US 20160342147A1

(19) United States

(12) Patent Application Publication (10) Pub. No.: US 2016/0342147 A1

Iskandar et al. (43) Pub. Date: Nov. 24, 2016

(54) METHODS AND SYSTEMS FOR APPLYING RUN-TO-RUN CONTROL AND VIRTUAL METROLOGY TO REDUCE EQUIPMENT RECOVERY TIME

(71) Applicant: **Applied Materials, Inc.**, Santa Clara, CA (US)

(72) Inventors: **Jimmy Iskandar**, Fremont, CA (US); **Jianping Zou**, Austin, TX (US); **Parris C.M. Hawkins**, Los Altos, CA (US); **James Moyne**, Canton, MI (US)

(21) Appl. No.: **14/716,838**

(22) Filed: **May 19, 2015**

Publication Classification

(51) **Int. Cl.**

G05B 19/402 (2006.01)

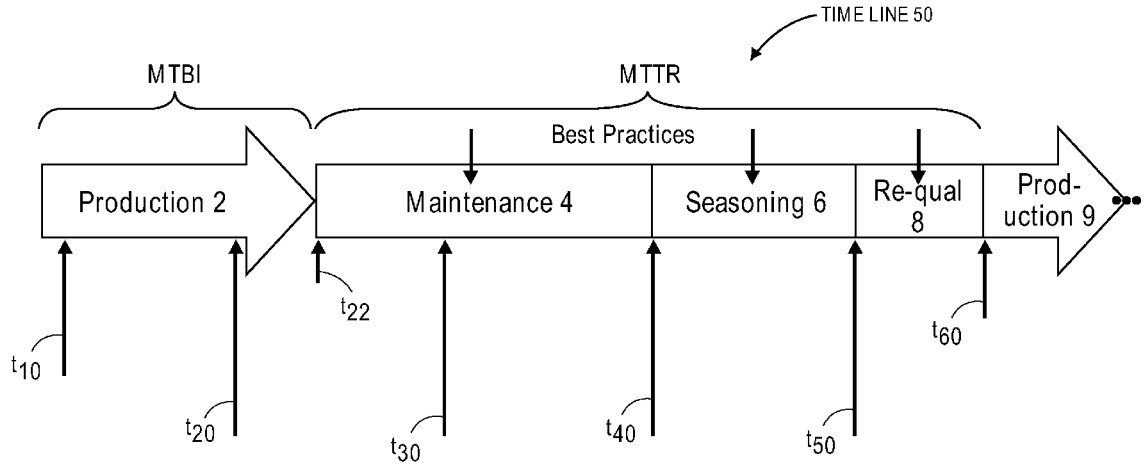
G05B 19/404 (2006.01)

(52) **U.S. Cl.**

CPC ***G05B 19/402*** (2013.01); ***G05B 19/404*** (2013.01); *G05B 2219/40164* (2013.01)

(57) **ABSTRACT**

Described herein are methods, apparatuses, and systems for reducing equipment repair time. In one embodiment, a computer implemented method includes collecting, with a system, data including test substrate data or other metrology data and fault detection data for maintenance recovery of at least one manufacturing tool in a manufacturing facility and determining, with the system, a relationship between tool parameter settings for the at least one manufacturing tool and at least some collected data including the test substrate data. The method further includes utilizing zero or more virtual metrology predictive algorithms and at least some collected data to obtain a metrology prediction and applying multivariate run-to-run (R2R) control modeling to obtain a state estimation including a current operating region of the at least one manufacturing tool based on the test substrate data and obtain at least one tool parameter adjustment for at least one target parameter for the at least one manufacturing tool. Applying multivariate run-to-run (R2R) control modeling to obtain tool parameter adjustments for at least one manufacturing tool occurs after maintenance to reduce maintenance recovery time and to reduce requalification time.



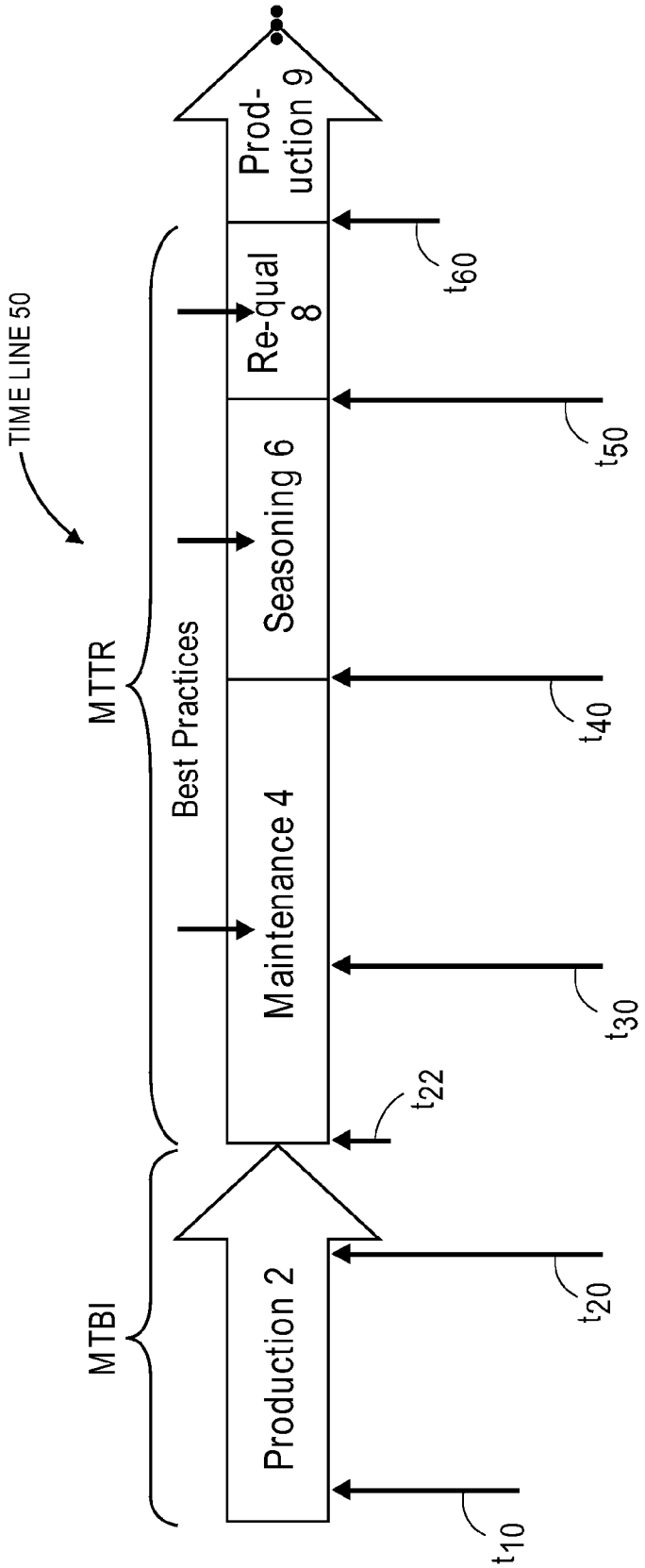

TIME LINE 50
MTBI
MTTR
Best Practices
Production 2
Maintenance 4
Seasoning 6
Re-qual 8
Prod-uction 9
t10
t20
t22
t30
t40
t50
t60

FIG. 1

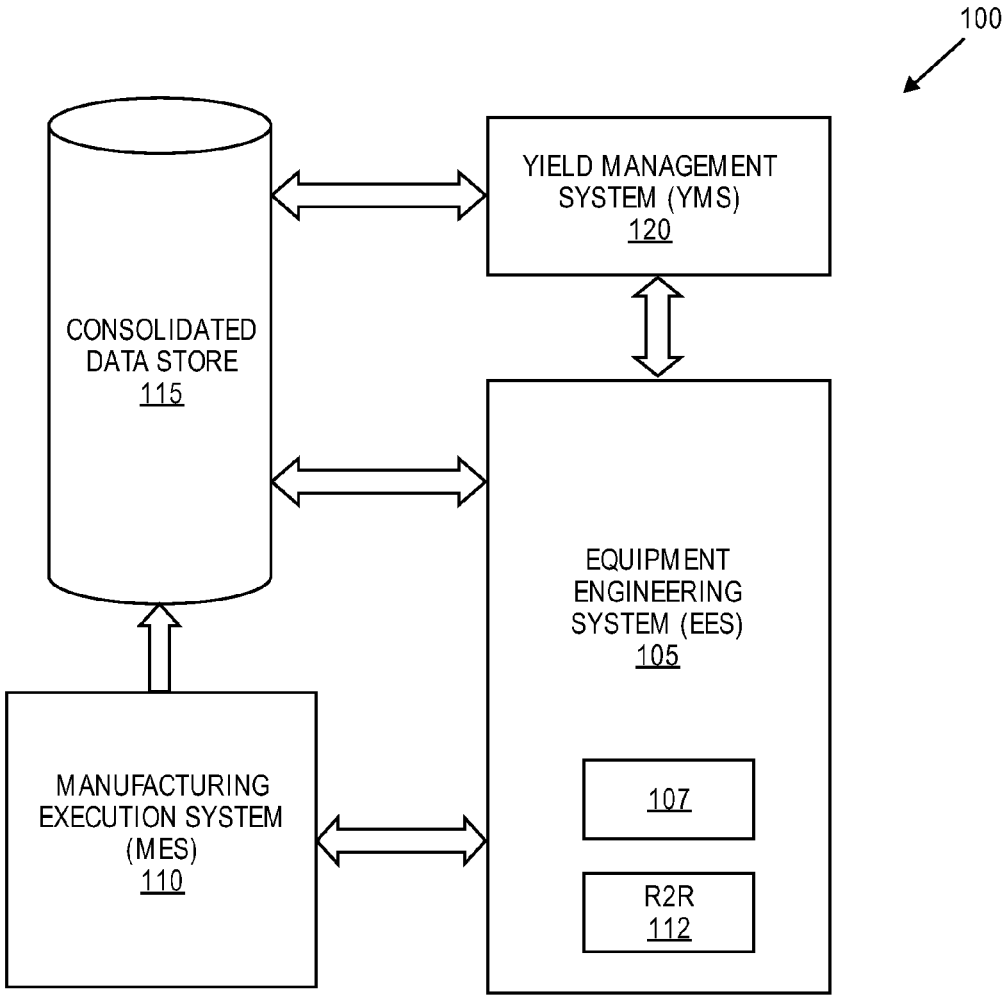

100
CONSOLIDATED DATA STORE 115
YIELD MANAGEMENT SYSTEM (YMS) 120
EQUIPMENT ENGINEERING SYSTEM (EES) 105
107
R2R 112
MANUFACTURING EXECUTION SYSTEM (MES) 110

FIG. 2

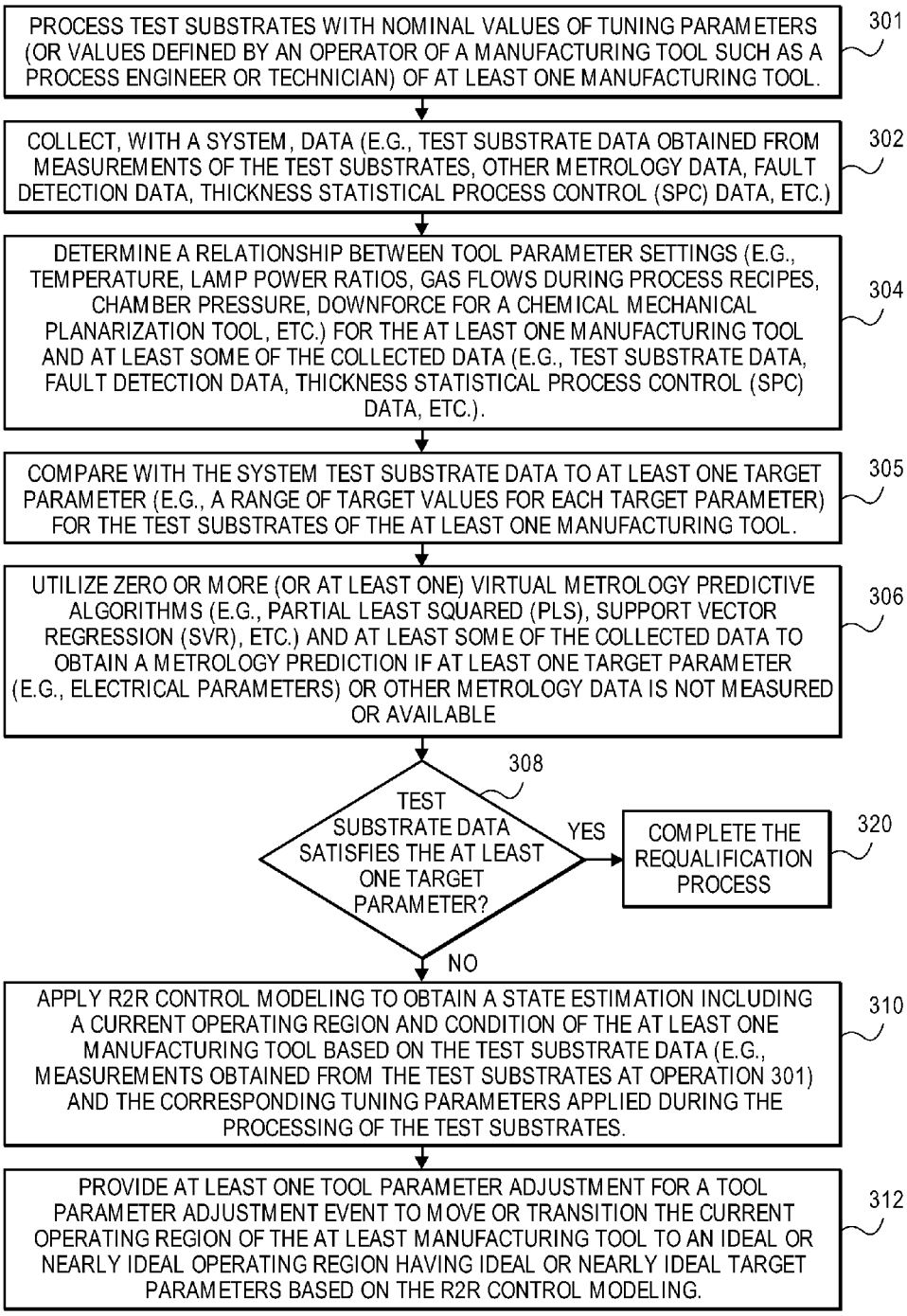

PROCESS TEST SUBSTRATES WITH NOMINAL VALUES OF TUNING PARAMETERS (OR VALUES DEFINED BY AN OPERATOR OF A MANUFACTURING TOOL SUCH AS A PROCESS ENGINEER OR TECHNICIAN) OF AT LEAST ONE MANUFACTURING TOOL.
301
COLLECT, WITH A SYSTEM, DATA (E.G., TEST SUBSTRATE DATA OBTAINED FROM MEASUREMENTS OF THE TEST SUBSTRATES, OTHER METROLOGY DATA, FAULT DETECTION DATA, THICKNESS STATISTICAL PROCESS CONTROL (SPC) DATA, ETC.)
302
DETERMINE A RELATIONSHIP BETWEEN TOOL PARAMETER SETTINGS (E.G., TEMPERATURE, LAMP POWER RATIOS, GAS FLOWS DURING PROCESS RECIPES, CHAMBER PRESSURE, DOWNFORCE FOR A CHEMICAL MECHANICAL PLANARIZATION TOOL, ETC.) FOR THE AT LEAST ONE MANUFACTURING TOOL AND AT LEAST SOME OF THE COLLECTED DATA (E.G., TEST SUBSTRATE DATA, FAULT DETECTION DATA, THICKNESS STATISTICAL PROCESS CONTROL (SPC) DATA, ETC.).
304
COMPARE WITH THE SYSTEM TEST SUBSTRATE DATA TO AT LEAST ONE TARGET PARAMETER (E.G., A RANGE OF TARGET VALUES FOR EACH TARGET PARAMETER) FOR THE TEST SUBSTRATES OF THE AT LEAST ONE MANUFACTURING TOOL.
305
UTILIZE ZERO OR MORE (OR AT LEAST ONE) VIRTUAL METROLOGY PREDICTIVE ALGORITHMS (E.G., PARTIAL LEAST SQUARED (PLS), SUPPORT VECTOR REGRESSION (SVR), ETC.) AND AT LEAST SOME OF THE COLLECTED DATA TO OBTAIN A METROLOGY PREDICTION IF AT LEAST ONE TARGET PARAMETER (E.G., ELECTRICAL PARAMETERS) OR OTHER METROLOGY DATA IS NOT MEASURED OR AVAILABLE
306
308
TEST SUBSTRATE DATA SATISFIES THE AT LEAST ONE TARGET PARAMETER?
YES
COMPLETE THE REQUALIFICATION PROCESS
320
NO
APPLY R2R CONTROL MODELING TO OBTAIN A STATE ESTIMATION INCLUDING A CURRENT OPERATING REGION AND CONDITION OF THE AT LEAST ONE MANUFACTURING TOOL BASED ON THE TEST SUBSTRATE DATA (E.G., MEASUREMENTS OBTAINED FROM THE TEST SUBSTRATES AT OPERATION 301) AND THE CORRESPONDING TUNING PARAMETERS APPLIED DURING THE PROCESSING OF THE TEST SUBSTRATES.
310
PROVIDE AT LEAST ONE TOOL PARAMETER ADJUSTMENT FOR A TOOL PARAMETER ADJUSTMENT EVENT TO MOVE OR TRANSITION THE CURRENT OPERATING REGION OF THE AT LEAST MANUFACTURING TOOL TO AN IDEAL OR NEARLY IDEAL OPERATING REGION HAVING IDEAL OR NEARLY IDEAL TARGET PARAMETERS BASED ON THE R2R CONTROL MODELING.
312

FIG. 3

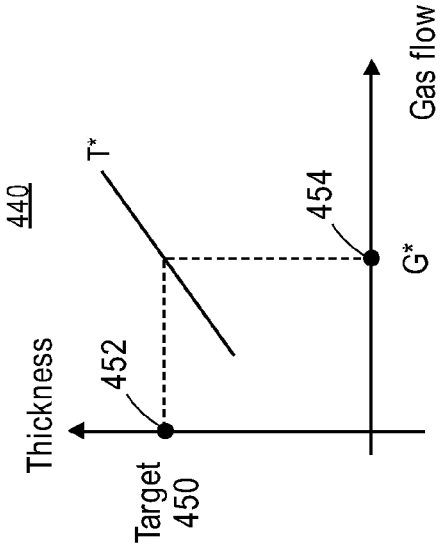


FIG. 4C

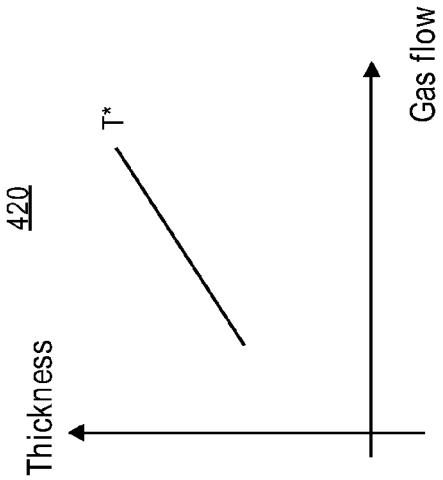


FIG. 4B

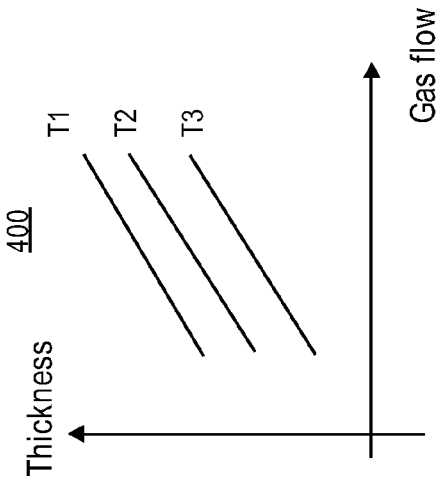


FIG. 4A

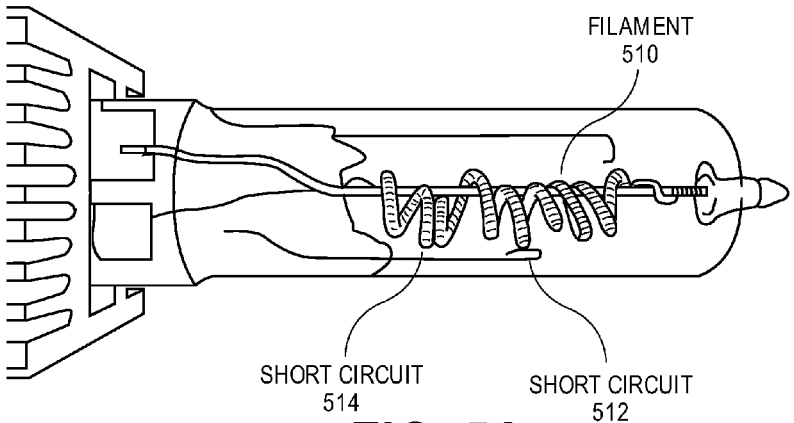


FIG. 5A

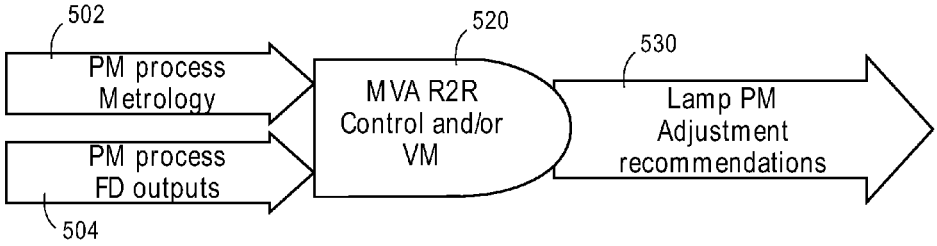


FIG. 5B

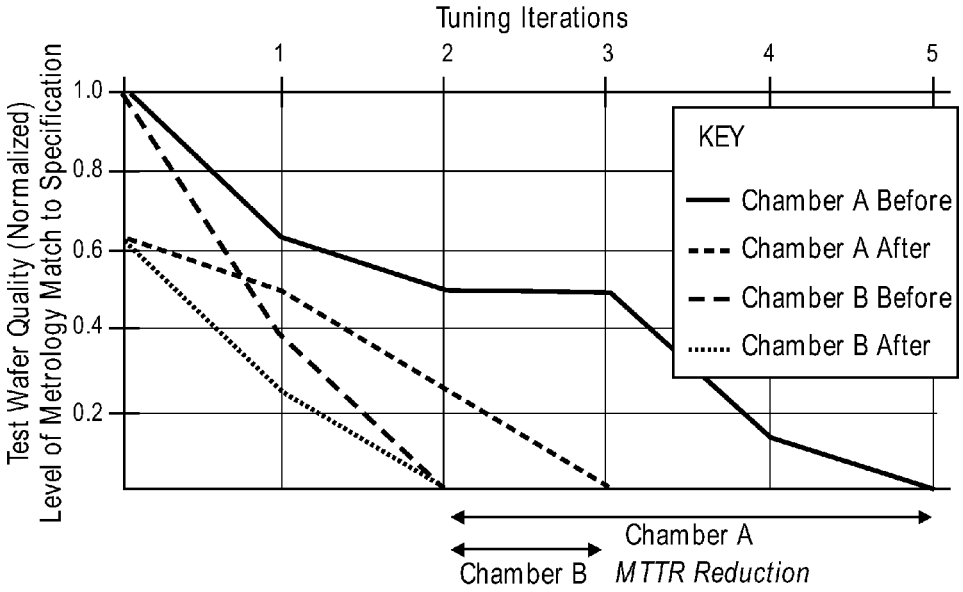


FIG. 6

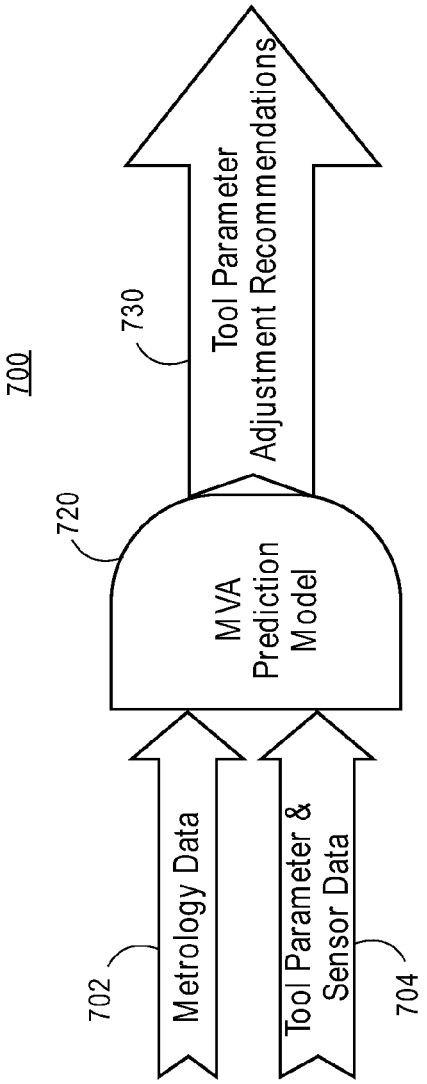

700
730
Tool Parameter Adjustment Recommendations
720
MVA Prediction Model
Metrology Data
Tool Parameter & Sensor Data
702
704

FIG. 7

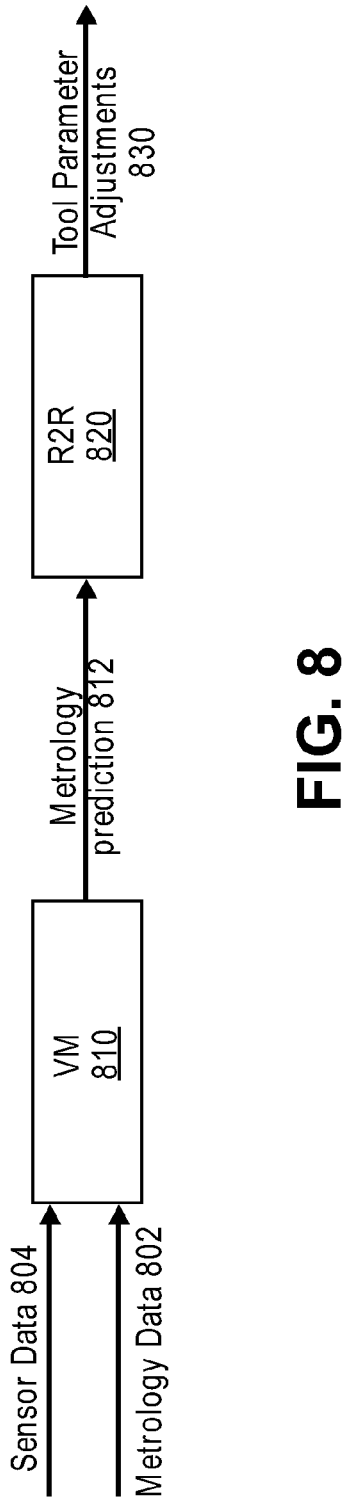

800
Tool Parameter Adjustments 830
R2R 820
Metrology prediction 812
VM 810
Sensor Data 804
Metrology Data 802

FIG. 8

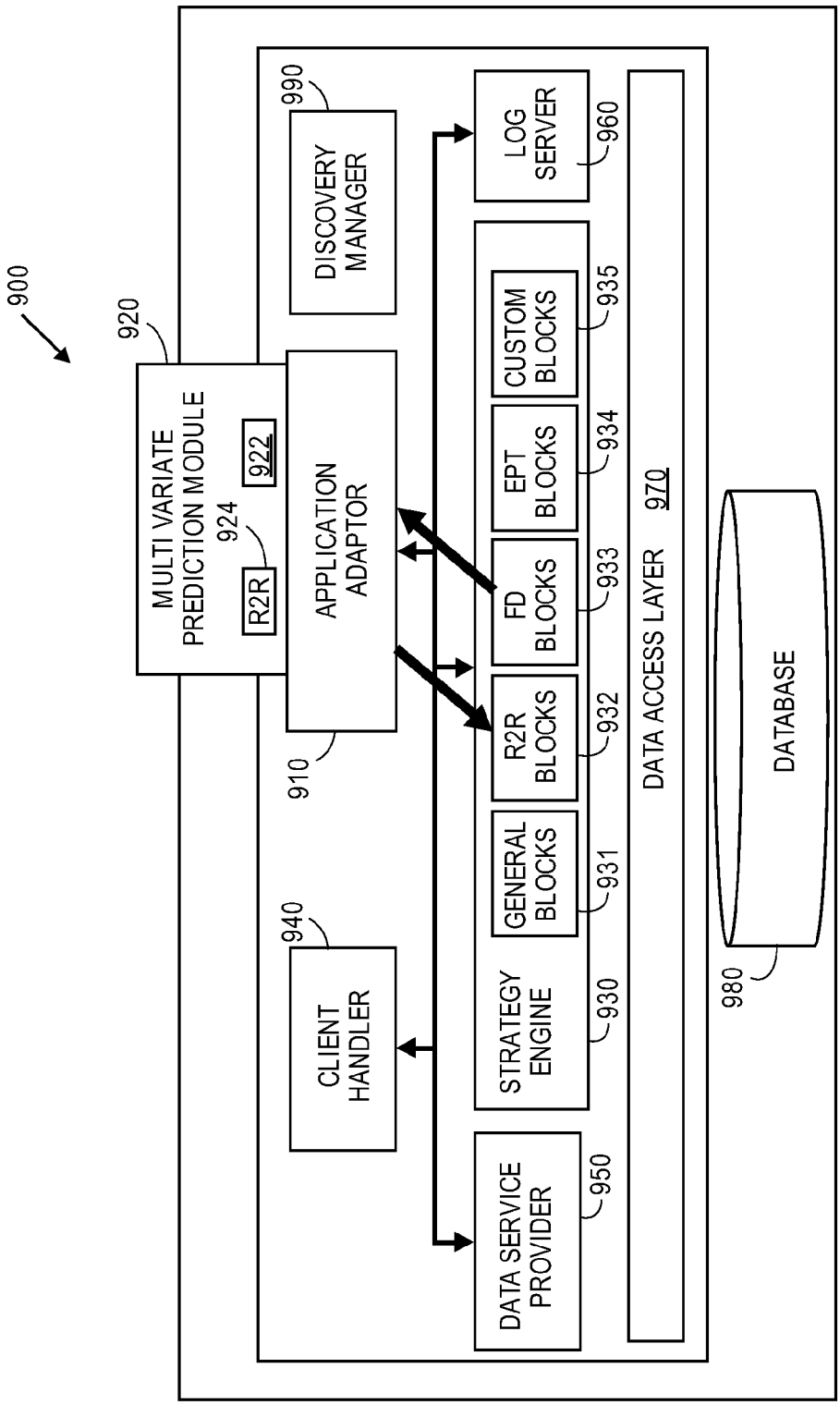

900
920
MULTI VARIATE PREDICTION MODULE
922
924
R2R
APPLICATION ADAPTOR
910
990
DISCOVERY MANAGER
940
CLIENT HANDLER
950
DATA SERVICE PROVIDER
930
STRATEGY ENGINE
931
GENERAL BLOCKS
932
R2R BLOCKS
933
FD BLOCKS
934
EPT BLOCKS
935
CUSTOM BLOCKS
960
LOG SERVER
970
DATA ACCESS LAYER
980
DATABASE

FIG. 9

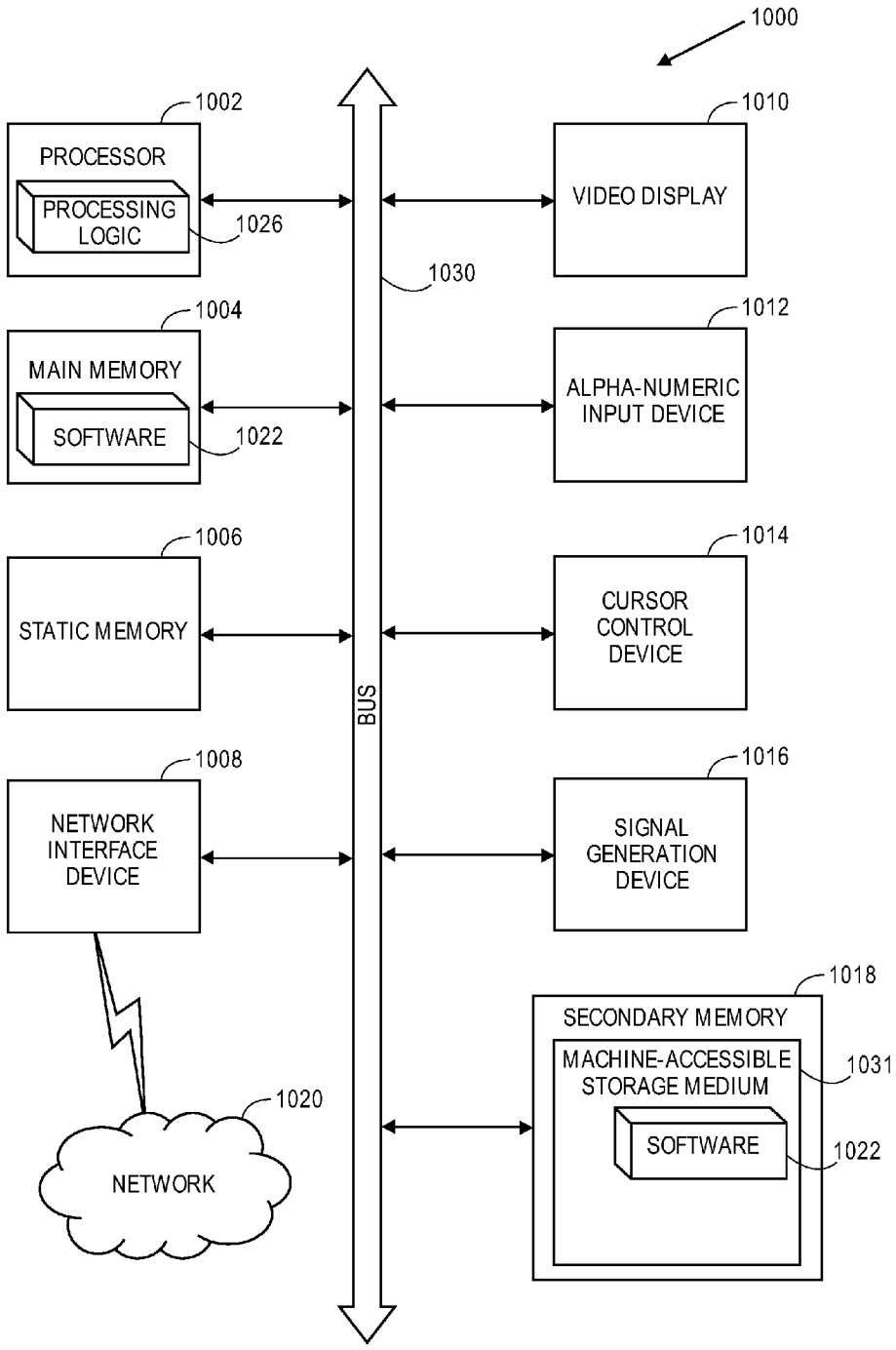

1000
1002
PROCESSOR
PROCESSING LOGIC
1026
1004
MAIN MEMORY
SOFTWARE
1022
1006
STATIC MEMORY
1008
NETWORK INTERFACE DEVICE
1020
NETWORK
BUS
1030
1010
VIDEO DISPLAY
1012
ALPHA-NUMERIC INPUT DEVICE
1014
CURSOR CONTROL DEVICE
1016
SIGNAL GENERATION DEVICE
1018
SECONDARY MEMORY
MACHINE-ACCESSIBLE STORAGE MEDIUM
1031
SOFTWARE
1022

FIG. 10

METHODS AND SYSTEMS FOR APPLYING RUN-TO-RUN CONTROL AND VIRTUAL METROLOGY TO REDUCE EQUIPMENT RECOVERY TIME

TECHNICAL FIELD

[0001] Embodiments of the present invention relate to methods and systems for applying run-to-run control and virtual metrology to reduce equipment recovery time including mean-time-to-repair (MTTR) for equipment and components.

BACKGROUND

[0002] In manufacturing there are a number of processes where maintenance is a requirement either at specific intervals or in response to an event such as a broken component or low quality production. Following the maintenance there is often a process that is executed whereby the equipment is "requalified" to a certain state such as "ready to return to production". This requalification can be a long and iterative process whereby process and equipment parameters are adjusted or "tuned". After a tuning iteration the equipment is evaluated, e.g., by producing a test product and then measuring the quality of the test product. If the evaluation indicates that the equipment or process has not met certain criteria another tuning iteration is conducted. This iterative process is often manual, and even if partially automated, is often addressed in a univariate adhoc fashion where a few of the total set of parameters are tuned at each iteration. The time taken for these tuning iterations is considered to be part of the mean-time-to-repair (MTTR) for the equipment.

SUMMARY

[0003] Described herein are methods, apparatuses, and systems for reducing equipment repair time. In one embodiment, a computer implemented method includes collecting, with a system, data including test substrate data or other metrology data and fault detection data for maintenance recovery of at least one manufacturing tool in a manufacturing facility and determining, with the system, a relationship between tool parameter settings for the at least one manufacturing tool and at least some collected data including the test substrate data. The method further includes utilizing zero or more virtual metrology predictive algorithms and at least some collected data to obtain a metrology prediction and applying multivariate run-to-run (R2R) control modeling to obtain a state estimation including a current operating region of the at least one manufacturing tool based on the test substrate data and obtain at least one tool parameter adjustment for at least one target parameter for the at least one manufacturing tool. Applying multivariate run-to-run (R2R) control modeling to obtain tool parameter adjustments for at least one manufacturing tool occurs after maintenance to reduce maintenance recovery time and to reduce requalification time.

[0004] In another embodiment, a computer system includes a memory to store one or more sets of instructions and a processor that is coupled to the memory. The processor is configured to execute instructions to collect data including test substrate data or metrology data and fault detection data for maintenance recovery of at least one manufacturing tool in a manufacturing facility, determine a relationship between tool parameter settings for the at least one manufacturing tool and at least some collected data including the test substrate data. The method further includes utilizing zero or more virtual metrology predictive algorithms and at least some collected data to obtain a metrology prediction and applying multivariate run-to-run (R2R) control modeling to obtain a state estimation including a current operating region of the at least one manufacturing tool based on the test substrate data and obtain at least one tool parameter adjustment for at least one target parameter for the at least one manufacturing tool.

BRIEF DESCRIPTION OF THE DRAWINGS

[0005] The present invention is illustrated by way of example, and not by way of limitation, in the figures of the accompanying drawings and in which:

[0006] FIG. **1** is a time line of a maintenance recovery process in accordance with one embodiment;

[0007] FIG. **2** illustrates an exemplary architecture of a manufacturing environment **100** for reducing maintenance time (e.g., MTTR) in accordance with one embodiment;

[0008] FIG. **3** illustrates a flow diagram of one embodiment for a computer implemented method of multivariate analysis utilizing run-to-run control and virtual metrology to reduce MTTR and improve G2G time during post preventative maintenance (PM) recovery;

[0009] FIG. **4**A illustrates a plot **400** of thickness versus gas flow for different temperatures of a deposition tool in accordance with one embodiment;

[0010] FIG. **4**B illustrates a plot **420** of thickness versus gas flow for a specific temperature T* of a deposition tool at post PM in accordance with one embodiment;

[0011] FIG. **4**C illustrates a plot **440** of thickness versus gas flow for a temperature T* of a deposition tool in accordance with one embodiment, and finding the recommended gas flow for a desired thickness target;

[0012] FIG. **5**A illustrates lamp failure modes in accordance with one embodiment;

[0013] FIG. **5**B illustrates a diagram in which multivariate R2R control with VM is applied in accordance with one embodiment;

[0014] FIG. **6** illustrates a diagram in which multivariate R2R and VM models are applied during maintenance recovery in accordance with one embodiment;

[0015] FIG. **7** illustrates a diagram in which multivariate R2R control with VM is applied in accordance with one embodiment;

[0016] FIG. **8** illustrates a diagram in which multivariate R2R control with VM is applied in accordance with one embodiment;

[0017] FIG. **9** illustrates an exemplary architecture of a system (e.g., an equipment engineering system (EES)), in accordance with one embodiment; and

[0018] FIG. **10** illustrates a block diagram of an exemplary computer system, in accordance with one embodiment of the present invention.

DETAILED DESCRIPTION

[0019] Described herein are methods, apparatuses, and systems for multivariate analysis utilizing run-to-run control and virtual metrology to reduce MTTR during post preventative maintenance (PM) recovery. In some embodiments, systems and methods for reducing the time for tuning iterations (e.g., by reducing the needed number of iterations)

results in reduced MTTR and reduced green-to-green (G2G) time (i.e., the time between production-worthy states). Embodiments of this invention reduce the MTTR and G2G time by reducing the number of tuning iterations required to bring an equipment or manufacturing tool to a specified state after a maintenance or other non-production event. The methods and systems of the present disclosure leverage capabilities that include "run-to-run" (R2R) control and virtual metrology (VM).

[0020] Following maintenance there is often a process that is executed in which the equipment is "requalified" to a certain state such as a ready to return to production state. FIG. **1** is a time line of a maintenance recovery process in accordance with one embodiment. There are a number of techniques that can be used during the production cycle (from producing wafers during production state **2**, through predicting and scheduling maintenance state **4**, seasoning state **6**, requalification state **8** and returning to a production state **9** after a maintenance event) that can improve production capabilities. MTBI is defined as mean-time-between-interrupts for a production state **2**. Many of these techniques are components or extensions of existing Advanced Process Control (APC) systems capabilities and can therefore leverage the data management environment provided by an existing manufacturing system's APC infrastructure. The specific capabilities of the solution, their definitions, and example of their manner of utilization are described as follows.

[0021] Fault Detection (FD) is the technique of monitoring and analyzing variations in tool and/or process data to detect anomalies. Fault detection includes both univariate and multivariate statistical analysis techniques. FD analysis is often used to identify excursions. Also FD analysis output feed EHM, PdM and VM solutions (see below).

[0022] Equipment Health Monitoring (EHM) is the technology of monitoring tool parameters to assess the tool health as a function of deviation from normal behavior. EHM is not necessarily predictive in nature, but is often a component of predictive systems. EHM can be used during production (e.g., t_{10}) to monitor tool health and during the maintenance recovery process to assess "fingerprints" indicating successful maintenance procedures (e.g., t_{40}), ready to move to requalification (e.g., t_{50}) or during requalification (e.g., t_{60}) to help determine if a component is ready to return to a production state (e.g., maintenance success verification).

[0023] Predictive Maintenance (PdM) is the technology of utilizing process and equipment state information to predict when a tool or a particular component in a tool might need maintenance, and then utilizing this prediction as information to improve maintenance procedures. This could mean predicting and avoiding unplanned downtimes and/or relaxing un-planned downtime schedules by replacing schedules with predictions. PdM solutions (e.g., PdM at t_{22}) have been illustrated to provide a number of benefits including reduction of unscheduled downtime.

[0024] Run-to-Run (R2R) control is the technique of modifying recipe or other equipment parameters, or the selection of control parameters between runs to improve processing performance. A "run" can be a batch, lot, or an individual substrate, wafer, or other product. R2R control (e.g., t_{20}) is typically used during production to improve processes through improved closeness to quality targets and reduce variability of quality parameters. R2R control (e.g., t_{30}) can also be used during a maintenance state to determine maintenance settings or process adjustments.

[0025] Virtual Metrology (VM) is the technology of prediction of post process metrology variables (e.g., either measurable or nonmeasurable) using process and wafer state information that could include upstream metrology and/or sensor data. Typical uses of VM are to enhance the R2R control capabilities (e.g., t_{10}, t_{30}) and reduce average production cycle time by reducing the need for metrology. Best practices and domain knowledge are procedures that leverage understanding of or experience with the equipment and process and related components to improve capabilities throughout the production cycle.

[0026] In the following description, numerous details are set forth. It will be apparent, however, to one skilled in the art, that the present invention may be practiced without these specific details. In some instances, well-known structures and devices are shown in block diagram form, rather than in detail, in order to avoid obscuring the present invention.

[0027] Some portions of the detailed descriptions which follow are presented in terms of algorithms and symbolic representations of operations on data bits within a computer memory. Unless specifically stated otherwise, as apparent from the following discussion, it is appreciated that throughout the description, discussions utilizing terms such as "collecting", "predicting", "performing", "adjusting", "comparing", or the like, refer to the action and processes of a computer system, or similar electronic computing device, that manipulates and transforms data represented as physical (electronic) quantities within the computer system's registers and memories into other data similarly represented as physical quantities within the computer system memories or registers or other such information storage, transmission or display devices.

[0028] Embodiments of the present invention also relates to an apparatus for performing the operations herein. This apparatus may be specially constructed for the required purposes, or it may comprise a general purpose computer selectively activated or reconfigured by a computer program stored in the computer. Such a computer program may be stored in a computer readable storage medium, such as, but not limited to, any type of disk including floppy disks, optical disks, CD-ROMs, and magnetic-optical disks, read-only memories (ROMs), random access memories (RAMs), EPROMs, EEPROMs, magnetic or optical cards, or any type of media suitable for storing electronic instructions, each coupled to a computer system bus.

[0029] The algorithms and displays presented herein are not inherently related to any particular computer or other apparatus. Various general purpose systems may be used with programs in accordance with the teachings herein, or it may prove convenient to construct more specialized apparatus to perform the required method steps. The required structure for a variety of these systems will appear as set forth in the description below. In addition, the present invention is not described with reference to any particular programming language. It will be appreciated that a variety of programming languages may be used to implement the teachings of the invention as described herein.

[0030] The present invention may be provided as a computer program product, or software, that may include a machine-readable medium having stored thereon instructions, which may be used to program a computer system (or other electronic devices) to perform a process according to

the present invention. A machine-readable medium includes any mechanism for storing information in a form readable by a machine (e.g., a computer). For example, a machine (e.g., a computer) readable storage medium includes read only memory ("ROM"), random access memory ("RAM"), magnetic disk storage media, optical storage media, flash memory devices, etc.

[0031] FIG. **2** illustrates an exemplary architecture of a manufacturing environment **100** for reducing maintenance time (e.g., MTTR), in accordance with one embodiment. The manufacturing environment **100** may be a semiconductor manufacturing environment, an automotive manufacturing environment, aerospace equipment manufacturing environment, medical equipment manufacturing environment, display and solar manufacturing environment, etc. In one embodiment, the manufacturing environment **100** includes an equipment engineering system (EES) **105**, a VM multi-algorithm predictive subsystem **107** within the EES system **105** or some other system coupled to the EES via a network, a manufacturing execution system (MES) **110**, a yield management system (YMS) **120** and a consolidated data store **115**. The EES **105**, MES **110**, YMS **120** and consolidated data store **115** may be connected via a network (not shown), such as a public network (e.g., Internet), a private network (e.g., Ethernet or a local area Network (LAN)), or a combination thereof.

[0032] The manufacturing execution system (MES) **110** is a system that can be used to measure and control production activities in a manufacturing environment. The MES **110** may control some production activities (e.g., critical production activities) or all production activities of a set of manufacturing equipment (e.g., all photolithography equipment in a semiconductor fabrication facility), of a manufacturing facility (e.g., an automobile production plant), of an entire company, etc. The MES **110** may include manual and computerized off-line and/or on-line transaction processing systems. Such systems may include manufacturing machines, metrology devices, client computing devices, server computing devices, databases, etc. that may perform functions related to processing.

[0033] In one embodiment, the MES **110** is connected with a consolidated data store **115**. The consolidated data store **115** may include databases, file systems, or other arrangements of data on nonvolatile memory (e.g., hard disk drives, tape drives, optical drives, etc.), volatile memory (e.g., random access memory (RAM)), or combination thereof. In one embodiment, the consolidated data store **115** includes data from multiple data stores (e.g., a YMS data store, a maintenance data store, a metrology data store, process data stores, etc.) that are interconnected. The consolidated data store **115** may store, for example, historical process information of manufacturing recipes (e.g., temperatures, pressures, chemicals used, process times, etc.), equipment maintenance histories, inventories, etc. The consolidated data store **115** may also store data generated by the MES **110**, YMS **120** and/or EES **105**. For example, the EES **105** may store fault detection and characterization data in the consolidated data store **115**, the YMS **120** may store yield analysis data in the consolidated data store **115**, and the MES **110** may store historical process information in the consolidated data store **115**. This permits each of the YMS **120**, EES **105** and MES **110** to leverage data generated by the other systems. The consolidated data store **115** may reside on one or more computing devices hosting any of the MES **110**, the YMS **120** and EES **105**, or on one or more different computing devices.

[0034] The EES **105** is a system that manages some or all operations of a manufacturing environment (e.g., factory). The EES **105** may include manual and computerized off-line and/or on-line transaction processing systems that may include client computing devices, server computing devices, databases, etc. that may perform the functions of equipment tracking, dispatching (e.g., determining what material goes to what processes), product genealogy, labor tracking (e.g., personnel scheduling), inventory management, costing, electronic signature capture, defect and resolution monitoring, key performance indicator monitoring and alarming, maintenance scheduling, and so on.

[0035] The EES **105** draws inferences from, reports out, and/or acts upon the combined information that is collected and stored in the consolidated data store **115** and/or the metrology data and process data that is reported by the MES **110**. For example, EES **105** can act as an early warning system (e.g., predict scrap, initiate product rework, etc.), provide bottleneck analysis, provide asset management (e.g., reduce unscheduled equipment downtime, reduce scheduled equipment downtime, reduce MTTR), improve lean practices, etc. The EES **105** can be used to gain an understanding of the manufacturing environment **100**, and can enable a user to determine an efficiency of the manufacturing environment **100** and/or how to improve all or components of the manufacturing environment **100**. In one embodiment, the EES **105** includes components (e.g., VM multi-algorithm predictive subsystem **107** having VM module with prediction algorithm switching module, multivariate R2R controller **112**, etc.) that enable the EES **105** to utilize and determine predictive algorithms for adaptive virtual metrology, perform R2R control, reduce MTTR, and reduce green-to-green (G2G) time, which is a time period between production production-worthy states.

[0036] The yield management system (YMS) **120** analyzes end-of-line data such as electronic test (e-test) data to determine product yield. The end-of-line data may include wafer acceptance testing (WAT), wafer sort results and/or final test operations. The yield manager **120** can provide product yield trends, lot level analysis of product yield, yield correlation to manufacturing processes, statistical analysis of yield, etc. In one embodiment, the YMS **120** uses integrated circuit design, visible defect, parametric and e-test data to identify causes of low yield.

[0037] In one example, with many maintenance events in semiconductor manufacturing, process "tuning" is required as part of the maintenance recovery process, where test wafers are processed and measured and the process is adjusted based on the results. The process is determined ready-for-production when the test wafer measurements meet specified quality criteria. This tuning can oftentimes be costly both in terms of wafers and lost production time. The tuning process itself can often be inexact with adjustments determined manually and often in a univariate (one-by-one or a-few-by-one) fashion.

[0038] In one embodiment, the tuning process can be improved by utilizing multivariate R2R control along with VM (as necessary) to more precisely determine tuning recommendations and reduce tuning iteration steps. A multivariate analysis is based on a statistical principle of mul-

tivariate statistics in which observation and analysis of more than one statistical outcome variable occurs at a time.

[0039] FIG. **3** illustrates a flow diagram of one embodiment for a computer implemented method of multivariate analysis utilizing run-to-run control and virtual metrology to reduce MTTR and improve G2G time during post preventative maintenance (PM) recovery. The method may be performed by processing logic that may comprise hardware (e.g., circuitry, dedicated logic, programmable logic, microcode, etc.), software (such as instructions run on a processing device), or a combination thereof. In one embodiment, a computer implemented method **300** is performed by the equipment engineering system **105** or some other system (e.g., a system hosting a VM multi-algorithm prediction subsystem **107**, R2R controller, and coupled to the EES **105** via a network). The computer implemented method **300** is designed to transition a manufacturing tool to an ideal or nearly ideal operating region after PM (or any maintenance) with some constraints. The ideal or nearly ideal operating region is defined by key parameters (e.g., thickness profile, electrical properties, etc.). Constraints may include tuning parameters (e.g., gas flows, temperature) that have certain boundaries and possible relationships with other tuning parameters or variables in order for the tool to be qualified for a production state. The tool is transitioned to the production state typically using multiple iterations of test substrates and adjusting tuning parameters.

[0040] Referring to FIG. **3**, the computer implemented method **300** includes processing test substrates with nominal values of tuning parameters (or values defined by an operator of a manufacturing tool such as a process engineer or technician) of at least one manufacturing tool at operation **301**. The computer implemented method **300** includes collecting data (e.g., test substrate data obtained from measurements of the test substrates, other metrology data, fault detection data, thickness statistical process control (SPC) data, etc.) by a system (e.g., an equipment engineering system) at operation **302**. The collected data includes data associated with a manufacturing process, the at least one manufacturing tool and/or a manufactured product. Processing logic of the system determines a relationship between tool parameter settings (e.g., temperature, lamp power ratios, gas flows during process recipes, chamber pressure, downforce for a chemical mechanical planarization tool, etc.) for the at least one manufacturing tool and the collected data (e.g., test substrate data, other metrology data, fault detection data, thickness statistical process control (SPC) data, etc.) at operation **304**. Processing logic then compares test substrate data to at least one target parameter (e.g., a range of target values for each target parameter) for the test substrates of the at least one manufacturing tool at operation **305**. If at least one target parameter (e.g., electrical parameters) or metrology data is not measured or available, then processing logic of the system utilizes zero or more (or at least one) virtual metrology predictive algorithms (e.g., Partial Least Squared (PLS), Support Vector Regression (SVR), etc.) and at least some of the collected data to obtain a metrology prediction for the at least one target parameter or metrology data that is not measured or available at operation **306**.

[0041] Processing logic of the system determines whether the test substrate data satisfies the at least one target parameter (e.g., within a range of target values for each target parameter) at operation **308**. If so, then the processing logic completes the requalification process at operation **320**.

[0042] Otherwise, processing logic then applies R2R control modeling (e.g., linear, nonlinear) to obtain a state estimation including a current operating region and condition of the at least one manufacturing tool based on the test substrate data (e.g., measurements obtained from the test substrates at operation **301**) and the corresponding tuning parameters applied during the processing of the test substrates at operation **310**. The processing logic of the system provides recommended tool parameter adjustments of a tool parameter adjustment event to move or transition the current operating region of the at least manufacturing tool to an ideal or nearly ideal operating region having ideal or nearly ideal target parameters based on the R2R control modeling at operation **312**. A virtual metrology predictive algorithm if virtual metrology is necessary is tuned prior to or during its use in a tool parameter adjustment event of the tool parameter adjustments The method proceeds to operation **301** for a next iteration with the recommended (or similar) tool parameter adjustments having at least one different tuning parameter than the initial iteration at operation **301**. In this manner, the method **300** reduces a tool or component downtime after PM or unplanned maintenance during maintenance recovery and requalification which results in higher product output. Thus, better utilization of manufacturing tools increases profits for the manufacturing environment.

[0043] In another example, the method **300** does not include utilizing one or more virtual metrology predictive algorithms to obtain a metrology prediction for the at least one target parameter that is not measured or available at operation **306**. FIGS. **4**A-**4**C illustrate one implementation of the method **300** for a deposition tool in accordance with one embodiment. FIG. **4**A illustrates a plot **400** of thickness versus gas flow for different temperatures of a deposition tool in accordance with one embodiment. The different temperatures includes T**1**, T**2**, and T**3**. R2R control modeling uses this plot **400** to determine a current operating region and condition of the deposition tool based on the test substrate data (e.g., thickness measurements obtained from the test substrates, operation **301**) illustrated in FIG. **4**A and the corresponding tuning parameters (e.g., temperature, gas flow) applied during the processing of the test substrates. If test substrate data is not available, then VM can be used for predicting metrology data. The R2R control modeling models this plot **400** with the following equation:

$$\begin{bmatrix} y_{CentralThickness} \\ y_{Ge\%} \end{bmatrix} = \begin{bmatrix} f_1(x_{GeH4}, x_{DCS}, x_{HCl}, x_{B2H6}) \\ f_2(x_{GeH4}, x_{DCS}, x_{HCl}, x_{B2H6}) \end{bmatrix}$$

[0044] FIG. **4**B illustrates a plot **420** of thickness versus gas flow for a temperature T* of a deposition tool in accordance with one embodiment. R2R control modeling obtains a state estimation including a current operating region and condition of the deposition tool as illustrated in plot **420**. The R2R control model estimate state for the deposition tool with the following equation:

$$\begin{bmatrix} y_{CentralThickness} \\ y_{Ge\%} \end{bmatrix} = \begin{bmatrix} f_1^*(x_{GeH4}, x_{DCS}, x_{HCl}, x_{B2H6}) \\ f_2(x_{GeH4}, x_{DCS}, x_{HCl}, x_{B2H6}) \end{bmatrix}$$

[0045] FIG. **4**C illustrates a plot **440** of thickness versus gas flow for a temperature T* of a deposition tool for modeling predictive control in accordance with one embodiment. This plot **440** includes a target **450** having a target central thickness **452** and a target gas flow **454** (e.g., target Ge dopant % for set of gas flows). R2R control modeling provides recommended tool parameter adjustments to move or transition the current operating region of the deposition tool to an ideal or nearly ideal operating region having ideal or nearly ideal target parameters based on the R2R control modeling. The R2R control modeling models the ideal or nearly ideal operating region for the deposition tool with the following equation:

$$\begin{bmatrix} x_{GeH4} \\ x_{DCS} \\ x_{HCl} \\ x_{B2H6} \end{bmatrix} = \min_{x_{GeH4}, x_{DCS}, x_{HCl}, x_{B2H6}} \left\{ \begin{matrix} \left| y^{Target}_{CentralThickness} - f^{*}_{1}(x_{GeH4}, x_{DCS}, x_{HCl}, x_{B2H6}) \right| \\ \left| y^{Target}_{Ge\,\%} - f^{*}_{2}(x_{GeH4}, x_{DCS}, x_{HCl}, x_{B2H6}) \right| \end{matrix} \right\}$$

[0046] For one example in semiconductor manufacturing, a R2R control maintenance recovery approach can be applied to a thermal process, where the lamp maintenance effort can be costly and time consuming.

[0047] FIG. **5**A illustrates lamp failure modes in accordance with one embodiment. In a typical system, lamps can fail unexpectedly causing unscheduled downtime and scrap. The lamp failure modes include a filament **410** that is sagging below a center line, a short circuit **412** between filament helix and support pillar, and a short circuit **414** between turns. The maintenance recovery can be time consuming as there are usually multiple post-maintenance (i.e., after lamp kit replacement) iterations of lamp parameter "tuning" that include running a number of test wafers with specific characterization recipes, analyzing metrology data, and making hardware and software adjustments. This process continues until the metrology data meets specified quality criteria. Four to ten iterations of this type are not uncommon leading to MTTR on the order of 2 days or more.

[0048] FIG. **5**B illustrates a diagram in which multivariate R2R control with VM is applied in accordance with one embodiment. PM process metrology **502** is utilized along with VM models based on FD output data **504** to determine a state of the system. PM tuning models utilize this state information to determine tuning advices in a multivariate fashion. The result is that fewer tuning iterations are required to bring the chamber to a satisfactory matched state for release back into production.

[0049] FIG. **6** illustrates a diagram in which multivariate R2R and VM models are applied during maintenance recovery in accordance with one embodiment. In one example, more than one tuning iteration is usually required because the R2R control tuning model often has to be re-centered with the first set of metrology results. This is due to the variability in and length of time between PMs. Note also that VM information used to enhance the determination of a system state has been shown to provide an improved R2R control system capability. However, depending on the maintenance event type and tuning procedures, it may not always be necessary (i.e., PM process metrology may be sufficient). The diagram **600** illustrates test wafer quality (normalized) on a vertical axis versus tuning iterations for chambers A and B on a horizontal axis. For chamber A with no R2R control and VM, 5 iterations were need for maintenance recovery. For chamber A with R2R control and VM, only 2 iterations were need for maintenance recovery. Thus, the R2R control and VM during the maintenance recovery reduces the MTTR by 3 iterations.

[0050] For chamber B with no R2R control and VM, 3 iterations were need for maintenance recovery. For chamber B with R2R control and VM, only 2 iterations were need for maintenance recovery. Thus, the R2R control and VM during the maintenance recovery reduces the MTTR by 1 iteration.

[0051] In one example of a thin film deposition PM (e.g., CVD PM, epitaxial PM, etc.), a recovery period typically takes at least five tuning iterations for testing processing recipes with test substrates, performing metrology (e.g., measuring thickness profiles, determining dopant concentrations, etc.) for multiple recipes, and then making tuning adjustments for returning a film deposition tool to a production state. This causes PM recovery time period of greater than 3 days in which the deposition tool cannot be used in the production state for producing product.

[0052] FIG. **7** illustrates a diagram in which multivariate R2R control with VM is applied in accordance with one embodiment. Process metrology data **702** (e.g., SPC data, test substrate data, FD data, film thickness SPC data, etc.) and tool parameter and sensor data for at least one manufacturing tool are received as inputs for a multivariate prediction model **720** to determine state information of at least one system, equipment, or manufacturing tool. Process tuning models of the MVA prediction model utilize this state information to determine tuning advices in a multivariate fashion. The result is that fewer tuning iterations are required to bring the system or tool to a satisfactory state for release back into a production state.

[0053] In one example of MTTR modeling, a system collects historical test substrate data (e.g., FD data, film thickness SPC data, etc.). The system then determines a relationship between tool parameters settings and SPC data that corresponds to the tool parameter settings. Multivariate models are then utilized to rapidly identify critical parameters of the manufacturing tool to be adjusted or tuned. The models can identify values for multivariate variables or parameters that are out of tool or process specifications and then make appropriate corrections. In this manner, a downtime (i.e., non-production state) of the manufacturing tool is significantly reduced resulting in additional product output. For example, a number of tuning iterations can be reduced from at least 5 to 2 or 3 tuning iterations.

[0054] FIG. **8** illustrates a diagram in which multivariate R2R control with VM is applied in accordance with one embodiment for reducing maintenance recovery time. Process metrology data **802** (e.g., SPC data, test substrate data, FD data, film thickness SPC data, etc.) and tool parameter and sensor data **804** for at least one manufacturing tool are received as inputs for at least one of the VM module **810** and the run-to-run control module **820**. The VM module **810** utilizes at least one prediction algorithm for a virtual metrology function which can be a linear or nonlinear function F (u_k) with u_k being sensor data (e.g., temperature, lamp power, lamp power ratios, gas flows for processing gases during a processing recipe, etc.) for at least one manufac-

turing tool at time k. The linear or nonlinear function F (u_k) generates a metrology prediction **812** based on at least the sensor data **804**. The metrology prediction **812** may also be based on metrology data **802**. The R2R controller **820** receives the metrology prediction **812** and determines tool parameter adjustments **830** based on the metrology prediction and R2R parameters including sensor data, a state x_k at time k (e.g., a state of the manufacturing tool at time k such as), a state x_{k+1} at time k+1 (e.g., a state of the manufacturing tool at time k+1), sensor noise w_k, metrology measurement noise v_k, metrology measurement y_k at time k, a state transition function f(*), and observation function g(*).

[0055] In one embodiment, the R2R controller **820** utilizes the following equations for generating tool parameter adjustments **830**:

$$x_{k+1}=f(x_k,u_k,w_k)$$

$$y_k=g(x_k)+v_k$$

[0056] Improved knowledge of a state x_{k+1} at time k+1 (e.g., a state of the manufacturing tool at time k+1) and identification of critical parameters leads to a reduced number of tuning iterations for tool parameters adjustments **830**. The manufacturing tool can be returned to a production state in a shorter time period with reduced maintenance recovery and requalification.

[0057] In another embodiment, the R2R controller **820** does not need the metrology prediction **812** for determining tool parameter adjustments **830**.

[0058] In this manner, the R2R controller **820** utilizes this state information to determine tuning advices in a multivariate fashion.

[0059] In one example, the VM module **810** and R2R controller **820** are utilized to make adjustments to tool parameters based on a first set of input parameters (e.g., 3-5 input parameters). After the adjustments are made to tool parameters (e.g., process recipes) then the VM module **810** and R2R controller **820** are again utilized to make adjustments to tool parameters based on a different second set of input parameters (e.g., 3-5 input parameters).

[0060] FIG. **9** illustrates an exemplary architecture of a system (e.g., equipment engineering system (EES)), in accordance with one embodiment. In one embodiment, the system **900** is implemented with an Applied E3™ APC Infrastructure in which methods of the present disclosure are integrated. The EES **900** leverages an E3 application adapter **610** that provides an interface to Web services. Multivariate prediction module **920** can be integrated through Web services. This multivariate prediction module **920** integration approach enables rapid prototyping, customization, and technology transfer. The multivariate prediction module **920** includes a predictive VM module **922** that enables the EES **900** to utilize and determine predictive algorithms for adaptive virtual metrology and also R2R control module **924** for reducing tuning iterations for post maintenance recovery.

[0061] The adapter **910** communicates with the strategy engine **930**, the client handler **940**, the data service provider **950**, and the log server **960**. The strategy engine **930** includes general blocks **931**, run to run blocks **932** (e.g., R2R controller, R2R module), FD blocks **933**, EPT blocks **934**, and custom blocks **935**. The FD blocks **933** obtain FD data. The run to run blocks **932** include pre-configured or adaptive R2R models for implemented operations of methods and embodiments of the present disclosure. The EPT blocks **934** obtain equipment performance tracking information. The data access layer **970** provides access to a database **980**. This database **980** includes process data, FDC/EPT/R2R data, control rules, and data collection plans. The discovery manager **990** provides discovery features for identifying capabilities integrated into the system. The strategy engine is used to govern the interaction of blocks in terms of "strategies" to achieve specific objectives in response to events received.

[0062] For example, for substrate-to-substrate control (e.g., Wafer-to-Wafer (W2W) Control), a strategy housed by the strategy engine **930** could be envisioned that captures FD outputs from a FD implementation formulated with the FD blocks **933** and stored in the database **980**, sends this information to a formulation in the multivariate prediction module **920** (integrated via the web-services adaptor **910**) for calculation of VM outputs (e.g., metrology predictions), determination of tool parameter adjustments using R2R **924** (or alternatively R2R **932**), and output this tool parameter adjustments for reducing tuning iterations after PM and during requalification state. Collected metrology data is used to update VM models.

[0063] There are a number of extensions to prediction algorithms that utilize feedback of actual output measurement data, such as metrology or yield analysis, to continually improve or "tune" the prediction models. As an example, NIPALS and EWMA (Exponentially Weighted Moving Average) are two documented adaptive extensions to the Project on Latent Structure prediction mechanisms. In one embodiment of this invention, the VM algorithms are tuned as necessary at the start of an MTTR event to account for changes in process, equipment or other conditions between downtimes that require an adjustment of the VM model. The type and level of adjustment can be determined by techniques such as a VM switching algorithm. These various extensions for handling the dynamics perform differently depending on the prediction and adaptation environment. Further many of the extensions also represent a tradeoff between computational complexity or time, and accuracy.

[0064] VM models include a predictive algorithm having a VM prediction equation:

$$S=B*t+c$$

[0065] In some embodiments, S is a predicted output, B represents a matrix, t is an input factor, and c is zero'th order term. S, B, t, and c are components vectors or matrices. Given two prediction adaptation algorithms EWMA and NIPALS, EWMA is fast and easy, but can be inaccurate when the VM equation changes. The EWMA can utilize zero'th order adaptation of the VM equation (e.g., updates the "c" vector). NIPALS is complex, but more accurate. NIPALS reformulates the VM equation (e.g., updates both "B" and "c"). The VM multi-algorithm prediction subsystem **107** may compare predictions of metrology data (Y') to actual metrology data (Y) on occasion with this difference being E.

[0066] FIG. **10** illustrates a diagrammatic representation of a machine in the exemplary form of a computer system **1000** in accordance with one embodiment within which a set of instructions, for causing the machine to perform any one or more of the methodologies discussed herein, may be executed. In alternative embodiments, the machine may be connected (e.g., networked) to other machines in a Local Area Network (LAN), an intranet, an extranet, or the Inter-

net. The machine may operate in the capacity of a server or a client machine in a client-server network environment, or as a peer machine in a peer-to-peer (or distributed) network environment. The machine may be a personal computer (PC), a tablet PC, a set-top box (STB), a Personal Digital Assistant (PDA), a cellular telephone, a web appliance, a server, a network router, switch or bridge, or any machine capable of executing a set of instructions (sequential or otherwise) that specify actions to be taken by that machine. Further, while only a single machine is illustrated, the term "machine" shall also be taken to include any collection of machines (e.g., computers) that individually or jointly execute a set (or multiple sets) of instructions to perform any one or more of the methodologies discussed herein.

[0067] The exemplary computer system **1000** includes a processor **1002**, a main memory **1004** (e.g., read-only memory (ROM), flash memory, dynamic random access memory (DRAM) such as synchronous DRAM (SDRAM) or Rambus DRAM (RDRAM), etc.), a static memory **1006** (e.g., flash memory, static random access memory (SRAM), etc.), and a secondary memory **1018** (e.g., a data storage device), which communicate with each other via a bus **1030**.

[0068] Processor **1002** represents one or more general-purpose processing devices such as a microprocessor, central processing unit, or the like. More particularly, the processor **1002** may be a complex instruction set computing (CISC) microprocessor, reduced instruction set computing (RISC) microprocessor, very long instruction word (VLIW) microprocessor, processor implementing other instruction sets, or processors implementing a combination of instruction sets. Processor **1002** may also be one or more special-purpose processing devices such as an application specific integrated circuit (ASIC), a field programmable gate array (FPGA), a digital signal processor (DSP), network processor, or the like. Processor **1002** is configured to execute the processing logic **1026** for performing the operations and steps discussed herein.

[0069] The computer system **1000** may further include a network interface device **1008**. The computer system **1000** also may include a video display unit **1010** (e.g., a liquid crystal display (LCD) or a cathode ray tube (CRT)), an alphanumeric input device **1012** (e.g., a keyboard), a cursor control device **1014** (e.g., a mouse), and a signal generation device **1016** (e.g., a speaker).

[0070] The secondary memory **1018** may include a machine-readable storage medium (or more specifically a computer-readable storage medium) **1031** on which is stored one or more sets of instructions (e.g., software **1022**) embodying any one or more of the methodologies or functions described herein. The software **1022** may also reside, completely or at least partially, within the main memory **1004** and/or within the processing device **1002** during execution thereof by the computer system **1000**, the main memory **1004** and the processing device **1002** also constituting machine-readable storage media. The software **1022** may further be transmitted or received over a network **1020** via the network interface device **1008**.

[0071] The machine-readable storage medium **1031** may also be used to store one or more subsystems of a yield management system (YMS) **1020**, an equipment engineering system (EES) **105** and/or a manufacturing execution system (MES) **110** (as described with reference to FIG. **1**), and/or a software library containing methods that call subsystems of a YMS, EES and/or MES. The machine-readable storage medium **1031** may further be used to store one or more additional components of a manufacturing information and control system (MICS), such as a decision support logic component, a real-time monitor, and/or an execution logic component. While the machine-readable storage medium **1031** is shown in an exemplary embodiment to be a single medium, the term "machine-readable storage medium" should be taken to include a single medium or multiple media (e.g., a centralized or distributed database, and/or associated caches and servers) that store the one or more sets of instructions. The term "machine-readable storage medium" shall also be taken to include any medium that is capable of storing or encoding a set of instructions for execution by the machine and that cause the machine to perform any one or more of the methodologies of the present invention. The term "machine-readable storage medium" shall accordingly be taken to include, but not be limited to, solid-state memories, and optical and magnetic media.

In one embodiment, a computer system includes a memory to store one or more sets of instructions and a processor that is coupled to the memory. The processor is configured to execute instructions to collect data including test substrate data and fault detection data for maintenance recovery of at least one manufacturing tool in a manufacturing facility, determine a relationship between tool parameter settings for the at least one manufacturing tool and at least some collected data including the test substrate data. The method further includes utilizing zero or more virtual metrology predictive algorithms and at least some collected data to obtain a metrology prediction and applying multivariate run-to-run (R2R) control modeling to obtain a state estimation including a current operating region of the at least one manufacturing tool based on the test substrate data and obtain at least one tool parameter adjustment for at least one target parameter for the at least one manufacturing tool. In one example, the R2R control modeling utilizes the following parameters: sensor data obtained from a sensor of the at least manufacturing tool, state at time k, state at time k+1, sensor noise, metrology measurement noise, metrology measurement at time k, a state transition matrix, a process sensitivity matrix, and an observation model matrix.

[0072] In one example, the virtual metrology predictive algorithm is tuned prior to or during its use in a tool parameter adjustment event of the at least one tool parameter adjustment. In one embodiment, the collected data includes a thickness profile and a dopant concentration for maintenance recovery of a deposition tool. The tool parameter adjustments include adjusting a temperature parameter, lamp power ratios, and gas flow parameters for the deposition tool.

[0073] In one example, applying multivariate run-to-run (R2R) control modeling to obtain tool parameter adjustments for the at least one manufacturing tool occurs after maintenance to reduce maintenance recovery time and to reduce requalification time.

[0074] It is to be understood that the above description is intended to be illustrative, and not restrictive. Many other embodiments will be apparent to those of skill in the art upon reading and understanding the above description. Although the present invention has been described with reference to specific exemplary embodiments, it will be recognized that the invention is not limited to the embodiments described, but can be practiced with modification and alteration within the spirit and scope of the appended claims.

Accordingly, the specification and drawings are to be regarded in an illustrative sense rather than a restrictive sense. The scope of the invention should, therefore, be determined with reference to the appended claims, along with the full scope of equivalents to which such claims are entitled.

What is claimed is:

1. A computer implemented method comprising:

collecting, with a system, data including test substrate data or other metrology data and fault detection data for maintenance recovery of at least one manufacturing tool in a manufacturing facility;

determining, with the system, a relationship between tool parameter settings for the at least one manufacturing tool and at least some collected data including the test substrate data;

utilizing zero or more virtual metrology predictive algorithms and at least some collected data to obtain a metrology prediction; and

applying multivariate run-to-run (R2R) control modeling to obtain a state estimation including a current operating region of the at least one manufacturing tool based on the test substrate data and obtain at least one tool parameter adjustment for at least one target parameter for the at least one manufacturing tool, wherein applying multivariate run-to-run (R2R) control modeling to obtain tool parameter adjustments for at least one manufacturing tool occurs after maintenance to reduce maintenance recovery time and to reduce requalification time.

2. The computer implemented method of claim **1**, wherein the R2R control modeling utilizes the following parameters: sensor data obtained from a sensor of the at least manufacturing tool, state at time k, state at time k+1, sensor noise, metrology measurement noise, metrology measurement at time k, a state transition matrix, a process sensitivity matrix, and an observation model matrix.

3. The computer implemented in method of claim **1**, wherein the virtual metrology predictive algorithm is tuned prior to or during its use in a tool parameter adjustment event of the at least one tool parameter adjustment.

4. The computer implemented method of claim **1**, wherein the collected data includes a thickness profile and a dopant concentration for maintenance recovery of a deposition tool.

5. The computer implemented method of claim **4**, wherein the tool parameter adjustments includes adjusting a temperature parameter, lamp power ratios, and gas flow parameters for the deposition tool.

6. The computer implemented method of claim **1**, further comprising:

determining whether the test substrate data satisfies the at least one target parameter.

7. A computer-readable storage medium comprising executable instructions to cause a processor to perform operations, the instructions comprising:

collecting, with a system, data including test substrate data or metrology data and fault detection data for maintenance recovery of at least one manufacturing tool in a manufacturing facility;

determining, with the system, a relationship between tool parameter settings for the at least one manufacturing tool and at least some collected data including the test substrate data;

utilizing zero or more virtual metrology predictive algorithms and at least some collected data to obtain a metrology prediction; and

applying multivariate run-to-run (R2R) control modeling to obtain a state estimation including a current operating region of the at least one manufacturing tool based on the test substrate data and obtain at least one tool parameter adjustment for at least one target parameter for the at least one manufacturing tool, wherein applying multivariate run-to-run (R2R) control modeling to obtain tool parameter adjustments for at least one manufacturing tool occurs after maintenance to reduce maintenance recovery time and to reduce requalification time

8. The computer-readable storage medium of claim **7**, wherein the R2R control modeling utilizes the following parameters: sensor data obtained from a sensor of the at least manufacturing tool, state at time k, state at time k+1, sensor noise, metrology measurement noise, metrology measurement at time k, a state transition matrix, a process sensitivity matrix, and an observation model matrix.

9. The computer-readable storage medium of claim **8**, wherein the virtual metrology predictive algorithm is tuned prior to or during its use in a tool parameter adjustment event of the at least one tool parameter adjustment.

10. The computer-readable storage medium of claim **7**, wherein the collected data includes a thickness profile and a dopant concentration for maintenance recovery of a deposition tool.

11. The computer-readable storage medium of claim **10**, wherein the tool parameter adjustments includes adjusting a temperature parameter, lamp power ratios, and gas flow parameters for the deposition tool.

12. The computer implemented method of claim **7**, further comprising:

determining whether the test substrate data satisfies the at least one target parameter.

13. A computer system comprising:

a memory to store one or more sets of instructions; and

a processor, coupled to the memory, is configured to execute instructions to:

determining, with the system, a relationship between tool parameter settings for the at least one manufacturing tool and at least some collected data including the test substrate data;

utilizing zero or more virtual metrology predictive algorithms and at least some collected data to obtain a metrology prediction;

applying multivariate run-to-run (R2R) control modeling to obtain a state estimation including a current operating region of the at least one manufacturing tool based on the test substrate data and obtain at least one tool parameter adjustment for at least one target parameter for the at least one manufacturing tool, wherein applying multivariate run-to-run (R2R) control modeling to obtain tool parameter adjustments for at least one manufacturing tool occurs after maintenance to reduce maintenance recovery time and to reduce requalification time.

14. The computer system of claim **13**, wherein the R2R control modeling utilizes the following parameters: sensor data obtained from a sensor of the at least manufacturing tool, state at time k, state at time k+1, sensor noise, metrol-

ogy measurement noise, metrology measurement at time k, a state transition matrix, a process sensitivity matrix, and an observation model matrix.

15. The computer system of claim **14**, wherein the virtual metrology predictive algorithm is tuned prior to or during its use in a tool parameter adjustment event of the at least one tool parameter adjustment.

16. The computer system of claim **13**, wherein the collected data includes a thickness profile and a dopant concentration for maintenance recovery of a deposition tool.

17. The computer system of claim **16**, wherein the tool parameter adjustments includes adjusting a temperature parameter, lamp power ratios, and gas flow parameters for the deposition tool.

18. The computer system of claim **13**, further comprising:

determining whether the test substrate data satisfies the at least one target parameter.

* * * * *