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Prediction of laser cutting heat affected zone by extreme learning machine

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ABSTRACT

Heat affected zone (HAZ) of the laser cutting process may be developed based on combination of different factors. In this investigation the HAZ forecasting, based on the different laser cutting parameters, was analyzed. The main goal was to predict the HAZ according to three inputs. The purpose of this research was to develop and apply the Extreme Learning Machine (ELM) to predict the HAZ. The ELM results were compared with genetic programming (GP) and artificial neural network (ANN). The reliability of the computational models were accessed based on simulation results and by using several statistical indicators. Based upon simulation results, it was demonstrated that ELM can be utilized effectively in applications of HAZ forecasting.

1. Introduction

Recently there is an increase in research in the field of laser cutting process because laser machining offers an attractive alternate among all nonconventional machining due to improved end product quality, low cost, short processing time, smoothness and precise cuts, narrow width and small heat affected zone (HAZ) [1]. By controlling the different process parameters of laser, precision cuts can be made for different geometry and complex shape [2]. Laser cutting is a non-contact, abrasion less technique eliminates tool wear, machine-tool deflections, vibrations and cutting forces and can be used for almost all type of materials [3].

The interest of manufacturers using laser cutting is the optimization of the productivity and the subsequent quality of components made by the laser cutting process. Both aspects are governed by the selection of appropriate laser process parameters, which are unique for each material and thickness. These parameters include laser power, cutting speed and assist gas parameter [4]. These parameters are usually adjusted and tuned to provide the quality of cut desired, but this consumes exhaustive amounts of time and effort and still good quality cutting conditions may not be found. Laser cut quality cannot be easily predicted. This is due to the dynamic nature of the laser cutting process, and it is particularly clear when cutting ferrous alloys using oxygen as an assisting gas. The oxidation reactions with iron and other alloying elements add another source of heat and material removal occurs at two moving and often interacting fronts, the oxidation front and the laser beam front. There are several investigations of the HAZ during the laser cutting process.

Cai et al. [5] was aimed at introducing the laser induced thermal-crack propagation (LITP) technology to solve the silicon-glass double layer wafer dicing problems in the packaging procedure of silicon-glass device packaged, investigating the feasibility of this idea, and studying the crack propagation process of LITP cutting double layer wafer. The analysis of experimental results and numerical simulation results was shown that dual laser beam revision the separation path technology can effectively revise the deviation of the separation path in asymmetry linear cutting glass with LITP [6]. In order to develop a detailed map of cracks and understand the root cause of cracking, a comprehensive microstructural and numerical analysis was performed by Chamanfar et al. [7]. Jebbari et al. [8] was shown that the absorbed power melts a part of the material and preheats the part that would be manufactured during the following interaction time. The numerical predictions of the mechanical properties in the HAZ was shown that there are large variations both in yield stress and work hardening depending on the distance from the weld line [9]. McDaniels et al. [10] was found that the HAZ did not appear to have an adverse effect on the high-cycle fatigue behavior. The predicted temperature distribution is correlated with the HAZ and a critical temperature range corresponding to the maximum depth of the HAZ is identified using a combination of metallography, hardness testing, and thermal modeling [11]. Parametric studies showed that the depth and width of the heat affected zone

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increased with an increase in the laser power and decreased with an increase of the laser spot size and the laser scan speed [12]. The thermal model can be used to determine the laser parameters for a given cut geometry that will yield no residual heat affected zone in the material after cutting.

Even though a number of new mathematical functions have been proposed for modeling of the HAZ, in this investigation the main aim was to overcome high nonlinearity by applying the soft computing method. Soft computing can be used as alternative to analytical approach since soft computing offers advantages such as no required knowledge of internal system parameters, compact solution for multi-variable problems.

In this study laser cutting of Glass Fiber Reinforced Plastic Composites has been carried out to predict HAZ. Three input parameters: laser power, cutting speed and gas pressure were taken under experimental investigation to find the effect and consequently models have been developed to predict the HAZ in context of cutting parameters.

In this investigation the main aim was to overcome high nonlinearity since HAZ parameters are endogenous variables by applying the soft computing method. Recently, the Extreme Learning Machine (ELM) has been introduced as a soft computing algorithm for single layer feed forward neural network (NN) [13,14]. It is capable to solve problems caused by gradient descent based algorithms like back propagation which applies in artificial neural networks (ANNs) and to decrease required time for training NN. It has been proved that by utilizing the ELM, learning becomes very fast and it produces good generalization performance [15]. It has been widely utilized for the estimation of problems in many different fields of water resources [16–18].

In this investigation the main goal is to anticipate HAZ by using ELM approach. The primary objective is to analyze the HAZ forecasting based on laser power, cutting speed and gas pressure.

2. Methodology

2.1. Heat affected zone

The experimental specimen was made of Glass Fiber Reinforced Plastic Composite in which E-glass chopped fibers were used as reinforcement material and polyester resin as matrix material. The size of the material was 300 mm × 200 mm × 5 mm. All experiments were performed using a fiber laser cutting machine (Sahajanand Laser Technology Limited, Gandhinagar) with CNC work table having maximum output power 2000 W in continuous mode. The laser beam was focused using a 125 mm focal length lens, the nozzle diameter was 1.5 mm and the nozzle tip distance was 1.5 mm. All parameters were precisely controlled as the machine is equipped with PLC controller. The machine was capable of using nitrogen and oxygen as an assist gas at right angle and coaxially to the laser beam. By trial experiments it was decided to use nitrogen as inert gas.

For measurement of HAZ, straight cuts of about 50 mm in length were made on sheet and they were measured using 3D microscope MITUTOYO/QS-L2010ZB. Five readings were taken throughout the length on both side of the cut and then average is taken for each cut.

In experiments, number of fixed and independent parameters were involved. The fixed parameters were focal length, nozzle diameter, nozzle tip distance and material thickness and the values are as mention above whereas the variable parameters were laser power, cutting speed and gas pressure. Input and output parameters which are used in this investigation are listed as bellow:

- input 1 Laser power (Watt)
- input 2 Cutting speed (mm/min)
- input 3 Gas pressure (Bar)
- output Heat affected zone (HAZ) (mm)

2.2. Extreme Learning Machine

Huang et al. [19,20] developed Extreme Learning Machine (ELM) as a novel learning algorithm for single hidden layer feed forward networks (SLFNs).

This approach has some priority compared with conventional neural networks including: 1) ELM is easy to use, and the method not only makes learning extremely fast but also produces good generalization performance [19,20]; 2) in conventional neural networks all the parameters of the networks such as learning rate, learning epochs and local minima are tuned iteratively by using such learning algorithms; 3) ELM can be easily implemented and can obtain the smallest training error and the smallest norm of weights [19,20].

In Fig. 1 the schematic topological structure of ELM network is shown. For M arbitrary samples $(\mathbf{x}_i, \mathbf{t}_i)$, in which $\mathbf{x}_i=[x_{i1}, x_{i2}, \dots, x_{in}]^T\in\mathbf{R}^n$ and $\mathbf{t}_i=[t_{i1}, t_{i2}, \dots, t_{in}]^T\in\mathbf{R}^m$, standard single hidden layer feed forward networks (SLFNs) with N hidden nodes and activation function $g(x)$ are modeled as follows [19,20]:

$$\sum_{i=1}^{M}\beta_i g_i(\mathbf{x}_j) = \sum_{i=1}^{M}\beta_i g(w_i.\, x_j + b_i) = o_j,\ j = 1, \dots, N \tag{1}$$

where $w_i=[w_{i1}, w_{i2}, \dots, w_{in}]^T$ is the weight vector between input and hidden nodes, $\beta_i=[\beta_{i1}, \beta_{i2}, \dots, \beta_{in}]^T$ is the weight vector between output and hidden nodes, and b_i is the threshold of the ith hidden node. That standard single hidden layer feed forward networks with M hidden nodes with activation function $g(x)$ as follows:

$$\sum_{i=1}^{M}\beta_i g(w_i.\, \mathbf{x}_j + b_i) = \mathbf{t}_j,\ j = 1, \dots, N. \tag{2}$$

The activation function can also be written as

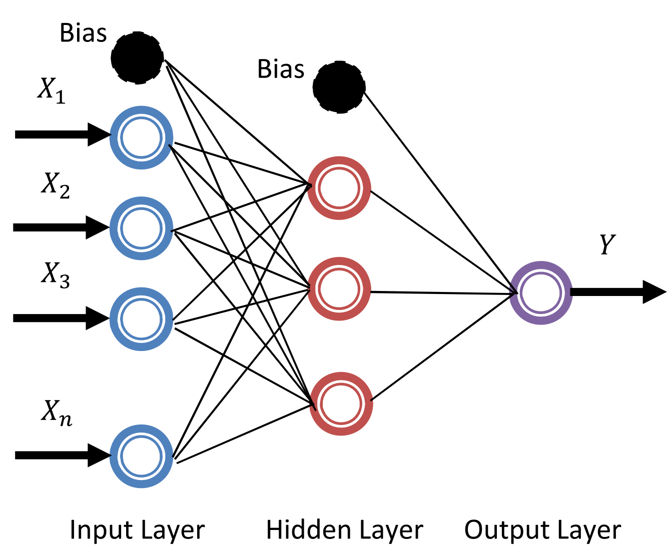

Fig. 1. The topological structure of the extreme learning machine network used in this study.