Title	An advanced binary slime mould algorithm for feature subset selection in structural health monitoring data
Authors(s)	Ghiasi, Ramin, Malekjafarian, Abdollah
Publication date	2022-08-26
Publication information	Ghiasi, Ramin, and Abdollah Malekjafarian. "An Advanced Binary Slime Mould Algorithm for Feature Subset Selection in Structural Health Monitoring Data." CERAI, 2022.
Conference details	The 2022 Civil Engineering Research in Ireland (CERI) and Irish Transportation Research Network (ITRN) Conference, Dublin, Ireland, 25-26th August 2022
Publisher	CERAI
Item record/more information	http://hdl.handle.net/10197/26013

An advanced binary slime mould algorithm for feature subset selection in structural health monitoring data

Ramin Ghiasi[1], Abdollah Malekjafarian[1]
[1]Structural Dynamics and Assessment Laboratory, School of Civil Engineering, University College Dublin, D04V1W8 Dublin, Ireland
email: rghiasi.s@gmail.com, abdollah.malekjafarian@ucd.ie

ABSTRACT: Feature selection (FS) is an important task for data analysis, pattern classification systems, and data mining applications. In this paper, an advanced version of binary slime mould algorithm (ABSMA) is introduced for feature subset selection to enhance the capability of the original slime mould algorithm (SMA) for processing of measured data collected from monitoring sensors installed on structures. In the first step, structural response signals under ambient vibration are pre-processed according to statistical characteristics for feature extraction. In the second step, extracted features of a structure are reduced using an optimization algorithm to find a minimal subset of salient features by removing noisy, irrelevant and redundant data. Finally, the optimized feature vectors are used as inputs to the surrogate models based on radial basis function neural network (RBFNN). A benchmark dataset of a wooden bridge model is considered as a test example. The results indicate that the proposed ABSMA shows better performance and convergence rate in comparison with four well-known metaheuristic optimizations. Furthermore, it can be concluded that the proposed feature subset selection method has the capability of more than 80% data reduction.

KEY WORDS: Feature selection; Binary slime mould algorithm; Surrogate model, Data reduction.

1 INTRODUCTION

Vibration-based structural health monitoring (SHM) has been widely explored over the past decades. Avci et al. [1] and Das et al. [2] presented a comprehensive review of various vibration-based damage detection methods and their applications to civil structures and infrastructures. Recently, with the fast development in sensing technologies [3], [4], signal processing techniques [5], [6], and machine learning [7], [8], a number of advanced methods have been proposed [10,11]. Gharehbaghi al. [9] recently reviewed the new development of SHM for civil engineering structures.

In vibration-based SHM, damage identification is performed from vibration signals measured simultaneously at different locations of the structure [10]. Damage detection can be performed in the time domain from the raw sensor data or in the feature domain, in which damage-sensitive features are first extracted from the time series, This process is referred to as feature extraction [11].

Another importing step in extracting the useful information and signal processing is FS [12], [13]. FS is generally used in machine learning, especially when the learning task involves high-dimensional datasets. The primary purpose of FS is to choose a subset of available features, by eliminating features with little or no predictive information and also redundant features that are strongly correlated [12]–[14]. The availability of large amounts of data represents a challenge to classification analysis. For example, the use of many features may require the estimation of a considerable number of parameters during the classification process. Ideally, each feature used in the classification process should add an independent set of information. Often, however, features are highly correlated, and this can suggest a degree of redundancy in the available information which may have a negative impact on classification accuracy (CA) [12]. Thus, the FS approaches is needed to tackle these problems.

For a large number of features, evaluating all states is computationally non-feasible and therefore metaheuristic search methods are required. Due to the inefficiency of traditional search approaches in solving complex combinatorial optimization problems various metaheuristics have been proposed, such as Particle Swarm Optimization (PSO)[15], Genetic Algorithm (GA)-based attribute reduction [16], Gravitational Search Algorithm (GSA) [17].

The metaheuristic algorithms above-mentioned strengths motivated us to present a metaheuristic-based method for FS in SHM. SMA [18] is a novel and robust metaheuristic algorithm proposed to solve continuous problem and it's inspired by the propagation and foraging of the slime mould and includes a unique mathematical model. However, considering that the FS is a combinatorial optimization problem, a binary version of SMA is used [19], and its performance is improved by incorporating two new operators in algorithm: mutation and crossover.

The main focus of this research is facilitating the processing of large data set in SHM [20]. Accordingly, the integrated system consists of three blocks is used in this paper. Firstly, statistical characteristics of structural response signals under ambient vibration are extracted, and feature vectors are obtained. Subsequently, the best feature subset is selected by the ABSMA algorithm based on desirability index using F-score [21]. In the final step, selected feature is employed for training the surrogate model based on RBFNN.

The proposed method's performance is evaluated statistically on benchmark dataset of wooden bridge model [22]. Furthermore, the efficacy of using ABSMA as the main algorithm for FS is compared to Binary Particle Swarm Optimization (BPSO) [15], binary Harris hawks optimization(BHHO) [23], binary whale optimization algorithm (BWOA) [24] and binary farmland fertility optimization algorithm (BFFA) [25]. Moreover, the impact of various transfer functions on accuracy of ABSMA is also accessed

2 DAMAGE DETECTION PROCEDURE BASED ON THE PROPOSED ALGORITHM

Figure 1 presents a summary of the method employed in this paper for an optimal feature subset selection and health monitoring of structures. The method consists of three main blocks:
(A) The Feature Extraction Block, (B) The FS Block and (C) The Feature Classification Block.

Figure 1. Summary of damage detection approach

2.1 Feature Extraction block: Statistical Features (SF)

Time-domain vibrational signals collected from sensors can be pre-processed to form feature vectors using the functions shown in Table 1. The features of each sensor are: root mean square, variance, skewness, kurtosis, crest factor, the maximum and range of acceleration response signal of each sensor [26].

Table 1. Time-domain features

Feature	Function
Root mean square	$rms = \sqrt{\frac{\sum_{n=1}^{N}(x(n))^2}{N}}$
Variance	$var = \sigma^2 = \frac{\sum_{n=1}^{N}(x(n) - mean(x))^2}{(N-1)}$
Skewness	$skewness = \frac{\sum_{n=1}^{N}(x(n) - mean(x))^3}{(N-1)\sigma^3}$
Kurtosis	$kurtosis = \frac{\sum_{n=1}^{N}(x(n) - mean(x))^4}{(N-1)\sigma^4}$
Crest factor	$crest = \frac{\max \lvert x(n)\rvert}{rms}$
Maximum value	$max = \max \lvert x(n)\rvert$
Range	$range = \max\lvert x(n)\rvert - \min\lvert x(n)\rvert$

These features represent the energy, the vibration amplitude and the time series distribution of the signal in time-domain [26].

2.2 FS Block: ABSMA

In second block, the best subset of extracted features will be selected using ABSMA based on the objective function that will describe in next subsection. SMA is proposed by [18] based on the oscillation mode of slime mould in nature. The proposed SMA has several features with a unique mathematical model that uses adaptive weights to simulate the process of producing positive and negative feedback of the propagation wave of slime mould based on bio-oscillator and to form the optimal path for connecting food with excellent exploratory ability and exploitation propensity. For complete details, please refer to main paper by Li et al. [18]. The logic of SMA is shown in Figure 2.

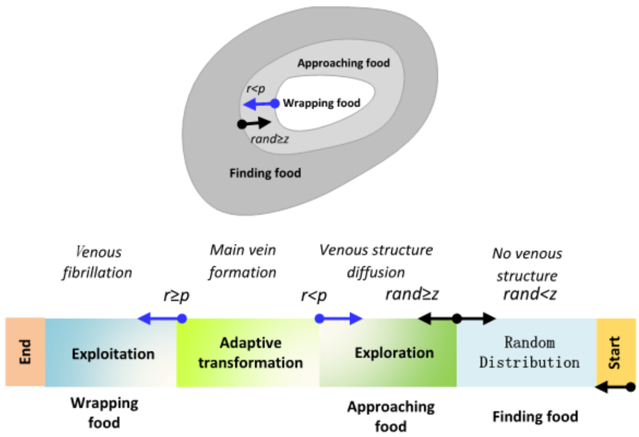


Figure 2. The overall steps of SMA [18].

2.2.1 Binary Slime mould algorithm (BSMA)

All meta-heuristics start with the initialization step to spread the solutions within the search space of the optimization problem. Accordingly, the proposed algorithm is initialized by creating a population of n moulds. Each mould which represents a solution to the optimization process that has d dimensions equal to the number of features in the used dataset. The FS problem is considered a discrete problem as it is based on choosing a number of features that provides the machine learning methods with better CA. Therefore, for each dimension, the proposed algorithm is randomly initialized with a value of 1 for the accepted feature or 0 as the rejected one as shown in Figure 3. This provides the representation of an initial solution for the FS. Then, at the end of each iteration, each mould has a solution in the form of a binary vector with the same length as the number of the features, where 1 means selecting and 0 means deselecting the corresponding feature. This process continues for all iterations and at last, the best feature subset with the least classification error of the classifier is suggested as the best result.

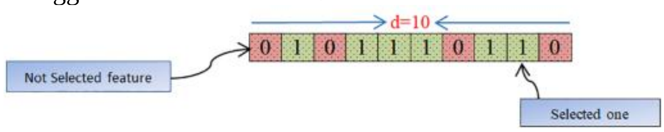


Figure 3. An initial solution to the FS.

It should be noted that, the values generated by the standard SMA are continuous, but the features in FS problems are binary: 0 (selected feature) and 1 (not selected) values. Therefore, a wide range of transfer functions belonging to the family of the V-Shaped and S-Shaped functions [19] has been supposed to convert continuous values into binary.
Selected V-Shaped and S-shaped transfer functions are listed in Table 2. A transfer function receives a real value from the standard SMA as an input and then normalizes this value between 0 and 1 using one of the formulas in Table 2. The normalized value is then converted to a binary value using Eq. (2) [19] .

$$S_{binary} = f(x) \begin{cases} 1, & if\ S(a) > 0.5 \\ 0, & otherwise \end{cases} \quad (1)$$

Table 2. V-Shaped and S-shaped transfer function.

V-Shaped	S-Shaped
V1, $F(a) = \left\lvert \frac{2}{\pi} \tan^{-1}(\frac{\pi}{2} a) \right\rvert$	S1, $F(a) = \frac{1}{1+e^{-a}}$
V2, $F(a) = \lvert \tanh(a) \rvert$	S2, $F(a) = \frac{1}{1+e^{-2a}}$
V3, $F(a) = \left\lvert \frac{a}{\sqrt{1+a^2}} \right\rvert$	S3, $F(a) = \frac{1}{1+e^{-\frac{a}{2}}}$
V4, $F(a) = \left\lvert \mathrm{erf}(\frac{\sqrt{\pi}}{2} a) \right\rvert$	S4, $F(a) = \frac{1}{1+e^{-\frac{a}{3}}}$

2.2.2 Fitness Function

The fitness function (FF) is an important factor for the speed and the efficiency of ABSMA algorithm. In this study, the fitness function of ABSMA is developed based on the surrogate model accuracy and the efficiency of selected subset of features. The surrogate model (RBFNN) accuracy is obtained by the evaluation of the test data classification using the trained model. In addition, efficiency of the selected subset of features are evaluated using the F-score to measure desirability of the features. ABSMA selects the vector with the smallest fitness value when the completion conditions are satisfied. The fitness function of ABSMA is formed as follows:

$$FF = 1 - \left[W \times (Classification\ Accuracy) + (1 - W) \times \left(\frac{1}{\mathrm{n}} \sum_{i=1}^{n} F_{score_i} \right) \right] \quad (2)$$

where W is weighting factor between 0 to 1 and n is the total number of features.

2.2.3 Measure the desirability of features: F-score

A desirability value, for each feature generally represents the attractiveness of the features, and can be any subset evaluation function like an entropy-based measure or rough set dependency measure [27]. In this paper, F-score will be used as index for measuring the desirability of the features. The F-score is a measurement to evaluate the discrimination ability of the feature $\boldsymbol{i}$. Eq. (3) defines the F-score of the $\boldsymbol{i^{th}}$ feature. The numerator specifies the discrimination among the categories of the target variable, and the denominator indicates the discrimination within each category. A larger F-score implies to a greater likelihood that this feature is discriminative [21].

$$F_{score_i} = \frac{\sum_{k=1}^{c} \left(\bar{x}_i^k - \bar{x}_i \right)^2}{\sum_{k=1}^{c} \left[\frac{1}{N_i^k - 1} \sum_{j=1}^{N_i^k} \left(x_{ij}^k - \bar{x}_i^k \right)^2 \right]} \quad (3)$$

where c is the number of classes and $\mathbf{n}$ is the number of features; N_i^k is the number of samples of the feature i in class k, ($\boldsymbol{k} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{c}$; $\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{n}$), x_{ij}^k is the $\boldsymbol{j}$-th training sample for the feature $\boldsymbol{i}$ in class k, ($j = 1,2, \dots, \boldsymbol{N_i^k}$), $\boldsymbol{x_i}$ is the mean value of feature $\boldsymbol{i}$ of all classes and x_{ik} is the mean value of feature $\boldsymbol{i}$ of the samples in class $\boldsymbol{k}$ [21].

It should be mentioned that the features selected by the proposed algorithms are evaluated with the well-known metrics precision, recall, accuracy, F1- score and Feature-Reduction index (F_r). In this paper, the CA is used to define the quality function of a solution, which is the percentage of samples correctly classified and evaluated as Eq. (4):

$$CA = \frac{Number\ of\ samples\ correctly\ classified}{Total\ number\ of\ samples\ taken\ for\ exprimentation} \quad (4)$$

Another parameter which is used for comparison is the average feature reduction F_r, to investigate the rate of feature reduction:

$$F_r = \frac{n - p}{n} \quad (5)$$

where n is the total number of features and p is the number of selected features by the FS algorithm F_r is the average feature reduction. The more it is close to 1, the more features are reduced, and the classifier complexity is less.

2.2.4 Advanced version of binary slime mould algorithm

In the proposed BSMA, two ideas from GA [28] are implement on the BSMA to enhances its capability for the FS and solve low population diversity. The new solutions in GA are created by the two operators: crossover and mutation. In the crossover operator, two solution sets are selected randomly and some portions are exchanged, thereby creating two new solutions. In the mutation operator, a randomly selected bit of a particular solution is mutated; means the 1 is changed to 0 and 0 is changed to 1. Therefore, in the first step of proposed method, a random solution is generated, and then a crossover operation is applied to the randomly generated solution and the best solution. Next, the solution obtained from the crossover operation is given as inputs to the mutation operation. The main intention of these operations is increase population diversity and escapes from local optimal points and improve solutions' quality.

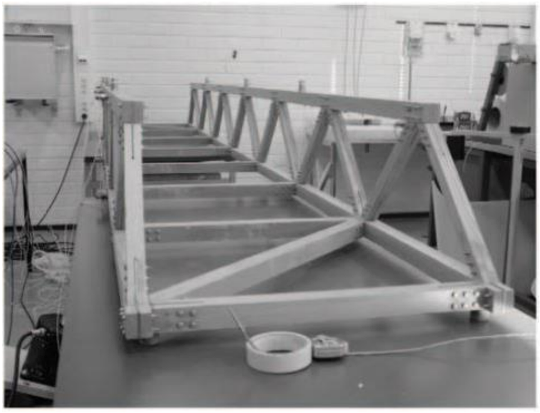
2.3 *Feature Classification Block: RBFNN*

In the final block of the employed framework, a well-trained surrogate model is applied to classify various condition of the structure. In these models, the input matrix will include the selected features and the outputs are the corresponding damage conditions. In recent years, many neural network models have been proposed or employed for various components of SHM in order to perform pattern classification, function approximation, and regression [29], [30]. Among them, the RBF network is a type of feed forward neural networks that learns using a supervised training technique. Lowe and Broomhead [31] were the first researchers that exploited the use of the RBF for designing neural networks. Radial functions are a type of function in which the response reduces or grows monotonically with the distance from the center point. It has been shown that the RBF networks are able to approximate any reasonable continuous function mapping with a satisfactory level of accuracy [32].

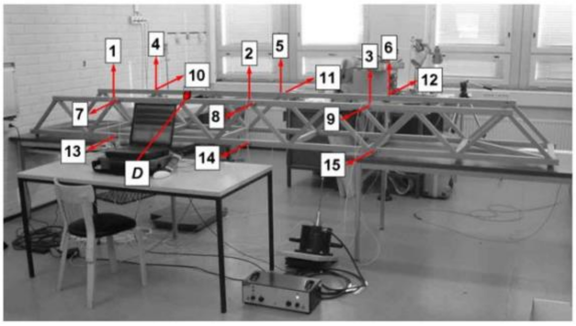
3 EXPRIMENTAL RESULTS

In this section, a benchmark data set is used to show the effectiveness of the proposed FS algorithm. The data set collected in the laboratory of Helsinki Polytechnic Stadia [22], [33] is employed in this paper. The structure was a timber bridge model as shown in Figure 4. In order to excite the lowest modes, a random excitation was generated with an electrodynamic shaker to activate the vertical, transverse, and torsional modes. The response was measured at three different longitudinal positions by 15 accelerometers. The frequency of sampling was 256 Hz and the measurement period was 32 s. The data were filtered below 64 Hz and re-sampled for sufficient redundancy. The measurements were repeated several times and it was noticed that the dynamic properties of the structure vary due to the environmental changes. The main influencing factors were assumed to be the changes in the temperature and humidity.

In the SHM community, there are various schemes for modelling damage scenarios, mainly damage modelled by decreasing the modulus of elasticity or the stiffness parameter of elements [8]. Moreover, some researchers used additional mass as an indicator of damage [34]. In the case of experimental case studies, using an additional mass is popular mainly because of its simplicity. In the benchmark data set that is used in this paper, Kullaa [22] modelled damage by adding mass. As described in the original paper [22] five artificial damage scenarios were introduced by adding small point masses of different sizes on the structure. The mass sizes were 23.5, 47.0, 70.5, 123.2 and 193.7 gr. The point masses were attached on the top flange, 600 mm left from the midspan (Figure 4). The added masses were relatively small compared to the total mass of the bridge (36 kg), where the highest mass increase was only 0.5 %. The total number of experiments were carried out on the structure was 273. The 190 measurements were selected as the training data. The test data consisted of both healthy and abnormal systems measurements. It is worth mentioning that the total number of extracted features for each experiment based on Table 1 is: 15 sensors ×7 features=105 features.



(a) Wooden bridge model



(b) Wooden bridge with the locations of sensors and damage (D) are indicated [22].

Figure 4. Wooden bridge

3.1 *Impact of transfer functions on the ABSMA*

In this subsection, the impact of the transfer functions on the ABSMA's performance is investigated. For providing the stochastic behaviour of metaheuristic optimization algorithms (MOAs), the performance of the algorithms is compared using the best, worst, average and standard deviation (SD) of the obtained fitness values over 20 independent runs in Table 3. Columns ABSMA-V1, ABSMA-V2, ABSMA-V3, ABSMA-V4, ABSMA-S1, ABSMA-S2, ABSMA-S3, and ABSMA-S4 gives the results of the transfer functions V1, V2, V3, V4, S1, S2, S3, and S4, respectively.

As stated above, MOAs have stochastic nature and in each independent run, they may have slightly different results. Therefore, for comparing their performance, researchers [12], [13] consider the best, worst, average, and standard deviation of fitness values. Therefore, according to the results of Table 3, ABSMA-V2 has shown better performance in most indexes (best, average, and worst) in comparison with other transfer functions. Therefore, V2 is selected as the transfer function in this study.

Table 3. The best fitness values under eight different transfer functions

	ABSMA-V1	ABSMA-V2	ABSMA-V3	ABSMA-V4
Best	0.07	0.04	0.09	0.1
Average	0.11	0.07	0.11	0.13
Worst	0.14	0.12	0.13	0.15
SD	0.02	0.02	0.01	0.02
	ABSMA-S1	ABSMA-S2	ABSMA-S3	ABSMA-S4
Best	0.11	0.1	0.07	0.05
Average	0.13	0.12	0.09	0.07
Worst	0.14	0.14	0.11	0.1
SD	0.01	0.01	0.01	0.01

3.2 *CA of metaheuristic optimization algorithms*

In this section, the accuracy and effectiveness of the proposed framework for feature extraction/selection in SHM domain is evaluated. Furthermore, the results obtained by the proposed ABSMA algorithm are compared to BPSO [15], BHHO [23], BWOA [24], and BFFA [25] which are reported to be good algorithms in FS [19]. The parameters need to be set in these algorithms are set to the best values are reported in the original papers. The population size for all the algorithms is 50 and the maximum iterations is set to be 200. The weighting factor W in the fitness function is varied from 0.6 to 0.9 to get the different sets of features. The results are averaged over 20 independent runs in each data set and by every algorithm.

Table 4 gives the mean of the CA, best, worst, average and SD of the results for each algorithm. The number in the brackets in each table slot shows the ranking of each algorithm. A comparison of the average precision, recall, F1 score and the amount of F_r for other algorithms are given in Table 5. It can concluded from these tables that the proposed ABSMA algorithm can obtain, in most of cases, better CA using a smaller feature set, compared to other algorithms

Table 4. CA of each algorithm for the tested datasets of Wooden bridge

	ABSMA	BHHO	BPSO	BWOA	BFFA
Mean of CA (Rank)	**0.94** (1)	0.87 (2)	0.81 (4)	0.86 (3)	0.8 (5)
Best	0.04	0.09	0.12	0.09	0.13
Average	0.07	0.13	0.17	0.13	0.19
Worst	0.12	0.16	0.22	0.16	0.23
SD	0.02	0.02	0.03	0.02	0.03

Table 5. Comparison of the performance (precision, recall, F1-score and F_r) of the algorithms on Wooden bridge

Metrics	ABSMA	BHHO	BPSO	BWOA	BFFA
Precision	0.94	0.88	0.83	0.87	0.81
Recall	0.96	0.92	0.87	0.91	0.86
F1-score	0.95	0.90	0.85	0.89	0.83
F_r	0.81	0.714	0.667	0.743	0.619

The extended results are also shown in Figures 5-6. From these figures, one may admit that ABSMA not only finds smaller feature subsets than the other algorithms, but also the number of selected features also decreases much faster.

It can be concluded that the ABSMA provides a higher degree of exploration than the other algorithms, which enables it to explore the search space to find a solution that selects a smaller number of features and better performance.

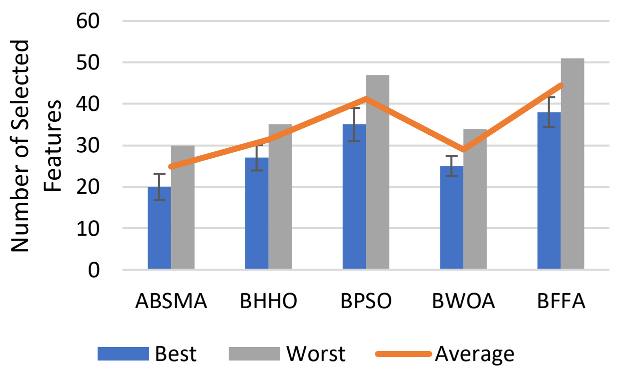


Figure 5. Number of selected features of each optimization algorithms

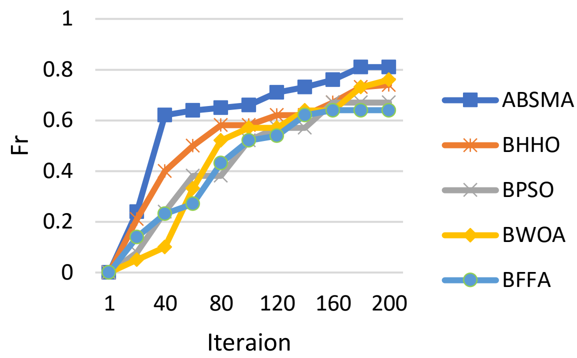


Figure 6. Average of Fr for each optimization algorithms with respect to number of iterations

It is worth to note that, the FS method proposed in this study is a supervised wrapper-based FS method [13]. Generally, in comparison with the filter model, the wrapper model could achieve a higher CA and tend to have a smaller subset size; however, it has high time complexity [12].

Finally, according to the results shown, adding desirability index, mutation and crossover operators to the BSMA increases the exploration of the search and guide the algorithm to more salient features.

4 CONCLUSIONS

In this paper, a new framework is presented for the FS for SHM problems. Furthermore, an ABSMA is presented for enhance capability of SMA in this domain. The mutation and crossover operators are employed in the original BSMA to the proposed ABSMA which could increase diversity and prevent excessive convergence during the optimization process, and local optimal trap escape. A data set collected from a timber bridge is employed in this paper. The ABSMA is initially evaluated using eight transfer functions that convert continuous solutions to binary ones, in which the best transfer function (transfer function V2) is selected. The results obtained from the proposed algorithm were compared with 4 state-of-the-art metaheuristic-based algorithms including BHHO, BPSO, BWOA and BFFA. The results of the experiments indicate that a significant improvement in the proposed algorithm compared to other ones. Moreover, the proposed framework can remove the irrelevant and redundant information by choosing useful features as the input of the surrogate model. It is shown that the proposed FS approach based on the ABSMA optimization algorithm reaches a better feature set in terms of CA and the number of selected features.

5 ACKNOWLEDGEMENT

This publication has emanated from research conducted with the financial support of Science Foundation Ireland under Grant number 20/FFP-P/8706.

REFERENCES

[1] O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, and D. J. Inman, “A review of vibration-based damage detection in civil

structures: From traditional methods to Machine Learning and Deep Learning applications," *Mech. Syst. Signal Process.*, vol. 147, p. 107077, 2021.

[2] S. Das, P. Saha, and S. K. Patro, "Vibration-based damage detection techniques used for health monitoring of structures: a review," *J. Civ. Struct. Heal. Monit.*, pp. 1–31, 2016.

[3] A. Malekjafarian, E. J. Obrien, P. Quirke, and D. Cantero, "Railway Track Loss-of-Stiffness Detection Using Bogie Filtered Displacement Data Measured on a Passing Train," *Infrastructures*, vol. 6, no. 93, pp. 1–17, 2021.

[4] R. Corbally and A. Malekjafarian, "A data-driven approach for drive-by damage detection in bridges considering the influence of temperature change," *Eng. Struct.*, vol. 253, no. December 2021, p. 113783, 2022.

[5] A. Silik, M. Noori, W. A. Altabey, and R. Ghiasi, "Selecting optimum levels of wavelet multi-resolution analysis for time-varying signals in structural health monitoring," *Struct. Control Heal. Monit.*, vol. 28, no. 8, 2021.

[6] A. Silik, M. Noori, W. A. Altabey, J. Dang, R. Ghiasi, and Z. Wu, "Optimum wavelet selection for nonparametric analysis toward structural health monitoring for processing big data from sensor network: A comparative study," *Struct. Heal. Monit.*, 2021.

[7] A. Malekjafarian, F. Golpayegani, C. Moloney, and S. Clarke, "A Machine Learning Approach to Bridge-Damage Detection Using Responses Measured on a Passing Vehicle," *Sensors*, vol. 19, no. 4035, 2019.

[8] R. Ghiasi, P. Torkzadeh, and M. Noori, "A machine-learning approach for structural damage detection using least square support vector machine based on a new combinational kernel function," *Struct. Heal. Monit.* , vol. 15, no. 3, pp. 302–316, May 2016.

[9] V. R. Gharehbaghi *et al.*, "A Critical Review on Structural Health Monitoring: Definitions, Methods, and Perspectives," *Arch. Comput. Methods Eng.*, pp. 1–27, 2021.

[10] G. F. Gomes, Y. A. D. Mendez, P. da S. L. Alexandrino, S. S. da Cunha, and A. C. Ancelotti, "A review of vibration based inverse methods for damage detection and identification in mechanical structures using optimization algorithms and ANN," *Arch. Comput. Methods Eng.*, pp. 1–15, 2018.

[11] L. Zhong, H. Song, and B. Han, "Extracting structural damage features: Comparison between PCA and ICA," in *Intelligent Computing in Signal Processing and Pattern Recognition*, Springer, 2006, pp. 840–845.

[12] S. Kashef and H. Nezamabadi-pour, "An advanced ACO algorithm for feature subset selection," *Neurocomputing*, vol. 147, pp. 271–279, 2015.

[13] S. Kashef, H. Nezamabadi-pour, and B. Nikpour, "Multilabel feature selection: A comprehensive review and guiding experiments," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 8, no. 2, p. e1240, 2018.

[14] H. Liu and L. Yu, "Toward integrating feature selection algorithms for classification and clustering," *IEEE Trans. Knowl. Data Eng.*, no. 4, pp. 491–502, 2005.

[15] L.-Y. Chuang, C.-H. Yang, and J.-C. Li, "Chaotic maps based on binary particle swarm optimization for feature selection," *Appl. Soft Comput.*, vol. 11, no. 1, pp. 239–248, 2011.

[16] I.-S. Oh, J.-S. Lee, and B.-R. Moon, "Hybrid genetic algorithms for feature selection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 11, pp. 1424–1437, 2004.

[17] E. Rashedi and H. Nezamabadi-pour, "Feature subset selection using improved binary gravitational search algorithm," *J. Intell. Fuzzy Syst.*, vol. 26, no. 3, pp. 1211–1221, 2014.

[18] S. Li, H. Chen, M. Wang, A. Asghar, and S. Mirjalili, "Slime mould algorithm : A new method for stochastic optimization," *Futur. Gener. Comput. Syst.*, vol. 111, pp. 300–323, 2020.

[19] B. Abdollahzadeh, S. Barshandeh, H. Javadi, and N. Epicoco, "An enhanced binary slime mould algorithm for solving the 0 – 1 knapsack problem," *Eng. Comput.*, no. 0123456789, 2021.

[20] C. Cremona and J. Santos, "Structural Health Monitoring as a Big-Data Problem," *Struct. Eng. Int.*, vol. 28, no. 3, pp. 243–254, 2018.

[21] C.-L. Huang, "ACO-based hybrid classification system with feature subset selection and model parameters optimization," *Neurocomputing*, vol. 73, no. 1–3, pp. 438–448, 2009.

[22] J. Kullaa, "Distinguishing between sensor fault, structural damage, and environmental or operational effects in structural health monitoring," *Mech. Syst. Signal Process.*, vol. 25, no. 8, pp. 2976–2989, 2011.

[23] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, "Harris hawks optimization: Algorithm and applications," *Futur. Gener. Comput. Syst.*, vol. 97, pp. 849–872, 2019.

[24] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016.

[25] H. Shayanfar and F. S. Gharehchopogh, "Farmland fertility: A new metaheuristic algorithm for solving continuous optimization problems," *Appl. Soft Comput.*, vol. 71, pp. 728–746, 2018.

[26] A. Widodo, B.-S. Yang, and T. Han, "Combination of independent component analysis and support vector machines for intelligent faults diagnosis of induction motors," *Expert Syst. Appl.*, vol. 32, no. 2, pp. 299–312, Feb. 2007.

[27] R. Jensen, "Combining rough and fuzzy sets for feature selection." Citeseer, 2005.

[28] M. Melanie, *An Introduction to Genetic Algorithms*. The MIT Press, 1999.

[29] W. A. Altabey, M. Noori, T. Wang, R. Ghiasi, S.-C. Kuok, and Z. Wu, "Deep learning-based crack identification for steel pipelines by extracting features from 3d shadow modeling," *Appl. Sci.*, vol. 11, no. 13, 2021.

[30] A. Malekloo, E. Ozer, M. Alhamaydeh, and M. Girolami, "Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights," *Struct. Heal. Monit.*, vol. 0, no. 0, pp. 1–50, 2021.

[31] D. Lowe and D. Broomhead, "Multivariable functional interpolation and adaptive networks," *Complex Syst.*, vol. 2, pp. 321–355, 1988.

[32] J. Park and I. W. Sandberg, "Universal approximation using radial-basis-function networks," *Neural Comput.*, vol. 3, no. 2, pp. 246–257, 1991.

[33] J. Kullaa, "Eliminating environmental or operational influences in structural health monitoring using the missing data analysis," *J. Intell. Mater. Syst. Struct.*, vol. 20, no. 11, pp. 1381–1390, 2009.

[34] E. Papatheou, G. Manson, R. J. Barthorpe, and K. Worden, "The use of pseudo-faults for damage location in SHM : An experimental investigation on a Piper Tomahawk aircraft wing," *J. Sound Vib.*, pp. 1–20, 2013.