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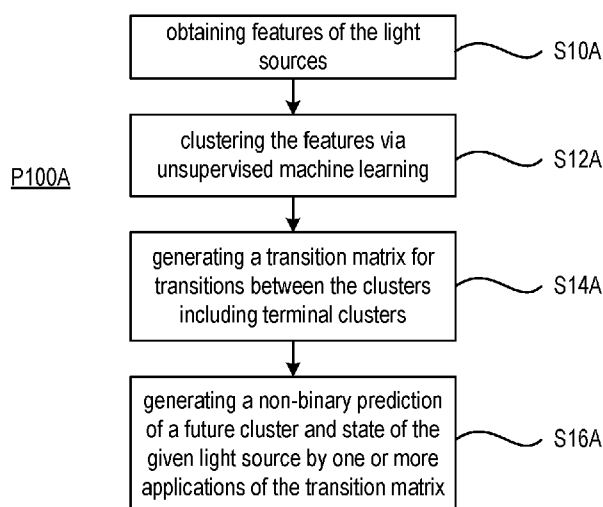
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(54) **Title:** METHODS FOR PREDICTING STATES OF LIGHT SOURCES



(57) **Abstract:** A method for predicting states of light sources, including laser systems, includes obtaining features of the light sources representing operational aspects of the light sources; clustering the features into clusters with a machine learning algorithm utilizing unsupervised learning, the clusters representing states of the light sources; generating a transition matrix between the clusters representing transition probabilities of transitions of the light sources between the clusters after an interval of time, the clusters including one or more terminal clusters from which the probability of transition to another cluster is zero; and for a given light source having features corresponding to a given cluster and state, generating a non-binary prediction of a future cluster and state of the given light source by one or more applications of the transition matrix.

FIG. 1A



METHODS FOR PREDICTING STATES OF LIGHT SOURCESCROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims priority of US application No. 63/510,915, filed June 29, 2023, titled
5 METHODS FOR PREDICTING STATES OF LIGHT SOURCES, and US application No. 63/567,039, filed March 19, 2024, titled METHODS FOR PREDICTING STATES OF LIGHT SOURCES, which are incorporated herein in its entirety by reference.

TECHNICAL FIELD

10 [0002] The present disclosure relates to methods for predicting states of light sources such as laser systems, particularly to methods for predicting states of light sources used in providing light to a lithography apparatuses.

BACKGROUND

15 [0003] Light, which can be laser radiation, that is used for semiconductor photolithography is typically supplied by a system referred to as a light source or, sometimes, a laser system. These light sources produce ultraviolet radiation as a series of pulses at specified repetition rates, for example, in the range of about 500 Hz to about 6 kHz. Performance and uptime are critical to the users of such light sources at photolithography exposure facilities in light of the high economic value generated
20 during the semiconductor manufacturing process.

SUMMARY

[0004] In some general aspects, a method is provided for predicting states of light sources including laser systems, the method including obtaining features of the light sources, the features representing
25 operational aspects of the light sources; clustering, with a machine learning algorithm utilizing unsupervised learning, the features into clusters, the clusters representing states of the light sources; generating a transition matrix between the clusters, the transition matrix representing transition probabilities, after an interval of time, of transitions of the light sources between the clusters, the clusters including one or more terminal clusters from which the probability of transition to another
30 cluster is zero; and for a given light source having features corresponding to a given cluster and state, generating a non-binary prediction of a future cluster and state of the given light source by one or more applications of the transition matrix.

[0005] Implementations can include one or more of the following features. The light sources can be members of a group of similar light sources having similar components, methods of operation, and
35 features. The method can further include calculating a probability of transition within a given time between a first cluster and a second cluster utilizing a Markov chain by a repeated application of the transition matrix. The first cluster can represent the current state of a given light source and the

second cluster can be a terminal cluster. The interval of time can be in the range of one hour to one week. The interval of time can be one day.

[0006] The features of the light sources can include historical data from a set of similar light sources. The features of the light sources can include features of two or more modules of the light sources. The features of the light sources can include features of a master oscillator (MO) module and features of a power amplifier (PA) or power ring amplifier (PRA) module.

[0007] Generating a transition matrix between the clusters can include using the historical data to generate probabilities, after the interval of time, of transitions of light sources between the clusters. The method can further include checking the probability of transition between a first cluster and a second cluster within a given time limit utilizing a Markov chain by repeated application of the transition matrix repeated up to the time limit.

[0008] The method can further include obtaining updated features of the light sources, the updated features representing updated operational aspects of the light sources; clustering, with a machine learning algorithm utilizing unsupervised learning, the features and the updated features into updated clusters, the updated clusters representing states of the light sources; generating an updated transition matrix between the updated clusters, the updated transition matrix representing transition probabilities, after an interval of time, of transitions of the light sources between the updated clusters, the updated clusters including one or more terminal clusters from which the probability of transition to another updated cluster is zero; and for a given light source having features corresponding to a given updated cluster, generating a non-binary prediction of a future updated cluster and state of the given light source by one or more applications of the updated transition matrix. The updated terminal clusters can be different from immediately prior terminal clusters.

[0009] The features can include one or more time-dependent or history-dependent features. The one or more time-related or history-dependent features can include one or more rates of change of one or more aspects of the light sources. The one or more time-related or history-dependent features can include one or more measures of variability of one or more aspects of the light sources. The one or more time-related or history-dependent features can include one or more measures of central tendency of one or more aspects of the light sources.

[0010] In additional general aspects, a method for predicting states of light sources such as laser systems, is provided, the method including obtaining features of the light sources, the features representing operational aspects of the light sources, the features including one or more time-dependent or history-dependent features; clustering, with a machine learning algorithm utilizing unsupervised learning, the features into respective clusters representing respective states of the light sources; generating a transition matrix representing the respective probabilities of transitions of the light sources between the respective clusters after an interval of time; and generating a probability matrix representing the probability of a given light source being in each respective cluster after N of the intervals of time by raising the transition matrix to the power of N.

[0011] Implementations can include one or more of the following features. The one or more time-dependent or history-dependent features can include one or more rates of change of one or more aspects of the light sources. The one or more time-dependent or history-dependent features can include one or more measures of variability of one or more aspects of the light sources. The one or more time-dependent or history-dependent features can include one or more measures of central tendency of one or more aspects of the light sources. The clusters can include one or more clusters from which the probability of transition to another cluster is zero.

[0012] In additional general aspects, a method of testing for a significant change in the distribution of light source data or features is provided, specifically for data or features for use by a model for prediction, detection, simulation, or the like, and specifically for detection of a change in the distribution relative to the distribution of corresponding data used for training the model. The method includes determining a cumulative distribution function of model training data; determining a cumulative distribution function of the data for use by the model for prediction, detection, simulation, or the like (the “modeling data”); and determining whether the cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at any point, by more than a tolerance value.

[0013] Implementations can include one or more of the following.

[0014] If the cumulative distribution function of the modeling data does not vary from the cumulative distribution function of the training data, at any point, by more than the tolerance value, repeatedly (a) reducing the tolerance value, and (b) determining whether the cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at any point, by more than the tolerance value, until the cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at some point, by more than the tolerance value; and reporting the last and/or the second-to-last tolerance value.

[0015] The tolerance value can be within the range of greater than zero to 0.1.

[0016] The details of one or more implementations are set forth in the accompanying drawings and the description below. Other features will be apparent from the description and drawings, and from the claims.

DRAWING DESCRIPTION

[0017] FIG. 1A is a flowchart of an implementation of a procedure for predicting states of light sources.

[0018] FIG. 1B is a flowchart of another implementation of a procedure for predicting states of light sources.

[0019] FIG. 2A is a diagram of an example of multiple clusters or states of light sources, showing the probabilities or transition between the clusters or states after a specified interval of time.

[0020] FIG. 2B is a diagram of another example of multiple clusters or states of light sources, showing transition probabilities of transitions between the clusters or states after the interval of time.

[0021] FIG. 3 is an example of a transition matrix corresponding to the diagram of FIG. 2B, with rows and columns labeled with the corresponding clusters of FIG. 2B.

5 [0022] FIG. 4 is an example of computed probabilities, resulting from raising the transition matrix of FIG. 3 to the power of 14, of transitioning from and to the clusters shown after 14 intervals of time.

[0023] FIG. 5 is a block diagram of an example of a light source or laser system, in this case a deep ultraviolet (DUV) light source, with which the process described herein can be used.

10 [0024] FIG. 6 is a block diagram of an example of a lithography apparatus that can be used with the light source of FIG. 5.

[0025] FIGS. 7A-7D are graphs illustrating a method of testing for a significant change in the distribution of light source data or features.

DETAILED DESCRIPTION

15 [0026] FIG. 1A is a flowchart of an implementation of a procedure for predicting states of light sources. A “state” of a light source, as used herein, refers to a physical and/or operational condition of the light source characterized by the light source having features falling within one of multiple clusters of features previously determined and/or defined by the use of unsupervised machine learning using historical data including such features. “Features” used in this sense includes measurements
20 directly from light sources or light source modules or from equipment or devices related to or connected to light sources, and values calculated based on such measurements, such as calculated performance metrics and the like, measured and/or calculated over time. Such features characterize at least in part or otherwise relate to the operation, performance, or condition of the light sources.

[0027] As seen in FIG. 1A, a procedure or method P100A for predicting states of light sources
25 includes obtaining features of the light sources (S10A). As mentioned and as discussed in more detail below including with respect to FIG. 5, the features represent or relate to operational aspects of the light sources. The procedure P100A further includes clustering the features via unsupervised machine learning (S12A) into clusters representing or corresponding to states, generating a transition matrix for transitions between the clusters, with the clusters including terminal clusters (defined and
30 discussed in more detail below) (S14A), and generating a non-binary prediction of a future cluster and state of the given light source by one or more applications of the transition matrix (S16A).

[0028] FIG. 1B is a flowchart of another implementation of a procedure for predicting states of light sources. As seen in FIG. 1B, a procedure or method P100B for predicting states of light sources includes obtaining features of the light sources, with the features including one or more time-
35 dependent or history-dependent features (S10B). The procedure P100B further includes clustering the features via unsupervised machine learning (S12B), generating a transition matrix for transitions between the clusters (S14B), and generating a non-binary prediction of a future cluster and state of the

given light source by one or more applications of the transition matrix (S16B). Aspects and details regarding the use and application of the procedures or methods P100A and P100B are discussed below.

[0029] Features representing operational aspects of the light sources can be obtained over time by sensing or detecting and storing operational aspects of the light sources over time. For successful prediction of future states, the light sources can be a group of similar light sources having similar components, methods of operation, and similar features that are detected and stored. Features can include performance measures or other metrics, and can include one or more time-dependent or history-dependent features or metrics. Features can include, for example, bandwidth and center wavelength, pulse energy, average power, peak intensity, power per pulse, and energy efficiency. Measures of trends, central tendency, and/or rates of change of any of these can also be features. In this way some time- and/or history-dependent behavior can be represented in the prediction method disclosed herein.

[0030] Having obtained the features representing operational aspects of the light sources, the features are then clustered using “unsupervised” machine learning. Unsupervised learning is a type of machine learning that uses algorithms to analyze and cluster unlabeled datasets, allowing the algorithm to discover relationships that may otherwise be hidden. The term “unsupervised” does not imply complete absence of human interaction or oversight, however. The features (understood as the data corresponding to or representing the features) can first be prepared, such as by normalizing distributions of individual features, and such as by removing extreme outliers. Also, some clustering algorithms require pre-specification of the number of clusters, such that clustering can be optimized by trials of different numbers of clusters and comparative evaluations of the results. Once a finite set of useful clusters has been obtained, the clusters represent the state space of the light source or laser system such that a “cluster” and a “state” (of a light source or laser system having features that falling within the cluster) can be considered synonymous. A subject matter expert can interpret or characterize the clusters, or at least some of the clusters, such as those with high probability of transitioning to themselves (those with high stability, high probability of being in the same cluster/state after a given interval of time), so that cluster (state) information can be understood or used appropriately by others.

[0031] Various algorithms can be used for clustering, including but not limited to affinity propagation, agglomerative clustering, BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies), DBSCAN (Density-Based Spatial Clustering of Applications with Noise), k-means or mini-batch k-means, mean shift, OPTICS (Ordering Points To Identify the Clustering Structure), spectral clustering, and Gaussian mixture model. Adjustable parameters within these algorithms may generally require multiple runs followed by comparative evaluations of the results to find an optimized parameter setting producing a useful finite cluster set.

[0032] Once useful clusters have been defined, a probability matrix can be generated using the collected and stored features or “historical data.” Based on the historical percentage of transitions from each given cluster to each other cluster (out of all transitions from the given cluster), an expected probability of transition, after a given or pre-selected specified time interval, from each cluster to each other cluster, is determined. The specified time interval can be chosen based on the available historical data, such as by choosing a time frequency equal to or greater than the sampling frequency of most or all of the historical data. The specified time interval could be short, such as only 10 minutes or even less, for instance, but could also be long, such as one week or more, but typically would be within the range of one hour to one week, with one day being a potentially useful interval.

[0033] FIG. 2A is a diagram of an example of multiple clusters, clusters C1, C2, and C3, representing states of light sources, and showing the percentage probabilities of transition (represented by the arrows) between the clusters or states after the specified interval of time, such as one day. For example, there is a 10% probability that the state C3 of the light source will transition to a state C1 after the specified interval of time. As shown in FIG. 2A, some clusters, clusters TC1, TC2, and TC3 in this example, are terminal clusters, defined as clusters in which there is no probability of transition to another state and which result in (i.e., require) deinstallation of a light source module in a light source such as light source 564 discussed below with respect to FIG. 5. Such terminal clusters thus represent states in which major maintenance actions with significant downtime are required to return the light source to a condition appropriate for use in photolithography. Identification and/or classification of such terminal clusters can be performed by a subject matter expert as or after the clusters have been defined. FIG. 2B is a diagram of another example of multiple clusters representing states of light sources, essentially identical to FIG. 2A except that only one terminal cluster TC, which may be in the form of a consolidation of more than one terminal cluster is defined for ease of the discussion relative to FIGS. 3 and 4 below.

[0034] With reference to FIGS. 2A and 2B, and assuming for this example that the specified time interval is one day (24 hours), clusters C1, C2, and C3 are all clusters or states in which the light source is capable of producing light useful for photolithography. But the clusters or states C1, C2, and C3 are not very similar to each other, as may be seen from an inspection of the transition probabilities represented in the figures. Cluster or state C1 is the most stable cluster or state, with light sources in cluster or state C1 having a 94.99% probability of being in cluster or state C1 after one day, and having only a 0.01% probability of being in a terminal cluster or state after one day. Light sources in cluster or state C1 have a 4.9% probability of being in cluster or state C2 after one day, and only a 0.1% probability of being in cluster or state C3 after one day. From similar inspection of clusters C2 and C3 and their respective transition probabilities as shown, it can be seen that cluster or state C2 has an intermediate level of stability corresponding to a 40% chance of being in cluster or state C2 after one day, while C3 is quite unstable and carries the relatively high probability of 60% being in a terminal cluster or state (TC of FIG. 2B or TC3 of FIG. 2A) after one day.

[0035] Once clusters have been defined and transition probabilities are known, a transition matrix can be formed representing the respective probabilities of transition of the light sources between the respective clusters after the specified interval of time, assumed as one day for this example, such as the transition matrix M of FIG. 3. The transition matrix is generated by forming a square matrix having a number of rows and columns equal to the number of clusters. Rows of the transition matrix represent the current cluster (state) of a given light source and columns represent the cluster (state) of that light source after one interval of time (one day in this example). The transition matrix M shown in FIG. 3 corresponds to the diagram of FIG. 2B, with rows and columns labeled with the corresponding clusters. Reading row C1 left to the right shows the probability of a light source in C1 being in C1 after one time interval or day, then the probability of being in C2 within one day, and so forth, as indicated by the column headings. Since each row contains the probabilities for a transition from that row's cluster (state) to all other possible clusters (states), the sum of each row is equal to one. Not that the relative order of the row and columns does not affect the function of the transition matrix, but the convention of using the same order for row and columns allows easier recognition and location of the cells of the matrix.

[0036] Using a transition matrix such transition matrix M of FIG. 3, a probability matrix representing the probability of a given light source or laser system (starting in a given cluster) being in each respective cluster, after N of the intervals of time, can be generated by raising the transition matrix to the power of N, or in other words, multiplying the matrix M by itself N-1 times. FIG. 4 is an example of the computed probabilities resulting from raising the transition matrix of FIG. 3 to the power of 14, of transitioning from any of the clusters to any of the clusters after the passage of 14 intervals of time, e.g. 14 days in this example. In other words, FIG. 4 shows a matrix M14 (with row and column labels added) produced by the matrix operation $[M]^{14}$ on the matrix M of FIG. 3. The resulting matrix M14 of FIG. 4 thus represents the predicted probabilities, for a given light source starting in a given cluster as labeled (at left) in the rows of matrix M14, of being in the cluster as labeled in the columns (at the top) after the passage of 14 days. For example, as shown in FIG. 4, a light source in cluster C1 has a 67.16% predicted chance of being in cluster C1 after 14 days, and 24.73% chance of being in terminal cluster TC. Note that the interval of time used is not limited to one day, and can be selected to have any desired duration down to the period or frequency of the historical data used. Note also that a probability matrix can be generated for any number of intervals of time desired, not just for 14 as in this example. Fourteen days is used, as an example only, of one common or convenient time for future state prediction. Stated generally, the probabilities in the probability matrix, generated by raising the transition matrix M to the power N, provide a non-binary (more than two-state) prediction of the future cluster (future state) of a light source or laser system, at a point in the future of N times the interval of time, by applying the transition matrix M N times (in other words, by raising the transition matrix M to the power N).

[0037] As a potential additional benefit to the processes and methods disclosed herein, the defined clusters and their associated states can be studied statistically based on the available historical data, such that additional characteristics might be recognized of light sources in particular states, characteristics that might otherwise remain undetected. The transition matrix itself can also be analyzed, such as to discover high probability paths that lead to undesired states—whether terminal clusters (terminal states) or other undesired states such as states that may be undesired in particular applications of light sources. Identification of high-probability paths to such undesired states can potentially be used to discover ways to reduce the probability of such paths, reducing the probability of arriving at or passing through such undesired states.

[0038] The Markov-chain style analysis and prediction techniques disclosed herein do not represent a perfect fit of Markov mathematics or statistics to the operation of light sources. Markov statistics generally require time-independence and path (or history) independence of the state-change probabilities, conditions which are not met in the actual light sources or laser systems at issue here. In the present processes and methods, however, time-dependent and/or history dependent features can be and/or are used in the features chosen for clustering. Thus the “geography” of time- and/or history-related effects is incorporated somewhat into the clustering and transition probability determinations.

[0039] As an additional aspect, the features used to perform the clustering, determine the transition probabilities, and to produce the transfer matrix and estimate probabilities therewith can be updated periodically by the addition of updated features to the features previously used. Also, older features can optionally be removed from the features previously used. The resulting updated features produce updated clusters that can be different than the previous clusters, and can even include terminal clusters different from previous terminal clusters. Different, updated transition probabilities are also produced. A different, updated transition matrix is also produced and then used to estimate probable states of the light sources, until a next subsequent update of the features. In implementations, upon prediction of a terminal state, such as at or above a given probability and within a given time, a recommendation for immediate later scheduled preventative or preemptive maintenance can generated and optionally transmitted to one or more maintenance persons or organizations. Alternatively, preventative or preemptive maintenance can be automatically initiated immediately or at an automatically selected then-future time.

[0040] FIG. 5 is a block diagram of an example of a light source 564 or laser system, in this case a deep ultraviolet (DUV) source, with which the processes and methods described herein can be used. FIG. 6 is a block diagram of an example of a lithography apparatus 610 that can be used with the DUV source of FIG. 5. With reference to FIGS. 5 and 6, the light source or laser system 564 is a dual-stage pulsed laser system that produces a pulsed light beam 505, which is directed to a photolithography exposure apparatus 610 of FIG. 6. The laser system 564 includes a solid state or gas discharge master oscillator (MO) system 560, a power amplification (PA) system such as a power ring amplifier (PRA) system 565, relay optics 570, and an optical output subsystem 575. This laser system

564 is a deep UV (DUV) laser system 564 and the pulsed light beam 505 has a wavelength in the DUV wavelength range, which includes wavelengths from, for example, about 100 nanometers (nm) to about 400 nm.

[0041] The MO system 560 can include, for example, an MO chamber module 561, in which electrical discharges between electrodes (not shown) can cause lasing gas discharges in a lasing gas to create an inverted population of high energy molecules, such as including argon, krypton, or xenon to produce relatively broad band radiation that is line narrowed to a relatively very narrow bandwidth and center wavelength selected in a line narrowing module ('LNM') 562. The MO system 560 can also include an MO output coupler (MO OC) 563, which can include a partially reflective mirror, forming, with a reflective grating (not shown) in the LNM 562, an oscillator cavity in which the MO system 560 oscillates to form a seed output pulse. The MO system 560 can also include a line-center analysis module (LAM) 564. The LAM 564 can include, for example, an etalon spectrometer for fine wavelength measurement and a coarser resolution grating spectrometer.

[0042] The relay optics 570 shown in FIG. 5 can include an MO wavefront engineering box (WEB) 571 that serves to redirect the output of the MO system 560 toward the PA system 565, and can include, for example, beam expansion with, for example, a multi prism beam expander (not shown) and coherence busting, for example, in the form of an optical delay path (not shown).

[0043] The PA system 565 includes a PRA chamber module 566, which is also an oscillator, for example, formed by injection of the output light beam from the MO system 560 and output coupling optics (not shown) that can be incorporated into a PRA WEB 567 and can be redirected back through a gain medium in the chamber 566 by way of a beam reverser 568. The PRA WEB 567 can incorporate a partially reflective input/output coupler (not shown) and a maximally reflective mirror for the nominal operating wavelength (which can be at around 193 nm for an ArF system) and one or more prisms. The PA system 565 optically amplifies the output light beam from the MO system 560.

[0044] The optical output subsystem 575 can include a bandwidth analysis module (BAM) 576 at the output of the PA system 565 that receive the output light beam of pulses from the PA system 565 and picks off a portion of the light beam for metrology purposes, for example, to measure the output bandwidth and pulse energy. The output light beam of pulses then passes through an optical pulse stretcher module (OPuS) 577 and an output combined autoshutter metrology module (CASMM) 578, which can also be the location of a pulse energy meter which can also be a source of features in the form of stored signals and resulting data. One purpose of the OPuS 577 can be to convert a single output pulse into a pulse train. Secondary pulses created from the original single output pulse can be delayed with respect to each other. By distributing the original laser pulse energy into a train of secondary pulses, the effective pulse length of the light beam can be expanded and at the same time the peak pulse intensity reduced.

[0045] One or more (or even all) of the components (such as the MO chamber 561, the LNM 562, the MO WEB 571, the PRA chamber 566, the PRA WEB 567, the OPuS 577, the BAM 576) of the

laser system 564 can provide one or more features representing operational aspects of the laser system 564, such as, for example, operational aspects of one or more of the components MO chamber 561, the LNM 562, the MO WEB 571, the PRA chamber 566, the PRA WEB 567, the OPuS 577, the BAM 576, and other components not shown. The features representing operational aspects of the laser system 564 can relate to performance of the laser system 564, such as power output, power output variability, central wavelength, spectral width (such as FWHM), and/or energy efficiency. The features representing operational aspects of the laser system 564 can relate to performance of specific components (or “modules”) of the laser system 564, including two or more or three or more modules. Example features include power output, power output variability, central wavelength, spectral width (such as FWHM), and/or energy efficiency of the MO chamber 561 considered by itself, or of the PRA chamber 566 considered by itself, or together with the MO chamber 561. The features representing operational aspects of the laser system 564 can relate to one or more service durations, such as service durations (or “duration of use” since last replacement or servicing), whether measured in units of time or laser pulses or both, for example. The features representing operational aspects of the laser system 564 can relate to one or more measures of trends, such as measures of central tendency including such measures applied to moving windows, rates of change, measures of variability or stability, and so forth. In other words, features representing operational aspects of the laser system 564 can include one or more time-dependent or history-dependent features such as those mentioned above or others. Features such as these, collected over time and stored for many such light sources are then clustered as discussed above.

[0046] The photolithography exposure apparatus 610 of FIG. 6 processes a wafer 611 received by a wafer holder or stage 612. The light beam 505 is a pulsed light beam that includes pulses of light separated from each other in time. The photolithography exposure apparatus 610 can be a liquid immersion system or a dry system. Microelectronic features can be formed on the wafer 611 in part by, for example, exposing portions of a layer of radiation-sensitive photoresist material on the wafer 611 with the light beam 505.

[0047] Use of the predictive processes and methods disclosed herein allow more flexible prediction of future light source or laser system states, including states involving significant maintenance or downtime requirements. Flexibility is increased relative to two-state predictive techniques by allowing for generation of probability estimates for multiple states, not just two. Flexibility is increased relative to methods requiring pre-definition of states by using unsupervised learning so that significant clusters or states) can potentially be found that might otherwise not be apparent. Flexibility is increased relative to prediction techniques having a binary division of time in that predictions can be made at the resolution of N , the predefined or preselected interval of time, and also at any multiple of N , as desired.

[0048] It can be important to detect significant changes in the distribution of data used by a model for modeling relative to the distribution of the data used for training the model in that the performance of

the model can suffer if the modeling data distribution is sufficiently different. FIGS. 7A-7D are graphs illustrating a method of testing for a significant change in the distribution of light source data or features used by a model for prediction, detection, simulation, or the like, relative to the distribution of corresponding data used for training the model. With reference to FIGS. 7A, 7B and 7C, the method includes determining a cumulative distribution function TD of an item of model training data such as shown in FIG. 7A, determining a cumulative distribution function PD of the data for use by the model for prediction, detection, simulation, or the like (the “modeling data”) such as shown in FIG. 7B or FIG. 7C, and determining whether the cumulative distribution function of the modeling data varies, upward or downward, from the cumulative distribution function TD of the training data, at any point, by more than a tolerance value TV, or in other words, determining whether the cumulative distribution function PD of the data for modeling use falls within upper and lower boundaries UB and LB spaced above and below the cumulative distribution function TD of the training data by the tolerance value TV. The tolerance value TV can be within a range such as greater than zero to 0.1, or 0.01 to 0.2, or 0.5 to 0.1. In the example shown in FIG. 7B, the cumulative distribution function PD of the modeling data varies from the cumulative distribution function TD of the training data by more than the tolerance value TV, or in other words, the cumulative distribution function PD of the data for modeling use falls (in part) outside the lower boundary LB spaced below the cumulative distribution function TD of the training data by the tolerance value TV. This supports a conclusion that the distribution of the data for modeling varies significantly from the distribution of the training data. In the example shown in FIG. 7C, in contrast, the cumulative distribution function PD of the data for modeling use falls within upper and lower boundaries UB and LB spaced above and below the cumulative distribution function TD of the training data by the tolerance value TV. This supports a conclusion that the distribution of the data for modeling does not vary significantly from the distribution of the training data.

[0049] With reference to FIG. 7D, as an alternative or additional implementation of the method if the cumulative distribution function PD of the modeling data does not vary from the cumulative distribution function of the training data TD, at any point, by more than the tolerance value TV, as in FIG. 7C, then the tolerance value TV can be reduced successively until the cumulative distribution function PD of the modeling data varies from the cumulative distribution function TD of the training data, at at least some point P, by more than the tolerance value TV. The lowest tolerance value TV not exceeded, or the largest tolerance value exceeded by the cumulative distribution function PD of the modeling data (or both) can then be returned to another process or method or reported.

[0050] The implementations can be further described in the following numbered clauses:

1. A method for predicting states of light sources including laser systems, the method including: obtaining features of the light sources, the features representing operational aspects of the light sources; clustering, with a machine learning algorithm utilizing unsupervised learning, the features into clusters, the clusters representing states of the light sources; generating a transition matrix

between the clusters, the transition matrix representing transition probabilities, after an interval of time, of transitions of the light sources between the clusters, the clusters including one or more terminal clusters from which the probability of transition to another cluster is zero; and for a given light source having features corresponding to a given cluster and state, generating a non-binary prediction of a future cluster and state of the given light source by one or more applications of the transition matrix.

2. The method as in clause 1, wherein the light sources are members of a group of similar light sources having similar components, methods of operation, and features.

3. The method as in clause 1, further including calculating a probability of transition within a given time between a first cluster and a second cluster utilizing a Markov chain by a repeated application of the transition matrix.

4. The method as in clause 3, wherein the first cluster represents the current state of a given light source and the second cluster is a terminal cluster.

5. The method as in clause 1 wherein the interval of time is in the range of one hour to one week.

6. The method as in clause 1 wherein the interval of time is one day.

7. The method as in clause 1 wherein the features of the light sources include historical data from a set of similar light sources.

8. The method as in clause 7 wherein the features of the light sources include features of two or more modules of the light sources.

9. The method as in clause 7 wherein the features of the light sources include features of a master oscillator (MO) module and features of a power amplifier (PA) or power ring amplifier (PRA) module.

10. The method as in clause 7 wherein generating a transition matrix between the clusters includes using the historical data to generate probabilities, after the interval of time, of transitions of light sources between the clusters.

11. The method as in clause 1, further including checking the probability of transition between a first cluster and a second cluster within a given time limit utilizing a Markov chain by repeated application of the transition matrix repeated up to the time limit.

12. The method as in clause 1, further including: obtaining updated features of the light sources, the updated features representing updated operational aspects of the light sources; clustering, with a machine learning algorithm utilizing unsupervised learning, the features and the updated features into updated clusters, the updated clusters representing states of the light sources; generating an updated transition matrix between the updated clusters, the updated transition matrix representing transition probabilities, after an interval of time, of transitions of the light sources between the updated clusters, the updated clusters including one or more terminal clusters from which the probability of transition to another updated cluster is zero; and for a given light source having features corresponding to a

given updated cluster, generating a non-binary prediction of a future updated cluster and state of the given light source by one or more applications of the updated transition matrix.

13. The method as in clause 12, wherein the updated terminal clusters are different from immediately prior terminal clusters.

5 14. The method as in clause 1 wherein the features include one or more time-dependent or history-dependent features.

15. The method as in clause 14 wherein the one or more time-related or history-dependent features include one or more rates of change of one or more aspects of the light sources.

10 16. The method as in clause 14 wherein the one or more time-related or history-dependent features include one or more measures of variability of one or more aspects of the light sources.

17. The method as in clause 14 wherein the one or more time-related or history-dependent features include one or more measures of central tendency of one or more aspects of the light sources.

18. A method for predicting states of light sources such as laser systems, the method including: obtaining features of the light sources, the features representing operational aspects of the light
15 sources, the features including one or more time-dependent or history-dependent features;
clustering, with a machine learning algorithm utilizing unsupervised learning, the features into respective clusters representing respective states of the light sources; generating a transition matrix representing the respective probabilities of transitions of the light sources between the respective clusters after an interval of time; and generating a probability matrix representing the
20 probability of a given light source being in each respective cluster after N of the intervals of time by raising the transition matrix to the power of N.

19. The method as in clause 18 wherein the one or more time-dependent or history-dependent features include one or more rates of change of one or more aspects of the light sources.

20. The method as in clause 18 wherein the one or more time-dependent or history-dependent features
25 include one or more measures of variability of one or more aspects of the light sources.

21. The method as in clause 18 wherein the one or more time-dependent or history-dependent features include one or more measures of central tendency of one or more aspects of the light sources.

22. The method as in clause 18 wherein the clusters include one or more clusters from which the probability of transition to another cluster is zero.

30 23. A method of testing for a significant change in the distribution of light source data for use by a model for prediction, detection, simulation, or the like, relative to the distribution of corresponding data used for training the model, the method including: determining a cumulative distribution function of model training data; determining a cumulative distribution function of the data for use by the model for prediction, detection, simulation, or the like (the “modeling data”); and determining whether the
35 cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at any point, by more than a tolerance value.

24. The method of clause 23 further including, if the cumulative distribution function of the modeling data does not vary from the cumulative distribution function of the training data, at any point, by more than the tolerance value, then repeatedly (a) reducing the tolerance value, and (b) determining whether the cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at any point, by more than the tolerance value, until the cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at some point, by more than the tolerance value; and reporting the last and/or the second-to-last tolerance value.

25. The method of clause 23 wherein the tolerance value is within the range of greater than zero to 0.1.

[0051] The above-described implementations and other implementations are within the scope of the following claims.

CLAIMS

1. A method for predicting states of light sources including laser systems, the method comprising:
obtaining features of the light sources, the features representing operational aspects of the
5 light sources;
clustering, with a machine learning algorithm utilizing unsupervised learning, the features
into clusters, the clusters representing states of the light sources;
generating a transition matrix between the clusters, the transition matrix representing
transition probabilities, after an interval of time, of transitions of the light sources between the
10 clusters, the clusters including one or more terminal clusters from which the probability of transition
to another cluster is zero; and
for a given light source having features corresponding to a given cluster and state, generating
a non-binary prediction of a future cluster and state of the given light source by one or more
applications of the transition matrix.
15
2. The method as in claim 1, wherein the light sources are members of a group of similar light sources
having similar components, methods of operation, and features.
3. The method as in claim 1, further comprising calculating a probability of transition within a given
20 time between a first cluster and a second cluster utilizing a Markov chain by a repeated application of
the transition matrix.
4. The method as in claim 3, wherein the first cluster represents the current state of a given light
source and the second cluster is a terminal cluster.
25
5. The method as in claim 1, wherein the interval of time is in the range of one hour to one week.
6. The method as in claim 1, wherein the interval of time is one day.
- 30 7. The method as in claim 1, wherein the features of the light sources comprise historical data from a
set of similar light sources.
8. The method as in claim 7, wherein the features of the light sources comprise features of two or
more modules of the light sources.

9. The method as in claim 7, wherein the features of the light sources comprise features of a master oscillator (MO) module and features of a power amplifier (PA) or power ring amplifier (PRA) module.

5 10. The method as in claim 7, wherein generating a transition matrix between the clusters comprises using the historical data to generate probabilities, after the interval of time, of transitions of light sources between the clusters.

11. The method as in claim 1, further comprising checking the probability of transition between a first
10 cluster and a second cluster within a given time limit utilizing a Markov chain by repeated application of the transition matrix repeated up to the time limit.

12. The method as in claim 1, further comprising:

15 obtaining updated features of the light sources, the updated features representing updated operational aspects of the light sources;
clustering, with a machine learning algorithm utilizing unsupervised learning, the features and the updated features into updated clusters, the updated clusters representing states of the light sources;
generating an updated transition matrix between the updated clusters, the updated transition matrix representing transition probabilities, after an interval of time, of transitions of the light sources
20 between the updated clusters, the updated clusters including one or more terminal clusters from which the probability of transition to another updated cluster is zero; and
for a given light source having features corresponding to a given updated cluster, generating a non-binary prediction of a future updated cluster and state of the given light source by one or more applications of the updated transition matrix.

25

13. The method as in claim 12, wherein the updated terminal clusters are different from immediately prior terminal clusters.

14. The method as in claim 1, wherein the features include one or more time-dependent or history-
30 dependent features.

15. The method as in claim 14, wherein the one or more time-related or history-dependent features include one or more rates of change of one or more aspects of the light sources.

35 16. The method as in claim 14, wherein the one or more time-related or history-dependent features include one or more measures of variability of one or more aspects of the light sources.

17. The method as in claim 14, wherein the one or more time-related or history-dependent features include one or more measures of central tendency of one or more aspects of the light sources.

18. A method for predicting states of light sources such as laser systems, the method comprising:

5 obtaining features of the light sources, the features representing operational aspects of the light sources, the features including one or more time-dependent or history-dependent features;

clustering, with a machine learning algorithm utilizing unsupervised learning, the features into respective clusters representing respective states of the light sources;

10 generating a transition matrix representing the respective probabilities of transitions of the light sources between the respective clusters after an interval of time; and

generating a probability matrix representing the probability of a given light source being in each respective cluster after N of the intervals of time by raising the transition matrix to the power of N.

19. The method as in claim 18, wherein the one or more time-dependent or history-dependent features include one or more rates of change of one or more aspects of the light sources.

20. The method as in claim 18, wherein the one or more time-dependent or history-dependent features include one or more measures of variability of one or more aspects of the light sources.

21. The method as in claim 18, wherein the one or more time-dependent or history-dependent features include one or more measures of central tendency of one or more aspects of the light sources.

22. The method as in claim 18, wherein the clusters include one or more clusters from which the probability of transition to another cluster is zero.

23. A method of testing for a significant change in the distribution of light source data for use by a model for prediction, detection, simulation, or the like, relative to the distribution of corresponding data used for training the model, the method comprising:

30 determining a cumulative distribution function of model training data;

determining a cumulative distribution function of the data for use by the model for prediction, detection, simulation, or the like (the “modeling data”); and

determining whether the cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at any point, by more than a tolerance value.

24. The method of claim 23, further comprising:

if the cumulative distribution function of the modeling data does not vary from the cumulative distribution function of the training data, at any point, by more than the tolerance value, then repeatedly (a) reducing the tolerance value, and (b) determining whether the cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at any point, by more than the tolerance value, until the cumulative distribution function of the modeling data varies from the cumulative distribution function of the training data, at some point, by more than the tolerance value; and

reporting the last and/or the second-to-last tolerance value.

- 10 25. The method of claim 23, wherein the tolerance value is within the range of greater than zero to 0.1.

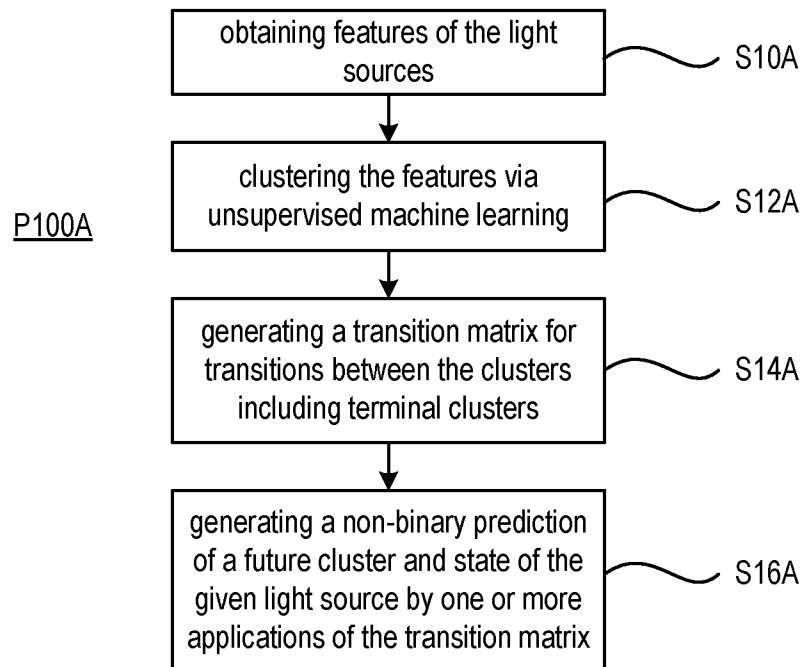


FIG. 1A

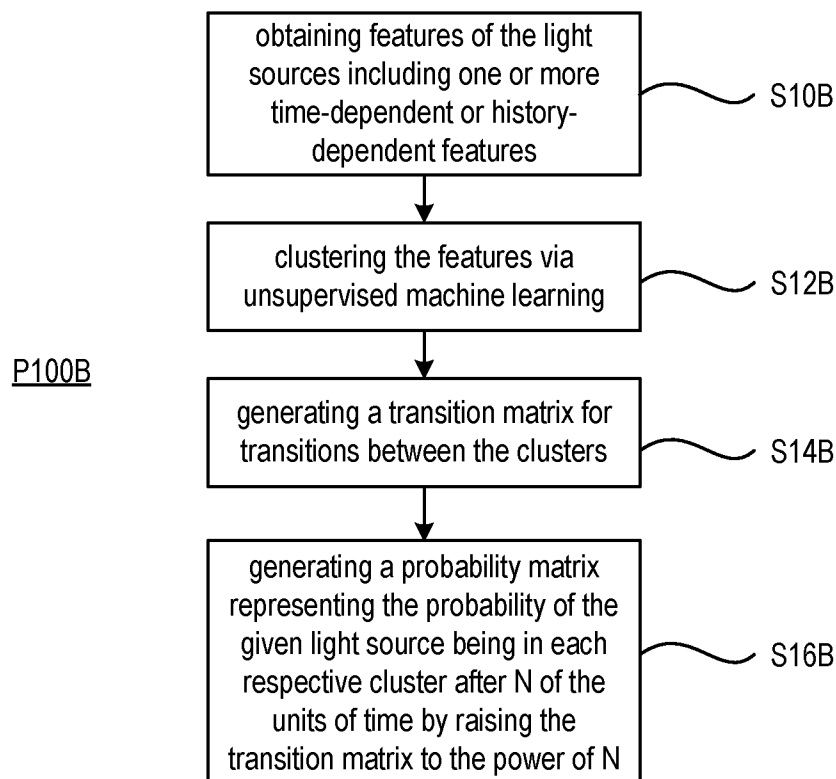


FIG. 1B

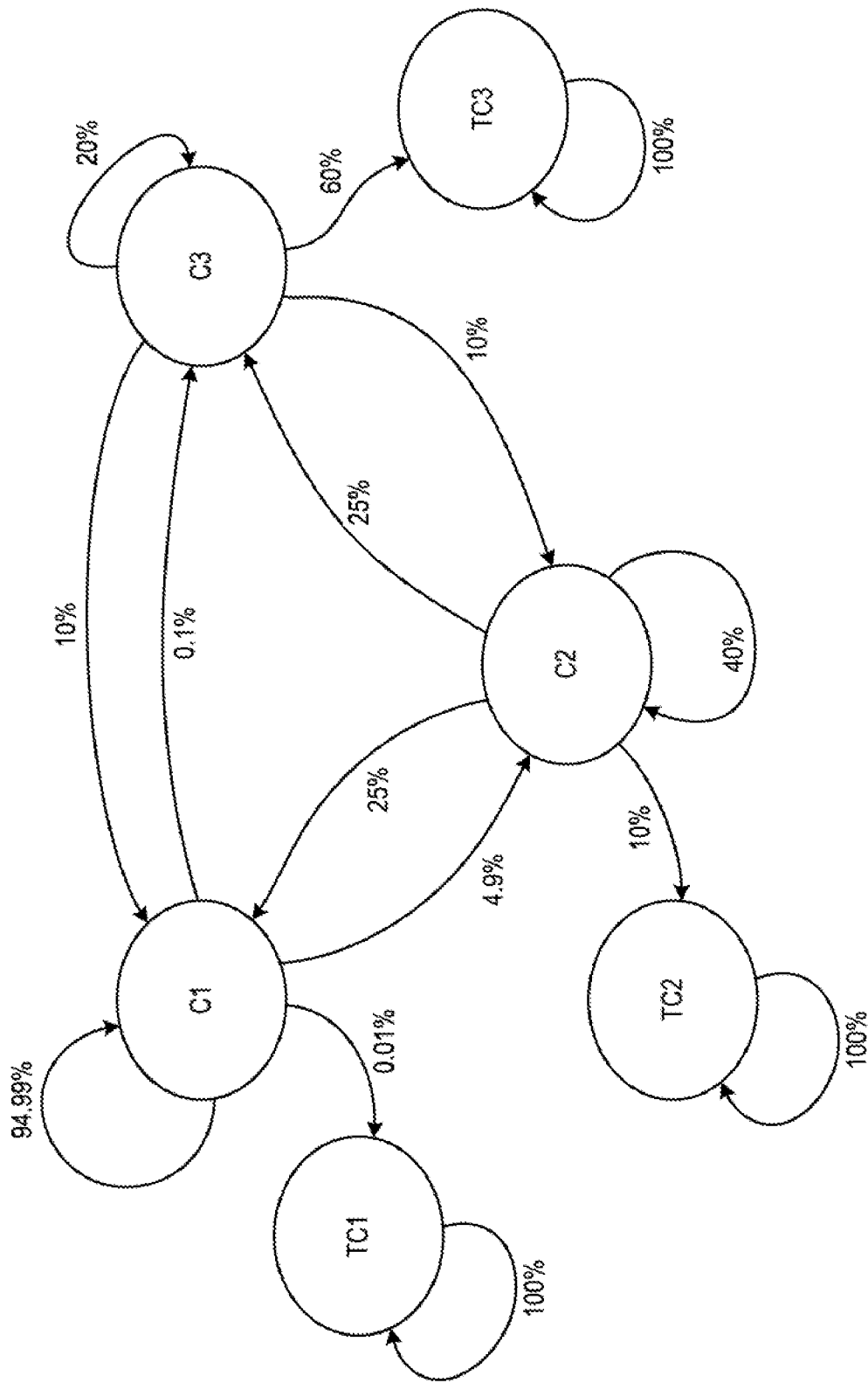


FIG. 2A

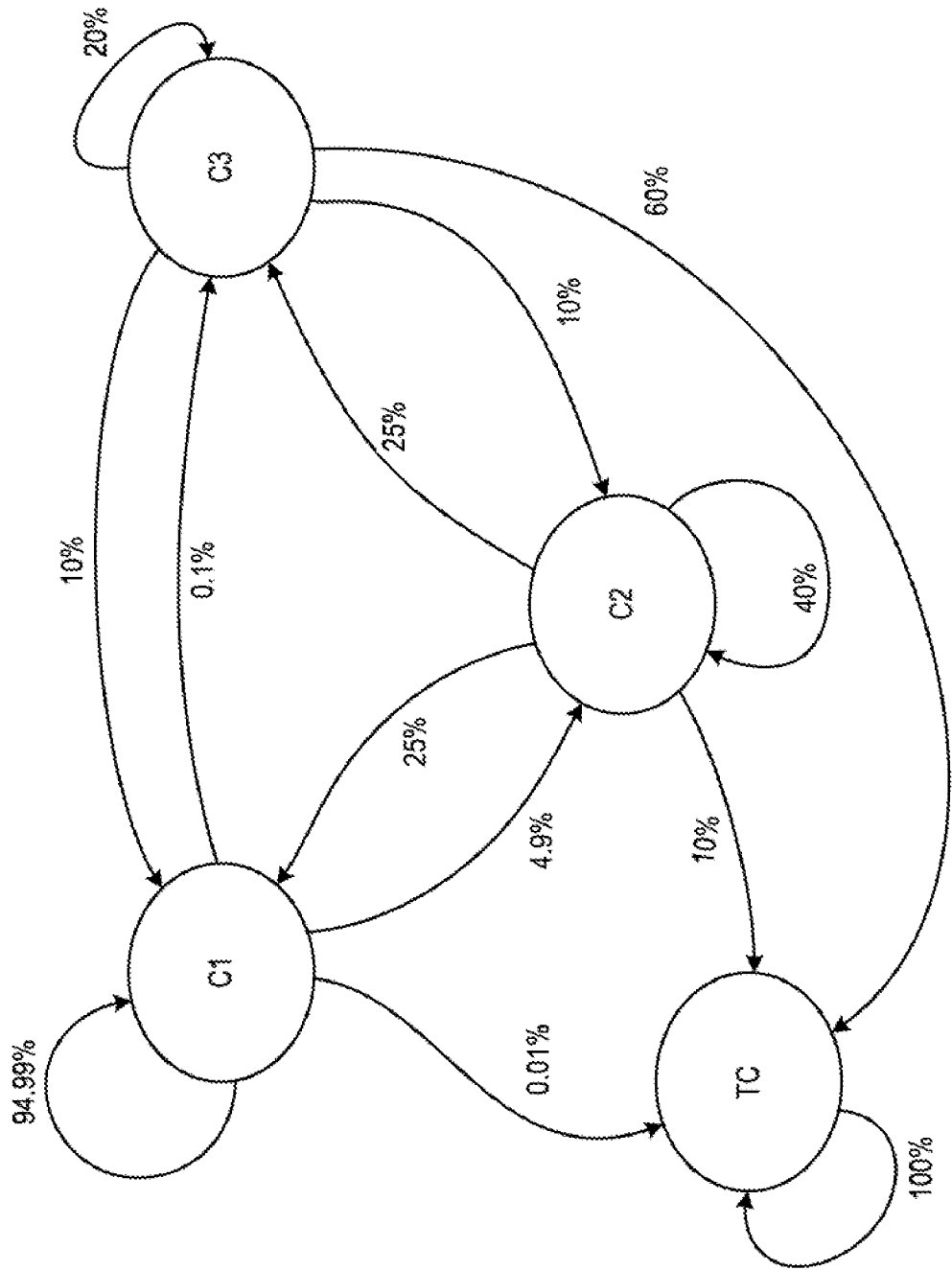


FIG. 2B

	C1	C2	C3	TC
C1	0.9499	0.049	0.001	0.0001
C2	0.25	0.40	0.25	0.10
C3	0.10	0.10	0.20	0.60
TC	0	0	0	1

M 

FIG. 3

	C1	C2	C3	TC
C1	0.6716	0.0607	0.0204	0.2473
C2	0.3488	0.0316	0.0106	0.6090
C3	0.1316	0.0119	0.0040	0.8525
TC	0	0	0	1

M14 

FIG. 4

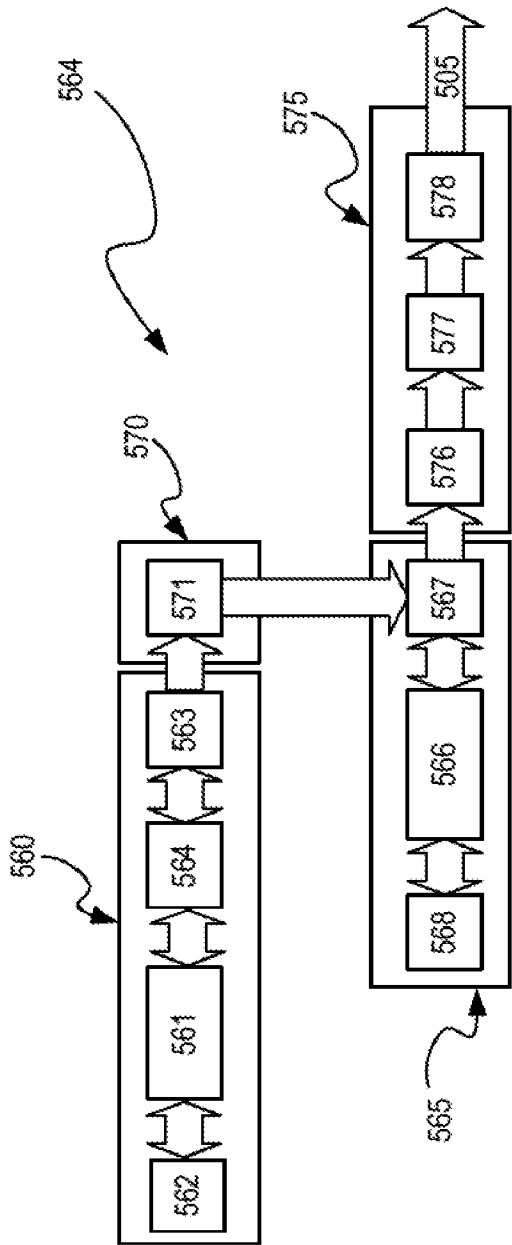


FIG. 5

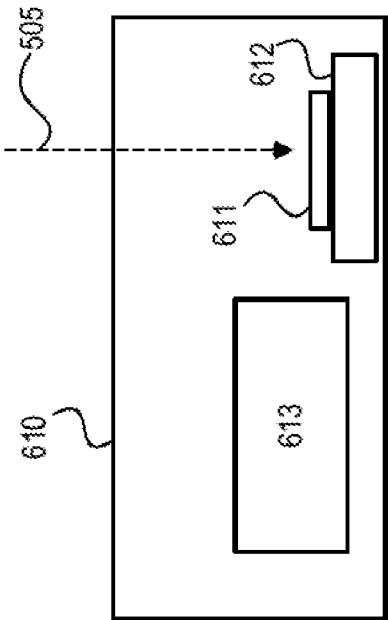


FIG. 6

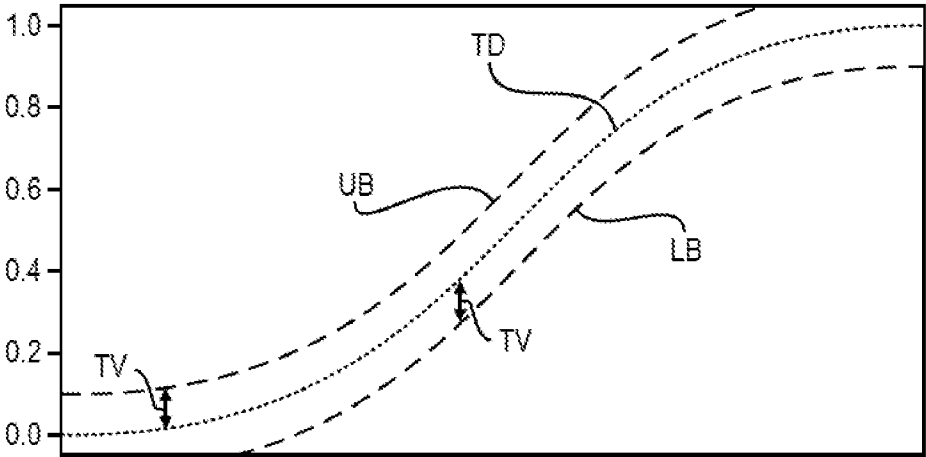


FIG. 7A

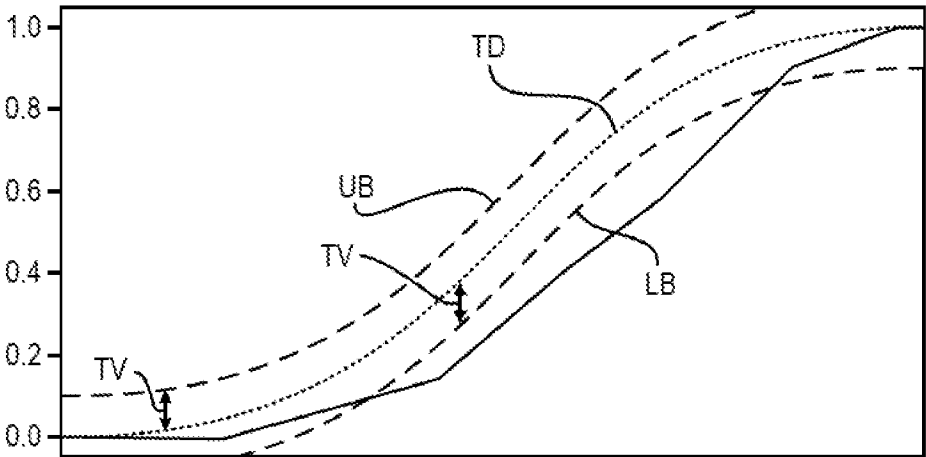


FIG. 7B

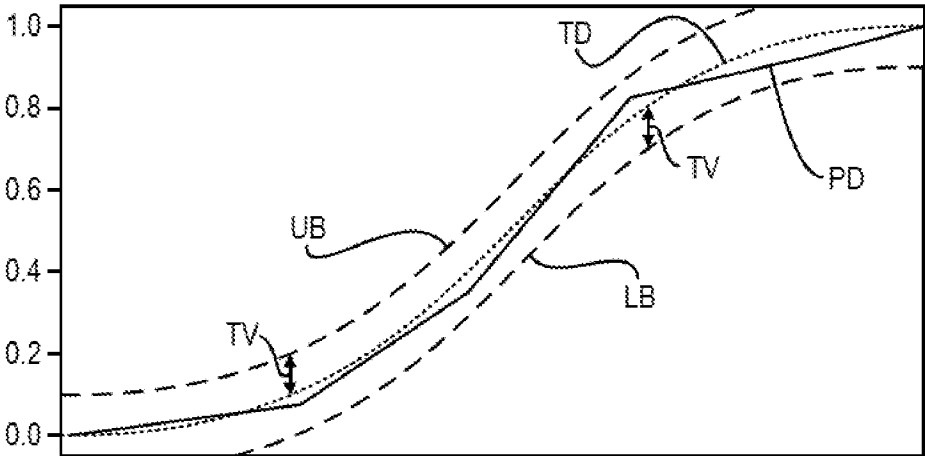


FIG. 7C

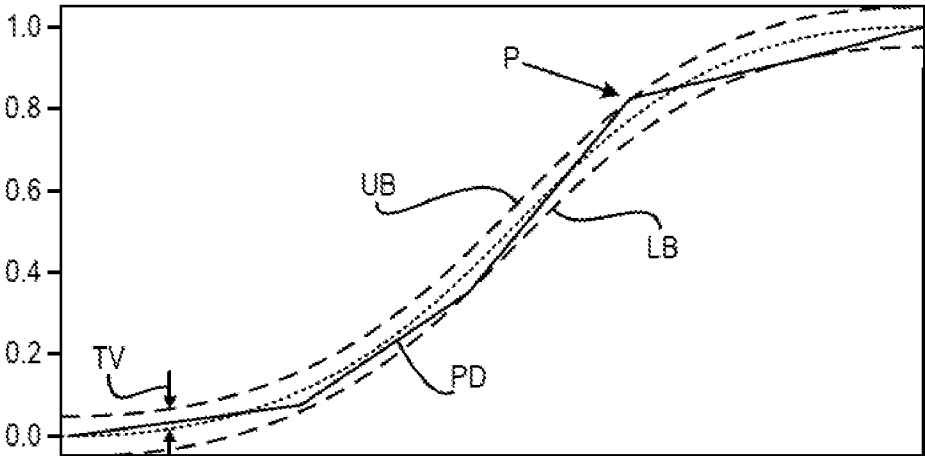


FIG. 7D

INTERNATIONAL SEARCH REPORT

International application No

PCT/IB2024/054830

A. CLASSIFICATION OF SUBJECT MATTER

INV. G03F7/20 G06N3/00

ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

G03F H01S G06N

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal, WPI Data

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	US 2013/207544 A1 (KASKEY JEFFREY [US] ET AL) 15 August 2013 (2013-08-15) abstract figure 9 paragraphs [0002], [0014], [0015], [0035], [0040], [0057] - [0062] -----	1 - 22
X	US 2017/262772 A1 (TAKIGAWA HIROSHI [JP] ET AL) 14 September 2017 (2017-09-14) abstract figure 1 paragraphs [0002], [0028], [0141] ----- - / - -	1 - 22



Further documents are listed in the continuation of Box C.



See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search

13 September 2024

Date of mailing of the international search report

14/11/2024

Name and mailing address of the ISA/

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Authorized officer

Andersen, Ole

INTERNATIONAL SEARCH REPORT

International application No
PCT/IB2024/054830

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT		
Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	STROCK JACOB P ET AL: "The development of a machine learning-based excimer laser performance simulator for engineering maintenance decisions", METROLOGY, INSPECTION, AND PROCESS CONTROL XXXVII, vol. 12496, 27 April 2023 (2023-04-27), pages 1-14, XP060180066, ISSN: 0277-786X, DOI: 10.1117/12.2658043 ISBN: 978-1-5106-6099-1 the whole document -----	1 - 22

INTERNATIONAL SEARCH REPORT

International application No.
PCT/IB2024/054830

Box No. II Observations where certain claims were found unsearchable (Continuation of item 2 of first sheet)

This international search report has not been established in respect of certain claims under Article 17(2)(a) for the following reasons:

1. ☐ Claims Nos.:
because they relate to subject matter not required to be searched by this Authority, namely:
2. ☐ Claims Nos.:
because they relate to parts of the international application that do not comply with the prescribed requirements to such an extent that no meaningful international search can be carried out, specifically:
3. ☐ Claims Nos.:
because they are dependent claims and are not drafted in accordance with the second and third sentences of Rule 6.4(a).

Box No. III Observations where unity of invention is lacking (Continuation of item 3 of first sheet)

This International Searching Authority found multiple inventions in this international application, as follows:

see additional sheet

1. ☐ As all required additional search fees were timely paid by the applicant, this international search report covers all searchable claims.
2. ☐ As all searchable claims could be searched without effort justifying an additional fees, this Authority did not invite payment of additional fees.
3. ☐ As only some of the required additional search fees were timely paid by the applicant, this international search report covers only those claims for which fees were paid, specifically claims Nos.:
4. ☒ No required additional search fees were timely paid by the applicant. Consequently, this international search report is restricted to the invention first mentioned in the claims;; it is covered by claims Nos.:

1 - 22

Remark on Protest

- ☐ The additional search fees were accompanied by the applicant's protest and, where applicable, the payment of a protest fee.
- ☐ The additional search fees were accompanied by the applicant's protest but the applicable protest fee was not paid within the time limit specified in the invitation.
- ☐ No protest accompanied the payment of additional search fees.

FURTHER INFORMATION CONTINUED FROM PCT/ISA/ 210

This International Searching Authority found multiple (groups of) inventions in this international application, as follows:

1. claims: 1-22

Processor-implemented-method for predicting states of light sources including laser systems.

The method comprises steps of clustering features and generating a non-binary prediction of a future cluster and state of a given light source.

This authority considers, that the reference to a machine-learning-algorithm implies that the method is processor-implemented.

2. claims: 23-25

Method of testing for a significant change in the distribution of light source data.

The method comprises steps of determining and analysing a cumulative distribution function of model training data.

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No
PCT/IB2024/054830

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		US	2017262772 A1	14-09-2017
