

## **SYSTEM AND METHOD FOR ESTIMATING A FAILURE PROBABILITY OF ONE OR MORE INFRASTRUCTURE ASSETS**

### **TECHNICAL FIELD**

[0001] Various aspects of this disclosure relate to systems and methods for estimating a failure probability of one or more infrastructure assets.

### **BACKGROUND**

[0002] As infrastructure asset (e.g., electrical utility infrastructure, water infrastructure, road and transportation infrastructure, etc., etc.) ages, maintenance is needed to maintain performance while minimizing costs. To maximize the reliability and performance of infrastructure assets throughout their life cycle, the assets owner usually needs to schedule different maintenance plans based on the asset health condition, which can be quantified by failure probability and remaining useful life (RUL). Effective asset management that accounts for failure rates and RUL can facilitate informed decision-making, such as renewal planning, intervention timing adjustments, and life cycle cost optimization. Without timely renewal and anomaly detection, failure of infrastructure assets may result in service interruptions, economic losses, and even cascading blackouts.

[0003] For those infrastructure assets operated under different conditions and deteriorated differently, their specific condition monitoring data can be used to identify abnormality, quantify risks and prioritize replacements. However, there is no universal criterion or approach for dealing with various condition datasets for different types of assets. Ideal infrastructure asset management portfolios seek to prioritize the unhealthy assets, which is based on identifying the abnormalities in measured assets condition, quantifying the relative degree-of-outlier and health conditions of assets, and interpreting the health condition of assets into their failure probability, and remaining useful life (RUL). Given effective asset health estimations, customized renewal schemes can be developed for explainable and interpretable management of different infrastructure assets, depending on their condition monitoring probability density and the degree of outlier they exhibit.

[0004] Asset health evaluation is essential to asset management because it allows proactive identification of potential risks before a costly renewal. By regularly renewing the identified unhealthy infrastructure assets based on the monitored condition data,

organizations can ensure a high reliability level and secure health status for infrastructure assets. As such, if the assets (for example transformers) can be maintained in low failure probability and low abnormality status that alike young healthy assets, the risks of their failure can be probabilistically minimized. In order to analyse the assets failure probability based on condition monitoring, the conditional probability principles can be applied, which could leverage the cluster distance and degrees of outlier as quantitative measure to interpret the equivalent failure probability (and equivalent age in the Weibull model) for assets. Current practice involves some industrial standards for abnormal values of specific assets (e.g., dissolved gas values for certain types of transformers) based on experimental statistics. However, when available monitoring variables, condition monitors, or referred standards change (e.g., for different transformer designs), previous experience and standards may no longer be effective. In addition, such system uses weightage values adjusted by the expert and it introduce problems such as black box model, readjustment of the weightage, validation of the weightage, and masking effect due to weighted summation. Therefore, asset health estimation and corresponding management should rely on the specific failure probability distribution for the assets and consider the prior condition monitoring variables. To accurately and effectively evaluate the health condition and failure probability of assets, the assets owners need to build up asset-specific failure probability statistic model, determine the mostly-correlated condition monitoring variables, integrate abnormality quantification methods, as well as analyse the equivalent failure probability (and physical age) for the infrastructure assets given both age and condition monitoring.

[0005] Machine-learning-based health estimation and management methods typically heavily rely on labelled assets database, which is barely available for most realistic scenarios. Additionally, many healthy assets are usually unnecessarily replaced, causing waste of resources and disruption of services. Given the limitations and inefficiencies of existing infrastructure asset management methods, more advanced and adaptive assets health evaluation and management method considering failure probability and condition monitoring are desirable. However, due to the diversity and specificity for assets' condition monitoring, the existing experiments-based approaches generally suffer from narrow application scope and lack of adaption for different assets designs.

### SUMMARY

[0006] Various embodiments concern a method for estimating a failure probability of one or more assets, comprising receiving, for each of a plurality of assets, operating condition data of the assets, separating the assets into a plurality of groups taking into account the operating condition data of the assets, determining, for each group, an expected asset health index of the assets belonging to the group, determining an operating condition monitoring data feature of an asset to be evaluated, determining, for each group, a conditional probability that the asset to be evaluated belongs to the group taking into account the operating condition monitoring data feature of the asset to be evaluated and condition monitoring data features of the assets belonging to the group and estimating a probability of failure of the asset to be evaluated by the summation of the conditional probability of belonging to each group times the expected asset health index of each groups.

[0007] For example, according to various embodiments, a method for asset health evaluation and management is provided, including constructing statistics distribution of assets failures, estimating the failure probability of assets through a combination of a statistical failure probability model and condition data, separating the assets into a plurality of groups taking into account the operating condition data of the assets, determining, for each group, an expected asset health index via the conditional probability of belonging to the group, determining an operating condition monitoring data anomaly measure (outlier or clustering) feature of an asset to be evaluated, determining, for each group, a conditional probability that the asset to be evaluated belongs to the group taking into account the operating condition monitoring data feature of the asset to be evaluated, wherein the probability of belonging to the group is calculated based on the conditional probability given the condition monitoring data can be observed as prior event, determining, the expectation of equivalent age, equivalent failure probability, and equivalent asset health index given the condition monitoring data as prior event, wherein the respective expected asset health index is calculated by the conditional probability of belonging to the group (given condition data as prior event) times the asset health index of the corresponding group.

[0008] According to one embodiment, the assets can be separated into groups according to their ages (as young/old age groups or different individual ages), or clustering distance.

[0009] According to one embodiment, determining the conditional probability that the asset to be evaluated belongs to the group includes determining, for each asset, an anomaly

measure (degree-of-outlier, or clustering distance) of the condition monitoring data feature of the asset, determining, for each group, a distribution of the anomaly measure (degree-of-outlier, or clustering distance) of the condition monitoring data feature within the group (i.e. of the assets belonging to the group), determining, for the asset to be evaluated, the anomaly measure (degree-of-outlier, or clustering distance) of the condition monitoring data feature of the asset to be evaluated, determining, for each group, the conditional probability that the asset to be evaluated belongs to the group by determining a probability that the anomaly measure (degree-of-outlier, or clustering distance) of the condition monitoring data feature of the asset to be evaluated has according to the distribution of the anomaly measure (degree-of-outlier, or clustering distance) of the condition monitoring data feature of the assets belonging to the group.

[0010] According to one embodiment, separating the assets into the plurality of groups includes separating the assets into the plurality of groups, such that, for every two groups, the distributions of the anomaly measure (degree-of-outlier, or clustering distance) of the condition monitoring data feature of the assets belonging to the groups differ by at least a predetermined threshold (e.g. have different peaks such that the probability distributions are different).

[0011] According to one embodiment, the method includes determining, for each asset, at least one condition monitoring data feature from its condition monitoring data, and separating the assets into the plurality of groups according to their condition monitoring data features.

[0012] According to one embodiment, the expected asset health index is normalized by the expected probabilities of failures and the maximum allowed probabilities of failure.

[0013] According to one embodiment, the expected asset health index of the groups are normalized values using the expected probabilities of failures as allowable probabilities of failure.

[0014] According to one embodiment, the groups have different expected asset ages (e.g. an average asset age of the assets belonging to the group), and the probability of failure of the asset to be evaluated is determined by determining a statistical failure probability from a Weibull model and an equivalent age of the asset to be evaluated, wherein the equivalent age is by the summation (over the groups) of the conditional probability of belonging to each group (given condition data as prior event) times the expected asset age of the group.

[0015] According to one embodiment, the method includes determining a relation between asset age and probability of failure of the assets and determining the probability of failure of the asset to be evaluated from the equivalent asset age of the asset to be evaluated according to the relation between asset age and probability of failure.

[0016] According to one embodiment, the relation is determined by fitting a Weibull distribution to the assets.

[0017] According to one embodiment, the method includes visualizing the separation of assets into the groups and re-separating the assets into groups in response to a corresponding user input.

[0018] According to one embodiment, the method includes separating the assets into groups using an unsupervised machine learning algorithm.

[0019] According to one embodiment, the operating condition data includes sensor measurement data.

[0020] According to one embodiment, separating the assets into the plurality of groups taking into account the operating condition data of the assets includes filtering the operating condition data to remove operating condition data that is not correlated with asset health.

[0021] According to one embodiment, a method for controlling (managing) assets is provided including estimating a failure probability for the one or more assets according to any one of the embodiments described above and controlling (managing) the one or more assets according to the estimated failure probability.

[0022] According to one embodiment, the method includes classifying each of the one or more assets into a healthy or unhealthy asset according to the estimated failure probability and controlling (managing) the one or more assets according to the classification.

[0023] According to one embodiment, the method includes outputting an alert in case the one or more assets have been classified as unhealthy.

[0024] According to one embodiment, the method includes triggering a replacement of the one or more assets if they have been classified as unhealthy.

[0025] According to one embodiment, the method includes taking the one or more assets out of service if they have been classified as unhealthy.

[0026] According to one embodiment, a data processing system is provided including a communication interface, a memory and a processing unit configured to perform the method of any one of the embodiments described above.

[0027] According to one embodiment, a computer program element is provided including program instructions, which, when executed by one or more processors, cause the one or more processors to perform the method of any one of the embodiments described above.

[0028] According to one embodiment, a computer-readable medium is provided including program instructions, which, when executed by one or more processors, cause the one or more processors to perform the method of any one of the embodiments described above.

### BRIEF DESCRIPTION OF THE DRAWINGS

[0029] The invention will be better understood with reference to the detailed description when considered in conjunction with the non-limiting examples and the accompanying drawings, in which:

- FIG. 1 illustrates the modelling of a system.
- FIG. 2 shows a diagram with the cumulative distribution function of the two-parameter Weibull distribution for three different combinations of parameters.
- FIG. 3 illustrates a framework for an asset health evaluation method based on a combination of statistical model and condition monitoring based failure probability calculation.
- FIG. 4 illustrates the first step of the health evaluation method, which builds up a baseline Weibull failure probability model and a relationship between the remaining useful life and allowable failure probability from a set of assets.
- FIG. 5 illustrates separation of the assets into different groups based on their degree of outlier, condition clustering, or industrial rules.
- FIG. 6 illustrates the data-driven calculation of degree-of-outlier for condition monitoring data and the formulation of an asset condition radar model.
- FIG. 7 shows a flow chart illustrating the constructing the cluster-based condition group separation.
- FIG. 8 illustrates the process for constructing the probability distribution of condition indicator(s) for each of the separated groups.
- FIG. 9 illustrates the process to calculate the probability of belonging to each condition groups based conditional probability, as well as the calculation of expected equivalent age and failure probability.

- FIG. 10 show the examples of utilizing the asset health evaluation method combining the Weibull model, degree-of-outlier, and kernel probability, group separation, and conditional probability of condition monitoring data.
- FIG. 11 shows the effectiveness of quantile normalization to interpret the remaining useful life into different asset AHI (Asset Health Index) values while keeping the same data distribution.
- FIG. 12 shows a flow diagram illustrating a method for estimating a failure probability of one or more assets.
- FIG. 13 shows a data processing system according to an embodiment.

### DETAILED DESCRIPTION

[0030] The following detailed description refers to the accompanying drawings that show, by way of illustration, specific details and embodiments in which the disclosure may be practiced. These embodiments are described in sufficient detail to enable those skilled in the art to practice the disclosure. Other embodiments may be utilized and structural, and logical changes may be made without departing from the scope of the disclosure. The various embodiments are not necessarily mutually exclusive, as some embodiments can be combined with one or more other embodiments to form new embodiments.

[0031] Embodiments described in the context of one of the devices or methods are analogously valid for the other devices or methods. Similarly, embodiments described in the context of a device are analogously valid for a vehicle or a method, and vice-versa.

[0032] Features that are described in the context of an embodiment may correspondingly be applicable to the same or similar features in the other embodiments. Features that are described in the context of an embodiment may correspondingly be applicable to the other embodiments, even if not explicitly described in these other embodiments. Furthermore, additions and/or combinations and/or alternatives as described for a feature in the context of an embodiment may correspondingly be applicable to the same or similar feature in the other embodiments.

[0033] In the context of various embodiments, the articles “a”, “an” and “the” as used with regard to a feature or element include a reference to one or more of the features or elements.

[0034] As used herein, the term “and/or” includes any and all combinations of one or more of the associated listed items.

[0035] In the following, embodiments will be described in detail.

[0036] FIG. 1 illustrates the modelling of a system.

[0037] Data 102 is gathered which holds information about the time of failures of devices of equipment 101 (e.g. a fleet of vehicles, a set of machines etc.), i.e. of a set of assets. The data 102 may for example indicate a time at which devices (e.g. vehicle components) have failed. It is therefore also referred to as failure data. An asset (e.g. device) health model 103 is generated from the failure data 102. So, the asset health model 103 may for example model a failure probability per asset (e.g. device) depending on the life-time (e.g. time since start of operation) of the asset. The statistical (failure) model 103 can for example predict the total number of failures of a fleet of assets (e.g. vehicles, machine etc.) for a given period and/or estimate the remaining useful life (RUL) for the assets.

[0038] An example of a probability distribution which may be fitted to information contained in the failure data 102 as part of the asset health model 103 is a two-parameter Weibull distribution which has the probability density function (pdf) and the cumulative distribution function (cdf)

$$f(t; \beta, \eta) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^\beta} \text{ and } F(t; \beta, \eta) = 1 - e^{-\left(\frac{t}{\eta}\right)^\beta}. \quad (1)$$

[0039] A controller 104 (e.g. a data processing device such as a server computer controlling the equipment, in particular in response to user commands) and/or human operator (e.g. engineer) may then use the asset health model 103 for controlling (managing) the equipment group, i.e. perform asset health management, e.g. deactivate an asset (which has a high probability of failure, e.g. above a tolerable threshold), i.e. take the asset out of service, perform maintenance of the asset, replace the asset (e.g. a machine component), change operating parameters of the asset (to reduce risk of failure or impact of failure), supplement backup assets etc.

[0040] FIG. 2 shows a diagram 200 with the cumulative distribution function of the two-parameter Weibull distribution for three different combinations of the (two) parameters  $\beta$  and  $\eta$ . The variable  $t$  for example refers to the time, e.g. a time since starting operation of an asset

of the equipment group 101 and  $F(t)$  for example is the probability that the asset has failed since the beginning of its operation until time  $t$ .

[0041] According to various embodiments, an asset health evaluation method (in particular by calculating a probability of failure) based on a combination of a statistical failure probability model (e.g. Weibull) and a condition-monitoring-based failure probability (conditional probability) calculation model (which may for example both be part of the asset health model 103) is provided. According to various embodiments, the statistical failure rate model and the data-driven health condition analysis model are integrated in three steps as illustrated in FIG. 3.

[0042] FIG. 3 illustrates a framework for an asset health evaluation method based on the combination of statistical (Weibull) model 304 and condition monitoring based failure probability calculation. A conditional distribution is used to calculate a failure probability of an asset to be evaluated given an anomaly measure (degree-of-outlier) of the asset to be evaluated or a condition monitoring data feature of the asset (used for clustering). The remaining useful life and physical age of the asset can be derived from the failure probability using the baseline Weibull model 304. Health condition (e.g. sensor) data monitored for an asset statistically determines the failure probability (and equivalent age) of the asset by shifting the location 305 of the asset's current age state to a safer or more risky region.

[0043] In a first step 301, according to various embodiments, an asset failure distribution model is established by fitting the Weibull distribution model 304. The failure probability is divided into four risk levels according to probability failure rate (including in particular a range of acceptable probability failure rate).

[0044] FIG. 4 illustrates the first step of the health evaluation method, which builds up a baseline Weibull failure probability model 401 and a relationship between the remaining useful life (RUL) and allowable failure probability from a set of assets.

[0045] The failure rate and failure probability of the assets is derived using parametric regression. Considering an acceptable failure probability (e.g. of an owner of the assets), an AHI (Asset Health Index) of each asset is calculated and located on the model (see FIG. 3 and FIG. 4). Eventually, the remaining useful life is derived based on the time difference from present to the time AHI reaches 0 (which may be seen as end-of-life indication). The Weibull model 304, 401 is applied to determine the probability of failure for an asset under investigation (i.e. an asset whose health should be evaluated), which characterizes the time-

to-failure distribution by leveraging two key parameters: the shape parameter ( $\beta$ ) and the scale parameter ( $\eta$ ). By representing the failure behaviour of assets with the Weibull model as baseline, the various types of failure patterns are captured, including constant failure rates, incremental failure rates, and decreasing failure rates. Upon estimating the Weibull model parameters, the general probability of failure with respect to the age of assets is calculated. However, the deviation from expected behaviour and conditions cannot be represented in this model. Therefore, according to various embodiments, condition monitoring variables are integrated into the asset health model 103 using the next step.

[0046] Accordingly, a second step 302, asset condition monitoring (e.g. abnormality detection) is integrated to refine the asset health estimation results. By considering the assets with different operating conditions as different groups, an abnormality can be quantified with a degree-of-outlier or other clustering (or grouping) feature.

[0047] FIG. 5 illustrates (as second step 302 of the asset health evaluation method) separation of the (training) assets into different groups based on their degree of outlier 501, condition clustering 502, or industrial rules 503.

[0048] With such a group separation and anomaly measures (degree-of-outlier or clustering feature distance), a group-specific probability of failure (i.e. a probability of failure for each group (e.g. age group or cluster)) can be analytically determined. The asset condition data degree of outlier (or clustering distance) can be used to more accurately determine the probability of failure of an asset to be evaluated, which leads to more accurate and actionable insights for asset management and maintenance planning. Such condition monitoring detects early signs of degradation and potential failure. By analysing the anomaly measure (degree of outlier or clustering distance), assets may be identified that may require additional attention or maintenance intervention. With the data of degree-of-outlier (or clustering distance) for assets, kernel density estimation can be utilized to separate the different asset groups with different layers. Statistically, the probability of an asset belonging to a respective group with different distinguishable failure probability (and thus age to which the failure probability corresponds according to the Weibull distribution) can be calculated. So, according to various embodiments, an asset health estimation (and e.g. management) method exploits the condition monitoring data, identify correlated indicators for health estimation, quantify the indicators degree of outlier, and utilizes conditional probability to estimate the health condition of assets.

[0049] As shown in FIG. 5, as alternative to the grouping such that they are separated by different degree-of-outlier distributions, a data-driven condition clustering 502 may be used to distinguish normal and abnormal condition monitoring data, identify significant patterns for health condition, and utilize identified patterns to estimate the health condition of assets. For this, before clustering, the raw condition monitoring data (e.g. sensor data from various sensors like temperature, pressure etc.) is normalized and a feature extraction method is used to reduce the dimension of the normalized condition monitoring data and generate, for each asset, a (normalized) clustering feature (or feature value or vector). The reduction of the conditioning monitoring data to a clustering feature may enhance the efficiency of the clustering. Then, clusters of assets are formed such that assets (e.g. objects) in the same cluster are similar (in terms of the clustering features) and assets in different clusters are distinct (i.e. the difference between their clustering features is higher than that between assets within the same cluster). Different clustering techniques may be tested with different measures of (feature) similarity. After getting the clustered asset groups, the failure probability distribution (and corresponding age in the Weibull model) of the assets within each group can be estimated based on kernel density functions. Then, Wasserstein distance is calculated to measure the distance between condition distributions of two group. If the Wasserstein distance of any two group cannot meet the pre-set criteria, this clustering is considered as unsuccessful. The condition distribution-based method is based on the prior knowledge that, if a clustering is considered as successful in this context, assets within the same clustered group should have similar health status.

[0050] In the third step 303, conditional probability is utilized to calculate the equivalent failure probability (and physical age) for an asset under investigation. Given the degree-of-outlier or the clustering feature, the probability of an asset belonging to each group with different failure probabilities can be calculated with the conditional probability on the estimated kernel density function. The expectation of failure probability is calculated by summing up the expected failure probability for each group (or cluster) multiplied by the conditional probability of belonging to this group (or cluster). Based on such failure probability (y-axis in FIG. 1) calculation, the equivalent age (x-axis in the Weibull probability depiction in FIGs. 3 and 4) can be also determined based on the Weibull model 304, 401, and then the asset RUL can be calculated by subtracting the maximum allowable operation year with the equivalent age given the failure probability.

[0051] This approach also allows for the accurate estimation of asset health even in cases where the condition monitoring data may be noisy or incomplete. By leveraging the varying probability distributions among different condition groups, this method can provide a more reliable and accurate estimate of asset health compared to traditional methods. In addition, the use of kernel probability density enables the identification of abnormal or unhealthy conditions that may not be readily apparent from the raw condition monitoring data. This can help to identify potential issues before they become more serious and costly to repair. The AHI serves as a comprehensive measure to gauge the overall health and performance of the asset.

[0052] In the following, the steps of the asset health evaluation method as illustrated in FIG. 3 is described in more detail.

[0053] The asset health evaluation (e.g. followed by asset health management) based on failure probability and condition monitoring includes, according to one embodiment, as described above, identifying a degree-of-outlier (with regard to health condition (e.g. sensor) data), relative health condition, failure probability, and remaining useful life, for all assets under investigation and, e.g., prioritizing the management of unhealthy ones (e.g. replacing them).

[0054] As shown in FIG. 3, the first step 301 includes estimating the failure rate distribution of a (training) set of assets (i.e. historical behaviour of assets of the asset type for which health should be evaluated) based on fitting a Weibull distribution 304. The Weibull distribution is a continuous distribution for failure distribution analysis. According to various embodiments, the two parameter Weibull distribution is used to build up the baseline failure probability model 301 for infrastructural assets.

[0055] The probability density function of the Weibull distribution and the cumulative probability function are given above in equation (1) where  $\beta$  is the shape parameter,  $\eta$  is the scale parameter and  $t$  is the respective time stamp, i.e. for example the service age of the respective infrastructural asset. In FIG. 3 and FIG. 4, the cumulative distribution of the Weibull distribution is shown so the probability for time  $t$  indicates the probability that an asset has failed at time  $t$  (i.e. fails at time  $t$  or earlier). Accordingly, the cumulative distribution function (CDF) of the Weibull distribution  $F(t)$  can be seen to indicate the failure rate  $\lambda(t)$  (i.e., indicates the number of failures occurred in the equipment up to time  $t$ ).

[0056] By means of the Weibull model 304, 201, the baseline relationship between age and failure probability is established. Different risk levels can be determined by users (or stakeholders) based on respective application scenarios. Given the age of an assets and its location on the estimated Weibull model 304, 201 (i.e. its x-axis position) its failure probability can be estimated. The probability of failure (PoF) of the asset indicates the probability that the equipment will have failed at time t. Its value lies within the range from 0 to 1 while the value of the failure rate can be higher than 1. For example, the definition of the (infrastructural) asset reliability, which is denoted as R(t) at time t

$$R(t) = e^{H(t)} = \exp\left[-\int_0^t \lambda(\tau) \cdot d\tau\right] \quad (2)$$

is used, where H(t) is the cumulative failure probability and exp(.) is the natural base exponential function. Thus, the probability of failure of the asset at time t (denoted as PoF(t)) can be written as:

$$\text{PoF}(t) = 1 - R(t) = 1 - \exp\left[-\int_0^t \lambda(\tau) \cdot d\tau\right] \quad (3)$$

[0057] In the second step 302, condition groups are separated, i.e. the assets (of the training set) are grouped (e.g. clustered) into groups (e.g. clusters) according to conditioning (monitoring) data. The purpose of this step is to incorporate conditioning monitoring data from asset condition monitoring as health estimation information into the baseline PoF model (as given by the fitted Weibull distribution 304, 201). The raw condition monitoring data (e.g. sensor data like for example a value for one or more variables such as temperature etc.) is normalized to eliminate the unit differences of different monitoring variables.

[0058] Using the normalized condition variables, a correlation matrix is computed to evaluate the correlation strength and direction between variable pairs in condition monitoring:

$$\text{corr}(\mathbf{X}) = \begin{bmatrix} 1 & \dots & \dots & \frac{E[(X_1 - \mu_1)(X_n - \mu_n)]}{\sigma(X_1)\sigma(X_n)} \\ \dots & 1 & \dots & \frac{E[(X_2 - \mu_2)(X_n - \mu_n)]}{\sigma(X_2)\sigma(X_n)} \\ \dots & \dots & \dots & \dots \end{bmatrix} \quad (4)$$

where, the closer the value is to 1 (or -1), the stronger a relationship; the closer a number is to 0, the weaker the relationship. The condition monitoring variables with higher correlation with health condition and asset failure probability (and age) for example have higher importance or weighting after fine-tuning. Thus, for example, key condition indicators can be

identified while operating condition information without correlation to the health or age of assets can be removed from the further process.

[0059] Then, as shown in FIG. 5, the set of assets are separated into different groups. The degree-of-outlier 501, feature clustering 502 or industrial standard 503 can be used as separation criteria (i.e. for determining whether the groups are sufficiently separated by the respective grouping or clustering). The group separation enables the calculation of conditional probability of belonging to each group (as well for equivalent age), as the probability distribution of conditions can be constructed separately for those groups.

[0060] Considering the fact that the majority of assets should be in normal operation condition statistically, the health condition can be reflected by its failure probability for most of the cases. Thus, the different groups (e.g. clusters) should have distinct and separable failure probability distributions. Such distribution-based method enables users to evaluate the effectiveness of the clustering. Additionally, other criteria such as silhouette plots and standard cluster evaluation metrics from machine learning may be employed for model selection. This method ensures effective data clustering, revealing patterns related to asset health status, and allows the calculation of an asset's failure probability based on the weighted average of cluster centres.

[0061] The degree-of-outlier separation criterion 501 is based on condition degree-of-outlier. For the normalized asset condition data, the degree-of-outlier can be used as numerical indicator to find an abnormality. In order to quantify the extent to which an observation (in the normalized condition data) deviates from the typical values of the asset conditions, the degree-of-outlier  $D$  is for example calculated based on the interquantile range and Tukey's Fence:

$$D = \sum_i \text{Max} \left[ \frac{X_i - Q_{i,50}}{Q_{i,95} - Q_{i,5}}, 0 \right] \quad (5)$$

where  $X_i$  represents the  $i$ th asset (normalized) condition monitoring variable. If the data point's value distance to the median is larger than the distance between lower fence (e.g., 5% quantile  $Q_{i,5}$ ) and upper fence (e.g., 95% quantile  $Q_{i,95}$ ), its degree of outlier will be larger than 1. Thus, the modelling for degree-of-outlier includes the distance between monitoring and the medians, as well as the interquantile ranges that describe the spread of data.

[0062] FIG. 6 illustrates the data-driven calculation of degree-of-outlier for condition monitoring data and the formulation of an asset condition radar model 601. The abnormal assets inherently have high value of degree-of-outlier and can be effectively identified with the assets condition radar.

[0063] Based on assets degree of outlier  $D$ , the abnormality and numeric value of degree-of-outlier may be visualized to help engineers to better understand the health conditions of assets. By interpreting the degree-of-outlier  $D$  as the radius of indicator on a radar, the condition radar plot model 601 may for example be provide to enable visualized management of asset abnormality.

[0064] The assets are separated into different groups, which enables straightforward calculation of conditional probability for belonging to each group. It should be noted that the degree of outlier is not directly used for grouping. Instead, the grouping is constructed by checking whether the degree of outlier is separable (has a different distribution of outlier degree) for each group.

[0065] As illustrated in FIG. 6, the grouping is for example done based on different ages (e.g. three categories: young group, mature group, and old group), with each group showing a different distribution of degree-of-outlier. This means that in this case, the operating condition taken into account for the separation is the age of the assets (but it may also be measured sensor data like temperature etc. as mentioned above). Then, given a degree-of-outlier for an asset to be evaluated, the conditional probability of the asset belonging to each group can be calculated. When data is sufficient, the grouping can be also based on individual age as shown in Figure 9.

[0066] Each individual age has a degree-of-outlier distribution, and different age assets have different distributions of outlier. Then, given a degree-of-outlier, the conditional probability of belonging to each group can be quantified, as described below in the detailed description of step 303. Clusters are formed by comparing the D-values distribution of the assets. If the degree-of-outlier distribution is not separable for each group, then another grouping criteria may be used (e.g. clustering distance, see below).

[0067] For instance, for 10 assets, 5 assets are young and 5 assets are old, young assets' degree-of-outlier distribution is between 1 to 6, while the old asset outlier distribution is 4 to 20. Each group has different D-values a probability distribution (fitted by kernel density estimation). Given the outlier degree 10, then this asset is highly likely to be an old asset

based on conditional probability. As long as the D-values distribution is different/separable for those groups, conditional probability can be applied afterward to determine the likelihood of belonging to each group given the D-values.

[0068] Similar to degree-of-outlier group separation, the grouping may be done using a clustering method taking into account the asset's current measured operating condition, enabling a more dynamic representation of different types of asset health condition, which can also be utilized to calculate the failure probability, equivalent age, RUL, and asset health index. The clustering-based assets health condition evaluation method includes the following steps:

[0069] (1) Collecting data from sensors attached to the asset, such as vibration sensors, temperature sensors, pressure sensors, or any other relevant sensors.

[0070] (2) Preprocessing the data to remove noise, outliers, and irrelevant information.

[0071] (3) Extracting (relevant, e.g. critical) operation condition features to reduce the dimension of input. By identifying the most important features and removing the irrelevant or redundant ones, the data representation can be simplified without losing critical information. For example, dimensionality reduction techniques, including PCA (Principal Component Analysis) and t-distributed Stochastic Neighbour Embedding (t-SNE), are taken as candidate model for testing and selection.

[0072] (4) Applying a clustering algorithm to the extracted operation condition features to identify different health patterns or groups in the data. Usable clustering techniques, e.g., k-means, hierarchical clustering, density-based clustering, etc. are taken as candidate clustering model for further testing and selection.

[0073] (5) Fitting the failure probability distribution of each clustered groups by KDE method. Then calculate the Wasserstein distance of failure probability distributions between each two clusters. Wasserstein distance measures the distance between two probability distributions by calculating the minimum amount of work required to transform one distribution into the other. If the Wasserstein distance of any two group cannot meet the pre-set criteria, return to the model selection stage to fine-tune hyper parameters or chose a different kind of clustering algorithm, dimension reduction technique, or distance measurement matrix. Finally, it is ensured that different clustered groups have distinct and separable failure probability distributions.

[0074] (6) Iteratively implement this process until the selected model combination achieve satisfactory clustering results with enough distances between each two failure probability distributions.

[0075] For an asset to be evaluated (as step 303 of the process), the operation condition features that have been used for the clustering in (1) are determined for the asset to be evaluated are determined. Then, the probability that it belongs to the various clusters can be determined, and the asset's expected failure probability can be determined by summation of conditional probability of belonging to each cluster (given condition data as prior event) times the average failure probability of each clusters .

[0076] Alternatively, the clustering distance is calculated by the normalized condition variables (from condition monitoring data, like CO<sub>2</sub> concentration, CH<sub>4</sub> concentration, temperature etc.), instead of using the probability of failure (PoF) as separation criteria. As long as each group (can be a different age group) has a different clustering distance distribution, then given a clustering distance, the likelihood of belonging to each group can be calculated. The distribution of clustering distances can be calculated for each group. The clustering distance is the Euclidean distance between an asset (i.e. its the normalized condition monitoring variables) and its cluster's average normalized condition variables (which can also be denoted as the cluster's centroid). This measures how far apart the asset is from the centre or average of its cluster in the multidimensional space defined by the normalized condition variables. Similarly, the distance between any asset and other clusters' centroids may be calculated. This gives a degree with which an asset belongs to a certain group.

[0077] FIG. 7 shows a flow chart 700 illustrating the constructing the cluster-based condition group separation. It includes, as described above, normalization of condition monitoring data 701, dimension reduction 702, grouping/clustering 703, calculation of probability distribution for each cluster 704 (e.g. degree-of-outlier, clustering distance, or probability of failure), iterating until a grouping has been achieved, optionally visualization (e.g. as the condition radar model 601) 705 and checking 706 (e.g. by a human expert), whether the visualized separation makes sense (and redoing the grouping/clustering if it does not). Finally the grouping may be used in 707 to determine an expected probability of failure for an asset to be evaluated, which is what is done in step 303 and explained in detail in the following.

[0078] Step 303 is to utilize conditional probability (with condition monitoring data) to calculate the expected probability of failure (PoF) of an asset to be evaluated.

[0079] FIG. 8 illustrates the process for constructing the probability distribution of condition indicator(s) for each of the separated groups. As is shown in FIG. 8, in case of the grouping criteria being degree-of-outlier or clustering distance, the probability density functions for the distribution of degree-of-outlier (or clustering distance) are utilized to correlate the assets' degree-of-outlier and its probability of belonging to for different groups with inherently different failure probabilities. For example, the probability density function with respect to degree of outlier (or clustering distance) is derived based on kernel density estimation (KDE), which a non-parametric method to estimate the probability density function of a random variable:

$$K(x) = \frac{1}{h\sqrt{2\pi}} e^{-0.5\left(\frac{x-x_i}{h}\right)^2} \quad (6)$$

$$KDE_j = \frac{1}{n} \sum_{i=1}^{i=n} \frac{1}{h\sqrt{2\pi}} e^{-0.5\left(\frac{x_j-x_i}{h}\right)^2} \quad (7)$$

where  $K$  is the kernel function that is non-negative and integrates to 1,  $n$  is the number of data points,  $h$  is the bandwidth.

[0080] By separating the assets into different groups corresponding to different operating conditions (and therefore different probabilities of failure), the correspondingly probability density of degree-of-outlier for each group can be calculated. Then, based on the probability density, the likelihood that the assets belong to each particular group (and expected failure probability) can be determined. With the definitions of conditional probability, the estimated health condition (failure probability and physical age) can be calculated based on the expectation for the failure probability belonging to different groups (or clusters), given the certain monitored degree-of-outlier as the condition  $D$  in conditional probability. The conditional probability is utilized to calculate the failure probability for assets. Given the degree-of-outlier (or, similarly, the clustering distance), the probability of an asset belonging to each age group can be calculated with the conditional probability on the estimated kernel density function. For the KDE function of probability with respect to degree of outlier  $D$ , the probability of the asset belonging to group  $x$  (or cluster  $x$ ) writes as:

$$P_{x|D} = \frac{P(x \cap D)}{P(D)} \quad (8)$$

Then, the expectation of equivalent age (or equivalent failure probability) is calculated by summing up the expected group-specific failure probability for each group (or cluster) multiplied by the conditional probability of belonging to this group (or cluster). With the separated asset groups and clusters, the equivalent age (or equivalent failure probability  $PoF_e$ ) for an asset is calculated based on:

$$E[Age|D] = \frac{\sum_i^N P_{i|D} A_i}{\sum_i^N P_{i|D}} \quad (9)$$

where, the  $P_{i|D}$  represents the probability of asset belonging to  $i$  group (or cluster).  $E[Age|D]$  represents the expected equivalent age of assets given the condition  $D$  of assets. By taking this equivalent age into the Weibull model, the corresponding failure probability for assets can be also calculated.

[0081] The conditional probability can be also leveraged to calculate other health-related variables. For example, when the number of separated group is 3 and denoted as  $x$ ,  $y$ ,  $z$  group, the equivalent failure probability for an asset  $PoF_e$  can be calculated based on:

$$PoF_e = \frac{(P_{x|D} PoF_x + P_{y|D} PoF_y + P_{z|D} PoF_z)}{P_{x|D} + P_{y|D} + P_{z|D}} \quad (10)$$

where, the  $P_{x|D}$ ,  $P_{y|D}$ ,  $P_{z|D}$  represent the probability of asset belonging to  $x$  group (or cluster),  $y$  group (or cluster), and  $z$  group (or cluster), respectively.  $PoF_x$ ,  $PoF_y$ ,  $PoF_z$  represent the statistical probability of failure for different groups (or clusters) of assets.

[0082] By calculating the expected  $PoF$  for the assets (e.g. infrastructure assets), the asset health can be quantitatively evaluated and the assets management can be effectively conducted.

[0083] Based on the asset  $PoF$ , the corresponding equivalent age (on x-axis) can be calculated. After statistically obtaining the physical age of assets, the condition-based failure probability  $PoF_e$  can be incorporated as the  $t_{age}$  into the baseline  $PoF$  (Weibull) model 304 and RUL model. As shown in FIG. 3, the location of an asset on the baseline model can be automatically moved leftwards or rightwards to indicate the actual health condition of assets. Then, the remaining useful life (RUL) can be estimated based on the acceptable failure probability. The RUL indicates the remaining service time of an infrastructural asset. It is the

time that the asset deteriorates from the current condition to the failure condition or failure threshold, as illustrated in FIG. 4. A first point 402 indicates the current health condition of the infrastructural asset. A second point 403 is the point that the asset health index (AHI) reaches 0, corresponding to failure of the asset. The time between the two points 402, 403 is viewed as the remaining useful life. Consequently, the assets can be managed based on the estimated health condition of assets. If the health conditions of assets are worse than that of healthy assets, the assets are at risk of failing or requiring maintenance in the near future. The RUL of the infrastructural asset can be calculated with:

$$RUL = t_{PoFmax} - t_{EquivalentAge} \quad (11)$$

where  $t_{PoFmax}$  is the time when the infrastructural asset HI reaches 0. The  $t_{EquivalentAge}$  is its current service age. With this explainable data-driven health estimation and management process, the maintenance or replacement decisions about the prioritized assets can be optimally scheduled.

[0084] FIG. 9 illustrates the process to calculate the probability of belonging to each condition groups based conditional probability, as well as the calculation of expected equivalent age and failure probability. The location of asset (equivalent age in FIG. 3) can be moved onwards or downwards based on the condition monitoring data.

[0085] FIG. 10 show the examples of utilizing the asset health evaluation method combining the Weibull model, degree-of-outlier, and kernel probability, group separation (clustering), and conditional probability of condition monitoring data.

[0086] Finally, to numerically estimate the health condition of the asset, a universal asset health index (AHI) model (valued between 0 to 1) can be established based on the asset failure probability.

[0087] FIG. 11 shows the effectiveness of quantile normalization to interpret the remaining useful life into different asset AHI values while keeping the same data distribution.

[0088] To interpret the remaining useful life (from long to short) into the asset health index (ranged in 1 to 0 for healthy to unhealthy) and retain the original statistical distribution, the quantile normalization method with effectiveness shown in FIG. 11 can be used. The quantile normalization method works by ranking the intensity or count values of all samples and then taking the average of the ranked values for each sample.

[0089] A verification process can be executed to ensure that the health evaluation system effectively identify the abnormal assets with quantification of RUL. If more effective

conditional indicator is identified and insignificant indicator can be removed, the weighting for degree-of-outlier and clusters will be further fine-tuned to align the actual health condition of assets.

[0090] In summary, according to various embodiments, a method is provided as illustrated in FIG. 12.

[0091] FIG. 12 shows a flow diagram illustrating a method for estimating a failure probability of one or more assets.

[0092] In 1201, for each of a plurality of assets, operating condition data of the asset is received.

[0093] In 1202, the assets are separated into a plurality of groups taking into account the operating condition data of the assets (for example condition monitoring data features (extracted from condition monitoring data) or age).

[0094] In 1203, for each group, an expected asset health index is determined (including normalized PoF, expected PoF or expected equivalent age) of the assets belonging to the group (e.g. by a baseline failure probability model).

[0095] In 1204, an operating condition monitoring data feature of an asset to be evaluated is determined.

[0096] In 1205, for each group, a conditional probability that the asset to be evaluated belongs to the group is determined taking into account the operating condition monitoring data feature of the asset to be evaluated (e.g. using it directly or determining its degree-of-outlier) and condition monitoring data features of the assets belonging to the group (e.g. by determining the degree-of-outlier distribution of the group or the clustering distance distribution of the group).

[0097] In 1206, a probability of failure of the asset to be evaluated is estimated by the summation (over the groups) of the conditional probability of belonging to each group times the expected asset health index of the group (wherein for each group, the conditional probability is for example determined by the probability distribution of an anomaly measure for the group given condition data (e.g. the operating condition monitoring data feature of the asset to be evaluated) as prior event).

[0098] According to various embodiments, in other words, a method for estimating a failure probability of one or more assets which allows distinguishing unhealthy assets based on condition monitoring. It provides a universal approach based on data-driven assets health

estimation and enables an asset health management method considering the probability distribution for diverse condition monitoring variables.

[0099] According to various embodiments, a system for infrastructure asset health evaluation is provided leveraging a combination of statistical failure probability and asset condition monitoring. With a synergistic combination of the Weibull model, condition clustering, outlier detection, kernel probability density, and conditional probability, the proposed asset health evaluation system and method provides condition-aware asset-specific failure probability and remaining useful life, which ultimately facilitates informed decision-making for efficient asset maintenance.

[00100] The approach of FIG. 12 and in particular the integrated failure probability modelling, data-driven condition monitoring based asset health estimation, degree-of-outlier, and conditional probability study described herein can be applied in any infrastructural asset health status estimation problem.

[00101] The method (in particular group separation and clustering-based asset health index system) can be applied to a variety of industrial fields. This allows for the creation of an asset health index (asset physical age) that can be used to identify potential issues before they become serious problems. By analysing the data from these clusters, the users can gain insights into the health of the assets and make informed decisions about maintenance and replacement. Compared to existing method, the advantage of this method is that consistent and reliable clustering results can be obtained. Also, this system has no requirements on the domain or sources of monitoring data and is highly adaptive to various categories of assets. Overall, the flexibility and adaptability of this clustering-based asset health index system make it a valuable tool for industrial applications. It has the potential to improve asset management and reduce downtime, leading to increased productivity and profitability.

[00102] The method described herein fills the gap of how to quantitatively analyse the RUL for different types of infrastructure assets considering its actual conditions. Compared with the current existing asset health modelling methods, the proposed method is specified in combining the actual health status monitoring and statistical failure probability estimation of infrastructural assets. Compared with the currently existing methods for asset renewal and maintenance scheduling, the proposed can provide comprehensive and distinctively quantify the health condition of assets based on all available information. The underlying reason for insecurity and the corresponding most effective solution can be identified.

[00103] The method of FIG. 12 is for example carried out by a data processing system (e.g. a computer or multiple computers) as illustrated in FIG. 13.

[00104] FIG. 13 shows a data processing system 1300 according to an embodiment.

[00105] The data processing system 1300 includes a communication interface 1301 (e.g. configured to receive condition monitoring data, e.g. via user input and/or from sensors). The data processing system 1300 further includes a processing unit 1302 and a memory 1303. The memory 1303 may be used by the processing unit 1302 to store, for example, data to be processed, such as the failure data and the derived life-time information. The data processing system is configured to perform the method of FIG. 12.

[00106] According to various embodiments, a system for estimating the health conditions of infrastructure assets based on the combination of statistical failure probability and asset condition monitoring is provided, including: a. a Weibull model for determining the failure probability of the assets considering the age; b. a condition monitoring degree-of-outlier mechanism for quantifying asset abnormal conditions; c. a condition clustering mechanism for grouping assets with similar conditions; d. a kernel probability density function for estimating the probability density of asset conditions for different groups; e. a conditional probability component for calculating the equivalent age and failure probability, identifying unhealthy assets using the assets' condition monitoring data.

[00107] According to one embodiment, the estimation of the health conditions of infrastructure assets has considered the integration of condition monitoring data and the Weibull model to estimate failure probability.

[00108] According to one embodiment, the Weibull model calculates the baseline failure probability without considering condition monitoring data, which calculates failure probability based on asset age, operational parameters, and environmental factors.

[00109] According to one embodiment, the condition monitoring degree-of-outlier mechanism employs a statistical method to detect abnormal asset conditions.

[00110] According to one embodiment, the kernel probability density function uses non-parametric estimation techniques to model the distribution of asset conditions for different groups of assets.

[00111] According to one embodiment, wherein the condition clustering mechanism employs unsupervised machine learning algorithms to group assets based on their condition monitoring data.

[00112] According to one embodiment, the condition degrees-of-outlier are visualized and analysed with condition outlier Radar and kernel density estimation, further including a step of generating reports or visualizations to communicate the estimated health conditions of the assets. Any abnormality can be observed from the condition outlier Radar.

[00113] According to one embodiment, a conditional probability component calculates the likelihood of asset belonging to each group (as well as equivalent age and failure probability) given the asset's condition monitoring data, which can be integrated in the failure probability in the Weibull model.

[00114] According to one embodiment, the equivalent physical age of assets based on failure probability is determined using the Weibull model, taking the failure probability of conditional probability calculation results as input and correlating the failure probability with the remaining useful life (RUL) and asset health index.

[00115] According to one embodiment, alerts or notifications are provided to asset managers when an unhealthy asset is identified.

[00116] According to one embodiment integrating the estimated health conditions, failure probability, and remaining useful life are integrated into a maintenance planning or asset management system.

[00117] The methods described herein may be performed and the various processing or computation units and the devices and computing entities described herein (in particular the various modules described above) may be implemented by one or more circuits. In an embodiment, a "circuit" may be understood as any kind of a logic implementing entity, which may be hardware, software, firmware, or any combination thereof. Thus, in an embodiment, a "circuit" may be a hard-wired logic circuit or a programmable logic circuit such as a programmable processor, e.g. a microprocessor. A "circuit" may also be software being implemented or executed by a processor, e.g. any kind of computer program, e.g. a computer program using a virtual machine code. Any other kind of implementation of the respective functions which are described herein may also be understood as a "circuit" in accordance with an alternative embodiment.

[00118] While the disclosure has been particularly shown and described with reference to specific embodiments, it should be understood by those skilled in the art that various changes in form and detail may be made therein without departing from the spirit and scope of the invention as defined by the appended claims. The scope of the invention is thus indicated by

the appended claims and all changes which come within the meaning and range of equivalency of the claims are therefore intended to be embraced.

**CLAIMS**

1. A method for estimating a failure probability of one or more assets, comprising:  
Receiving, for each of a plurality of assets, operating condition data of the asset;  
Separating the assets into a plurality of groups taking into account the operating condition data of the assets;  
Determining, for each group, an expected asset health index of the assets belonging to the group;  
Determining an operating condition monitoring data feature of an asset to be evaluated;  
Determining, for each group, a conditional probability that the asset to be evaluated belongs to the group taking into account the operating condition monitoring data feature of the asset to be evaluated and condition monitoring data features of the assets belonging to the group; and  
Estimating a probability of failure of the asset to be evaluated by the summation of the conditional probability of belonging to each group times the expected asset health index of each groups.
2. The method of claim 1, wherein the assets are separated into groups according to their ages.
3. The method of claim 1, wherein determining the conditional probability that the asset to be evaluated belongs to the group comprises:  
Determining, for each asset, an anomaly measure of the condition monitoring data feature of the asset;  
Determining, for each group, a distribution of the anomaly measure of the condition monitoring data feature of the assets belonging to the group;  
Determining, for the asset to be evaluated, the anomaly measure of the condition monitoring data feature of the asset to be evaluated;  
Determining, for each group, the conditional probability that the asset to be evaluated belongs to the group by determining a probability that the anomaly measure of the condition monitoring data feature of the asset to be evaluated has according to the

distribution of the anomaly measure of the condition monitoring data feature of the assets belonging to the group.

4. The method of claim 3, wherein separating the assets into the plurality of groups comprises separating the assets into the plurality of groups, such that, for every two groups, the distributions of the anomaly measure of the condition monitoring data feature of the assets belonging to the groups differ by at least a predetermined threshold.
5. The method of claim 1, comprising determining, for each asset, at least one condition monitoring data feature from its condition monitoring data and separating the assets into the plurality of groups according to their condition monitoring data features.
6. The method of any one of claims 1 to 5, wherein the expected asset health index of the groups are normalized values using the expected probabilities of failures as allowable probabilities of failure.
7. The method of any one of claims 1 to 6, wherein the expected asset health index is normalized by the expected probabilities of failures and the maximum allowed probabilities of failure.
8. The method of any one of claims 1 to 7, wherein the groups have different expected asset ages, and the probability of failure of the asset to be evaluated is determined by determining a statistical failure probability from a Weibull model and an equivalent age of the asset to be evaluated, wherein the equivalent age is determined by the summation (over the groups) of the conditional probability of belonging to each group (given condition data as prior event) times the expected asset age of the group.
9. The method of claim 8, comprising determining a relation between asset age and probability of failure of the assets and determining the probability of failure of the asset to be evaluated from the equivalent asset age of the asset to be evaluated according to the relation between asset age and probability of failure.

10. The method of claim 9, wherein the relation is determined by fitting a Weibull distribution to the assets.
11. The method of any one of claims 1 to 10, comprising visualizing the separation of assets into the groups and re-separating the assets into groups in response to a corresponding user input.
12. The method of any one of claims 1 to 11, comprising separating the assets into groups using an unsupervised machine learning algorithm.
13. The method of any one of claims 1 to 12, wherein the operating condition data comprises sensor measurement data.
14. The method of any one of claims 1 to 13, wherein separating the assets into the plurality of groups taking into account the operating condition data of the assets comprises filtering the operating condition data to remove operating condition data that is not correlated with asset health.
15. Method for controlling assets comprising estimating a failure probability for one or more assets according to any one of claims 1 to 14 and controlling the one or more assets according to the estimated failure probability.
16. The method of claim 15, comprising classifying each of the one or more assets into a healthy or unhealthy asset according to the estimated failure probability and controlling the one or more assets according to the classification.
17. The method of claim 16, comprising outputting an alert in case the one or more assets have been classified as unhealthy.
18. The method of claim 16 or 17, comprising triggering a replacement of the one or more assets if they have been classified as unhealthy.

19. The method of any one of claims 16 to 18, comprising taking the one or more assets out of service if they have been classified as unhealthy.
20. A data processing system comprising a communication interface, a memory and a processing unit configured to perform the method of any one of claims 1 to 19.
21. A computer program element comprising program instructions, which, when executed by one or more processors, cause the one or more processors to perform the method of any one of claims 1 to 19.
22. A computer-readable medium comprising program instructions, which, when executed by one or more processors, cause the one or more processors to perform the method of any one of claims 1 to 19.