出國報告(出國類別：出席國際研討會發表論文)

出席 2008 年 IEEE 機器人與自動化國際研討會報告

服務機關：國防大學理工學院電機電子工程學系
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出國時間：97 年 5 月 18 日至 97 年 5 月 25 日

摘要

本次出國之目的為參加於美國加州巴莎迪那市(Pasadena, California, USA)舉行之2008 年IEEE 機器人與自動化國際研討會(2008 IEEE International Conference on Robotics and Automation, ICRA 2008)，並發表學術研究論文。ICRA 2008國際研討會之主題為”Human-Centered Robotics, the movement toward robotics technology that aids in the course of human everyday life.”本次會議共有從47 個國家，1478 篇論文投稿，審查結果僅661 篇（僅約45%）獲接受於本次大會發表。大會於95年5月19日及5月20日排定有22個機器人與自動化相關之Tutorial及Workshop，並利用5月21日至23日3天之時間，同一時間12至13場次(Parallel Tracks)，將所有論文利用口頭方式公開發表，本人在本次會議發表論文乙篇「虛擬量測之嶄新變數篩選法則」，安排於5月23日下午場次報告。

目次

一、目的

本次出國之目的爲參加於美國加州巴莎迪那市(Pasadena, California, USA)舉行之2008 年IEEE 機器人與自動化國際研討會(2008 IEEE International Conference on Robotics and Automation)，並發表論文乙篇，經費來源爲行政院國家科學委員會補助國內專家學者出席國際學術會議經費。

二、過程

本次2008年IEEE 機器人與自動化國際研討會於97 年5 月19 日至23日在美國加州巴莎迪那市舉行。本次大會主題爲”Human-Centered Robotics, the movement toward robotics technology that aids in the course of human everyday life.”本次會議共有從47 個國家，1478 篇論文投稿，審查結果僅661 篇（僅約45%）獲接受於本次大會發表。

本次大會於95年5月19日及5月20日排定有22個機器人與自動化相關之Tutorial及Workshop，並利用5月21日至23日3天之時間，同一時間12至13場次(Parallel Tracks)，將所有論文利用口頭方式公開發表，本人在本次大會口頭發表論文乙篇，安排於5月23日下午場次報告，論文資料如下：

（中文題目：虛擬量測之嶄新變數篩選法則）

Tung-Ho Lin, Fan-Tien Cheng, Aeo-Juo Ye, Wei-MingWu, and Min-Hsiung Hung, “**A Novel Key-variable Sifting Algorithm for Virtual Metrology**,” in *Proceedings of 2008 IEEE International Conference on Robotics and Automation*, Pasadena, California, USA, pp. 3636-3641, May 19-23, 2008.

三、心得

本次大會之特色除了3 場邀請之專題演講(Invited Plenary Talks)外，首次於ICRA會議舉辦機器人競賽，從世界各地來之學生隊伍，帶著他們的機器人到會場參加比賽。此外，也舉辦了機器人連環漫畫競賽(Robot Comics Contest)，爲學生舉辦之社交聯誼活動，以及4 個交誼接待活動都屬於本次會議之創舉。大會也安排有18 展示攤位(展示廠商包含了iRobot, Microsoft Research, Segway, 與 Willow Garage 等)，展覽各式機器人、MAV、發展軟體等。本次國際學術會議，國內有多位的專家學者參加，包括：台大電機系羅仁權教授與傅立成教授、成大製造所鄭芳田教授、交通大學電機與控制系胡竹生與宋開泰教授等人。其中成大製造所鄭芳田教授榮獲2008 IEEE Fellow，於晚宴中上台接受大會表揚。

整體而言，本次大會相當成功。除了參加人數眾多外，各項首次舉辦之競賽與活動也爲大家所讚許，值得國內舉辦國際研討會時參考。

四、建議事項

最後，感謝國科會提供經費補助國內專家學者出席國際研討會，也期盼國內學者能繼續積極參與國際學術活動並發表論文，以期提升我國之國際學術地位。

五、攜回資料名稱及內容

1. Proceedings CD of 2008 IEEE International Conference on Robotics and Automation.

附錄：虛擬量測之嶄新變數篩選法則論文內容

2008 IEEE International Conference on
Robotics and Automation
Pasadena, CA, USA, May 19-23, 2008

A Novel Key-variable Sifting Algorithm for Virtual Metrology

Tung-Ho Lin*, *Student Member, IEEE*, Fan-Tien Cheng*, *Fellow, IEEE,*
Aeo-Juo Ye*, Wei-Ming Wu*, and Min-Hsiung Hung**, *Senior Member, IEEE*

Abstract –This work proposes an advanced key-variable selecting method, the neural-network-based stepwise selection (NN-based SS) method, which can enhance the conjecture accuracy of the NN-based virtual metrology (VM) algorithms. Multi-regression-based (MR-based) SS method is widely applied in dealing with key-variable selecting problems despite that it may not guarantee finding the best model based on its selected variables. However, the variables selected by MR-based SS may be adopted as the initial set of variables for the proposed NN-based SS to reduce the SS process time. The backward elimination and forward selection procedures of the proposed NN-based SS are both performed by the designated NN algorithm used for VM conjecturing. Therefore, the key variables selected by NN-based SS will be more suitable for the said NN-based VM algorithm as far as conjecture accuracy is concerned. The etching process of semiconductor manufacturing is used as the illustrative example to test and verify the VM conjecture accuracy. One-hidden-layered back-propagation neural networks (BPNN-I) are adopted for establishing the NN models used in the NN-based SS method and the VM conjecture models. Test results show that the NN model created by the selected variables of NN-based SS can achieve better conjecture accuracy than that of MR-based SS. Simple recurrent neural networks (SRNN) are also tested and proved to be able to achieve similar results as those of BPNN-I.

***Index Terms*—**Virtual metrology (VM), multi-regression-based stepwise selection (MR-based SS), neural-network-based stepwise selection (NN-based SS).

I. INTRODUCTION

In current practice of semiconductor manufacturing, equipment-monitoring is performed by periodically measuring one production wafer that is pre-selected within each cassette (also called "FOUP" in semiconductor industry) while the quality of other production wafers beyond the measuring wafer is unknown. Thus, equipment abnormality may not be discovered in time and many defective production wafers may have been produced. This may result in a great wafer yield loss. An on-line and wafer-to-wafer (W2W) monitoring alternative is to apply the virtual metrology (VM) technology [1], [2]. Also referred to as predictive metrology [3], VM can be adopted to conjecture the processing quality of every wafer using the process data of production equipment without physically conducting quality measurement. Through VM, the quality of each wafer can be known immediately right after the process data are obtained to ensure prompt detection of equipment anomaly and avoid defective products [2].

In the semiconductor industry, run-to-run (R2R) control is an important technique for enhancing process capability [4]. And Lot-to-lot (L2L) advanced process control (APC) is now widely applied in the semiconductor manufacturing process. As the size of electronic devices shrink gradually, W2W APC has become essential for critical stages to improve production yield [3], [4]. W2W APC requires the metrology values of each wafer; however, it will be very time-consuming and highly expensive to obtain each individual wafer's actual metrology value by physical measurement. Therefore, VM is a good resolution for being applied in W2W APC [2], [5]. To implement VM in W2W APC, high conjecture accuracy needs to be primarily considered [2], [6].

For achieving high VM conjecture accuracy, it is essential to select near-optimal set of variables that can represent the actual property of production equipment. If too many variables are chosen, irrelevant ones may be included, which will add noise and affect the conjecture accuracy [7], [8]. However, if too few variables are selected, it may also lead to failure in achieving high conjecture accuracy [9]. Among all the variable-selecting methods, multi-regression-based stepwise selection (denoted MR-based SS) is the most widely applied one to choose a limited number of variables for inclusion in the MR models, which is commonly used for solving prediction problems [10]. Nevertheless, the variables selected by MR-based SS may not be suitable for optimizing those neural-network-based (denoted NN-based) VM conjecture models used in [2], [6], [11], and [12] as far as conjecture accuracy is concerned.

To improve the NN-based VM conjecture accuracy, this work proposed an advanced method called NN-based SS. The proposed method utilizes the initial set of variables suggested by MR-based SS and performs backward elimination and forward selection procedures repeatedly by the designated NN algorithm used for VM conjecturing to find the key-variables that have dominant contributions to VM conjecture accuracy. The most common NN algorithms used for VM conjecturing are back-propagation neural networks (BPNN) [6], [11], [12] and simple recurrent neural networks (SRNN) [2], [6]. In this

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paper, one-hidden-layered BPNN (BPNN-I) are adopted as the designated algorithm for evaluating the NN-based SS method and the VM conjecture model. The variable-selecting results of both MR-based and NN-based SS methods as well as expert-recommended process variables (denoted ER-based variables) are used to establish different VM models for comparing their conjecture accuracy. The semiconductor etching process is selected as the illustrative example for accuracy comparison. Test results show that the NN models created by the selected variables of NN-based SS can achieve superior conjecture accuracy than those of MR-based SS and ER-based. Besides, SRNN has also been tested and proved to be able to achieve similar results as those of BPNN-I.

The remainder of this paper is organized as follows. Section 2 briefs the MR-based SS method and details the proposed NN-based SS methods. Next, Section 3 presents and compares the experimental results of ER-based, MR-based SS, and NN-based SS methods. The implications of experimental results and implementation consideration are also discussed here. Finally, a summary and conclusions are made in Section 4.

II. MR-BASED AND NN-BASED STEPWISE SELECTION METHODS

This section introduces the MR-based SS and the proposed NN-based SS methods.

2.1 MR-based SS Method

Both forward selection and backward elimination steps are included in the MR-based SS procedure. Initially there are no variables in the MR model. The forward selection begins with adding the variable that has the greatest contribution into the MR model. Then, the backward elimination will decide which entered variable will be deleted. Repeat the foregoing procedures until the MR model stop entering or removing any variables. Finally, close the variable-selecting procedure and take the variables within the MR model as the final selection [13].

The MR-based SS method possesses the advantages of fast computation and easy implementation. Nevertheless, Anderson, *et al.* [14] concluded that the MR-based SS method cannot guarantee finding the best set of variables for optimizing the conjecture model. However, the MR-based SS selecting result may be utilized as the initial set of variables for the proposed NN-based SS method to reduce the iterations in the backward elimination and forward selection procedures.

2.2 NN-based SS Method

The NN-based SS method also has forward selection and backward elimination procedures. However, because the MR-based SS selecting result is assigned as the initial set of variables, the NN-based SS process starts with backward elimination. Within both the backward elimination and forward selection steps, the designated NN algorithm is applied. Therefore, the variable-selecting result of NN-based SS is suitable for the designated NN-based VM conjecture model.

Based on the flow chart of the NN-based SS method shown in Fig. 1, the procedures are detailed as follows.

● Step 1. To reduce the iterations of backward elimination and forward selection, MR-based SS is adopted to generate the initial m_i (i=0, where i is the iteration number of backward elimination and forward selection procedures) set of input variables for NN-based SS. Besides, the variable p is assigned to be zero initially and k represents the total number of

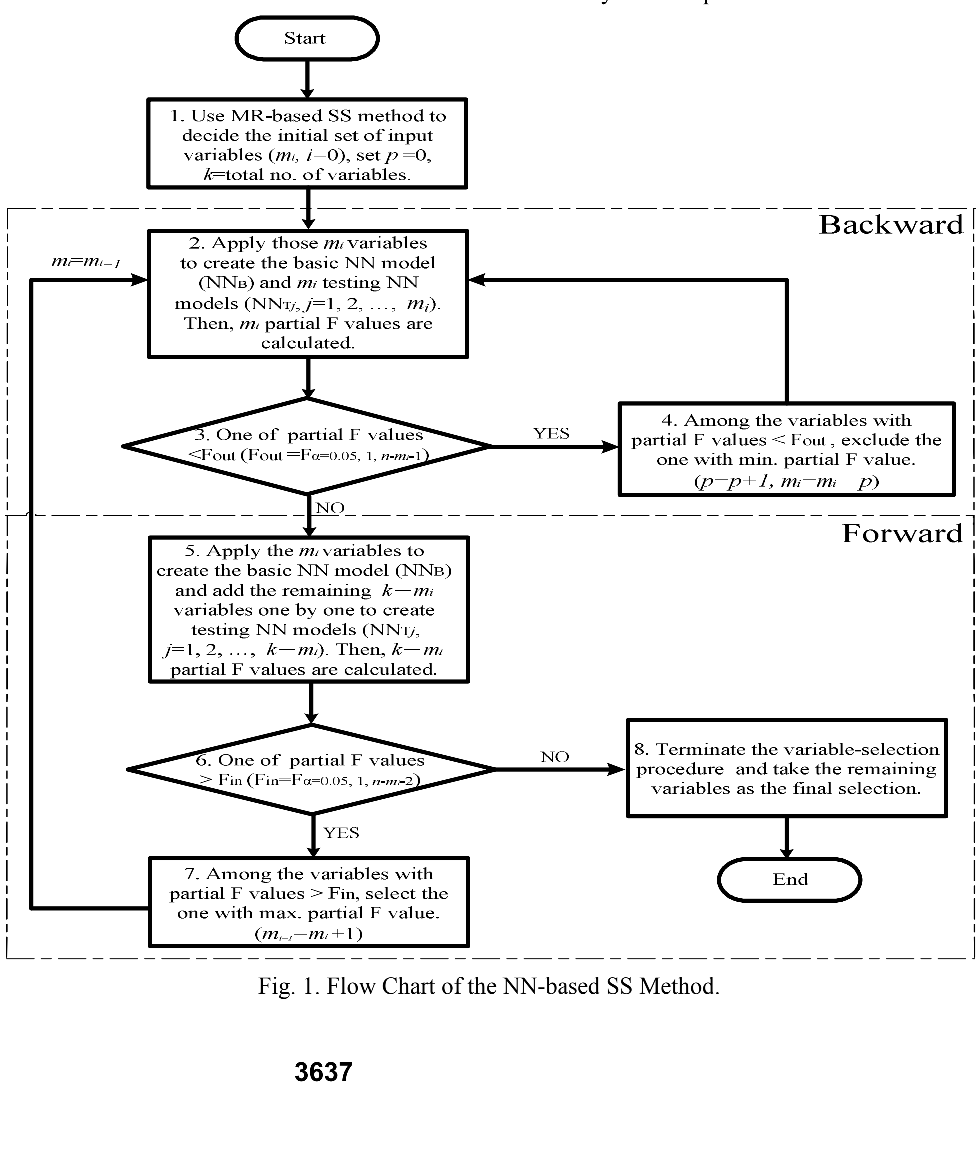


Fig. 1. Flow Chart of the NN-based SS Method.

process variables.

- ●Step 2. The backward elimination procedure starts with applying those m_i variables to create the basic NN model (NN_B). Then, delete the first variable among those m_i ones and apply the remaining $m_i - 1$variables to create the first testing NN model (NN_{T1}). Repeat the same procedure until a total of m_i testing NN models (NN_{Tj}, j=1, 2, …, m_i) are created. With those NN_B and NN_{Tj}, m_i partial F values [14] are calculated.
- ●Step 3. Check whether at least one of the m_i partial F values is smaller than the pre-selected threshold value (denoted F_{out}) ($F_{out}=F_{\alpha=0.05,\ 1,\ n-m_i-1}$), where n represents the modeling sample size [14]. If the answer is yes, then the system enters Step 4; else the backward elimination procedure finishes and the system enters the forward selection procedure.
- ●Step 4. Among the variables whose partial F values are smaller than F_{out}, exclude the one with minimal partial F value and let $p=p+1$, $m_i=m_i-p$.
- ●Step 5. The forward selection procedure commences with applying those m_i variables to create the basic NN model (NN_B). Then, add the first variable among those $k-m_i$ ones and apply the m_i+1 variables to create the first testing NN model (NN_{T1}). Follow the same procedure until a total of $k-m_i$ testing NN models (NN_{Tj}, j=1, 2, …, $k-m_i$) are created. With those NN_B and NN_{Tj}, $k-m_i$ partial F values are calculated.
- ●Step 6. Check whether at least one of the $k-m_i$ partial F values exceeds the predetermined threshold value (denoted F_{in}) ($F_{in}=F_{\alpha=0.05,\ 1,\ n-m_i-2}$). If the answer is yes, then the system enters Step 7; else the system goes to Step 8.
- ●Step 7. Among the variables whose corresponding partial F values exceeding F_{in}, select the one with maximal partial F value to enter the NN model ($m_{i+1}=m_i+1$). Then, let $m_i=m_{i+1}$ and return to Step 2.
- ●Step 8. Because all the corresponding partial F values are smaller than F_{in}, the variable-selecting procedure is terminated and the remaining variables are the final selection.

The definitions of the partial F, F_{out}, and F_{in} values mentioned above are the same as those used for MR-based SS and can be found in [14], [15], [16]. Statistically, the partial F value provides a basis for determining whether the variable deleted from (or added into) the model will cause a significant reduction in the sum of squares due to error (denoted SSE) [14] by comparing with the F_{out} (or F_{in}) value.

According to the forgoing definition, the F_{in} value is specified to be slightly greater than the F_{out} value to make it relatively more difficult for a variable to be added into than to be deleted from the model [16]. As such, we can select the variables with the most significant contribution into the model and avoid a variable being continually entered and removed. Moreover, a popular method used in [15] is to set the F_{in} and F_{out} values as 4.0 and 3.9, which is roughly determined by $F_{\alpha=0.05,\ 1,\ n-m_i-1=50}=4.03$. However, in general, the sample size (n) and the number of variables (m_i) within the model may not be always fixed. Therefore, in this work, the F_{out} and F_{in} values are defined as depending on n and m_i.

III. Illustrative Example

This illustrative example is based on a piece of semiconductor etching equipment in Taiwan. The example involves 248 sets of sample data. Except for the 248th set, which is for the conjecture test, the other 247 sets of sample data are all used for building the VM model. The first 247 sets of sample data (process data; X_i, i=1, 2, …, 247) belong to 247 sampling wafers collected from 247 cassettes. Each cassette contains 25 or less wafers. For a normal manufacturing process, each cassette only has a sampling wafer that has the corresponding actual metrology value. Thus, those process data of all the 247 sampling wafers and their corresponding actual metrology values (y_i, i=1, 2, …, 247) are adopted for establishing the models used in the ER-based, MR-based SS, and NN-based SS methods.

For evaluating the conjecture accuracy, not only the regular sampling wafer but all the other 24 wafers in the testing (248th) cassette are measured. Therefore, the process data of all the 25 wafers in the testing cassette are used to obtain VM values, whereas the corresponding actual metrology values of those 25 wafers are taken as the basis for evaluating the VM conjecture accuracy.

According to the physical properties of production equipment and the expertise of equipment engineers, among 36 equipment sensors and 12 processing steps, only 66 comparatively important variables (x_1, x_2, …, x_{66}) are considered as ER-based variables and become the inputs of MR-based SS. Those ER-based variables are listed in Table I.

The conjecture accuracy of the ER-based, MR-based SS, and NN-based SS methods was quantified by the maximum error (*MaxError*) and the mean absolute percentage error (*MAPE*) [2], [11]. The formulae are represented as follows.

$$MAPE = \frac{\sum_{i=1}^{q} |(\hat{y}_i - y_i)/y|}{q} \times 100\% \tag{1}$$

$$MaxError = \max\left\{ \frac{|\hat{y}_i - y_i|}{y} \times 100\%,\ i = 1, 2, \cdots, q \right\} \tag{2}$$

where $\hat{y}_i$ is the conjecture value, y_i is the real metrology value, y is the target value, and q is the conjecture sample size. The closer the *MaxError* and *MAPE* values are to zero, the better the accuracy of the VM conjecture model can achieve. *MAPE* represents the average conjecture error of VM.

The computer used in this example is Core 2 Duo 6400 (2.13GHz) with a memory size of 2G. Microsoft Windows XP is adopted as the operating system. The test results and their implications as well as implementation consideration are detailed as follows.

3.1 Variable-Selecting Results

As mentioned previously, F_{out} is determined by the pre-selected level of significance (α) (set to be 0.05) [14], one numerator degree of freedom (denoted df) (one variable deleted), and $n - m_i - 1$ denominator df [14] (referring to Step 3 of Fig. 1). In this case, the modeling sample size (n) equals 247. For example, to delete one variable from the model with original 8 (=m_i) variables, then the F_{out} value is computed as $F_{out}=F_{\alpha=0.05, 1, 247-8-1}=F_{\alpha=0.05, 1, 238}=3.8808$. If one of the computed m_i partial F values in the backward elimination procedure (Step 2 of Fig. 1) is smaller than F_{out}, then this corresponding variable may be deleted (Step 4 of Fig. 1).

Next, the F_{in} value is decided by the specified α (=0.05), one numerator df (one variable added), and $n-m_i-2$ (derived from $n-(m_i+1)-1$) denominator df [14] (Step 6 of Fig. 1). For instance, to add one into the model with original 8 (=m_i) variables, the F_{in} value is calculated as $F_{in}=F_{\alpha=0.05, 1, 247-8-2}=F_{\alpha=0.05, 1, 237}=3.8810$. If one of the computed $k-m_i$ partial F values in the forward selection procedure (Step 5 of Fig. 1) is greater than F_{in}, then this corresponding variable may be added (Step 7 of Fig. 1).

Tables II and III represent the variable-selecting results of MR-based and NN-based SS methods, respectively. The number of their selected variables (chosen from the original 66 ones) turn out to be only ten and nine, respectively. The ten MR-based selected variables are {1, 4, 10, 36, 43, 45, 51, 53, 56, 66} and the nine NN-based selected ones are {1, 5, 29, 36, 45, 51, 53, 56, 66}. Seven

TABLE I
LIST OF ER-BASED VARIABLES

Variable Code	Sensor Name	Step No.	Variable Code	Sensor Name	Step No.
1	Flow Sensor _1	Step 5	34	Valve Sensor_2	Step 5
2	Flow Sensor _2	Step 5	35	Pressure Sensor _3	Step 5
3	Flow Sensor _3	Step 5	36	Voltage Sensor _3	Step 5
4	Flow Sensor _4	Step 5	37	Flow Sensor _1	Step 7
5	Signal Sensor _1	Step 5	38	Signal Sensor _1	Step 7
6	Signal Sensor _2	Step 5	39	Signal Sensor _2	Step 7
7	Signal Sensor _3	Step 5	40	Signal Sensor _3	Step 7
8	Flow Sensor _5	Step 5	41	Flow Sensor _2	Step 7
9	Pressure Sensor _1	Step 5	42	Pressure Sensor _1	Step 7
10	Valve Sensor_1	Step 5	43	Valve Sensor_1	Step 7
11	Pressure Sensor _2	Step 5	44	Pressure Sensor _2	Step 7
12	Voltage Sensor _1	Step 5	45	Voltage Sensor _1	Step 7
13	Power Sensor _1	Step 5	46	Power Sensor _1	Step 7
14	Power Sensor _2	Step 5	47	Power Sensor _2	Step 7
15	Power Sensor _3	Step 5	48	Power Sensor _3	Step 7
16	Power Sensor _4	Step 5	49	Power Sensor _4	Step 7
17	Voltage Sensor _2	Step 5	50	Voltage Sensor _2	Step 7
18	Flow Sensor _6	Step 5	51	Flow Sensor _3	Step 7
19	Capacitance Sensor _1	Step 5	52	Capacitance Sensor _1	Step 7
20	Capacitance Sensor _2	Step 5	53	Capacitance Sensor _2	Step 7
21	Capacitance Sensor _3	Step 5	54	Capacitance Sensor _3	Step 7
22	Capacitance Sensor _4	Step 5	55	Capacitance Sensor _4	Step 7
23	Temp Sensor _1	Step 5	56	Temp Sensor _1	Step 7
24	Temp Sensor _2	Step 5	57	Temp Sensor _2	Step 7
25	Temp Sensor _3	Step 5	58	Temp Sensor _3	Step 7
26	Temp Sensor _4	Step 5	59	Temp Sensor _4	Step 7
27	Temp Sensor _5	Step 5	60	Temp Sensor _5	Step 7
28	Temp Sensor _6	Step 5	61	Temp Sensor _6	Step 7
29	Temp Sensor _7	Step 5	62	Temp Sensor _7	Step 7
30	Flow Sensor_7	Step 5	63	Flow Sensor _4	Step 7
31	Flow Sensor_8	Step 5	64	Valve Sensor_2	Step 7
32	Flow Sensor_9	Step 5	65	Pressure Sensor _3	Step 7
33	Flow Sensor_10	Step 5	66	Pre-Y	NA[a]

[a]Pre-Y data are collected from the previous process. Thus, they don't belong to any step of the current process.

TABLE II
VARIABLE-SELECTING RESULTS OF MR-BASED SS

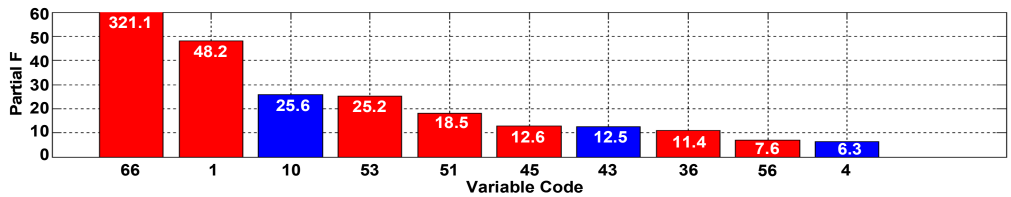
Variable Code	Sensor Name	Step No.
1	Flow Sensor _1	Step 5
$\boxed{4}$ [b]	Flow Sensor _4	Step 5
$\boxed{10}$ [b]	Valve Sensor_1	Step 5
36	Voltage Sensor _3	Step 5
$\boxed{43}$ [b]	Valve Sensor_1	Step 7
45	Voltage Sensor _1	Step 7
51	Flow Sensor _3	Step 7
53	Capacitance Sensor _2	Step 7
56	Temp Sensor _1	Step 7
66	Pre-Y	NA[a]

[a]Pre-Y data are collected from the previous process. Thus, they don't belong to any step of the current process.
[b]The variables in square will be deleted by NN-based SS.

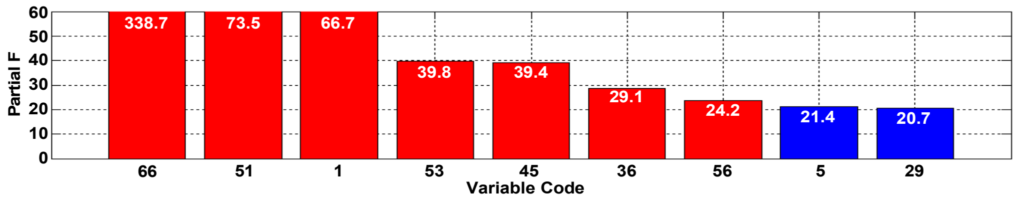
TABLE III
VARIABLE-SELECTING RESULTS OF NN-BASED SS

Variable Code	Sensor Name	Step No.
1	Flow Sensor _1	Step 5
$\boxed{5}$ [b]	Signal Sensor _1	Step 5
$\boxed{29}$ [b]	Temp Sensor _7	Step 5
36	Voltage Sensor _3	Step 5
45	Voltage Sensor _1	Step 7
51	Flow Sensor _3	Step 7
53	Capacitance Sensor _2	Step 7
56	Temp Sensor _1	Step 7
66	Pre-Y	NA[a]

[a]Pre-Y data are collected from the previous process. Thus, they don't belong to any step of the current process.
[b]The variables in square are added by NN-based SS.



(a) MR-based SS.



(b) NN-based SS.

Fig. 2. Partial-F Pareto Charts of MR-based and NN-based SS Methods.

variables selected by MR-based SS remain in the NN-based SS result. Figure 2 depicts the partial-F Pareto charts of MR-based SS and NN-based SS methods. The seven variables in red {1, 36, 45, 51, 53, 56, 66} are the common ones selected by both SS methods. Among those common variables, Variable 66 is the one with maximal partial F value in either group of selected variables. Further, MR-based SS includes Variables {4, 10, 43} into the MR model, whereas NN-based SS deletes Variables {4, 10, 43} and adds Variables {5, 29} instead in the NN model.

3.2 VM Conjecture Results

Table IV and Fig. 3 illustrate the VM conjecture results based on the NN models generated by the ER-based, MR-based, and NN-based SS methods. As shown in Table IV, $\overline{\text{MaxError}}$ and $\overline{\text{MAPE}}$ stand for the mean values of 30 MaxErrors and MAPEs for conjecturing those 25-evaluating samples 30 times, respectively. Table IV illustrates that the $\overline{\text{MaxError}}$ s for the NN models of ER-based, MR-based SS, and NN-based SS are 2.38%, 1.87%, and 1.70%, respectively. And the $\overline{\text{MAPE}}$ s based on the NN models of ER-based, MR-based SS, and NN-based SS are 1.11%, 1.01%, and 0.89%, respectively.

TABLE IV
VM CONJECTURE RESULTS OF VARIOUS SELECTION METHODS (using BPNN-I)

Variable-selecting Method	Accuracy (%)	
	$\overline{\text{MaxError}}$	$\overline{\text{MAPE}}$
ER-based	2.38	1.11
MR-based SS	1.87	1.01
NN-based SS	1.70	0.89

TABLE V
VM CONJECTURE RESULTS OF VARIOUS SELECTION METHODS (using SRNN)

Variable-selecting Method	Accuracy (%)	
	$\overline{\text{MaxError}}$	$\overline{\text{MAPE}}$
ER-based	2.88	1.12
MR-based SS	2.09	1.04
NN-based SS	1.84	0.96

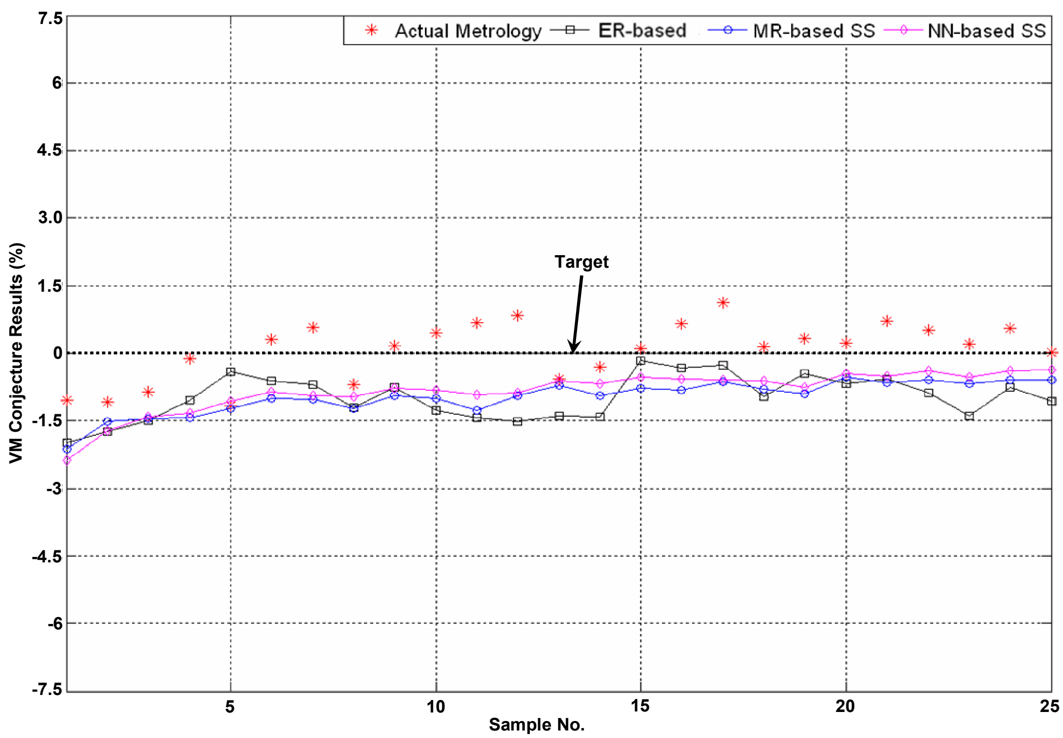


Fig. 3. VM Conjecture Results of ER-based, MR-based SS, and NN-based SS Methods (using BPNN-I).

According to the data shown in Table IV, apparently, the NN model based on NN-based SS has the best conjecture accuracy. In other words, although NN-based SS selects the least number of variables comparing to that of ER-based and MR-based SS (referring to Tables II, III and Fig. 2), its VM conjecture model still achieves superior accuracy. This result reveals that NN-based SS can select the most critical variables among the original ones to prevent unimportant variables from affecting the VM conjecture accuracy [7]. Moreover, by applying the Pair-T hypothesis test [17], significant difference of VM conjecture accuracy between the MR-based SS and NN-based SS methods is verified.

Besides BPNN-I, the authors also apply SRNN as the designated NN algorithm for all the experiments. Experimental results show that SRNN can achieve the similar results (as shown in Table V) as BPNN-I. Table V illustrates that the $\overline{\text{MaxError}}$s for the NN models of ER-based, MR-based SS, and NN-based SS are 2.88%, 2.09%, and 1.84%, respectively. And the $\overline{\text{MAPE}}$s based on the NN models of ER-based, MR-based SS, and NN-based SS are 1.12%, 1.04%, and 0.96%, respectively.

The etching equipment for experiment has three chambers. Different chamber has different physical property. Therefore, those three chambers should have their own VM conjecture models as far as VM conjecture accuracy is concerned. The experimental results mentioned above belong to one of the three chambers. In fact, experiments of the other two chambers have also been performed in this work and similar results are obtained. Therefore, it is concluded that the NN model created by the selected variables of NN-based SS can indeed achieve better conjecture accuracy than that of MR-based SS.

V. Summary and Conclusions

An advanced key-variable selecting method called "NN-based SS" for enhancing VM conjecture accuracy is proposed in this paper. An etching process of semiconductor manufacturing is selected as the illustrative example to test and compare the VM conjecture accuracy of the ER-based, MR-based SS, and NN-based SS methods. BPNN-I are adopted as the designated NN algorithm for creating the NN model of NN-based SS and MR-based SS and the VM conjecture models. Test results show that the NN models created by the selected variables of NN-based SS can achieve better VM conjecture accuracy than that of ER-based and MR-based SS. Besides, SRNN has also been tested and been proven to be able to achieve similar results as those of BPNN-I. Therefore, to enhance the VM conjecture accuracy, it is recommended to adopt the NN-based SS as the variable-selecting method for creating the NN-based VM conjecture models.

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