International Journal on Advanced Science Engineering Information Technology

Vol.12 (2022) No. 6
ISSN: 2088-5334

Dynamic Analysis of Soil-Structure Interaction using Ensemble-based Modified Ant Lion Optimization Algorithm

Ponnala Ramaiah [a,*], Sanjeet Kumar [a]

[a] *Civil Engineering, K L University Vaddeswaram, Guntur, India*
*Corresponding author: *ponnala_ramaiah@yahoo.com*

***Abstract*— In recent decades, the analysis of dynamic characteristics of Soil-Structure Interaction (SSI) has become an emerging research topic, where the SSI is defined as the structure's motion and the soil's response. The SSI is an important problem in solid and monstrous structures, which are built on delicate ground that changes the dynamic properties of the structures. The main objective of this research article is to propose an ensemble machine-learning algorithm for predicting the dynamic response and characteristics of SSI problems. After collecting the data from 57 structures, the data pre-processing is accomplished using Min-Max Normalization (MMN) and Max Normalization (MN) techniques that superiorly rescale the unstructured data for better prediction. Further, the data optimization is carried out using the Modified Ant Lion Optimization (MALO) algorithm that effectively optimizes the dimensionality of the data, where this process reduces the computational complexity and improves the prediction accuracy of dynamic characteristics in SSI modeling. Finally, the optimized data is given as the input to the ensemble classifier, which is a combination of Support Vector Machine (SVM) and ID3 for classifying the dynamic characteristics related to SSI, which are period Lengthening (PL), Super Structure Acceleration (SSA) and Pile Head Acceleration (PHA). The simulation results confirmed that the ensemble-based MALO algorithm improved performance in predicting the dynamic response and characteristics of SSI problems by error value. Whereas the proposed algorithm, on average, reduced 0.01-to-0.5 error value compared to the existing machine learning algorithms.**

***Keywords*— Ant lion optimization algorithm; decision tree; max-normalization; min-max normalization; soil-structure interaction; support vector machine.**

Manuscript received 30 Sep. 2021; revised 15 Mar. 2022; accepted 6 Jun. 2022. Date of publication 31 Dec. 2022.

I. INTRODUCTION

In recent times, seismic assessment has been essential for post-earthquake [1] and pre-earthquake decision-making analysis [2]. The seismic analysis is fundamental for network capacity management [3] and post-earthquake repair [4]. In civil engineering structures, the use of structural control systems is an increasing trend [5], where the reason for applying structural control systems is to decrease the structural vibrations to provide a comfortable and safe life to people [6]. As stated previously, several undesired vibrations have occurred due to natural calamities, such as earthquakes [7] and wind [8]. Hence, the structural control system has proven to be an effective approach in mitigating dynamic responses [9], and the structural control system is extensively employed in several civil structures along with energy dissipation devices [10]. The dynamic response of a structure on soft soil differs from that of an exciting structure, which is supported on firm soil [11]. The soil media [12], degree of structure [13], flexibility [14], and inertial properties [15] make SSI conceivable to scatter the vitality of the seismic waves. A few studies related to SSI response prediction is given as follows. Farfani et al. [16] combined a Support Vector Machine (SVM) and Artificial Neural Network (ANN) to predict SSI response. In this literature, three real-time datasets were utilized for training and testing the ANN to reduce the over-fitting issue by cross-validation. The neural network model effectively predicted the seismic behavior by employing parallel vectorial analysis in SVM. The experimental investigation showed that the developed model significantly predicted the SSI system's seismic response and dynamic properties with better accuracy and limited time consumption compared to the finite element methods.

In contrast, many neurons were utilized in the ANN model, which may lead to vanishing gradient concerns. Bekdaş and Nigdeli, [17] developed a hybrid optimization algorithm to design an optimum Tuned Mass Damper (TMD) for seismic structures considering SSI. In this study, two metaheuristic algorithms, the bat algorithm, and the harmony search algorithm were combined to analyze seismic structures using earthquake records. TMD's damping ratio, period, and mass were considered the optimum design variables and the design constraints. The proposed hybrid optimization algorithm identifies a precise optimum value and minimizes the optimization objectives. The computational complexity of hybrid optimization algorithms was higher than individual algorithms, which needs to be addressed as a future extension.

Ramaiah and Kumar [18] developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) with an opposition-based bat optimization algorithm to enhance prediction accuracy in SSI modeling. The experimental result showed that the developed algorithm effectively solves the problem of seismic structure response and achieves better accuracy with limited computational time compared to other individual algorithms like ANN and SVM. However, the computational cost of the ANFIS algorithm was high because of gradient learning and complex structure. Lin et al. [19] initially created a model for coupled SSI-magnetorheological damper systems, and then the motion equation was derived from the calculation model for seismic response. Further, a semi-active control approach, a modified crow search algorithm with a fuzzy logic control system, was introduced to estimate the voltage of magnetorheological dampers. The experimental analysis showed that the developed approach obtained effective performance compared to the existing approaches. The 2D bin packing was a major issue in the crow search algorithm that degraded the prediction performance in a large dataset.

Naranjo-Pérez, et al. [20] developed a new hybrid algorithm combining a harmony search algorithm and an unscented Kalman filter to determine the optimum parameters related to SSI, which was simulated in terms of a spring-damper element. The developed hybrid algorithm determines the optimum parameters by reducing the relative difference between the experimental and numerical properties of the soil structures system. In this study, the presented hybrid algorithm performance was tested in a real case study that involved an integral footbridge. Here, the parameter identification is applicable for structure systems that need to be applied for soil and structure systems. Won and Shin [21] applied ANN model to predict the seismic building performance at a given shear wave velocity and the Poisson ratio of soil. In this study, a single degree of freedom system was utilized for creating a dataset, and then the neural network performance was discussed using the R2 coefficient. The prediction accuracy of ANN in SSI modeling was better than other machine learning techniques. As mentioned earlier, the ANN model includes two major concerns: vanishing gradient and computational cost. To highlight the aforementioned issues, an ensemble-based MALO algorithm is proposed in this article for the dynamic analysis of SSI. The major contributions of this research paper are mentioned below.

- Developed MMN and MN techniques to rescale the collected data that fastened the procedure of sorting, creating, and searching the indexes.
- Proposed MALO algorithm for optimizing or decreasing the dimensionality of normalized data that efficiently reduces the "curse of dimensionality" issue and computational complexity. By using the MALO algorithm, the computational complexity of the system is linear.
- Ensemble classification technique: a combination of SVM and ID3 classifiers is introduced to classify SSI's dynamic responses and characteristics. The proposed ensemble-based MALO algorithm performance is validated using error value and compared with the existing algorithms.

This paper is structured as follows. A detailed explanation of the proposed ensemble-based MALO algorithm is given in Section II. The simulation results of the proposed ensemble-based MALO algorithm are discussed in Section III. The conclusion of this research work is described in Section IV.

II. Materials and Methods

In this research article, the proposed model consists of four phases: data collection, pre-processing, optimization, and classification. In this scenario, the proposed ensemble-based MALO algorithm forecasts dynamic responses as well as characteristics of SSI problems. The dataset includes 57 structures, which are collected under many seismic tremors. The main objective of the proposed model is to lessen the complexity and analysis time of SSI modeling. The MALO algorithm optimizes the collected attributes to improve the structure performance, and then the prediction is accomplished using the ensemble machine learning technique. The dynamic properties of structures, including damping proportion and basic period, are assessed by using the proposed model.

A. Data pre-processing

After collecting the data, the normalization techniques: MMN and MN are used to overcome issues such as dominant features and the presence of outliers. Let us consider a dataset $D$with f attributes and N instances, which is mathematically represented in equation (1).

$$D = \{x_{i,n}, y_n | i \in f \ and \ n \in N\} \qquad (1)$$

Where y represents the class label and x denotes the data to be learned by a machine learning technique. The undertaken normalization techniques: MMN and MN, do not make multiplicative effects on the collected data that significantly decrease the outlier effects. Here, the minimum and maximum values of unstructured or collected data are utilized for rescaling in MMN and MN techniques. At first, the MN technique is a variant of MMN, where each attribute is rescaled within the range of -1 to 1 [22-23]. By categorizing every attribute by its maximum value, MN technique rescales the unstructured data, which is defined in equation (2).

$$x_{i,n}^{'} = \frac{x_{i,n}}{max(|x_i|)} \qquad (2)$$

Correspondingly, the MMN technique linearly scales the unstructured data to pre-defined lower and upper bounds. In this scenario, the unstructured data is rescaled within the range of 0 to 1, and -1 to 1, which is mathematically determined in equation (3).

$$x_{i,n}^{'} = \frac{x_{i,n} - min(x_i)}{max(x_i) - min(x_i)} (nMax - nMin) + nMin \qquad (3)$$

Where min and max values represent a maximum and minimum value of i^{th} attribute. The lower and upper bounds rescale the un-structured or collected data with $nMin$ and

$nMax$. In this study, (MMN0) [0, 1] and (MMN1) [-1, 1] scales are utilized for SSI response prediction. Normalization techniques: MMN and MN are utilized to preserve the relation between normalized data based on the data's mean and standard deviation [24].

B. Data optimization

After normalizing the data, optimization is accomplished using MALO algorithm. The ALO algorithm delivers multiple solutions for optimizing the concerns related to the "curse of dimensionality". Generally, the ALO algorithm mimics the behavior of ant lion, and the process involved in the MALO algorithm is given as follows.

Step 1: At first, ant population is set in the walk space.

Step 2: In each iteration, an objective function is used for analyzing the ant fitness.

Step 3: The ant randomly walks into the search space.

Step 4: In 1st iteration, the ant lion location is assumed as ant position, which is changed based on ant movement.

Step 5: The ant lion is an elite, which has an impact on the ant movements in all directions.

Step 6: The ant lion is replaced with elite if it delivers an effective impact on the ant movements.

Step 7: Repeat steps 2 to 6, until the algorithm has obtained a satisfactory result.

Step 8: The elite ant lion's fitness value and its position provide effective estimation [25].

MALO algorithm aims to identify and analyze the position of ant. At first, ant randomly walks in the search space (normalized data x_i'), as mathematically defined in equation (4).

$$x_i' = \frac{(x^t{}_i - k_i)\times(p^t{}_i - q^t{}_i)}{(l_i - k_i)} + q^t{}_i \tag{4}$$

Where, $p^t{}_i$ specifies minimum variable at t^{th} iteration, t represents random walk, $q^t{}_i$ represents maximum i^{th} variable at t^{th} iteration, $k^t{}_i$ and $l^t{}_i$ represents minimum and maximum random walk respectively. After random walk, catch the ant using equation (5).

$$AL^t{}_v = A^t{}_u, \text{ If } f(A^t{}_u) < f(AL^t{}_v) \tag{5}$$

Where, AL indicates ant-lion, A represents ant, v indicates selected ant-lion, and u denotes ant-lion position. The final step in the MALO algorithm is elitist, where the fitness function of the ant-lion is selected. In the ant-lions gravity, the random walk is towards the selected ant-lion, whereas the random walk of the elite ant-lion is accomplished using tournament selection methodology [26]. Using equation (6), the corresponding ant-lion is selected based on the roulette wheel. Where R states the random walk of ant-lion and E represents the random walk of the elite at i^{th} iteration. In order to decrease the complexity and analysis time in SSI modeling, MALO algorithm is proposed, and its modification is done in equation (5). The MALO algorithm's parameter settings are as follows; population size is 50, number of iterations is 100, and number of runs is 10. After optimizing the attribute related to SSI modelling, the ensemble machine learning technique accomplishes the prediction. The flowchart of MALO algorithm is given in figure 1.

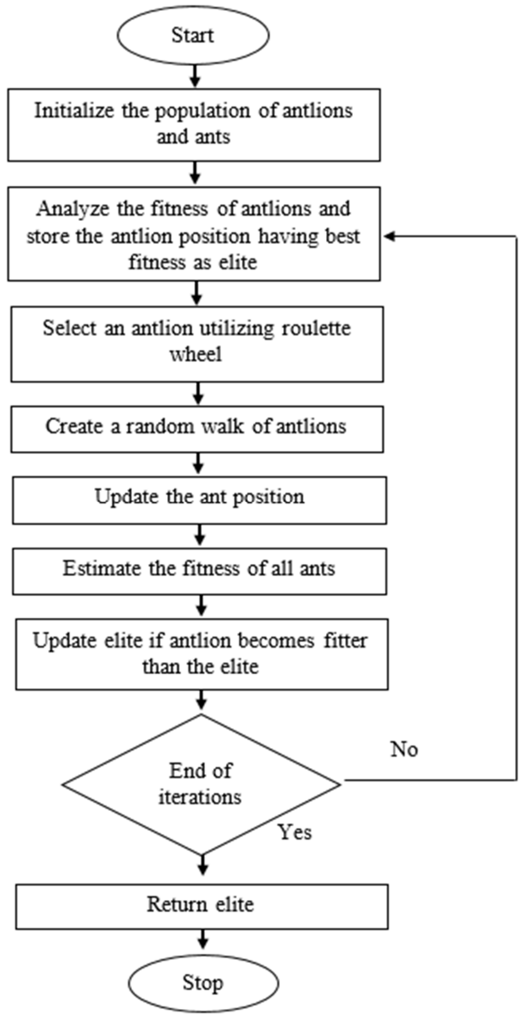

Fig. 1 Flowchart of MALO algorithm

$$A^t{}_u = \frac{R^t{}_A + R^t{}_E}{2} \tag{6}$$

C. Classification

After data optimization, the ensemble classifier is accomplished by utilizing two machine learning classifiers: decision tree (ID3 technique) and SVM. The ensemble classifier enhances the classification results compared to individual classifiers. The main objective of an ensemble classifier is to learn a set of classification techniques and vote for the best results. The ensemble classifier reduces the spread or dispersion of the model's performance. The ID3 is a greedy technique that generates a decision tree based on the top-to-down technique. The input and output of ID3 are very clear compared to other classification techniques. All categories of the attributes are involved in generating an ID3 that creates wide and shallow trees. The ID3 technique selects the test attributes by estimating and comparing the information gains. If the class attributes C has different features m then the class labels are indicated as $C_i(i = 1,2,\dots,m)$. Additionally, the number of samples S_i in the class are denoted as $S_i(i = 1,2,\dots,m)$. Information I required to classify S is mathematically determined in equation (7) [27].

$$I\ (S_1, S_2, \dots . S_m) = -\sum_{i=1}^{m} \quad p_i log_2 p_i \tag{7}$$

Where, p_i represents the probability of instances. Let us consider the attributes f having different values z in the training dataset $\{f_1, f_2, f_3 \ldots f_z\}$. If f is a nominal attribute, then the attributes split S into z sub-sets such that $\{S_1, S_2, S_3 \ldots . S_z\}$. Nevertheless, the instances in S_j have dissimilar class labels. Let S_{ij} is an attribute set whose class labels are C_i in the sub-set $\{S_j | f = f_j, j \in 1,2, \ldots z,\ S_j \in S\}$, where attribute $f = f_j$ [28]. The information required to split the training dataset is defined in equation (8).

$$E(f) = \sum_{i=1}^{z} \frac{(s_{1j}+s_{2j}+\cdots+s_{mj})}{s} \times I(s_{1j} + s_{2j} + \cdots + s_{mj}) \quad (8)$$

The more purity of a sub-set is mathematically determined in equation (9).

$$I\left(S_{1j}, S_{2j}, \ldots . S_{mj}\right) = -\sum_{i=1}^{m} p_{ij} \log_2 p_{ij} \quad (9)$$

Where, p_{ij} represents the probability of instances that belongs to class C_i. Further, the information gain of f is determined using equation (10).

$$Information\ gain\ (f) = I\,(S_1, S_2, \ldots . S_m) - E(f) \quad (10)$$

The attributes f with maximum information gain are used as the test attributes to the internal node in a decision tree. In this manner, the required information is used to classify instances, which should be minimal. Additionally, SVM is a discriminative classifier that is specified by a distinct hyperplane. The SVM classifier can process higher-dimension data, so it is extensively used in several applications. Specifically, the SVM classifier performs well in solving a 2-class problem associated with structure principles and vapnik-Chervonenkis theories [29], [30]. The general formula to determine linear discriminant function is mathematically stated in equation (11).

$$w.x + b = 0 \quad (11)$$

The optimal hyperplane in SVM classifier is utilized to classify the samples or instances without noise that is mathematically defined in equation (12). Further, decrease $\|w^2\|$ in equation (12), so the optimization issue is reduced using the saddle point of Lagrange multipliers α_i. The optimum discriminant function $o(x)$ is mathematically defined in equation (13).

$$pi[w.x + b] - 1 \geq 0, i = 1,2, .. N \quad (12)$$

$$o(x) = sign\left\{\left(w^* x\right) + b^*\right\} = sign\left\{\sum_{i=1}^{N} \alpha_i^* . pi\left(x_i^* - x\right) + b^*\right\} \quad (13)$$

Lastly, interior product $(x_i^* - x)$ is interchanged using linear-kernel function $k(x, x')$ in equation (13) that reduces the computational complexity, while using high dimensional data. Further, linear separability of the optimized samples is enhanced, and the discriminant function is rewritten as stated in equation (14). The experimental investigation of the proposed model is briefly denoted in section 4.

$$o(x) = sign\left\{\sum_{i=1}^{N} \alpha_i^* . pi.k\left(x, x_i\right) + b^*\right\} \quad (14)$$

III. Results and Discussion

In this segment, SSI's dynamic responses and characteristics are discussed using the proposed ensemble-based MALO algorithm. In this scenario, the proposed algorithm performance is validated utilizing MATLAB 2019 software tool, which runs on a computer with 16 GB random access memory, 8TB hard disk, and Intel core i9 processor. The analysis of SSI is performed with the collected data, which is stated in table 1. The collected data includes SSI consequences for 57 structures, which have dissimilar structure systems that are collected under several seismic tremors. In this study, the dynamic characteristics: PHA, PL and SSA are investigated on the basis of mass, Peak Base Accelerator (PBA), length, Amplitude Factor (AM), and number of pile structure. Validation tests between the real and the obtained results of testing data are described as follows.

TABLE I
Experimental Data

Input					**Output**		
PBA	**AM (m/s)**	**Mass (kg)**	**Length (m)**	**N-pile**	**SSA (%)**	**PHA (%)**	**PL (%)**
0.01	0.22	193	7.72	4	0.05	0.05	1.15
0.04	0.54	46.06	2.20	1	0.13	0.05	1.10
0.08	0.96	193	7.73	4	0.13	0.13	1.20
0.15	2.09	44	2.20	1	0.85	0.35	1.05
0.26	3.74	90	0.60	1	0.94	0.75	1.10
0.32	4.59	90	0.64	1	1	0.90	1.07
0.47	5.79	193.02	7.73	4	0.70	0.45	1.20

Tables 2 and 3 give the analysis of dynamic properties: SSA, PL, PHA and error rates for individual classifiers and the proposed ensemble classifier. By investigating tables 2 and 3, the proposed ensemble classifier obtained the finest solution compared to the individual classifiers: SVM, and ID3. As seen in tables 2 and 3, the ensemble classifier with MALO algorithm has significantly decreased the error value in all three cases (SSA, PL and PHA) compared to SVM classifier with MALO algorithm, and ID3 classifier with MALO algorithm.

Correspondingly, tables 4 and 5 investigate the dynamic characteristics: SSA, PL, PHA and error rates for different optimization algorithms (bat algorithm, ALO and MALO) with ensemble classifier. The proposed MALO algorithm with ensemble classifier has obtained good performance compared to other optimization algorithms with ensemble classifier.

TABLE II
SIMULATION RESULTS OF INDIVIDUAL AND ENSEMBLE CLASSIFIER WITH MALO ALGORITHM

PHA				**SSA**				**PL**			
Modified ALO algorithm											
Data	ID3	SVM	Ensemble	Data	ID3	SVM	Ensemble	Data	ID3	SVM	Ensemble
0.76	0.82	1.04	0.54	0.93	0.83	1.03	0.57	1.1	0.95	0.82	0.46
0.88	0.83	1.12	0.39	1.02	0.96	1.05	0.68	1.05	0.90	0.85	0.30
0.18	0.53	1.09	0.23	0.09	0.92	1.12	0.70	1.27	0.79	1.02	0.73
0.13	0.44	0.87	0.19	0.26	0.80	1.20	0.37	0.26	0.84	1.12	0.68
0.47	0.76	0.73	0.49	0.67	0.78	0.84	0.49	0.67	0.95	0.98	0.39

TABLE III
ERROR VALUE OF INDIVIDUAL AND ENSEMBLE CLASSIFIER WITH MALO ALGORITHM

PHA				**SSA**				**PL**			
Modified ALO algorithm											
Data	ID3	SVM	Ensemble	Data	ID3	SVM	Ensemble	Data	ID3	SVM	Ensemble
0.76	0.54	0.60	0.05	0.93	0.35	0.26	0.05	1.1	0.36	0.24	0.03
0.88	0.82	0.25	0.03	1.02	0.43	0.20	0.07	1.05	0.48	0.33	0.01
0.18	0.64	0.12	0.04	0.09	0.89	0.13	0.09	1.27	0.62	0.19	0.03
0.13	0.58	0.10	0.07	0.26	0.42	0.12	0.11	0.26	0.60	0.18	0.02
0.47	0.40	0.09	0.01	0.67	0.47	0.18	0.02	0.67	0.57	0.17	0.01

TABLE IV
SIMULATION RESULTS OF DIFFERENT OPTIMIZATION ALGORITHMS WITH ENSEMBLE CLASSIFIER

PHA				**SSA**				**PL**			
Ensemble classifier											
Data	Bat	ALO	MALO	Data	Bat	ALO	MALO	Data	Bat	ALO	MALO
0.76	0.80	1.09	0.54	0.93	0.80	1.10	0.57	1.1	0.98	0.85	0.46
0.88	0.72	1.14	0.39	1.02	0.95	1.06	0.68	1.05	0.92	0.87	0.30
0.18	0.59	1.10	0.23	0.09	0.87	1.09	0.70	1.27	0.81	1.04	0.73
0.13	0.48	0.80	0.19	0.26	0.88	1.13	0.37	0.26	0.89	1.19	0.68
0.47	0.70	0.75	0.49	0.67	0.75	0.87	0.49	0.67	0.92	1.02	0.39

TABLE V
ERROR VALUE OF DIFFERENT OPTIMIZATION ALGORITHMS WITH ENSEMBLE CLASSIFIER

PHA				**SSA**				**PL**			
Ensemble classifier											
Data	Bat	ALO	MALO	Data	Bat	ALO	MALO	Data	Bat	ALO	MALO
0.76	0.50	0.68	0.05	0.93	0.38	0.13	0.05	1.1	0.29	0.22	0.03
0.88	0.80	0.28	0.03	1.02	0.23	0.12	0.07	1.05	0.24	0.13	0.01
0.18	0.59	0.18	0.04	0.09	0.72	0.19	0.09	1.27	0.30	0.16	0.03
0.13	0.32	0.19	0.07	0.26	0.49	0.14	0.11	0.26	0.20	0.17	0.02
0.47	0.48	0.13	0.01	0.67	0.25	0.19	0.02	0.67	0.17	0.12	0.01

A. Comparative analysis

The comparative analysis between the proposed and the existing algorithms are given in Table 6. Farfani et al. [16] combined both SVM and ANN classifiers to predict SSI response. Further, Ramaiah and Kumar [18] introduced a new algorithm: ANFIS with Opposition based bat optimization algorithm for improving the prediction accuracy in SSI modeling. The graphical comparison of the proposed and the existing algorithms in terms of three dynamic characteristics (SSA, PL and PHA) is denoted in figure 2.

B. Discussion

Compared to these existing papers, the proposed ensemble-based MALO algorithm obtained better performance in predicting SSI response. In this research paper, optimization is an integral part, which effectively optimizes the parametric values related to SSI. The computational complexity of the system and the "curse of dimensionality" issue are reduced by optimizing or selecting the relevant attributes. The computational complexity of ensemble-based MALO algorithm is linear $O(n)$, where n states input size and O indicates the order of magnitude.

TABLE VI
COMPARATIVE ANALYSIS BETWEEN THE PROPOSED AND THE EXISTING ALGORITHMS

PHA					**SSA**					**PL**				
Data	**SVM [16]**	**ANN [16]**	**ANFIS [18]**	**Proposed**	**Data**	**SVM [16]**	**ANN [16]**	**ANFIS [18]**	**Proposed**	**Data**	**SVM [16]**	**ANN [16]**	**ANFIS [18]**	**Proposed**
0.76	1.04	0.73	0.79	0.54	0.93	1.03	0.91	0.94	0.57	1.1	0.82	0.87	1.08	0.46
0.88	1.12	0.98	0.85	0.39	1.02	1.05	0.91	0.98	0.68	1.05	0.85	0.81	1.08	0.30
0.18	1.09	0.83	0.20	0.23	0.09	1.12	0.87	0.17	0.70	1.27	1.02	0.80	0.78	0.73
0.13	0.87	0.78	0.18	0.19	0.26	1.20	0.66	0.38	0.37	0.26	1.12	1.02	0.66	0.68
0.47	0.73	0.76	0.68	0.49	0.67	0.84	0.95	0.78	0.49	0.67	0.98	0.99	0.88	0.39

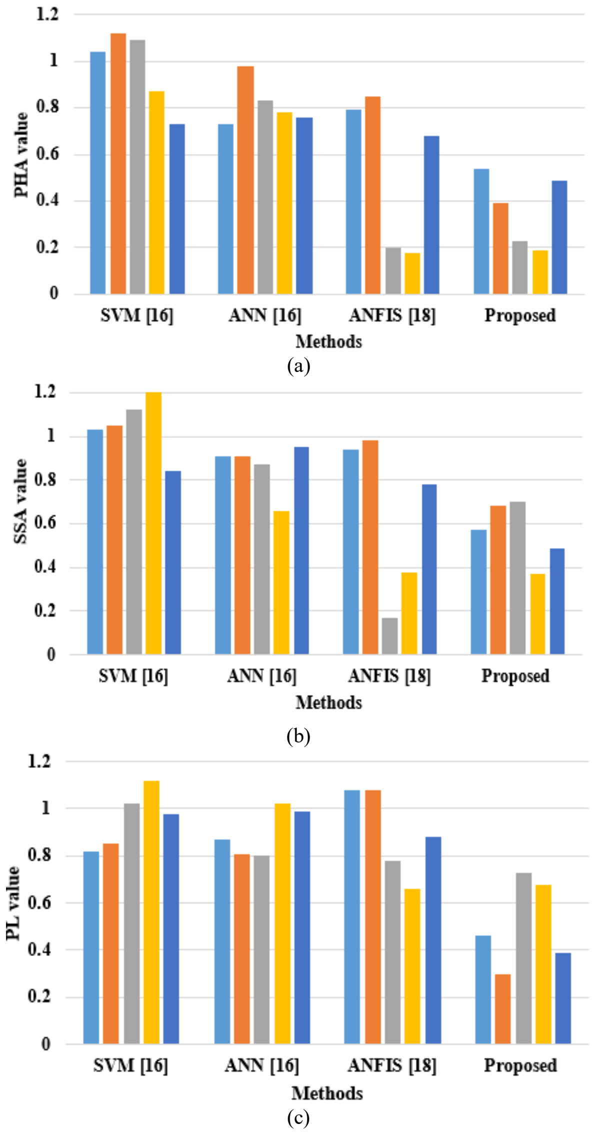

Fig. 2. Graphical comparison of proposed and the existing algorithms; a) PHA, b) SSA, and c) PL characteristics

IV. Conclusion

This research article proposes an ensemble-based MALO algorithm to predict the dynamic responses and characteristics of SSI problems. This article includes three major steps: data pre-processing, data optimization and classification. Here, two effective normalization techniques known as MMN and MN are utilized to rescale the collected data that fasten the process of searching, creating and sorting the indexes. Next, the MALO algorithm is introduced for data optimization, which significantly reduces the computational complexity and curse of dimensionality problems. Lastly, classification is accomplished using an ensemble classifier (SVM + ID3) for classifying the dynamic characteristics related to SSI such as SSA, PL and PHA. In this article, the dynamic characteristics are analyzed based on number of pile structure, peak base accelerator, amplitude factor, length and mass. As seen in comparative analysis phase, the proposed ensemble-based MALO algorithm reduced 0.01 to 0.5 error value on an average compared to existing algorithms like SVM, ANFIS, and ANN. The proposed ensemble-based MALO algorithm can be validated on complex structures with detailed SSI information in future work.

Nomenclature

Parameters	Definition
x	Data
y	Class label
min and max	Minimum and maximum value of i^{th} attribute
t	Random walk
AL	Ant-lion
A	Ant
v	Selected ant-lion
u	Ant-lion position
R	Random walk of ant-lion
E	Random walk of elite at i^{th} iteration
p_i	Probability of instances

References

[1] S. Liu, P. Li, W. Zhang, and Z. Lu, "Experimental study and numerical simulation on dynamic soil-structure interaction under earthquake excitations," *Soil Dyn. Earthquake Eng.*, vol. 138, pp. 106333, Nov. 2020. https://doi.org/10.1016/j.soildyn.2020.106333

[2] S. Radkia, R. Rahnavard, H. Tuwair, F. A. Gandomkar, and R. Napolitano, "Investigating the effects of seismic isolators on steel asymmetric structures considering soil-structure interaction," *Struct.*, vol. 27, pp. 1029-1040, Oct. 2020. https://doi.org/10.1016/j.istruc.2020.07.019

[3] M. I. Peerun, D. E. L. Ong, C. S. Choo, and W. C. Cheng, "Effect of interparticle behavior on the development of soil arching in soil-structure interaction," *Tunnelling Underground Space Technol.*, vol. 106, pp. 103610, 2020. https://doi.org/10.1016/j.tust.2020.103610

[4] F. Homaei, and M. Yazdani, "The probabilistic seismic assessment of aged concrete arch bridges: The role of soil-structure interaction," *Struct.*, vol. 28, pp. 894-904, Dec. 2020.

[5] R. Scarfone, M. Morigi, and R. Conti, "Assessment of Dynamic soil-structure interaction effects for tall buildings: A 3D numerical approach," *Soil Dyn. Earthquake Eng.*, vol. 128, no. 1, pp. 105864, Jan. 2020, DOI: 10.1016/j.soildyn.2019.105864.

[6] A. Krishnamoorthy, and S. Anita, "Soil-structure interaction analysis of a FPS-isolated structure using finite element model," *Struct.*, vol. 5, pp. 44-57, Feb. 2016. DOI: 10.1016/j.istruc.2015.08.003.

[7] Y. Lu, I. Hajirasouliha, and A. M. Marshall, "An improved replacement oscillator approach for soil-structure interaction analysis considering soft soils," *Eng. Struct.,* vol. 167, pp. 26-38, Jul. 2018. DOI: 10.1016/j.engstruct.2018.04.005.

[8] S. F. Fathizadeh, A. R. Vosoughi, and M. R. Banan, "Considering soil-structure interaction effects on performance-based design optimization of moment-resisting steel frames by an engineered cluster-based genetic algorithm," *Eng. Optim.*, vol. 53, no. 3, pp. 440-460, Mar. 2021. DOI: 10.1080/0305215x.2020.1739278.

[9] M. Azimi, and A. M. Yeznabad, "Swarm-based parallel control of adjacent irregular buildings considering soil-structure interaction," *Journal of Sensor and Actuator Networks*, vol. 9, no. 2, pp. 18, Mar. 2020. DOI: 10.3390/jsan9020018.

[10] J. Gong, D. Zou, X. Kong, J. Liu, and K. Chen, "A coupled meshless-SBFEM-FEM approach in simulating soil-structure interaction with cross-scale model," *Soil Dyn. Earthquake Eng.*, vol. 136, no. 1, pp. 106214, Sep. 2020. DOI: 10.1016/j.soildyn.2020.106214.

[11] J. Naranjo-Pérez, M. Infantes, J. F. Jiménez-Alonso, and A. Sáez, "A collaborative machine learning-optimization algorithm to improve the finite element model updating of civil engineering structures," *Eng. Struct.*, vol. 225, pp. 111327, Dec. 2020. DOI: 10.1016/j.engstruct.2020.111327.

[12] A. Kaveh, K. B. Hamedani, S. M. Hosseini, and T. Bakhshpoori, "Optimal design of planar steel frame structures utilizing meta-heuristic optimization algorithms," *Struct.*, vol. 25, pp. 335-346, Jun. 2020. DOI: 10.1016/j.istruc.2020.03.032.

[13] L. V. Andersen, "Dynamic soil-structure interaction of polypod foundations," *Comput. Struct.*, vol. 232, no. 2, pp. 105966, May. 2020. DOI: 10.1016/j.compstruc.2018.07.007.

[14] E. N. Tochaei, T. Taylor, and F. Ansari, "Effects of near-field ground motions and soil-structure interaction on dynamic response of a cable-stayed bridge," *Soil Dyn. Earthquake Eng.*, vol. 133, no. 5, pp. 106115, Jun. 2020. DOI: 10.1016/j.soildyn.2020.106115.

[15] S. Hoseini, A. Ghanbari, and M. R. Nazari, "Estimation of soil-pile stiffness under the bridge piers considering soil-structure interaction using artificial neural network model," *Journal of Engineering Geology*, vol. 14, no. 2, pp. 283-308, Aug. 2020.

[16] H. A. Farfani, F. Behnamfar, and A. Fathollahi, "Dynamic analysis of soil-structure interaction using the neural networks and the support vector machines," *Expert Syst. Appl.*, vol. 42, no. 22, pp. 8971-8981, Dec. 2015. DOI: 10.1016/j.eswa.2015.07.053.

[17] G. Bekdaş, and S. M. Nigdeli, "Metaheuristic based Optimization of Tuned Mass Dampers under Earthquake Excitation by Considering Soil-Structure Interaction," *Soil Dyn. Earthquake Eng.*, vol. 92, pp. 443-461, Jan. 2017. DOI: 10.1016/j.soildyn.2016.10.019.

[18] P. Ramaiah, and S. Kumar, "Dynamic analysis of soil structure interaction (SSI) using ANFIS model with OBA machine learning approach," *International Journal of Civil Engineering and Technology*, vol. 9, no. 11, pp. 496-512, Nov. 2018.

[19] X. Lin, S. Chen, and W. Lin, "Modified crow search algorithm-based fuzzy control of adjacent buildings connected by magnetorheological dampers considering soil-structure interaction," *J. Vib. Control.*, vol. 27, no. 1-2, pp. 57-72, Jan. 2021. DOI: 10.1177/1077546320923438.

[20] J. Naranjo-Pérez, J. F. Jimenez-Alonso, and A. Sáez, "Parameter identification of the dynamic winkler soil-structure interaction model using a hybrid unscented kalman filter-multi-objective harmony search algorithm," *Adv. Struct. Eng.*, vol. 23, no. 12, pp. 2653-2668, Sep. 2020. DOI: 10.1177/1369433220919074.

[21] J. Won, and J. Shin, "Development of artificial neural network model for prediction of seismic response of building with soil-structure interaction," *Journal of the Korean Geotechnical Society*, vol. 36, no. 8, pp. 7-15, Aug. 2020. https://doi.org/10.7843/kgs.2020.36.8.7.

[22] L. Munkhdalai, T. Munkhdalai, K. H. Park, H. G. Lee, M. Li, and K. H. Ryu, "Mixture of activation functions with extended min-max normalization for forex market prediction," IEEE Access, vol. 7, pp. 183680-183691, Dec. 2019. DOI: 10.1109/access.2019.2959789.

[23] S. Jain, S. Shukla, and R. Wadhvani, "Dynamic selection of normalization techniques using data complexity measures," *Expert Syst. Appl.*, vol. 106, pp. 252-262, Sep. 2018. DOI: 10.1016/j.eswa.2018.04.008.

[24] L. Friedman, and O. V. Komogortsev, "Assessment of the effectiveness of seven biometric feature normalization techniques," *IEEE Trans. Inf. Forensics Secur.*, vol. 14, no. 10, pp. 2528-2536, Oct. 2019. DOI: 10.1109/TIFS.2019.2904844.

[25] M. Wang, C. Wu, L. Wang, D. Xiang, and X. Huang, "A feature selection approach for hyperspectral image based on modified ant lion optimizer," *Knowledge Based Syst.*, vol. 168, pp. 39-48, Mar. 2019. DOI: 10.1016/j.knosys.2018.12.031.

[26] S. K. Dinkar, and K. Deep, "An efficient opposition based lévy flight ant-lion optimizer for optimization problems," *Journal of Computational Science*, vol. 29, pp. 119-141, Oct. 2018. DOI: 10.1016/j.jocs.2018.10.002.

[27] S. Yang, J. Z. Guo, and J. W. Jin, "An improved Id3 algorithm for medical data classification," *Comput. Electr. Eng.*, vol. 65, pp. 474-487, Jan. 2018. DOI: 10.1016/j.compeleceng.2017.08.005.

[28] S. Sathyadevan, and R. R. Nair, "Comparative analysis of decision tree algorithms: ID3, C4. 5 and random forest," *Computational Intelligence in Data Mining*, vol. 1, pp. 549-562, Dec. 2015. DOI: 10.1007/978-81-322-2205-7_51.

[29] R. Vijayarajeswari, P. Parthasarathy, S. Vivekanandan, and A. A. Basha, "Classification of mammogram for early detection of breast cancer using SVM classifier and hough transform," *Measurement*, vol. 146, no. 1, pp. 800-805, Jun. 2019. DOI: 10.1016/j.measurement.2019.05.083.

[30] M. Tanveer, C. Gautam, and P. N. Suganthan, "Comprehensive evaluation of twin SVM based classifiers on UCI datasets," *Appl. Soft Comput.*, vol. 83, pp. 105617, Jul. 2019. DOI: 10.1016/j.asoc.2019.105617.