Chapter 23
Identification of Important Parameters for Laser Photoresist Removal Process by ANFIS Methodology

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Abstract Laser photoresist removal in gaseous media is based on different parameters or factors like energy of laser pulse, frequency of pulse repetition and flow rate of gas. A statistical soft computing approach was applied in this article in order to determine which parameters have the most influence on the photoresist removal process by laser. As statistical approach adaptive neuro fuzzy inference system (ANFIS) was used since the methodology can handle strongly nonlinear data. By selected the most important factors one can adjust the photoresist removal process in order to produce the best final product. For the selecting process three input parameters are used: laser energy, rate of pulse repetition of laser and flow rate of hydrogen gas. These parameters are selected for the analyzing since these are independent variables. Pulse of laser repetition is selected as the most important factor for the photoresist removal process. Predictive models were created based on ANFIS network and corresponding results are compared with standard conventional approaches.

Keywords Laser · Photoresist removal · Prediction · Gas media · ANFIS · Running head · Laser photoresist removal process

23.1 Introduction

In order to fabricate microsystem there is need for perform several steps which include deposition of thin-film, patterning of polymer resist and etching. There are positive-tone and negative-tone resists process. Photoresist removal is performed by wet cleaning by chemicals. However the chemicals are very expensive and could harm environment. There are many attempts to reduce cost and damage of environment of the photoresist removal process.

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A concept for the laser-assisted removal of material has been proposed in article [1] for achieving nanoscale correction in next-generation functional microstructures such as nanostructured photoresist surfaces and micro 3-D objects fabricated using microstereolithography. Positive photoresists are photosensitive materials widely used in lithographic processes in microelectronics and optics for component relief manufacturing and when exposed to ultraviolet radiation, chemical reactions are induced that modify their physical–chemical properties [2]. Details of fabrication route for photoresist template has been presented in article [3], which is useful in surface texturing of technologically important thin films such as solar absorbers, transparent conducting oxides (TCOs) and metals. The highly crosslinked epoxy remaining after development is difficult to remove reliably from high aspect ratio structures without damaging or altering the electroplated metal [4]. SU-8 photoresist maintained good resolution in thick film. A new route for pattern formation based on atmospheric pressure plasma directed assembly during photoresist removal has been presented in article [5] where the results shown the potential of atmospheric plasma directed assembly for uniform, large-area and open-air pattern definition for application in modern nanofabrication. In the [6–8] further consideration are explained in detail. Hydrogen radical process for photoresist removal by use of hot W catalyst has been investigated for a possible application to advanced Cu/low-k dielectric interconnects in LSI and results suggested that the hydrogen radical process for resist removal with W catalyst is promising for production of advanced interconnects [9]. Ozonated water cleaning systems have been used to remove photoresist and organic contaminants on silicon wafers and natural organic matter and bacteria in drinking water [10]. All-wet processes are gaining a renewed interest for the removal of post-etch photoresist (PR) in semiconductor manufacturing but changes in regulations call for a reduction in the environmental, safety & health (ESH) impact of solvents used [11].

In this study was analyzed a technique of photoresist removal without hazard chemical and without high temperature. This is a dry process by laser ablation and under presences of hydrogen gas medium. The main goal was to investigate how the three operating parameters, laser energy, rate of pulse repetition and rate of gas flow, have impact on the photoresist removal process by laser in medium of hydrogen gas. In order to do the analyzing there is need for an advanced computational models like soft computing or computational intelligence. Therefore in this article is used adaptive neuro fuzzy inference system or ANFIS [12–16]. The output factor is etch depth of the photoresist surface.

Fig. 23.1 Experimental setup of photoresist removal

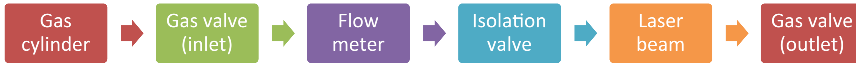

Fig. 23.2 Experimental procedure of gas handling for photoresist removal

Table 23.1 Input and output factors of the plasma arc cutting process

Input factors			Output factor
in1: Flow rate (lpm)	in2: Laser pulse repetition (Hz)	in3: Laser Energy (mJ)	Etch Depth (μm)
0.6–1.2	10–40	40–60	13.4–122.7

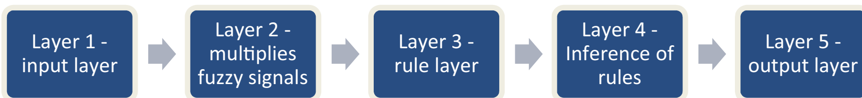

Fig. 23.3 ANFIS layers

23.2 Methodology

23.2.1 Experimental Procedure

Figure 23.1 shows the total experimental procedure of the photoresist removal by laser ablation system. The laser pulse has wavelength of 248 nm with pulse duration of 25 ns. Frequency of pulse repetition is in range 10–50 Hz. In this study is performed mask projection technique. Gas handling setup is shown in Fig. 23.2. For the photoresist removal process cylindrical chamber is used which has inlet and outlet connections with valves. Photoresist polymer E1020 is used in this study. Table 23.1 shows the numerical values (minimum and maximum) of the input and output factors which are used and obtained during photoresist removal process.

23.2.2 ANFIS Methodology

As shown in Fig. 23.3, the ANFIS network contains five levels. The fuzzy inference system lies at the heart of the ANFIS network. Layer 1 accepts the inputs and uses membership functions to convert them to fuzzy values. The bell-shaped membership function is employed in this study because it has the maximum potential for non-linear data regression.

Bell-shaped membership functios is defined as follows:

$$\mu(x) = bell(x;\ a_i,\ b_i,\ c_i) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{23.1}$$

where $\{a_i, b_i, c_i\}$ is the parameters set and x is input.

The second layer multiplies the first layer's fuzzy signals and produces the rule's firing strength. The rule layers are the third layer, and they normalize all of the signals from the second layer. The fourth layer does rule inference and converts all signals to crisp values. The last layers summed all of the signals and provided a clean output value.

23.3 Results

23.3.1 Accuracy Indices

Performances of the proposed models are presented as root means square error (RMSE), Coefficient of determination (R^2) and Pearson coefficient (r) as follows:

– RMSE:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{23.2}$$

– Pearson correlation coefficient (r):

$$r = \frac{n\left(\sum_{i=1}^{n} O_i \cdot P_i\right) - \left(\sum_{i=1}^{n} O_i\right) \cdot \left(\sum_{i=1}^{n} P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - \left(\sum_{i=1}^{n} O_i\right)^2\right) \cdot \left(n\sum_{i=1}^{n} P_i^2 - \left(\sum_{i=1}^{n} P_i\right)^2\right)}} \tag{23.3}$$

– Coefficient of determination (R^2):

$$R^2 = \frac{\left[\sum_{i=1}^{n} \left(O_i - \overline{O_i}\right) \cdot \left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n} \left(O_i - \overline{O_i}\right) \cdot \sum_{i=1}^{n} \left(P_i - \overline{P_i}\right)} \quad (23.4)$$

where P_i and O_i are known as the experimental and forecast values, respectively, and n is the total number of dataset.

23.3.2 ANFIS Results

Table 23.2 shows the prediction errors for the photoresist removal process for single input parameter and two parameters combinations as well. Training errors (trn) shows influence of the inputs for the photoresist removal process. Smaller training error more influence on the photoresist removal process. Checking errors (chk) is used for overfitting tracking between training and checking data.

Here one can see there is no overfitting since checking errors track training errors (Figs. 23.4 and 23.5). As can be seen input factor 2 or laser pulse repetition has the smallest training error or the most impact on the photoresist removal process. Furthermore combinations of 2 and 3 or laser pulse repetition and laser energy is the optimal combination for the photoresist removal process. This combination has the most influence on the photoresist removal process.

Table 23.2 Prediction errors for the photoresist removal process

ANFIS model 1: in1 – > trn = 34.1, chk = 30.2
ANFIS model 2: in2 – > trn = 12.3, chk = 6.5
ANFIS model 3: in3 – > trn = 29.6, chk = 38.2
ANFIS model 1: in1 in2 – > trn = 11.2, chk = 7.1
ANFIS model 2: in1 in3 – > trn = 29.6, chk = 38.1
ANFIS model 3: in2 in3 – > trn = 2.7, chk = 9.7

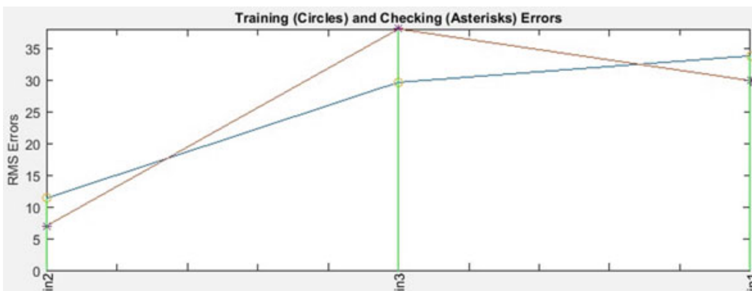

Fig. 23.4 Single input RMS errors

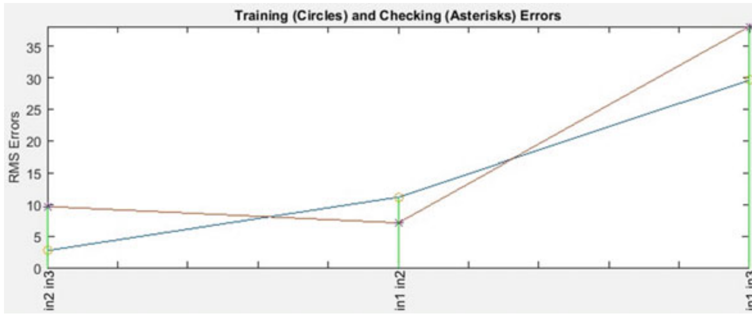

Fig. 23.5 Two inputs combinations RMS errors

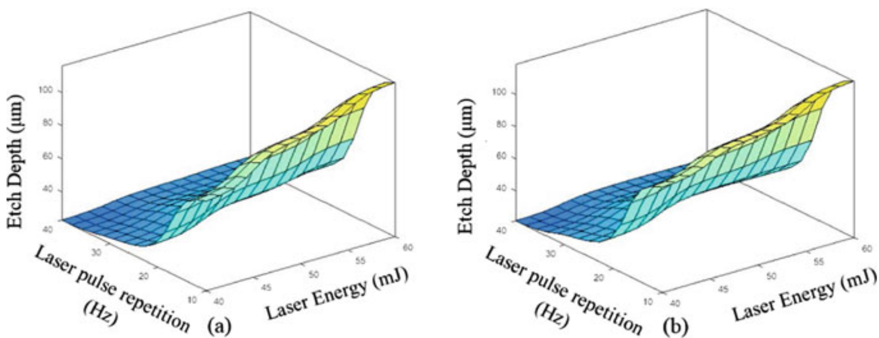

Fig. 23.6 ANFIS prediction of etch depth based on different parameter combination: **a** flow rate: 0.6 lpm and **b** flow rate: 0.8 lpm

Figures 23.6, 23.7 and 23.8 shows ANFIS prediction of etch depth based on combination of different input parameters. One can observe etch depth variation in depend on different input parameters.

Figure 23.9 shows scatter plot of ANFIS prediction of etch depth during photoresist removal process. There can be noted high correlation coefficient therefore high prediction accuracy. There are small number of experimental points which are not aligned through the correlation line.

Finally Table 23.3 shows statistical indicators for prediction of etch depth. As benchmark models for comparison purpose RSM (response surface methodology) [17] and ANN (artificial neural network) [17] are used.

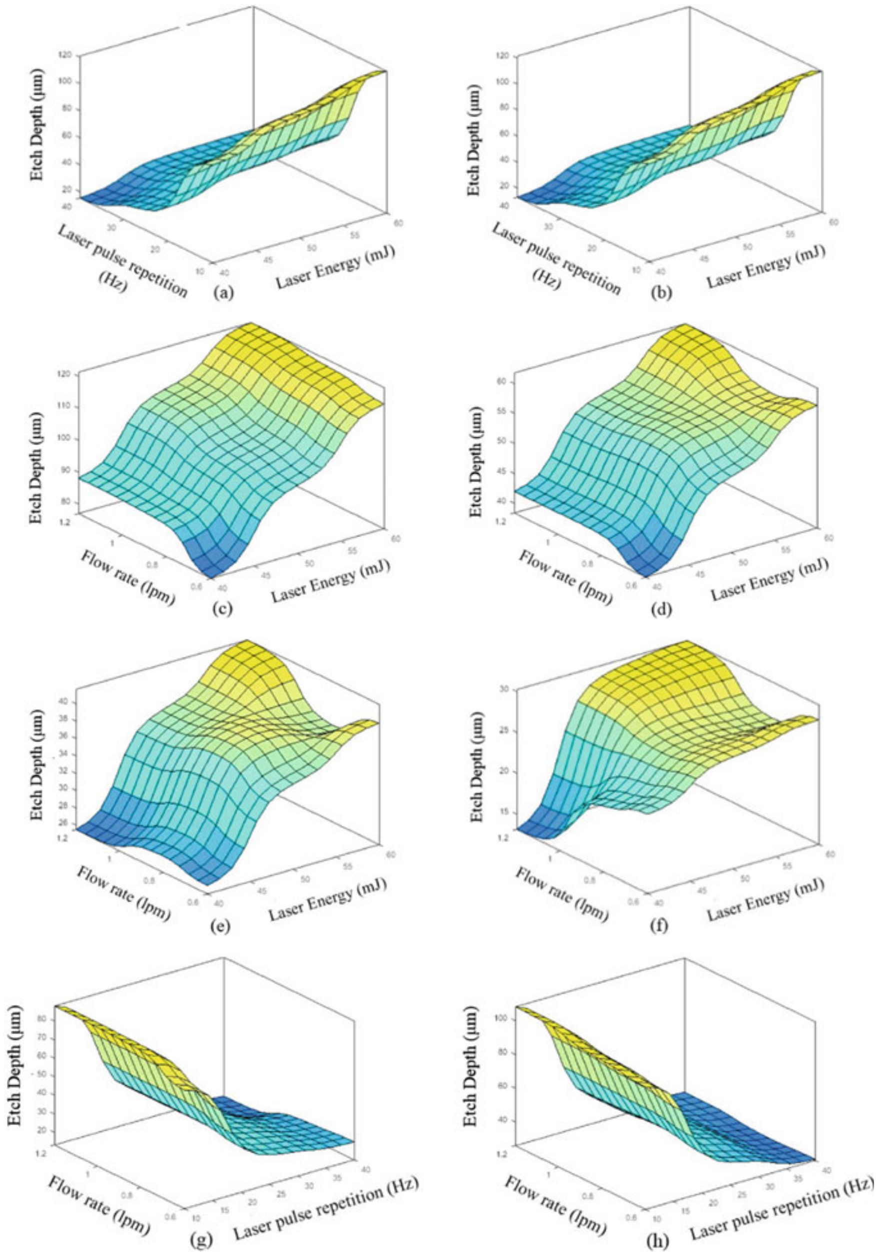

Fig. 23.7 ANFIS prediction of etch depth based on different parameter combination: **a** flow rate: 1 lpm, **b** flow rate: 1.2 lpm, **c** laser pulse repetition: 10 Hz, **d** laser pulse repetition: 20 Hz, **e** laser pulse repetition: 30 Hz, **f** laser pulse repetition: 40 Hz, **g** laser Energy: 40 mJ and **h** laser Energy: 50 mJ

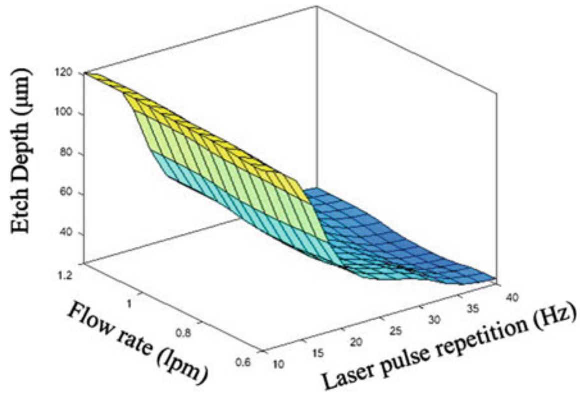

Fig. 23.8 ANFIS prediction of etch depth: Laser Energy 60 mJ

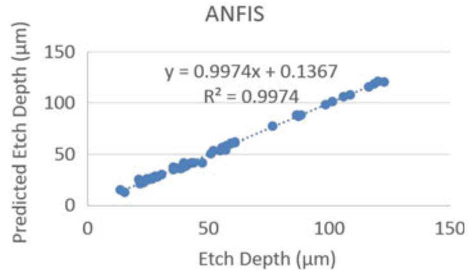

Fig. 23.9 Scatter plot of ANFIS prediction of etch depth

Table 23.3 Statistical indicator for the prediction of etch depth

Statistical indicators	ANFIS	ANN [17]	RSM [17]
r	0.9987	0.9977	0.9918
R^2	0.9974	0.9954	0.9838
RMSE	1.5964	2.1956	4.0067

23.4 Conclusion

Laser photoresist removal under gaseous media is based on different parameters. In this article a statistical soft computing approach was applied to determine which parameters have the most influence on the photoresist removal process by laser.

Adaptive neuro fuzzy inference system (ANFIS) was used to select the most important factors one can adjust the photoresist removal process in order to produce the best final product. For the selecting process three input parameters are used: laser energy, rate of pulse repetition of laser and flow rate of hydrogen gas. Based on obtained results pulse of laser repetition is selected as the most important factor for the photoresist removal process. ANFIS can eliminate the vagueness in the process in order to produce the best prediction conditions. In other words ANFIS network was

used to convert the multiple performance characteristics into the single performance index.

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