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High speed end-milling optimisation using Particle Swarm Intelligence

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Analysis and modelling

ABSTRACT

Purpose: In this paper, Particle Swarm Optimization (PSO), which is a recently developed evolutionary technique, is used to efficiently optimize machining parameters simultaneously in high-speed milling processes where multiple conflicting objectives are present.

Design/methodology/approach: Selection of machining parameters is an important step in process planning therefore a new methodology based on PSO is developed to optimize machining conditions. Artificial neural network simulation model (ANN) for milling operation is established with respect to maximum production rate, subject to a set of practical machining constraints. An ANN predictive model is used to predict cutting forces during machining and PSO algorithm is used to obtain optimum cutting speed and feed rate.

Findings: The simulation results show that compared with genetic algorithms (GA) and simulated annealing (SA), the proposed algorithm can improve the quality of the solution while speeding up the convergence process. PSO is proved to be an efficient optimization algorithm.

Research limitations/implications: Machining time reductions of up to 30% are observed. In addition, the new technique is found to be efficient and robust.

Practical implications: The results showed that integrated system of neural networks and swarm intelligence is an effective method for solving multi-objective optimization problems. The high accuracy of results within a wide range of machining parameters indicates that the system can be practically applied in industry.

Originality/value: An algorithm for PSO is developed and used to robustly and efficiently find the optimum machining conditions in end-milling. The new computational technique has several advantages and benefits and is suitable for use combined with ANN based models where no explicit relation between inputs and outputs is available. This research opens the door for a new class of optimization techniques which are based on Evolution Computation in the area of machining.

Keywords: Machining; End-milling; Particle Swarm Optimization

1. Introduction

Increasing productivity, decreasing costs, and maintaining high product quality at the same time are the main challenges manufacturers face today. The proper selection of machining parameters is an important step towards meeting these goals and thus gaining a competitive advantage in the market [1]. Many researchers have studied the effects of optimal selection of machining parameters of end milling [2]. It can be formulated and solved as a multiple objective optimization problem [3]. In practice, efficient operation of milling operation requires the simultaneous

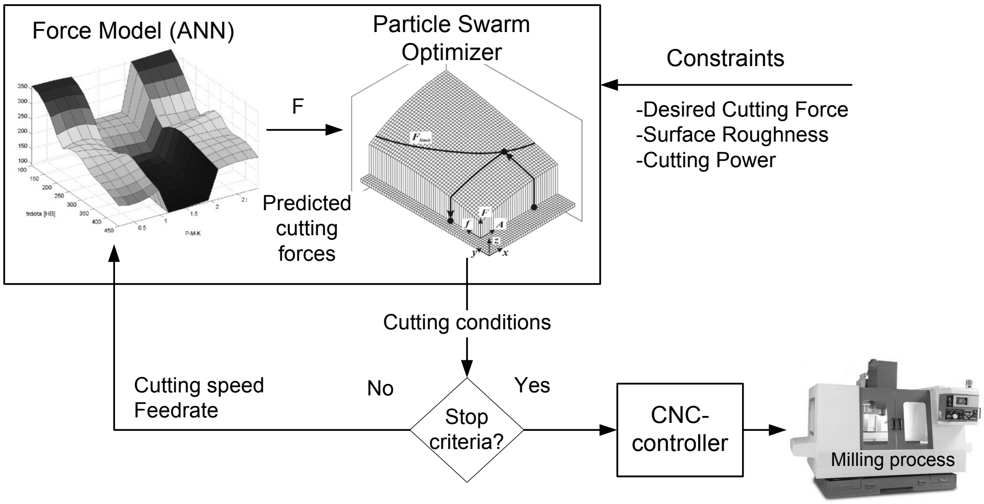

Fig. 1. PSO based neural network optimization scheme

consideration of multiple objectives, including maximum tool-life, desired roughness of the machined surface, target operation productivity, metal removal rate, etc [4]. In some instances, parameter settings that are optimal for one defined objective function may not be particularly suited for another objective function. Traditional optimization methods are difficult and the only way is to reduce the set of objectives in to a single objective and handle it accordingly. Therefore evolutionary algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO) are more convenient and usually utilized in multiobjective optimization problems. These methods are summarized by [5]. The PSO is an efficient alternative over other stochastic and population-based search algorithms, especially when dealing with multi-objective optimization problems. It is relatively easy to implement and has fewer parameters to adjust compared to genetic algorithms. As mentioned above, neural networks are used to model complex relationships in the process, and an integrated system of neural networks and particle swarm optimizer is utilized in solving multi-objective problems observed in milling operations (Fig. 1).

2. Particle swarm optimisation

Particle Swarm Optimization (PSO) is a relatively new technique, for optimization of continuous non-linear functions [6]. It was first presented in 1995.

Jim Kennedy discovered the method through simulation of a simplified social model, the graceful but unpredictable choreography of a bird swarm [7]. PSO is a very simple concept, and paradigms are implemented in a few lines of computer code. It requires only primitive mathematical operators, so is computationally inexpensive in terms of both memory requirements and speed. PSO has been recognized as an evolutionary computation technique [8] and has features of both genetic algorithms (GA) and evolution strategies (ES). Other evolutionary computation (EC) techniques such as genetic algorithm (GA) also utilize some searching points in the solution space. It is similar to a GA in that the system is initialized with a population of random solutions.

While GA can handle combinatorial optimization problems, PSO can handle continuous optimization problems. However, unlike a GA each population individual is also assigned a randomized velocity, in effect, flying them through the solution hyperspace. PSO has been expanded to handle also the combinatorial optimization problems and both discrete and continuous variables as well. Unlike other EC techniques, PSO can be realized with only small program. Namely PSO can handle mixed-integer nonlinear optimization problems with only small program.

The feature of PSO is one of the advantages compared with other optimization techniques. Natural creatures sometimes behave as a swarm. One of the main goals of artificial life researches is to examine how natural creatures behave as a swarm and reconfigure the swarm models inside a computer.

3. Basic of particle swarm optimisation

According to the background of PSO and simulation of swarm of bird, researchers [9] developed a PSO concept. Namely, PSO is basically developed through simulation of bird flocking in two-dimension space. The position of each agent is represented by XY axis position and also the velocity is expressed by vx (the velocity of X axis) and vy (the velocity of Y axis).

Modification of the particle position is realized by the position and velocity information. Bird flocking optimizes a certain objective function. Each agent (particle) knows its best value so far (pbest) and its XY position. This information is analogy of personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among (pbests). This information is analogy of knowledge of how the other agents around them have performed.

Each agent tries to modify its position using the following information: - the current positions (x, y), - the current velocities (vx, vy), - the distance between the current position and (pbest) -

the distance between the current position and (gbest). This modification can be represented by the concept of velocity. The general flow chart of PSO can be described as follows:

Step. 1: Generation of initial condition of each agent. Initial searching points (s_i^0) and velocities (v_i^0) of each agent are usually generated randomly within the allowable range.

Step. 2: Evaluation of searching point of each agent. The objective function value is calculated for each agent. If the value is better than the current pbest of the agent, the pbest value is replaced by the current value.

Step. 3: Modification of each searching point.

Step. 4: Checking the exit condition. Otherwise, go to step 2.

Figure 2 shows the general flow chart of PSO strategy.

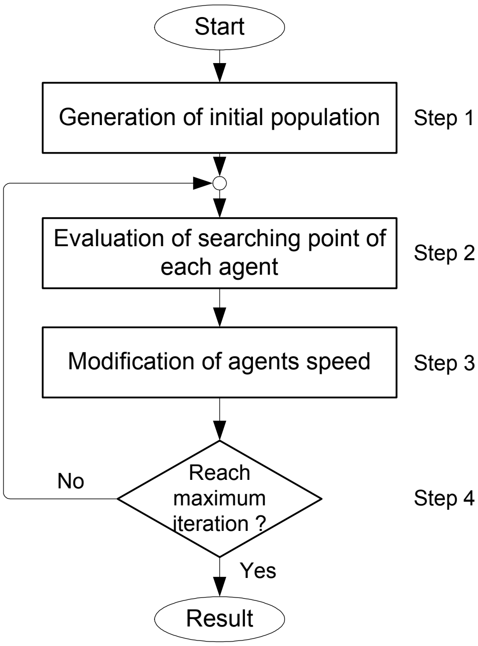

Fig. 2. A general PSO algorithm

With the objective to improve the rate of convergence of the PSO, Abido [9] proposed some modifications to the existing PSO. These modifications relate to the use of best ever position, maximum velocity, inertia, craziness, elite particle and elite velocity.

4. Adaptation of PSO technique to milling optimisation problem

In order to search for optimal process parameters, neural network model of cutting force was integrated with particle swarm optimizer. The architecture of system is shown in Figure 1.

The optimization process executes in two phases. In first phase, the neural prediction model on the basis of recommended cutting conditions generates 3D surface of cutting forces, which represent the feasible solution space for the PSO algorithm. The cutting force surface is limited with planes which represent the constraints of cutting process. Seven constraints, which arise from technological specifications, are considered during the optimization process [10].

PSO algorithm generates a swarm of particles on the cutting force surface during the second phase. Swarm of particles flys over the cutting force surface and search for maximal cutting force. The coordinates of a particle which has found the maximal (but still allowable) cutting force represent the optimal cutting conditions. Figure 3 shows the PSO flowchart of optimization of milling process.

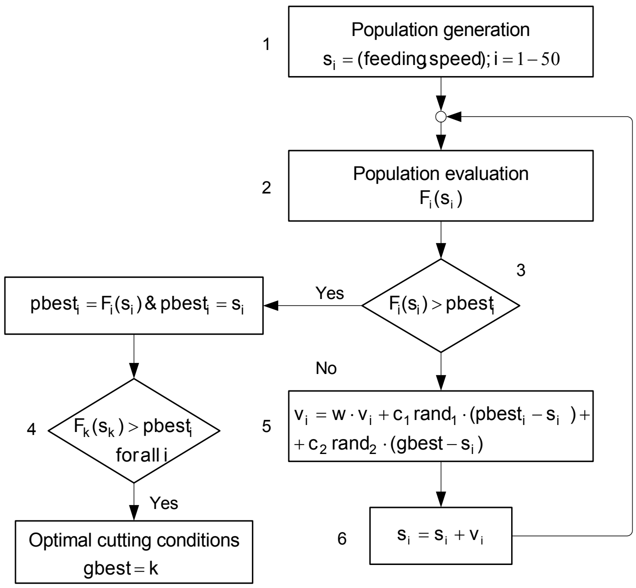

Fig. 3. PSO algorithm for optimization of cutting conditions

5. PSO optimisation of cutting conditions Test case

The repeatability and robustness of the PSO algorithm, is demonstrated with the following test case. To examine the stability and robustness of the proposed optimization strategy, the system is first analyzed by simulations, then the system is verified by experiments on a CNC milling machine (type HELLER BEA1) for Ck 45 and 16MnCrSi5 XM steel workpieces [11]. The ball-end milling cutter (R220-20B20-040) with two cutting edges, of 20 mm diameter and 10° helix angle was selected for experiments [12]. Cutting conditions are: milling width R_D=3 mm, milling depth A_D=5 mm and cutting speed v_c=80 m/min, $n \leq 2000$ min^{-1}, $10 \leq f \leq 900$ mm/min, $F(f, n) \leq Fref = 600$ N. The objective function is determined by neural cutting force model (cutting force simulator). The goal of this case is to maximize the force function under given constraints [13]. This problem is solved using the PSO algorithm. In PSO, 50 particles were used and search continues until error gradient is smaller than a specified value. Matlab® code simulates the trained neural network to predict cutting forces at given cutting distances and these values are used to calculate the objective function which PSO algorithm attempts to maximize. The results are tabulated in Table 1. Each run corresponds to each time the program is run to find the optimum machining parameters. Table 1 shows optimal cutting conditions along with the number of generations it took to reach that optimum.

Table 1.
Repeatability of results

Run	n [min^{-1}]	f [mm/min]	F [N]	Effective Nr. of iterations
1	1998	808.2	598	22
2	1995	810.1	600	25
3	1997	811.2	600	28
4	1997	819.7	598	32
5	2000	819.1	598	22

This optimization method has higher convergence, unlike traditional methods and it is always successful in finding the global optimum. The machining time is reduced by 35% as a result of optimizing the feed and speed [14].

6. Conclusion and future research

This study has presented multi-objective optimization of end milling process by using neural network modeling and Particle swarm optimization. A neural network model was used to predict cutting forces during machining and particle swarm optimization was used to obtain optimum cutting speed and feed rate. A set of seven constraints were used during optimization. Next, neural force model was used to predict the objective function. Next, the PSO algorithm is used to optimize both feed and speed for a typical case found in industry. Both feed and speed were considered during optimization. The experimental results show that the MRR is improved by 28%. Machining time reductions of up to 20% are observed. This paper opens the door for a new class of EC based optimization techniques in the area of machining.

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