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*Published in:*
Reliability Engineering and System Safety

*DOI:*
10.1016/j.ress.2021.107536

Published: 01/06/2021

**Document Version**
Publisher's PDF, also known as Version of record

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*Please cite the original version:*
Mancuso, A., Compare, M., Salo, A., & Zio, E. (2021). Optimal Prognostics and Health Management-driven inspection and maintenance strategies for industrial systems. *Reliability Engineering and System Safety, 210*, [107536]. https://doi.org/10.1016/j.ress.2021.107536
Optimal Prognostics and Health Management-driven inspection and maintenance strategies for industrial systems

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A R T I C L E   I N F O

Keywords:
Predictive maintenance
Prognostics and Health Management
Influence diagrams
Decision Programming
Value of Perfect Information
Gas turbine

A B S T R A C T

The performance of the Prognostics and Health Management (PHM) depends both on the functioning of the measurement acquisition system and on the actual state of the system being monitored. The dependencies between these systems must be considered when developing optimal inspection and maintenance strategies. This paper presents a methodology to support the definition maintenance strategies for PHM-equipped industrial systems. The methodology employs influence diagrams when seeking to maximize the expected utility of system operation. The optimization problem is solved by mixed-integer linear programming, subject to budget and technical constraints. Chance constraints can be also included, for instance to curtail risks based on measures such as the Value at Risk (VaR) and the Conditional Value at Risk (CVaR) of system operation. The viability of the methodology is demonstrated by optimizing the inspection and maintenance strategy for a gas turbine equipped with PHM solution. The computation of the Value of Perfect Information (VoPI) provides additional insights on maintenance management.

1. Introduction

Digitalization is a fundamental driver of Industry 4.0, a novel paradigm which enhances production efficiency through information and communication technologies [1,2]. These technologies also provide the foundation for Predictive Maintenance for industrial components and systems, whereby condition monitoring data is employed to perform three tasks:

(i) detection of abnormal states, by identifying deviations from normal operating conditions in production processes, manufacturing equipment and products;
(ii) diagnostics, by classifying abnormal states;
(iii) prognostics, by predicting the evolution of abnormal states up to failure.

Detection, diagnostics and prognostics constitute the Prognostics and Health Management (PHM, [3–6]). These tasks help implement efficient, just-in-time and just-right maintenance strategies by selecting the right action for the right component at the right time, thus maximizing production revenues and minimizing costs and losses, including assets [7]. Furthermore, PHM performance metrics have been introduced to characterize errors in detection, diagnostics and prognostics [8,9]. Based on these metrics, several models have been developed to optimize Operations and Maintenance strategies [7] and investments in PHM capabilities [10–13].

A main limitation of Predictive Maintenance models is the assumption that sensors always provide correct measurements, although in practice sensors may malfunction: freezing (or constant), noise, spike (or short), drift and quantization are the most common sensor malfunctions [14]. Faulty sensors may provide inaccurate measurements of the monitored physical parameters, affecting the performance of the PHM algorithms by conveying inaccurate or misleading information about the actual system state. This can cause false positive and false negative alarms, resulting in unnecessary system downtimes and large financial losses. For example, the spillover effect (cross-sensitivity [15]) is known to propagate the anomalous monitoring data from a faulty sensor to other healthy signals, causing difficulties in choosing the correct maintenance action (i.e., fix or replace the sensor).

The detection of a sensor malfunction, which is often performed through sensor data validation, has been addressed by different methods, including Auto Associative Neural Network (AANN, [16]), Nonlinear Partial Least Squares Modelling (NLPLS, [17]), Principal Component Analysis (PCA, [18,19]), Auto Associative Kernel Regression [20,21]...
and Multivariate State Estimation Technique (MSET, [22]). However, also algorithms for sensor validation are affected by errors that depend on the health state of the monitored system. Specifically, if the monitored system does not work correctly, sensor validation is less effective in detecting incoherent deviations of the faulty sensor values with respect to data provided by other sensors. The main reason is that sensor validation algorithms are generally trained by signal data generated by healthy system operation only. Based on this training data, the algorithm learns to reconstruct the behaviour of the monitored signals when the system operates normally, which differs from those acquired when the system operates in a degraded state. Although the change in the signal behaviour is fundamental to the early detection of the system anomaly, it nonetheless lowers the performance of the sensor validation algorithms, because they have not been trained in the degraded setting.

In PHM-equipped systems, maintenance strategies refer to two sequential actions: first, the inspection of either the sensors or the industrial system; second, the necessary repairs depending on the inspection outcomes. The costs of the sequential actions are very different, with different effects on the health state of the industrial system and uncertainties about the PHM performance.

The above considerations suggest that the definition of optimal maintenance strategy in Predictive Maintenance must be framed as a multi-stage decision problem, encoding the mutual dependence between the performances of the PHM solution and the sensor validation algorithms [23–25]. On this topic, Driessen et al. [26] present a cost evaluation of maintenance strategies for a single-component system, which is periodically subject to imperfect inspections. Do et al. [27] evaluate different maintenance strategies for a deteriorating system in which the inspection strategy is based on the residual useful life. Papakonstantinou and Shinozuka [28] employ Partially Observable Markov Decision Processes (POMDP) to optimize inspection and maintenance strategies based on stochastic models and uncertain structural data in real time. Literature reviews (e.g., [29,30]) call for increased attention to optimization models on condition-based maintenance, but do not account for the imperfect performance of condition monitoring and inspections [31–33].

Influence diagrams [34] are one of the well-established techniques for structuring and solving multi-stage decision problems. They are commonly solved, for instance, through local transformations such as arc reversals and node removals in the diagram [35]. Tatman et al. [36] develop the equivalent decision tree representation, which is solved by dynamic programming [37]. Nonetheless, these standard techniques have limitations. First, they rely on the “no-forgetting” assumption, meaning that earlier decisions are known when making later ones. Although this may be not too limiting in practice, the information flow in industrial practice can at times be disrupted due to communication failures. Second, the use of dynamic programming is restrictive in that the objective function cannot include risk measures such as Value-at-Risk or semi-absolute deviation, which reflect the variability of the objective function.

To overcome these limitations, we employ the Decision Programming approach proposed by Sala et al. [38], which employs Mixed Integer Linear Programming (MILP, [39,40]) to solve multi-stage decision problems under uncertainty. Specifically, we employ Decision Programming to identify the optimal inspection and maintenance strategy for an industrial system with realistic PHM capabilities and sensor validation algorithms: each combination of states of the nodes of the influence diagram is mapped onto the two-stage decision maximizing the system utility. To the authors’ best knowledge, this is the first time that a maintenance strategy support model is developed in this practical setting, considering realistic PHM capabilities and sensor validation algorithms.

In current industrial practice, the effective design, implementation and use of PHM solutions is mainly driven by expert judgement [41]. Srinivasan and Parlikad [42] propose a methodology to estimate the monetary benefits of condition monitoring based on Partially Observable Markov Decision Process (POMDP). Muker et al. [43] develop a model to assess the costs and benefits of continuous monitoring for residential photovoltaic systems. The proposed methodology in the present paper is guaranteed to provide the optimal inspection and maintenance strategies based on state estimates of both the industrial system and its monitoring devices. Investment decisions for improving the current PHM solution are also supported, because it is possible to compare the corresponding optimal expected system utility with the situation in which the PHM would provide perfect information on the system state.

In the following, Section 2 develops the problem formulation. Section 3 presents the optimization model and the Value of Perfect Information. Section 4 proposes a case study from industry, concerning the optimization of inspection and maintenance strategies of a gas turbine. Section 5 discusses the potential and limitations of the proposed methodology. Finally, Section 6 concludes the paper and outlines extensions for future research.

2. Formulation of the influence diagram

An influence diagram is a directed acyclic graph that represents probabilistic causal dependencies between events and decisions [34]. Fig. 1 shows an example of influence diagram for inspection and maintenance strategies, which consists of three types of nodes:

(i) chance nodes C (represented by circles) indicate random events of system state;
(ii) decision nodes D (represented by squares) indicate possible choices of inspections and maintenance actions;
(iii) value nodes U (represented by hexagons) indicate the utility of system operation.

Dependencies between nodes \( N = C \cup D \cup U \) are represented by directed arcs \( A \subseteq \{(i,j)|i,j \in N, i \neq j\} \). Specifically, arc \( (i,j) \in A \) connects node \( i \) to node \( j \) so that the state at node \( j \) is conditionally dependent on that at node \( i \). The direct predecessors of node \( j \) belong to the information set \( I(j) = \{i \in N|(i,j) \in A\} \). The arcs directed to chance nodes indicate on what other nodes this chance node depends on, as specified by the corresponding conditional probability table. The arcs which lead to decision nodes denote what information is available when making the decision. Because the network is acyclic, the nodes can be indexed with consecutive integers so that the indexes of nodes \( i \in I(j) \) are lower than the index of node \( j \). In influence diagrams, arcs from any chance or decision node can lead to other chance, decision and value nodes with a higher index. There cannot be arcs from value nodes to chance or decision nodes.

Node \( j \in C \cup D \) corresponds to the variable \( X_j \), whose realization \( s_j \) assumes values in the discrete set of states \( S_j \). The meaning of these variables is different for chance and decision nodes. The states of chance nodes denote the health state of the system components [44]. These states represent mutually exclusive events, for which the uncertainty in the realization is described by the probability distribution on the states \( S_j \). If the chance node does not depend on other nodes (no incoming arcs), \( \mathbb{P}(X_j) \) is the unconditional probability distribution on the set \( S_j \). For each chance node \( j \in C \) with non-empty information set \( I(j) \), the conditional probability of the state \( s_j \in S_j \) depends on the information state \( s_{i(j)} \) which belongs to the Cartesian product

\[
S_{i(j)} = \bigotimes_{i \in I(j)} S_i,
\]

defined by the combinations of states for all nodes in the information set. Thus, the conditional probability is \( \mathbb{P}(X_j = s_j|X_{i(j)} = s_{i(j)}) \), where \( X_{i(j)} = s_{i(j)} \) denotes that the realizations of the variables \( X_i \) for nodes \( i \in I(j) \) are the same as those in the information state \( s_{i(j)} \). The states of decision nodes correspond to choices of different inspection and maintenance strategies which influence the degradation/restoration process.
of the industrial system modelled through probabilistic transitions between the states. The degradation/restoration process is illustrated in Fig. 4 for a gas turbine with 5 states, whereas Table 1 presents illustrative transition probability values. The decision $X_j$ at node $j \in D$ depends on the information state $s_I(j)$ which defines what information is available when making the decision.

A local strategy at decision node $j \in D$ is a function $Z_j$ which maps all information states for this node to corresponding decisions $Z_j : S_I(j) \rightarrow S_j$. The binary variables $z(s_j | s_I(j))$ model the local strategy $Z_j$ such that

$$Z_j[s_I(j)] = s_j \Leftrightarrow z(s_j | s_I(j)) = 1.$$  \hfill (2)

Specifically, the local strategy of decision node $j \in D$ depends on the information state $s_I(j)$, meaning that the choices of actions depend on the information provided by sensors and inspections. A combination of local strategies for all decision nodes $D$ is called a global strategy $Z$.

A scenario path $s$ is a specific combination of states $s_j$ of all chance and decision nodes. Thus, the set of all possible scenario paths is $S = \times_{j \in C \cup D} S_j$, each scenario path defining a specific combination of random events and a respective global strategy of actions. For a global strategy $Z$, the probability of scenario path $s$ is

$$P(s) = \prod_{j \in C} P[X_j = s_j | X_I(j) = s_I(j)],$$  \hfill (3)

if $Z$ is such that it consists of local strategies $Z_j$ such that $Z_j[s_I(j)] = s_j$, and 0 otherwise. In summary, the probability $\pi(s)$ of scenario path $s$ is

![Influence diagram for programming inspections and maintenance of a turbine.](image)
Finally, each scenario path \( s \) is associated with a consequence whose value \( V(s) \) represents the utility of system operation discounted by the costs of deploying of the selected actions. The value nodes \( U \) encode the values \( V(s) \) for all scenario paths \( s \). It is possible to consider multiple value nodes, but in this paper we focus on a single objective optimization in which the aim is to maximize the utility of system operation, subject to possible resource and risk constraints.

3. Optimization model

The optimal global strategy can be found through a mixed-integer linear programming model formulation, proposed by Salo et al. [38]. In this model, the probability \( \pi(s) \) of scenario path \( s \) is defined by

\[
\sum_{j \in S_j} z[j, s_{ij}(j)] = 1, \quad \forall j \in D, \forall s_{ij}(j) \in S_{ij}(j) \tag{5}
\]

\[
0 \leq \pi(s) \leq p(s), \quad \forall s \in S \tag{6}
\]

\[
\pi(s) \geq p(s) + \sum_{j \in D} z[j, s_{ij}]-|D|, \quad \forall s \in S \tag{7}
\]

\[
\pi(s) \leq z[j, s_{ij}], \quad \forall s \in S \tag{8}
\]

If \( z[j, s_{ij}] = 1 \) for all \( j \) in scenario path \( s \), then probability \( \pi(s) \) is the upper bound \( p(s) \) because constraints (6) and (7) imply

\[
\begin{cases}
0 &\leq \pi(s) \leq p(s) \\
\pi(s) &\geq p(s)
\end{cases}
\tag{10}
\]

On the other hand, if any binary variable \( z[j, s_{ij}] \) is 0 for any \( j \) in scenario path \( s \), then probability \( \pi(s) = 0 \) because constraint (8) implies \( \pi(s) \leq 0 \).

The optimal global strategy \( Z^* \) is the strategy that maximizes the expected utility of system operation so that

\[
E[V(Z)] = \sum_{s \in S} \pi(s)V(s) \tag{11}
\]

subject to constraints (5)–(9). Specifically, constraints (5) ensure that only one strategy \( s_j \) is taken at each decision node \( j \) in \( D \) for every information state \( s_{ij}(j) \in S_{ij}(j) \). Constraints (6) bound the probabilities \( \pi(s) \) of scenario paths \( s \in S \). Constraints (7) ensure that the scenario probabilities \( \pi(s) \) cannot be smaller than their upper bounds \( p(s) \) for scenario path \( s \) such that \( z[j, s_{ij}]=1 \), \( j \in D \). Constraints (8) ensure that only those scenario paths for which \( z[j, s_{ij}]=1 \) for all \( j \in D \) can have positive probabilities. Finally, constraints (9) specify the domain of all binary variables \( z[j, s_{ij}] \).

In addition, the optimization model can include technical constraints that affect the deployment of inspection and maintenance strategies. For instance, the constraint

\[
z[j, s_{ij} \in S_{ij}(j), s_{ij}[j] \subseteq S_{ij}(j) \times S_{ij}(\ell) \tag{12}
\]

means that the action \( s_j \) cannot be deployed unless action \( s_{ij} \) is employed, regardless of the information states \( s_{ij}(j) \) and \( s_{ij}(\ell) \) of nodes \( j \) and \( \ell \).

3.1. Risk constraints

Let \( Q(s_{ij}) \) be the cost of inspection/maintenance action \( s_j \) at decision node \( j \) in \( D \) for the information state \( s_{ij}(j) \), then the total cost \( Q(s) \) of implementing the actions for scenario path \( s \in S \) is

\[
Q(s) = \sum_{j \in D} Q(s_{ij}) z[j, s_{ij}]. \tag{13}
\]

For each scenario path \( s \in S \), it is possible to require that the total cost of inspection and maintenance strategies is lower than the budget \( B \), so that \( Q(s) \leq B \). If this constraint is too strict, chance constraints can be introduced, for instance to limit the probability of exceeding the budget to \( \beta \in [0, 1] \) as

\[
\sum_{s \in S \mid Q(s) > B} \pi(s) \leq \beta. \tag{14}
\]

One can also consider constraints on risk measures, for instance to bound the Value at Risk (VaR) and the Conditional Value at Risk (CVaR) of system operation [45]. At probability level \( \alpha > 0 \), the Value at Risk of global strategy \( Z \) is

\[
VaR_{\alpha}(Z) = \{ t \in R \mid \sum_{s \in S} \pi(s) < \alpha \}, \tag{15}
\]

where the sum of probabilities considers only the scenario paths for which the value \( V(s) \) meets or exceeds the target level \( t \) in \( R \).

In addition to the VaR, constraints on the Conditional Value at Risk (CVaR) limit the expected shortfall in the worst performing scenario paths [46]. Thus, the Conditional Value at Risk of global strategy \( Z \) is the expected value of the \( \alpha \)-tail distribution of the utility function so that

\[
CVaR_{\alpha}(Z) = VaR_{\alpha}(Z)[a - \sum_{s \in S \mid V(s) < VaR_{\alpha}(Z)} \pi(s)] + \sum_{s \in S \mid V(s) < VaR_{\alpha}(Z)} \pi(s)V(s). \tag{16}
\]

Conditional Value at Risk is a coherent risk measure: unlike VaR, it also reflects the shape of the distribution tail. For this reason, it is commonly considered a more informative risk measure than VaR [47].

3.2. Value of perfect information

The Value of Perfect Information (VoPI) refers to the expected increase of system utility that can be gained by obtaining perfect information about the system state. Thus, VoPI quantifies the willingness to pay for the transition from the current PHM solution to the perfect one [48]. As mentioned in Section 1, PHM monitoring and
system inspections provide imperfect information about the state of the industrial system. In this framework, it is possible to compute VoPI as the difference between the optimal expected value for two situations: (i) when the system state is correctly observed and (ii) when the system state is observed with possible errors. The first situation corresponds to perfect information on the system state, whereas the second situation to imperfect information. Consequently, the VoPI can be computed as

$$\text{VoPI} = \mathbb{E}[V(Z^*)|\text{Perfect Information}] - \mathbb{E}[V(Z^*)].$$

(17)

In the case of inspection and maintenance strategies, perfect information refers to a situation in which sensors and inspections correctly indicate the state of the industrial system [49]. Specifically, the system state is reported correctly by the monitoring system with probability one if and only if the monitored state equals the actual system state, and zero otherwise. Perfect information makes it possible to select the optimal global strategy $Z^*$, which may differ from the optimal global strategy $Z$ with imperfect information.

The VoPI represents the increase in expected value when the maintenance strategy can be decided based on perfect information about the system state [50]. This provides insights into the value of investing in improving the PHM solution. Note that this analysis can be performed before any additional information, by assuming the collection of perfect measurement data.

4. Case study

The case study presents a framework to define the optimal maintenance strategy of a gas turbine equipped with PHM solution and sensor validation algorithms, which provide imperfect information on the current state of the turbine and its sensors. In industrial practice, the PHM of a turbine relies on hundreds of sensors tracking the health states of a large number of components with different impacts on turbine operation. For illustrative purposes, we assume that global indicators on the states of the turbine and PHM solution are available.

The turbine undergoes periodic inspection and maintenance strategies, which are selected every 4000 working hours based on the PHM solution. Fig. 1 shows the influence diagram for planning the turbine inspections and maintenance, composed of the set of chance nodes (circles), the set of decision nodes (squares) and the value node (hexagon). In particular, node $H$ refers to the working hours of the turbine, which are technically referred to as fired hours. The realizations are discrete states with time interval of 4000 h so that $s_H \in \{0, 4000, 8000, 12000, 16000, 20000, \ldots\}.

(18)

Node $H$ is deterministic, which can be considered as a degenerate chance node with probability one for the current state only. This representation is useful for modelling the causal dependence between (i) the turbine states and (ii) sensor states from the working hours of the turbine, allowing the optimization problem to be solved for each of the states of working hours.

The fired hours affect the sensor state $s_{SS}$ and the turbine state $s_{TS}$, which implies $I(SS) = I(TS) = \{H\}$. The sensor and the turbine states are qualitative evaluations included in the sets

$$s_{SS}, s_{TS} \in \{\text{Excellent, Good, Fair, Poor, Failing}\}.$$

(19)

Multi-state degradation modelling has recently received much attention in reliability and maintenance engineering [44,51,52]. Multi-state models allow for more granularity in the characterization of degradation processes than binary models in which the state can be indicated only by two (extreme) states, ‘good’ and ‘failed’. Such a binary-state assumption is not adequate in many real-life applications.

The number of states can often be derived from descriptive maintenance data. For instance, in industrial applications such as gas turbines [53,54], maintenance teams can assign a qualitative tag to specify the observed health condition of the equipment at the time of inspection. In other cases, the evolution of degradation processes can be sub-divided into successive phases which exhibit physically different degradation mechanisms [55] and which can therefore be described by corresponding multi-state model. Finally, it may be possible to infer the states by applying unsupervised learning algorithms [56].

The optimization approach presented in this paper is not limited to 5 system states, because the number of states can depend on the specific application. Nevertheless, 5 states is more than the use of 3–4 states which is typical in the field of application of the present case study [53,55]. Generally, the definition of discrete states calls for the measurement of meaningful deviations of degradation measures which may be recorded on a continuous scale. The definition of discretized scale needs to offer a legitimate balance of three factors: (i) the scale should be granular enough so that the maintenance policy can be tailored by mapping each state into action recommendations, (ii) the scale should be meaningful enough to get reliable probability estimates on each state with the available data and information and (iii) the scale should be limited to the strictly needed states to avoid modelling and computational challenges.

Figs. 2 and 3 illustrate the probability distributions of turbine and sensor states, respectively. Specifically, the probability of these states depend on the fired hours $H$ (horizontal line), in keeping with the conditional probabilities $P[X_{SS} = s_{SS}|X_H = s_H]$ and $P[X_{TS} = s_{TS}|X_H = s_H]$. These values can be inferred from the inspection outcomes, when the multi-state degradation setting is adopted in the turbine maintenance practice [32,57].

Based on machine-learning models [58], the PHM algorithms provide following estimates of the sensor state and the turbine state

$$s_{SE}, s_{TE} \in \{\text{Excellent, Good, Fair, Poor, Failing}\}.$$

(20)

The sensor state estimate $s_{SS}$ depends on both the actual state of the sensor and the turbine state. The turbine state estimate $s_{SE}$ depends on both its actual state and the sensor state estimate, because the sensor validation affects the PHM performance.

The PHM estimates on sensors and turbine provide information for the Inspection Decision, in the set

$$s_{ID} \in \{\text{None, Sensor Check, Condition Monitoring}\}.$$

(21)

where Sensor Check indicates an analysis of the signal data to detect faulty sensors and Condition Monitoring refers to a maintenance action on the monitoring devices. Neither action requires the turbine to stop, and the sensor condition results $s_{SR}$ is in the set

$$s_{SR} \in \{\text{Excellent, Good, Fair, Poor, Failing}\}.$$

(22)

If no inspection is performed ($s_{ID} = \text{None}$), the sensor condition results $s_{SR}$ correspond to the sensor state estimate $s_{SS}$ provided by the PHM. If some form of inspection is performed ($s_{ID} = \text{Sensor Check}$ or $s_{ID} = \text{Condition Monitoring}$), the sensor condition results $s_{SR}$ report the sensor state $s_{SS}$ correctly with 95% probability. The observation is erroneous with 5% probability, which has been equally distributed across the two incorrect states close to the sensor state.

The sensor inspection provides relevant information on the accuracy of the turbine state estimate $s_{TS}$. Specifically, it supports the definition of the turbine condition results $s_{TR}$ such that

$$s_{TR} \in \{\text{Excellent, Good, Fair, Poor, Failing}\}.$$

(23)

The turbine condition results $s_{TR}$ on the turbine state depend on the turbine state $s_{TS}$, the turbine state estimate $s_{TE}$ and the sensor condition results $s_{SR}$. If no inspection is performed ($s_{ID} = \text{None}$), the turbine condition results $s_{TR}$ correspond to the turbine state estimate $s_{TE}$ provided by the PHM. If the inspection is Sensor Check, the turbine condition results $s_{TR}$ correspond to the turbine state $s_{TS}$ with a probability which depends on the sensor condition results $s_{SR}$. Finally, if the inspection is Condition Monitoring, the turbine condition results $s_{TR}$ report the turbine state $s_{TS}$ correctly with 98% probability. The observation is erroneous with 2% probability, which has been equally distributed across the two incorrect states close to the turbine state.
The condition results $s_{SR}$ and $s_{TR}$ on the sensor state and the turbine state provide information for the Maintenance Decision, in the set $s_{MD} \in \{\text{None, Level1, Level2}\}$, where Level1 restores the turbine state to 4000 h earlier and Level2 restores the turbine state effectively to 0 h of operation, i.e. as good as new. Fig. 4 shows the degradation/restoration process of the turbine and the PHM solution. Arrows indicate probabilistic transitions between states during the next 4000 h for the selected maintenance strategy. For illustration, Table 1 reports the transition probabilities for the degradation and renovation of the turbine. For example, if the turbine is currently in state $s_{TS} = \text{Good}$ and the maintenance strategy $s_{MD} = \text{Level2}$ is selected, the turbine is in state $s_{TS} = \text{Excellent}$ with probability 99% and in state $s_{TS} = \text{Good}$ with probability 1% after the next 4000 h.

The transition probabilities are embedded in the influence diagram in Fig. 1 and employed to determine the probabilities of the scenario paths, as described in Eq. (3). These probability estimates (including Table 1) are illustrative in that they do not originate from any real system specifically. Rather, they have been generated by the authors in order to represent realistic values for such engineering systems and to illustrate the insights that are supported by the methodological developments. These developments, rather than the numerical parameters as such, constitute the main contribution of the paper.

The turbine state $s_{TS}$ and maintenance strategy $s_{MD}$ affect the Turbine Flow, which has the following discrete values $s_{TF} \in \{\text{Excellent, Good, Fair, Poor, Failing}\}$. (25)
The turbine flow rate impacts the utility of the system operation, reduced by the costs of inspections $s_{ID}$ and maintenance $s_{MD}$. Fig. 5 shows illustrative utilities based on the state of the turbine flow, whereas Table 2 shows the costs for inspection and maintenance actions. The utilities and costs are illustrative units but have not been derived from an actual industrial system.

To solve the influence diagram, it is necessary to define the turbine fired hours, the conditional probability tables and the system utilities. These parameters are provided in the online appendix in Excel format. The solution of the optimization model provides the optimal inspection and maintenance strategies for every level of fired hours and for each information state which is available when making these decisions. For illustration, Tables 3 and 4 present the optimal inspection and maintenance strategies of the turbine at $H = 16000$ fired hours, respectively. Specifically, the inspection strategy depends on the estimates $s_{SE}$ and $s_{TE}$ of the sensor and turbine states, whereas the maintenance strategy depends on the condition results $s_{SR}$ and $s_{TR}$ of the inspections.

The optimal inspection strategy is such that no inspection is performed if the sensor state estimate is Excellent, Good or Fair and if the turbine state estimate is Poor or Failing. On the other hand, Condition Monitoring needs to be performed if the sensor state estimate is Poor or Failing for specific circumstances of the turbine state estimate. Furthermore, the optimal maintenance strategy shows not to perform any maintenance if the turbine state estimate is Excellent, Good or Fair, but Level 1 maintenance should be performed if the turbine state is Poor. If the turbine state estimate is Failing, the optimal maintenance strategy depends on the sensor state estimate: Level 2 maintenance is necessary if the sensor state estimate is Excellent or Good and Level 1 maintenance otherwise.

The solutions in Tables 3 and 4 need to be examined together. Specifically, when the turbine state estimate is a degraded state (Poor or Failing), the optimal global strategy is to proceed with maintenance actions, without improving the accuracy of the estimate of the turbine state through inspections. This choice depends on the high reliability of the monitoring devices. On the other hand, when the estimate of the turbine is in a healthy state (Excellent, Good or Fair), the choice on the inspections depends on the estimated state of the monitoring devices. Thus, the optimal global strategy is to inspect the turbine when the sensors are expected to be degraded. The above optimization results are based on the specific numerical values of the model parameters. Thus, the optimal maintenance strategies could be different for other parameter values, such as the transition probabilities in the influence diagram.

Fig. 6 illustrates the optimal expected utility of the system and the respective Value of Perfect Information, for each discrete state of the turbine fired hours. To model perfect information on the system state,
The probabilities of the estimates $s_{SE}$ and $s_{TE}$ of the sensor and turbine states are defined as

$$P[X_{SE} = s_{SE} \mid X_{SS} = s_{SS}, X_{TS} = s_{TS}] = \begin{cases} 1, & \text{if } s_{SE} = s_{SS} \\ 0, & \text{otherwise}, \end{cases}$$

(26)

$$P[X_{TE} = s_{TE} \mid X_{SE} = s_{SE}, X_{TS} = s_{TS}] = \begin{cases} 1, & \text{if } s_{TE} = s_{TE} \\ 0, & \text{otherwise}. \end{cases}$$

(27)

In the model, the number of fired hours is known with certainty, but there is uncertainty about the system state and the outcomes of inspection and maintenance decisions. In effect, this uncertainty stems from the stochasticity of the components’ degradation mechanisms. When the number of fired hours is higher, it is more likely, for instance, that the turbine and sensor states are “poor” or “failing”. As shown in Fig. 6, this implies that the expected value of system performance does deteriorate. Yet, although there is more uncertainty about the actual turbine and sensor states, there is also more value in reducing this uncertainty, as indicated by the higher VoPI values for increasing fired hours. This is in line with a common result in VoI theory [59], i.e., when there is more uncertainty about the system state (on which the performance of the system depends), there is usually more value to knowing what state the system is in.

Besides employing risk measures as constraints of the optimization model, it is possible to analyse the VaR and CVaR of the optimization solutions to better understand the results. This analysis provides additional insights on these solutions without the need to specify the threshold probability $\alpha$ and target level $t$ before the optimization. For some choices of the parameters $\alpha$ and $t$, these parameters could be so stringent that the optimization model has no feasible solutions. For this reason, an ex-post analysis of the results bypasses this issue, avoiding optimization runs with long computational times.

Fig. 7 shows the cumulative probability of the utility for the optimal global strategy $Z^\ast$ at $H = 16\,000$ h. From this probability distribution, it is possible to compute VaR of $Z^\ast$ and CVaR of $Z^\ast$ at probability level $\alpha$, as defined in Eqs. (15) and (16). Table 5 lists the VaR and CVaR of system operation at different probability levels $\alpha$ by increasing the $\alpha$ value, both the VaR and the CVaR also increase.

For the analysed probability levels $\alpha$, the CVaR is higher than zero only for $\alpha > 0.1$. In view of these results, the optimal global strategy for $H = 16\,000$ h involves limited risks in that the expected utilities will be negative with probability of less than 10%.
A drawback of this methodology is that the conditional probability tables can become large when the number of states of system components and sensors. This drawback may limit the applicability to large-scale industrial systems which could, however, be modelled by building and linking their sub-systems. On the other hand, the high availability of data from the Industrial Internet of Things (IIoT) makes it possible to derive more accurate probability parameters for the optimization. One could also consider imprecise model parameters for probabilities or the costs and impacts of inspection and maintenance strategies. These could be synthesized in the optimization to obtain robust solutions [63]. The above challenges as well as extensions of the framework to industrial systems with a larger number of system states will be addressed in future research.

6. Conclusion

In this paper, we have developed a methodology for the optimal selection of inspection and maintenance strategies for industrial systems equipped with PHM. These strategies maximize the value for the company deriving from system operation, computed as the system utility discounted by the costs for inspection and maintenance actions.

The framework employs influence diagrams to model causal dependencies between system states and decisions on inspection and maintenance strategies. Based on Decision Programming, the optimization model defines the optimal global strategies for the system, accounting for budget and technical constraints. The solution is obtained through a mixed-integer linear problem, which considers all possible scenario paths on the system states and decisions. The viability of the methodology has been illustrated with an example concerning a gas turbine equipped with PHM.

Overall, this paper shows the need to consider the unreliability of the PHM solution in the choice for inspection and maintenance strategies, because the optimal global strategies depend on both healthy or degraded states of the industrial system and the state of the monitoring devices.

Acknowledgements

The research has been supported by the project Platform Value Now, funded by the Strategic Research Council of the Academy of Finland (grant number 314207). The case study has been performed using Julia Programming language with the technical support of M.Sc. Juho Andelmin.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ress.2021.107536.

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