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Overview of Support Vector Machine in Modeling Machining Performances

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Abstract

In machining, the process of modeling and optimization are challenging tasks and need proper approaches to qualify the requirements in order to produce high quality of products with less cost estimation. There are a lot of modeling techniques that have been discovered by researches. In the recent years the trends were towards modeling of machining using computational approaches such as support vector machine (SVM), artificial neural network (ANN), genetic algorithm (GA), artificial bee colony (ACO) and particle swarm optimization (PSO). This paper reviews the application of SVM, classified as one of the popular trends in modeling techniques for both types of machining operations, conventional and modern machining. Generally, support vector machine is a powerful mathematical tool for data classification, regression and function estimation and also widely used for modeling machining operations. In SVM, there are several types of kernel function that used in SVM training parameters such as linear, polynomial, radial basis function (RBF), sigmoid and Gaussian kernel function. Review shows that RBF kernel function was widely applied in SVM as a kernel function in modeling machining performances.

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Keywords: Machining,; Modeling Technique; Support Vector Machine

1. Introduction

Nowadays, machining is the most important and widely used in manufacturing process instead of forming, molding, and casting processes. Generally, machining can be defined as a process of removing material from a workpiece in the form of chips. There are two types of machining processes; which are conventional and modern machining [1, 2, 3, 4, 5]. Several common conventional machining operations include milling, grinding, turning and drilling while modern machining operations include electrical discharge machining (EDM), Wire Electrical discharge machining (WEDM), Electrochemical machining (ECM) and abrasive waterjet (AWJ) [6]. For the conventional machining operations, milling is the

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process of producing flat or curve surfaces and prismatic shapes, grinding is the process to improve the surface finish and/or for maintaining the tolerance, turning to produce axisymmetric components and lastly drilling is the process to make holes.

In the recent years, machining technology has been improved significantly to meet the requirements of manufacturing in different fields. Researchers have found and developed many new techniques and modern tools of machining. Hence, this machining process will be continuously evolved from time to time, as the proper and wide understanding and knowledge in machining process has a large bearing of machining [7]. Due to the uncertainty and complexity in modeling the machining operations, computational approaches are being preferred applied to physics-based models for the modeling, prediction and optimization of machining parameters. Computational approaches become new trend in recent research for modeling machining parameters. It became exaggerate from time to time since it gave a best result to the researchers. According to Zain et al [4], computational approaches were managed to estimate the optimal process parameters, leading to the minimum value of machining performance. In view of the importance of SVM in machining, this paper is an attempt to review the previous studies on the application of SVM in the machining parameters for the last decade.

2. Overview of SVM

SVM is a new machine learning method based on statistic learning theory and it is classified as one of computational approach developed by Vapnik [8]. Based on the structural risk minimization (SRM) principal, SVM can get decision-making rules and achieve small error for independent tests set and hence can solve the learning problems efficiently [9]. Recently SVM is applied to solve the problems such as nonlinear, local minimum and high dimension. In many practical applications, SVM can ensure higher accuracy for a long-term prediction compared to other computational approaches.

SVM is based on the concept of decision planes that define decision boundaries. SVM creates a hyperplane by using a linear model to implement nonlinear class boundaries through some nonlinear mapping input vectors into a high-dimensional feature space [10]. In SVM, there is some unknown and nonlinear dependency for example in mapping of function $\gamma = f(\chi)$ between some high-dimensional input vector x and scalar output γ (or the vector output y as in the case of multiclass SVM). No information regarding the underlying joint probability functions and one must contribute a distribution-free learning. Training data set D= $\{(x_i, y_i) \in X \text{ x } Y\}$, $I = 1$, l where l stands for training data pairs and it is same to the size of training data set D. Frequently y_i is stated as d_i, where d stands for desired target value. So, SVM is a part of supervised learning techniques.

There are three major advantages of SVM, they are 1) Only two parameters to be chosen, upperbound and the kernel parameter, 2) unique, optimal and global for solving a linearly constrained quadratic problem, the solution of, 3) good generalization performance due to the implementation of SRM principal. Due to these advantages, a number of studies have been conducted by researchers concerning SVM theory and application [11, 12].

3. SVM application for conventional machining operations

The prediction of machining performances such as surface roughness, cutting force and tool life need a proper optimization of the process since it is the challenging part in machining. Instead, it has been recognized that cutting condition such as cutting speed, feed rate and depth of cut should be selected to optimize the economics of machining process [13].The most common machining process that used SVM as optimization and modeling technique includes prediction of surface roughness, tool breakage and tool wear .

Hsueh and Yang [14] proposed a new diagnosis technique for tool breakage in face milling using SVM. The process parameters involved in this research are depth of cut, feed per tooth, spindle speed and cutting diameter. The considered kernel functions are linear, polynomial and radial basis function (RBF).

Researchers used the feature of spindle displacement signals into the kernel-based SVM decision function to monitor tool breakage. The proposed technique is confirmed highly sensitive, robust and reliable.

Least square SVM (LS-SVM) was considered to predict the surface roughness of milling aluminium alloy [15]. The model is developed to analyze the effect of process parameter such as spindle speed, feed rate, spindle acceleration, depth of cut, rake angle and tool diameter for surface roughness. Training and testing pattern vector have been recognized before LS-SVM training. RBF was selected as a kernel training function due to the high regression precision. γ and σ training parameters were determined by 5-fold cross validation procedures. LS-SVM has given a reasonable accuracy and gives 8 % average error.

Caydas and Ekici [16] applied SVM to developed prediction models for surface roughness in turning process of AISI 304 austenitic stainless steel. The considered process parameters are cutting speed, feed rate and depth of cut while RBF as a kernel function. Three different SVM models were developed. Namely, LS-SVM, spider SVM and SVM-KM. Spider SVM gave the best prediction model for surface roughness.

Wang et al [17] applied LS-SVM for prediction model of surface roughness for grinding machining operation. Linear, polynomial, Gauss RBF and sigmoid function are considered as the kernel function. Result shows that LS-SVM was outperformed the RBF-NN in terms of minimum surface roughness value.

Dong et al [18] introduced a novel model based on LS-SVM for prediction of surface roughness machining operation. 54 groups of data about surface roughness and four kinds of parameters were selected to analyze the prediction model. The prediction of surface roughness in milling operation are done by changing different parameters such as spindle speed, desired rate, cutting depth and milling blade number. Hence, the results are recorded to analyze the relation between machining parameters and surface roughness of work piece. In the training process, RBF was selected as a kernel function. From the experiment, the proposed prediction model is validated in theory and experimental, and it has shown that the model can describe the influence of spindle speed, desired rate and cutting depth to the surface roughness of work piece by milling.

4. SVM application for modern machining operations

Modern machining used chemical, thermal or electrical process to remove material in machining process. Zhang et al [19] applied SVM with multi-objective to develop a hybrid model for processing parameters optimization in micro-EDM. Researchers assigned discharge peak current, pulse duration, pulse-off time, capacitance, electrode rotating speed and servo reference speed as process parameters. All these parameters influence processing time (PT) and electrode wear (EW) in quite different ways. PT and EW are important input objectives. Since these parameters influence the output objectives in quite an opposite way, it is not easy to find an optimized combination of these processing parameters which make both PT and EW minimum. Thus, researchers adopted SVM to establish a micro-EDM process model based on the orthogonal test. Orthogonal test is designed to provide input and output data for training and testing SVM model. Gaussian function is used as a kernel function for this model.

Zhang and Sui [20] proposed a condition monitoring method for rolling element bearings based on auto-regressive (AR) model and SVM in EDM machining. The SVM model improved the traditional classification of the defect effectively such as local minimization problem, the choice of NN structure and overfitting problems. SVM obtained such a good results in the bearing condition monitoring of mechanical components. Process parameter that used in this model includes motor loads, frequency, outer diameter, inner diameter, thickness and pitch diameter. SVM model was compared with NN and RBF-NN and the correct classification rates are 91 % and 93% respectively. While the correct classification rate of the proposed method is 95%.

Sugumaran et al [21] developed fault diagnostics of roller bearing using neighborhood score multi-class SVM in EDM machining. Roller bearing is one of the most widely used rotary elements in a rotary machine. RBF is used as a kernel function. This research used kernel based neighborhood score multi-class SVM for classification and decision tree for addressing the future selection process. The study on using a multi-class SVM showed the effectiveness in diagnosing the fault conditions of the bearing.

5. Conclusion

A review of application of SVM in machining modeling has been presented. From the review, we found that SVM was widely used for modeling of machining performances such as surface roughness, tool wear, tool breakage and fault diagnosis for both conventional and modern machining. SVM also is a multi objective modeling tool that can meet the requirements of the machining operation for finding sets of solutions based on combination with suitable variable.

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