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Signal analysis and real-time monitoring for wafer polishing processes using the ch computing environment †

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Abstract

There are several processes used in the silicon wafer fabrication industry to achieve the planarity necessary for photolithography requirements. Polishing is one of the important processes which influence surface roughness in the manufacturing of silicon wafers. As the level of a silicon wafer surface directly affects device line-width capability, process latitude, yield, and throughput in the fabrication of microchips, it is necessary for it to have an ultra precision surface and flatness. The surface roughness in wafer polishing is affected by many process parameters. To decrease the surface roughness of the wafer, controlling the polishing parameters is very important. Above all, a real-time monitoring technology of the polishing parameters is necessary for the control. In this study, parameters affecting the surface roughness of the silicon wafer are measured in real-time. In addition comparing the predicted value is done according to the process parameters using the artificial neural network. Through these results, we conduct research on the efficient parameters of silicon wafer polishing. Required programs are developed using the Ch computing environment.

Keywords: Real-time monitoring; Silicon wafer; Surface roughness; Polishing; Ch computing

1. Introduction

Due to the rapid development of semiconductor, the size of the device is getting smaller and the diameter of the wafer keeps increasing. Therefore the global planarization of a wafer surface is stricter than before [1].

Silicon wafers have been extensively used as material for Integrated Circuit (IC) substrates. In the semiconductor industry, the single crystal silicon is used to manufacture more than 90% of the semiconductor devices. To get the cost of semiconductors down, a wafer is needed to have a larger diameter. Before taking the form of a wafer, the single crystal silicon has to pass several machining processes, such as ingot growing, slicing, lapping, surface grinding, edge profiling, and polishing. An essential purpose of these processes is to acquire the ultra precision surface of the wafer. Silicon wafer which is utilized as the starting material because most of the microchip fabrication has to be very flat, so that circuits are able to be printer on them by several processes. The flatness of a wafer directly affects the device line-width capability, process latitude, yield, and throughput of devices. The feature sizes of semiconductor devices will continue to diminish and this tendency is going to demand increasingly flatter wafers. Single side final polishing is a very important process from the point of view of finally stabilizing - the wafer before the device process is performed on it Owing to its importance, final polishing has attracted more and more interest among investigators [2-5].

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All manufacturing processes need to decide the optimal process condition for the efficient and economical processing. Wafer polishing is a very important process at the point of view of stabilizing the wafer before the device process is executed. However, the final wafer polishing is hard to select the optimal condition. The reason is that wafer final polishing is a complex machining process with many interactive parameters [6]. Therefore, to control the parameters for the production of the ultra precision surface roughness, the real-time monitoring technology of the polishing parameters is necessary.

This study carried out research on an efficient polishing process for ultra precision wafer machining. The experiments are based on the real-time monitoring of polishing parameters and the artificial neural network trained in using polishing parameters such as pressure and wheel speed. This experimental research about real-time monitoring, especially in the wafer final polishing process, has never been performed previously. This allows for an efficient and optimal polishing of wafers using the adequate polishing condition with high efficiency and without unnecessary experiments and additional costs. To acquire the optimal parameters, load-cell and infrared temperature sensor were used. The performances of each signal processing algorithm using the artificial neural network are then compared. Required programs are developed using the Ch computing environment.

2. Mechanism of the final wafer polishing

In most of the chemical mechanical polishing (CMP) or wafer polishing machine, the polishing pad is circular and the wafer is placed down in a head unit down and forced against the pad while the pad platen, or table, is rotated on its own axis. The axis of rotation for the polishing pad is offset by the distance of the pad radius relative to the axis of rotation of the wafer. In this mechanism, the polishing process is performed over the whole wafer surface when the polishing pad rotational velocity and wafer rotational velocity are the same.

Final wafer polishing is carried out by the process which is combined mechanical factor and chemical factor. Mechanical factor involves the use of a removal machining with the polishing grain within the slurry. Chemical factor, on the other hand, is a chemical response phenomenon over the wafer surface.

Slurry abrasive produced by the chemical is distributed onto the pad surface and transported to the polish site by the concentric grooves on the pad surface. The slurry reacts with the wafer surface creating a weakened layer that is removed by the rotating polishing pad. It is the combination of the chemical and

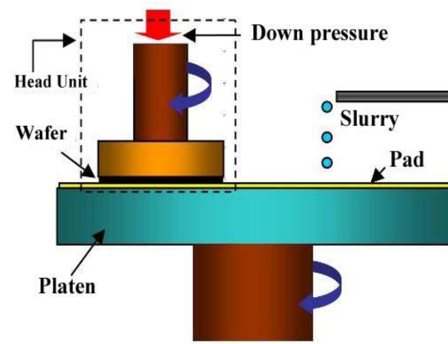


Fig. 1. The mechanism of the final wafer polishing.

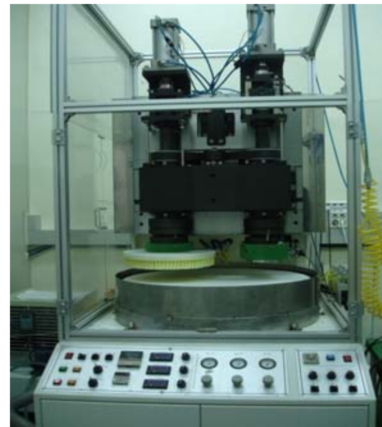
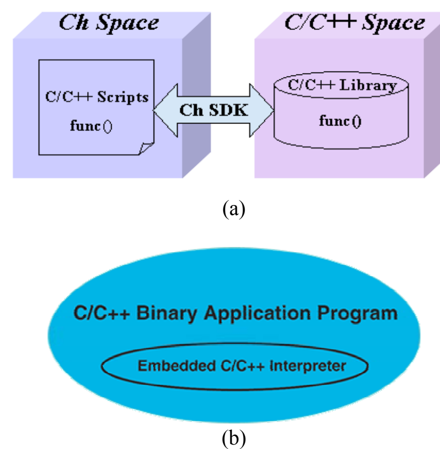


Fig. 2. Final wafer polishing system.



(a)

(b)

Fig. 3. Schematic diagram for Ch SDK and Embedded Ch.

mechanical actions that achieves material removal. Mechanical factors are associated with the polishing pad, polishing grain and physical correlation on the wafer surface. Chemical factors are mainly decided by the viscosity of the slurry, relative velocity of wafer, hardness of grain, characteristics of pad and lubrication characteristic of the wafer curvature.

Fig. 1 shows the schematic diagram of a typical final wafer polishing. After the wafer is fitted on the chuck of the head unit, relative speed is achieved with the rotation of the table and the head. Machining is implemented by having the slurry interact with the wafer surface. Fig. 2 presents the entire assembly of the final wafer polishing system.

3. Monitoring system using the Ch computing environment

3.1 Ch computing environment

Ch is a C/C++ interpreter that was originally developed by Cheng based on the need for a mechatronic-independent task-level programming environment. Ch is an open architecture integration language environment for the integration of mechatronic systems in agile manufacturing, interactive motion control, rapid prototyping, web-based remote motion control, and as a learning tool for motion control. The schematic diagram is displayed in Fig. 3 [7, 8].

3.2 Real-time monitoring system

This paper suggests real-time monitoring system using the Ch computing environment for the efficiency and optimization of machining condition during the final wafer polishing. The Ch computing environment supports the convenient real-time monitoring system for the polishing parameters in present the data acquisition system. Fig. 4 illustrates the final wafer polishing system structure based on the previously mentioned concept. The data acquisition system used in this experiment consists of the load-cell, infrared temperature sensor and A/D board, which is an 8 channel interface board (IOtech, WaveBook 512E). In the A/D board, the analogue signal will be transformed into a digital signal so that the Ch script is

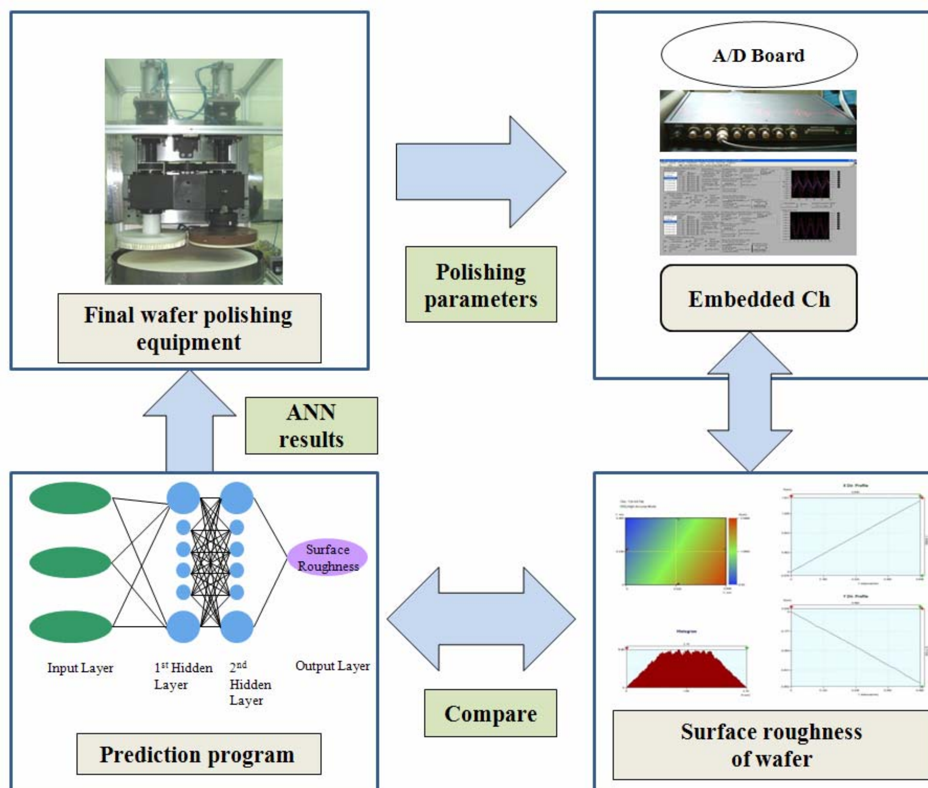


Fig. 4. Real-time monitoring system of the final wafer polishing.

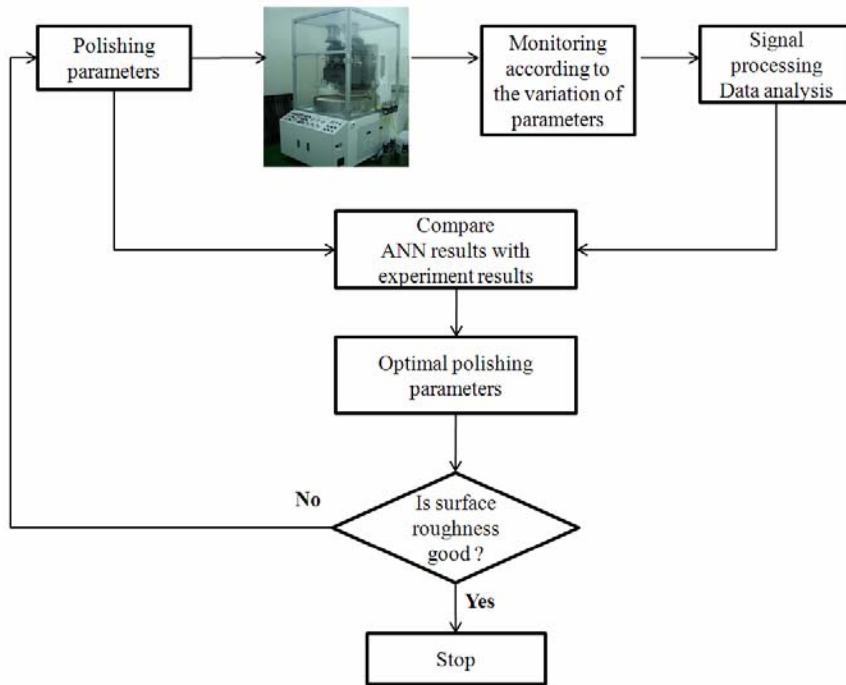


Fig. 5. Flowchart of the real-time monitoring on the final wafer polishing.

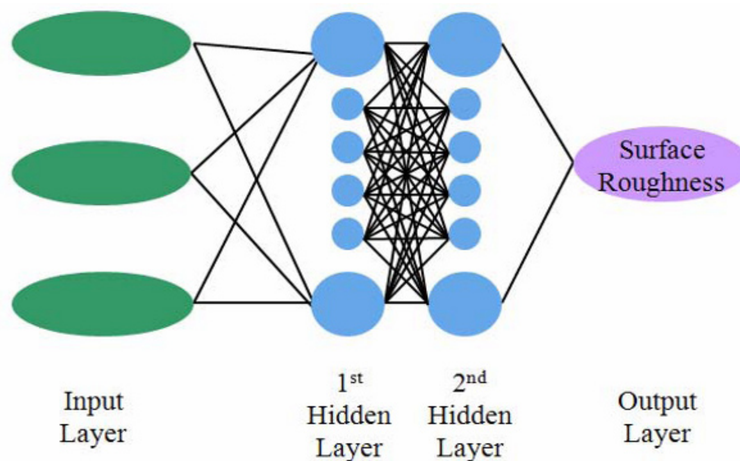


Fig. 6. Schematic illustration of ANN for the surface roughness in this experiment.

able to read and receive the data. Fig. 5 shows the whole flow of the real-time monitoring system on the final wafer polishing.

3.3 Surface roughness

The surface roughness is a measure of the quality of a product. It is also an element that highly affects fabrication cost. It describes the geometry and surface textures of the machined portion. Even though there are several ways to present surface roughness, Ra (Roughness average) is a representative value in a measure of surface roughness [9]. Ra is defined as the calculation of the profile from the center line in the measurement range. It can be explained by the mathematical expression:

$$Ra = \frac{1}{L}\int_0^L |y(x)||dx| \qquad (1)$$

where L is the sampling length, y is the profile curve and x is the profile direction.

4. Artificial neural networks (ANN)

The Artificial Neural Networks (ANN) is born from approach of developing intelligent systems by simulation the biological structure and the work of the human brain. It is accepted by most scientists that the human brain is a type of computer. The origins of neural networks are based on efforts to model the information processing in biological systems, which may rely largely on parallel processing as well as implicit instructions based on the recognition of patterns of sensory input from external sources [10].

4.1 Backpropagation (BP) algorithm

The ANN learns problems similar to how the human brain recognizes them. Establishing the connections between neurons determines the structure of the net-work. In addition training connections to obtain desired results determines the learning algorithm of the network. BP algorithm is based on the main principle of minimization of errors in a neural network output and the modification of network values according to the minimized values [11]. Fig. 6 represents a schematic illustration of BP algorithm in this experiment. The three layer of the network architecture include the input layer, the hidden layer and the output layer. These layers include several processing units known as neurons.

They are connected with each other by variable weights to be determined. A neuron in the network produces its input by processing the net input through an activation function which is usually nonlinear. There are several types of activation functions used for the BP. But the sigmoidal activation function is the most utilized.

The difference between the target output and practical output, learning error, for a sample p, as follows [10]:

$$E_p = \frac{1}{2}\sum_{k=1}^{K}(d_{pk} - o_{pk})^2 \quad (2)$$

where d_{pk} and o_{pk} are the desired and calculated outputs for the kth output, respectively. K denotes the number of neuron in the output of the network. The average error for whole system is obtained by:

$$E_p = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{K}(d_{pk} - o_{pk})^2 \quad (3)$$

where P is the total number of instances. For the purpose of minimizing E_p, the weights of the inter-connections are adjusted during the training procedure until the expected error is achieved. To adjust the weights of the networks, the process starts at the output neuron and works backward to the hidden layer. The weighs in BP based on the delta learning rule can be expressed as follows:

$$w_{ij} = w_{ij}^{old} + \Delta w_{ij} \quad (4)$$

$$\Delta w_{ij} = -\eta \frac{\partial E_p}{\partial w_{ij}} out_j \quad (5)$$

where out_j is the jth neuron output, and η is the learning rate parameter controlling the stability and rate of convergence of the network, which is a constant between 0 and 1. In this experiment, ANN using two hidden layers was used.

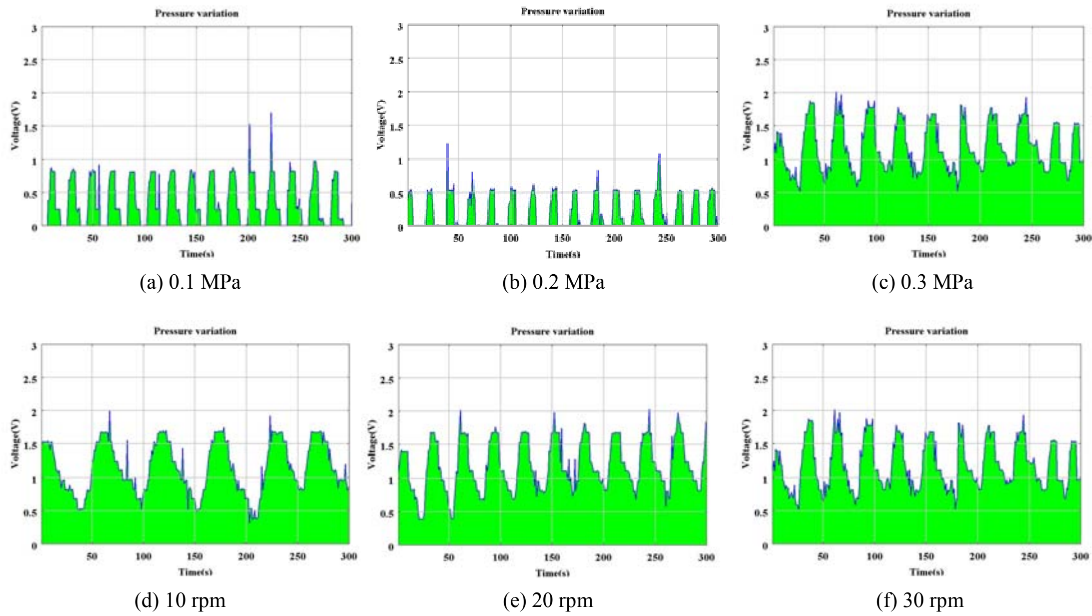
5. Experimental work

5.1 Sensor signal processing with real-time monitoring

The final polishing conditions used in this experiments are as follows: pressure of 0.1MPa, 0.2MPa and 0.3MPa, and wheel speed of 10rpm, 20rpm and 30rpm. The wafer is machined for five minutes.

A load-cell measuring the normal force conveyed on the wafer is fitted between the pneumatic actuator and the carrier head. An infrared temperature sensor is set up for an observation of the temperature variations on the polishing pad. In the A/D board, the analogue signal delivered from a load-cell and infrared temperature sensor will be transformed into a digital signal so that the Ch computing environment is able to read and receive the data.

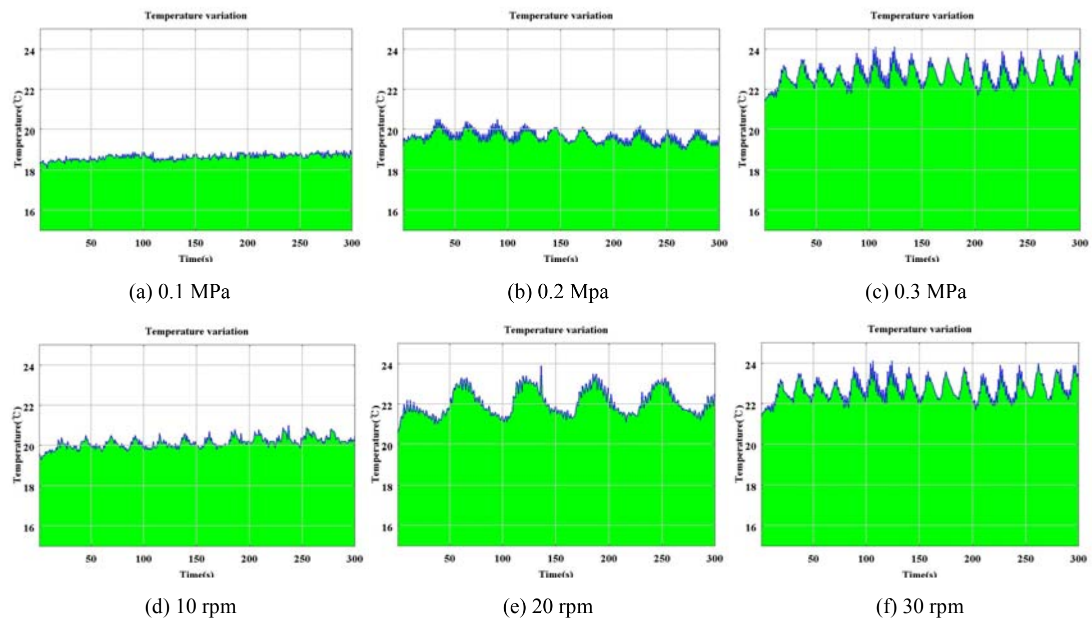
Fig. 7 presents the pressure variation using the Ch computing environment on the wafer according to parameters (a), (b) and (c) by the variation of pressure, and (d), (e) and (f) by the variation of wheel speed. When the pressure conditions are 0.1MPa and 0.2MPa, the variation of pressure on the wafer tends to be more stabilized than in the pressure condition of 0.3MPa. In the variation of wheel speed, pressure changes on all conditions tend to be uniform.



(a) 0.1 MPa (b) 0.2 MPa (c) 0.3 MPa

(d) 10 rpm (e) 20 rpm (f) 30 rpm

Fig. 7. Pressure variation on the wafer according to parameters using the Ch computing environment ((a), (b) and (c) by the variation of pressure, and (d), (e) and (f) by the variation of wheel speed.



(a) 0.1 MPa (b) 0.2 Mpa (c) 0.3 MPa

(d) 10 rpm (e) 20 rpm (f) 30 rpm

Fig. 8. Temperature variation on the pad according to parameters using the Ch computing environment ((a), (b) and (c) by the variation of pressure, and (d), (e) and (f) by the variation of wheel speed).

Fig. 8 indicates the temperature variations using the Ch computing environment on the pad according to parameters (a), (b), and (c) by the variation of pressure, and (d), (e), and (f) by the variation of wheel speed. As the pressure rises in each condition, the change of temperature on the pad tends to be getting higher. In the variation according to the wheel speed, it seems to be unstable in relation to the conditions.

As shown by the experiments, there are many variations in the results according to the conditions of

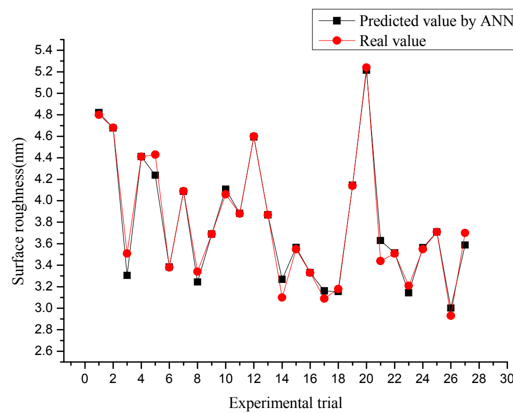


Fig. 9. Comparison between the predicted values by ANN and the real experimental values.

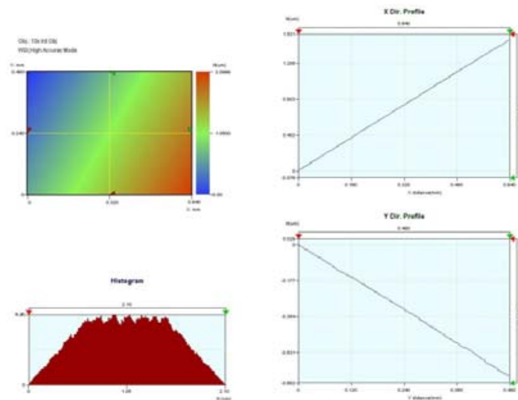


Fig. 10. Measurement feature of a wafer by Nano-View.

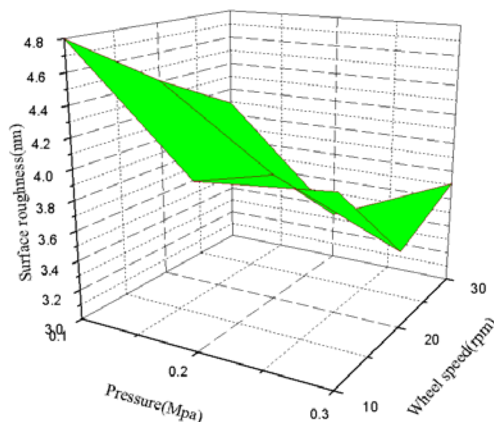


Fig. 11. Variations of the surface roughness according to the polishing conditions.

parameters. It is very consumptive and non-effective. Therefore, it is necessary to control the parameters for the efficient machining. Accordingly, in this paper, a prediction method using the ANN is applied for the selection of an optimal condition. It is illustrated in the next chapter.

5.2 Estimation of results by ANN

As described previously, it is important to select the optimal polishing parameters for the efficient machining in the final wafer polishing porcesses. The final wafer polishing is a complex machining method. The conservative selections of the polishing conditions would have to undergo trial and error. As such the unsuitable selection of machining conditions would cause detrimental results that would waste the machining time and cost. It is very difficult for operators to select the optimal working conditions in many different types of parameters, such as pressure and wheel speed.

The final wafer polishing conditions were optimized based on the minimum surface roughness. After finishing the ANN train, the ANN was tested using the different data from the trained data. During the testing process, the input values of the network are pressure and wheel speed, and the output value of network is the corresponding surface roughness. The experimental results have been graphically compared with the results obtained from the training network as shown in Fig. 9. Fig. 10 presents a measurement feature of the wafer by Nano-View which is a non-contact surface profiler.

6. Conclusion

This paper suggests the real-time monitoring using the Ch computing environment for the optimization of machining condition during the final wafer polishing. In these experiments, several signal of sensors were monitored in real time using the Ch computing environment. Moreover, this study which is rarely performed in before, proposed an efficient polishing process for the ultra precision wafer machining based on the real-time monitoring of polishing parameters. The real-time monitoring system for the polishing parameters presented the data acquisition system, the Ch computing environment, and the results of measuring the surface roughness of wafer. In the A/D board, the analogue signal delivered from a load-cell and an infrared temperature sensor was transformed into a digital signal so that the Ch script was able to read and receive the data.

The various experimental graphs are plotted by the

Ch computing environment. In the case of pressure variation according to the parameters, the pressure conditions are 0.1MPa and 0.2MPa, the variation of pressure on the wafer tends to be more uniformed than the pressure condition of 0.3MPa. In the variation of wheel speed, pressure changes in all conditions tend to be uniform. In the case of temperature variation according to parameters, it is found that as the polishing pressure increases, the variation of temperature on the pad ascends. In the variation according to the wheel speed, it is unstable in accordance with the conditions.

The prediction method using the ANN for the selection of an optimal condition was investigated by a requiring managing parameters for efficient machining. The ANN trained data were derived using the polishing parameters such as pressure and wheel speed.

For the evaluation of the results on the machining process of the silicon wafer by the ANN, the predicting values on the optimal condition of the artificial neural network and the real experiment results with respect to the surface roughness of machined wafers were compared. The comparison of result values is little except some points.

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