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Preliminary Study of an Intelligent Sampling Decision Scheme for the AVM System

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***Abstract*—Wafer inspection plays a significant role in monitoring the quality of production wafers. However, it requires measuring tools and additional cycle time to do real metrology, which is costly and time-consuming. Therefore, reducing sampling rate to as low as possible is a high priority for many factories to reduce production cost. The most common way for inspecting process quality is to apply periodic sampling. If a manufacturing process is stable, then virtual metrology (VM) may be applied for monitoring the quality of wafers while real metrology is unavailable. Nevertheless, if a production variation occurs between periodic samplings, no real metrology is available during this period for updating the VM models, which may result in un-reliable VM predictions. The authors have developed the automatic virtual metrology (AVM) system for various VM applications. Therefore, this paper focuses on applying various indices of the AVM system to develop an Intelligent Sampling Decision (ISD) scheme for reducing sampling rate while VM accuracy is still sustained.**

***Index Terms*—Automatic Virtual Metrology (AVM) System, Intelligent Sampling Decision (ISD) Scheme.**

I. Introduction

Production processes of semiconductor manufacturing are complicated and cost-intensive. Therefore, it is essential for manufacturers to maintain high quality and yield during wafer manufacturing processes by assuring process stabilities and production tools' health. To do so, most semiconductor manufacturers applied periodic sampling inspections of wafers in manufacturing processes to verify the acceptability of the process quality. The conventional method assumes that no abnormal circumstances will occur in the production processes other than those of regular periodic sampling wafers. If a process tool variation or a production fault appears during the period between samplings (as shown at t_{p14} of Fig. 1), then the abnormality will not be detected. This may result in large manufacturing loss due to the fact that many defected wafers may have been produced unconsciously.

To solve the problem mentioned above, the best solution is to monitor every single wafer in the production process for total inspection. However, total physical inspection requires more metrology tools, which lead to higher production cost and more cycle time. Thus, the other approach is here to apply virtual metrology (VM) [1].

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Applying VM in manufacturing process, sampling inspection with metrology delay can be converted into real-time and on-line total inspection [2]. Nevertheless, characteristics of process tools might change over time; therefore, scattered real measurements are still essential to update VM models and inspect product quality. Traditionally, only one or two wafers are sampled in a lot, which is also called a FOUP or cassette with maximally 25 wafers in it. As shown in Fig 1, nos. 2 and 25 wafers are sampled in a 25-wafers lot periodically. These sampled wafers are defined as metrology wafers and other wafers which have been processed but no measurement available are called process wafers. By applying this sampling strategy, if process-related status changes (such as preventive-maintenance (PM) operation, process-tool malfunction, recipe change, etc.) occur between samplings, it may cause an out-of-control (OOC) drift or shift of process quality as shown at t_{p14} in Fig. 1. Since there is no real measurement inspection to make sure whether the drift at t_{p14} does affect the quality of the product at t_{p14} or not, a miss detection of defect may occur unconsciously. On the other hand, if no status changes occur and the process tool is healthy and steady, it will be unnecessary to sample wafers that have the same characteristics for inspection and for updating the VM models. It is due to the fact that VM results in this case will be accurate enough to monitor process quality. In conclusion, the sampling rate can be reduced if no status changes and the process tool is healthy and steady.

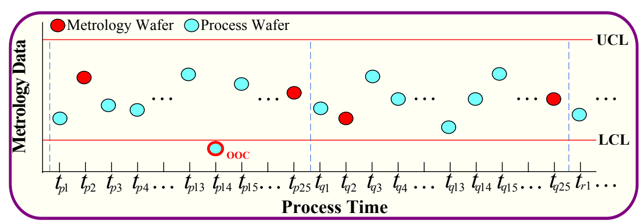

Fig. 1 Traditional Sampling Method
(Sample Two Wafers per Lot Periodically)

Previous work concerning sampling strategies is surveyed as follows. The most frequently used methods for determining when to sample are based on monitoring the variations of production states that contain process parameters and tool's health status. Holfeld *el al.* [4] pointed out it is necessary to increase sampling when encountering manufacturing disturbances that include external disruptions (e.g., tool maintenance, tool repair, or recipe adjustment) and internal disruptions (such as disruptions detected by sensor signals or metrology). Lee [5] and Munga *et al.* [6] brought up the concept of dynamic sampling to utilize a more effective inspection and to increase the throughput of inspection tools without affecting the production quality which may achieve the goal of cycle time reduction.

Furthermore, a study by Nduhura-Munga *et al.* [7] generalized sampling methods into three categories: static, adaptive, and dynamic samplings. Benefits and drawbacks of each category were discussed in [7], showing significant improvements from static to dynamic through adaptive sampling techniques. These sampling methods are to achieve the goal of using real inspections provided to monitor the whole production process and the sampled wafers are the representative for the other related ones. One example of adaptive sampling was proposed by Boussetta and Cross [8]. However, a drawback of adaptive sampling is that it only modifies the sampling rate based on the initial sampling plan. To tackle the problems that adaptive sampling encountered, dynamic sampling is a more advanced way of sampling which can select the best lot or wafer to measure depending on the states of production. However, dynamic sampling has some limitations. Nduhura-Munga *et al.* [7] hence suggested that the next step in development of sampling technique is the "predictive" sampling that selects a lot before it is actually available for sampling, e.g. lots being processed on production tools whose next step is metrology. Such "predictive" sampling strategies will require additional information on production flows [7].

Kurz *et al.* [9] proposed a "predictive" sampling decision system in semiconductor manufacturing using virtual metrology (VM). By Bayesian theorem with two-stage decision model and VM, expected value of measurement information is calculated by Monte Carlo integration to indicate process state and to decide which wafer to be measured in SDS [9]. Since proper sampling decisions strongly depend on the accuracy of the VM system, to enhance the usability of the SDS, Kurz *et al.* [10] further proposed several approaches for dynamically assessing VM reliability using real metrology data. However, in real-time and on-line operations, reliability of a VM value cannot be evaluated by applying its corresponding real-metrology one because if real metrology is available then this real-metrology value should be utilized directly and its corresponding VM value is redundant and useless [12].

The authors have developed the automatic virtual metrology (AVM) system [2] for various VM applications. However, the merits of the AVM system have not been totally shown in mass-production environments, yet. One of the merits is to reduce the sampling rate for decreasing the capex and cycle time such that the total production cost can be reduced. Therefore, the purpose of this paper is to develop an Intelligent Sampling Decision (ISD) scheme for reducing sampling rate while VM accuracy is still sustained by applying process data quality evaluation index (DQI_X) [11], global similarity index (GSI) [12], and metrology data quality evaluation index (DQI_y) [11] of the AVM system to monitor and assess the variations of process and metrology data as well as checking the occurrence of status changes that include preventive maintenance, tool repair, or recipe adjustment, etc.

The remainder of this paper is organized as follows. Section 2 details the ISD scheme. Section 3 then presents the illustrative example. Finally, summary and future work are stated in Section 4.

II. Intelligent Sampling Decision (ISD) Scheme

As mentioned previously, if no status-changes occur and the process tool is healthy and steady, the sampling rate may be reduced from the original setting. For example, two metrology wafers exist in a 25-wafers FOUP as shown in Fig. 1; this original sampling-rate setting may be reduced to one metrology wafer per FOUP (50% reduction, CASE 1/2) or further one metrology wafer for two FOUPs (75% reduction, CASE 1/4). When external and/or internal disruptions occur, real metrology should be added to update the VM models of the AVM system for maintaining the VM accuracy [2][3]. As such, the number of metrology wafers in a physical FOUP will not be fixed. To accommodate this variation, the concept of virtual cassette (VC) [13] will be adopted in ISD.

A VC is defined to contain many process wafers and one metrology wafer; those process and metrology wafers are produced by the same chamber. Moreover, a VC starts collecting process wafers that are processed by a specific chamber one by one and ends collecting until a metrology wafer of that same chamber has been obtained. As such, each VC may have various numbers of wafers depending on when metrology wafer is collected. By applying the VC, the advanced dual-phase VM algorithm can update dynamically and recalculate Phase-II VM value (VM_{II}), reliance index (RI), and GSI for all wafers in the same VC [3]. The total number of wafers in a VC is denoted as "m", which is the size of VC.

Before designing the ISD scheme, all the possible external and internal disruptions should be identified and defined. In this paper, external disruptions are called status changes while internal disruptions are detected by the DQI_X, GSI, and/or DQI_y indexes of the AVM system. As a result, the ISD scheme needs to consider five scenarios: stable process, status change, abnormal DQI_X, abnormal GSI, and abnormal DQI_y. These five scenarios are described below.

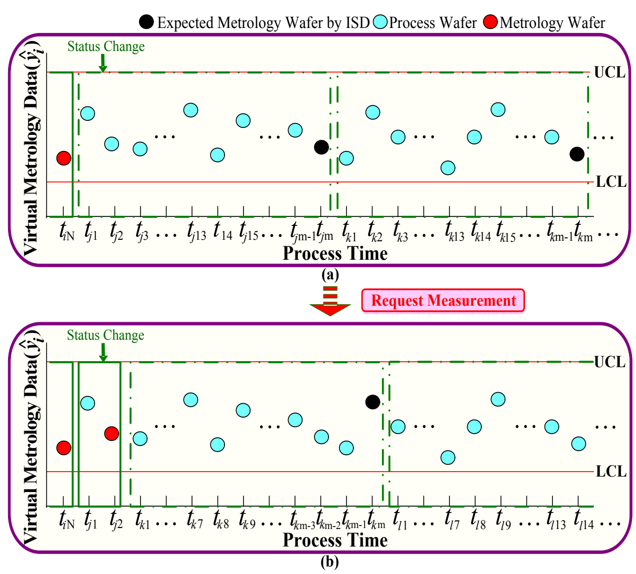

Fig. 2 Response of ISD When Status Change Occurs (a) Before Status Change, (b) After Status Change.
: The Confirmed VC, : The Expected VC.

Scenario 1: Stable Process

If no status-changes occur and all of the DQI_X, GSI, and DQI_y indexes are within their individual thresholds in a manufacturing process, then this process is stable. In general, the VM models need not to be updated under a stable process. Therefore, the default setting of ISD is to have a wafer measurement for each N wafers produced, where N can be assigned as large as possible. In this scenario, the size of VC, m, equals to N. As shown in Fig. 2 (a), wafers processed on t_{im}, t_{jm}, and t_{km} are scheduled to be sampled; therefore, if the manufacturing process remains steady, these wafers will become t_{iN}, t_{jN}, and t_{kN}, respectively and be requested by ISD to have real metrology for inspection and tuning/retraining of VM models.

Scenario 2: Status Change

A possible status change may occur when either tool maintenance, tool repair, or recipe adjustment is performed. Observing Fig. 2, when a status change happens between t_{j1} and t_{j2}, then ISD will request a real measurement for the wafer processed on t_{j2} to update VM models. The VC_j, which t_{j2} is in, also changes dynamically from N wafers in the cassette, as shown in Fig. 2 (a), to only 2 wafers as in Fig. 2 (b). Furthermore, the next expected metrology wafer changes from the wafer processed on t_{jm} in Fig. 2 (a) to t_{km} in Fig. 2 (b).

Scenario 3: Abnormal DQI_X

The function of DQI_X is to check the quality of process data [11]. To prevent abnormal process data from deteriorating VM models, the wafer with abnormal DQI_X value should not be selected for measurement; in other words, this wafer's measurement will be skipped. Two cases of DQI_X abnormality may be encountered as described below.

(1) If the wafer with abnormal DQI_X is simply a process wafer, then no real measurement will be performed; while this abnormal event will be recorded and a corresponding alarm will be sent.

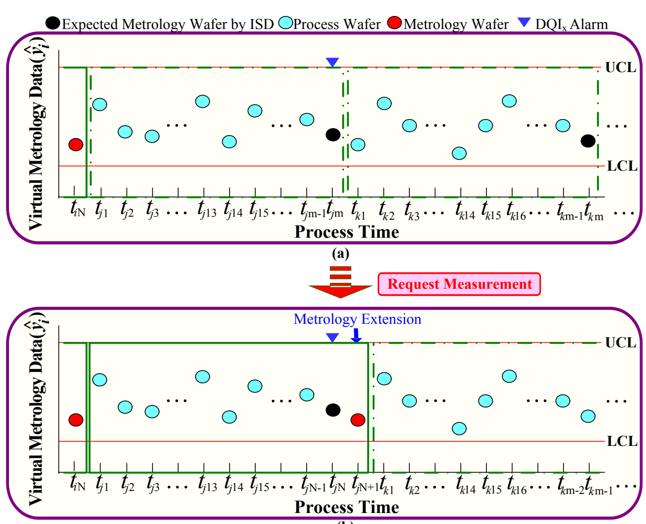

Fig. 3 Response of ISD When Abnormal DQI_X Appears on Expected Metrology Wafer
(a) Abnormal DQI_X on Expected Metrology Wafer,
(b) Extension of Metrology Due to DQI_X Abnormality.

(2) On the other hand, if the abnormal-DQI_X wafer is originally scheduled to be measured, which is also called an expected metrology wafer, measurement for this wafer shouldn't be performed. Instead, the request for measurement should be changed to the next wafer. As shown in Fig. 3 (a), wafer processed on t_{jm} is reported as DQI_X abnormal; therefore, the scheduled measurement is then changed from t_{jN} to t_{jN+1} in Fig. 3 (b). Since wafer processed on t_{jN+1} in Fig. 3 (b) has normal value of DQI_X, it will be the metrology wafer in VC_j. This will result in having (N+1) wafers in VC_j.

Scenario 4: Abnormal GSI

The purpose of GSI is to evaluate deviations of process data [12]. A process-data deviation of a wafer may result in a deviation of its corresponding metrology datum. As such, this process wafer needs to be inspected. However, if a GSI alarm just happens once, then this may be a false alarm generated by noise. To confirm that a real deviation is detected, at least two consecutive GSI alarms should be alerted. In general, when deviation (i.e. shift or drift) of process data occurs, it will sustain and the corresponding GSI alarms will be on continuously until the cause of the deviation is fixed. Therefore, to prevent ISD from sending measurement requests endlessly, it is necessarily to set a breakpoint. Considering the above factors, ISD is designed to request additional measurements when GSI abnormalities are accumulated to merely 2 and 4. As shown in Fig. 4 (a), the AVM system keeps sending out GSI alarms from t_{jN-9} to t_{jN-5}, then ISD will request additional metrology investigations on the 2nd and 4th abnormal wafers processed at t_{jN-8} and t_{jN-6}, respectively. After the measurement operations of these two wafers, the corresponding VC_j and VC_k will dynamically be changed to the ones shown in Fig. 4 (b).

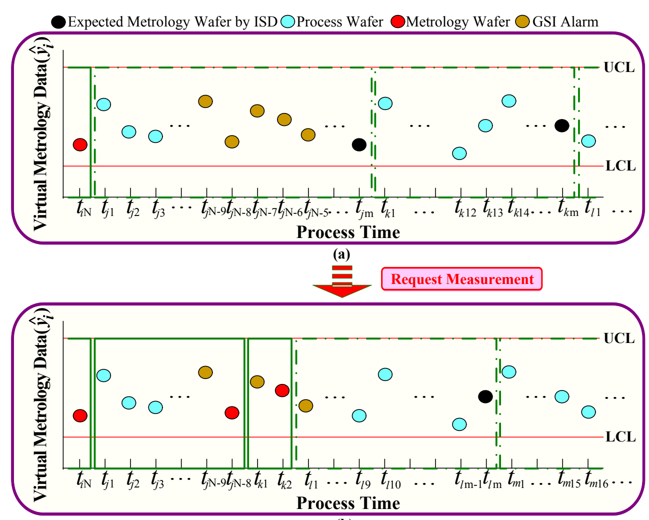

Fig. 4 Response of ISD When Detecting Continuous GSI Alarms
(a) Five Wafers in Abnormal GSI Sequence,
(b) Additional Measurements for the 2nd and 4th Wafers in the Abnormal GSI Sequence.

Scenario 5: Abnormal DQI_y

After receiving metrology data, the AVM system can then check DQI_y for evaluating the quality of metrology data [11]. If the quality is not good, this metrology data cannot be used for updating VM models. Instead, another measurement should be requested immediately after the DQI_y alarm is issued. Such as in Fig. 5(a), the wafer processed at t_{jm} receives its real metrology with abnormal DQI_y at process time t_{k13}. Therefore, another measurement is needed on t_{k13} which will force the VC_j from having N wafers to N+13 wafers as depicted in 5(b) if this certain wafer's DQI_y value at t_{N+13} is normal. After describing the five scenarios, the operational flowchart of the ISD scheme can then be designed.

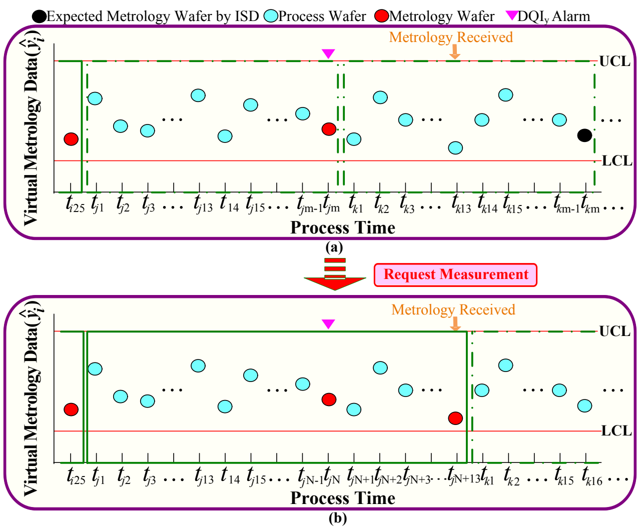

Fig. 5 Response of ISD When Receiving Abnormal DQI_y
(a) Abnormal DQI_y Detected on the Received Metrology Value, (b) Additional Measurement Requested and Received.

2.1 Operational Flowchart of the ISD Scheme

Before starting to design the operational flowchart of the ISD scheme, two parameters, M and N, need to be defined: M is the original static sampling count for request measurement; while N is the desired sampling count for request measurement when sampling-rate reduction is considered. The flowchart of the ISD scheme for taking care of Scenarios 1-4 is shown in Fig. 6 and is explained as follows.

Step 1. When the time difference of process-activation between the previous and current process wafers exceeds one day, then the current process wafer is considered as the first wafer after idling. And if so, then it needs to request measurement (Step 8-2) so the VM models can be updated.

Step 2. Increase Sampling Count by one whenever the ISD scheme is triggered.

Step 3. To prevent ISD from sending request of measurement for a long period of time due to consecutive DQI_X abnormal events, a maximal tolerable number (N+5) of wafers without measurements in a row should be defined. As such, when Sampling Count is greater than or equal to N+5, it will jump to Step 8-2 to request measurement. However, if Sampling Count has not reached this threshold, it will go to Step 4.

Step 4. A status change may cause a shift or drift in the manufacturing process when comparing with normal historical data in the VM models. The process wafer immediately after each status change therefore is essential to request measurement for inspection, that is, Step 8-2.

Step 5. If a wafer has bad DQI_X value, then a warning will be sent to process engineer and execute Step 8-1 to skip measurement.

Step 6. Whenever the Sampling Count is equal to or greater than N, which means the current process wafer is either the one expected to be measured or the previous wafer with DQI_X abnormality, the procedure will go to Step 8-2 to request measurement. On the contrary, Step 7-1 will be performed if the Sampling Count is less than N.

Step 7-1. If the process data of the current process wafer is not similar with the historical process data, namely abnormal GSI occur, then the next decision in Step 7-2 will be made.

Step 7-2. From Step 7-1, the judgment of GSI abnormality is taken into account. The next step is to check whether it is the 2nd or 4th wafer in the abnormal GSI sequence or not. If the answer is yes, then execute Step 8-2 to request measurement, else jump to Step 8-1 to skip measurement. The rationale of Steps 7-1 and 7-2 is explained in Scenario 4: Abnormal GSI.

Step 8-1. Simply let the process wafer to skip measurement.

Step 8-2. To request measurement for this current process wafer such that it becomes a metrology wafer. At the same time, Sampling Count is reset to zero.

Eventually, the ISD scheme should be integrated into the advanced dual-phase algorithm of the AVM system [2]. This integration is explained below.

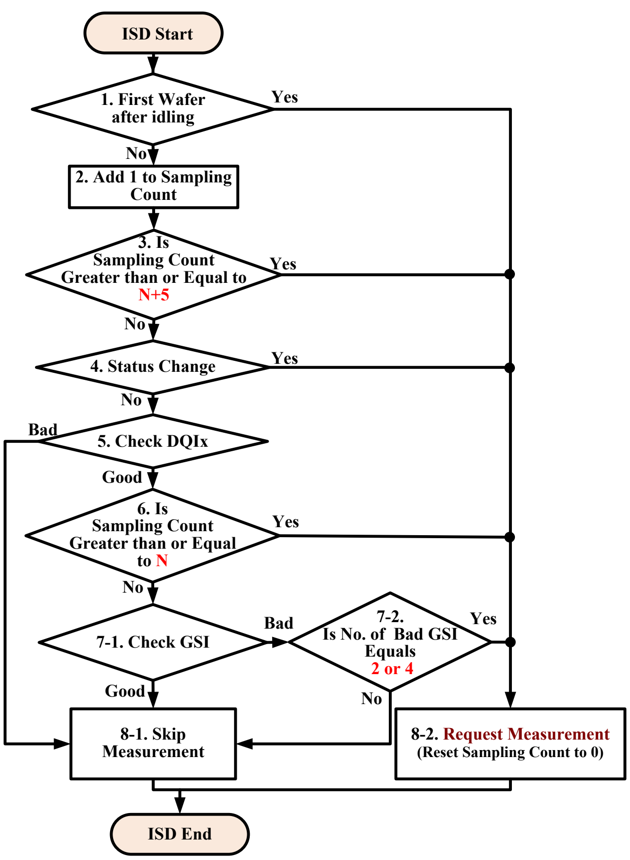

Fig. 6 Operational Flowchart of the Intelligent Sampling Decision (ISD) Scheme.

2.2 Advanced Dual-Phase Algorithm with ISD Scheme

The inclusion of the ISD scheme into the advanced dual-phase algorithm [2] is shown in Fig. 7. The ISD scheme is embedded at the bottom of the right-hand side of Fig. 7 to become the last operation of the Phase-I algorithm. After finishing all the original Phase-I operations, the ISD scheme is applied to decide whether this process wafer should request measurement or not.

Observing the left-hand side of Fig. 7, the operation: "Request Next Process Wafer Measurement" is also inserted into the Phase-II loop of the advanced dual-phase algorithm after detecting a DQI_y abnormality. This measurement request is enforced by setting the Sampling Count to N. In other words, when a DQI_y abnormality occurs, the Sampling Count is set to N. This action enforces the current process wafer in ISD to be measured for compensating the loss that the original DQI_y abnormal wafer cannot be utilized to update VM models. The rationale of the above description is explained in Scenario 5: Abnormal DQI_y.

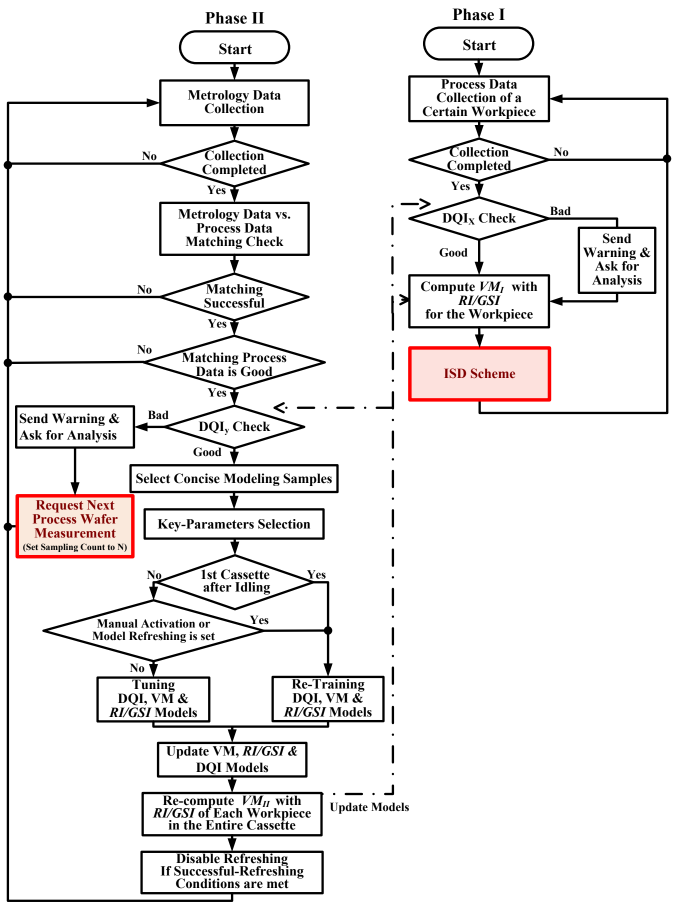

Fig. 7 Advanced Dual-Phase Algorithm with ISD Scheme.

III. ILLUSTRATIVE EXAMPLE

An emulated example of reducing the sampling rate to 1/2 and 1/4 of the original setting using paired data of process and metrology values of 180 wafers from a plasma-enhanced chemical vapor deposition (PECVD) process in a semiconductor foundry in Taiwan was setup. With the test data being paired up, M is set to be 1. To reach the goal of reducing sampling rate to 1/2 and 1/4, N in the ISD scheme should be set to 2 and 4, respectively. For the case of 1/4 and under the condition of no external or internal disruptions, only 1 out of 4 wafers will be sampled for measurement and updating the VM models, the real metrology values of the rest 3/4 wafers will only be used for evaluating the prediction accuracy.

The spread-out results of running numbers 41-120 of this emulated example are shown in Fig. 8. Those wafers which have been sampled and used for updating VM models are called tuning samples, while the others are called measurements samples. Observing running nos. 41-84 in Fig. 8, it shows that only 1 out of 4 original samples is selected for updating the VM models because the manufacturing process is stable. However, a maintenance operation causing status change appears in the time period between running number 84 and 85. Then, the ISD acknowledges it and immediately sends a measurement request at running number 85 for updating the VM models. This action is indicated as a red triangle at running number 85 in Fig. 8. Moreover, another abnormal events caused by GSI and DQI_y examinations happened on running number 100. After the detection of two consecutive GSI alarms (GSI values < GSI threshold as shown at the bottom of Fig. 8), running number 100 is then requested to be measured, which is indicated as an inverted red triangle in Fig. 8. After obtaining the metrology value of running number 100, the AVM system detects that its DQI_y value is abnormal.

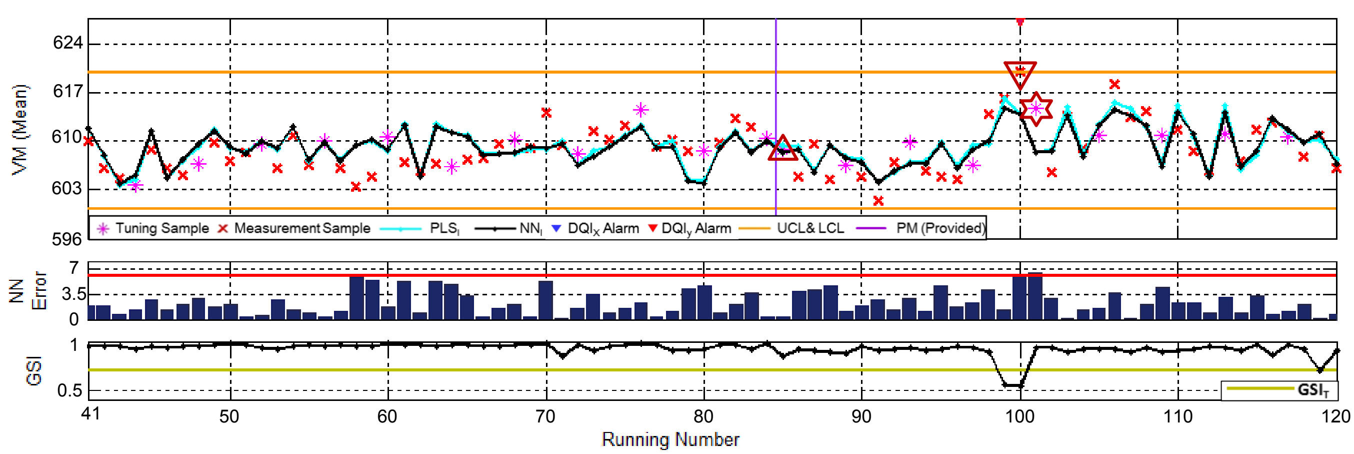

Fig. 8 Example of Sampling Rate Reduction to 1/4 using ISD Scheme

Therefore, additional measurement is requested at running number 101, as indicated in red star in Fig. 8, to make up for the loss of running number 100 that cannot be used to update VM models. After running number 101, again, only 1 out of 4 original samples is selected for updating the VM models because the stability of the manufacturing process is resumed.

Table I shows the accuracy comparison of sampling rate reduction from the original setting (1/1) to 1/2 and 1/4 of the original setting using the ISD scheme with those 180 test wafers. As shown in Table I, the mean absolute percentage errors (MAPEs) and 95% maximal errors (MaxErr) of the original (1/1), ISD (1/2), and ISD (1/4) cases are almost identical for both the Phase-I neural-network (NN_I) and Phase-I partial least square (PLS_I) VM results, where NN and PLS are two prediction algorithms utilized by the AVM system.

Table I Accuracy Comparison of Sampling Rate Reduction using ISD Scheme

Sampling Rate		MAPE (%)		95% MaxErr (%)	
		NN_I	PLS_I	NN_I	PLS_I
Original	1/1	0.41	0.42	0.86	0.81
ISD	1/2	0.40	0.40	0.87	0.90
ISD	1/4	0.40	0.41	0.88	0.91

In conclusion, ISD provides a way to reduce sampling rate by dynamically determining the need to request measurement for the current process wafer. If no external or internal disruptions happen in the manufacturing process, then the sampling rate can be reduced to a preferred level. On the other hand, if any change or disruption occurs in the manufacturing process, additional measurements can be requested. These additional measurements are then used for updating VM models and inspecting product quality. As a result, ISD can not only reduce sampling rate, but also keep VM accuracy at an acceptable level which is able to provide qualified total inspection for various applications.

IV. Summary and Conclusions

The proposed ISD scheme can reduce sampling rate whenever a manufacturing process and process tool are stable. On the other hand, with external and/or internal disruptions appear in the manufacturing environment, the ISD scheme will request additional measurements to update the VM models for maintaining the VM accuracy. Based on the example of a PECVD process in a foundry, the ISD scheme has been proven to be a powerful algorithm that can reduce the sampling rate to one fourth of the original setting and remain similar VM accuracy simultaneously. By sampling rate reduction, the capex and process cycle time of the metrology tools can be decreased proportionally such that the total production cost can be lowered. However, the settings, such as N or M, in ISD are set manually in this paper. How to create these settings automatically and optimally for easy ISD implementation would be the future work.

Acknowledgment

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