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Modified drilling process of AISI 1045 steel: A hybrid optimization

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ABSTRACT

The hybrid methods, such as minimum quantity lubrication (MQL) and ultrasonic vibration (UV) can be employed in the drilling process to improve cutting condition and tool life. In the present study, an experimental analysis has been carried out on drilling process under four types of condition (i.e. Ordinary, MQL, UV, and UV-MQL) where thrust force (Fz) and surface roughness (Ra) were measured for certain rotational spindle speeds and feeding rates. Then a hybrid optimization method proposed based on a prediction model using least square support vector machine (LS-SVM) and grey relational analysis for determination of optimum point. Obtained findings evidence that UV drilling outperformed ordinary and MQL methods. It significantly decreases thrust force and surface roughness compared to ordinary condition in single objective optimization problem. Then optimum point, for both Fz and Ra for UV drilling, has been evaluated under an investigation of multi-objective optimization (i.e. grey relational analysis). Furthermore, lower built-up edge on the drill bit caused better surface quality in UV-MQL drilling. This process produces short and broken chips which is directly effects on friction coefficient and in consequence cutting forces. LS-SVM shows superior performance on optimization of problems on account of its training speed and accuracy in which for optimum point (N = 931 RPM and f = 90 mm/min) similar Fz and Ra were obtained with approximately 6% error.

1. Introduction

During drilling process, tool is continuously in contact with workpiece and this increases temperature due to friction. Friction directly affects cutting forces and surface roughness. Therefore, application of MQL and UV have been proposed to improve this condition [1–4]. MQL is a useful method in the type of lubrication which is capable to minimize environmental impact by significantly reduction of coolant consumption. It is done by spraying small amount of coolant fluid on the surface of tool. Thin layer of coolants reduce direct contact between cutting edge of drill bit and workpiece so it reduces friction [5]. Besides, ultrasonic assisted cutting is another machining process in which high frequency vibration changes chip formation [6]. This process causes reduction of chip contact with drill bit surface which significantly decreases cutting force and improve surface quality.

Since modeling and optimization of hybrid drilling processes, for specific parameters such as thrust force and surface roughness are complex therefore artificial intelligence and statistical methods based on experimental data are recommended to find optimal solution. A research has been done on ultrasonic drilling of pure titanium and its alloy by Dvivedi and Kumar [7], and Taguchi's method was employed to evaluate optimal setting of cutting parameter for minimum surface roughness. Response surface methodology and Genetic Algorithm (GA) were employed for optimization of drilling process with MQL by Nam et al. [8]. In their study, the optimal point of the process factor was found which minimize drilling torques and thrust force. In a study reported by Saravanan et al. [9] multi-objective optimization has been carried out by use of GA to find optimal value of the torque of drill bit and feeding rate for minimum hole eccentricity limit and maximum material removal rate. GA was used as an artificial intelligent techniques in many other studies [10–13] in order to predict function and optimize data. In a drilling process, Surface roughness of UDIMET 720 sample was estimated regarding to input values of cutting speed feed and thrust force by an Artificial Neural Network (ANN). In this research which has been done by Vrabel' et al. [14], input data were collected from experiment setup and it illustrates how to employ ANN in monitoring condition in drilling. Comparable study with similar approach has been done by Akin and Karpuz [15] in case of roughness estimation. Research on drilling by Gaitonde and karnik [16] attempted to develop the application of particle swarm optimization using ANN. In this study machine has been trained by proposed ANN to find optimal value of feed and

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angle point which minimize burr height and burr thickness during drilling process. In such a case Particle Swarm Optimization (PSO) was used to search for optimal point. Similar work has been done for ANN without PSO in drilling by Gaitonde and karnik [17] in 2007. Noorul Haq et al. [18], evaluated optimal values of cutting speed, feed and point angle correspond to multi responses amounts of surface roughness, cutting force and torque. This approach was done with orthogonal array and grey relational analysis and then contribution of parameters was determined by ANOVA. Grey relational has been used to determine the optimal drilling parameters where minimize burr height and surface roughness by Tosun [19].

Application of hybrid methods such as MQL and UV assisted machining makes prediction of cutting forces and surface roughness complex to some extent. Specifically, when the amount of data is small, even artificial intelligence method and data mining approaches have limitation to estimate and optimize the process performances, as well. In such situation, an accurate estimating tool like support vector machine (SVM) can be applicable. In the present study novel alternative of support vector machine namely least square support vector machine (i.e. LS-SVM) was proposed to develop function estimation of experimental inputs and outputs (i.e. target) data sets for the ultrasonic vibration and minimum quantity lubrication drilling process. Rotational speed (N) and feeding rate (f) are considered as input data sets and the average roughness (Ra) and thrust force (Fz) are response. Relationship between inputs and each target values (i.e. Ra and Fz) can be estimated by LS-SVM and then once optimal point of minimum Ra and Fz separately and once together as multi response optimization are implemented by grey analysis.

2. Methodology

In this section primarily principal support vector machine and its least square version are explained and next grey relational analysis for multi-objective optimization is described with correspond mathematical models. Finally two step optimization (i.e. single and multi-objective optimization) algorithm are drawn and explained in order to clarify procedure of optimization.

2.1. Principal of SVM and LS-SVM

At the beginning, support vector machine was introduced to solve patter recognition problems [20]. This method is able to map data into higher dimensional space and by making an optimal hyper plane can separate the data. Separated data is used as function to classify patterns or find relationship between input and outputs. Depends on separable and inseparable data input sets, various models for SVM can be used.

Based on the developments carried out in this area, for last version of SVM, Least Square Support Vector Machine (LS-SVM) introduced by [21] to employed as prediction of inseparable data sets. Support values for LS-SVM are proportional to the errors, while for classical SVM they considered zero. Following sections present mathematical models of SVM and LS-SVM which have been provided by Suykens and Vandewalle in 1999 [21].

2.1.1. Support vector Machine (SVM)

It assume a given training set of n data points $\{x_i, y_i | 1 \leq i \leq n\}$, where $x_i \in R^n$ is the input point and $y_i \in R$ is the output point. The support vector machine is about to make a classifier as following form:

$$y(x) = sign\left[\sum_{i=1}^{n} \alpha_i y_{ki} K(x, x_i) + b\right] \tag{1}$$

where α_i are constants which can be obtained after training the machine and b is a constant can be termed as bios. $K(x, x_i)$ can be termed as kernel function in which its various form is illustrated in Table 1. There are three common kernel Linear, Polynomial and Radial Basis Function (RBF) such that their respect functions have been presented. For nonlinear problems commonly RBF are employed.

Once to solve this optimization problem it is better to create Lagrangian function:

$$\mathcal{L}_1(w, b, \xi_i; \alpha_i, v_i) = \Im_1(w, \xi_i) - \sum_{i=1}^{n} \alpha_i \{y_i [w^T \varphi(x_i) + b]\} - 1 + \xi_i\} - \sum_{i=1}^{n} \gamma_i \xi_i \tag{2}$$

where

$$min_{w, \xi_i} \Im_1(w, \xi_i) = \frac{1}{2} w^T w + c \sum_{i=1}^{n} \xi_i \tag{3}$$

where coefficients $\alpha_i \geq 0 \gamma_i \geq 0 (i = 1, \ldots, n)$ are the lagrangian multipliers and ξ_i is error for inseparable data however γ_i is termed as regularization parameter as well. The solution to find optimal point can be obtain by following conditions:

$$\begin{cases} \frac{\partial \mathcal{L}_1}{\partial w} = 0 \quad \rightarrow \quad w = \sum_{i=1}^{n} \alpha_i y_i \varphi(x_l) \\ \frac{\partial \mathcal{L}_1}{\partial b} = 0 \quad \rightarrow \quad \sum_{i=1}^{n} \alpha_i y_i = 0 \\ \frac{\partial \mathcal{L}_1}{\partial \xi_i} = 0 \quad \rightarrow \quad 0 \leq \alpha_i \leq c, \\ \qquad\qquad\qquad i = 1, \ldots, n, \end{cases} \tag{4}$$

If $\varphi(x)^T \varphi(x_i) = k(x, x_i)$, Eq. (3) can be rewrite as follow:

$$max_{\alpha_i} Q_1(\alpha_i; k(x_i, x_m)) = -\frac{1}{2} \sum_{i,k=1}^{n} y_i y_m k(x_i, x_m) \alpha_i \alpha_m + \sum_{i=1}^{n} \alpha_i \tag{5}$$

which is subject to:

$$\sum_{i=1}^{n} \alpha_i y_i = 0, 0 \leq \alpha_i \leq c, i = 1, \ldots, n, \tag{6}$$

Eq. (5) is written based on kernel function so that it is not required to calculate w and $\varphi(x)$ in order to find the decision surface [22].

2.1.2. Least squares support vector Machines (LS-SVM)

The SVM classifier by help of least square error model can be rewritten as Lagrangian function:

$$\mathcal{L}_2(w, b, e; \alpha) = \Im_2(w, b, e) - \sum_{i=1}^{n} \alpha_i \{y_i [w^T \varphi(x_i) + b] - 1 + e_i\} \tag{7}$$

where $\min_{w,b,e} \Im_2(w, b, e) = \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{i=1}^{n} e_i^2$, and by applying Karush-Kuhn-Tucker (KKT) conditions [22] for optimality

Table 1
Common Kernel Functions.

Kernel	Function	Comments
Linear	$x.x_i$	It is a particular case of Polynomial function
Polynomial	$[(x, x_i) + 1]^p$	Power p is specified a priori by the user
Radial Basis Function	$e^{\left(\frac{x - x_i}{\sigma}\right)^2}$	The width σ^2 is specified a priori by user

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