# Application of Neural Inverse Modeling Scheme to Optimal Parameter Tuning Filter Scanner

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**Abstract - Generally, the yield rate of semiconductors is the major factor that affects directly the price of semiconductors. For a high yield rate of semiconductors, the air inside the room is needed to be purified and high efficient filters are used for this. The filter are made of super-fine fiber and certain pinholes can be easily produced on the filter's surface by inadvertent manufacturing. As these pinholes are not easily detected with the bare sight, these pinholes exert a negative impact to filtration performance of the filter. In this research, not only the automatic test equipment for detecting pinholes is proposed, but also inverse modeling scheme based on artificial neural network is applied for tuning of its important parameters.**

## I. Introduction

Recently, the rapid progress of semiconductor industry propelled the increase of manufacturing lines for semiconductors. Generally, the yield rate of semiconductors from the output line is the major factor that affects directly the price of semiconductors, so for a high yield rate of semiconductors, the air inside the output line is needed to be purified and filters with high efficiency are used for this. Also, in compliance with highly developed society, contemporary world got interested in health-care more than before and the desire of breathing fresh air increases according to the latest air cleaners developed for companies and dwellings that are on the market. Filters used for this purpose are ULPA (Ultra Low Penetrating Air) and HEPA (High Efficiency Particulate Arrestor) and these filters are made of super-fine fibers. But, because this fiber is very thin, the pinholes can easy be produced on the filter's surface by inadvertent manufacturing. As these pinholes are not easily detected with the bare sight, many man-hours are required. If it were not for its location and its reparation, filtration performance of the filter will be deteriorated. For this, workers in most filter manufacturing company perform scanning of the filter surface with measuring device for particle counter. When the pinholes on the surface are pinpointed, the locations are marked. If the repair of pinholes is possible in a certain degree, this damaged part of the filter is repaired. But this kind of modification is very difficult to do and this is the cause of worker's duty evasion by backbreaking work. In this research, an automatic test equipment for detecting pinholes occurred on a ULPA or HEPA filter surface is proposed. The proposed equipment consists of 1-axis robot system which can move sensor module for scanning and detecting pinholes on the surface of filter and ventilation system controlled by inverter which can supply the lower part of filter with air. For the system to operate efficiently, several parameters should be optimized. In this research for the tuning of these parameters, inverse modeling scheme based on artificial neural network is applied. Furthermore, some experiments are executed to verify its applicability.

## II. Automatic test equipment for detecting pinholes

In the following we will explain about the whole structure of automatic test equipment for detection of pinholes of HEPA and ULPA filter. The structure of the proposed system is shown in the figure 1.

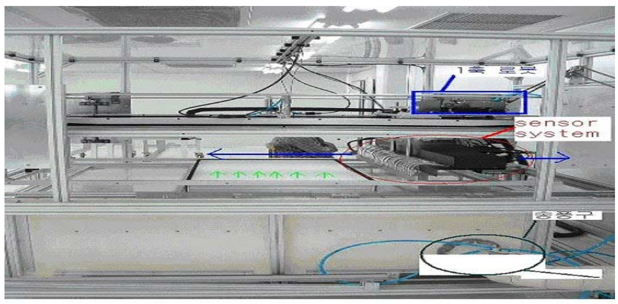


Fig. 1. The structure of automatic test equipment for pinholes detection

The proposed system consists of 1-axis robot system which can move sensor module for scanning and detecting pinholes on the surface of filter and ventilation system controlled by inverter which can supply the lower part of filter with air.

## A. The ventilating system

For the effective detection of pinholes on the surface of the filter, air should be drawn upward through the filter. If there are pinholes on the surface of the filter, the air that passes through the pinholes is not filtered and includes some particles. The air from the part without pinholes is filtered and includes no particles. According to the size and type of filter, ventilation system executing these kinds of functions must control the amount of airflow. If the amount of atmospheric dust is under the specified number, we should mix the airflow with DOP (Di-Octyl-Phthalate). The structure of ventilation system is shown in figure 2.

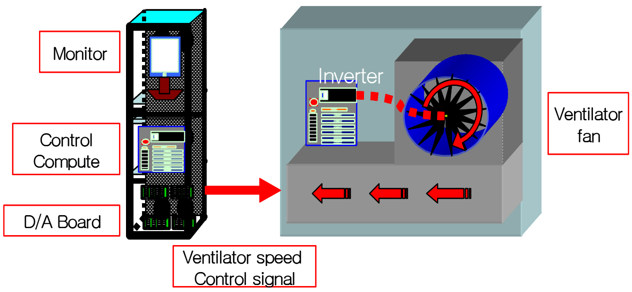


Fig. 2. The structure of the ventilation system

## B. Particle detection system

Particle detection system which is composed of several parts is placed in the upper position of test equipment and it functions as a particle counter which counts the particles included in the air out of pinholes. As the figure 3 shows, the particle detection sensor plays an important role in particle detection system. The vacuum pump connected to particle detection sensor draws out air through orifice nozzle which makes the airflow constant. The particles included in the airflow are counted by using a laser beam. If the laser beam hits particles in the drawn air, the diffusion of light happens and this diffusion is detected by particle detection system. Therefore, the transformation of the magnitude of light diffusion into electrical signal is possible and the counting of particles in the air is made by simply counting the signal peaks. The particle detection system of HEPA and ULPA filters is designed to react to size of 0.3um particle. Particle detection sensor is used together with analog signal conditioning unit and microprocessor as an interface of computer.

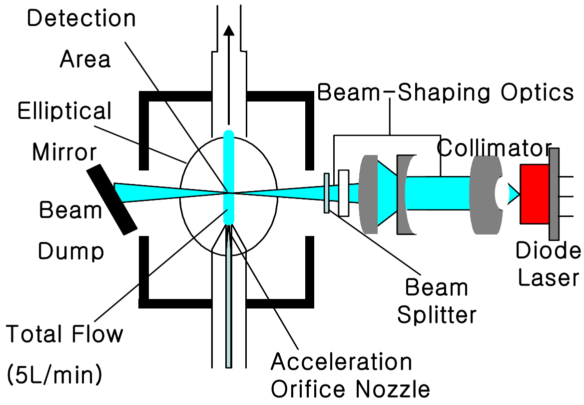


Fig. 3. Structure of particle detection system

## C. 1-Axis robot system

Transfer system is used for scanning the filter surface of particles detection system back and forth. During the scanning, real time monitoring is executed.

## D. Real time control and monitoring system

For the effective operation of the automatic test equipment, real-time control and monitoring system is needed. It can give operator information on the current operation status such as speed of ventilation system and locations of detected pinholes. Furthermore, it can also control the several solenoid valves and relays for its startup and shutdown. For this, we developed real-time control and monitoring system by using Visual Basic. It can read the output of 24-particle detection sensors and display the locations of pinholes from the filter surface. Schematic diagram of real time monitoring system is shown in figure 4.

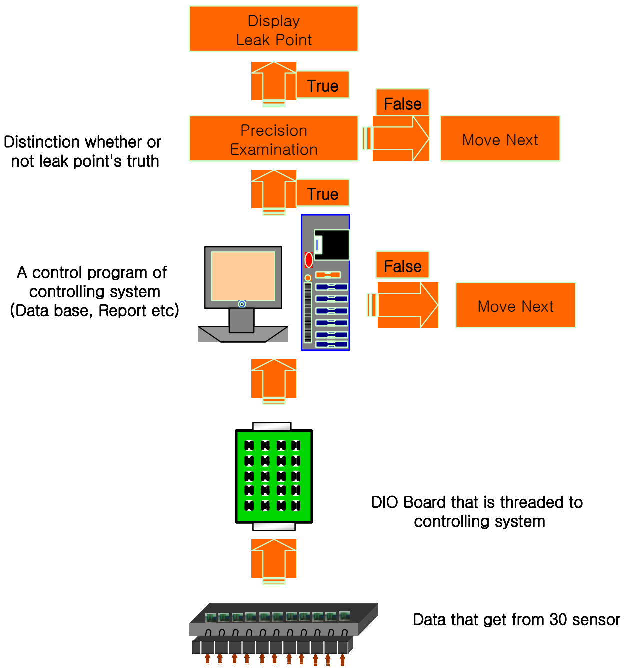


Fig 4. The diagram of the real time control and monitoring system

## E. Tuning parameters related with test equipment

For effective detection of pinholes on the filter surface, several parameters in the system should be tuned and optimized. Parameters which should be tuned are as follows: speed of airflow in ventilation system, amount of DOP, inter time delay between 1st and 2nd measurement in the particle detection system.

# III. Neural inverse modeling scheme

Neural inverse modeling scheme shown in Fig. 5 is used to tune the optimal parameters of automatic test equipment.

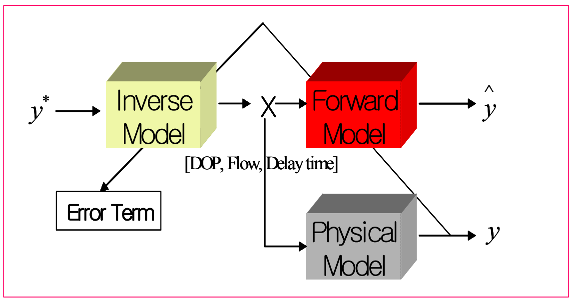


Fig 5. Neural inverse modeling scheme for tuning optimal parameter

In this picture, the forward model is used for modeling real process and it requires an input/output pattern for learning forward model. To acquire useful learning patterns it is desirable to use the input pattern that has various frequency elements to excite characteristics of the system. Once the learning of the forward neural model is completed, as it is shown in fig. 5, another neural network called inverse model is placed in front of the forward model. This neural network acts as a reverse model for the real process and its input to the inverse model is the same with the output of forward model. Inverse model and forward model are learned to have 1:1 mapping relationship. But direct learning of reverse model is impossible because the desired output of inverse model can not be known. In this research, learning scheme for inverse model proposed by Michael A. Casey has been utilized[1, 2].
The whole system is shown in Fig. 6. It has a structure of 4-layer neural network and the learning method is different for each model. The rear part of the neural network is the forward model and it is learned by using the input/output pattern of real process. Once the learning of forward model is completed, learning of front part of neural network is continued until the whole neural network should be learned to have 1:1 mapping relationship. During the learning of front part of system, error between the actual output of the network and desired output occurs as in the case of others. However, this error is propagated backward without changing the bias and the weights related with the real part of neural network. Once the learning of whole system is completed, the front part of the system can be used for interpolation of inexperienced input data.

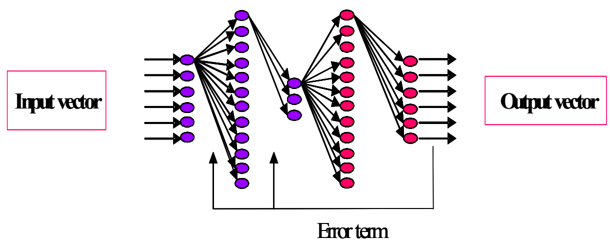


Fig 6. Learning of inverse mode

# IV. Application of neural inverse modeling scheme to filter test equipment

The automatic filter test equipment has the tuning parameters such as DOP density, speed of ventilation system and delay time between 1st and 2nd measurement for its better performance. The real process can be thought of as a black box which has a certain input/output characteristics. The input to the system can be a DOP density, speed of ventilation system and delay time and its output can be Hamming distances for each mark points and false rate. The desired output pattern for optimized parameters should be something like Fig. 7. However, the actual output pattern is like Fig. 8 for its wrong tuning of parameters. Optimal parameters should be found until the actual output pattern becomes like Fig. 7.

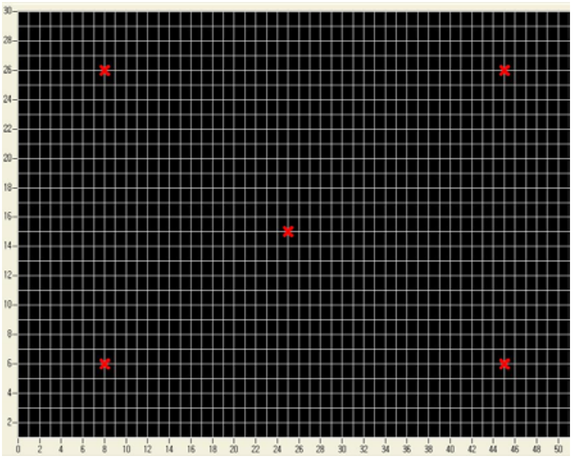

Fig 7. Desired output pattern

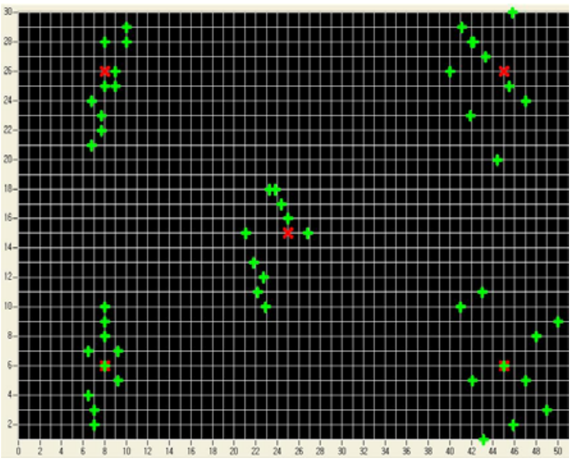

Fig 8. Actual output pattern

## A. Learning of forward neural model

For the learning of forward model, DOP density, speed of ventilation system and Delay time are used as input and Hamming distance at each mark points(1,2,3,4,5) and false rate are used as output. Forward model consists of the Input layer with 3 neurons, the Hidden layer with 12 neurons and the output layer with 6 neurons. The learning should be continued until the error between the target and the network output comes to SSE (Sum Square Error) 0.0001. The structure of Forward model network is shown in fig.9.

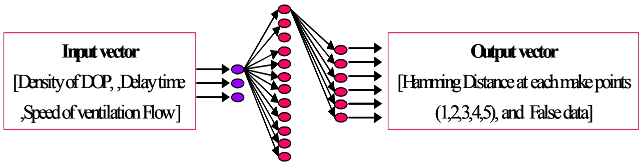


Fig 9. Structure of the forward model

## B. Learning of Inverse model

As it is shown in Fig. 6, the Inverse model is placed in front of the forward model and its weights and bias are changed to minimize the SSE while the weights and bias related with forward model are not changed. That is, the weight and bias of the forward model is unaffected by the back-propagated error. Inverse model consist of the input layer with 6 neurons, the hidden layer with 12 neurons and the output layer with 3 neurons. For obtaining the optimal parameters of the test equipment, the learning of inverse model has been performed with the input/output data. With the learned inverse model, we can obtain the optimal parameters for the system. The desired value of DOP density is 0.5976 and speed of ventilation system is 0.6134 and Delay time is 0.6578. The system measurement pattern for these optimized parameters is obtained as in Fig. 10.

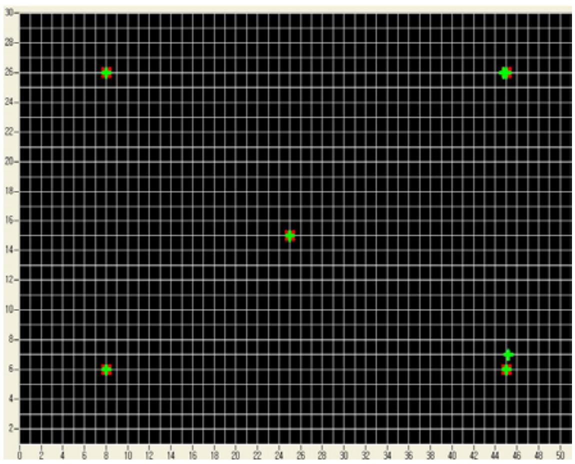

Fig. 10. Measurement pattern for the optimized system parameter

## V. Conclusion

In this research, the inverse modeling scheme based on neural network is introduced for the optimal parameter tuning of automatic filter test equipment. The inverse neural model can be successfully trained. The performance of the filter test system can be verified by applying the optimized parameters to the system.

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## Reference

[1] Jordan, M.I. & Rumelhart, D.E., "Forward models: supervised learning with a distal teacher", Cognitive Science, Vol.16, pp307-354, 1992

[2] Michael A. Casey, "Understanding musical sound with Forward models and Physical models", Connection Sci., Vol.6, pp.355-371, 1994

[3] Jang, J.S.R and Sun, C.-T., "Functional equivalence between radial basic function network and fuzzy inference systems", IEEE Trans, Neural Networks, Vol.4, No.1, pp.156-159, 1993

[4] J. Moody and C. Darken. Fast learning in networks of locally-tuned processing units. Neural Computation, Vol.1, pp. 281-294,1989

[5] J. Moody and C. Darken. Learning with localized receptive fields. In D. Touretzky, G.Hinton, and T. Sejnowski, editors, Proc. of the 1988 Connectionist Models Summer School. Carnegie Mellon University, Morgan Kaufmann Publishers, 1988