Available online at www.sciencedirect.com
SciVerse ScienceDirect
Ceramics International 39 (2013) 1991–2002
CERAMICS INTERNATIONAL
www.elsevier.com/locate/ceramint

Modeling Charpy impact behavior of Al6061/SiC_p laminated nanocomposites by genetic programming

Ali Nazari, Vahidreza Abdinejad*

Department of Materials Science, Saveh Branch, Islamic Azad University, Saveh, Iran

Received 8 August 2012; received in revised form 15 August 2012; accepted 16 August 2012
Available online 24 August 2012

Abstract

In this work, 4 different gene expression programming models were conducted to predict Charpy impact energy of Al6061-SiC_P laminated nanocomposites produced by mechanical alloying. The differences between the models were in their number of genes, head size and chromosomes as well as their linking function. To build the models, 171 pair input-target data were gathered from the literature, randomly divided into 133 and 38 data sets and then were respectively trained and tested by the proposed models. The thickness of layers, the number of layers, the adhesive type, the crack tip configuration, the content of SiC nanoparticles and the test trial number were 6 independent input parameters. The output parameter was Charpy impact energy of the laminated nanocomposites. Although the entire models proposed high performance outcomes, the best performance model had the absolute fraction of variance, the mean absolute percentage error and the root mean square error of 0.9826, 10.217 and 12.432, respectively. All of the training and testing results in the models showed an appropriate performance for predicting Charpy impact energy of Al6061/SiC_p laminated nanocomposites in the considered range.
© 2012 Elsevier Ltd and Techna Group S.r.l. All rights reserved.

Keywords: Al/SiC_P nanocomposite; Impact behavior; Mechanical alloying; Gene expression programming

1. Introduction

Unsuitable impact behavior of Al/SiC_P composites make their use limited in applications with appropriate energy requirement. The conducted works on impact energy of these materials are confined which may be as a result of the specified low impact energy. Zahedi et al. [1,2] investigated Charpy impact energy of Al/SiC_P composites and reported relatively low energies for the specimens produced in different conditions and by different methods. This has been reported in Ortega-Celaya et al. [3] work in which Al/SiC_P composites were fabricated by pressureless infiltration with different types of SiC_P.

One of the best methods to increase impact energy of engineering materials is producing laminated nanocomposites. Laminated composites are alternately separated by discrete interfaces, because of their capability of arresting propagating cracks under impact loading conditions are interesting. This effect is related to the interfaces delaminated under dynamic conditions and is responsible of the high fracture resistance of the composites, much better than the constitutive material components individualy [4]. In the previous work [5], the effect of lamination on different types of Al/SiC_P nanocomposites was studied. It was reported that lamination of the suggested compositions could produce specimens with impact energy even 4 times greater.

Soft computing techniques such as artificial neural networks (AANs), adaptive neuro-fuzzy interfacial systems (ANFIS), fuzzy logic (FL) and genetic programming (GP) and its extension, gene expression programming (GEP) are common models used especially when the number of the accessable data are appropriate. In the previous study [5], ANNs were employed to predict Charpy impact energy of laminated Al/SiC_P nanocomposites. In the present work GEP has been utilized to evaluate this property. Application of GP and GEP in different engineering problems are reported. For instance, Cevik and Guzelbey [6] predicted the ultimate strength of metal plates in compression by

*Corresponding author.
E-mail address: vabdinejad@yahoo.com (V. Abdinejad).

0272-8842/$ - see front matter © 2012 Elsevier Ltd and Techna Group S.r.l. All rights reserved.
http://dx.doi.org/10.1016/j.ceramint.2012.08.051

GEP. They conducted a simple model with 3 genes, different linking functions and head sizes and obtained results with suitable performance. In the other work, Cevik [7] proposed a GP-based modeling for the formulation of web crippling strength of cold-formed steel decks for various loading cases. Eskil and Kanca [8] developed GP for the formulation of martensite start temperature (M_s) of Fe–Mn–Si shape memory alloys for various compositions and heat treatments.

In the present study, GEP was selected for predicting and presenting suitable formulation of Charpy impact energy of laminated Al/SiC_P nanocomposites. In the previous work [5], ANNs were employed to predict this property. The superiority of GEP model proposed here with respect to the previously ANN-based model is the GEP capability to provide straightforward equations for predicting Charpy impact energy of the considered laminated nanocomposites by means of the input parameters. Hundred and seventy one pairs of input-target data were gathered from the previous work [5], randomly divided into 133 and 38 data sets and then were respectively trained and tested by the proposed models. Such as that work [5], the thickness of layers, the number of layers, the adhesive type, the crack tip configuration, the content of SiC nanoparticles and the test trial number were considered as 6 independent input parameters.

2. Data collection

The required data were collected from the previous work [5]. Al6061 powder with the average particles size of 75 μm produced by nitrogen gas atomization were mixed by SiC nanoparticles with the particle sizes less than 100 nm and then ball-milled under argon atmosphere. Specimens with 2, 3 and 5 vol% of SiC nanoparticles were prepared in this stage. Aluminum cans with the specific dimensions were stored in a steel mold, filled by the produced powder in several layers and finally cold-pressed under a pressure of 220 MPa. Afterwards, the produced nanocomposites were extruded. Three types of laminates, including 2, 5 and 10-layer specimens, along with the monolithic specimen were considered for studying the influence of laminate architecture on the impact resistance. The layers thickness in 2, 5 and 10-layer specimens were 5, 2 and 1 mm, respectively. The layers were connected to produce 10-mm thick specimens with 3 different adhesive types. Charpy impact energy of the specimens was measured in crack divider and crack arrester configurations. Tables 1 and 2 show the Charpy impact energy values for the collected data. For more details about preparing the specimens and conducting the experiments, please study Ref. [5].

3. Gene expression programming structure

An extension to genetic algorithms, genetic programming (GP) was first proposed by Koza [9]. "GP is a domain of independent problem solving approach in which computer programs are evolved to solve, or approximately solve, problems based on the Darwinian principle of reproduction and analogs of naturally occurring genetic operations such as reproduction, crossover and mutation". The complete theory of GP could be achieved from [10].

Gene expression programming (GEP), a population-based evolutionary algorithm developed by Ferreira is directed descendent of GP [10]. "In GEP, individuals are encoded as linear strings of fixed size (genome), which are expressed later as non-linear entities with different size and shapes. These entities are known as expression trees (ETs). Usually, these individuals are composed of only 1 chromosome, which, in turn, can have 1 or more genes, divided in head and tail parts. ETs are the expression of a chromosome, and they undergo the selection procedure, guided by their fitness value, so as to generate new individuals. During reproduction, the chromosomes, rather than the respective ET, are modified by the genetic operator [10]". Again, the complete explanations on GEP could be acquired from [10].

In this study, as seen in Figs. 1–4, the expression trees of 4 different GEP models which were named GEP1, GEP2, GEP3 and GEP4, respectively were constructed for formulation of Charpy impact energy (CVN) of laminated nanocomposites. d0, d1, d2, d3, d4 and d5 in Figs. 1–4 represent the values for input layers which are consisted of the thickness of layers (T), the number of layers (N), the adhesive type (A), the crack tip configuration (C), the content of SiC nanoparticles (S) and the test trial number (K), respectively, in accordance to the type of collected data from the literature. In GEP1 and GEP3, the number of used genes (Sub-ETs) was 6 and in GEP2 and GEP4 was 7. The linking function was addition in GEP1 and GEP2 and multiplication in GEP3 and GEP4. In training and testing of GEP1 to GEP4 models, T, N, A, C, S and K were input data and CVN was the independent output data. Among 171 experimental sets collected from the literature, 133 sets were randomly chosen as a training set for GEP1 to GEP4 modeling and the remaining 38 sets were used for testing the proposed models. The modeling was performed by GeneXprotools 4.0 software.

"For this problem, firstly, the fitness, f_i, of an individual program, i, is measured by [10]

$$f_i = \sum_{j=1}^{C_t} \left(M - \left|C_{(ij)} - T_j\right|\right) \tag{1}$$

where M is the range of selection, $C_{(i,j)}$ is the value returned by the individual chromosome i for fitness case j (out of C_t fitness cases) and T_j is the target value for fitness case j. If $\left|C_{(ij)} - T_j\right|$ QUOTE (the precision) is less than or equal to 0.01, then the precision is equal to zero, and $f_i = f_{max} = C_t M$. In this case, $M = 100$ was used, therefore, $f_{max} = 1000$. The advantage of this kind of fitness functions is that the system can find the optimal solution by itself [10]".

Afterwards the set of terminals T and the set of functions F to create the chromosomes are preferred,

Table 1
Input and target values for Charpy impact energy of Al/SiC_P laminated nanocomposites gathered from the previous works [5] used in training set.

Series	Thickness of layer (mm)	Number of layers	Adhesive type[a]	Crack tip configuration[b]	SiC content (vol%)	Test trial number	Charpy impact energy (KJ/m^2)
1	10	1	0	1	2	1	81
2	10	1	0	1	2	3	80
3	10	1	0	1	3	1	118
4	10	1	0	1	3	3	115
5	10	1	0	1	5	1	49
6	10	1	0	1	5	2	59
7	5	2	1	2	2	2	148
8	5	2	1	2	2	3	164
9	5	2	2	2	2	1	147
10	5	2	2	2	2	3	173
11	5	2	3	2	2	1	172
12	2	5	1	2	2	1	212
13	2	5	1	2	2	2	200
14	2	5	1	2	2	3	185
15	2	5	2	2	2	1	219
16	2	5	3	2	2	2	199
17	2	5	3	2	2	3	231
18	1	10	1	2	2	1	245
19	1	10	1	2	2	3	272
20	1	10	2	2	2	1	254
21	1	10	2	2	2	2	272
22	1	10	2	2	2	3	281
23	1	10	3	2	2	2	259
24	1	10	3	2	2	3	233
25	5	2	1	2	3	3	214
26	5	2	2	2	3	1	220
27	5	2	2	2	3	2	201
28	5	2	2	2	3	3	215
29	5	2	3	2	3	1	225
30	5	2	3	2	3	3	220
31	5	2	3	2	5	3	108
32	2	5	1	2	3	2	279
33	5	2	1	2	2	1	150
34	2	5	2	2	3	1	272
35	2	5	2	2	3	2	260
36	2	5	2	2	3	3	257
37	2	5	3	2	3	1	256
38	2	5	3	2	3	2	280
39	2	5	3	2	3	3	277
40	1	10	1	2	3	1	300
41	1	10	1	2	3	2	306
42	1	10	1	2	3	3	321
43	1	10	2	2	3	1	342
44	1	10	2	2	3	2	353
45	1	10	3	2	3	1	312
46	1	10	3	2	3	2	339
47	1	10	3	2	3	3	333
48	5	2	1	2	5	2	95
49	5	2	1	2	5	3	108
50	5	2	2	2	5	1	97
51	5	2	2	2	5	3	98
52	5	2	3	2	5	1	102
53	5	2	3	2	5	2	111
54	2	5	1	2	5	1	141
55	2	5	1	2	5	2	136
56	2	5	2	2	5	1	151
57	2	5	2	2	5	2	163
58	2	5	3	2	5	1	139
59	2	5	3	2	5	2	128
60	2	5	3	2	5	3	129
61	1	10	1	2	5	2	199

Table 1 (*continued*)

Series	Thickness of layer (mm)	Number of layers	Adhesive type[a]	Crack tip configuration[b]	SiC content (vol%)	Test trial number	Charpy impact energy (KJ/m^2)
62	1	10	1	2	5	3	196
63	1	10	2	2	5	2	220
64	1	10	2	2	5	3	228
65	1	10	3	2	5	1	203
66	1	10	3	2	5	3	189
67	5	2	1	3	2	1	242
68	5	2	1	3	2	2	236
69	5	2	2	3	2	1	234
70	5	2	2	3	2	2	230
71	5	2	2	3	2	3	253
72	5	2	3	3	2	1	240
73	5	2	3	3	2	2	239
74	5	2	3	3	2	3	265
75	2	5	1	3	2	2	285
76	2	5	1	3	2	3	298
77	2	5	2	3	2	1	312
78	2	5	2	3	2	3	308
79	2	5	3	3	2	1	290
80	2	5	3	3	2	2	309
81	1	10	1	3	2	1	350
82	1	10	1	3	2	2	363
83	1	10	2	3	2	1	381
84	1	10	2	3	2	2	399
85	1	10	3	3	2	1	360
86	1	10	3	3	2	2	372
87	1	10	3	3	2	3	375
88	5	2	1	3	3	2	300
89	5	2	1	3	3	3	272
90	5	2	2	3	3	1	294
91	5	2	2	3	3	3	304
92	5	2	3	3	3	1	274
93	5	2	3	3	3	2	291
94	5	2	3	3	3	3	275
95	2	5	1	3	3	1	348
96	2	5	1	3	3	3	369
97	2	5	2	3	3	1	372
98	2	5	2	3	3	2	386
99	2	5	2	3	3	3	385
100	2	5	3	3	3	1	389
101	2	5	3	3	3	3	364
102	1	10	1	3	3	1	412
103	1	10	1	3	3	2	429
104	1	10	1	3	3	3	428
105	1	10	2	3	3	2	450
106	1	10	2	3	3	3	465
107	1	10	3	3	3	1	460
108	1	10	3	3	3	2	472
109	1	10	3	2	5	2	214
110	5	2	1	3	2	3	257
111	5	2	1	3	5	2	175
112	5	2	1	3	5	3	158
113	5	2	2	3	5	1	172
114	5	2	2	3	5	2	169
115	5	2	2	3	5	3	172
116	5	2	3	3	5	1	151
117	5	2	3	3	5	2	169
118	2	5	3	3	3	2	381
119	1	10	2	3	3	1	438
120	2	5	1	3	5	2	210
121	2	5	1	3	5	3	184
122	2	5	2	3	5	1	195
123	2	5	2	3	5	2	196
124	2	5	3	3	5	1	184

Table 1 (*continued*)

Series	Thickness of layer (mm)	Number of layers	Adhesive type[a]	Crack tip configuration[b]	SiC content (vol%)	Test trial number	Charpy impact energy (KJ/m^2)
125	2	5	3	3	5	2	190
126	2	5	3	3	5	3	193
127	1	10	1	3	5	2	261
128	1	10	1	3	5	3	251
129	1	10	2	3	5	1	253
130	1	10	2	3	5	2	269
131	1	10	2	3	5	3	267
132	1	10	3	3	5	2	286
133	1	10	3	3	5	3	289

[a]0, 1, 2 and 3 are respectively for monolithic nanocomposite, neat epoxy, rubber-modified epoxy and SiC-filled epoxy adhesives.
[b]1, 2 and 3 are respectively for monolithic nanocomposite, crack divider configuration and crack arrester configuration.

Table 2
Input and target values for Charpy impact energy of Al/SiC_P laminated nanocomposites gathered from the previous works [5] used in testing set.

Series	Thickness of layer (mm)	Number of layers	Adhesive type[a]	Crack tip configuration[b]	SiC content (vol%)	Test trial number	Charpy impact energy (KJ/m^2)
1	10	1	0	1	2	2	94
2	10	1	0	1	3	2	106
3	10	1	0	1	5	3	60
4	5	2	2	2	2	2	148
5	5	2	3	2	2	2	161
6	5	2	3	2	2	3	150
7	2	5	2	2	2	2	228
8	2	5	2	2	2	3	207
9	2	5	3	2	2	1	200
10	1	10	1	2	2	2	245
11	1	10	3	2	2	1	252
12	5	2	1	2	3	1	212
13	5	2	1	2	3	2	198
14	5	2	3	2	3	2	239
15	2	5	1	2	3	1	259
16	2	5	1	2	3	3	278
17	1	10	2	2	3	3	328
18	5	2	1	2	5	1	94
19	5	2	2	2	5	2	93
20	2	5	1	2	5	3	152
21	2	5	2	2	5	3	139
22	1	10	1	2	5	1	190
23	1	10	2	2	5	1	206
24	2	5	1	3	2	1	272
25	2	5	2	3	2	2	289
26	2	5	3	3	2	3	292
27	1	10	1	3	2	3	349
28	1	10	2	3	2	3	384
29	5	2	1	3	3	1	295
30	5	2	2	3	3	2	281
31	2	5	1	3	3	2	351
32	1	10	3	3	3	3	445
33	5	2	1	3	5	1	168
34	5	2	3	3	5	3	160
35	2	5	1	3	5	1	209
36	2	5	2	3	5	3	206
37	1	10	1	3	5	1	241
38	1	10	3	3	5	1	280

[a]0, 1, 2 and 3 are respectively for monolithic nanocomposite, neat epoxy, rubber-modified epoxy and SiC-filled epoxy adhesives.
[b]1, 2 and 3 are respectively for monolithic nanocomposite, crack divider configuration and crack arrester configuration.

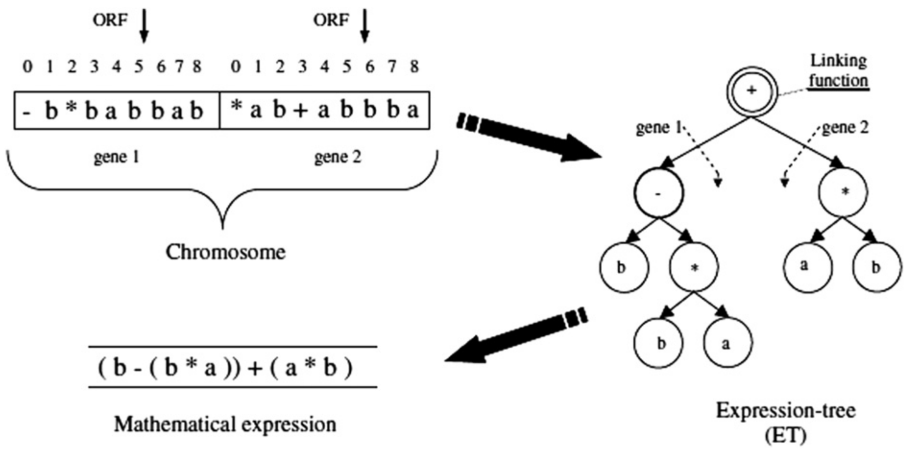

Fig. 1. Chromosome with 2 genes and its decoding in GEP [10].

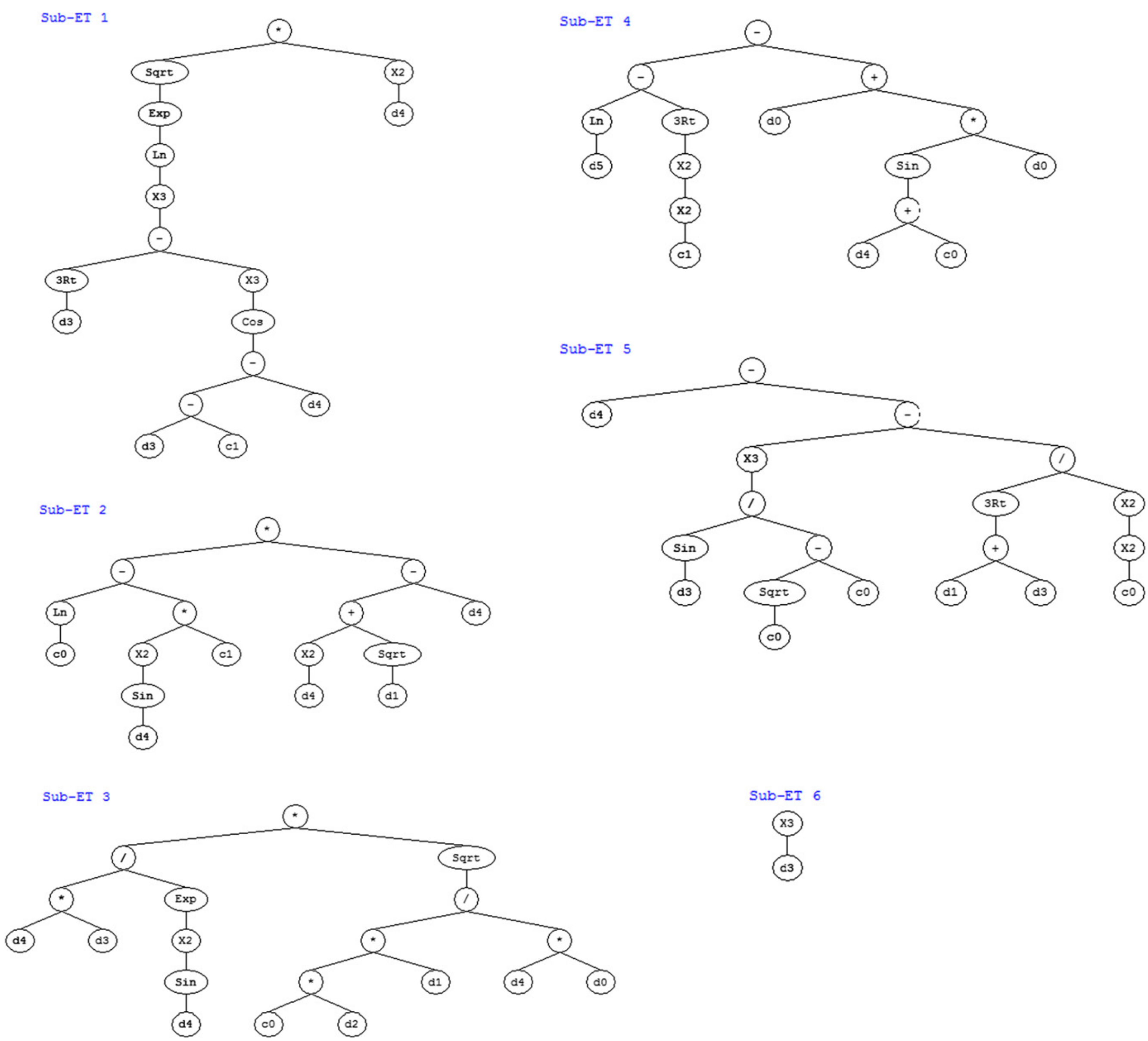

Fig. 2. Expression tree with 6 genes and addition as linking function for predicting Charpy impact energy of the considered Al/SiC$_P$ laminated nanocomposites in GEP1 model.

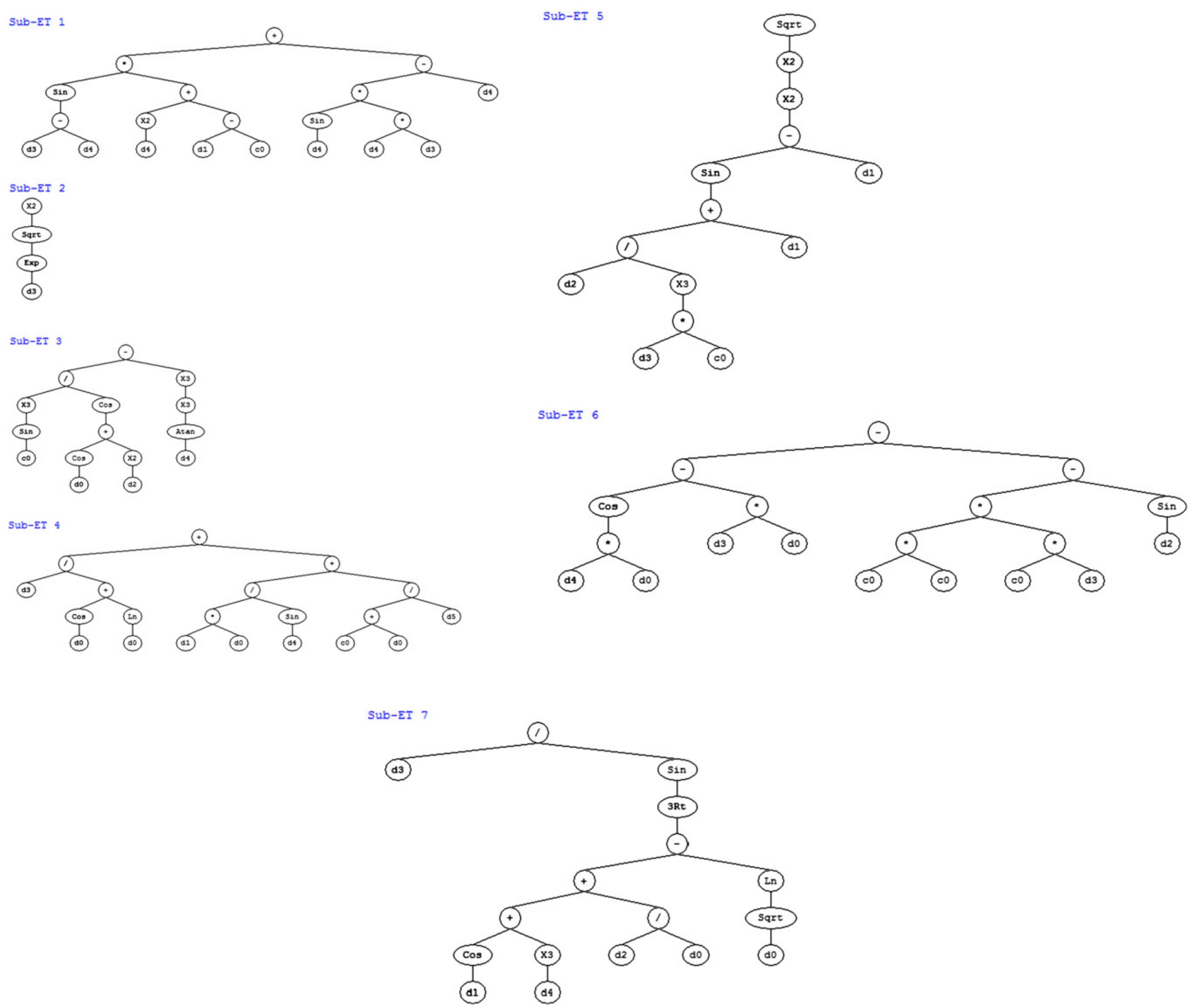

Fig. 3. Expression tree with 7 genes and addition as linking function for predicting Charpy impact energy of the considered Al/SiC$_P$ laminated nanocomposites in GEP2 model.

namely, $T=\{T, N, A, C, S, K\}$ and 4 basic arithmetic operators ($+$, $-$, $*$, $/$) and some basic mathematical functions (Sqrt, third root, x^2, x^3, ln, Exp, sin, cos, Arctan) were used [10].

Another major step is to choose the chromosomal tree, i.e., the length of the head and the number of genes. In GEP1 to GEP4 approach models, initially a single gene and two lengths of heads was used and these parameters then were increased 1 after another during each run, and the training and testing sets performance of each model were monitored to obtain the highest performance formulations [10]. In this study, for GEP1 and GEP2 models, head sizes of 12 and for GEP3 and GEP4 models, that of 14 were observed to have the highest influence on the performance of the models.

Finally, a combination of all genetic operators (mutation, transposition and crossover) was utilized as set of genetic operators. Parameters of the training of the GEP1 to GEP4 approach models are given in Table 3. For the GEP1 to GEP4 approach models, chromosomes 30 and 40 were observed to be the best of generation individuals predicting the Charpy impact energy of Al/SiC$_P$ laminated nanocomposites. Explicit formulations based on the GEP1 to GEP4 approach models for Charpy impact energy values could be obtained by

$$CVN=f(T, N, A, C, S, K) \tag{2}$$

The related formulations could be obtained by the procedure shown in Fig. 1 [10].

4. Predicted results and discussion

The related equations of GEP1 to GEP4 models obtained from Figs. 2–5 are in accordance to Eqs. (3)–(6), respectively;

$$J_{CVN}(\text{GEP1}) = S^2\left(\sqrt[3]{C}-\cos^3(C-S-4.56)\right)^{1.5} + \left(2.26-8.59\sin^2(S)\right)\left(S^2-S+\sqrt{N}\right)$$

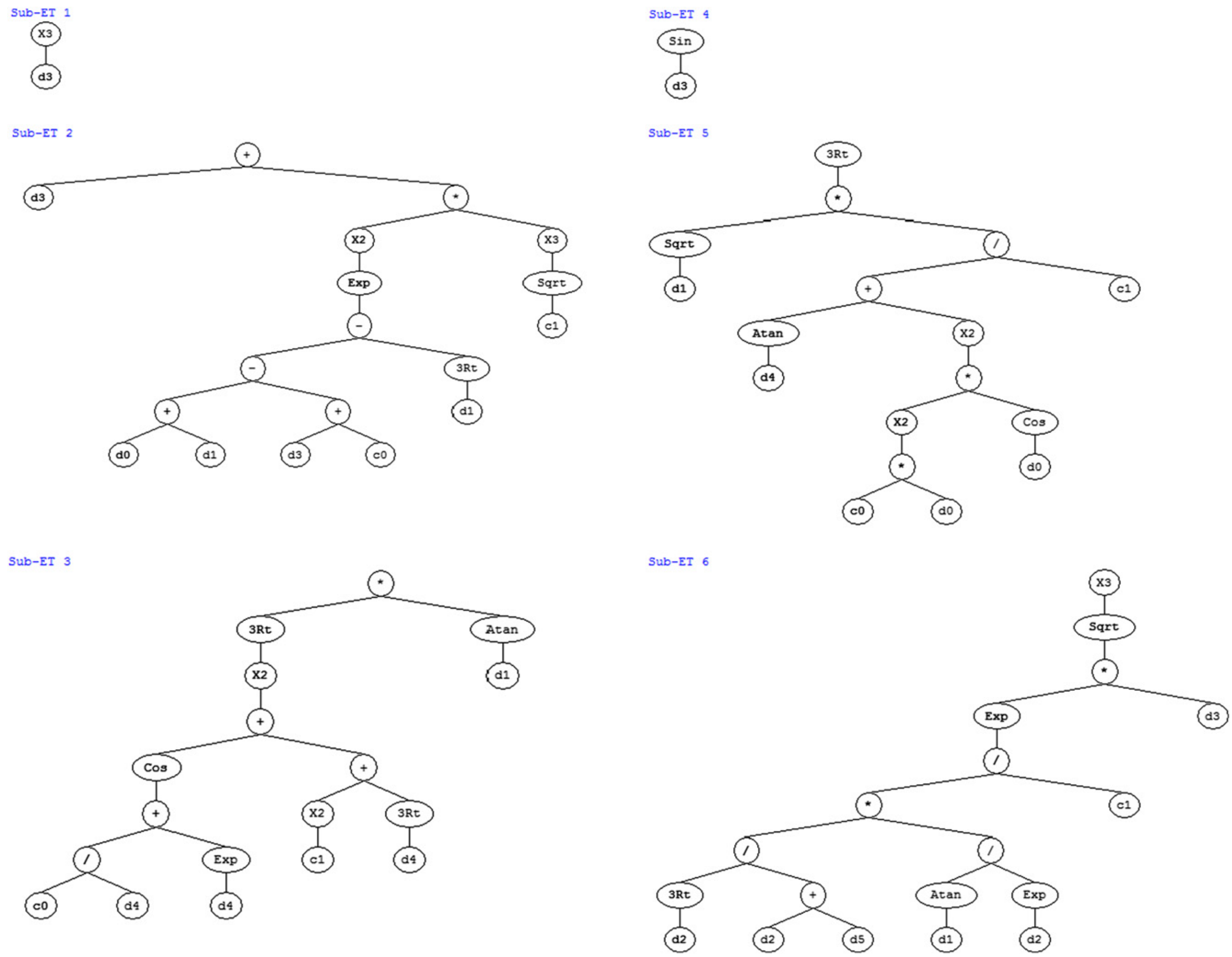

Fig. 4. Expression tree with 6 genes and multiplication as linking function for predicting Charpy impact energy of the considered Al/SiC$_P$ laminated nanocomposites in GEP3 model.

Table 3
Parameters of GEP approach models.

Parameter definition		GEP1	GEP2	GEP3	GEP4
P1	Number of genes	6	7	6	7
P2	Chromosomes	30	30	40	40
P3	Head size	12	12	14	14
P4	Linking function	Addition	Addition	Multiplication	Multiplication
P5	Mutation rate	0.044	0.055	0.044	0.055
P6	Inversion rate	0.1	0.1	0.1	0.1
P7	One-point recombination rate	0.3	0.3	0.3	0.3
P8	Two-point recombination rate	0.3	0.3	0.3	0.3
P9	Gene recombination rate	0.1	0.1	0.1	0.1
P10	Gene transposition rate	0.1	0.1	0.1	0.1
P11	Constants per gene	5	5	5	5
P12	Weight of functions	7	7	7	7
P13	Upper bound	10	10	10	10
P14	Lower bound	−10	−10	−10	−10

$$+\left(\frac{CS}{\mathrm{Exp}\left(\sin^2(S)\right)}\right)\sqrt{\frac{5.73NA}{TS}}+\ln(K)-13.9-T$$

$$-T\sin(S-6.71)+S-65\sin^3(C)-143.8\sqrt[3]{N+C}+\mathrm{C}^3 \qquad (3)$$

$$J_{CVN}(\mathrm{GEP2})=\sin(C-S)\left(S^2+N-3.83\right)+CS\sin(S)-S+\mathrm{Exp}(C)-\frac{0.45}{\cos(A^2+\cos(T))}-\mathrm{Arctan}^9(S)+\frac{C}{\cos(T)+\ln(T)}+\frac{TN}{\sin(S)}$$

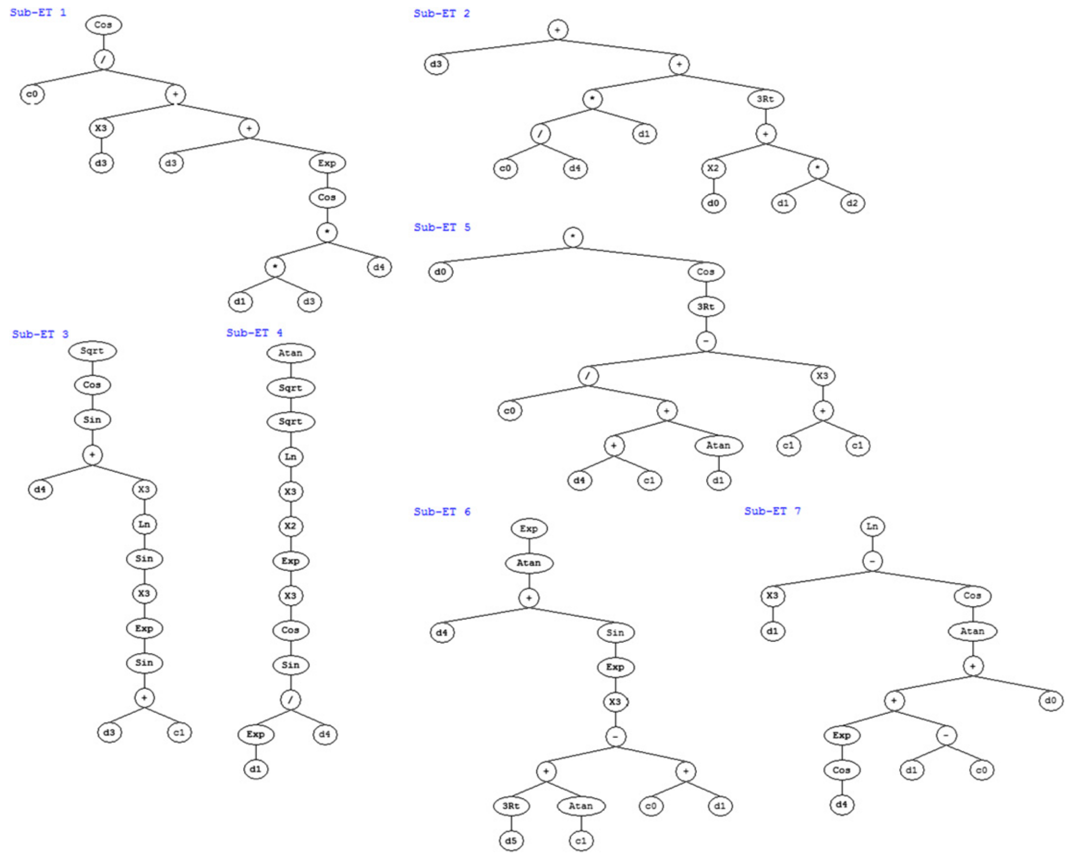

Fig. 5. Expression tree with 7 genes and multiplication as linking function for predicting Charpy impact energy of the considered Al/SiC_P laminated nanocomposites in GEP4 model.

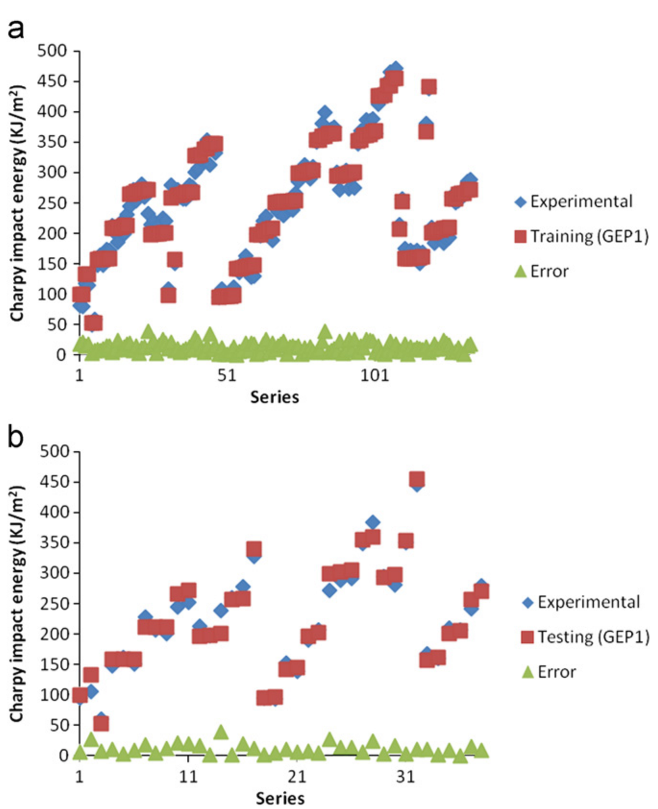

Fig. 6. The correlation of the measured and predicted Charpy impact energy values of the considered Al/SiC_P laminated nanocomposites in (a) training and (b) testing phase for GEP1 model.

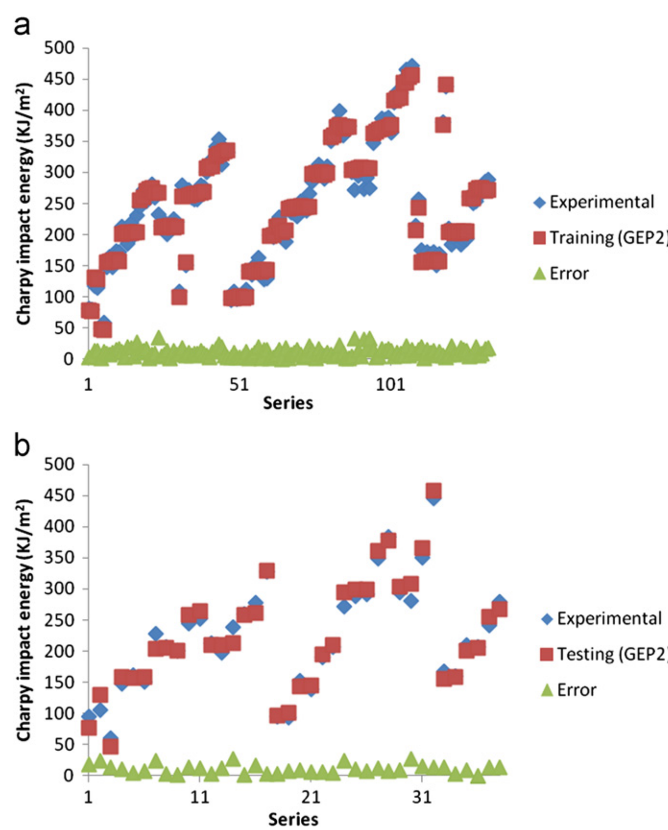

Fig. 7. The correlation of the measured and predicted Charpy impact energy values of the considered Al/SiC_P laminated nanocomposites in (a) training and (b) testing phase for GEP2 model.

$$+\frac{T-7.16}{K}+\left(\sin\left(-1.38\frac{A}{C^3}+N\right)-N\right)^2$$
$$+cos(TS)-TC+73.5C+\sin(A)$$
$$+\frac{C}{\sin\sqrt[3]{\cos(N)+S^3}+\frac{A}{T}-0.5\ln(T)} \quad (4)$$

J_{CVN}(GEP3)

$$=1.63C^3\left(C+29.5\,\mathrm{Exp}^2\left(T+N-C-\sqrt[3]{N}-9.52\right)\right)$$
$$\mathrm{Arctan}(N)\left(\cos\left(-\frac{4.28}{S}+\mathrm{Exp}(S)\right)+\sqrt[3]{S}+0.46\right)^{2/3}$$
$$\sin(C)N^{1/6}\sqrt[3]{\left(\mathrm{Arctan}(S)+\left(0.1T^2\cos(T)\right)^2\right)}$$
$$\left(0.83\,C\mathrm{Exp}\left(\sqrt[3]{A}\frac{\mathrm{Arctan(N)}}{(A+K)\mathrm{Exp}(A)}\right)\right)^{1.5} \quad (5)$$

$$J_{CVN}(\mathrm{GEP4})=\cos\left(\frac{7.84}{C^3}+C+\mathrm{Exp}(\cos(NCS))\right)$$
$$\left(C+4.36\frac{N}{S}+\sqrt[3]{T^2}+NA\right)$$
$$\sqrt{\cos\left(\sin\left(S+\left(\ln\left(\sin\left(\mathrm{Exp}^3(\sin(1.13+C))\right)\right)\right)^3\right)\right)}.$$
$$\mathrm{Arctan}\left(\cos^{4.5}\left(\sin\left(\frac{\mathrm{Exp}(N)}{S}\right)\right)\right)^{1/4}T$$
$$\cos\sqrt[3]{\frac{-7.54}{S-6.35+\mathrm{Arctan}(N)}+2048\,\mathrm{Exp}}$$
$$\left(\mathrm{Arctan}\left(S+\sin\left(\mathrm{Exp}\left(\sqrt[3]{K}-\mathrm{N}-0.43\right)^3\right)\right)\right)\ln$$
$$\left(N^3-\cos(\mathrm{Arctan}(T+N+\mathrm{Exp}(\cos(S))-8.99))\right) \quad (6)$$

In this study, the error arisen during the training and testing of GEP1 to GEP4 models can be represented as absolute fraction of variance (R^2), Mean absolute percentage error (MAPE) and root mean square error (RMSE) which are calculated by Eqs. (7)–(9), respectively [10]:

$$R^2=1-\left(\frac{\sum_i(t_i-o_i)^2}{\sum_i(o_i)^2}\right) \quad (7)$$

$$MAPE=\frac{1}{n}\sum_i\left|\frac{t_i-o_i}{t_i}\right|100 \quad (8)$$

$$RMSE=\sqrt{\frac{1}{n}\sum_i(t_i-o_i)^2} \quad (9)$$

where t is the target value, o is the output value and n is the number of data sets in each of training and testing phases.

All the results obtained from experimental studies and predicted by using the training and testing results of GEP1 to GEP4 models are given in Figs. 6–9, respectively. R^2, MAPE and RMSE values were shown in Table 4 for the

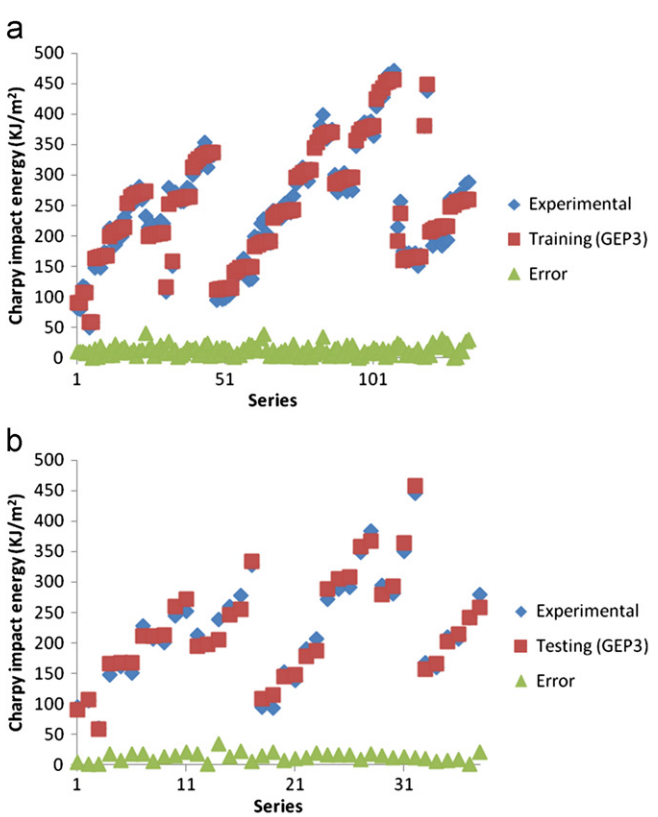

Fig. 8. The correlation of the measured and predicted Charpy impact energy values of the considered Al/SiC$_P$ laminated nanocomposites in (a) training and (b) testing phase for GEP3 model.

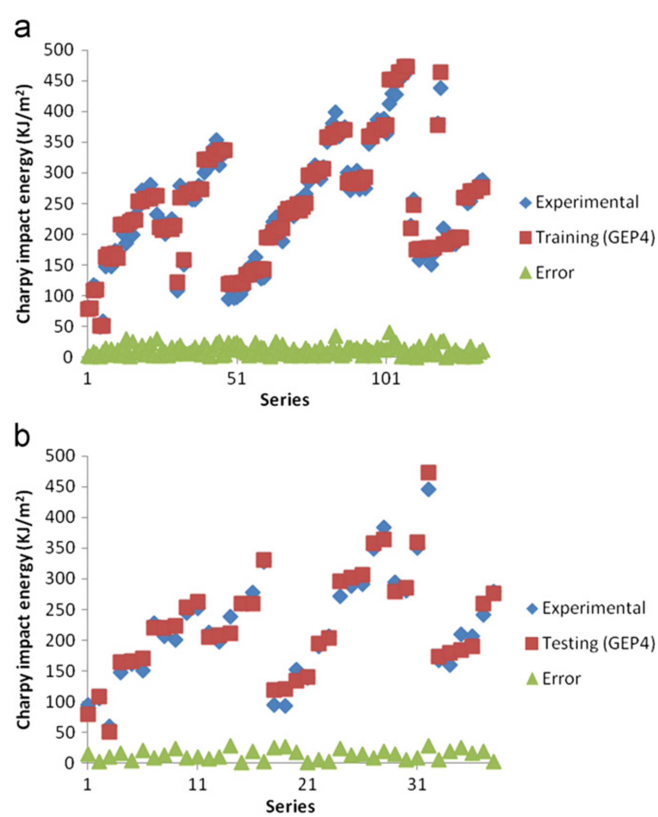

Fig. 9. The correlation of the measured and predicted Charpy impact energy values of the considered Al/SiC$_P$ laminated nanocomposites in (a) training and (b) testing phase for GEP4 model.

training and testing data. As it is seen in Figs. 6–9, the values obtained from the training and testing in GEP1 to GEP4 models are very close to the experimental results. The results of testing phase in Figs. 6–9 show that the GEP1 to GEP4 models are capable of generalizing between input and output variables with reasonably good predictions.

Table 4
Statistical calculations from GEP1 to GEP6 training and testing phases.

Model	GEP1		GEP2		GEP3		GEP4	
Phase	Training	Testing	Training	Testing	Training	Testing	Training	Testing
R^2	0.9769	0.9752	0.9826	0.9811	0.9769	0.9718	0.9796	0.9696
MAPE	11.986	10.728	10.217	10.317	11.719	12.522	10.886	13.110
RMSE	14.377	13.683	12.432	12.613	14.364	14.411	13.590	15.429

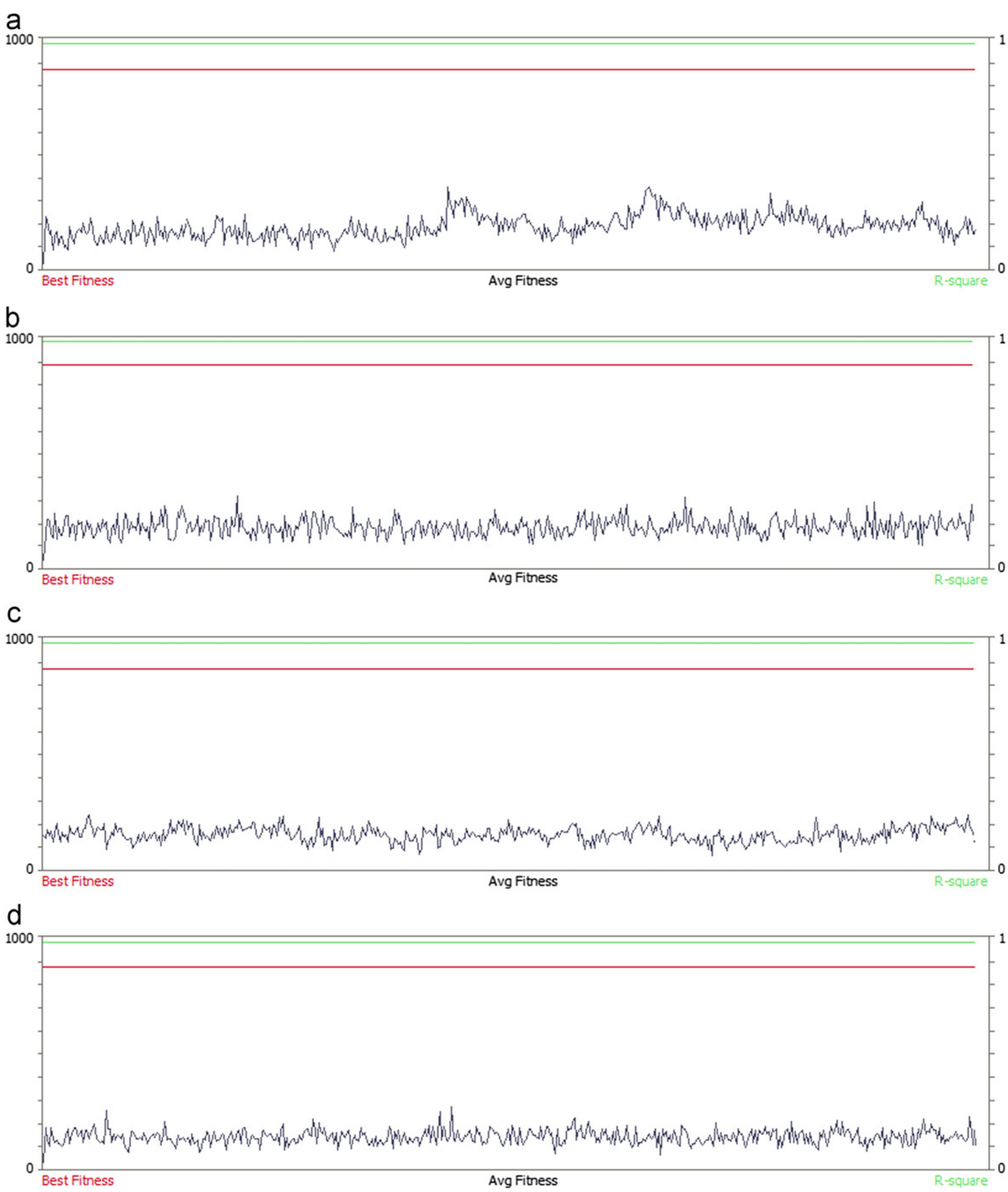

Fig. 10. Fitness factor versus generation iteration for (a) GEP1, (b) GEP2, (c) GEP3 and (d) GEP4 models.

The performance of GEP1 to GEP4 models is shown in Figs. 6–9. The best value of R^2 is 0.9826 for training set in GEP2 model. The minimum value of R^2 is 0.9696 for testing set of GEP4 model. The minimum value of MAPE is 10.217 for training set in GEP2 model. The maximum value of MAPE is 13.110 for testing set in GEP4 model. Finally, the minimum value of RMSE is 12.432 for training set in the GEP2 model and the maximum value of RMSE is 15.429 for testing set in GEP4 model. All of R^2, MAPE and RMSE values show that the proposed GEP1 to GEP4 models are suitable and can predict the Charpy impact energy values very close to the experimental values.

Finally, Fig. 10 shows fitness factor versus generation iteration for GEP1 to GEP4 models, respectively. This figure shows that the presented models are suitably trained and the final results in the studied range are of reliability that one may consider these models for predicting Charpy impact energy values of the considered Al/SiC_P laminated nanocomposites.

5. Conclusions

Four different GEP models were proposed for predicting Charpy impact energy values of the considered Al/SiC_P laminated nanocomposites. In GEP1 and GEP2 models, addition was set as linking function, 30 chromosomes and the head size of 12 was used and 6 and 7 genes were utilized, respectively. On the other hand, multiplication as linking function, 40 chromosomes and head size of 14 were used in GEP3 and GEP4 models together with 6 and 7 genes, respectively. The acquired results indicated that GEP can be an alternative approach for the evaluation of Charpy impact energy of Al/SiC_P laminated nanocomposites. The best values of R^2, MAPE and RMSE were 0.9826, 10.217 and 12.432, respectively all in training set of GEP2 model. Comparison between GEP in terms of R^2, MAPE and RMSE values showed that GEP models are capable to predict suitable results for Charpy impact energy of Al/SiC_P laminated nanocomposites in the studied range.

References

[1] A.M. Zahedi, H.R. Rezaie, J. Javadpour, M. Mazaheri, M.G. Haghighim, Processing and impact behavior of Al/SiC_P composites fabricated by the pressureless melt infiltration method, Ceramics International 35 (2009) 1919–1926.

[2] A.M. Zahedi, J. Javadpour, H.R. Rezaie, M. Mazaheri, The effect of processing conditions on the microstructure and impact behavior of melt infiltrated Al/SiC_P composites, Ceramics International 37 (2011) 3335–3341.

[3] F. Ortega-Celaya, M.I. Pech-Canul, J. Lopez-Cuevas, J.C. Rendon-Angeles, M.A. Pech-Canul, Microstructure and impact behavior of Al/SiC_P composites fabricated by pressureless infiltration with different types of SiCp, Journal of Materials Processing Technology 183 (2007) 368–373.

[4] F. Carreno, J. Chao, M. Pozuelo, O.A. Ruano, Microstructure and fracture properties of an ultrahigh carbon steel-mild steel laminated composite, Scripta Materialia 48 (2003) 1135–1140.

[5] A. Nazari, V. Abdinejad, Artificial neural networks for prediction Charpy impact energy of Al6061/SiC_p-laminated nanocomposites, Neural Computing and Applications (2012)http://dx.doi.org/10.1007/s00521-012-0996-0.

[6] A. Cevik, I.H. Guzelbey, A soft computing based approach for the prediction of ultimate strength of metal plates in compression, Engineering Structures 29 (2007) 383–394.

[7] A. Cevik, A new formulation for web crippling strength of cold-formed steel sheeting using genetic programming, Journal of Constructional Steel Research 63 (7) (2007) 867–883.

[8] M. Eskil, E. Kanca, A new formulation for martensite start temperature of Fe–Mn–Si shape memory alloys using genetic programming, Computational Materials Science 43 (4) (2008) 774–784.

[9] J.R. Koza, Genetic Programming: on the Programming of Computers by Means of Natural Selection, MIT Press, Cambridge (MA, USA), 1992.

[10] M. Sarıdemir, Genetic programming approach for prediction of compressive strength of concretes containing rice husk ash, Construction and Building Materials 24 (2010) 1911–1919.