New Trends and Issues Proceedings on Advances in Pure and Applied Sciences

No 12 (2020) 15-23

www.propaas.eu

Training of ANFIS with simulated annealing algorithm on flexural buckling load prediction of aluminium alloy columns

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Suggested Citation:

Haznedar, B., Bayraktar, R., Yayla, M. & Demirkol, M. D. (2020).Training of ANFIS with simulated annealing algorithm on flexural buckling load prediction of aluminium alloy columns. *New Trends and Issues Proceedings on Advances in Pure and Applied Sciences.* (12), 15–23.

Received date December 2, 2019; revised date;February 5, 2020 accepted date April 22, 2020.

Selection and peer review under responsibility of Prof. Dr. Dogan Ibrahim, Near East University, Cyprus.

Abstract

In this study, we propose a simulated annealing algorithm (SA) to train an adaptive neurofuzzy inference system (ANFIS). We performed different types of optimization algorithms such as genetic algorithm (GA), SA and artificial bee colony algorithm on two different problem types. Then, we measured the performance of these algorithms. First, we applied optimization algorithms on eight numerical benchmark functions which are sphere, axis parallel hyper-ellipsoid, Rosenbrock, Rastrigin, Schwefel, Griewank, sum of different powers and Ackley functions. After that, the training of ANFIS is carried out by mentioned optimization algorithms to predict the strength of heat-treated fine-drawn aluminium composite columns defeated by flexural bending. In summary, the accuracy of the proposed soft computing model was compared with the accuracy of the results of existing methods in the literature. It is seen that the training of ANFIS with the SA has more accuracy.

Keywords: Soft computing, ANFIS, simulated annealing, flexural buckling, aluminium alloy columns.

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1. Introduction

The usage of aluminium in structural operations has increased rapidly in the past decade due to its various benefits such that durability/heaviness ratios, disintegration resistance, nice appearance, easy overhaul and finally the competing price of it with the other materials (Galambos, 1998; [3], [7], [9]

These benefits of aluminium induce it to use as columns in structural operations broadly. The problem of buckling of aluminium columns is a complicated work which contains several breakdown categories and causes to problems in the estimation of critical buckling load. Especially, when plastic buckling is detected, proceeding turns into difficult situation [1].

The attitude of aluminium area is identified by pressure-distension curve of material in cases such as flexural buckling of aluminium composite columns. Since pressure-distension curve of aluminium composites is nonlinear, it is possible to model it by using Ramberg—Osgood expression. Other than the nonlinearity of supplies, the flexural buckling of aluminium composite is affected, i.e., heat-treated aluminium composites have better proof stresses than not heat-treated aluminium composites [8].

There are several important studies on the tests of columns composing from aluminium in literature. In 1997, Chou and Rhodes made an experimental work on columns and plates about buckling. In 2002, Singer et al. made searches on the flexural strength of aluminium composite columns. In 2009, [1]. proposed a method for the load prediction of flexural buckling of aluminium composite columns with soft computing techniques [1].

This article intends to present a different way for flexural bending load estimation of heat-treated aluminium composite columns. For this purpose, adaptive neurofuzzy inference system (ANFIS) is optimised by some optimization algorithms such as genetic algorithm (GA), artificial bee colony algorithm (ABC) algorithm and simulated annealing algorithm (SA). The accuracy of suggested models is shown in the following sections.

2. Soft computing techniques

The idea behind soft computing is to form the cognitive approach model of human intelligence. In other words, soft computing is the establishment of conceptual consciousness in machines. Soft computing is more tolerant, unlike strict computational methods, not only in uncertainty and inaccurate situations but also in partial accuracy and approach issues.

The soft computing approach based on neurofuzzy and SA is the scope of this study described in this section.

2.1. Adaptive neurofuzzy inference system

ANFIS is a type of network system combined from Sugeno type fuzzy system with neural training capability. The essential objective of ANFIS is to enhance the parameters of the corresponding fuzzy logic system by utilising input–output sets by using some algorithms. The boost of parameters is performed in a manner that real value and targeted output have a minimum error between them.

There are two different parameters of ANFIS which are consequent and antecedent parameters. These parameters play a role to connect different fuzzy layers to each other, and the optimization of these parameters trains the model. There are basically five layers for ANFIS models. A basic model of ANFIS is shown in Figure 1 [4].

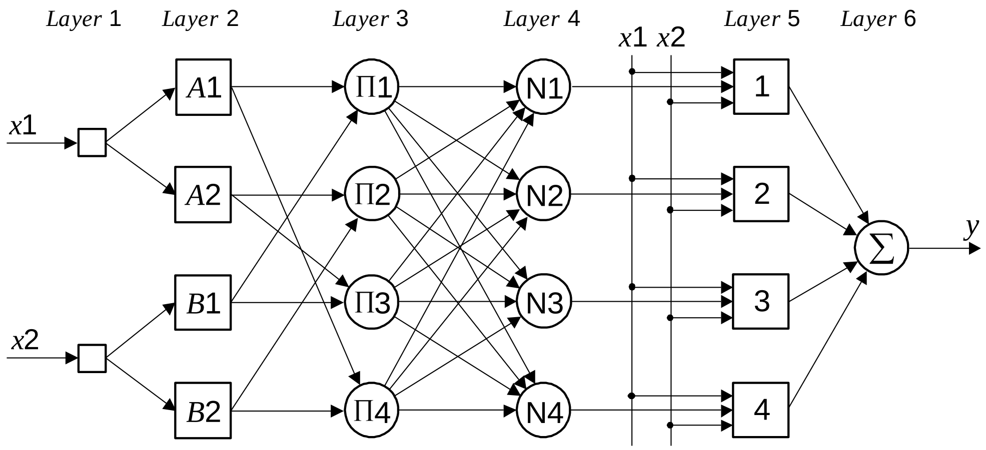

Figure 1. ANFIS structure

A. Layer 1

The name of the first layer is the fuzzification layer. In this layer, signals are collected from every single node which is transferred to other layers. The output of this layer (O_{11}) is shown in Equations (1) and (2).

$$O_{1i} = \mu A_i(x) \qquad i = 1,2 \tag{1}$$

$$O_{1i} = \mu B_{i-2}(x) \qquad i = 3,4 \tag{2}$$

Where A_i and B_i are some membership functions dependingon the input values, andμA_i and μB_i are the degree of the membership of these functions. Forthe Gaussian membership function,μA_i is found by Equation (3).

$$\mu A_i = e^{-\frac{1}{2}\left(\frac{x-c}{a}\right)^2} \qquad i = 1,2 \tag{3}$$

In the previous equation, a_i and c_i are the central and sigma parameters of the function of membership.

B. Layer 2

The name of the second layer is the rule layer. In this layer, the firing strength of each rule is measured with degrees of memberships obtained from Layer 1.

$$O_{2i} = w_i = \mu A_i(x).\mu B_i(y) \qquad i = 1,2 \tag{4}$$

C. Layer 3

This layer is also called the normalization layer, and the input of each node shows the rule weights. After the normalization process, new rule weights are obtained as the output of each node.

$$O_{3i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{5}$$

D. Layer 4

This layer is named as a defuzzification layer. In this layer, each node has a function, and the defuzzification process is applied to function parameters.

$$O_{4i} = \overline{w_i}.f_i = \overline{w_i}.(p_i x + q_i y + r_i) \qquad i = 1,2 \tag{6}$$

E. Layer 5

The output of the created ANFIS system is obtained. However, the number of outputs is determined according to the problem to be solved [6].

$$O_{5i} = f = \sum \overline{w_i}.f_i = \frac{\sum w_i.f_i}{\sum w_i} \qquad i = 1,2 \tag{7}$$

2.2. Simulated annealing algorithm

Simulated annealing is a probabilistic approach algorithm. It is used in numerical and discrete applications that cannot be modelled with a mathematical function and time-consuming problems. It aims to find the best solution as soon as possible by evaluating the function that will be optimised only. In other words, simulated annealing tries to find the global minimum or maximum of a function or measurement. The important thing in this algorithm is that, between the two cases, the selection is made according to the *P* probability value.

For example, between cases c_1 and c_2, the selection is made according to $P(e_1, e_2, T)$ probability value, and e_1, e_2 are the energy values for that calculated as given in Equations(1) and (2) [5], [9].

$$e_1 = E(c_1) \tag{8}$$

$$e_2 = E(c_2) \tag{9}$$

In addition to all of these, SA can produce more than one solution for the same problem, so it is important both for analysing the problem characteristic and modelling the problem.

3. Simulation results

The simulation work consists of two parts: the optimization studies on benchmark functions and training ANFIS network to predict the strength of heat-treated fine-drawn aluminium composite columns defeated by flexural bending.

3.1. Simulation studies on benchmark functions

In this section, eight well-known numerical benchmark functions shown in Table 1 are employed to determine the performance of the proposed SA algorithm. Those are sphere, Axis parallel hyper-ellipsoid, Rosenbrock, Rastrigin, Schwefel, Griewank, sum of different powers and Ackley functions.

Table 1. Numerical test functions used in the simulations

Notation	Test function	Formulation
f_1	Sphere	$f_1 = \sum_{i=1}^{D} x_i^2$
f_2	Axis parallel hyper-ellipsoid	$f_2 = \sum_{i=1}^{D} i x_i^2$
f_3	Rosenbrock	$f_3 = \sum_{i=1}^{D} 100\left(x_1^2 - x_2\right)^2 + \left(1 - x_1\right)^2$
f_4	Rastrigin	$f_4 = 20A + \sum_{i=1}^{D}\left(x_i^2 - 10\cos\left(2\pi x_i\right)\right), A = 10$

f_5	Schwefel	$f_5 = \sum_{i=1}^{D} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$
f_6	Griewank	$f_6 = 1 + \sum_{i=1}^{D}\left(\frac{x_i^2}{4000}\right) - \prod_{i=1}^{D}\left(\cos\left(\frac{x_i}{\sqrt{i}}\right)\right)$
f_7	Sum of different powers	$\sum_{i=1}^{D} \lvert x_i \rvert^{i+1}$
f_8	Ackley	$f_8 = 20 + e - 20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right)$

The proposed SA was executed five times with different initial solutions. After trials, the number of temperature points is taken as 100, the number of iterations for each temperature point is 12 and the temperature reducing factor is taken as 0.1. The solutions for the functions, parameter bounds and resolutions for each test function are shown in Table 2. The best results obtained by using SA algorithm on benchmark test functions are shown in Table 3.

Table 2. Number of parameters, solutions, parameter bounds and length of solution for the test functions

Notation	Number of parameters (*D*)	Solution		Parameter bounds	
		xi	*f(x)*	Lower	Upper
f_1	30	0.0	0.0	−5.12	5.12
f_2	30	0.0	0.0	−5.12	5.12
f_3	30	1.0	0.0	−2.048	2.048
f_4	30	0.0	0.0	−5.12	5.12
f_5	30	420.968	−12.569	−500	500
f_6	30	0.0	0.0	−600	600
f_7	30	0.0	0.0	−1	1
f_8	30	0.0	0.0	−32.768	32.768

Table 3. The best results obtained by using SA algorithm on benchmark test functions

Notation	Test functions	Mean	SD	Best	Worst
f_1	Sphere	2.222E − 24	3.700E − 25	1.876E − 24	2.805E − 24
f_2	Axis parallel hyper-ellipsoid	8.965E − 22	1.564E − 21	1.198E − 24	3.686E −21
f_3	Rosenbrock	2.582E+01	2.924E+01	8.126E+00	7.529E+01
f_4	Rastrigin	8.437E+01	9.579E+00	7.064E+01	9.551E+01
f_5	Schwefel	4.904E+03	2.724E+02	4.522E+03	5.211E+03
f_6	Griewank	0.000E+00	0.000E+00	0.000E+00	0.000E+00
f_7	Sum of different powers	0.000E+00	0.000E+00	0.000E+00	0.000E+00
f_8	Ackley	3.562E − 12	6.736E − 13	2.537E − 12	4.399E − 12

The benchmark functions are also optimised with the GA and ABC algorithms. For the GA algorithm, the mutation rate, population size and crossing over rate are chosen as 50, 0.8 and 0.1, respectively. For the ABC control parameters in this study, the limit, colony size and maximum cycle number are selected successively as 50, 100 and 500. In Table 4, the performance of SA algorithm is compared with the GA and ABC algorithms. When all the results are examined, it is seen that the performance of SA in terms of reaching the optimum solution is better than the performances of GA and ABC.

Table 4. Comparison of SA algorithm with GA and ABC algorithms

Test functions	GA		ABC		SA (Proposed)	
	Mean	SD	Mean	SD	Mean	SD
Sphere	1.35E+00	0.3388	0.9942	0.0085	2.222E − 24	3.700E − 25
Axis	2.28E−02	0.0291	0.9987	0.0013	8.965E − 22	1.564E −21
Rosenbrock	1.26E+02	24.177	0.0151	0.0102	2.582E+01	2.924E+01
Rastrigin	3.57E+01	5.2478	0.0469	0.0262	8.437E+01	9.579E+00
Schwefel	9.38E+02	206.82	0.5771	0.5221	4.904E+03	2.724E+02
Griewank	4.63E+00	0.7455	0.9995	0.0009	0.000E+00	0.000E+00
Sum of different powers	1.02E − 03	0.0000	0.9996	0.0004	0.000E+00	0.000E+00
Ackley	6.81E+00	0.4525	0.4317	0.1568	3.562E − 12	6.736E − 13

3.2. Simulation studies on training ANFIS by using SA algorithm

The main focus of this study is the strength prediction of heat-treated extruded aluminium alloy columns failing by flexural buckling and its closed-form solution by means of soft computing techniques, namely, ANFIS and SA, based on experimental results from the literature. Therefore, an extensive literature survey has been performed for available experimental results on flexural buckling load of heat-treated aluminium columns. Afterwards, the experimental results (104 tests) are taken [1]. The datasets for test and training are randomly selected among experimental results, where 83 sets are training set and 21 sets are test set.

Genfis 3 function in MATLAB programming platform is used in order to identify the type of membership function in ANFIS models. In the created ANFIS model, the number of inputs is 6. For each input, the membership function is selected as gauss, the number of membership functions is 10 and also the number of fuzzy rules is 10. ANFIS has two parameter types that have to be updated. Those are antecedent and conclusion parameters. In this study, ANFIS is optimised SA algorithm for the prediction of heat-treated extruded aluminium alloy columns. The ANFIS models are also optimised with GA and ABC algorithms to compare with the proposed method. Thus, 160 parameters in total are optimised. The control parameters of SA, GA and ABC are defined in 'Simulation studies on benchmark functions'. In addition, the performance of the proposed method is compared with the results that are taken from the literature and that belong to the neural network (NN) and gene expression programming (GEP) [1]. The obtained results are evaluated by different error functions which are *MSE, RMSE and MAPE (%).* As a result of simulation studies, the train and test prediction error with optimal parameter values of the ANFIS models is shown in Tables 5 and 6.

Table 5. The comparison of train errors of proposed soft computing models

	MSE	*RMSE*	*MAPE (%)*	R^2
NN [1]	81.172	9.0095	3.4212	0.9930
GEP [1]	221.400	14.8790	6.1607	0.9820
ANFIS-GA	220.564	14.8514	8.8727	0.9671
ANFIS-ABC	109.3925	10.4591	4.6026	0.9837
ANFIS-SA	77.798	8.8203	3.1711	0.9956

Table 6. The comparison of test errors of proposed soft computing models

	MSE	*RMSE*	*MAPE (%)*	R^2
NN [1]	285.520	16.8970	7.3772	0.9860
GEP [1]	644.060	25.3780	16.504	0.9650
ANFIS-GA	199.439	14.1223	8.1107	0.9754
ANFIS-ABC	110.2270	10.4989	6.0531	0.9857
ANFIS-SA	107.9067	10.3878	5.0691	0.9862

RMSE error values are obtained following the simulation studies, and the error values belong to different methods and are taken from the literature shown in Tables 5 and 6. From the results, it is clearly seen that the performance of the approach suggested in this study has quite high success comparing to the other methods. The correlation coefficient of experimental results for training and testing sets is also shown in Figures 2 and 3. The predicted results obtained by the proposed method and the actual results of train and test dataset are shown in Figures 4 and 5. According to the prediction errors in Tables 5 and 6, the results of the proposed ANFIS-SA model are more accurate compared to existing models proposed by [1]. Furthermore, the proposed method is more successful than other ANFIS models that are optimised by GA and ABC.

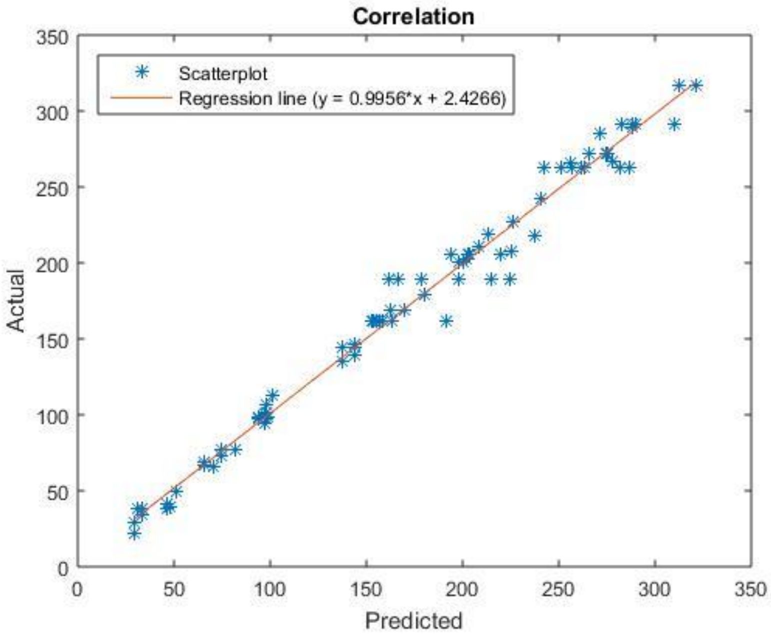

Figure 2. The correlation coefficient of experimental results for train data

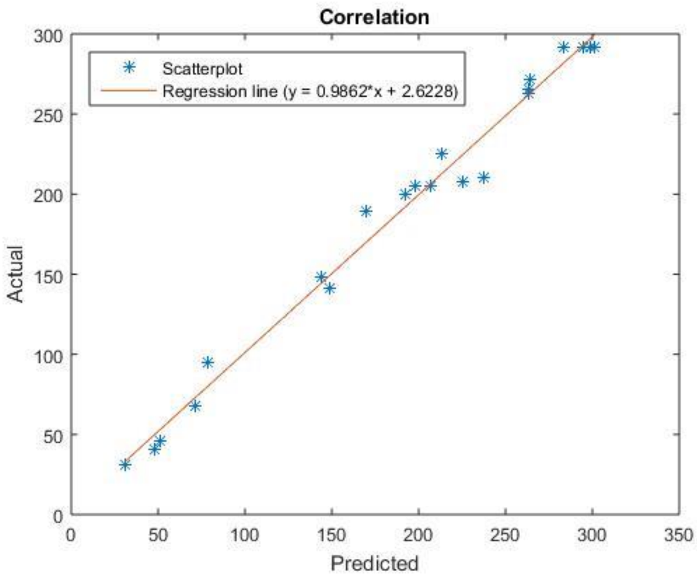

Figure 3. The correlation coefficient of experimental results for test data

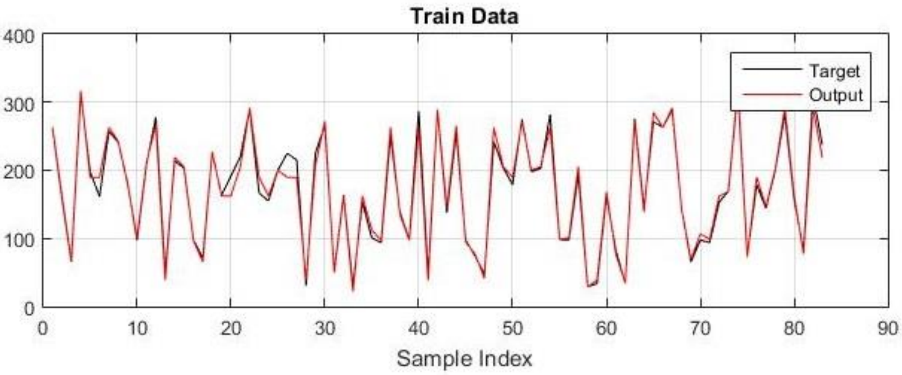

Figure 4. Predicted and actual results of train data

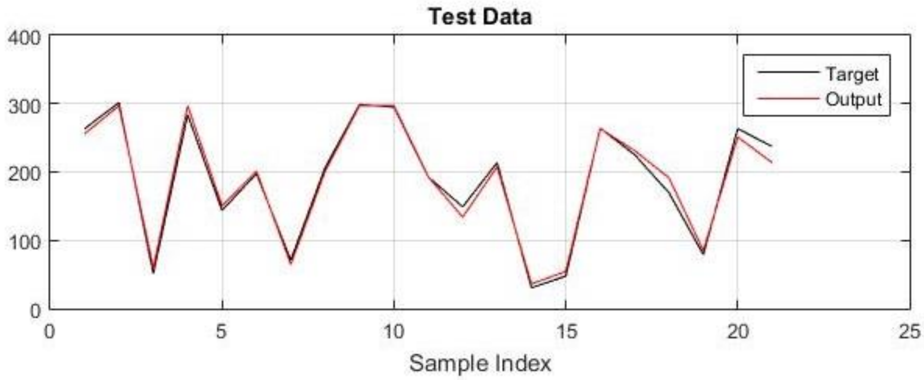

Figure 5. Predicted and actual results of test data

4. Conclusion

This study presents an alternative soft computing technique that combined with ANFIS and SA for the strength prediction of extruded aluminium alloy columns failing by flexural buckling. Experimental data used for the training of soft computing models are obtained from the literature. The obtained results showed that ANFIS models could predict experimental results more successfully. SA is also more successful than GA and ABC algorithms while optimising the ANFIS model. The success of the SA algorithm is also tested on benchmark function. Thus, betters solutions are provided, and the SA algorithm performance is validated. When the results shown in Tables 5 and 6 are examined, the train and test error values are close to each other. Hence, it indicates that the results are reliable, and the methods used are robust than other soft computing methods which exist in the literature [1].

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