Journal of Materials Processing Technology 172 (2006) 283–290

Journal of Materials Processing Technology

www.elsevier.com/locate/jmatprotec

Drill wear monitoring using back propagation neural network

S.S. Panda [a], A.K. Singh [a], D. Chakraborty [a,*], S.K. Pal [b]

[a] *Mechanical Engineering Department, Indian Institute of Technology Guwahati, Guwahati 781 039, India*

[b] *Mechanical Engineering Department, Indian Institute of Technology Kharagpur, Kharagpur 721 302, India*

Received 1 June 2004; received in revised form 1 June 2004; accepted 6 October 2005

Abstract

Present work deals with prediction of flank wear of drill bit using back propagation neural network (BPNN). Drilling operations have been performed in mild steel work-piece by high-speed steel (HSS) drill bits over a wide range of cutting conditions. Important process parameters have been used as input for BPNN and drill wear has been used as output of the network. Inclusion of chip thickness as an input in addition to conventional parameters leads to better training of the network. Performance of the neural network has been found to be satisfactory while validated with experimental result.

Keywords: Flank wear; Artificial neural network; Drilling; Chip thickness

1. Introduction

Drill wear is a very important issue in manufacturing industries. Drill wear not only affects the surface roughness of the hole, but also influences the life of the drill bit. Wear in drill bit is characterized as flank wear, chisel wear, corner wear and crater wear. Since wear on drill bit dictates the hole quality and tool life of the drill bit, online monitoring and prediction of drill wear is an important area of research. Many works have been reported in the broad field of tool condition monitoring.

Lin and Ting [1] studied the effect of tool wear as well as other cutting parameters on the current force signals, and established the relationship between the force signals and tool wear as well as the other cutting parameters.

Lin and Ting [2] in another work used back propagation neural network with sample and batch mode, and observed faster convergence of error in the case of sample mode. EI-Wardany et al. [3] used the vibration signal in drill condition monitoring. They presented a study using the kurtosis of the time domain and area under the power spectrum curve to monitor various type of drill wear. Lee et al. [4] used the abductive network modeling for drilling process for predicting the tool life, tool wear and surface roughness. Optimal network architecture is prepared based on predicted square error criterion. Xiaoli and Tso [5] used the regression model for monitoring the tool wear based on current signals of spindle motor and feed motor. Liu et al. [6] used the algorithm for synthesis of polynomial network for predicting (ASPNS) the corner wear in drilling operation. Choudhury and Raju [7] developed a regression model to measure the flank wear and corner wear of a drill bit in cutting operation. Kim et al. [8] used the William drill model for predicting and validating the progressive drill wear based on spindle motor power consumption. Davim and Antonio [9] used the evolution strategy for identifying the type of wear in poly-crystalline diamond (PCD) drill bit with metal matrix composite as workpiece. They used the Pareto optimal solution in the genetic algorithm for maximization of tool life and minimization of drill wear. Ertunc and Loparo [10] used decisions fusion center algorithm (DFCA) for monitoring online tool wear condition in drilling process, and used various numerical methods for predicting the condition of tool wear land. Tsao [11] used the radial basis function network (RBFN) and adaptive based radial basis function network (ARBFN) to predict the flank wear, and compared their result with experimentally obtained data. Nouari et al. [12] used the third wave advantage software for predicting the tool chip interface temperature, which is major factor for drill wear formation in the dry condition. Abbu-Mahfouz [13] used the vibration signature analysis for predicting the wear rate in drilling. He estimated three different patterns of vibration signature like harmonic wavelets coefficient, power spectra density

* Corresponding author. Tel.: +91 361 2582666; fax: +91 361 2690762.
E-mail address: chakra@iitg.ernet.in (D. Chakraborty).

0924-0136/$ – see front matter © 2005 Elsevier B.V. All rights reserved.
doi:10.1016/j.jmatprotec.2005.10.021

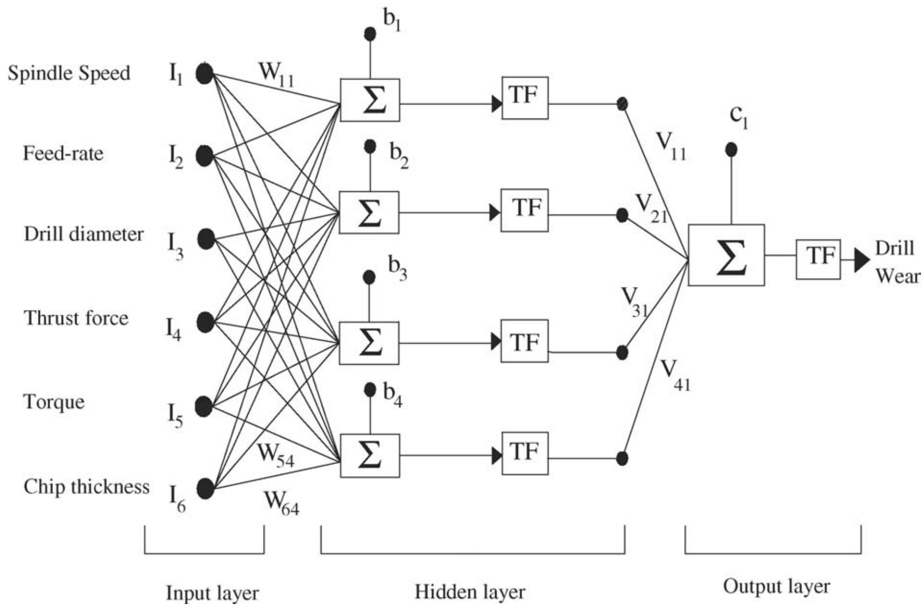

Fig. 1. Neural network with six input nodes and one output node.

and first Fourier transformation (FFT). All these are inputs to the neural network model. Kim and Ramulu [14] used multiple objective linear programming models for optimizing drill hole quality with different cutting conditions such as speed and feed-rate.

2. Back propagation neural network

Back propagation neural network (BPNN) has been used in the present work. Basic structure of back propagation neural network having input, hidden and output layers is shown in Fig. 1.

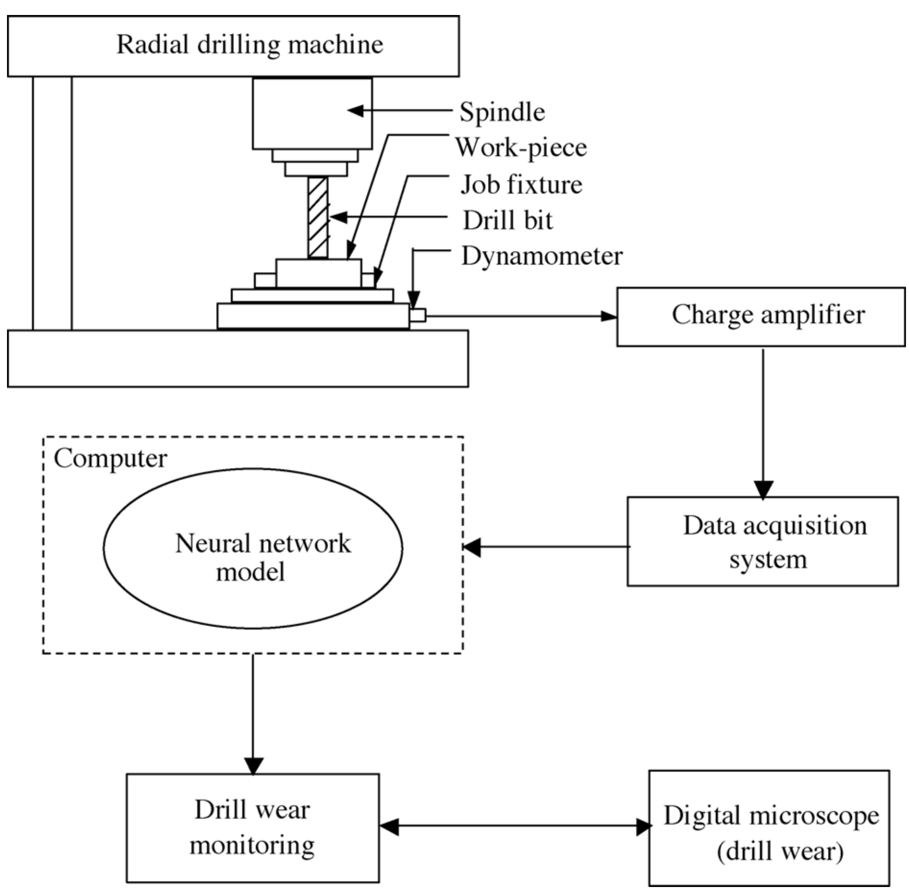

Fig. 2. Schematic diagram of the experimental set-up.