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Determination of cutting parameters for silicon wafer with a Diamond Wire Saw using an artificial neural network

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ABSTRACT

An Artificial Neural Network (ANN) simulation was utilized to predict surface roughness values (R_a) for a Silicon (Si) ingot cutting operation with a Diamond Wire Saw (DWS) cutting machine. Experiments were done on a DWS cutting machine to obtain data for training, testing and validation of the ANN. The DWS cutting operation had three parameters affecting surface quality: spool speed, z axis speed and oil ratio in a coolant slurry. Other parameters such as wire tension, wire thickness, and work piece diameter were assumed as constant. The DWS cutting machine performed 28 cutting operations with different values of the selected three parameters and new cutting parameters were derived for different cutting conditions to achieve the best surface quality by using the ANN. Wafers 400 μm thick were cut from a *n*-type single crystalline Si ingot in a STX 1202 DWS cutting machine. R_a values were measured three times from different regions of the wafers. In ANN simulation 70% of R_a values were used as training, 15% of R_a values were used as validation and 15% of R_a values were used to test data in ANN. The ANN simulation results validated training output data with success above 99%. Consequently, the R_a values corresponding to the cutting parameters, and also proper cutting parameters for specific R_a values were determined for DWS cutting using the ANN.

1. Introduction

In solar cell production, growing and cutting ingot into wafers (wafering) comprise 28% of the total cost distribution of solar module production (Anspach et al., 2014; Ranjan et al., 2011; Schwinde et al., 2015). In recent decades, cutting single crystalline and polycrystalline Si ingot with DWS became a conventional method due to its higher production capability, low material consumption, precise thickness determination and low R_a values (Zhuang et al., 2016; Bidiville et al., 2015; Sun et al., 2004; Pei et al., 2004; Yu et al., 2012). Despite these advantages, however, there are some disadvantages such as high duration of cutting time, expensive and high quantity coolant slurries, corrugated surface shape formation, and diamond wire and silicon wafer breakage due to non-optimized cutting parameters. All of these issues increase the total production cost of a solar cell (Schwinde et al., 2015; Bidiville et al., 2015; Yu et al., 2012). Moreover, the surface quality of wafers obtained after a cutting process directly affects the duration, energy and material consumption of the lapping operation (Schwinde et al., 2015). Thus, DWS parameters must be determined precisely to optimize material and energy consumption, minimize R_a values and control total process duration (Wu et al., 2014).

An Artificial Neural Network (ANN) is a simple and cost-effective method to derive new parameters and predict results for all science branches. It is mostly used to discover complex relations between input and output data that may not be recognized by theoretical expressions (Çetinel et al., 2006; Boutorh and Guessoum, 2016; Zăvoianu et al., 2013; Oliveira et al., 2015). In ANN, some data are used for training the network, which provides network weights to achieve desired results (Boutorh and Guessoum, 2016; Ahmadizar et al., 2015). A network consists of three layers such as an input layer, hidden layer and output layer. The neurons are connected to each other by trained weights. Back propagation (BP) is the most common method for training networks to minimize errors (Çetinel et al., 2006). A feedforward ANN is also another method used for training ANN. Feedforward

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ANNs learn much like a human brain, but they don't need a specific user for a defined problem algorithm. An additional feature is an inherent generalization ability (Boutorh and Guessoum, 2016; Benardos and Vosniakos, 2007; Ahmed and Hasegawa, 2013; Düğenci et al., 2015; Yaghini et al., 2013). Because feedforward ANNs are static networks, they do not have any feedback elements and do not include any delays. Thus, results are computed directly by feedforward connections between input data (Boutorh and Guessoum, 2016). Together, these capabilities make ANN the best choice for complex non-linear relations in many engineering applications due to its precise and correct outputs (Düğenci et al., 2015; Ozturk et al., 2016).

Obtaining a surface with a low R_a in the cutting operation is significant in many engineering applications. There are several studies for finalizing a surface with a desired R_a by using parameters derived with artificial intelligence. For instance, Zain et al. (2010) predicted surface R_a in a machining process using ANN. They collected 24 instances of data from samples machined with uncoated, TiAlN coated, and SN_{TR} coated cutting equipment. Their method utilized a feedforward back propagation algorithm with Traingdx for training, Learngdx for learning, MSE for the performance function, and Logsis for a transfer function. Several ANN models were utilized to determine the best ANN structure. A 3-1-1 network structure machined with SN_{TR} coated cutting equipment gave the best R_a values. Another R_a study with ANN was performed by Mia and Dhar for hard turning using a coolant (Mia and Dhar, 2016). For input data, they used material feed rate, cutting speed, material hardness and cutting conditions including dry and high pressure coolant jet environments. ANN was trained with Levenberg-Marquardt (Trainlm), Bayesian regularization (BR) and scaled conjugate gradient (SCG). Root mean square error (RMSE) was used to calculate the performance function. The effects of parameters on R_a values were determined in a developed model with a regression coefficient (R) higher than 0.997. Kumar et al. (2014), studied R_a determination of titanium alloys during electric discharge machining using a hybrid Taguchi-ANN approach and a feedforward back propagation algorithm. A Levenberg-Marquardt (Trainlm) algorithm was used for the training network. Tansig and Purelin were preferred for the transfer function in the input and output layers. Tiryaki et al. (2014) used ANN to model R_a for a wood machining process with the aim of low operation duration and energy consumption. They selected wood species, number of saws, cutting depth, wood zone, and abrasive grain size as input data for their ANN. Çaydaş and Hasçalık (2008) studied ANN and a regression analysis method to predict R_a values in an abrasive waterjet machining process. Traverse speed, water jet pressure, standoff distance, abrasive grit size and abrasive flow rate parameters were used as input data to predict R_a. Feedforward back propagation ANN was used consisting of 13 input neurons, 22 hidden neurons and one output neuron. Karayel (2009) used ANN to predict and control R_a in computer numerically controlled (CNC) turning machine. There were three input data: cutting depth, cutting speed, material feed speed. Despite the considerable research in this area, there is no study with any type of artificial intelligence approach predicting R_a values that correspond to determined parameters for a Si ingot cutting process in a DWS cutting machine.

In this study, we determined new cutting parameters that predicted new R_a values corresponding to these parameters for a DWS process with ANN for the first time. Firstly, 28 wafers were cut with two different coolant options in a STX 1202 DWS machine and R_a values were measured. Secondly, data collected from measurements were rearranged and used to train a feedforward ANN with back propagation. Thirdly, new operating conditions were determined and simulated in a trained ANN to predict R_a values for new operating conditions. This study utilized a feedforward back propagation multilayer ANN and trained with a scaled conjugate gradient algorithm (SCGA). Consequently, a R_a corresponding to several cutting parameters and several optimum cutting parameters for specific R_a values were predicted. Results obtained from the simulation were represented graphically and evaluated in terms of R_a, cutting duration, material and energy consumption. The best cutting parameters were determined to minimize the surface R_a, cutting duration, and material and energy consumption for the next steps.

2. Experimental and method

In a DWS process, z axis speed, spool speed and coolant oil ratio are major factors on surface R_a, which are adjustable in a STX 1202 DWS cutting machine. As such, these three parameters were selected for experimental study. A simple general factorial design was adopted for experimentation. Cutting operations were performed in a STX 1202 DWS cutting machine with a capacity of a maximum 5 m/s spool speed and 10 mm/min z axis speed. Due to many wire breakages at high cutting speeds and low spool speeds, cutting parameters were selected between 2.5 to 4.5 m/s and 0.5 to 1 mm/min for spool speed and the z axis speed, respectively with a pure oil coolant. Process parameters and their factor levels are summarized in Table 1. A Mitutoyo SJ 210 instrument was used in surface R_a measurements. To understand the effects of cutting parameters on R_a, material and energy consumption, and cutting duration per one wafer, R_a values were recorded for a specific spool speed, z axis speed and coolant oil ratio. This was done because extended operating durations always increases material and energy consumption. Spool speed and z axis speed should be adjusted properly to cutting duration for the lowest R_a. Hence, high R_a values extend process durations for lapping because of deep DWS damage on a Si wafer, as shown in Fig. 1.

Moreover, some DWS damage remained after a chemical texturization process because of non-optimized cutting parameters. A SEM image of a sample wafer surface subjected to our study is given in Fig. 2. There are many deep DWS prints between upright pyramidal shapes formed in a micro texturization process. This deep damage decreases total efficiency and creates weak regions that can result in wafer breakages, thus impacting subsequent steps in solar cell production.

Measurements were repeated three times from different points on the wafers and average R_a values were considered for ANN simulation. The operating technique for the DWS cutting system is given schematically in Fig. 3. The main driver provides the spool speed for a diamond wire in the right and left direction. All system moves through the z direction to cut the Si ingot into wafers. The Si ingot was tightly fastened on a table to prevent vibrations to the diamond wire and Si ingot. Dogit cutting oil was used as coolant slurry, which is soluble in water. Wafers were washed in distilled water, acetone and a 5% HF solution for the cleaning step.

Table 1
Cutting settings used in experiments.

Spool speed (m/s)	z Axis speed (mm/min)	Coolant oil [%]
2.5	0.5	100
3.0	0.75	
3.5	1.0	
4.0		
4.5		
2.5	1.0	30
3.0	2.0	
3.5		
3.75		
4.0		
4.5		
5.0		