set of feature models 320 are received by a numerical optimizer component 330. The set of target properties 310 can be received as input from a user. The set of target properties 310 can include multiple features and respective targets for each feature, where each target corresponds to an expected or desired value or range of values for its corresponding feature. Examples of targets include “mean,” “less than,” “greater than,” “low as possible,” “profile goal,” etc. A profile goal allows a user to specify a profile across the wafer. In this illustrative example, the set of target properties 310 specifies a thickness feature having a corresponding target of “mean” and expected or desired value of 1000 Angstroms (Å) (i.e., the goal for thickness is a mean thickness of 1000 Å), a resistivity feature having a corresponding target of “greater than” and a value of 2.03 Ohm-meters (i.e., the goal for resistivity is a resistivity greater than 2.03 Ohm-meters), and a stress feature having a corresponding target of “low as possible” (i.e., as close to zero as possible).

[0050] The set of feature models 320 is shown including a number of feature models. In some implementations, the set of feature models 320 includes a set of regression models. For example, the feature models can include MIMO models (e.g., spatial MIMO models). Each individual feature model targets a particular feature. For example, the feature models shown in the system 300 include a thickness feature model 322, a resistivity feature model 324 and a stress feature model 326. In some examples, a smaller subset of the inputs, or “set of relevant inputs,” can be identified as the primary factors impacting the on-wafer characteristics, with other operations/parameters being pre or post processing operations preparing for specific actions. Thus, the feature models can be created for each feature based on the set of relevant inputs. Inputs of a feature model 320 may include manufacturing parameters (e.g., process parameters, hardware parameters). Output of a feature model may be metrology data or performance data. For example, inputs of a feature model may be temperature, pressure, and flow rate, and the output of the feature model may be thickness. Each feature model 320 may output a corresponding feature (e.g., type of metrology data, type of performance data, etc.). As will be described in further detail herein, the use of individualized feature models for respective features can enable greater control over achieving the desired characteristics.

[0051] In some implementations, a design of experiment (DoE) technique is used to generate the set of feature models 320. DoE techniques can be used to detect wafer sensitivity in view of changing recipe parameters. DoE is the design of any information-gathering exercise where variation is present. DoE analysis is the analysis of data generated from execution of a DoE (i.e., DoE data). In some implementations, DOE data includes recipe parameters, recipe parameter values, and measurements (e.g., wafer measurements). For example, for a DoE

predicted wafer performance behavior. Matching can be performed to generate the offset 252 by searching for offsets from the inputs defined in the recipe 242 that will make the current or predicted performance behavior match a desired or expected performance behavior corresponding to the recipe 242. That is, the offset 252 corrects for any change or drift in performance behavior (e.g., on-wafer performance) resulting from mismatch between the current or predicted performance behavior and the expected or desired performance behavior. In alternative implementations, the offset 252 can be a new set of recipe settings for generating a recipe (e.g. using the recipe creation component 240).

[0064] In some implementations, the current or predicted performance can be measured by any suitable metrology technique. Examples of metrology techniques include on-board metrology, inline metrology and virtual metrology.

[0065] On-board metrology can refer to measurements performed on the devices themselves within a die or on test structures having features similar to the devices. Depending on the measurement techniques used, the test structures may include, but are not limited to, structures similar to logic or memory devices that are on the wafers. On-board metrology can be based on optical measurements (e.g., collecting optical emission spectra in-situ from devices or test structures, or macro 2D mapping using optical targets) or other types of measurements. These optical or other measurements can be inside the chamber (in-situ), or outside the chamber (ex-situ), but still under vacuum, or, at the factory interface (not necessarily under vacuum) on a process platform that may have multiple chambers.

[0066] Inline metrology can refer to measurements that may be performed outside of a processing chamber, but without having to take the wafer out of the production line. An example of in-line metrology is scanning electron microscope (SEM), the advanced versions of which may offer high precision and broad modality. Advanced SEMs may include back-scattered electron (BSE) sensors in addition to secondary emission detectors, and ability to measure electron emission at various tilt angles and various landing energy, ranging from hundreds of electron-volt to tens of kilo electron-volts. SEMs have the capability of creating a broad database of metrology data in a non-destructive manner. SEM-based in-line metrology customized with electron beam (“e-beam”) simulation, data collection, image characterization and feature extraction as well as statistical analysis may be referred to as “customized metrology.” An advanced SEM tool may be used as the foundation of high-precision, non-destructive three-dimensional feature level profiling which is at the heart of customized metrology.

CLAIMS

What is claimed is:

1. A method comprising:

receiving, by a processing device, a set of feature models, each feature model of the set of feature models corresponding to a respective feature associated with processing of a component;

receiving, by the processing device, a set of target properties for processing the component, wherein the set of target properties comprises, for each feature, a respective target;

determining, by the processing device based on the set of feature models, one or more sets of predicted processing parameters in view of the set of target properties;

generating, by the processing device, one or more candidate process recipes each corresponding to a respective one of the one or more sets of predicted processing parameters, wherein the one or more candidate process recipes each correspond to a set of predicted properties comprising, for each feature, a respective predicted property value resulting from component processing; and

selecting, by the processing device from the one or more candidate process recipes, a process recipe for processing the component.

2. The method of claim 1, wherein the set of feature models is a set of spatial multiple-input multiple-output (MIMO) models.

3. The method of claim 1, wherein generating the one or more candidate process recipes comprises using numerical optimization to minimize a difference between a target property and a corresponding predicted property.

4. The method of claim 3, wherein generating the one or more candidate process recipes comprises:

obtaining a cost function based on the set of feature models and the set of target properties; and

minimizing the cost function to obtain each set of predicted properties.

5. The method of claim 1, further comprising:

failing, by the processing device, to identify a candidate process recipe that satisfies each target property of the set of target properties;

wherein the process recipe comprises a set of Pareto efficient recipe parameters.

6. The method of claim 1, further comprising causing, by the processing device, a process tool to process the component using the process recipe.

7. The method of claim 1, further comprising:

receiving, by the processing device, an expected performance for processing the component using the process recipe, and an observed performance for processing the component using the process recipe;

determining, by the processing device, that a difference between the expected performance and the observed performance does not satisfy a threshold condition; and

generating, by the processing device, a new process recipe for processing the component based on the difference.

8. A system comprising:

a memory and

a processing device coupled to the memory, the processing device to perform operations comprising:

receiving a set of feature models, each feature model of the set of feature models corresponding to a respective feature associated with processing of a component;

receiving, by the processing device, a set of target properties for processing the component, wherein the set of target properties comprises, for each feature, a respective target;

determining one or more sets of predicted processing parameters in view of the set of target properties;

generating one or more candidate process recipes each corresponding to a respective one of the one or more sets of predicted processing parameters, wherein the one or more candidate process recipes each correspond to a set of predicted properties comprising, for each feature, a respective predicted property value resulting from component processing; and

selecting, from the one or more candidate process recipes, a process recipe for processing the component.

9. The system of claim 8, wherein the set of feature models is a set of spatial multiple-input multiple-output (MIMO) models.

10. The system of claim 8, wherein generating the one or more candidate process recipes comprises using numerical optimization to minimize a difference between a target property and a corresponding predicted property.

11. The system of claim 10, wherein generating the one or more candidate process recipes comprises:

obtaining a cost function based on the set of feature models and the set of target properties; and

minimizing the cost function to obtain each set of predicted properties.

12. The system of claim 8, wherein the operations further comprise:

failing to identify a candidate process recipe that satisfies each target property of the set of target properties;

wherein the process recipe comprises a set of Pareto efficient recipe parameters.

13. The system of claim 8, wherein the operations further comprise causing a process tool to process the component using the process recipe.

14. The system of claim 13, wherein the operations further comprise:

receiving an expected performance for processing the component, and an observed performance for processing the component using the process recipe;

determining that a difference between the expected performance and the observed performance does not satisfy a threshold condition; and

generating a new process recipe for processing the component based on the difference.

15. A non-transitory machine-readable storage medium storing instructions which, when executed by a processing device, cause the processing device to perform operations comprising:

receiving a set of feature models, each feature model of the set of feature models corresponding to a respective feature associated with processing of a component;

receiving, by the processing device, a set of target properties for processing the component, wherein the set of target properties comprises, for each feature, a respective target;

determining one or more sets of predicted processing parameters in view of the set of target properties;

generating one or more candidate process recipes each corresponding to a respective one of the one or more sets of predicted processing parameters, wherein the one or more candidate process recipes each correspond to a set of predicted properties comprising, for each feature, a respective predicted property value resulting from component processing; and

selecting, from the one or more candidate process recipes, a process recipe for processing the component.

16. The non-transitory machine-readable storage medium of claim 15, wherein the set of feature models is a set of spatial multiple-input multiple-output (MIMO) models.

17. The non-transitory machine-readable storage medium of claim 15, wherein generating the one or more candidate process recipes comprises using numerical optimization to minimize a difference between a target property and a corresponding predicted property by:

obtaining a cost function based on the set of feature models and the set of target properties; and

minimizing the cost function to obtain each set of predicted properties.

18. The non-transitory machine-readable storage medium of claim 15, wherein the operations further comprise:

failing to identify a candidate process recipe that satisfies each target property of the set of target properties;

wherein the process recipe comprises a set of Pareto efficient recipe parameters.

19. The non-transitory machine-readable storage medium of claim 15, wherein the operations further comprise causing a process tool to process the component using the process recipe.

20. The non-transitory machine-readable storage medium of claim 15, wherein the operations further comprise:

receiving an expected performance for processing the component, and an observed performance for processing the component using the process recipe;

determining that a difference between the expected performance and the observed performance does not satisfy a threshold condition; and

generating a new process recipe for processing the component based on the difference.