideration two separate phases as teacher and student, besides that community i.e. population (sn) is a class where many students exist, each candidate solution in the optimization process for j=1, 2,..., sn is represented by a student. In addition to this, a teacher is assumed and selected as the most informed/experienced person about an issue among all students in the class (Rao et al., 2011). In this regard, training of students is realized by the teacher (Eq. (12)), which is defined as the best solution in the first stage, and here, improvement of knowledge level and mean results for a specific subject of all students are provided that teacher conveys own information to other students in a specific rate known as teaching factor (TF) (Rao et al., 2011; Rao, 2016).

$$X_{i,\text{new}} = X_{i,j} + \text{rand}\ (\ )\left(X_{i,g_{\text{best}}} - (TF)\, X_{i,\text{mean}}\right) \tag{12}$$

$$TF = \text{round}\left(1 + \text{rand}\ (\ )\right) \tag{13}$$

In the duration of the student phase, two different solutions (n and m) are selected as randomly among all students that improving knowledge level, and this level is updated again as expressed in Eq. (14) based on objective function value (in case minimization of the problem) (Rao, 2016). The expressions with descriptions of optimization members and algorithm parameters are given in Table 1.

$$X_{i,\text{new}} = \begin{cases} OF_n < OF_m, & X_{i,j} + \text{rand}\ (\ )\left(X_{i,n} - X_{i,m}\right) \\ OF_n > OF_m, & X_{i,j} + \text{rand}\ (\ )\left(X_{i,m} - X_{i,n}\right) \end{cases} \tag{14}$$

Table 1. Expressions with descriptions of optimization members and algorithm parameters.

Property	Notation	Description/Task
User-defined coefficient	sn	Number of all students as candidate solutions / Total population number within solution matrix
Member of process	$X_{i,\text{new}}$	The determined new solution value for i^{th} design variable
	$X_{i,j}$	Initial matrix value of j^{th} candidate solution namely student belong to i^{th} design variable
	$X_{i,g_{\text{best}}}$	The value of i^{th} design variable belong to the best solution (defined as teacher member) in terms of objective function quality
	$X_{i,\text{mean}}$	Mean value of all candidate solution values belonging to i^{th} design variable
	$X_{i,n}$	The value of i^{th} design variable for n^{th} candidate solution randomly-selected from initial matrix
	$X_{i,m}$	i^{th} design variable value of m^{th} candidate solution randomly-selected from initial matrix
	OF_n	Objective function value belonging n^{th} candidate solution
	OF_m	Objective function value belonging m^{th} candidate solution
Used functions in optimization application	rand ( )	A random number generating function between 0 and 1
	round ( )	Function that it rounds decimal number in parenthesis to closest integer number
	mean ( )	Function provides that averaging of member values within a specific number array
	min ( )	Function determining of the minimum one among values in certain amount

In the present study, the main purpose of using TLBO is that the algorithm provides the randomization and thus successfully optimization for design variables in the way of realizing the objective of the problem. The reason for this case is based on that TLBO has two different and sequential phases, which are producing the solutions by evaluating the best members and considering all of the population. In this respect, the optimization process can be carried out in two individual stages by handling the possibility of different solutions. Also, the flowchart of TLBO algorithm can be seen in Fig. 2.

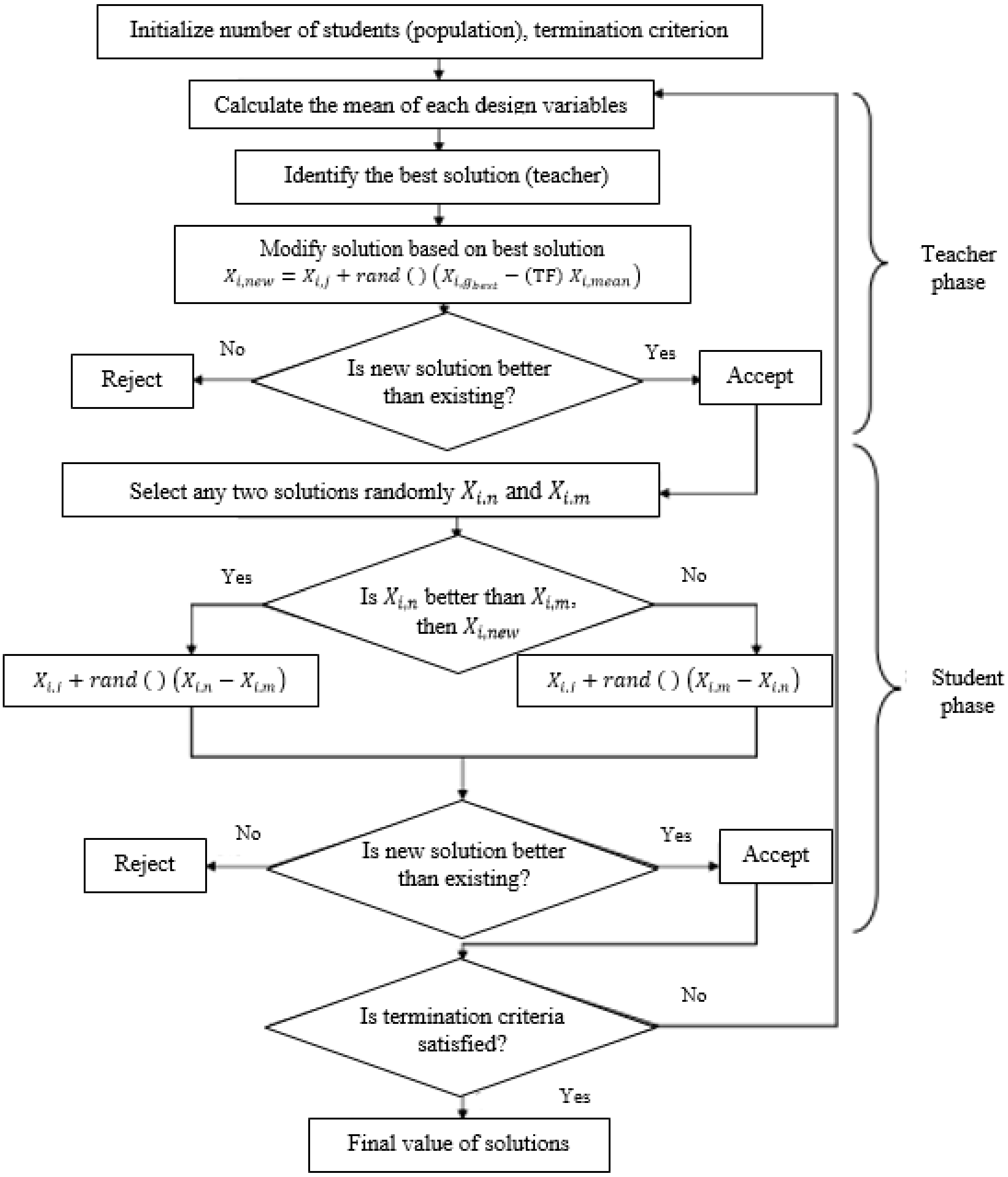

Fig. 2. The flowchart of TLBO (Rao et al., 2012).

5. Estimation Process via Multilayer Perceptrons (MLPs)

Multilayer perceptrons (MLPs) are one of the feed-forward artificial neural networks (ANNs) structure types that they have one input and one output layer together with one or more hidden layers. In these structures, there are many neurons, in other words, nodes taking place in these layers in the way of inspiration from neural cells within the natural mechanism of the human central neural system. In this sense, they perform to learn, analyze, solve problems, estimate, etc. by simulating the neural system and working system of it (Gardner and Dorling, 1998). In this respect, a decision-making model has developed thanks to the usage of different design combinations data, which were provided via optimization process by learned by MLPs that it takes place as "neural net fitting" within MATLAB R2018a program applications (MATLAB Mathworks). By this means, a speedy process for estimating optimal design properties with the minimum total bar length becomes a possible application.

However, some of the design parameters, which are considered in the optimization process, will not be taken as constant in the machine learning operation applied for developing this decision-making model in the second step. In this way, a training set is generated via properties of optimum parameters belonging to various design combinations together with target function values corresponding to them, besides, Table 2 where the mentioned variable values are expressed, can be seen below.

Table 2. Properties of input ranges used for training.

Input parameters	Task	Ranges	Increment amount	Unit
P_1	Load applied on 1st node	95-100	0.25	kN
P_2	Load applied on 2nd node	45-50	0.25	kN
A	Section areas of truss bars	90-100	1	mm^2

In here, loads as P_1 and P_2 with A are three inputs, and three outputs are optimum horizontal angles of bars (θ_1 and θ_2) and minimum total length of bars. It is stated that inputs and minimum bar length as objective function are adjusted in the range of [0, 0.6] by using a min-max normalization approach to be fitted and used in a similar range with other outputs (θ_1 and θ_2) (Eq. (15)) (Shamil, 2020). Where, $\bar{x}_i$ is the normalized value of ith data sample of any x attribute (x_i); $x_{\min}$ and $x_{\max}$ are biggest and smallest values within this attribute; $R_{\max}$ and $R_{\min}$ are limits defined as minimum and maximum, respectively, and they determine that normalization will be made in which ranges. Also, Fig. 3 shows the structure of the estimation model operated via MLPs.

$$\bar{x}_i = \left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}\right)(R_{\max} - R_{\min}) + R_{\min} \tag{15}$$

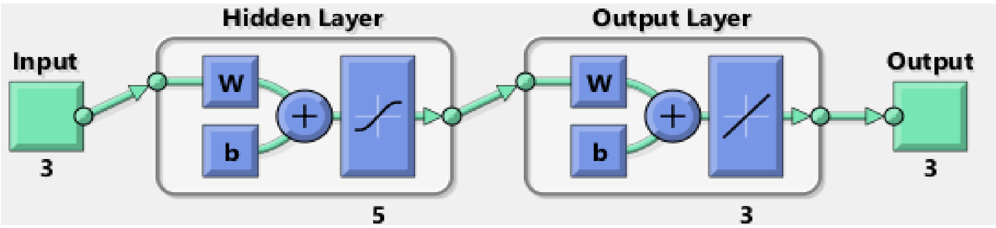

Fig. 3. Structure of decision-making model created for estimation of optimization data.

Furthermore, in the second step, a test and controlling dataset, which contains eight different optimum design combinations for a 5-bar truss structure, was generated to evaluate the principal learning model performance in terms of validation of test inputs and approximation to the target outputs. In this scope, for test combinations, some metrics (mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE)) were found for the errors, namely differences of test results according to real optimization outputs.

6. Numerical Examples

Correlation coefficients (R), which reflects the estimation and convergence success together with the degree of fitting between real values and predictions, were provided respect to training, validation, and test data, which belong to the main estimation model generated over dataset consisted from optimum results via TLBO, can be seen in Fig. 4. Also, error metrics are calculated as MAE, MSE and RMSE to observe the estimation performance of this model, and the results can be seen in Table 3.

As it can be seen from Fig. 4, all of the correlation results are pretty convenient, besides that each error rates are also extremely low in the meaning of successful convergence to real optimum results and validation of the model for design parameters and the normalized value of minimum total bar lengths (Table 3). In this regard, the model can be accepted as a usable tool and correct-estimator, and various new design data can be directly solved via this model to observe the desired optimum results without optimization processes. The generated test/controlling designs, and results of optimum parameters for them are given in Tables 4 and 5, respectively.

In Tables 6-8, concerning all test designs, MLPs estimations and errors for optimum parameter values and normalized minimum bar length were expressed with the aim of comparison via TLBO. Here, calculated metrics for error rates can be seen as MAE, MSE and RMSE.

Besides, estimations of normalized values of minimum total length of bars within Table 8, are benefited to figure out of actual values of the objective function as minimum bar length.

For this respect, normalizations are converted to real values as estimated data according to min-max normalization formulation, and detected results are evaluated by comparing them with optimum values (Table 9).

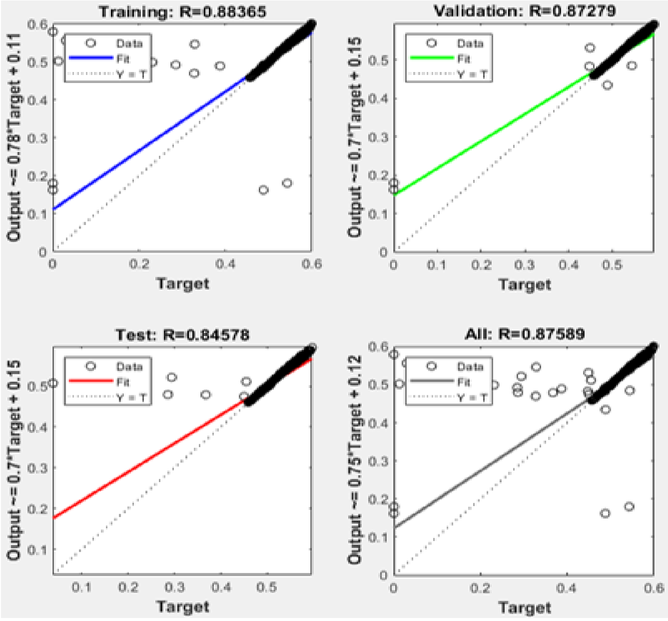

Fig. 4. Approximation and fitting performance of MLPs model for training, validation and testing data.

Table 3. Some evaluations for MLPs estimation model according to optimum results as training data.

Number of training sample for 5-bar truss	Error metrics		
	MAE	*MSE*	*RMSE*
θ_1 (rad)	1.24761e-03	1.95022e-04	1.39650e-02
θ_2 (rad)	1.24761e-03	1.95022e-04	1.39650e-02
Normalized (Min Total Length) (mm)	2.21334e-03	4.07848e-04	2.01952e-02

Table 4. Several combinations for test/controlling designs.

Cases for applied loads	Design number	Design parameters		
		P_1 (kN)	P_2 (kN)	A (mm²)
Between in defined limits	1	95.5	47.0	90.0
	2	100.0	49.25	100.2
	3	98.7	50.0	92.0
One of loads between in defined limits	4	95.8	52.0	91.3
	5	101.0	45.0	94.0
Except of defined limits	6	94.3	51.6	95.0
	7	102.6	44.5	92.5
	8	93.0	52.0	88.7

Table 5. Optimum values provided via TLBO for combinations of test designs.

Design number	TLBO results			Normalized (min total length) (mm)
	θ_1 (rad)	θ_2 (rad)	min $f(\theta_1.\theta_2)$: ΣL (mm)	
1	0.493203543	0.493203551	1135.3049	0.5560
2	0.474888911	0.474888922	1124.4249	0.5113
3	0.500114361	0.500114354	1139.5651	0.5735
4	0.500557327	0.500557337	1139.8412	0.5747
5	0.487223631	0.487223637	1131.6876	0.5412
6	0.483889577	0.483889577	1129.6983	0.5330
7	0.494758671	0.494758667	1136.2560	0.5599
8	0.503565683	0.503565688	1141.7252	0.5824

Table 6. Estimation results with errors of θ_1 compared with TLBO for each test design.

Design number	MLPs estimation	Errors according to TLBO	
	θ_1	Absolute error	Squared error
1	0.491908485	1.29506e-03	1.67717e-06
2	0.474715087	1.73824e-04	3.02148e-08
3	0.499395594	7.18767e-04	5.16626e-07
4	0.499640193	9.17134e-04	8.41135e-07
5	0.488572984	1.34935e-03	1.82075e-06
6	0.486492534	2.60296e-03	6.77539e-06
7	0.498448216	3.68954e-03	1.36127e-05
8	0.500770499	2.79518e-03	7.81306e-06
		MAE	MSE
	Mean	1.69273e-03	4.13589e-06
	RMSE		2.03369e-03

Table 7. Estimation results with errors of θ_2 compared with TLBO for each test design.

Design number	MLPs estimation	Errors according to TLBO	
	θ_2	Absolute error	Squared error
1	0.491908485	1.29507e-03	1.89391e-05
2	0.474715087	1.73834e-04	2.09410e-05
3	0.499395594	7.18759e-04	7.80162e-07
4	0.499640194	9.17144e-04	1.12704e-07
5	0.488572984	1.34935e-03	1.01318e-05
6	0.486492535	2.60296e-03	1.36866e-06
7	0.498448215	3.68955e-03	3.50331e-05
8	0.500770499	2.79519e-03	4.07105e-07
		MAE	MSE
	Mean	1.69273e-03	4.13589e-06
	RMSE		2.03369e-03

Table 8. Estimation results with errors of normalized values (min total length) compared with TLBO for each test design.

Design number	MLPs estimation	Errors according to TLBO	
	Normalized (min total length) (mm)	Absolute error	Squared error
1	0.491908485	1.29506e-03	1.67717e-06
2	0.474715087	1.73824e-04	3.02148e-08
3	0.499395594	7.18767e-04	5.16626e-07
4	0.499640193	9.17134e-04	8.41135e-07
5	0.488572984	1.34935e-03	1.82075e-06
6	0.486492534	2.60296e-03	6.77539e-06
7	0.498448216	3.68954e-03	1.36127e-05
8	0.500770499	2.79518e-03	7.81306e-06
		MAE	MSE
	Mean	1.69273e-03	4.13589e-06
	RMSE		2.03369e-03

Table 9. Converting the estimations of normalized values to actual results for minimum total bar length.

Design number	MLPs estimation	Errors according to TLBO	
	min $f(\theta_1.\theta_2)$: ΣL (mm)	Absolute error	Squared error
1	1134.6184	0.68649	0.47127
2	1124.4173	0.00758	0.00006
3	1139.2855	0.27961	0.07818
4	1139.2393	0.60190	0.36228
5	1132.8696	1.18197	1.39706
6	1131.3777	1.67941	2.82042
7	1139.4014	3.14534	9.89314
8	1139.8545	1.87075	3.49969
		MAE	MSE
	Mean	1.18163	2.31526
	RMSE		1.52160

7. Conclusions

In the present study, a hybrid application was conducted to determine numerical parameters for a structural engineering design problem as a truss model. In this respect, two independent phases were realized applied as metaheuristics-based optimization and machine learning estimation process, respectively. Here, for the first phase, optimum data for the training model was produced by utilizing a population-based optimization algorithm known as teaching-learning based optimization (TLBO); following, respect to the generation of a decision-making model, multilayer perceptrons (MLPs) were employed to estimate of defined outputs optimally, in the second phase.

For the current structural model as 5-bar, while considering of training and learning, estimation, and test processes of MLPs, this can be made as a comment that generated estimation model is very successful and capable in terms of estimating due to provided performance measurements such as correlation (almost R ≈ 88%), proper deviation and minimal errors (lower from 2% for all target outputs) among actual-predicted data. In this meaning, this model can be assumed as a predictor tool, and also benefited from converging to any parameter value of the presented structural model. Within this context, test and confirmation data were generated as different from training data which were produced intended for the usage of the establishment of the main estimation model only. According to the results of estimations and error rates, for test designs, it can be said that horizontal angles between bars and global axis (θ_1 and θ_2), and also minimum bar length (as normalized value) were determined with extremely small error amounts even if most test models' design parameters were considered as lower or upper levels from used input limits for training data.

On the other hand, the developed model is quite strong in the scope of foreseeing optimum values of best bar length, which was scaled/normalized to fit with other outputs, too. Here, it should be expressed that when estimated normalized values are transformed to target estimations for minimum bar length, definitely sufficient and remarkable error rates and so effectiveness arise according to actual optimization results for each test model. By this means, desired estimations for best bar lengths can be provided, too.

As a result, numerical estimation investigations were realized by using MPLs with the aim of detection process of objective parameters within any structural engineering design problem, and so a powerful, usable, and talented decision-making model was enhanced in terms of processing multiple data. Also, in future works, these methodologies can be evaluated for the different structural designs like reinforced concrete members, steel-frame models, slab systems, etc. To evaluate the optimization and machine learning technologies with a combination will be more valuable and usable for effective, optimal, and also cost and energy-effective solutions. Cause of these advantages, the mentioned and proposed methodology provides to decrease of the required effort, time and analysis steps besides that they make possible to precision measurements for the designs.

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