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A Simple Formulation In Computing Surface Roughness Of Az91d Magnesium Alloy Derived By Using Artificial Bee Colony (Abc) Algorithm

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Abstract

Because of the requirement for providing the minimum surface roughness, the methods related to determining the surface roughness have crucial importance in the manufacturing process. In this study, 18 experiments of AZ91D magnesium alloy based on the ball burnishing technique which is one of the simple, rapid, cost-effective and superfinishing process methods are carried out with the use of main process parameters such as the burnishing force, burnishing speed, feed rate and number of passes. Then, a novel and simple closed-form expression for the surface roughness is empirically derived by using the experimental results regarding AZ91D magnesium alloy together with the artificial bee colony (ABC) algorithm. The average percentage error between the measured and calculated results of the surface roughness for the AZ91D magnesium alloy is found to be 1.77%. In order to indicate the relative importance among the process parameters utilized in the proposed surface roughness expression, several parametric studies are also performed and reasonable results are obtained. Consequently, a closed–form formula for the surface roughness of AZ91D magnesium alloy, which can readily be used by the machine designers without any background in sophisticated mathematical techniques, is introduced.

Keywords: *Surface roughness, Modelling, Ball burnishing, Artificial bee colony algorithm, AZ91D magnesium alloy.*

1. Introduction

Due to the low density, high strength–to–weight ratio, high specific toughness, good machinability, adequate stability and rigidity, magnesium alloys have been widely studied and used in automotive, aerospace and defense industries [1–3]. On the other hand, the cast magnesium alloys may suffer from their limitations such as the ductility, low fatigue strength and the low fatigue resistance [4]. The surface properties of a machining parts, such as the surface roughness, dimensional and geometric precision, are very important in the manufacturing process due to influencing the cost of production and performance as well [5–7]. In the machining part process, the desired surface roughness is difficult to be obtained by using the conventional machining methods such as turning, milling and classical grinding [8].

The performed burnishing process as finishing operation is used in the machining parts. The ball burnishing, which is simple, rapid and cost–effective is one of most used process to obtain the better surface integrity of mechanical parts [9, 10]. The burnishing provides additional advantages such as increased surface hardness, fatigue, strength and wear resistance. The burnishing process is usually applied to obtain a good surface roughness. Furthermore, a good surface roughness can be obtained by using the burnishing method having cheap equipment and shorter processing time than classical methods. Therefore, the ball burnishing method can be a good candidate in the surface finishing process, such as lapping, honing, grinding or polishing [11]. The parameters like burnishing force, the number of passes, feed rate, burnishing speed, ball material, workpiece materials, ball size and lubricant are very important for the quality of the surface [12-16].

Recently, the many algorithms based on artificial intelligence (AI) have been improved and applied to different areas of the mechanical engineering with developing of the computer technology [17-20]. The presented techniques for the prediction of surface roughness or surface profile depend on the sequential

derivation of the mathematical by utilizing complex functions. Additionally, the applicability of proposed models based on artificial neural network is difficult in the practice. Therefore, the determination of surface roughness or surface takes much time and needs knowledge of mathematics.
In this study, to overcome with the above problems, a new and simple expression based on the used process parameters like number of passes, burnishing force, burnishing speed and feed rate has been improved by using the artificial bee colony (ABC) algorithm based AI in the calculating accurate surface roughness values for magnesium alloy (AZ91D).

2. Artificial bee colony (ABC) algorithm

Recently, the optimization techniques based on swarm intelligence (SI) have received great interest. In the development process of the optimization methods, particularly swarm–intelligence–based algorithms have become very popular. The optimization methods based on SI like an artificial bee colony, ant colony optimization, particle swarm optimization, cuckoo search and firefly algorithms have many advantages over conventional optimization algorithms [21-25]. Artificial bee colony (ABC) algorithm which is one of the most popular SI based methods was developed by observing the nourishment behavior of the honey bees [26–34]. In the algorithm, the nectar sources (food) represent the points of the possible solution in the given multi-dimensional search space. There are three of phases like the employed bees, onlooker bees and scout bees. Three types of bees fly around to find the best nectar sources. The artificial bees in the ABC algorithms begin by generating random solutions and it repeatedly attempts to discover better solutions by looking for possible solutions in the neighborhoods of the current best solutions in the given search space. If some solution is not improved by bees, these poor solutions are abandoned by bees. Each food source represents as a possible solution of problem and an employed bee is appointed to each food source. Also, the number of onlooker bee is equal of the number of employed bee. The food sources are exploited by the onlooker bees considering to nectar quality or fitness. Both onlooker and employed bees iteratively try to find the better location of food sources in the neighborhoods of their current food source. The food sources are exhausted by employed bee and then the employed bee becomes a scout bee to search further food sources once again.
The pseudocode of ABC algorithm is given bellow:
Initialization step:
2.1.Initialize the population of solutions xij

$$x_{ij} = x_j^{\min} + rand(0,1) * (x_j^{\max} - x_j^{\min}) \tag{1}$$

Here, i =1, 2, …, FS; j =1, 2, …, D. Where, FS and D indicate the number of food sources and the dimension of the optimization parameters, respectively.
2.2.Evaluate nectar amount (fitness) of the food sources.
2.3.Iteration=1
Repeat
Employed bee step:
Employed bees go to the food sources and detect their amounts.
2.4.Generate new solutions (food source positions) v_{ij} in the neighborhood of x_{ij} for the employed bees using the formula given below

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{2}$$

Here, $k \in$ 1, 2, …, FS and $j \in$ 1, 2, …, D are randomly selected indices. Although, k is detected randomly, it has to be dissimilar. ϕ_{ij} is a random number between [–1, 1].
2.5.Apply the greedy selection process between x_{ij} and v_{ij}.
Onlooker bee step:
The onlooker bees calculate the probability value of the sources.
2.6.Compute fitness values to minimize problems using the following equation:

$$fit_i(x_{ij}) = \begin{cases} \dfrac{1}{1+fit_i(x_{ij})} & \text{if } fit_i(x_{ij}) \geq 0, \\ 1+abs(fit_i(x_{ij})) & \text{if } fit_i(x_{ij}) < 0, \end{cases} \tag{3}$$

2.7.The probability value pi with which x_{ij} is selected by an onlooker bee can be computed by the expression given:

$$\rho_i = \frac{fit_i(x_{ij})}{\sum_{n=1}^{FS} fit_i(x_{ij})} \tag{4}$$

Normalize pi values into [0,1].

2.8.Generate the new solutions (new positions) vi for the onlookers from the solutions x_i , chosen depending on ρ_i , and evaluate them.
2.9.Apply the greedy selection process for the onlookers between x_i and v_i

Scout bee step:
If a source is abandoned by an employed bee, the scout bee is randomly sent to search the area for discovering new food sources.
2.10.Detect the abandoned solution (source), if it exists, and replace it with a new randomly produced solution x_i for the scout bee using the equation (1)
2.11.Memorize the best food source position (solution) achieved so far.
2.12.Iteration=Iteration+1.

Finalization:
Until iteration=Maximum Iteration Number (MIN) The flow chart of ABC algorithm is given in Fig. 1. In the first phase, the values of the possible solution about the nectar source position randomly produce between two previously given limitation values in the search space of the optimization problem. The fitness values of the produced nectar or food quality in respect of the amounts of the food are computed to evaluate the profitability as the firstly. At the onlooker bees phase, the probability of the solution values is calculated by considering the values of their fitness and the onlooker bees and the bees look for new solutions around food locations having high probability values. In the scout bees step, if a possible solution doesn't find a new good solution with high probability value after a specified number of trial limits, a new possible solution is randomly generated by a scout bee as the producing process of the possible solution in the initial step. Finally, the best solution point discovered in each step is saved in memory. These steps consecutively maintain until the specified MIN.

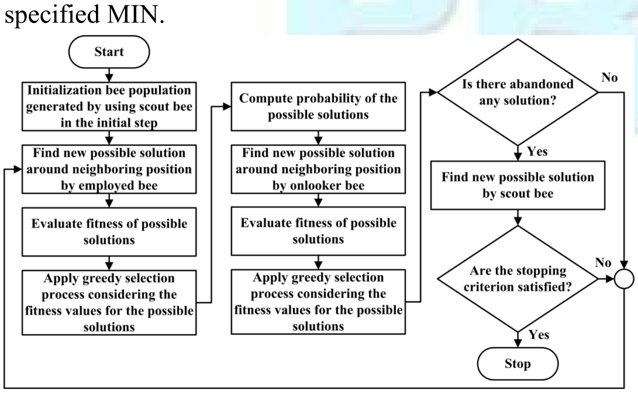


Fig. 1. The flow chart of the ABC algorithm

3. The derivation of the surface roughness expression

To derivate an calculated of values of the surface roughness for AZ91D magnesium alloy, the experimental results have been used for 18 samples having the surface roughness range of between 0.336 and 0.718 µm. There are four process parameters like number of passes, burnishing force (N), burnishing speed (rpm) and feed rate (mm/min). The AZ91D consisting of 90,14851% Magnesium (Mg), 9.21% Aluminum (Al), 0.45% Zinc (Zn), 0.17% Manganese (Mn), 0.0018% Iron (Fe), 0.00084% Beryllium (Be), 0.016% Silicon (Si), 0.002% Copper (Cu), 0.00085% Nickel (Ni) as a compound weight of the elements is produced. In order to optimize the surface roughness depended on process parameters, the reached experimental results are given in Table 1.
Four main process parameters which are the number of passes, burnishing force, burnishing speed and feed rate have been used in the experiment. The number of passes is changed between of 1 and 2. The burnishing force is in the range of 50 and 250. The burnishing speed is between 200 and 600, the feed rate is also between 0.1 and 0.5.

Table 1: The experimental results obtained by ball burnishing process

Experimental Number	Experimental design variables				Surface roughness– *Ra* (µm)
	Number of passes	Burnishing force (N)	Burnishing speed (rpm)	Feed rate (mm/ min)	
1	1	50	200	0.10	0.481
2	1	50	400	0.25	0.631
3	1	50	600	0.50	0.718
4	1	150	200	0.10	0.434
5	1	150	400	0.25	0.519
6	1	150	600	0.50	0.550
7	1	250	200	0.25	0.448
8	1	250	400	0.50	0.559
9	1	250	600	0.10	0.424
10	2	50	200	0.50	0.599
11	2	50	400	0.10	0.402
12	2	50	600	0.25	0.480
13	2	150	200	0.25	0.407
14	2	150	400	0.50	0.508
15	2	150	600	0.10	0.358
16	2	250	200	0.50	0.504
17	2	250	400	0.10	0.336
18	2	250	600	0.25	0.409

In order to construct the best model which is proper with the experimental parameters related to the surface roughness, the various models of the surface roughness formulations occurring the unknown coefficients (AI) together with the parameters (number of passes (x_1), burnishing force (x_2) burnishing speed (x_3) and feed rate

(x_4)) were established. The following total percentage error (*TPE*) as objective function was used in the ABC algorithm to be minimized.

$$TPE = \sum_{k=1}^{EN} \left[\left| \frac{Ra_{\exp_k} - Ra_{cal_k}}{Ra_{\exp_k}} \right| x100 \right] \quad (5)$$

where, $Ra_{\exp}$ and Ra_{cal} are the measured and calculated surface roughness values, respectively. The EN is the experiment number and is equal to 18. The values of ABC algorithm optimization parameters for this work are set as given in Table 2.

Table 2: The optimization process parameters of the ABC algorithm used in this study.

ABC algorithm parameters	Assigned values
Number of dimensions (*D*)	5
Population size (*NP*)	50
Trial number	*NP*D*

In order to appoint a surface roughness equation, a sequence of experiments was implemented, and the formulation Ra_{cal} producing satisfying results has been established as:

$$Ra_{cal} = \frac{1}{(K+L)}$$

$$K = a_1 + \sqrt{x_1} - 10.a_1.x_2^{a_2} + x_3^{-\frac{a_1}{10}}$$

$$L = a_3.\sqrt{x_4} + x_3.\left(\frac{x_1}{x_4}\right)^{a_4} + (x_1.x_4)^{a_5} \quad (6)$$

Note that the surface roughness equation models which were simpler and more complicated than that given by equation (a) were also tried. It was seen that the obtained results with simpler models were not in good agreement with the experimental results. But, the more complicated models also ensure little improvement in the TPE value. The given unknown coefficients in the effective surface roughness equation have been then detected as optimally and these coefficients are tabulated in Table 3.

Table 2: Coefficient values for the effective surface roughness equation of AZ91D determined by the ABC algorithm

Index (i)	1	2	3	4	5
a_i	1.234	-0.787	-2.729	-10.573	0.143

4 Numerical results and discussion

The surface roughness values of measured for 18 samples of AZ91D alloy well as their respective values calculated by using the proposed expression are tabulated in Table 4. It is clearly seen in Table 4 that the experiments 5, 6, 8, 10, 11 and 15 indicate the best results with the lowest error for surface roughness. Based on the calculations with formulation derived by using the ABC algorithm, the average percentage error (*APE*) between the measured *Ra* and calculated *Ra* was obtained as 1.77%. Fig. 2 shows the surface roughness results of the formulation derived by using the ABC and those of the measurements for the AZ91D alloy. As can be seen from Fig 2, the calculated surface roughness results are very close to the measured ones. This good agreement between the measured and our computed results promotes the correctness of the new surface roughness formulation derived by using the ABC. Also obtained a high correlation coefficient value between measured and calculated values of the surface roughness and R^2 is equal to 0.975. This result is shown that the measured and calculated values are close to each other's. Using the expression proposed in this study, one can easily compute the surface roughness of the AZ91D magnesium alloy using a scientific calculator since it does not require complicated mathematical transformations of sophisticated functions in the range of the process parameters

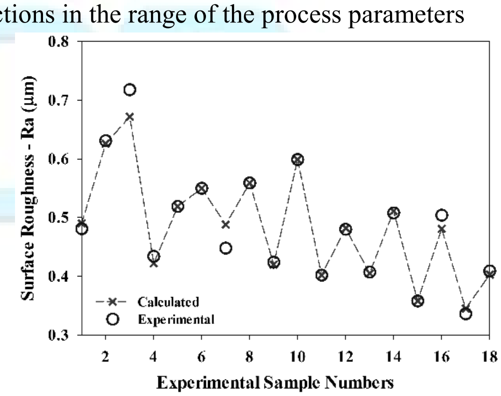
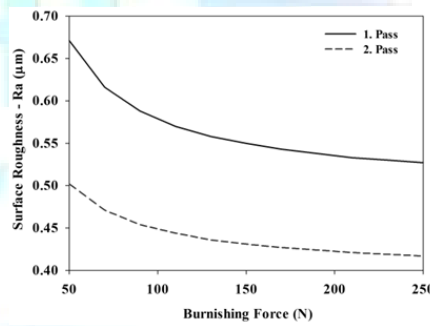


Fig. 2. The comparative graph of the calculated surface roughness and measured results

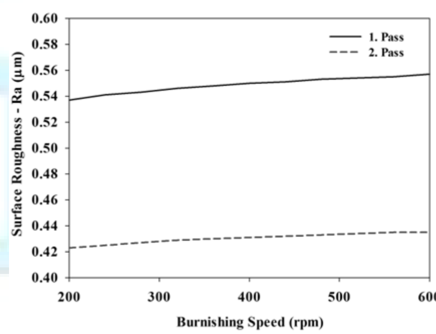
Table 4: Comparison of experimental and calculated *Ra* values with percent error

Experimental Number	Surface Roughness *Ra* (µm) Experimental	Surface Roughness *Ra* (µm) Calculated	Percent Error (%)
1	0.481	0.490	1.871
2	0.631	0.626	0.792
3	0.718	0.672	6.407
4	0.434	0.422	2.765
5	0.519	0.519	0.000
6	0.550	0.550	0.000
7	0.448	0.488	8.929
8	0.559	0.559	0.000
9	0.424	0.420	0.943
10	0.599	0.599	0.000
11	0.402	0.402	0.000
12	0.480	0.482	0.417
13	0.407	0.405	0.491
14	0.508	0.511	0.591
15	0.358	0.358	0.000
16	0.504	0.481	4.563
17	0.336	0.345	2.679
18	0.409	0.403	1.467
Average Percentage Error (*APE %*)			1.77

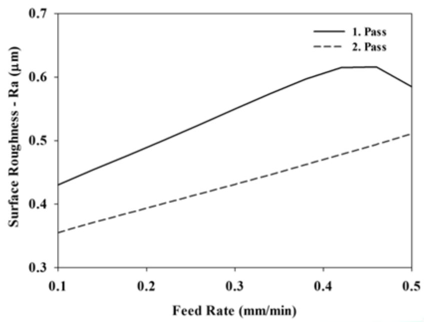
In order to investigate the effect of the process parameters on surface roughness formulation, the performed several parametric studies are given in Fig. 3 is plotted by using the derived formulation. While the values used in the figures are calculated, two of three process factors are fixed to a constant value. For the other factor, the value of the factor is increased according to a certain rate value selected in the range of lower and upper values and its effect on surface roughness is investigated. For situations of the first and second pass, the relationship of the between surface roughness and burnishing force is given in Fig. 3a. Here, the values of the burnishing speed and feed rate are equal to 400 and 0.3, respectively. It can be clearly seen from the Fig. 3a that while the burnishing force increases, the surface roughness value decreases. The burnishing force factor has performed extremely high changes on surface roughness between 50N and 150N range. The roughness performance curve trend gets more stable after 150N burnishing force. The relation of burnishing speed and surface roughness is illustrated in Fig. 3b. The burnishing force and feed rate value are 150 and 0.3. When burnishing speed rises, the surface roughness value increases. Since the burnishing ball passes several times on the same region, the increasing the revolutions make a negative effect on a work piece surface. However, that factor has not great effect as much as burnishing force. The variation graph of the between surface roughness and feed rate is given in Fig. 3c. The values of burnishing force and burnishing speed were chosen 150 and 400, respectively. For the first pass, the value of the surface roughness increases, as the feed rate value rises between 0 and 0.45. While the value of feed rate increases between 0.45 and 0.5, the surface roughness value decreases. However, in the second pass, while the feed rate value increases, the value of surface roughness rises. In all combinations, the first passes perform a large part of work and the second pass makes improvement and shows similar tendency except for the feed rate plot. The first pass has always great effects and it makes massive changes on a work piece surface like toughness and that causes different surface conditions for following passes. It is shown clearly seen from Fig. 3 that the burnishing force process parameter affects positive the surface roughness. Also, the feed rate and burnishing speed parameters have an effect negative on the surface roughness. However, the burnishing speed process parameter influences less the surface roughness than feed rate parameter.



(a)



(b)



(c)

Fig. 3. The effect of the process parameters on surface roughness formulation: a surface roughness -burnishing force, b surface roughness-burnishing speed and c surface roughness-feed rate

5 Conclusion

In this present study, a novel and simple closed-formula which yields better accuracy in calculating the values of the surface roughness of AZ91D magnesium alloy is proposed. The expression has been derived by using measured results of 18 samples having different parameters like number of passes, burnishing force, burnishing speed and feed rate values. The ABC algorithm which is one of the most recently presented SI–based algorithms, is utilized to derive an expression calculating the surface roughness of AZ91D magnesium alloy. It was demonstrated that the values obtained from the surface roughness expression are in very good agreement with the measured results and the presented expression provides more accurate and reliable results within lower average percentage and total absolute errors. The results investigation shown the all process parameters have different impact factors on surface roughness in burnishing process. Also, this formulation can readily be used by the machine designer without any background in sophisticated mathematical techniques for different designs requiring the usage of AZ91D magnesium alloy.

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References

[1] B. B. Buldum, A. Sik and I. Ozkul, “Investigation of Magnesium Alloys Machinability”, Int J of Electronics, Mechanical and Mechatronics Engineering. Vol. 2, No. 3, 2013, pp. 261.

[2] X-J. Cui, M-T. Li, R–S. Yang and Z–X. Yu, “Structure and Properties of a Duplex Coating Combining Micro-arc Oxidation and Baking Layer on AZ91D Mg alloy,” Applied Surface Science, Vol. 91, 2016, pp. 363.

[3] B. B. Buldum, “Analyzing the Machinability of Magnesium Alloy AZ91”, PhD thesis, Institute of Natural and Applied Sciences, Gazi Univ., Ankara, Turkey, 2013.

[4] Y. Fouad, M. Mhaede and L. Wagner, “Effects of Mechanical Surface Treatments on Fatigue Performance of Extruded ZK60 Alloy”, Fatigue & Fracture of Engineering Materials & Structure, Vol. 34, 2010, pp. 403.

[5] A. H. Suhail, N. Ismail, S. V. Wong and N. A. Abdul Jalil, “Optimization of Cutting Parameters Based on Surface Roughness and Assistance of Workpiece Surface Temperature in Turing Process,” American Journal of Engineering and Applied Science, Vol. 3, No. 1, 2010, pp.102.

[6] D. Mahajan and R. Tajane, “A Review on Ball Burnishing Process”, International Journal of Scientific and Research Publications, Vol. 3, No. 4, 2013, pp.1.

[7] M. Hamamci and E. S. Topal, “Consideration of Step-over Ratio in Optimization of Cutting Parameters for Surface Roughness during High Speed Machining”, Journal of the Balkan Tribological Association, Vol. 21, No. 4, 2015, pp. 753.

[8] P. Franco, M. Estrems and F. Fuara, “Influence of radial and axial runouts on surface roughness in face milling with round insert cutting tools”, Int J Mach Tool Manu, Vol. 44, 2004, pp. 1555–1565.

[9] L. N. Lopez de Lacelle, A. Rodriguez, A. Lamikiz, A. Celaya and R. Alberdi, “Five-axis Machining and Burnishing of Complex Parts for the Improvement of Surface Roughness”, Materials and Manufacturing Processes, Vol. 26, 2011, pp.997.

[10] U. Esme, “Use of Grey Based Taguchi Method in Ball Burnishing Process for the Optimization of Surface Roughness and Microhardness of AA 7075 Aluminum Alloy”, Materials and Technology, Vol. 44, No. 3, 2010, pp.129.

[11] A. Rodriguez, L. N. Lopez de Lacelle, A. Celaya, A. Lamikiz and J. Albizuri, “Surface Improvement of Shafts by the Deep Ball-burnishing Technique”, Surface & Coating Technology, Vol. 206, 2012, pp. 817.

[12] T. A. El-Taweel and M. H. El-Axir, “Analysis and Optimization of the Ball Burnishing Process through the Taguchi Technique”, The International Journal of Advanced Manufacturing Technology, Vol. 41, 2009, pp.301.

[13] A. Sabbas, “Analysis and Surface Roughness in the Ball Burnishing Process using Response Surface Methodology

and Desirability Function", Advances in Engineering Software, Vol. 42, 2011, pp.992.
[14] P. S. Dabeer and G. K. Purohit, "Effect of Ball Burnishing Parameters on Surface Roughness using Surface Roughness Methodology", Advances in Engineering Software, Vol. 42, 2011, pp. 992.
[15] A. A. Ibrahim, S. M. Abd Rabbo, M. H. El-Axir and A. A. Ebied "Center Rest Balls Burnishing Parameters Adaptation of Steel Components using Fuzzy Logic", Journal of Materials Processing Technology, Vol. 209, 2009, pp. 2428.
[16] K. O. Low and K. J. Wong, "Influence of Ball Burnishing on Surface Quality and Tribological Characteristics of Polymers under Dry Sliding Conditions", Tribology International, Vol. 44, 2011, pp. 144.
[17] U. Esme, A. Sagbas, F. Kahraman and M. K. Kulekci, "Use of Artıfıcıal Neural Networks in Ball Burnishing Process for The Prediction of Surface Roughness of AA 7075 Aluminum Alloy", Metarials and Technology, Vol. 42, 2008, pp. 215-219.
[18] A. Sagbas and F. Kahraman "Determination of Optimal Ball Burnishing Parameters for Surface Hardness", Metarials and Technology, Vol.43, 2009, pp.271-274.
[19] D. B. Patel and T. M. Patel "Determination of Optimal Ball Burnishing Parameters for Surface Roughness of Aluminum Alloy", Journal of Mechanical Engineering and Sciences, Vol. 4, 2013, pp. 472-478.
[20] U. Esme, M. K. Kulekci, D. Ustun, B. B. Buldum, Y. Kazancoglu and S. Ocalir, "Modeling and Optimization of CNC Milling of AISI 1050 Steel by a Regression Based Differential Evolution Algorithm (DEA)", Carl Hanser Verlag, Munchen Materials Testing, Vol. 58, 2016, pp. 7-8.
[21] M. Dorigo, "Optimization Learning and Natural Algorithms," PhD thesis, Politecnico di Milano, Italy, 1992.
[22] A. H. Gandomi, X. S. Yang, S. Talatahari and S. Deb, "Coupled eagle strategy and differential evolution for unconstrained and constrained global optimization", Computers & Mathematics with Applications, Vol. 63, 2012, pp. 191–200.
[23] J. Kennedy and R. C. Eberhart, "Particle swarm optimization", In: Proc. of IEEE International Conference on Neural Networks, Piscataway, NJ, 1995, pp. 1942–1948.
[24] X. S. Yang, "Firefly algorithms for multimodal optimization", In: Stochastic Algorithms. Foundations and Applications, SAGA 2009, Lecture Notes in Computer Sciences, Vol. 5792, 2009, pp. 169–178.
[25] X. S. Yang and A. H. Gandomi, "Bat algorithm: A novel approach for global engineering optimization", Engineering Computations, Vol. 29, No. 5, 2012, pp. 1–18.
[26] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm", J Glob Optim, Vol. 39, 2007, pp. 459–471.
[27] D. Karaboga and B. Akay, "A comparative study of Artificial Bee Colony algorithm", Appl Math Comput, Vol. 214, 2009, pp.108–132.
[28] B. Nozohour–Leilabady and B. Fazelabdolabadi, "On the application of artificial bee colony (ABC) algorithm for optimization of well placements in fractured reservoirs; efficiency comparison with the particle swarm optimization (PSO) methodology", Petroleum, Vol. 2, 2016, pp.79–89.
[29] D. Karaboga, B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," J Glob Optim, vol. 39, pp. 459–471, Jun. 2007.
[30] D. Karaboga and B. Gorkemli, C. Ozturk, N. Karaboga, "A comprehensive survey: artificial bee colony (ABC) algorithm and applications", Artıf Intell Rev, Vol. 42, 2014, pp. 21–57.
[31] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm", Appl Soft Comput, Vol. 8, 2007, pp. 687–697.
[32] M. S. Kıran and M. Gunduz, "A novel artificial bee colony–based algorithm for solving the numerical optimization problems", Int J Innov Comput I, Vol. 8, 2012, pp. 6107–6121.
[33] Z. Li, Z. Zhou, X. Sun and D. Guo, "Comparative Study of Artificial Bee Colony Algorithms with Heuristic Swap Operators for Traveling Salesman Problem", Intelligent Computing Theories and Technology 7996 of the series Lecture Notes in Computer Science, 2013, pp. 224–233.
[34] A. Baykasoglu, L. Ozbakır and P. Tapkan, "Artificial Bee Colony Algorithm and Its Application to Generalized Assignment Problem", In: Chan Felix TS, KumarTiwari M (ed.) Swarm Intelligence, Focus on Ant and Particle Swarm Optimization, 2007, pp. 113–144.