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Machining Process Optimization BY Colony Based Cooperative Search Technique

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Research of economics of multi-pass machining operations has significant practical importance. Non-traditional optimization techniques such genetic algorithms, neural networks and PSO optimization are increasingly used to solve optimization problems. This paper presents a new multi-objective optimization technique, based on ant colony optimization algorithm (ACO), to optimize the machining parameters in turning processes. Three conflicting objectives, production cost, operation time and cutting quality are simultaneously optimized. An objective function based on maximum profit in operation has been used. The proposed approach uses adaptive neuro-fuzzy inference system (ANFIS) system to represent the manufacturer objective function and an ant colony optimization algorithm (ACO) to obtain the optimal objective value. New evolutionary ACO is explained in detail. Also a comprehensive user-friendly software package has been developed to obtain the optimal cutting parameters using the proposed algorithm. An example has been presented to give a clear picture from the application of the system and its efficiency. The results are compared and analysed using methods of other researchers and handbook recommendations. The results indicate that the proposed ant colony paradigm is effective compared to other techniques carried out by other researchers.

Keywords: machining, turning, optimization, cutting parameters

0 INTRODUCTION

The selection of optimum cutting parameters is a very important issue for every machining process in order to enhance the quality of machining products, to reduce the machining costs and to increase the production rate. Due to machining costs of Numerical Control (NC) machines, there is an economic need to operate NC machines as efficiently as possible in order to obtain the required pay back. In workshop practice, cutting parameters are selected from machining databases or specialized handbooks, but they do not consider economic aspects of machining. The cutting conditions set by such practices are too far from optimum. Therefore, a mathematical approach has received much attention as a method for obtaining optimised machining parameters. For the optimisation of a machining process, either the minimum production time or the maximum profit rate is used as the objective function subject to the constraints. Optimization of cutting parameters is a difficult task [1], where the following aspects are required: knowledge of machining; empirical equations relating the tool life, forces, power, surface finish, etc., to develop realistic constrains; specification of machine tool capabilities; development of an effective optimization criterion; and knowledge of mathematical and numerical optimization techniques.

Optimization of machining parameters is complicated when a lot of constraints are included, so it is difficult for the non-deterministic methods to solve this problem. Conventional optimization techniques are useful for specific optimization problems and leaned to find local optimum solution. Consequently, non-traditional techniques were used in the optimization problem. Researchers [2] have done comparative analysis of conventional and non-conventional optimization techniques for CNC turning process. The optimization problem in turning has been solved by genetic Algorithms (GA), Tabu search (TS), simulated annealing (SA) and particle swarm optimisation (PSO) to obtain more accurate results [3]. Milfelner et al. [4] have described the multi objective technique of optimization of cutting conditions for turning process by means of the neural networks and particle swarm optimization (PSO) [5], taking into consideration the technological, economic

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and organization limitations. Further genetic GA and simulated annealing techniques have been applied to solve the continuous machining profile problem by [6]. They have shown that GA approach outperforms the simulated annealing based approach.

In this paper, a multi-objective optimization method, based on combination of ANFIS and ACO evolutionary algorithms, is proposed to obtain the optimum parameters in turning processes. The advantage with this approach is that it can be used for solving a diverse spectre of complex optimisation problems [7] and [8]. This paper also compares the results of ANFIS-ant colony algorithm with the GA and simulated annealing (SA). The results exhibit the efficiency of the ACO over other methods.

1 THE HYBRID ANFIS-ANTS APPROACH

The proposed approach consists of two main steps.

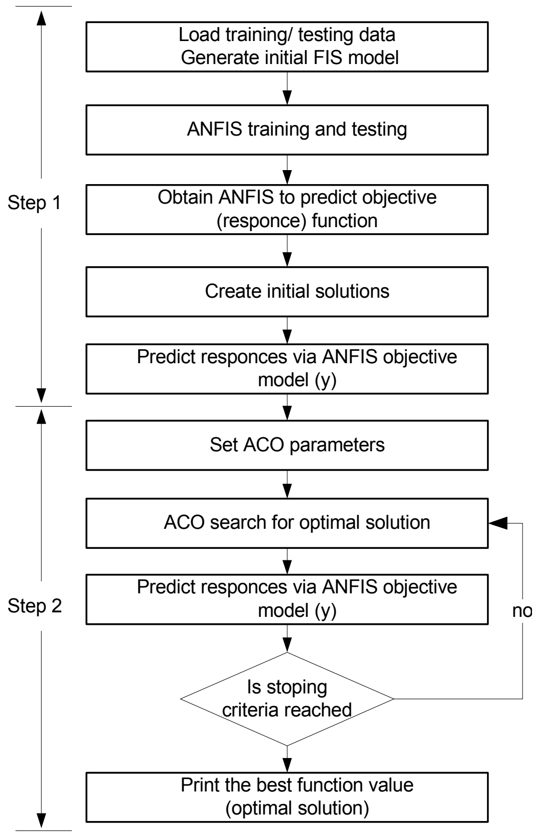

Fig.1. *Scheme of the proposed approach*

First, experimental data are prepared to train and test ANFIS system to represent the objective function (y). Finally, an ACO algorithm is utilized to obtain the optimum objective value. Figure 1 shows the flowchart of the approach.

Detail steps for optimization of cutting parameters by ANFIS-ants approach:

1. Entering of input data.
2. Generation of random cutting conditions-initial solutions.
3. Calculation of other values (P; F; MRR; C_p; T; R_a; T_p; y).
4. Preparation of data for training and testing of ANFIS.
5. Use of ANFIS model: The purpose of ANFIS is to predict the manufacturer's value function (y) in case of randomly selected cutting conditions.
6. Training and testing of ANFIS.
7. Optimization process: The cutting conditions where the function (y) has the maximum are the optimum cutting conditions. The extreme of the function (y). Since the function (y) is expressed with ANFIS, it means that the extreme of ANFIS is searched for.
8. Survey of optimum cutting conditions and the variables relevant to them.
9. Graphic representation of results and optimization statistic.

1.1. Machining Model Formulation

In CNC machine tools, the finished component is obtained through a number of rough passes and finish passes. The roughing operation is carried out to machine the part to a size that is slightly more than its desired size in preparation for the finish cut. The finish cut is called single-pass contour machining, which is machined along the profile contour. In this paper one roughing stage, and a finished stage are considered to machine the component from the bar stock.

The objective of this optimization is to determine the optimum machining parameters including cutting speed, feed rate and depth of cut in order to minimize the production cost (C_p) and to maximize production rate (represented by manufacturing time (T_p)) and cutting quality (R_a). The operation of turning is defined as a multi-objective optimization problem with limitation non-equations and with three conflicting objectives (production rate, operation cost, quality of machining). All the above-mentioned objectives are represented as a function of the cutting speed, feed rate and depth of cutting.

1.1.1 Production rate [9]

The production rate is measured as the entire time necessary for the manufacture of a product (T_p). It is the function of the metal removal rate (MRR) and of the tool life (T) [10];

$$T_p = T_s + V(1 + \frac{T_c}{T})/MRR + T_i \quad (1)$$

where T_s, T_c, T_i and V are the tool set-up time, the tool change time, the time during which the tool does not cut and the volume of the removed metal. In some operations the T_s, T_c, T_i and V are constants so that T_p is the function of *MRR* and *T*. The metal removal rate is expressed as:

$$MRR = 1000 \cdot v \cdot f \cdot a \quad (2)$$

1.1.2 The Cost function [9]

The unit production cost, C_p, for turning operations can be divided into three basic cost elements: the tool cost and tool replacement cost (C_t), cutting cost by actual time in cut (C_l) and overhead cost C_0, T is tool life.

The formula for calculating the above cost is used as given by [9].

Finally, by using the above mathematical manipulations, the unit production cost ($/piece) can be obtained as:

$$C_p = T_p\left(C_t/T + C_l + C_0\right) \quad (3)$$

1.1.3 Cutting quality [9]

The most important criterion for the assessment of the surface quality is roughness calculated according to:

$$R_a = k\, v^{x_1} f^{x_2} a^{x_3} \quad (4)$$

where x_1, x_2, x_3 and k are the constants relevant to a specific tool-workpiece combination.

1.1.4 Cutting condition constraints

The practical constraints imposed during the roughing and finishing operations are stated as follows [9].

Parameter bounds. The available range of cutting speed, feed rate and depth of cut are expressed in terms of lower and upper bounds. The bounds on feed rate and depth of cut is setup for the safety of the operator. The parameter bound values and constants are: $v_{min} \leq v \leq v_{max}$, $f_{min} \leq f \leq f_{max}$, $a_{min} \leq a \leq a_{max}$.

Tool-life constraint. The constraint on the tool life is taken as $T_{min} \leq T \leq T_{max.}$

Power constraint. The power required during the cutting operation should not exceed the available power of the machine tool. The power is given as:

$$P = \frac{k_f f_r^{\mu} d_r^{v} v_r}{6120\eta} , \quad (5)$$

where k_f , μ and v are the constants pertaining to specific tool-work piece combination and η is the power efficiency. The limitations of the power and cutting force are equal to: $P(v, f, a) \leq P_{max}$

In order to ensure the evaluation of mutual influences and the effects between the objectives and to be able to obtain an overall survey of the manufacturer's value system the multi-attribute function of the manufacturer (y) is determined. The cutting parameter optimization problem is formulated as the following multi-objective optimization problem: min T_p (v, f, a), min C_p (v, f, a), min R_a (v, f, a).

$$y = 0.42e^{(-0.22Tp)} + 0.17e^{(-0,26Ra)} + \frac{0.05}{\left(1+1.22T_p C_p R_a\right)} \quad (6)$$

A multiattribute value function is defined as a real-valued function that assigns a real value to each multiattribute alternative, such that more preferable alternative is associated with a larger value index than less preferable alternative.

1.2 Objective Function Modelling

First step uses an ANFIS to model the response (manufacturer's implicit multiattribute) function (y). The variables of this problem are velocity, feed rate and depth of cut, which can have any continuous value subject to the limits available. The ANFIS system needs three inputs for three parameters: cutting speed (v), feedrate (f) and depth of cutting (a). The output from the system is a real value (y). The relationship between the cutting parameters and manufacturer objective function is first captured via a neural network and is subsequently reflected in linguistic form with the help of a fuzzy logic based algorithm. Algorithm uses training examples as input and constructs the fuzzy if–then rules and the membership functions of the fuzzy sets involved in these rules as output.

Figure 2 shows the fuzzy rule architecture of ANFIS when triangular membership function is adopted. The architectures shown in Figure 2 consist of 32 fuzzy rules. During training in ANFIS, 140 sets of experimental data were used to conduct 400 cycles of training. ANFIS has proved to be an excellent universal approximator of non-linear functions. If it is capable to represent the manufacturer's implicit multiattribute function.

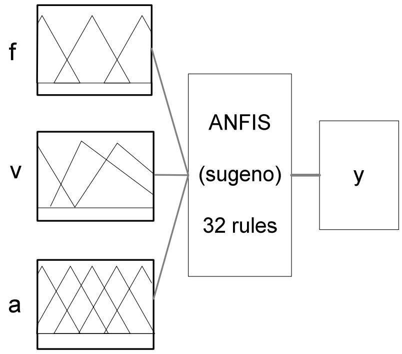

Fig. 2. *Fuzzy rule architecture of the triangular membership function*

Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows fuzzy systems to learn from the data they are modeling. FIS structure is a network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs. ANFIS applies two techniques in updating parameters. For premise parameters that define membership functions, ANFIS employs gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equations, ANFIS uses the least-squares method to identify them. This approach is thus called Hybrid Learning method since it combines the gradient descent method and the least-squares method.

ANFIS modeling process starts by:

1. Obtaining a data set (input-output data pairs) and dividing it into training and checking data sets.
2. Finding the initial premise parameters for the membership functions by equally spacing each of the membership functions
3. Determining a threshold value for the error between the actual and desired output.
4. Finding the consequent parameters by using the least-squares method.
5. Calculating an error for each data pair. If this error is larger than the threshold value, update the premise parameters using the gradient decent method as the following ($Q_{\text{next}}=Q_{\text{nov}}+\eta_{\text{d}}$, where Q is a parameter that minimizes the error, η the learning rate, and d is a direction vector).
6. The process is terminated when the error becomes less than the threshold value. Then the checking data set is used to compare the model with actual system. A lower threshold value is used if the model does not represent the system.

After training the estimator, its performance was tested under various cutting conditions. Test data sets collected from a wide range of cutting conditions in turning were applied to the estimator for evaluating objective function (y). The performance of this method turned out to be satisfactory for estimating of objective function (y), within a 2% mean error.

Once a multi-attribute value function is assessed and validated the ANFIS is used to decipher the manufacturer's overall preference and the multi-objective optimization problem will be reduced to a single objective maximization problem as follows:

$$\max_{\text{v,f,a}}\ y\left[T_{\text{p}}(v, f, a), C_{\text{p}}(v, f, a), R_{\text{a}}(v, f, a)\right] \quad (7)$$

2 ANT COLONY OPTIMIZATION-ACO

ACO is a non-traditional optimization technique in which the main idea underlying it is that of a parallelizing search over several constructive computational threads, all based on a dynamic memory structure incorporating information on the effectiveness of previously obtained results and in which the behavior of each single agent is inspired by the behaviour of real ants.

Special insects like ants, termites, and bees that live in a colony are capable of solving their daily complex life problems. These behaviours which are seen in a special group of insects are called swarm intelligence. Swarm intelligence techniques focus on the group's behaviour and study the decartelized reactions of group agents with each other and with the environment. The swarm intelligence system includes a mixture of simple local behaviours for creating a complicated general behaviour and there is no central control in it. Ants have the ability to deposit pheromone on the ground and to follow, in probability, pheromone previously deposited by other ants. By depositing this chemical substance, the ants leave a trace on their paths. By detecting this trace, the other ants of the colony can follow the path discovered by other ants to find food. For finding the shortest way to get food, these ants can always follow the pheromone trails. This cooperative search behaviour of real ants inspired the new computational paradigm for optimizing real life systems and it is suited for solving large scale optimization problem.

The first ACO algorithm, called ant system (AS) has been applied to the travelling salesman problem (TSP). Dorigo [7] proposed an ACO methodology for machining parameters optimization in a multi-pass turning model, which originally was developed by [8]. Recently, a modified ACO was presented as an effective global optimization procedure by introducing bi-level search procedure called local and global search. The important aspect in ACO is that the artificial ants select the solution.

2.1 ACO Algorithm of Process Optimization

The proposed continuous ACO for optimization of cutting conditions in multi-pass turning is shown as scheme in Figure 3. The distribution of ants is shown in Figure 4.

Initial solution. An initial solution of N will consist of 160 randomly generated solutions, with values that lie in the range of allowable cutting speed, depth of cut and feedrate. The 160 solutions are then sorted in ascending order with respect to the objective function.

The regions pertaining to minimum production cost are referred to as superior solutions, while regions pertaining to the maximum production cost are referred to as inferior solutions.

Distribution of ants. The total numbers of ants, A, is 80, which is half of N and is distributed as 72 for global (G) and 8 for local search (L).

An ACO utilizes bi-level procedures which include local and global searches.

Local search: With a local search, the L local ants select L regions from N regions and move in search of better fitness. Here L is 6, and L solutions are selected as per the current pheromone trail value. Local search ants select a region L with a probability $P_i(t) = \tau_i(t) / \sum \tau_k(t)$, where i is the region index and $t_i(k)$ is the pheromone trail on region i at time t. After selecting the destination the ant moves through a short distance (finite random increment 0.005).

Updating the pheromone trail value of new solution in local search. If the fitness is improved, the new solutions are updated to the current region. Correspondingly the regions position vector is updated. The variables of this problem are cutting speed, feedrate, depth of cut, all of which can have any continuous value subject to the limits imposed. The objective functions are calculated for each solution. In the continuous algorithm, the pheromone values are decreased after each iteration by:

$$\tau_i(t+1) = \rho \cdot \tau_i(t) \tag{8}$$

where ρ is the evaporation rate which is assumed to be 0.2 on a trial basis and $\tau_i(t)$ is the trail associated with solution at time t.

Global search. Using global search, global ants create G new regions by replacing the inferior solutions of the existing solutions.

The following three operations are performed on the randomly generated initial solution: (a) Random walk or cross over –90% of the solutions (randomly chosen) in the inferior solutions are replaced with randomly selected superior solutions; (b) Mutation – the process where by randomly adding or subtracting a value is done to each variable of the newly created solutions in the inferior region with a mutation probability; and (c) Trial diffusion – applied to inferior solutions that were not considered during random walk and mutation stages.

A global search is done sequentially by crossover, mutation and trial diffusion operations. The subsequent values of the variables of the child are set to the corresponding value of a randomly chosen parent with a crossover probability (0.75). Mutation operation adds or subtracts a value to/from each variable with mutation probability. The mutation step size is the same as the above distance $\Delta(T,R)$. After selecting the destination, the ant moves through a short distance ($\Delta(T,R) = R(1-r^{10(1-T)})$, where R is maximum search radius, r is a random number from [0,1], T is the total number of iterations of the algorithm.

Performing an ACO, ants are repeatedly sent to trail solutions in order to optimize the objective value. The total number of ants (denoted by A) is set as half the total number of trail solutions (denoted by S).

Trail diffusion. Here, two parents are selected at random from the parents region. The child can have:

1. the value of the corresponding variable of the first parent;
2. the value of the corresponding variable of the second parent; or
3. a combination arrived from the weighted average of the above X(child) $=\alpha\ x$(parent 1)$+[1-\alpha]x$ (parent 2), where α is a uniform random number in the range [0,1]. The probability of selecting the 3rd option is set equal to the mutation probability 0.75, and the probability of selecting the 1st and 2nd options is allotted a probability of 0.2.

Updating of pheromone trail value of new solution in global search. After the global search, the pheromone trail value of the new solutions is updated proportionally to the improvement in the objective value.

Sort the regions according to the function value. New solutions will be obtained after the global and local search. The solutions will also have the new pheromone trail values. The solutions are sorted in ascending order of the objective values and the best objective value is stored. The process is repeated for a specified number of iterations.

The ACO algorithm:

Step 1. Set parameter values including: S, A, ρ, τ_0, P_c, P_m, T, R, and bounds of each control factor.

Step 2. Create S trail solutions (v, f, a). Estimate the objective value of the trail solutions through the ANFIS model (y).

Step 3. Set the initial pheromone value of all trails.

Step 4. Repeat steps 6 to 8 until the stopping criteria has reached.

Step 5. Send L ants to the selected trail solutions for local search.

Step 6. If the solution is improved, move the ants to the new solution and update the pheromone value.

Step 7. Send G ants to global trails and generate their offspring by crossover and mutation.

Step 8. Evaporate pheromone for all trails.

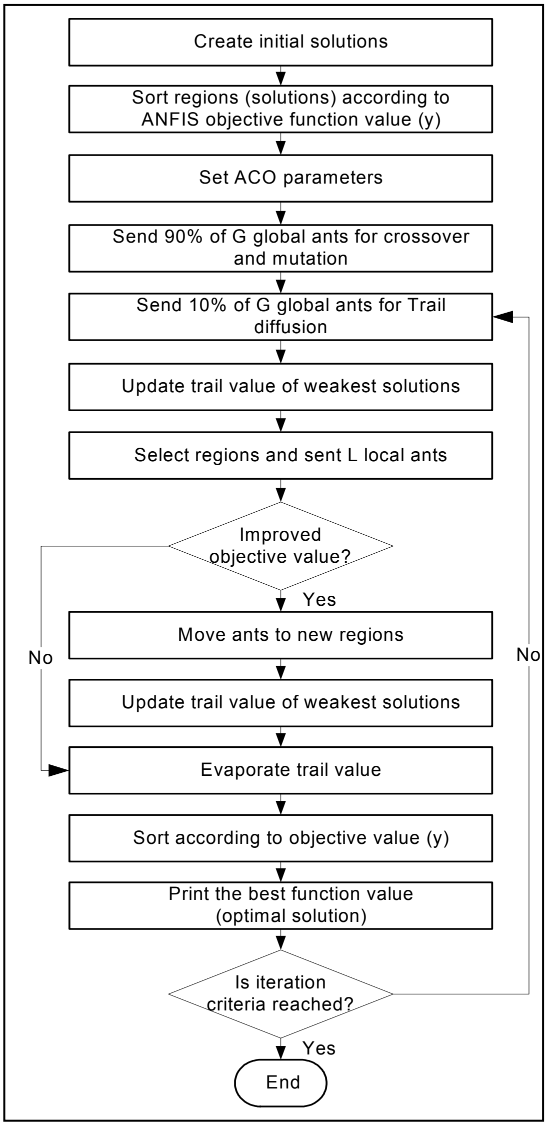

Fig. 3. *Scheme of the ACO algorithm*

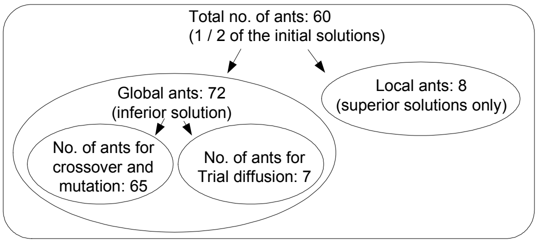

Fig. 4. *Distribution of search points (ants) in ACO algorithm*

3 COMPUTATIONAL RESULTS AND DISCUSSION

The ant colony optimization method combined with ANFIS prediction system was tested on the CNC lathe GF02. The work piece material is mild steel (Ck45) and the tool material has a carbide tip. The task is to find optimum cutting conditions for the process of turning with minimum costs.

Proposed ACO approach was compared with three non-traditional techniques (GA, SA and PSO). The results obtained from four techniques are given in Table 1. All the parameters and constraint sets are the same in all four cases. There is a total of 4 constraints. The proposed model is run on a PC 586 compatible computer using the Matlab language. The results revelled that the proposed method significantly outperforms the GA and SA approach. The proposed approach found an optimum solution of 12.461 for as low as 1 to 18 runs the genetic-based approach require as much as 1 to 500 runs to find an solution of 14.661.

This means that the proposed approach has 16.02% improvement over the solution found by GA approach and 23.08% over SA approach.

Moreover, the simulated annealing approach (SA/PS) of [14] also generated an inferior solution of 17.24 for as much as 901 to 1000 runs which means that the optimum solution of ACO algorithm has an improvement of 23.6%. It is observed that PSO has outperformed all other algorithms [16]. Next ACO, SA and GA are ranked according to costs obtained from algorithms. The costs obtained and optimum machining conditions are shown in Table 1. From the results, it is clear that the proposed ACO approach significantly outperforms the other two methods, such as GA and SA. Clearly, the ACO approach provides a sufficiently approximation to the true optimum solution.

4 CONCLUSION

In this paper, non-conventional optimization techniques ACO has been studied for the optimization of machining parameters in turning operations. The hybrid ANFIS-ants integrates neural network, fuzzy logic and continuous ant colony optimization to model the machining system and to optimize machining process. ACO algorithm is completely generalized and problem independent so that can be easily modified to optimize this turning operation under various economic criteria. It can obtain a near-optimum solution in an extremely large solution space within a reasonable computation time. The algorithm can also be

Table 1. *Comparison of results for ANFIS-ACO, GA, LP and PSO approach*

No.	Algorithm	Constraint set	Runs	Optimum solution v_{opt} [m/min]	f_{opt} [mm/rev]	a_{opt} [mm]	C_p [$]	Average optimiz. time [s]
1	PSO [11, 12]	tool-life; cutting force- power [13]; surface roughness;	1 to 25 1 to 150	101.211 103.377	0.231 0.217	0.44 0.51	12.461 **12.235**	3 7
2	Proposed ANFIS-ACO	tool-life; cutting force- power; surface roughness;	1 to 25 1 to 150	95.1926 97.433	0.3793 0.2934	0.84 0.89	12.423 **12.314**	2 6
3	SA [14]	tool-life; cutting force- power; surface roughness;	1 to 1000 1 to 1400	112.852 108.464	0.194 0.221	0.46 0.41	**16.152** 16.171	12 11
4	GA [15]	tool-life; cutting force- power; surface roughness;	1 to 150 1 to 500	102.165 98.122	0.039 0.313	1.268 0.612	18.394 **14.661**	7 9

extended to other machining problems such as milling operations. The results of the proposed approach are compared with results of three non-traditional techniques (GA, SA and PSO). Among the four algorithms, PSO outperforms all other algorithms.

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