Journal of Modern Processes in Manufacturing and Production, Volume 9, No. 1,Winter 2020

DOR: 20.1001.1.27170314.2020.9.1.5.7

Research Paper

Imperialist Competitive Algorithm (ICA) Approach for Optimization of the Surface Grinding Process

Ahmad Afsari[1*], Mohammad Ramezani[1], Shahin Heidari[2], Jafar Karimisharifabadi[1]

[1]Department of Mechanical Engineering, Shiraz Branch, Islamic Azad University, Shiraz, Iran

[2]Bone and Joint Diseases Research Center, Shiraz University of Medical Sciences, Shiraz, Iran

P. O. Box: 71348-14336, Shiraz, Iran

*Email of Corresponding Author: afsari@iaushiraz.ac.ir

Received: January 11, 2020; Accepted: April 10, 2020

Abstract

The imperialist Competitive Algorithm (ICA) is one of the recent meta-heuristic algorithms proposed to solve optimization problems. The Imperialist Competitive Algorithm is based on a socio-politically inspired optimization strategy. This paper presents an Imperialist Competitive Algorithm (ICA) to optimize the performance of a surface grinding operation. Moreover, the multi-objective optimization of a surface grinding process is suggested by using an evolutionary algorithm. Factors like depth of dressing, lead of dressing, workpiece speed and wheel speed are considered to minimize the production cost, surface roughness and to maximize the production rate. The suggested approach presents two constraints handling techniques: constraints handling strategy of ICA and penalty function method. The effectiveness of this algorithm for grinding operation is investigated by comparing the results to other algorithms available in the literature. Results show that the proposed algorithm in this work gives a better performance in a shorter time for the optimization of machining parameters in comparison to other works.

Keywords

Machining Parameters, Optimization, Surface Grinding, Imperialist Competitive Algorithm (ICA)

1. Introduction

One of the significant manufacturing processes in engineering industries is grinding. Optimization analysis of the grinding process seems very important because it based on obtaining the best possible surface quality, maximizing the production rate and minimizing the production cost. In the optimal selection for the grinding process, a variety of operating conditions such as depth and lead of dressing, wheel speed, and workpiece speed are considered [1].

Fortunately, a basis for achieving grinding parameter optimization presented through grinding process models published in former literature [2]. Since 2000, several studies had focused on potential approaches to optimization for the grinding process. Among all the studies those of Wen et al., Amity et al. and Malkin are mentioned [3-5]. Wen et al. proposed a quadratic programming (QP) approach, which used a multi-objective function model with a biased approach for optimization of surface grinding process [3]. Amity et al. described the technique of optimizing both grinding and dressing conditions for the maximum workpiece removal rate subjected to constraints on workpiece burn and surface finish in the adaptive control system [4]. The constraints of optimization during the grinding were mainly present by Malkin [5]. A variety of smart optimization techniques like the Hybrid Particle Swarm Optimization Algorithm (HPSO), Scatter Search (SS), Ant Colony Algorithm (ACO), etc. have been used to optimize the grinding variables: workpiece speed, wheel speed, lead of dressing and depth of dressing. Moreover, the Genetic Algorithms (GA) based optimization procedure was described by Saravan et al. This procedure used to optimize grinding conditions using a multi-objective function model [6]. Later, to obtain more accurate results Basker et al., Lee et al., Krishna, Pawar et al. , Krishna and Rao, and Zhang et al. applied the Differential Evolution (DE), the PSO, the ACO, the SS, the GA, and HPSO for the same model [2,7-11]. The Imperialist Competitive Algorithm (ICA) is a new meta-heuristic algorithm that was first suggested by Atashpaz-Gargari and Lucas in 2007 [12].

The ICA has not been used for machining parameter optimization yet. Therefore, there is an effort to apply the ICA to tackle the optimization of machining parameters of surface grinding. ICA could be used to find the optimal number of passes and optimal values of the cutting parameters for other machining parameters.

2. Mathematical model of the surface grinding process

2.1 Mathematical model of the surface determination of sub-objectives and variables for optimization

The rough grinding case is taken into account in this study. In this case, production cost and surface finish are chosen as the sub-objectives with the condition that the production rate value should not exceed the required value [2].

It is hard to optimize every variable because many of the process variables are involved in grinding. Fortunately, among all the process variables, some are more important while others are determining by the operators. For grinding process variables, namely lead of dressing [L], depth of dressing [doc], workpiece speed [VW], and wheel speed [VS] are considered as the optimization variables [2].

2.1.1 Production Cost

The production costs in the surface grinding process consist of the cost directly related to the grinding of the part, the cost of material consumption, and the cost of non-productive time. So, considering the three above-mentioned items, the formula of the total production cost CT ($/pc) is given according to Wen et al. [3].

$$
\begin{aligned}
CT = {} & \frac{M_c}{60p}\left(\frac{L_w + L_e}{V_w \times 1000}\right)\left(\frac{b_w + b_e}{f_b}\right)\left(\frac{a_w}{a_p} + S_p + \frac{a_w b_w L_w}{\pi D_e b_s a_p G}\right) + \\
& \frac{M_c}{60p}\left(\frac{S_d}{V_r} + t_1\right) + \frac{M_c t_{ch}}{60 N_t} + \frac{M_c}{60p}\frac{1}{N_d}\frac{\pi b_s D_e}{L V_s \times 1000} + \\
& C_s\left(\frac{a_w b_w L_w}{pG} + \frac{\pi Doc b_s De}{pN_d}\right) + \frac{C_d}{pN_{td}}
\end{aligned} \tag{1}
$$

Table 1 shows Surface grinding operation variables.

Table1. Surface grinding operation variables

	Meaning	Unit		Meaning	Unit
M_c	cost per hour labor and administration	$ per hour	b_s	the width of the wheel	Millimeters
P	the number of workpieces loaded on the table	pc	G	the grinding ratio	-
L_w	the length of the workpiece	Millimeters	S_d	the distance of wheel idling	Millimeters
L_e	the empty length of grinding	Millimeter	V_r	the speed of wheel idling	Millimeters per minute
b_w	the width of the workpiece	Millimeters	t1	the time of loading and unloading workpiece	Minutes
b_e	the empty width of grinding	Millimeters	t_{ch}	the time of adjusting machine tool	Minutes
f_b	the crossfeed rate	millimeters per pass	N_t	the batch size of work-pieces	pc
a_w	the total thickness of the cut	Millimeters	N_d	the total number of workpieces to be ground between two dressings	pc
a_p	the down feed of grinding	millimeters per pass	C_s	the cost of wheel	$ per cubic millimeter
S_p	the number of spark out grinding	pass	N_{td}	the total number of workpieces to be ground during the life of dresser	pc
D_e	the diameter of the wheel	Millimeters	C_d	the cost of dressing	$

2.1.2 Production Rate

The production rate is shown by the workpiece removal parameter WRP (cubic millimeters per minute newton) and is presented in Wen et al. as follows [3]:

$$WRP = 94.4\frac{(1+\frac{2Doc}{3L})L^{\frac{11}{19}}(V_wV_s)^{\frac{3}{19}}V_s}{D_e^{\frac{43}{304}}VOL^{0.47}d_g^{\frac{5}{38}}R_c^{\frac{27}{19}}} \qquad (2)$$

Where VOL= 1.33X+2.2S−8 is the wheel bond percentage (%), here, X = 0, 1, 2, etc., for wheel hardness H, I, J, etc., respectively, and S is the wheel structure numbers 4, 5, 6; dg is the grind size (millimeters), and R_c is the workpiece hardness (Rockwell hardness number) [2, 3].

2.1.3 Surface finish

The surface finish of the workpiece is mostly identified to be within a specific value Ra that is affected by wheel dressing parameters and the operation parameters. Its mathematical formula is defined as follows in Wen et al. [3]:

$$T_{ave} = 12.5\times10^{3}\,\frac{d_g^{\frac{16}{27}}\,a_p^{\frac{19}{27}}}{D_e^{\frac{8}{27}}}\,(1+\frac{Doc}{L})\times L^{\frac{16}{27}}\,(\frac{V_w}{V_s})^{\frac{16}{27}} \tag{3}$$

And

$$R_a = \begin{cases} 0.4587T_{ave}^{0.30} \;, & for\;\; 0 < T_{ave} < 0.254 \\ 0.7866T_{ave}^{0.72} \;, & for\;\; 0.254 < T_{ave} < 2.54 \end{cases} \tag{4}$$

T_{ave} is the average chip thickness during grinding.

2.2 Constraints

The main constraints considered in the machining process are variable constraints and process constraints. The process constraints in this study include machine tool stiffness, wheel wear parameter, thermal damage, and either surface finish (for rough grinding) [2].

2.2.1 Thermal damage constraint

High input of energy per unit volume of material removal is needed in the grinding process. All of the energy is changed into heat which is gathered in the grinding zone. This may cause thermal damage to the grinding surface of the workpiece. Workpiece burn is one of the most common types of thermal damage, which directly limits the production rate. According to experimental measurements and heat transfer analysis, it has been proved that burning happens in the zone where the temperature reaches the critical temperature. The critical temperature is directly related to specific energy, which includes sliding energy, plowing energy, and chip formation energy. Considering all these factors, the specific energy U is presented in terms of operating parameters by the following equation of Wen et al. [3]:

$$U = 13.8 + \frac{9.64\times10^{-4}V_s}{a_pV_w} + (6.9\times10^{-3} + \frac{2{,}102.4V_w}{D_eV_s})\times (A_0 + \frac{K_uV_sL_wa_w}{V_wD_e^{1/2}a_p^{1/2}})\frac{V_sD_e^{1/2}}{V_wa_p^{1/2}} \tag{5}$$

Where A0 is the initial wear flat area percentage (percent) and Ku is the wear constant (per millimeter).

And U* is the corresponding critical specific grinding energy, which causes the start of thermal damages. It can be shown in terms of the operating parameters in Wen et al. [3] as follows:

$$U^{*}=6.2+1.76\frac{D_e^{1/4}}{a_p^{3/4}Vw^{1/2}} \tag{6}$$

In practice, if the specific energy U exceeds the corresponding critical specific grinding energy U*, a workpiece burn happens. The thermal damage constraints can be identified as shown below according to the relationship between specific energy and grinding parameters.

$$U \le U^{*} \tag{7}$$

2.2.2 Wheel wear parameter constraint

Wheel wear parameter (WWP) is related to the grinding conditions and the details of wheel dressing which occurs before the grinding operations:

$$WWP = \frac{K_a a_p d_g^{5/38} R_c^{27/19}}{D_e^{1.2} VOL^{-43/304}} \times \frac{(1 + Doc/L) L^{27/19} (V_s/V_w)^{3/19} V_w}{1 + 2Doc/3L} \tag{8}$$

According to Equations (2) and (8), the wheel constraint could be obtained as follows:

$$WRP/WWP \ge G \tag{9}$$

2.2.3 Machine tool stiffness constraint

The workpiece removal rate should be reduced to eliminate grinding chatter. Chatter, in grinding, causes undulation roughness on the grinding wheel or workpiece surface and is highly undesirable. Moreover, wheel surface unevenness makes frequent wheel redressing necessary. Therefore, chatter worsens surface quality and decreases the machining production rate. As a result, for the selection of the operating parameters, chatter elimination is an important constraint. The relationship between operating parameters during grinding, grinding stiffness Kc (newtons per millimeter) is presented as follows:

$$K_c = \frac{1000 \times V_w \times f_b}{WRP} \tag{10}$$

And

$$K_c = \frac{1000 \times V_s \times f_b}{WWP} \tag{11}$$

It is suggested in this paper that the wheel wear stiffness during grinding and the grinding stiffness, as well as the static machine stiffness, must satisfy the following constraint:

$$\frac{1}{2K_c}\left(1 + \frac{V_w}{V_s G}\right) + \frac{1}{K_s} \ge \frac{|R_{em}|}{K_m} \tag{12}$$

Where Km is the static machine stiffness (newton's per millimeter), and Rem is the dynamic machine characteristic.

2.2.4 Surface finish constraint (for rough grinding)

The maximum production rates as well as maintaining a certain surface finish are needed for rough grinding. In this case, surface finish is a constraint whereas the production rate is selected as a sub-objective. The constraint could be shown as follows:

$$R_a \le R_a^{*} \tag{13}$$

Where Ra* is the surface finish limitation in the rough grinding (micrometers) operation.

2.3 Combined objective function model

Based on the analysis presented above, the optimization problem for the surface grinding problem could be expressed as a multi-objective, multi-variable, non-linear optimization problem with multi-constraints. Normalization of each sub-objective is suggested to deal with the large differences in numerical values between the sub-objectives. The combined weighted objective function to be minimized here is as follows:

$$COF(V_S,V_W,Doc,L)=W1\frac{CT}{CT^*}-W2\frac{WRP}{WRP^*}+W3\frac{R_a}{R_a^*} \quad (14)$$

Subjected to

$U \leq U^*$

$WRP/WWP \geq G$

$\frac{1}{2K_c}(1+\frac{V_W}{V_S G})+\frac{1}{K_S} \geq \frac{|R_{em}|}{K_m}$

$R_a \leq R_a^*$

For the finishing grinding where CT^* shows the expected limitation of production cost ($/pc), and W_i (i = 1, 2, 3) are the weighting factors where:

$0 < W_i < 1$ and $W1 + W2 + W3 = 1$

3. Imperialist competitive algorithm

The optimization problem can be identified as finding an argument X whose related cost f(x) is optimum, and it has been applied in various occasions like pattern recognition, scheduling, industrial planning, resource allocation, and so on. A set of algorithms were proposed in the past decades for solving optimization problems in different fields of science and engineering [3, 14, 15]. Among all these methods evolutionary algorithms, such as genetic algorithm, particle swarm optimization, ant colony optimization, bee algorithm, and simulated annealing could be mentioned.

ICA is an algorithm proposed by Atashpaz-Gargari and Lucas for the first time in 2007 and used for optimizing inspired by the imperialistic competition algorithm [3, 12]. It is also significantly relevant to some engineering applications [16-21]. Similar to other evolutionary algorithms, the proposed algorithm begins with an initial population. Colonies and imperialists that all together form some empires are two types of population individuals. Among these empires, imperialistic competition forms the basis of the proposed evolutionary algorithm. During this challenge, powerful empires take possession of their colonies and weak empires collapse. By using this algorithm, the optimum condition of most functions could be found. Imperialistic competition readily converges to a state in which only one empire exists and its colonies are in the same position and have the same imperialist [12]. In order to optimize the objective function, the suggested model-based on regression analysis is embedded into the ICA. The goal of optimization algorithms is to find an optimal solution in terms of the variables of the problem (optimization variables). We shape an array of variable values to be optimized. We use the term ‘’country’’ for this array here (in genetic algorithm terminology, this array is called ‘’chromosome’’). In an N Var-dimensional optimization problem, a country is a 1xN Var array. This array is defined as follows:

$$country = \left[p1, p2, p3, ..., p_{N_{\text{var}}} \right] \tag{15}$$

The cost of a country is found by evaluating the cost function f of the variables [12]. The variable values in the country are shown as floating-point numbers. Then

$$\cos t = f\,(country) = f\,(p1, p2, p3, ..., p_{N_{\text{var}}}) \tag{16}$$

Figure 1 shows the flowchart of the ICA algorithm. We generate the initial population of size N pop to start the optimization algorithm. To form the empires, we choose N imp of the most powerful countries. The remaining Ncol of the population will be the colonies, each of which belongs to an empire. Then, there will be colony and imperialist as two types of countries.

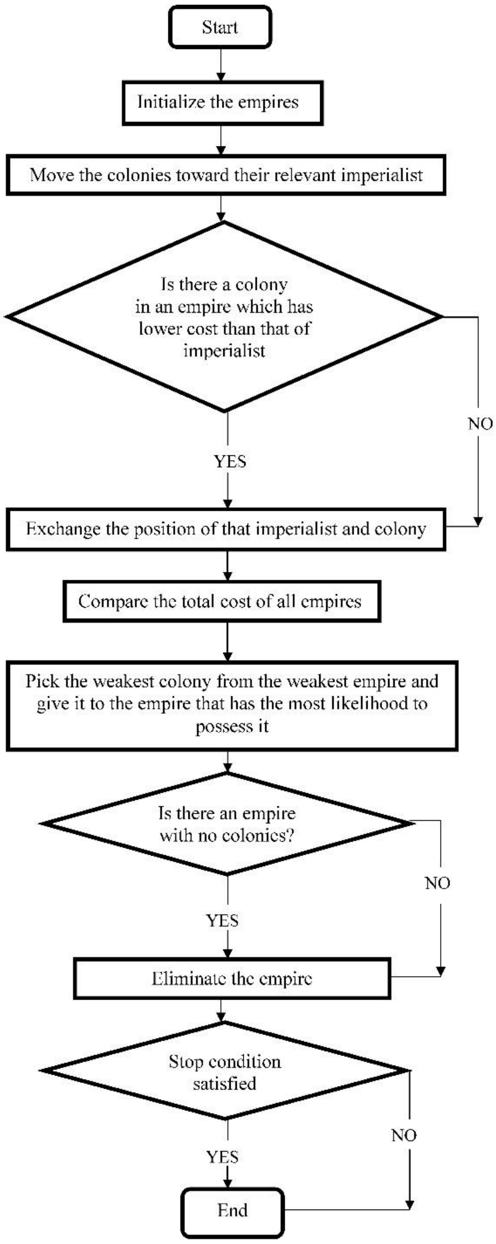

Figure1. Flowchart of the ICA algorithm [2]

We divide the colonies among the imperialists based on their power, in order to form the initial empires. That is, the initial number of colonies of an empire ought to be proportionate to its power. To do so, we define the normalized cost of an imperialist by C_n=c_n-max {ci}, where c_n is the cost of n_{th} imperialist and C_n is the normalized cost. The normalized power of each imperialist is defined by Atashpaz, having the normalized cost of all imperialists [12].

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \tag{17}$$

On the other hand, the normalized power of each imperialist would be the proportion of colonies that should be possessed by that imperialist. Therefore, the initial number of colonies of an empire will be:

$$N.C_n = round\{p_n . N_{col}\} \tag{18}$$

Where $N.C_n$ is the initial number of colonies of the nth empire, and Ncol is the number of all colonies. In order to divide the colonies, for each imperialist, we accidentally elect N.C. n of the colonies and give them to it. The imperialist along with these colonies will shape the n_{th} empire. In which, smaller (weaker) empires have less number of colonies, while bigger (powerful) ones have more. To find different points around the imperialist, a random amount of deviation to the direction of movement is added [8].

Table2. Parameters of the ICA for Parameter Optimization

Parameters	Value
Number of Countries	200
Number of Initial Imperialists	8
Number of Decades	200
Revolution Rate	0.3
Total Cost (Zeta)	0.2
Damp Ratio	0.99
Assimilation coefficient	2

4. Input Data

The following values in Table 2 are used as the input data for this optimization problem [2].

Table3. Numerical values of input data

Symbol	Description	Unit	Value
Mc	Cost per hour of labor and administration	$/h	30
p	Number of workpieces loaded on the table	pc	1
Lw	Length of workpiece	mm	300
Le	Empty length of grinding	mm	150
bw	Width of workpiece	mm	60
be	Empty width of grinding	mm	25
fb	Crossfeed rate	mm/pass	2
aw	The total thickness of the cut	mm	0.1(r)
			0.055(f)
ap	The down feed of grinding	mm/pass	0.0505(r)
			0.0105(f)
Sp	Number of spark out grinding	pass	2
De	Diameter of wheel	mm	355
bs	Width of wheel	mm	25
G	Grinding ratio		60
Sd	The distance of wheel idling	mm	100
Vr	Speed of wheel idling	mm/min	254
t1	Time of loading and unloading workpiece	min	5
tch	Time of adjusting machine tool	min	30
Nd	Total number of the workpiece to be ground between two dressings	pc	20
Nt	Batch size of the workpiece		12
Ntd	Total number of the workpiece to be ground during the life of dresser	pc	2000
Cd	Cost of dresser	$	25
Cs	Cost of wheel per mm3	$/mm3	0.003
CT∗	Expected production cost limitation	$/pc	10
Rc	Workpiece hardness (Rockwell hardness)		58
Ra∗	Surface finish limitation during rough grinding	μ m	1.8
VOL	Wheel bond percentage	%	6.99
dg	Grain size	mm	0.3
WRP∗	Workpiece removal parameter limitation	mm3/min N	20
Km	Static machine stiffness	N/mm	100,000
Rem	Dynamic machine characteristics		1
A0	Initial wear flat area percentage		0
Ku	Wear constant	mm−1	3.937×10^{-7}
Ka	Constant dependent on coolant and wheel grain type		0.0869

5. Results and comparisons

The optimum operating parameters such as total production cost (CT), production rate (WRP), surface finish [Ra] and combined objective function (COF) for rough grinding obtained by the genetic algorithm (GA), quadratic programming (QP], particle swarm optimizer (PSO], and hybrid particle swarm optimization (HPSO) are given in Table 3.

To evaluate the performance of the ICA algorithm proposed in this paper, we compare our results with those obtained from the approaches proposed by Wen et al., Saravanan et al., Baskar et al., Krishna and Rao, Pawar et al., Lee et al. and Zhang et al. by using the same cases. For a fair comparison with those approaches, the numerical values of input data shown in Table 3 and the user-defined bounds of process variables shown in Table 3 are all set to be the same with those given in the aforementioned references in this paper. The results obtained by the proposed ICA in this work and the comparisons with the results obtained from the original references which proposed some other methods and the results rechecked in this work are shown in Table 4. Table 4 shows the results of rough grinding operation with the maximization WRP and the minimization CT objectives subjected to $a_w = 0.1$ mm, $a_p = 0.0505$ mm/pass, and $R_a \leq 1.8$ µm. In Table 4, QP denotes the quadratic programming approach of Wen et al., GA is the genetic algorithm method of Saravanan et al., ACO denotes the ant colony optimization approach of Baskar et al., SS is the scatter search method of Krishna and Rao, DE denotes the differential evolution algorithm approach of Krishna and Rao, PSO is the particle swarm optimization method of Pawar et al., TSBDEA denotes the Taguchi sliding-based differential evolution algorithm method of Lee et al., and HPSO is the hyper particle swarm optimization method of Zhang et al. [2,3,6,7,8,10,11].

Table4. Results of optimization for rough grinding operation W1 = 0.5, W2 = 0.5, W3 = 0
(aw = 0.1 mm, ap = 0.0505 mm/pass, Ra ≤ 1.8 µm)

Method	References	Vs	Vw	Doc	L	CT	WRP	Ra	COF
QP	Wen et al. [3]	2,000	19.96	0.055	0.044	6.2	17.47	1.74	-0.127
GA	Saravanan et al. [4]	1,1998	11.3	0.101	0.065	7.1	21.68	1.79	-0.187
ACO	Baskar et al. [5]	2,010	10.19	0.118	0.081	7.5	24.20	1.80	-0.229
SS	Krishna and Rao [6]	2,023	10	0.129	0.068	8.3	25.41	1.79	-0.243
DE	Gopala Krishna [7]	2,023	10	0.13	0.1093	7.9	26.57	1.80	-0.249
PSO	Pawar et al. [8]	2,023	10	0.11	0.137	8.33	25.63	1.798	-0.224
TSBDEA	Lee et al. [9]	2,023	13.17	0.074	0.137	7.2668	23.7012	1.8000	-0.2292
HPSO	Zhang et al. [2]	2,023	13.2882	0.0729	0.137	7.2364	23.6424	1.8	-0.2292
ICA		1,1923	20.5	0.065	0.07	6.1176	19.9927	1.90	-.19394

6. Conclusions

In this paper, an Imperialist Competitive algorithm is performed to optimize surface grinding operation for better performance. The effectiveness of this algorithm for grinding operation has been demonstrated by comparing the results to other algorithms.

From obtained results by ICA, it can be concluded that the proposed algorithm gives an effective and powerful performance in a shorter time for the optimization of machining parameters for other conventional and unconventional machining operations.

7. References

[1] Yang, Y., Li, X. and Gao, L., 2013. June. Parameters optimization of a multi-pass milling process based on imperialist competitive algorithm. In Proceedings of the 2013 IEEE 17th International Conference on Computer Supported Cooperative Work in Design (CSCWD). 406-410.

[2] Zhang, G., Liu, M., Li, J., Ming, W., Shao, X. and Huang, Y., 2014. Multi-objective optimization for surface grinding process using a hybrid particle swarm optimization algorithm. The International Journal of Advanced Manufacturing Technology. 71(9-12):1861-1872.

[3] Wen, X.M., Tay, A.A.O. and Nee, A.Y.C. 1992. Micro-computer-based optimization of the surface grinding process. Journal of Materials Processing Technology. 29(1-3):75-90.

[4] Amitay, G., Malkin, S. and Koren, Y. 1981. Adaptive control optimization of grinding.

[5] Malkin, S. 1985. November. Practical approaches to grinding optimization. In Milton. C. Shaw Grinding Symposium, ASME Winter Annual Meeting. Miami Beach, FL. 289-299.

[6] Saravanan, R., Asokan, P. and Sachidanandam, M. 2002. A multi-objective genetic algorithm (GA) approach for optimization of surface grinding operations. International journal of machine tools and manufacture. 42(12):1327-1334.

[7] Baskar, N., Saravanan, R., Asokan, P. and Prabhaharan, G. 2004. Ants colony algorithm approach for multi-objective optimisation of surface grinding operations. The International Journal of Advanced Manufacturing Technology. 23(5-6):311-317.

[8] Lee, K.M., Hsu, M.R., Chou, J.H. and Guo, C.Y. 2011. Improved differential evolution approach for optimization of surface grinding process. Expert Systems with Applications. 38(5): 5680-5686.

[9] Krishna, A.G. 2007. Retracted: optimization of surface grinding operations using a differential evolution approach.

[10] Pawar, P.J., Rao, R.V. and Davim, J.P. 2010. Multiobjective optimization of grinding process parameters using particle swarm optimization algorithm. Materials and manufacturing processes. 25(6): 424-431.

[11] Krishna, A.G. and Rao, K.M. 2006. Multi-objective optimisation of surface grinding operations using scatter search approach. The International Journal of Advanced Manufacturing Technology. 29(5-6): 475-480.

[12] Atashpaz-Gargari, E. and Lucas, C. 2007. September. Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. IEEE congress on evolutionary computation. 4661-4667.

[13] Yazdipour, A. and Ghaderi, M.R. 2014. Optimization of weld bead geometry in GTAW of CP titanium using imperialist competitive algorithm. The International Journal of Advanced Manufacturing Technology. 72(5-8): 619-625.

[14] Shabani, M.O. and Mazahery, A. 2012. The GA optimization performance in the microstructure and mechanical properties of MMNCs. Transactions of the Indian Institute of Metals. 65(1):77-83.

[15] Ulas, H.B. 2014. Experimental determination of cutting forces and surface roughness when turning 50CrV4 steel (SAE 6150) and modelling with the artificial neural network approach. Transactions of the Indian Institute of Metals. 67(6): 869-879.

[16] Lucas, C., Nasiri-Gheidari, Z. and Tootoonchian, F. 2010. Application of an imperialist competitive algorithm to the design of a linear induction motor. Energy conversion and management, 51(7): 1407-1411.

[17] Gargari, E.A., Hashemzadeh, F., Rajabioun, R. and Lucas, C. 2008. A novel approach for PID controller design in MIMO distillation column process. International Journal of Intelligent Computing and Cybernetics. 1(3):337-355.

[18] Kamarian, S. 2013. Volume fraction optimization of four-parameter FGM beams resting on elastic foundation. Journal of Advanced Design and Manufacturing Technology. 6(4): 75-82.

[19] Towsyfyan, H., ADNANI, S.S. and Rashidian, R. 2014. Application of Imperialist Competitive Algorithm to optimization problems arising in welding process. Journal of Advanced Design and Manufacturing Technology. 7(3):65-72.

[20] Norouzi, G.S. and Akbarzadeh, A.R. 2015. Prismatic Series Elastic Actuator: Modelling and Control by ICA and PSO-Tuned Fractional Order PID. Journal of Advanced Design and Manufacturing Technology. 8(4):23-32.

[21] Fadaei, A., Gorbanpour, A. and Salarpour, A. 2016. Optimizing the Parameters Contributing to Riveting Quality Using Imperialist Competitive Algorithm and Predicting the Objective Function via the Three Models MLR, RBF, and ANN-GA. Journal of Advanced Design and Manufacturing Technology. 9(1):1-12.