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An Overview of PSO in Optimization of Machining Parameters

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ABSTRACT

In the current trends of optimizing machining process parameters, various evolutionary techniques such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO) and Artificial Bee Colony algorithm (ABC) have been used. This paper gives an overview of PSO techniques to optimize machining process parameter of both traditional and modern machining. Machining process parameters such as cutting speed, depth of cut and radial rake angle are mostly considered by researchers in order to minimize or maximize machining performances. From the review, the most machining process considered in PSO was multi-pass turning while the most considered machining performance was production costs

Keywords: *Machining; Optimization; Process Parameters; PSO*

1. INTRODUCTION

According to [1] there are five groups of manufacturing processes which includes casting, forming, powder metallurgy, joining and machining. Machining can be defined as the process of removing unwanted segment of metal workpiece in the form of chips. The machining process will shape the workpiece as desired and it is usually done using machine and cutting tools. The machining cutting process can be divided into two major groups which are i) cutting process with traditional machining (e.g turning, milling, boring and grinding) and ii) cutting process with modern machining (e.g electrical discharge machining (EDM) and abrasive waterjet (AWJ)). There are many researches that have been done in the areas of machining processes which mainly stressed on the tool, input work materials and machine parameter setting [2].
In the current trends of research in machining, various evolutionary techniques such as PSO, GA, SA and ACO and ABC have been considered by the researchers. It was reported that evolutionary techniques such as GA, SA and ACO for optimization process parameters have been applied in the traditional machining due to likely to deal with highly nonlinear, multidimensional and ill-behaved complex engineering problem [2, 3].

2. PSO Methodology

PSO technique was introduced by Kennedy and Eberhart [4] to solve continuous optimization problems Li et al. [5]. The swarm is composed of volume-less particles with stochastic velocities, each of which represents a feasible solution. The algorithm finds the optimal solution through moving the particles in the solution space.

The implementation of PSO is very simple and needs only a few lines programming code. It requires uncomplicated mathematical operators; therefore it is computationally economical in terms of both memory requirements and speed. PSO has features of both GA and evolution strategies Župerl et al [6]. The PSO framework for process parameter optimization is depicted in Figure 1. The steps of optimizing process parameters of milling operation using PSO was given by Župerl et al [6] as follows.

1. Generation and initialization of an array of 50 particles with random positions and velocities. Velocity vector has two dimensions, feed rate and spindle speed.
2. Evaluation of objective (cutting force surface) function for each particle.
3. The cutting force values are calculated for new positions of each particle. If a better position is achieved by particle, the pbest value is replaced by the current value.
4. Determination if the particle has found the maximal force in the population. If the new gbest value is better than previous gbest value, the gbest value is replaced by the current gbest value and stored. The result of optimization is vector gbest (feedrate, spindle speed).
5. Computation of particles' new velocity
6. Update particle's position by moving towards maximal cutting force.
7. Steps (i) and (ii) are repeated until the iteration number reaches a predetermined iteration

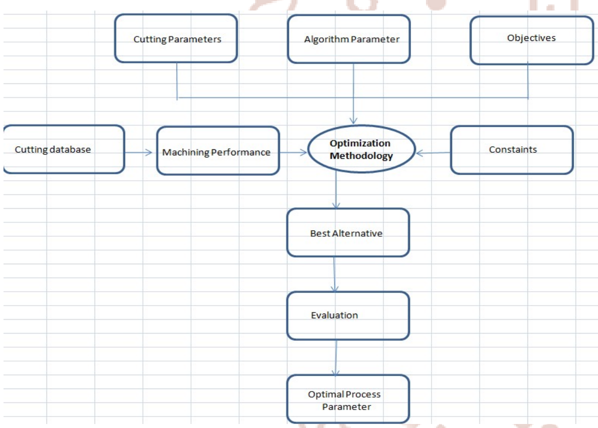

Fig -1.PSO framework for process parameters optimization [5]

3. PSO applications in machining

Zuperl et al. [6] employed PSO to optimize process parameters of milling machining. A predictive model was developed using ANN to predict the cutting forces during machining and PSO was used later to obtain optimal process parameters of milling machining such as cutting speed and feed rates. The results were compared with other evolutionary techniques such as GA and SA and proved that the proposed technique improved the quality of the solution while speeding up the convergence process. A new technique has been proposed by Huang et al. [7] by using the combination of wavelet neural network (WNN) algorithm and modified PSO for solving tool wear detection and estimation. By using the Daubechies-wavelet, the cutting power signal is decomposed into approximation and details. The energy and square-error of the signals in the detail levels is used as characters which indicating tool wear, the characters are input to the trained WNN to estimate the tool wear. The results of the experiments were compared with BP neutral network, conventional WNN and GA-based WNN. The results showed a faster convergence and more accurate estimation of tool wear.

According to Rao et al. [8], process parameters of electrochemical machining (ECM) such as the tool feed rate, electrolyte flow velocity, and applied voltage play a significant role in optimizing the measures of process performance. PSO was used to find the optimal combination of process parameters for an ECM operation. There are three machining performance measured which includes dimensional accuracy, tool life, and the MRR. The results of the proposed algorithm are compared with the previously published results obtained by using other optimization techniques. The process parameters of milling operation such as spindle speed and feed rate were considered to be optimized in the study of Li et al. [5]. The considered machining performances were cutting force, tool-life, surface roughness and cutting power. An algorithm for process parameters optimization known as cutting parameters optimization (CPO) was introduced and PSO technique was employed to optimize the process parameters. From the experimental results, the authors concluded that PSO in optimizing process parameters can converge quickly to a consistent combination of spindle speed and feed rate. An application was build in Duran et al. [9] to select suitable cutting tool geometry in a given combination of material work piece and cutting tool material. PSO was employed to find the optimal cutting tool geometry and evaluates a selected number of individuals (that represent a set of feasible tool angle) until a termination criteria is satisfied. In the experiments, a range of simulations were carried out to confirm the performance of the algorithm and to show the usefulness of the suggested approach. Chen and Li [10] proposed an improved PSO with opposition mutation (OMPSO) to select satisfied process parameter (depth of cut, feed rate, grit size) of grinding process. According to the researcher, OMPSO has the same tuning parameters as PSO and easy to use. The experiment result was compared to other evolutionary techniques such as GA, PSO and landscape adaptive PSO (LAPSO). It was obtained that the proposed technique was effective to solve grinding process optimization problem. The optimization of process parameters for constant cutting force was discussed based-on virtual machining by Zhao et al. [11]. PSO was employed to find the optimal process parameters (spindle speed and feed rate). The framework of virtual machining based cutting parameters optimization was established. Then two controlled experiments were conducted to demonstrate the effectiveness of cutting parameters optimization both with physical cutting and computer simulation. The results of experiment showed that machining process with constant cutting force can be achieved via cutting parameters optimization based on virtual machining. Tang et al. [12] investigated two-tool parallel turning (single pass and multipass) process parameters optimization problem. PSO was employed to determine optimal machining time. The results showed that the proposed technique performed better than exhaustive search algorithm in terms of machining time and required computational time.

Optimization of process parameters in turning operation was studied by Xi and Liao [13]. There are three objectives control parameters, which are machining time, machining accuracy and machining cost. The model was established using multiple targets nonlinear programming model. The process parameters were optimized using PSO. From the experimental results, the researchers found the optimal process parameters (cutting speed and feed rate) value is much smaller than the value calculated by the experience of the objective function value. The optimized cutting parameters values are better meet the user's optimization goals than obtained from the experience or manuals on the recommended values and more reference value. PSO was used in the research by Escamilla et al. [14] to find optimal process parameters of the titanium's machining process. For the modelling and prediction of the process outputs, ANN network was employed for Vertical Machining Center Bridgeport VMC 760. The machining the tool was an end mill coated with Aluminium Titanium Nitride (AlTiN). The obtained surface roughness value was 0.68 (μm) and the optimal process parameters values of speed, feed and depth of cut is 2798 (m/min), 425 (mm/rev) and 0.5 (mm) respectively. From the results of ANN modelling and PSO optimization, it can be successfully applied to multi-objective optimization of titanium's machining process. Modeling and optimizing process parameters in pulsed laser micromachining is the main focused in Ciurana et al. [15]. Selection of process operational parameters is highly critical for successful laser micromachining. The relation between process parameters and quality characteristics has been modeled with ANN. Predictions with ANNs have been compared with experimental work. Multiobjective PSO of process parameters for minimum surface roughness and minimum volume error is carried out. This result shows that the proposed model and swarm optimization approach are suitable to identify optimum process settings. In the research by Prakasvudhisarn et al. [16] process parameters of CNC end milling were selected such as feed rate, spindle speed, and depth of cut to find the minimum surface roughness. Support vector machine (SVM) was proposed to capture characteristics of roughness and its factors. PSO technique is then employed to find the combination of optimal process parameters. The results showed that cooperation between both techniques can achieve the desired surface roughness and also maximize productivity simultaneously. Srinivas et al. [17] proposed a methodology for selecting optimum machining parameters in multi-pass turning using PSO. The considered machining performances are production cost and machining time. PSO was implemented to obtain the set of cutting parameters that minimize unit production cost subject to practical constraints. The dynamic objective function approach adopted in the paper resolves a complex, multi-constrained, nonlinear turning model into a single, unconstrained objective problem. The best solution in each generation is obtained by comparing the unit production cost and the total non-dimensional constraint violation among all of the particles.

Razfar et al. [18] proposed a PSO-based neural network to create a predictive model for the surface roughness level that is based on experimental data collected on e face milling X20Cr13 stainless steel. The optimization problem is then solved using a PSO-based neural network for optimization system (PSONNOS). A good agreement is observed between the predicted surface roughness values and those obtained in experimental measurements performed using the predicted optimal machine settings. The PSONNOS is compared to the GA optimized neural network system (GONNS). PSO was used by Zheng and Ponnabalam [19] to optimize the multipass turning process which has rough machining and then a finish machining. The considered objective function is minimization of unit production cost. The performance is evaluated by comparing results of PSO with GA and SA that were reported by earlier researchers. Bharathi and Baskar [20] used three evolutionary optimization techniques such as SA, GA and PSO to explore the optimal machining process parameters for single pass turning operation, multi-pass turning operation, and surface grinding operation. The most affecting machining parameters are considered such as number of passes, cutting speed, feed, and depth of cut. The machining performances considered in this study are the production cost and the metal removal rate. The result of PSO is 4.7% and 1% better than GA and SA, respectively. In multi-pass turning operation, the result of PSO is 12.5% and 19.8% better than GA and SA, respectively. In grinding operation, the result of PSO is 6.2% and 1% better than GA and SA, respectively. PSO also gave better results compared to GA and SA in the three turning operations.

The machining performance considered in Bharathi and Baskar [21] are machining time and surface roughness. CNC turning machine was employed to conduct experiments on brass, aluminium, copper, and mild steel. PSO has been used to find the optimal machining parameters for minimizing machining time subjected to desired surface roughness. Physical constraints for both experiment and theoretical approach are cutting speed, feed, depth of cut, and surface roughness. It is observed that the machining time and surface roughness based on PSO are nearly same as that of the values obtained based on confirmation experiments; hence, it is found that PSO is capable of selecting appropriate machining parameters for turning operation. In the research by Farahnakian et al. [22] the effect of process parameters of high speed steel end mill such as spindle speed and feed rate are considered. Nanoclay (NC) content on machinability properties of polyamide-6/nanoclay (PA-6/NC) nanocomposites was studied for modeling cutting forces and surface roughness by using PSO-based neural network (PSONN). The results indicate that the nanoclay content on PA-6 significantly decreases the cutting forces, but does not have a considerable effect on surface roughness. The obtained results for modeling cutting forces and surface roughness also showed a remarkable training capacity of the proposed algorithm compared to the conventional neural network. Yang et.al [23] proposed a methodology, fuzzy PSO (FPSO) algorithm to distribute the total stock removal in each of the rough passes and the final finish pass which based on fuzzy velocity updating strategy to optimize the machining parameters implemented for multi-pass face milling. The optimum value of machining parameters including number of passes, depth of cut in each pass, speed, and feed are obtained to achieve minimum production cost. The proposed methodology for distribution of the total stock removal in each of passes is effective, and the proposed FPSO algorithm does not have any difficulty in converging towards the true optimum. From the given results, the proposed schemes may be a promising tool for the optimization of machining process parameters. Also in Yang et al.[24] the researchers proposed fuzzy global and personal best-mechanism-based multi-objective PSO (F-MOPSO) to optimize the machining parameters. The proposed algorithm was used to optimize the machining parameters is developed to solve such a multi-objective optimization problem in optimization of multi-pass face milling operation. It was found that the F-MOPSO does not have any difficulty in achieving well-spread Pareto optimal solutions with good convergence to true Pareto optimal front for multi-objective optimization problems. Costa et al. [25] used hybrid PSO for minimizing the production cost associated with multi-pass turning problems. The proposed optimization technique consists of a PSO-based framework wherein a properly embedded SA, namely an SA-based local search, aims both to enhance the PSO search mechanism and to move the PSO away from being closed within local optima. The used process parameters are cutting speed, feed rate and depth of cut. Five different test cases based on the multi-pass turning of a bar stock have been used for comparing the performance of the proposed technique with other existing methods. In Ganesan et al. [26], the machining parameters in multipass turning such as depth of cut, cutting speed and feed are considered. These process parameters were optimized using GA and PSO for minimization of production time. In GA the combination of optimal process parameters speed, feed and depth of cut achieved is 2185.714 (m/min), 0.22 (mm/rev) and 0.87 respectively with minimum production time = 3.131 (min). In PSO, combination of optimal process parameters speed, feed and depth of cut achieved is 3500.000000 (m/min), 0.367393 (mm/rev) and 0.010000 (mm) respectively with minimum production time = 0.000180 (min). It was found that PSO gave better results compared to GA.

Table 1: Summary of recent PSO techniques in optimizing machining process parameters

No.	Author / Year	Process Parameter	Machining Process	Machining performance	Remarks
1	Bharathi and Baskar [20]	Cutting speed, feed, depth of cut	Turning	Machining time, surface roughness	PSO is capable of selecting appropriate machining parameters for turning operation.
2	Farahnakian et al. [22]	Cutting speed, feed, depth of cut	End milling	Cutting forces and surface roughness	A very good training capacity of the proposed PSONN algorithm
3	Yang et al.[23]	Number of passes, depth of cut in each pass, speed, and feed	Multi-face milling	Production cost	The proposed schemes may be a promising tool for the optimization of machining process parameters
4	Yang et al.[23]	Number of passes, depth of cut in each pass, speed, and feed	Multi-pass face milling	Production cost	The F-MOPSO does not have any difficulty in achieving well-spread Pareto optimal solutions with good convergence to true Pareto optimal front for multi-objective optimization problems
5	Costa et al. [25]	Cutting speed, feed, depth of cut	Multi-pass turning	Production cost	The Performance of the proposed technique was compared with other existing methods.
6	Ganesan et al. [26]	Depth of cut, cutting speed and feed	Multi-pass turning	Production time	PSO produce better results than GA.
7	Razfar et al. [18]	Cutting speed, feed, depth of cut, engagement	Face milling	Surface roughness	A good agreement is observed between the Values predicted by the PSONNOS algorithm and experimental measurements.
8	Zheng and Ponnabalam [19]	Feed rate, cutting speed, depth of cut	Multi-pass turning	Production cost	PSO performs better than GA and SA.
9	Rao et al. [28]	Amplitude of ultrasonic vibration, frequency of ultrasonic vibration, mean diameter of abrasive particles, volumetric concentration of abrasive particles, and static feed force.	USM	MRR	The results of the presented algorithms are compared with the previously published results obtained by using GA.
10	Rao and Pawar [29]	Number of passes, depth of cut, cutting speed and feed	Multi-pass Milling	Production time	The results are compared with the previously published results obtained by using other optimization techniques.
11	Bharathi and Baskar [20]	Number of passes, cutting speed, feed, and depth of cut.	Single pass turning multi-pass turning, and surface grinding.	Production cost, MRR	From the results PSO give the best results compared to GA and SA in the three turning operation.
12	Xi and Liao [13]	Feed rate, cutting	Turning	Machining time, machining The optimized cutting speed accuracy and machining cost	The optimized parameters values are better cost meet the user's optimization goals.

13	Escamilla et al. [14]	Speed, feed and depth of cut	End milling	Surface roughness	PSO optimization it can be successfully applied to multi-objective optimization of titanium's machining process.
14	Ciurana et al. [15]	Laser fluence, position of focal plane, laser spot size. translation distance between subsequent laser pulses	Pulsed laser micro machining	Surface roughness, volume error	The proposed models and swarm optimization approach are suitable to identify optimum process settings.
15	Prakasvudhisarn et al. [16]	Speed, feed and depth of cut	CNC end millling	Surface roughness	Both techniques can achieve the desired surface roughness and also maximize productivity simultaneously.
16	Srinivas et al. [17]	Feed rate, cutting speed, depth of cut	Multi-pass turning	Production cost, machining time	The best solution in each generation is obtained by comparing the unit production cost and the total non-dimensional constraint violation among all of the particles.
17	Rao et al. [8]	Tool feed rate, electrolyte flow velocity, and applied voltage	ECM	Dimension accuracy, tool life, metal removal rate	The proposed algorithms are compared with the previously published results obtained by using other optimization techniques.
18	Li et al. [5]	Spindle speed, feed rate	Milling	Cutting force, tool-life, surface rougness and cutting power.	PSO in optimizing process parameters can converge quickly to a consistent combination of spindle speed and feed rate.
19	Duran et al. [9]	Cutting speed, power, feed speed, depth of cut	Various	Tool geometry	The selection of the appropriate cutting tool geometry is possible in real world environments.
20	Chen and Li [10]	Depth of cut, feed rate, grit size	Grinding	MRR	The proposed algorithm is an effective method for grinding process optimization problem.
21	Zhao et al. [11]	Spindle speed and feed rate.	Milling	Cutting forces	The machining process with constant cutting force can be achieved via process parameters optimization based on virtual machining.
22	Liu and Huang [27]	Feed and cutting	N/A	Cost performance	PSO is relevant for solving complicated nonlinear problem.
23	Tang et al. [12]	Spindle speed, feed, and depth of cut	Single and Multipass Turning	Machining time	The proposed algorithm is superior to the latter not only in terms of computational time but also in terms of performance.
24	Zuperl et al. [6]	Cutting speeds and feed rates	Milling	Cutting forces	Compared with GA and SA the proposed algorithm can improve the quality of the solution while speeding up the convergence process.
25	Huang et al. [7]	Spindle, Feed rate, width	End milling	Tool wear	The MPSO-trained WNN has a superior performance than BP-NN, conventional WNN, and GA-based WNN.

4. Conclusion

As depicted in Figure 2 and Figure 3 below, it can be summarized that the most machining processes considered in PSO was Multipass-turning followed by end milling and milling machining. For machining performance, the most machining performance measured was machining/production costs followed by surface roughness and machining/production time. From the various researches in the literature, it was proven that PSO performed better than other soft computing techniques such as GA and SA. PSO was employed by most researchers because of the simplicity and in addition it also has a features of both GA and evolution strategies.

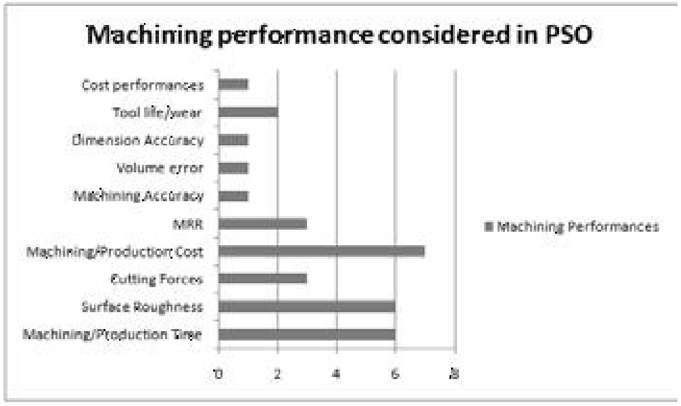

Fig 3: Machining performance considered in PSO

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Fig 2: Machining process considered in PSO

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