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Research Article

Self adaptive penalty method coupled with metaheuristic algorithms to optimization of varying geometrical parameters in drilling for multi hole parts

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ABSTRACT

In small workshops, a more number of holes on aero engine parts are drilled successively in one process to confirm positional accuracy. Because of the fast time-varying drill wear, the surface roughness of the holes is unstable and difficult to be satisfied. To the present end, this paper presents a varying-parameter drilling (VPD) method to enhance machining efficiency and hole surface roughness for multi-hole parts manufactured from Al 7075 alloys. This method uses varying cutting parameters for every hole to adapt to the varying drill wear. The major problem of this method deceit in an optimization issue during which the optimal combination of setting of cutting parameters have to be found, with the target of the interval and also the constaint of the opening surface roughness, because sequence of cutting parameter encompasses a important aspect and therefore the surface roughness of all the holes must be guaranteed, the challenge of this optimization issue is that the strict constraint with a sophisticated non-linear boundary of the feasible zone. To cope with the convergence complexity of the searching algorithm, a metaheuristic method supported particle swarm optimization (PSO) algorithm with a self-adaptive penalty method (SAPM) is applied. The drilled hole surface roughness is predicted with a radial basis function (RBF) neural network. The various types of drill wear comprising flank wear, crater wear, chisel wear and outer corner wear are considered and the grey relational analysis (GRA) is deployed to pick the input drill wear parameters to the network. The PSO algorithms integrate with the SAPM is used to search the overall optimal solution of the optimization problem. It is found that the satisfied solutions can be searched in all the trials with the proposed metaheuristic algorithms, even though the proportion of feasible solutions is severely fluctuant during the searching process. The drilling experiment confirm that, when compared with the fixed-parameter drilling, the proposed VPD and the metaheuristic algorithm method for solving the optimization problem can effectively improve machining efficiency and surface quality for drilling Al 7075 alloy multi-hole parts.

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INTRODUCTION

Drilling is a fundamental metal cutting operation has long been widely used in manufacturing industry. Drill wear affects surface quality of the hole. In drilling process, the worn outer corner of the drill rubs against the machined surface and directly affects the surface finish. On the other hand, the wear on the cutting lips and chisel edge will influence the mechanical and thermal load as well as the cutting stability. It also has strong impact on the surface quality of the hole, because tool vibration and the mechanical or thermal overloading may cause cracks on the hole inner wall. The cracks and other surface defects on the hole wall caused by drill wear is unacceptable in aerospace industry, because it may lead to premature in service failure of the key component, and it may even cause a catastrophic accident. To avoid low surface quality caused by drill wear, usually in workshops the drill is frequently changed during the successive drilling process. It largely raises the manufacturing time and production cost, and even so the surface quality of the holes is still hardly satisfied. Therefore, drilling parameter optimization is a crucial issue to be addressed. There has been lots of research on drilling parameter optimization. The most influential parameters or the main effect on the target variables related to hole quality, machining efficiency or production cost can be obtained based on statistical analysis for DOE. Kurt et al. used Taguchi method to select best process parameters for hole diameter accuracy and surface finish in the dry drilling of Al 2024 alloy. The process parameters considered in the DOE are cutting speed, feedrate, drilling depth and drill types. The analysis of S/N ratio, ANOVA and regression analysis were applied for parameter selection. Grey based Taguchi method was proposed [Reddy Sreenivasulu and Chalamalasetti SrinivasaRao, 2016] to obtain best combinations of cutting speed, feedrate and drill type to get minimum hole surface roughness and circularity deviation in drilling of Aluminium alloys. Also [R.Sreenivasulu, 2015] investigated the effect of cutting speed, feedrate, drill diameter, point angle and clearance angle on surface roughness, burr size and circularity deviation of the hole in drilling of Al 6061 through Taguchi method. The desirable parameters were selected with the analysis of S/N ratio and ANOVA. The grey relational analysis (GRA) is another effective technique to find out the relevance between the control factors and the response variables. D-form 3D technique to develop a model of the effect of cutting speed, feedrate, drill diameter and point angle on entry and exit face, thrust force and torque in drilling of aluminium alloys [Sreenivasulu et al, 2018]. The optimal parameters are obtained based on this model, and the Taguchi method to compare with the D-form 3D model. Also they utilized design of experiments to optimize drilling parameters for aluminium 2014 alloys and compare the results with artificial numeral network. ANN was used to attain the relationship between cutting parameters (spindle speed and feedrate) and various output parameters comprising surface roughness, ovality, thrust force and machining time[Kannan et al, 2014]. Genetic Algorithm used to optimize feedrate and drilling torque for a multi-objective problem where the hole eccentricity and material removal rate are chosen as two optimization objectives in drilling of carbon fiber reinforced plastic composite material [Saravanan et al, 2014]. Most previous research mainly focuses on finding an optimal setting of process parameters for drilling a specific hole to improve machining efficiency, hole quality and production cost. To this point, many brilliant research works have been made with comprehensive factors from the aspect of the drill, the hole and the drilling process. The target variables studied comprise hole quality (surface quality, accuracy of dimension and form, burr height and thickness), drilling thrust, drilling torque, vibration and flank wear. However, in the practical drilling operations in a workshop, one drill is often used for drilling a sequence of holes until the end of its service life. In this case, it is not advisable to use fixed parameters for drilling all the holes. The reason is that, the parameter settings used for drilling each hole not only determine the total manufacturing time, but also affect the drill wear. As drill wear is cumulative during drilling process and it affects hole surface quality, the parameters used for each hole have a correlation with the surface quality of the following holes to be machined. Therefore, different types of drill wear must be considered in the drilling parameter optimization. To address the problem of low surface quality and manufacturing efficiency in successive drilling operations for aluminium 7075 alloy, the successive drilling operations are considered as a whole process and the cutting parameter sequence is optimized in this paper, which is termed as the varying parameter drilling (VPD) strategy. The mathematical model of the optimization problem is established in which the optimization objective is processing time and the constraint is the tolerance of surface roughness. As hole surface roughness is influenced by the cutting parameters and the accumulated various types of drill wear in successive drilling process, in the solution updating procedure the change of the cutting parameters for one hole will cause overall changing of the surface roughness of its subsequent holes. Thus, the candidate solutions are difficult to stay within the feasible zone during the searching process. It affects the convergence rate and may even lead to nonconference. To handle this difficulty, a soft computing method using metaheuristic algorithm coupled with the self-adaptive penalty method (SAPM) is proposed. The novelty of this paper is that, the VPD is first introduced in the successive drilling operation of aluminium alloys to adapt to the first time-varying drill wear during the process, and a soft computing method to address the difficulty in solution solving of the corresponding optimization problem is proposed.

Problem Description

The aluminium 7075 alloy casings in aero engines usually have a high requirement of hole surface quality, because poor surface quality may easily cause fatigue damage in the harsh service condition. In workshops, for better positional accuracy of all the holes, the hole making operations are generally performed by successive drilling in one process. This process is often faced with troubles of low machining efficiency and hardly guaranteed surface quality due to the drill wear. The drill wear is related to the cutting parameters, and has an influence on the machining efficiency and hole surface quality together with the cutting parameters. As the number of holes is quite large, the drilling operations occupy a long processing time in the production cycle. As is known, the efficiency of drilling operations is proportional to the setting of feedrate. When the drill wear is excessive, the drill should be changed. It costs extra set-up time and increases the production cost. In traditional drilling operation of the multi-hole parts, fixed cutting parameters are used for all the holes. As drill wear is accumulated in the successive drilling process, the surface roughness of the holes is unstable and hardly to control with fixed cutting parameters. Accordingly, the cutting parameters are better to be adjusted for each hole as per the variation of the drill wear. In this paper, the varying-parameter drilling method (VPD) is presented, with a sequence of varied cutting parameters used for the successive drilling process. The main issue of the VPD is to find the optimal sequence of cutting parameters that minimize the processing time and guarantee the hole surface quality. The mathematical model of the optimization problem is developed in the next section.

MATHEMATICAL MODEL OF DRILLING PARAMETER OPTIMIZATION

The drilling parameter optimization is to maximize machining efficiency and guarantee hole surface quality at the same time. The solution, the optimization objective and the constraints are mathematically expressed in this section. A self-adaptive penalty method (SAPM) is proposed as the supporting algorithm of this optimization problem, and on this basis the fitness function for the searching algorithm is developed.

Solution

In the VPD, the cutting parameters are varied for each hole to achieve a global optimum for the successive drilling process. Accordingly, the solution of the optimization problem is described as a sequence of spindle speed and feedrate. It can be expressed by the matrix below

$$x = \begin{bmatrix} S_1 & S_2 & \cdots & S_n \\ f_1 & f_2 & \cdots & f_n \end{bmatrix} \tag{1}$$

Where x represents the solution of the optimization problem, ‘n’ is the number of holes to be machined, ’S’ is spindle speed and ’f ‘is feedrate. Each column of this matrix corresponds to the cutting parameters used for one hole. Compared to the traditional fixed-parameter drilling, the cutting parameters S and f in the VPD are adjustable for different holes. The cutting parameters used for each hole can be flexibly varied to better fit the fast variation of drill wear in drilling of aluminium 7075 alloy, to get shorter machining time and better hole quality of all the holes.

Optimization objective

To improve the manufacturing efficiency of multi number of holes, the optimization objective is to minimize the total processing time. In the successive drilling process, the processing time comprises three portions: machining time, idle motion time and tool changing time. The machining time is determined by the feedrate selected for each hole. The idle motion time consists of the time of tool approaching, retracting and moving to the next holes. It is restricted by the maximum permissible feedrate of the machine tool. During the successive drilling process, when the drill gets severe worn, the drill has to be changed and it costs the time for tool presetting and adjustment. As drill wear is usually serious in drilling difficult-to-cut materials, tool changing time should be considered in the total processing time. The total time for tool change is determined by the frequency of tool failure that is related to the drill wear rate. To optimize the total processing time, the idle motion time can be regarded as constant that can be shortened by setting a large fixed idle feedrate. Then, the objective function is given as

$$t = \sum_{i=1}^{n} \frac{D}{f_i} + T_c \cdot m + T_{idle} \tag{2}$$

Where‘t’ is the total processing time of the successive drilling process,’ n’ is the number of holes to be machined, ‘D’ is the nominal depth of the hole,’ f_i’ is the feedrate set for the th hole, ‘T_c’ is the tool changing time, ‘m’ is the total number of tool change, ‘T_{idle}’ is the idle motion time set as a constant.

Constraints

As aforementioned, the surface quality of the holes is unstable due to the varied drill wear and need to be controlled in the optimization. In workshops, the surface roughness is commonly adopted as the index of hole surface quality. As for the hole of a particular part, there is a tolerance requirement of the surface roughness. Therefore, in this study the tolerance of the hole surface roughness is adopted as the constraint. The R_a value is the most widely used parameter of surface roughness, which is calculated as

$$R_a = \frac{1}{L}\int_0^L |Y(l)|\, dl \tag{3}$$

Where 'L' is the sample length on the drilled hole wall, '*l*' is the ordinate along the sample length, 'Y' is the ordinate of the profile curve along the sample length, and R_a measures the arithmetic average deviation from the mean line of Y. Besides, the constraints of spindle speed and feedrate that are related to cutting performance and machine tool property should also be considered in the practical situation. Then, the constraints of the optimization problem can be given by

$$\begin{cases} R_a \le R_{a,max} \\ s_{min} \le s \le s_{max} \\ f_{min} \le f \le f_{max} \end{cases} \tag{4}$$

Where $R_{a,max}$ is the tolerance of the hole surface roughness, R_a is the spindle speed with its minimum value S_{min} and maximum value S_{max}, f is the feedrate with its minimum value f_{min} and maximum value f_{max}. The range of the cutting parameters [S_{min}, S_{max}] and [f_{min}, f_{max}] can be set as per the tool manufacturer's recommendation. As hole surface roughness is affected by various factors including cutting parameters, cutting force and tool wear [Ji W etal 2017], the ANN is used in this study to develop the complex nonlinear relations between hole surface roughness and all these influence factors, which is detailed in Section 4.

Fitness function

For the convenience of solving the above constrained optimization problem, it is usually converted to an unconstrained problem. The penalty function is the most widely used constraint handling technique for its effectiveness and simplicity [Woldesenbet YG et al 2009]. The main difficulty of the penalty method is to balance the optimization objective and the penalty to improve the convergence rate. When using the classic swarm intelligence algorithms like GA and PSO in the constrained optimization problem, some particles (candidate solutions) may be infeasible and the proportion of the feasible solutions is varied as the searching progresses. For the drilling parameter optimization problem, the boundary of the feasible zone is complex because there are too many possible settings for each cutting parameter in one solution and the relation between the constraint of surface roughness and cutting parameters is complex. In this case, there are two requirements for the penalty function: (a) infeasible particles should move into the feasible zone rapidly, (b) feasible particles should stay in the feasible zone and approach the optimum solution. To this end, a self-adaptive penalty method (SAPM) is proposed. On this basis, a new fitness function for the searching algorithm is developed. The procedure is detailed as follow.

Distance value

To overall evaluate each particle's degree of deviation from the optimum solution, a new parameter denoted as the distance value is introduced. The value of the objective function and the constraint violation are both included in the distance value. To this end, the objective value and constraint violation are normalized to balance their dimension. The objective value, i.e., the total processing time't' is normalized as follow

$$\tilde{t}(x) = \frac{t(x) - t_{min}}{t_{max} - t_{min}} \tag{5}$$

Where 'x' represents a particle in the searching algorithm,'t' is the value of objective function, $\bar{t}$ is the normalized objective value, t_{min} and t_{max} represent the possible maximum and minimum processing time, respectively. After the normalization, $\bar{t}(x)$ is confined within the range between 0 and 1. The constraint violation of each candidate solution in this optimization is the sum of the deviation of surface roughness R_a from the tolerance $R_{a,max}$ for all the holes. Then, the constraint violation of each particle is normalized as

$$\tilde{c}(x) = \frac{c(x)}{c_{max}} \quad 6)$$

Where,

$$c(x) = \max\left\{0, \sum\nolimits_i^n R_a^{(i)} - nR_{a,max}\right\}$$

is the value of constraint violation,

$$c_{max} = \max\nolimits_x c(x)$$

is the possible maximum value of constraint violation among all the distance value 'd' is formulated as

$$d(x) = \begin{cases} \tilde{c}(x) \;\; if \quad a_f = 0 \\ \sqrt{\tilde{t}(x)^2 + \tilde{c}(x)^2} \end{cases} \tag{7}$$

Where

$$(\alpha_f) = \frac{\text{number of feasible particles}}{\text{swarm size}}$$

is the proportion of the feasible particles among all the candidate solutions. The distance value is the measure of the distance each particle away from the optimum solution. From Eq. (7), the distance value is increased when the value of the objective function and the constraint violation increase. If all the particles in the swarm are infeasible ($\alpha_f = 0$), the distance value is equal to the constraint violation.

Self-adaptive penalty

The distance value measures the deviation of each particle from the optimum solution. In order to add penalty to infeasible particles for a higher convergence rate, the SAPM is established, with the penalty function given as follow

$$p(x) = (1-\alpha_f)X(x) + \alpha_f Y(x) \tag{8}$$

Where,

$$X(x) = \begin{cases} 0 & if \quad a_f = 0 \\ \tilde{c}(x) & otherwise \end{cases}$$

$$Y(x) = \begin{cases} 0 & if\ x\ is\ a\ feasible\ individual \\ & \tilde{t}(x)\ \ otherwise \end{cases}$$

From Eq.(8), two penalty values X(x) and Y(x) are added to make sure the penalty can be self-adaptive according to the proportion of feasible particles in the swarm: if there are a large proportion of feasible particles in the swarm, then the particles with high objective value are more penalized; and if there are few feasible particles, then those with high constraint violation are more penalized. The SAPM can help achieve two targets in the constrained optimization: (a) searching for more feasible solutions if there are few, (b) finding the optimum solution quickly if enough feasible particles are obtained.

Final fitness function

The final fitness function f(x) is obtained as the sum of the distance value d(x) and the penalty function p(x) as given below

$$f(x) = d(x) + p(x) \tag{9}$$

With the SAPM, the constrained drilling parameter optimization is transformed into an unconstrained optimization problem, and the candidate solutions will be penalized according to their deviation from the optimum solution as the searching process progresses. From Eq. (7)-(9), when there are no feasible particles in the swarm ($\alpha_f = 0$), the fitness function becomes f(x) = v(x). It only depends on the value of constraint violation. When the number of the feasible particles is increasing, the proportion of the objective value $\bar{t}(x)$ in the fitness function is raised. The penalty on the particles is in-process adjusted for fast convergence rate. In summary, the mathematical model of the optimization problem can be expressed by

$$\begin{aligned} find: x &= \begin{bmatrix} S_1 & S_2 & \cdots & S_n \\ f_1 & f_2 & \cdots & f_n \end{bmatrix}_{2\times n} \\ min: f(x) &= d(x) + p(x) \end{aligned} \tag{10}$$

The optimization problem for the VPD involves different cutting parameters of all the holes. There are too many possible settings. As the surface roughness of all the holes must be constrained within the tolerance, the boundary of the feasible zone is complex. Hence, the particles are prone to repeatedly moving into and out of the feasible zone in the searching process. The SAPM is able to adjust the fitness value according to the distance of the particles from the optimal solution and the proportion of feasible particles in the swarm. It is important for finding better solutions in the searching process so that the optimization can smoothly progress.

OPTIMIZATION PROCEDURE

After the fitness function of drilling parameter optimization is developed in Section 3, the next issue is to find the optimum solution that minimizes the fitness function. The flow chart of the optimization procedure is illustrated in Figure 1. As mentioned in Section 3.4, the fitness value is calculated from the optimization objective (total processing time) and the constraint (hole surface roughness). The processing time found from Eq. (2). While, the hole surface roughness has a complicated nonlinear relationship with various influence factors including cutting parameters, drill wear and drilling forces [Tsao CC, Hocheng H, 2008]. In this study, the relation between hole surface roughness and these factors is developed by the RBF neural network is an ANN approximator applies to build complex nonlinear relationship between the input and output data and it has been widely used for prediction in machining processes [Zhou J et al 2017]. Since the hole surface roughness is calculated with a RBF neural network, it is difficult to formulate the fitness function given in Eq. (9). On the other hand, the fitness function may be a non-convex function with multiple local optimums. In this case the classic gradient-based searching algorithm may be not effective. In this study, PSO is utilized to solve the optimization problem. PSO is a sort of meta-heuristic algorithms that has a strong global optimization capability proposed [Eberhart and Kennedy, 1995]. Due to its good performance and concise expression, it has been widely used in many fields referring to optimization, design, control and data mining [Han C et al, 2014]. This paper presents a data-driven optimization

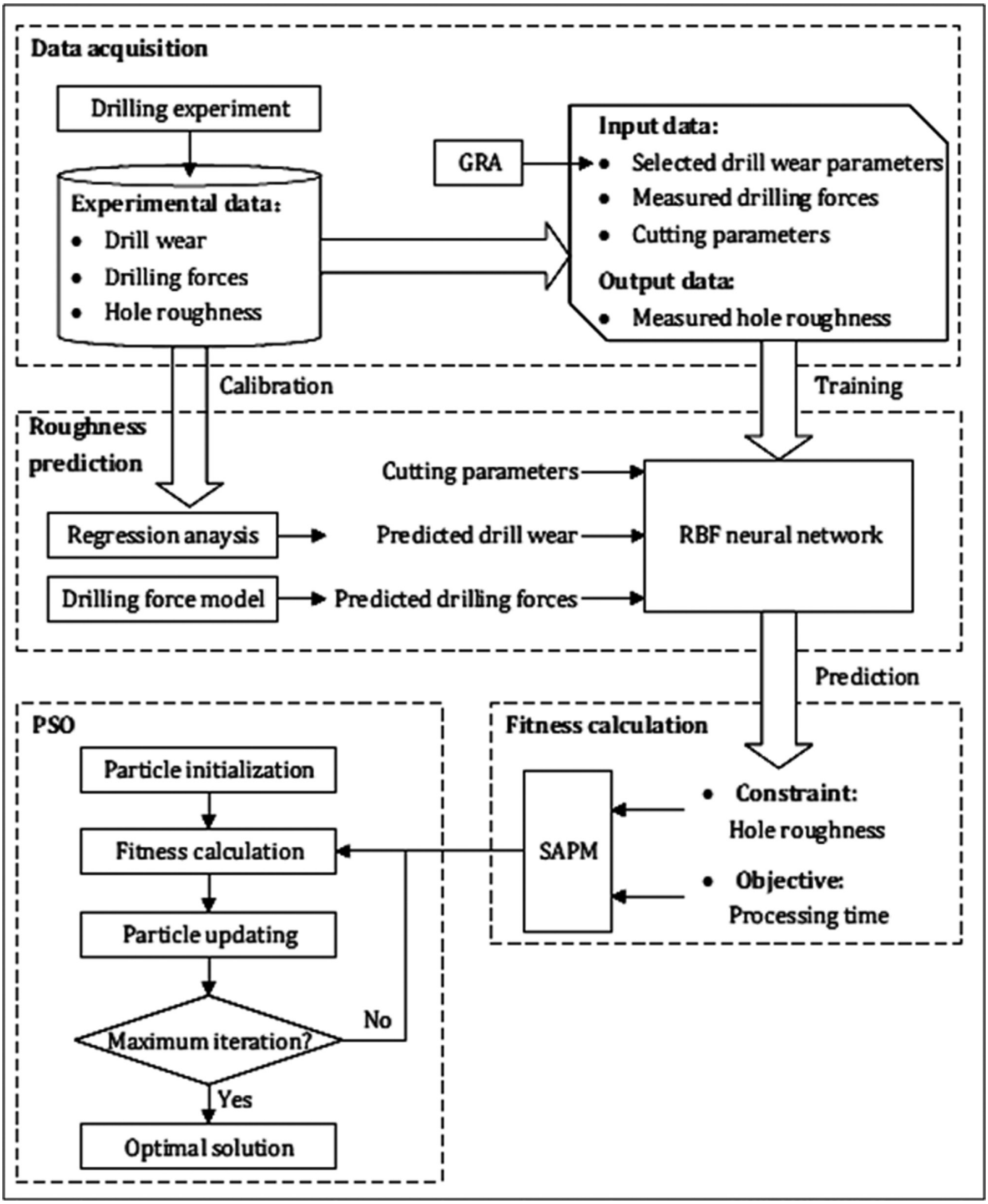

Figure 1. Overall optimization procedure.

method on the basis of the measured data from drilling experiments. The RBF neural network used to predict the surface roughness can be trained with the dataset of drill wear, drilling forces and hole surface roughness at different cutting parameters. Then, the fitness value can be obtained by the proposed SAPM, and PSO can be conducted with its updating rule. The procedure of each step is detailed in the following subsections.

Grey relational analyses of different drill wear types and surface roughness

The geometry of a standard twist drill is illustrated in Figure 2. In drilling of difficult-to-cut materials, drill wear is usually serious with various types on different edges such as flank wear, crater wear, chisel wear and outer corner wear. Since there are two cutting lips for a standard twist drill, the mean value of the two drill wear parameters is used for analysis in this study. Before these drill wear parameters are used as input features of the RBF neural network, it is necessary to investigate their relevance with the hole surface roughness, because the input features with weak relevance will cause low prediction accuracy and extra computation cost. To this end, the relevance of these different drill wear types to hole surface roughness are analyzed with GRA and the principal impact factors are selected as the input features. A grey system is a complex and multivariate system that has a level of information between black and white, where black means having no information and white represents having all information. GRA is an analysis method in grey system theory that measures the uncertain correlations between one main factor (the reference sequence) and the other factors (the comparison sequences) in a given system [Deng J 1989]. In this study, the relationship between various drill wear types and hole surface roughness are complex and uncertain, which can be considered as a grey system. In the drilling parameter optimization problem, the reference sequence is the hole surface roughness, which is the variable to be investigated. The comparison sequences are the different types of drill wear, which is the influence factor. The reference sequence X_o and each comparison sequence X_i can be expressed as follows

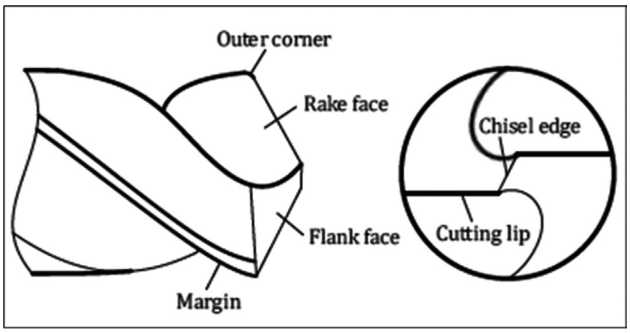

Figure 2. Geometry of a standard twist drill.

$$X_0 = [R_a(1) \quad R_a(2) \quad \dots \quad R_a(n)]^T \tag{11}$$

$$[X_1 \ X_2 \ X_3 \ X_4 \ X_5] = \begin{bmatrix} VB(1) & KB(1) & C_\psi(1) & C_\psi(1) & W(1) \\ VB(2) & KB(2) & C_\psi(2) & C_\psi(2) & W(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ VB(n) & KB(n) & C_\psi(n) & C_\psi(n) & W(n) \end{bmatrix} \tag{12}$$

Where 'n' is the number of the elements in the data sequence, and in this case referring to the number of measured holes. Since the unit and scale in each sequence are different, the normalization is necessary to conducted in order to keep the scale of data unified. The normalization formula is as follow

$$X_i^*(k) = \frac{X_i(k) - \min_k X_i(k)}{\max_k X_i(k) - \min_k X_i(k)} \tag{13}$$

Where X_i^* denotes the normalized data, $X_0^*(k)$ and $X_i^*(k)$ are the normalized element in the reference sequence (hole surface roughness) and the comparison sequences (drill wear parameters), respectively, $i \in \{1,2,3,4,5\}$ and $k \in \{1,2,3,4,\dots n\}$. In GRA, the measure of the relevance between the reference sequence and the comparison sequence is evaluated as the grey relational grade. To calculate the grey relational grade, the grey relation coefficient $\xi_{oi}(k)$ is first introduced to measure the relevance between the corresponding elements in two sequences, and it can be given by

$$\xi_{oi}(k) = \frac{\Delta_{min} + \rho\Delta_{max}}{\Delta_{oi}(k) + \rho\Delta_{max}} \tag{14}$$

$$\gamma_{oi} = \frac{1}{n}\sum_{k=1}^{n} \xi_{oi}(k) \tag{15}$$

The grey relational grade γ_{oi} describes the degree of relevance between the reference sequence and a comparison sequence. From its definition, for each comparison sequence, the greater γ_{oi} is the larger relevance it has with the reference sequence. In this study, the drill wear parameters with higher grey relational grade calculated from the measured data are selected as the input features of the neural network.

Prediction of drill wear and drilling forces

Drill wear and drilling forces are the input features of the RBF neural network for the prediction of the hole surface roughness. Drill wear is also involved in the calculation of tool changing time as mentioned in Section 3.2. Hence, drill wear and drilling forces should be calculated in the optimization. Since tool wear is a gradually cumulative process, the drill wear rate is introduced to calculate the drill wear parameters, which is defined as the incremental wear value of drilling per unit depth with the expression below

$$r_i = \frac{dwear_i}{dl} \tag{16}$$

Where 'r_i' is the wear rate of each wear type, $wear_i$ denotes a particular drill wear parameter, 'l' is drilling depth. The drill wear rate of different wear types can be estimated based on the measured drill wear data.

As the wear rate' r_i' is time varying, the drill wear can be calculated by integral

$$wear_i = \int_0^l r_i dl \tag{17}$$

After the different drill wear parameters are obtained, the drilling forces can be predicted according to the model given below

$$\begin{aligned} F &= \delta_{a,lip} K_{a,lip} A + \delta_{chisel} K_{chisel} l_{chisel} \\ T &= (\delta_{t,lip} K_{t,lip} A + \delta_{corner} K_{corner} l_{corner} \end{aligned} \tag{18}$$

Where is F the thrust force, T is the torque, A is the chip load, R is the drill radius, l_{chisel} and l_{corner} are the length of the chisel edge and the outer corner, $K_{a,lip}$ and $K_{t,lip}$ are the axial and tangential drilling force coefficients of the cutting lips, K_{chisel} and K_{corner} are the drilling force coefficient of chisel edge and outer corners $\delta_{a,lip}$, $\delta_{t,lip}$, δ_{chisel}, δ_{corner} are the four coefficients termed as the drill wear effect coefficients to describe the effects of various drill wear types on the corresponding drilling force coefficients. The drilling force coefficients and the drill wear effect coefficients can be calibrated in the drilling tests. When the drill wear is known, the drilling forces can be predicted as per this drilling force model. After then, the relations between drill wear, drilling forces and cutting parameters can be developed through experimental data.

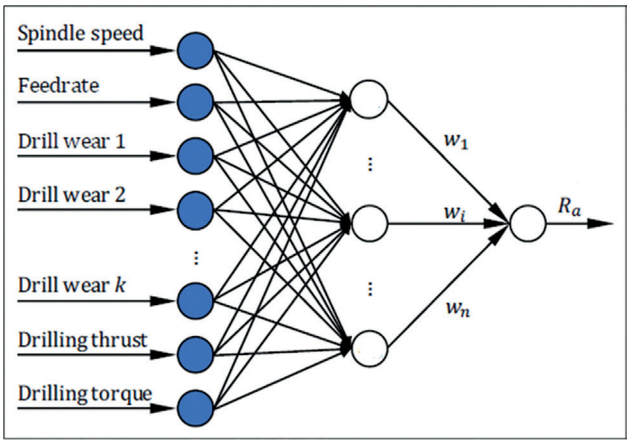

Figure 3. Structure of RBF neural network to predict hole surface roughness.

Prediction of surface roughness with RBF neural network

The nonlinear relationship between hole surface roughness and cutting parameters, drill wear and drilling forces are developed with RBF neural network. After the hole surface roughness is predicted with the RBF neural network, the fitness value expressed in Eq. (9) can be calculated with the SAPM mentioned in previous section. To be noted that, the network training is time-costing but conducted before the searching process with PSO, and the well-trained RBF neural network is then used for fitness calculation in the searching process (shown in Figure 3).

Searching of optimal solution with PSO

In this study, PSO is used to search for a global optimum solution of the drilling parameter optimization problem. With the fitness calculation procedure above, the searching procedure with PSO can be progressed according to the following steps.

Step 1: Particle initialization

The solution of the optimization problem is expressed as a matrix in Eq. (1). The initial particles can be randomly generated with the set value of the speed and feedrate within the feasible zone as per Eq. (4).

Step 2: Fitness calculation

The fitness value of each particle is obtained with the SAPM, in which the objective of processing time is calculated as per Eq. (2) and the constraint of surface roughness is predicted with the RBF neural network. In each iteration of PSO, the optimum location of each particle and the global optimum location in the swarm are recorded. In this study, the maximum iteration number is set as the termination condition. When the updating is executed with certain times, the global optimal solution is output as the final result, if the output sequence of cutting parameters is not satisfied the constraint in Eq. (4). To be noted that, as PSO is a meta-heuristic algorithm, it should have at least one feasible solution to guarantee the particles converging to a feasible solution. In the initialization step, when all the particles are infeasible, it is necessary to reinitialize the swarm until there exist's a feasible particle.

EXPERIMENTAL SETUP

In the present work, a radial drilling machine to perform different size of holes as per Taguchi's orthonal array for 3 level of factors on Aluminium 7075 alloy work pieces are chosen to conduct experimentation. The tools used for drilling operation are HSS-R (DIN 338) twist drills supplied by Miranda, INDIA (Figure 4). A Kistler type 9272, Kistler Instrumente AG, CH8408, Winterthur, Switzerland, four components dynamometer was used to measure thrust force and torque and the signal was processed to the computer by a type 5070 multichannel charge amplifier, data acquisition card and graphical images displaying mathematical processing of thrust force and torque signals recorded with Dynoware software 2825A. The selection of cutting parameters and their levels are depicted in table.1 as per Taguchi method.

RESULTS AND DISCUSSION

The drilling experiments were performed according to the procedure in detailed provided in previous Section. The measured data depicted in Table 2. After the experimental data are obtained, the optimization can be achieved as per the mathematical model and the optimization procedure given in previous. In this section, the results comprising the GRA of drill wear on surface roughness (shown in table.3), the prediction of drill wear and drilling forces, RBF neural network of surface roughness and the cutting parameter optimization with PSO are illustrated and discussed.

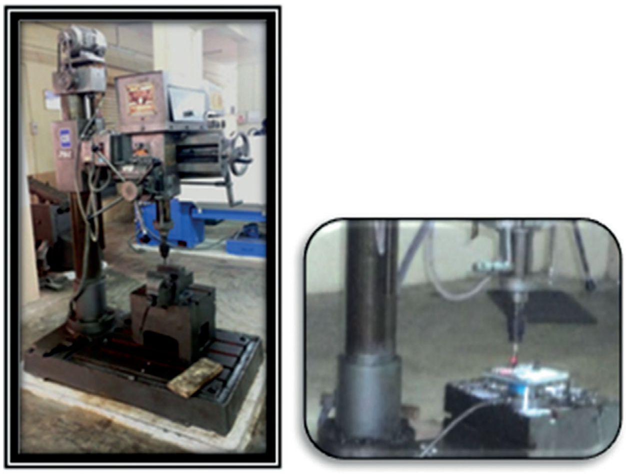

Figure 4. schatic diagram for drilling machine setup for experimentation.

Table 1. Drilling parameters and levels [21]

LEVEL	DRILLING PARAMETERS				
	Speed *s* (rpm)	Feed Rate *f*(mm/min)	Drill Dia. (mm)	Point Angle	Clearance Angle
1	465	18	8	100°	4^0
2	695	20	10	110°	6^0
3	795	26	12	118°	8^0

Grey relational analyses (GRA) of different drill wear types and surface roughness

The GRA was performed based on the measured data given in Table 2 from 27 holes drilled with different drill wear state. Let each type of wear values be the comparability sequence and the corresponding surface roughness be the reference sequence.

From the result, crater wear KB has the highest grey relational grade among all the drill wear types. It means crater wear has the largest relevance with the surface roughness. It is because the hole surface roughness is largely determined by the chip evacuation state and the chip morphology and evacuation process are affected by the rake face [20] which is identified from Figure 7. In drilling process, the rake

Table 2. Measured data in drilling experiment

Drill Wear					Ra	F	T
VB	KB	Cψ	Vψ	W	μm	N	Nm
24	250	352	530	46	0.197	281.69	113.1
32	278	298	528	32	0.165	235.24	155.7
26	242	245	459	26	0.253	395.95	219.7
34	234	452	527	65	0.197	232.09	171.5
36	311	275	551	36	0.189	291.19	173.5
22	295	354	467	42	0.216	265.49	127.3
18	265	375	375	16	0.238	336.63	199.1
42	260	395	415	25	0.218	286.74	157.3
41	350	405	525	24	0.273	252.26	158.3
38	328	475	565	96	0.232	241.79	134.1
29	368	315	605	54	0.178	237.26	156.2
41	284	335	625	26	0.237	395.95	219.7
42	289	235	575	86	0.245	262.09	144.5
48	309	415	495	78	0.245	208.19	165.2
37	310	345	395	65	0.251	265.46	137.4
51	323	290	385	38	0.262	346.63	274.1
57	425	457	685	97	0.186	286.74	147.3
28	465	398	643	52	0.229	252.26	232.1
62	475	367	592	92	0.278	241.69	213.1
35	502	346	618	89	0.248	236.54	177.7
30	552	209	627	42	0.222	395.95	219.7
57	525	324	678	82	0.241	272.09	184.5
46	545	528	691	74	0.241	298.19	165.3
44	475	478	725	78	0.152	365.49	241.4
62	495	187	705	64	0.141	396.63	249.1
59	625	192	515	67	0.158	286.74	197.3
54	605	286	555	91	0.187	362.26	238.1

Table 3. GRA Calculated data from table.2 for Surface Roughness

Grey relational coefficients					Grey relational grades
VB	KB	Cψ	Vψ	W	
0.5501	0.6242	0.5608	1.0000	0.6246	0.6568
0.7405	0.4353	0.7762	0.6539	0.4489	0.6135
0.3794	0.5291	0.3730	0.3707	0.6696	0.4949
0.5457	0.4469	0.7970	0.5795	0.8181	0.6195
0.5879	0.3333	0.5307	0.5712	0.8020	0.5372
0.4773	0.6113	0.6209	0.8500	0.8805	0.6722
0.4138	0.6309	0.4222	0.4834	0.8724	0.5418
0.4707	0.5513	0.5540	0.6454	0.5955	0.5385
0.3416	0.7468	0.6805	0.6403	0.3337	0.5264
0.4294	0.6704	0.7363	0.7930	0.6439	0.6227
0.6492	0.7065	0.7634	0.6512	0.4735	0.6337
0.4163	0.7971	0.3333	0.4545	0.6912	0.5175
0.3902	0.4609	0.6352	0.7193	0.9272	0.6026
0.3970	0.6940	1.0000	0.6070	0.8399	0.6475
0.3837	0.5339	0.6090	0.7680	0.9213	0.5962
0.3614	0.5783	0.4040	0.3333	0.9009	0.5050
0.6143	0.5870	0.5640	0.7017	0.5934	0.5869
0.4376	0.6820	0.6905	0.4034	0.3383	0.4882
0.3333	0.4520	0.7091	0.4459	0.6343	0.4846
0.4017	0.7374	0.7680	0.5547	0.4147	0.5589
0.4581	0.5645	0.4898	0.4302	0.6733	0.5010
0.4065	0.3818	0.5949	0.5299	1.0000	0.5674
0.3539	1.0000	0.5105	0.6065	0.7998	0.6661
0.8616	0.8427	0.4060	0.3855	0.8567	0.7119
1.0000	0.8136	0.5367	0.6728	0.8229	0.8077
0.8011	0.5042	0.5444	0.4887	0.5950	0.6147
0.5982	0.8081	0.3786	0.3917	0.3333	0.5307

face of the drill directly reacts with the generated chip flow. The continuous chips flow along the rake face and cause large stress and strain on the chip-tool interface (secondary deformation zone). Then, the chip flow is evacuated along the drill flute with high-speed relative motion with the hole wall due to the fast-rotating spindle, which causes large precision and friction on the hole wall that has significant effect on the surface finish. The next important factors are flank wear VB and outer corner wear W. The flank face and the outer corner of the drill are directly contacted with the work material in drilling process, and thus their wear state also play an important role on surface roughness. While, the chisel wear Cψ and Vψ has the lowest relevance with the surface roughness.

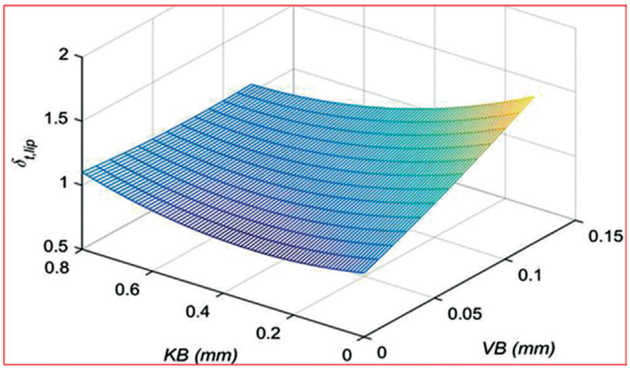

Figure 5. Response surface of wear coefficients (KB, VB).

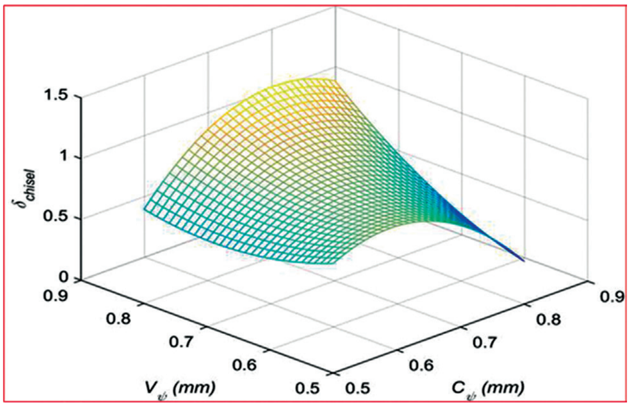

Figure 6. Response Surface of wear Coefficients (Vψ, Cψ).

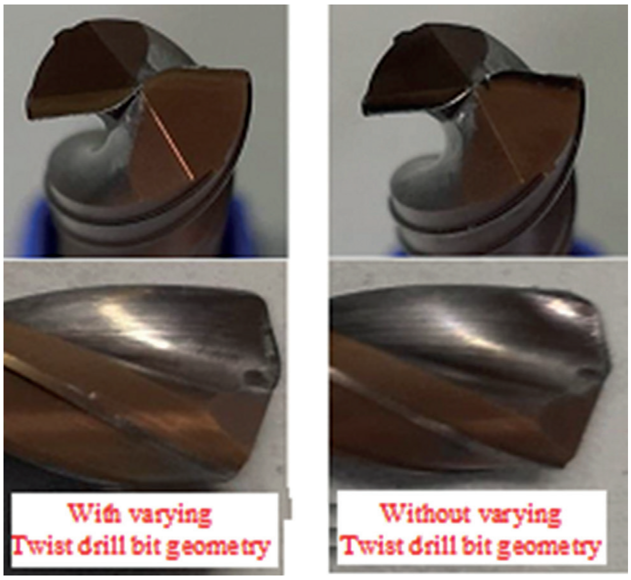

Figure 7. Drill bits images after successive drilling process.

From MATLAB response surface plots drawn (shown in figures 5 & 6) and analyzes the response of drill coefficients with respect to change of input factors. The grey relational grade for each drill wear type were obtained and shown in

Table 4. Average grey relational grade calculations from table 3 for surface roughness

Drilling parameters	Average grey relational grade by factor level		
	Level 1	Level 2	Level 3
VB	0.5779	0.5778	0.5955
KB	0.5648	0.6245	0.5618
Cψ	0.5878	0.6081	0.5553
Vψ	0.6090	0.5504	0.5918
W	0.5916	0.5997	0.5599

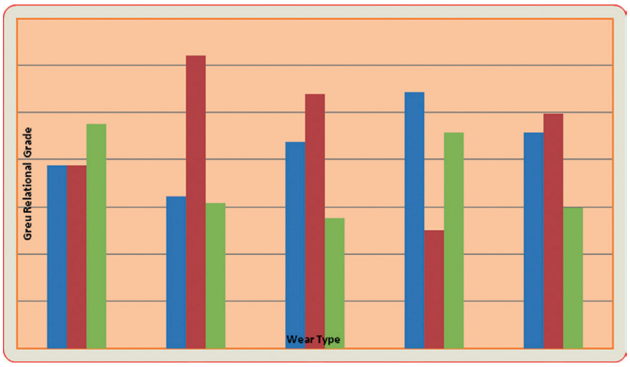

Figure 8. Effect of Grey relational grade of different drill wear types on surface roughness.

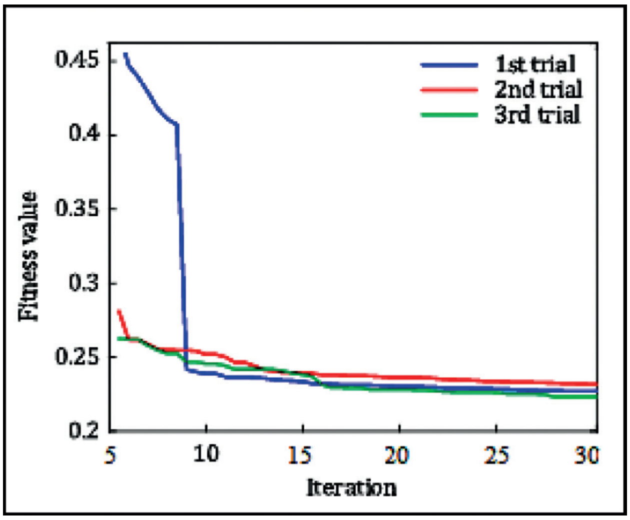

Figure 9. Inflence of fitness value in PSO with iteration.

Figure 8. Finally, compare the drills after successive drilling operation with VTD and without VTD (fixed parameter) and found that the proposed SAPM technique shows good agreement with other methods.

The fitness function values in all the three trials of PSO are diminishing step by step. The value of fitness is small

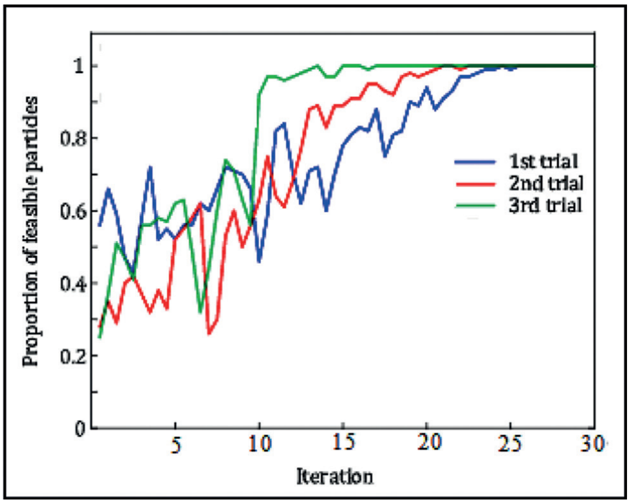

Figure 10. Proportion of feasible particles in PSO with iteration.

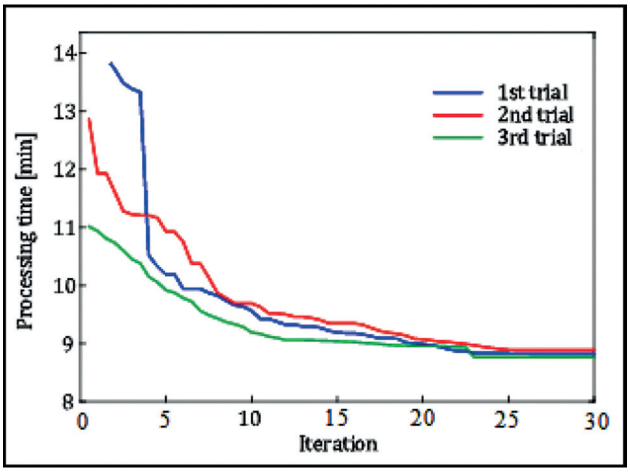

Figure 11. Variation of processing time with iteration.

due to the normalization process already mensioned in the grey relational analysis. From the result obtained the various fitness magnitudes at the closing of final iteration which shows optimized value out of three iterative values. To further investigate the effectiveness of the optimization method, the proportion of the feasible particles in each iteration step was output (see Fig. 9). During the searching process, the proportion of the feasible solutions is gradually increased and in the three trials all the particles are updated to the feasible zone after a certain number of iteration steps.

It can be seen that, the proportion of feasible particles among all the particles is continually changing in the searching process. Thus, it is necessary to adjust the penalty as the variation of the proportion of feasible particles, which makes the infeasible particles moving into the

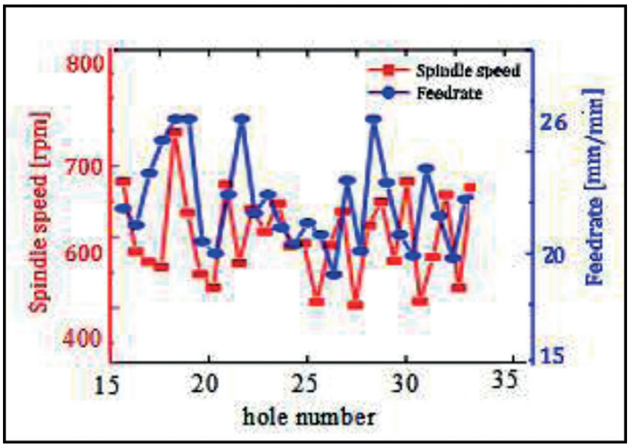

Figure 12. Optimal solution of VPD method for Al7075.

feasible zone and the feasible particles moving fast to the optimal solution. From the result, although the proportion ofthe feasible particles are fluctuant in the searching process of all the three trials, all the particles are moving into the feasiblezone in the end. It proves the effectiveness of the proposed SAPM. It can be seen that the processing time is continually decreasing with the iteration number. In the initial seven iteration steps of the first trial, the time cost is much longer than the other two trials. This is because the drill has to be changed once during the drilling process as per the best particle in the swarm then, a solution with no tool change has been found and the processing time is largely reduced. From Fig. 10, the proportion of feasible particles in this phase of the first trial is greater than the other trial. It is because the feasible solutions are easy to find with a tool change. From Fig. 11 and Fig. 12, although the best solution obtained is not the same at the end of the iteration, the time cost is largely reduced after the optimization and the surface roughness of all the holes is controlled with in the set tolerance. It also shows that the VPD with the proposed optimization method is able to control the drill wear and reduce the tool changing gtime. The reason is that the set tool changing time is the additional penalty in the objective function and the solution with less times of tool change has smaller fitness value.

CONCLUSIONS

This paper presents a varying-parameter drilling (VPD) method for aluminium 7075 alloy and its supporting algorithm for the involved optimization problem using particle swarm optimization (PSO) algorithm with self-adaptive penalty method (SAPM) is also proposed. This method aims at finding the optimal cutting parameter sequence of the successive drilling process to raise the machining efficiency and guarantee the surface quality of large number of holes. The major contributions and novelty are summarized as follows:

- Compared to the commonly used fixed-parameter drilling, the proposed VPD involves the cumulative drill wear in the optimization of the successive drilling process, and optimizes the successive drilling process as a whole.
- The optimization problem of VPD has a complex nonlinear constraint, the infeasible solutions in searching of PSO are unavoidable and their proportion is severely fluctuant as the searching progresses. To handle the complex boundary of the feasible zone and speed up the convergence, the SAPM as the supporting algorithm of the specific problem is proposed and validated.
- This study considers various drill wear types, and their correlations with hole surface roughness are investigated with GRA. This is more adapted to the practical situation in drilling of Al 7075 alloy materials aims at addressing the uppermost problems of low efficiency and uncontrolled surface quality of the holes in drilling.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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