# ISA-PHM – a Standardized Format for Storing and Utilizing Meta-data of Diagnostic and Prognostic Tests

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## ABSTRACT

The development and implementation of diagnostic and prognostic algorithms for smart maintenance purposes is hindered by the fundamental lack of relevant, complete and properly labeled data from fielded systems. This issue is partly tackled by the generation of well-defined datasets using numerical simulations or experimental set-ups in a laboratory environment. However, the widely varying formats of (the description of) these datasets make that data scientists need to invest heavily in interpreting the data and transforming it to a format that fit the model requirements. To reduce that effort and ensure a robust and consistent processing, this work proposes a standardized way of documenting such datasets. This ISA-PHM standard is based on the existing ISA metadata standard originating from life and biomedical sciences, that has been translated to the prognostics and health management (PHM) context. This is achieved by firstly structuring and generalizing the information required to document both diagnostic and prognostic (numerical or physical) experiments. This information is then carefully mapped to the ISA ontology, ensuring a complete and unambiguous documentation of any PHM-related test. The concept is demonstrated by application of ISA-PHM to three well-known public datasets (NLN-EMP, NASA milling data, CMAPSS) and a real failure. Finally, for the implementation, some practical software tools are presented (available on linked website) as well as the planned future extension towards collective data generation through distributed testing.

## 1. INTRODUCTION

The reliability and availability of systems are becoming more and more important in many sectors of industry, where companies are aiming to reduce maintenance costs and increase system performance or output. Simultaneously, the large number of sensors and improved ways of storing their outputs make that large amounts of data on the operational behavior of systems are available. Based on these two trends, many research projects now focus on the development of data-driven smart maintenance concepts, which aim to automatically detect faults, to diagnose systems or to even predict when future failures will occur.

Diagnostic methods aim to easily or even automatically detect or diagnose failures in systems (Rijsdijk, Wijnckel, & Tinga, 2024). Prognostic methods potentially offer even larger benefits, as they allow to predict future failures in a timely manner. The maintenance policy associated to prognostics is called Predictive Maintenance (PdM). It aims to schedule maintenance tasks just-in-time, and in that way effectively prevents failures as well as over-maintenance. At the same time, the predictions allow efficient planning of required man power and spare parts. Therefore, industry is eager to harvest the potential of PdM.

Many PdM methods and models have been proposed in the past decade, see e.g. the reviews on artificial intelligence (AI)-based methods (Khan & Yairi, 2018), system-level prognostics (Tamssaouet, Nguyen, Medjaher, & Orchard, 2022), PdM application (Zonta, da Costa, da Rosa Righi, de Lima, Silveira da Trindade, & Li, 2020) and maintenance optimization (de Jonge & Scarf, 2020; Pinciroli, Baraldi, & Zio, 2023). However, practical application of these prognostic methods is still rather limited (Akkermans, Basten, Zhu, & Van Wassenhove, 2024; Grubic, Redding, Baines, & Julien, 2011; Tiddens, Braaksma, & Tinga, 2022). Practitioners apparently encounter barriers that prevent them to apply the available methods in practice. In a recent paper (Tinga, 2025) the authors identified several barriers for the implementation of PdM. One of the dominant barriers found is the lack of relevant data.



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AI methods play an important role in these diagnostic and prognostic concepts, as algorithms must be trained to recognize specific (abnormal) patterns and trends in the collected sensor data. However, this sets specific requirements to the data in terms of type, quality and size (Alves da Silveira, 2025), as well as accurate labels. Data obtained from fielded systems, i.e. deployed in a real industrial setting, quite often does not meet these requirements, which severely limits the feasibility of diagnostics and prognostics. This is also shown by Hagmeyer, Mauthe and Zeiler (2021), proposing a set of six criteria to assess the quality of prognostics and health management (PHM) datasets. They also conclude that many available datasets, both from industrial practice and research projects, lack important info, particularly regarding labeling of the underlying data. Corrêa, Polpo, Small, Srikanth, Hollins and Hodkiewicz (2022) try to tackle this problem by automatically labeling plant data by both a rule-based and a data-driven approach. However, the encountered significant imbalance in the data, containing 1.2M non-event data points and only 64 events, and the observed ambiguity in manually assigned labels make the endeavor quite challenging.

The lack of relevant and applicable data can (partly) be solved by using dedicated datasets (Tinga, 2025), created by laboratory testing or using numerical simulation models. An overview of such datasets is provided by Mauthe, Steinmann, Neu and Zeiler (2025). Examples include the experimental NLN-EMP dataset (Bruinsma, Geertsma, Loendersloot, & Tinga, 2024) for faults in e-motor-pump systems, and the NASA CMAPSS dataset generated by a simulation model of an aircraft engine (Saxena, Goebel, Simon, & Eklund, 2008). The work by Zaghdoudi, Varnier, Hajri-Gabouj and Zerhouni (2024) recognizes the value of such datasets for PHM implementation, and focuses on assessing the similarity of the data with the original data from the considered system.

Apart from the limited number and sometimes questionable practical relevance (e.g. unrealistically large defects), the use of these benchmark datasets offers another challenge: the documentation of the data is often limited, and structured differently for every dataset. This makes application of the data for model training and testing quite tedious: the dataset needs to be fully explored and interpreted before it can be transformed into a format that can be used, and correctly labeled. And even then, details of the introduced faults (size, type, timing), operational conditions, and applied sensors are often missing.

Currently, there is no universally applied data standard for the field of PHM. Observation from a discussion panel on standards for PHM were reported by Bird and Shao (2013), and Vogl, Weiss and Donmez (2014) reviewed available standards, concluding that data management standards (e.g. ISO, IEC, MIMOSA (2013)) are existing, but focus on configuration and life cycle data in general. A specific standard for reporting and documenting failure (test) data is still lacking. More recently, Omri, Al Masry, Giampiccolo, Mairot and Zerhouni (2019) explored the data management requirements, with a focus on achieved product quality, in small and medium enterprises. They conclude that the required ‘creation of the production memory’ is challenging: some failure messages are recorded with different languages and many sensors are represented in different codes. In a follow-up paper (Omri, Al Masry, Mairot, Giampiccolo, & Zerhouni, 2021) they discuss several data quality aspects, but focus on the sensor data, and do not discuss the data labeling issue. Also in the related field of structural health monitoring (SHM) attempts have been made to standardize methods, as reviewed by Lehmann, Hille and Glišić (2025). However, there is no explicit attention for data and meta data registration.

Data standards are already applied in other research fields, typically focusing on making data FAIR. This implies that collected data should be Findable, Accessible, Interoperable and Reusable (Schultes, Magagna, Hettne, Pergl, Suchánek, & Kuhn, 2020). A good practice in that respect is the ISA standard (ISA-specs, 2016), widely used as the de-facto standard for standardizing metadata in life science, environmental and biomedical sciences. The backbone of this standard is a well-defined ontology, that is used to uniquely store the attributes of an experiment. Also in the SHM field ontologies have been proposed (Tsalapati & Koubarakis, 2023; Tsialiamanis, Wagg, Antoniadou, & Worden, 2021). However, these are quite broad, covering also analysis techniques and SHM methods, and due to the passive nature of SHM methods do not match well with controlled experiments. Therefore, due to its proven concept in documenting experiments, the ISA standard is taken as a starting point here for the development of a PHM (meta)data standard.

To enhance the use of datasets in diagnostic and prognostic model development, this paper proposes ISA-PHM as a new standardized method for documenting datasets. The focus will be on the meta-data, i.e. the description of the context and details of the executed test or simulation, rather than on the generated data itself. The existing ISA standard will in this work be adapted for use in PHM applications. This requires structuring the (required) information for diagnostic and prognostic tests in a generic way, and developing a method to consistently store that information in the ISA entities.

Datasets documented in this format (or data model) will be much easier to process for data scientist, as information on faults, operating conditions and sensors is always directly available and unambiguously linked to the (sub)sets of measurement data. This significantly simplifies combining datasets from different sources, which is typically required to create robust models that could also perform well on a variety of (slightly different) fielded systems. It is therefore expected that using this data model for transforming existing datasets and sharing newly generated datasets will considerably speed-up the process of diagnostic and prognostic model development.

This work has two main contributions. First, the requirements for documenting PHM related tests are structured and standardized, clearly revealing what meta-data should be stored for any test. Second, a standard for storing this meta-data in a transparent, consistent and retrievable manner is developed.

The remainder of this paper is organized as follows. In the next section, the limitations of existing datasets will be discussed in more detail. Section 3 will then introduce the proposed ISA-PHM standard, after briefly describing the existing ISA standard it is based on. Section 4 will show how the standard can be applied, using examples from existing datasets. Section 5 will discuss how this standard can be adopted in the PHM field for sharing datasets and enhancing model development. Finally, section 6 forwards some conclusions.

## 2. REQUIREMENTS AND LIMITATIONS OF EXISTING DATA

To structure the discussion on PHM-related data, this section will first introduce the different types of PdM analyses that can be performed (section 2.1). Then section 2.2 will discuss the limitations of existing data from fielded systems, lab tests or simulations. Finally, section 2.3 describes how several types of controlled experiments can assist in creating datasets that do meet the requirements.

### 2.1. Ambition Levels and Associated Data Requirements

In predictive maintenance, the ultimate goal is to predict (all) future failures within in a timely manner. However, that goal is quite challenging, and sometimes large benefits can already be obtained by being slightly less ambitious. To illustrate this, in smart maintenance four different ambition levels can be identified (Tinga, 2025):

1. Detection of failures: *is something wrong?*
2. Diagnosing failures: *what is wrong?*
3. Health assessment: *how wrong is it?*
4. Prognosis: *when is it expected to go wrong?*

For these different ambition levels the requirements in terms of data differ. For the first level, automatic detection of faults, typically an anomaly detection algorithm is applied. Such an algorithm only requires *unlabeled data* of the healthy system, and will detect when deviations occur. This type of data is readily available for real systems.

For the second level, focusing on diagnosing failures, a classification algorithm is used that can distinguish between different types of faults or failure modes. This requires *labeled data*, as the algorithm must be trained with data patterns associated to each of the expected fault types.

The third ambition level concerns health assessment, aiming to quantify the condition (e.g. on a scale from 0 – 100%). This can be achieved by either *measuring the condition* by dedicated condition monitoring techniques, or *deriving the condition* from other sensors. In both cases, the aim is to monitor the evolution of the system health over time. Condition monitoring can therefore be either direct, e.g. measuring profile depth on a car tire, or indirect, e.g. temperature or vibration monitoring. In the latter case, there is no direct relation between the measured quantity (vibration level) and the degradation of the system (e.g. bearing defect size), which makes it much more challenging to use the data for health assessment (as wil be discussed in 2.2).

For the highest ambition level of prognosis, the data requirements are the most demanding. As algorithms are expected to predict the (remaining) time to failure of a system, at least several examples of failures should be available in the training dataset. And as the degradation (and associated time to failure) largely depends on the loading and operating conditions, these conditions should preferably also vary in the dataset, but at least be known. This means that several *run-to-failure trajectories* must be available for model training.

### 2.2. Limitations of Data from Fielded Systems

The previous subsection discussed the four ambition levels and associated data requirements. In practice, many of those requirements cannot easily be met, as the following limitations in data availability are encountered in practical situations (Tinga, 2025):

- *No labeling*: most organizations register the observed faults and failures in their systems in a Computerized Maintenance Management System (CMMS). However, this registration is mostly limited to the date of occurrence, and lacks a precise and consistent description of the type of failure. The main reason is the limited knowledge and time that operators have to make these registrations. As a result, there are no proper labels for the sensor data of the machine, which makes training of classification algorithms very challenging;
- *No condition measurements*: the development of health assessment and prognostic algorithms requires a considerable set of degradation monitoring data. However, the dedicated sensors for condition monitoring required for that are (still) not common in industrial practice. Most sensors have been installed in systems for the purpose of monitoring (for safety reasons) and control. These process-related sensors can in some cases be used for PHM purposes, but most of the time provide irrelevant data, especially in the absence of labels (see previous point).
- *No threshold value*: a maintenance decision based on condition monitoring data can only be taken when a threshold value for the monitored quantity is available.

In case of a direct condition measurement (e.g. corrosion depth), the threshold can be based on functional or structural integrity criteria. But in case of indirect measurements, like vibration analysis and oil analysis, it is much more challenging to find a well-motivated threshold value. One option is then to use an experience-based (trial-and-error) threshold value, although running a system to failure is often not possible (see also next point). Furthermore, threshold values may vary when operating conditions change. Alternatively, as Keizers, Loendersloot and Tinga (2025b), showed, numerical models can sometimes be used to find a quantitative diagnostic relation that links the indirect measurement to the system health.

- *No run to failure data:* as previously discussed, predictive algorithms need run-to-failure data for training. However, the strong focus of maintenance on preventing failures results by definition in a situation with very limited availability of failure data. Especially for critical assets, like aircraft, industrial plants and military systems, the conservative character of current maintenance policies ensures that actual failures seldom occur. This is a huge challenge in developing prognostic methods, and also the most important reason that the large majority of academic papers uses artificial benchmark datasets for training and testing the proposed methods, e.g. de Pater, Reijns and Mitici (2022).
- *No operating history:* the strong dependability of degradation on load and operating histories (e.g. environment, speed, power setting) was mentioned before. Both for developing models and validating their generic applicability, well-documented operating conditions are crucial. However, this is very challenging in an industrial environment. While the proper registration of failures (see previous issues on run-to-failure and labelling) is already challenging, getting access to the full operational history of a system (which may cover a period of several years) is almost impossible in most organizations.

Due to these practical limitations, development and especially application of data-driven maintenance methods are still challenging.

### 2.3. Data Generation by (Lab) Testing

When suitable data cannot be obtained from registrations in industrial practice, alternative ways must be found. One such alternative is to use experiments to generate the required data. The advantage of this approach is that full control is gained over the design and execution of the experiments, and thus over the generated data and, more importantly, the labeling (meta-data). Numerical simulations can also be considered as (virtual) experiments, and offer even more flexibility in defining test conditions. However, the quality and relevance of the generated data depends largely on the quality and level of detail of the simulation model. In this work, the focus will be on physical experiments in a lab environment, but the approach and standardization will be fully applicable for numerical experiments as well.

For the generation of data that can meet the requirements for the four ambition levels in smart maintenance introduced in 2.1, two basic types of PHM tests can be defined:

- **Diagnostic test**: a well-defined fault or defect, or combination of faults, is introduced in a test-piece or system. This test piece is then tested (for typically a short period of time) under a specific operating condition, and the test piece response is measured by one or several sensors or measurement techniques.
  *Aim*: capture the data pattern(s) representative for the considered fault and operating condition;

- **Prognostic test** (or Degradation test): a test-piece or system is prepared either with a well-defined initial defect or without any defect. The test piece then undergoes (either constant or time-varying) loading for a prolonged period, preferably until failure. During the complete test, the test piece response is measured with a certain sampling rate (periodic or continuously) by one or several sensors or measurement techniques.
  *Aim*: capture the evolution of the data pattern(s) for a complete run-to-failure trajectory for the considered degradation mechanism and operating conditions;

An example of a diagnostic test is a test on a bearing test bench, where a defect is introduced in the bearing outer raceway (denoted as BPFO), and the response at a certain rotational speed is recorded with a vibration sensor (during a measurement period of 1-3 minutes) (Bruinsma et al., 2024). In a prognostic test, this bearing would be tested for a longer period (~ days – weeks) to force the initial defect to grow (preferably until failure), while over time the (changing) vibration response is monitored (Williams, Ribadeneira, Billington, & Kurfess, 2001).

Diagnostic tests can only be used for training algorithms for detection (unsupervised learning) or diagnostics (supervised learning). To develop and train health assessment and prognostic algorithms, the evolution of the system health over time must be included in the test results, which can only be achieved by prognostic tests. Moreover, for prognostic algorithms, aiming to predict the remaining useful life (RUL), the tests must be run till failure to also reveal the threshold at which failure occurs.

These two basic types of tests can be executed in three different ways, each with their pros and cons:

- **Lab experiments**: the test is executed in a laboratory, where a physical set-up is used to generate the data.
  *Pro*: loading and conditions can be fully controlled, behavior is rather realistic (actual physical system),

typically low noise and interference in measurements due to isolated environment, run to failure in many cases possible;
*Con*: number of available sensors may be restricted by hardware or costs, inclusion of (run-to-)failures sometimes challenging (costs, safety);

- **Numerical simulations**: the test is executed as a numerical experiment using a simulation model to generate the data.
  *Pro*: loading and conditions can be fully controlled, number of (virtual) sensors in principle infinite, inclusion of failures is safe and easy;
  *Con*: typically not very realistic, since accuracy depends on the fidelity of the model and noise level (if included) is estimated by the model builder;

- **Extraction from fielded systems**: the 'test' is executed by operating a real system under realistic conditions. Relevant data is only collected when (accidentally) a failure occurs.
  *Pro*: very realistic, highly relevant for tuning and testing developed methods;
  *Con*: no control over the encountered faults and loading or conditions (as these are just happening), number of sensors depends on hardware (often limited), operating till failure is almost impossible, typically high noise and interference due to neighboring systems;

The main difference between data obtained from experiments or simulations and field data is that in experiments faults with a specific severity or certain degradation processes can be introduced in a controlled manner, while in field data a certain fault or degradation is observed, and can only be defined (and preferably quantified) afterwards (by executing a Root Cause Analysis). However, properly documenting these real degradation patterns and failures, and combining them with test data, e.g. using Bayesian filters (Keizers, Loendersloot, & Tinga, 2025a) or Transfer Learning can significantly increase the accuracy, relevance and trustworthiness of models developed with experimental or simulation data.

The execution of a structured and well-designed test program can generate relevant datasets, that solve some of the limitations encountered for real data (as discussed in 2.2):

- *No condition measurements*: can be addressed by installing condition monitoring sensors in lab set-ups, and executing a series of diagnostic or prognostic tests under controlled operating conditions. This will reveal the degradation patterns for specific faults in specific operating conditions, or the evolution of the system condition over time;
- *No threshold value*: this can also be addressed in the prognostic tests with condition monitoring sensors. However, the tests should then be run-to-failure tests, allowing to determine at which measured condition the system actually fails;
- *No run-to-failure data*: as the risks of failure in a lab set-up are much lower than in a real system, run-to-failure tests are in many cases feasible. For numerical simulations there is even no risk at all, but it should be checked whether the model is sufficiently accurate to guarantee realistic run-to-failure results;

However, while these three limitations are tackled by executing test programs, still two important limitations remain: *No labeling* and *No operating history*. When tests are executed, but information on the introduced faults or applied operating conditions is missing, the generated data can still not be used for model development. The work in this paper therefore specifically focuses on these two issues, by proposing the ISA-PHM standard for completely documenting the details of (physical or numerical) experiments, and linking these to the specific (sub)sets of measurement data.

## 3. ISA-PHM FORMAT

Considering the limited documentation of most datasets currently available, as well as the requirements for PHM model development discussed in section 2.1, it can be concluded that there is a need for guidance in reporting the following meta-data of executed tests:

- Type of test (diagnostic, prognostic)
- Details of fault(s) (or degradation) inserted
- Operating conditions during test
- Details of measurements and sensors used
- Details of data-processing procedures

The proposed ISA-PHM standard aims to store all this meta-data in a well-defined manner, including an explicit link to the subsets in the raw measurement data. This makes it easy for data scientists to use the data for training and testing purposes.

In the next subsection, the original ISA standard, on which ISA-PHM is based, will be introduced. Subsection 3.2 will then provide all the details of the adapted ISA-PHM standard.

### 3.1. Original ISA Standard

The original ISA standard is used in biology, environmental and life sciences for documenting experiments (ISA-community, 2016; ISA-specs, 2016; ISA-tools, 2014). The name is derived from the three main elements: Investigation, Study and Assay, as shown in Figure 1. An *Investigation* (*I*) contains all the information needed to understand the overall

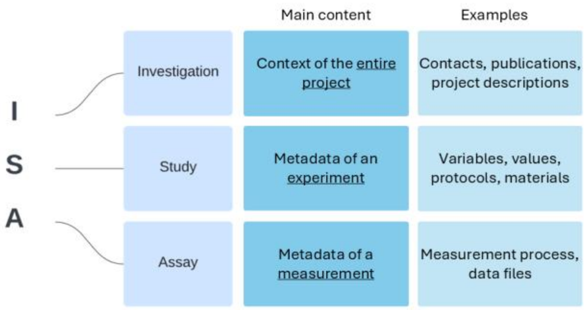



Figure 1. Basic elements of ISA standard.

goals and means used in an experiment. The *Studies* (*S*) describe all performed experiments, and the *Assay* (*A*) describes the measurements performed during one of the experiments. Each Investigation may be associated to one or more Studies, and for each Study there may be one or more Assays. The ISA standard describes unambiguously how the meta-data associated to the *I*, *S* and *A* should be recorded, following a predefined ontology. Figure 2 provides an overview of the main entities and their relations. While the ISA structure allows a fully standardized way of reporting experiment meta-data, there is still some freedom in deciding which experiment detail is stored in what ISA object. This is especially true when a different type of experiment, or even a completely different application field, like PHM, is considered. Therefore, the main contribution of the present work is this translation of PHM-relevant aspects to the original ISA entities.

The original interpretation of the various ‘entities’ (Figure 2) in ISA (applied to biological experiments) is as follows:

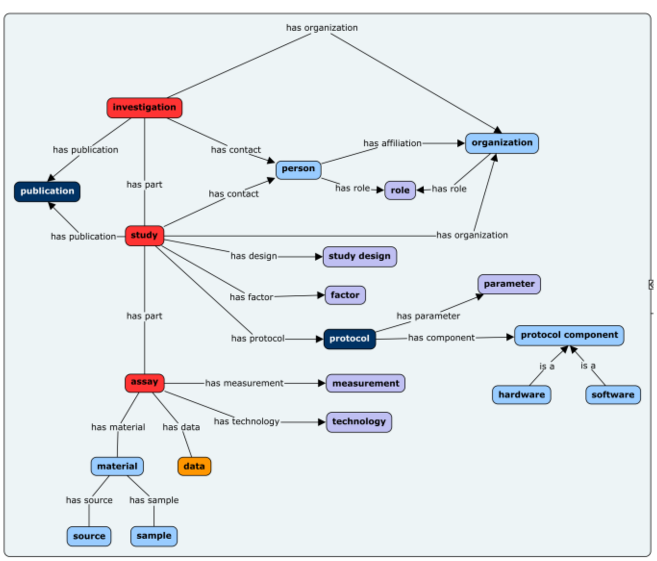



Figure 2. Overview of ISA main entities and their relations (ISA-specs, 2016).

‘Samples’ with ‘characteristics’ are obtained from a ‘source’ and go through a ‘sample manipulation process’, described by ‘protocols’ after which for each of the ‘manipulated samples’ the effect of variable *X* (expressed as ‘study factor’) on effect *Y* is measured, using a ‘measurement protocol’. The obtained ‘raw data’ is processed using a ‘data processing protocol’ yielding the final ‘processed data’.

This process is visualized in Figure 3, showing how a Sample flows through a testing process, and how this is documented in the various ISA entities. First the red (test definition) path is completed, followed by the blue (measurement) path. In the next subsection the interpretation of the ISA standard for PHM purposes will be defined.

### 3.2. ISA-PHM Definition

For the documentation of PHM test data a distinction is made between diagnostic and prognostic tests (see section 2.3). Due to the differences between these two types of tests, it is convenient to capture the documentation by two different templates. However, the data in these two templates is partly interoperable, as will be discussed in 3.2.3. Also some conventions on the input (3.2.4) and the two different output formats (3.2.5) will be discussed later.

#### 3.2.1. Diagnostic Tests

A thorough analysis of a range of PHM-related tests has revealed that a diagnostic test is fully characterized by the

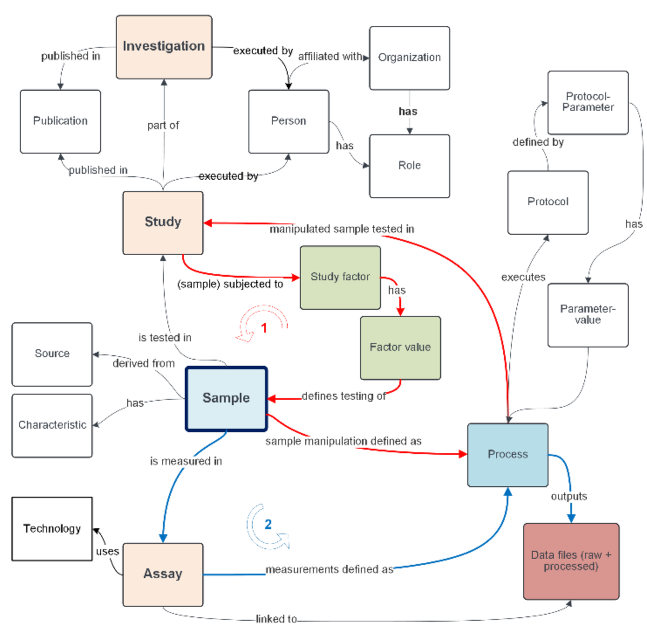



Figure 3. Visualization of the (ISA documentation) flow of a Sample in a testing process. Path 1 represents test matrix definition, path 2 the actual measurements (per test).

following four subsets of information:

1. **Project description**: general info on the complete test and associated dataset (title, aim, owner, location, publications, etc.);
2. **Test set-up description**: all details on the machine, system or structure that is used to execute the test on. As in PHM typically one (or a limited number) of set-ups is considered in a project, it is convenient to describe this once in the documentation. This is a major difference with regular ISA, as in biological tests typically a considerable number of samples is used in one investigation. In PHM tests this will only be the case when components (e.g. bearings) on a test rig can be exchanged to test multiple equivalent parts. But then still the major part of the set-up remains fixed;
3. **Description of all sensors**: all sensors and measurements used during the tests are described, including their accuracy and units, as well as the associated data or signal processing steps (e.g. filtering);
4. **Definition of the test matrix**: a description of all experiments that are executed. For a diagnostic test, each entry in this test matrix contains info on the following aspects:
   i. *fault*: description of the fault, its location, and severity in this specific test;
   ii. *operating conditions*: the values of all controlled parameters (denoted as independent variables) for this specific test;
   iii. *sensors*: the sensors or measurements that are used during this specific test to register the response of the system (i.e. the dependent variables), selected from the list defined in 3.;
   iv. *link to data*: specification of the file(s) that contain the measurement data (raw and/or processed) for each of the sensors used.

Note that the fourth aspect of the input (test matrix definition) is the most crucial part, as it connects the measurement data files (step 4.iv) to all its relevant labels. This connection ensures that the test is completely documented.

The next challenge is to store all this information in the ISA data model in a consistent manner. This requires to fully understand the ISA ontology, as well as the structure and details of PHM tests. That analysis has been done in this work, resulting in the following ISA-PHM interpretation of the various 'entities' in a diagnostic test:

> A 'generic test set-up' can be configured (e.g. specific components) according to 'characteristics'. This 'configured set-up' goes through an 'experiment preparation process', described by an 'experiment preparation protocol' to create a set of experiments (i.e. *test matrix*). For each of the experiments the influence of (independent) variables $X$ on resulting effect $Y$ in the considered experiment is measured, using a 'measurement protocol'. 'Study factors' are assigned to the 'configured test set-up', defining both the operating conditions and the faults introduced (both considered as independent variables $X$) for each experiment. The obtained 'raw data' is (optionally) processed using a 'data processing protocol' yielding the final 'processed data'.

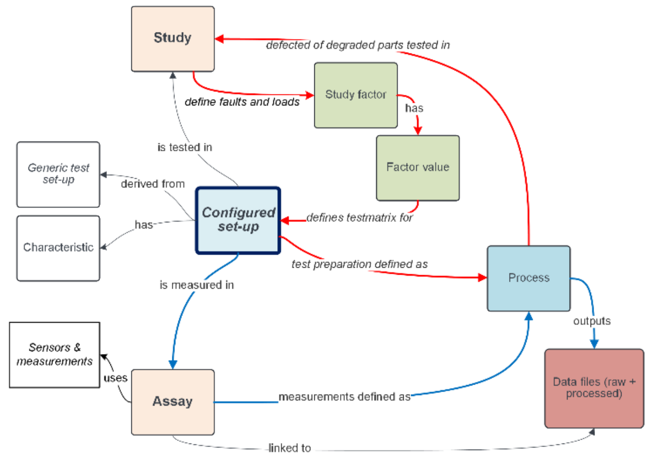



Figure 4. Interpretation of ISA for PHM applications. Elements that differ from original ISA are printed in italics. Investigation and Protocols are identical, so are omitted here.

A complete definition of this interpretation is given in Table 2 in Appendix A, and is visualized in Figure 4. It implies that an investigation ($I$) contains the description of a complete test program. Each individual experiment is stored as a Study ($S$). Such a Study then combines a (configured) test set-up (Sample), a specific fault introduced (Study Factor) and a set of operating conditions (also Study Factors). Further, each experiment also involves a number of sensors or measurements, which are specified at the Assay ($A$) level. Each Assay defines for one experiment (Study) one specific sensor or measurement, including the values of various Protocol Parameters (see explanation of Protocols below), like sensor location, sample rate, filter type, as well as the link to the single file containing the (raw or processed) measurement data. The relation between a Study (experiment) and Assay(s) (measurements) is defined at the level of the Investigation.

As a result, an Investigation ($I$) typically contains many Studies ($S$), determined by the (tested combinations of) faults and operating conditions (i.e. the *test matrix*), and each Study is associated to a list of Assays ($A$), determined by the number of sensors used. For example, a bearing test with two faults at two different severities, tested (full factorial) at three RPM settings contains 12 Studies. Using vibration monitoring sensors in three directions then yields three Assays per Study, so a total of 36 Assays.

As mentioned before, a major difference between regular ISA and ISA-PHM is the origin of the test objects. In biological studies, multiple Samples are taken from one or several Sources (materials), following a sample collection process (described in a Protocol), and these samples are then tested. In ISA-PHM, the test bench or test set-up is considered as the Source, while specific configurations of the set-up (e.g. with a specific bearing or pump impeller to be tested) are denoted as Samples. Details of the Sample are defined in its Characteristics, and tests are then executed on these samples.

Finally, in ISA 'Protocols' are used to describe the details of certain processes. These Protocols consist of a list of Parameters and their Parameter Values. The Parameters are defined generically in the Study, while their values for each specific measurement are defined in the Assay. In special cases, where more info is required than can be provided as Parameter and Value, a link to a separate descriptive file can be included. In ISA-PHM the following protocols are used:

- *Experiment preparation protocol*: describes in detail how the faults are introduced in (specified components of ) the set-up, their precise location and how the severity is quantified. As this is in most cases a rather lengthy description, possibly including figures or photos, typically a reference to a separate document is provided. This protocol is thus describing the sample collection process;
- *Measurement protocol*: provides all the details of the used sensors and measurement techniques, e.g. sensor type, location, accuracy, sample rate, etc.;
- *Processing protocol*: describes the details of the signal processing methods that are applied to the raw measurement data, e.g. Fast Fourier Transform, peak selection, or filtering details;

In this way, all relevant meta-data for any diagnostic test can be stored consistently in the ISA-PHM data model. The next subsection will describe how this works for a prognostic (degradation) test.

### 3.2.2. Prognostic Tests

The main characteristic of a prognostic or degradation test is that the fault or degradation is not constant, but evolves over time. Rather than detecting or classifying a fault, a prognostic test aims to quantify the degradation and to determine the (variation in) degradation rate during the test, preferably until failure. When this behavior is captured, it can be used to develop and train algorithms that can predict degradation and failures for similar systems. This implies that the duration of a prognostic test is typically (much) longer than for a diagnostic test. The consequence is that, in addition to the fault, also the operating conditions often vary over time. As this variation is crucial information for model development, it must be properly documented in ISA-PHM.

The input for a prognostic test is for the first three aspects identical to that of a diagnostic test (see 3.2.1):

1. **Project description**
2. **Test set-up description**
3. **Description of all sensors**

The main differences occur in the fourth aspect, i.e. the test matrix definition, due to the following considerations:

- *Evolving fault severity*: rather than introducing a fault with a specified severity on purpose, in a prognostic test the fault naturally develops from either an introduced initial defect or from the healthy state. This means that in ISA-PHM the fault (type or severity) cannot be defined by a single Study Factor Value as in a diagnostic test. Instead, it is defined by a time series of the fault severity, describing the fault development over time. This is achieved by linking the Study Factor 'fault severity' to a separate file, containing the sequence of fault severity values and associated time stamps (see also the data storage convention in 3.2.4).
- *Degradation as output rather than input*: in a diagnostic test a fault severity is often prescribed (input), while in a prognostic test the severity must be measured (periodically or continuously) during the test (output). This output is then used to specify (label) the fault severity, as discussed in the previous point. However, sometimes this degradation cannot be measured directly. In that case the remaining useful life (RUL) is often used as label instead. This RUL can only be determined for each time step $t_i$ after completion of the test, when the failure time $t_f$ is known: $RUL_i = t_f - t_i$. In ISA-PHM, this RUL value evolution can be stored in a separate file (time + value), and then again be linked to the Study Factor 'fault severity';
- *Changing operating conditions*: during long-term degradation tests, operating conditions will typically not be constant all the time. This can be caused by drifting of control systems or changes in environmental conditions (e.g. temperature, humidity). But also deliberately switching to another operating regime can be part of the test. Documenting the precise operating conditions is very important, and is achieved in ISA-PHM in the same way as for the degradation: rather than setting a fixed value for a Study Factor, a separate file (time + value) provides the time series of the operating conditions during the test;
- *Multiple runs (to failure)*: in degradation tests the Sample will typically not be identical at the beginning and the end of the test, due to the degradation that takes place during the test. Whereas repeated diagnostic tests can be considered as independent tests (and therefore be stored in separate Studies), this is not the case for prognostic tests. Sequential tests on the same sample are therefore considered as multiple runs within one experiment, which are all stored in one Study.

Based on these considerations, the specification of the test matrix for prognostic tests is defined as follows.

4. **Definition of the test matrix**: description of all experiments that are executed. For a prognostic test, each entry in this test matrix contains info on the following aspects:
    i. *fault/degradation*: description of the fault or degradation type and its location. Although the evolution of the fault severity over time (registered in a separate time series file) is actually an output, it should be connected to this definition of the intended degradation;
    ii. *sensors*: the sensors that are used during this specific test, selected from the list defined in 3.;
    iii. *runs*: specification of all the individual runs that are performed with the same sample, to ensure that these are considered as part of one experiment;
    iv. *operating conditions*: the values of all independent time-varying variables for each run of this specific test (registered in a separate time series file per variable and per run);
    v. *link to data*: specification of the file(s) that contain the measurement data (raw and/or processed) for each run and each of the sensors used.

Again, when this information is completely provided, the prognostic test program is fully documented, and can be unambiguously stored in the ISA-PHM data model. This is largely the same as for the diagnostic test, except for the four aspects discussed before. One notable difference is the documentation of multiple runs in one Study: these will be stored as consecutive rows in the Study file (see Figure 5b). The same holds for the Assay files: the various runs in one Study will also appear for a specific sensor in multiple rows in the associated Assay. Details on the ISA-PHM interpretation for prognostic tests are provided in Table 3 in Appendix A.

For documenting the time evolution of fault severity and operating conditions, ISA-PHM uses separate files (see 3.2.4), each containing the time stamps and the associated values of the considered parameter. While each file contains its own series of time stamps, it is required to link all these time stamps to one single reference time stamp (of the complete process). This will ensure that all parameters are synchronized, even when they are registered at different sample rates, which is required for algorithm development. Ensuring that all time stamps relate to the same reference (i.e. starting point $t_0$) and have the same unit (typically seconds) is therefore of utmost importance. This time reference information is stored in a Protocol Parameter Value in the Assays for each measurement / sensor. For the Study Factors (e.g. operating conditions, degradation) it is stored in an additional set of Study Factors: when a Study Factor (e.g. machine *RPM*) refers to a file, it is obligatory to add another Study Factor *RPM_time_reference* that stores the time reference information.

### 3.2.3. Interoperability of the Data

Although separate templates have been introduced for diagnostic and prognostic tests, the descriptions in the previous two subsections reveal that the differences are not fundamental. In fact, a prognostic test can be considered as a series of diagnostic tests (at increasing fault levels), where the faults are not directly controlled, but develop in a natural way. This implies that the data in one Study (experiment) in a prognostic test can be transformed into a series of Studies of a diagnostic test. The Study Factor Value for the fault severity in each of these Studies is obtained by selecting one of the values from the time series of fault severity from the prognostic test (with any chosen interval), provided that the degradation is explicitly measured, or the RUL has been determined afterwards. As in this way the timing and sequence information is lost, the diagnostic tests cannot be combined into a prognostic test again.

### 3.2.4. Measurement Data Storage Convention

Time series data collected in PHM tests can be stored using a range of file formats and storage technologies, depending on data volume, structure, and access requirements. Simple text-based formats, e.g. csv, are suitable for small, tabular datasets, while columnar and binary formats, e.g. Parquet, or HDF5, support efficient storage and high-performance access for large-scale experiments. Data may be stored on local file systems, networks, or object stores, and optionally backed by databases for indexing and retrieval. Although application of the ISA-PHM standard does not depend on (measurement) data format, a pragmatic choice has been made in this work to allow clear explanation in this paper, and generic applicability of the tooling developed. Therefore, the following convention is adopted:

- data is stored in text-based (comma separated value – csv) format;
- the output for each sensor (channel) or measurement is stored in a separate file (i.e. only one column with sensor data);
- a time stamp is provided in the 1st column of each measurement data file to ensure synchronization of different sensors, operating conditions, and defect evolution;

The isolated representation of individual sensor outputs for each experiment is essential for connecting it unambiguously to the meta-data of that specific measurement. The proposed single column (unique file) data format is one way of achieving that in a straightforward manner. However, if any other way of identifying these specific subsets in a larger data file is available, i.e. using specific pointers, GUIDs or DOIs, those can be used to link the meta-data to the measurement data, and creation of the separate files is not needed.

Note that the type of quantity measured and the selected measurement unit is free, and not prescribed by ISA-PHM. This choice is completely up to the person that is executing the test. The essence of ISA-PHM is that this choice is unambiguously documented, making it known to another person using the data, and allowing any required data processing step. Note further that 'time' is a generic term here, it can also represent any other relevant usage parameter like number of flights / cycles / starts, kilometers, etc., as long as this parameter is consistently used for all measurements.

When the proposed convention is adopted, but received data is stored in a different format, e.g. multiple columns in one data file, some preprocessing should be done to transform it to the prescribed format, before generating the meta-data in a format that satisfies the ISA-PHM data model.

Finally, the present paper focuses on the collection of time series of measurement data that can be expressed as (single) numerical values. However, the ISA-PHM standard is not restricted to that type of data. When experiments and measurements yield more complex output, for example images, video data, point clouds from LIDAR or GPS data, the files in which this data is stored can still be connected in a unique way to the metadata stored in ISA-PHM. This ensures unambiguous labeling, which is beneficial for further processing. In those cases the convention of storing the data in single column files does not hold, as a single measurement (e.g. an image or a GPS position) requires all information (e.g. a bitmap or a long/lat/alt representation) to be integrally stored.

### 3.2.5. ISA-PHM Output

When all required meta-data of a PHM test has been specified and connected to the right entities in the ISA-PHM standard as described in the previous subsections, the output of the process can be exchanged in two different serializations, as defined in the original ISA (ISA-specs, 2016):

- **ISA-Tab**: text-based output files in tab separated value (tsv) format. One Investigation file provides an overview of the set-up and test program (linking Studies (experiments) to Assays (measurements)). Additional (multiple) Study (see example in Figure 5) and Assay files provide the details of individual experiments and sensors. This output format can easily be viewed and edited in MS Excel, where separate *S* and *A* files can be stored in different work sheets, thus containing most information in one (Excel) file;

- **ISA-JSON**: text-based data representation using the JSON (JavaScript Object Notation) data format. All information (on *I*, *S* and *A*) is provided in one file (see example in Figure 6), that can easily be accessed via various programming languages;

| Source Name | Protocol REF | Sample Name | Characteristics [Motor bearing] | ..... | Factor Value [Fault Type] | Factor Value [Fault Position] | Factor Value [Fault Severity] | Factor Value [Motor Speed] | Unit.3 |
|---|---|---|---|---|---|---|---|---|---|
| Techport | Experiment preparation | Test set-up-0 | 6309.C4 | | BPFO | Center | 1 | 1480 | RPM |

*a)*

| Sample Name | Characteristics [Cutting insert] | Characteristics [Workpiece length] | Unit | ..... | Factor Value[Time] | Factor Value[Cutting speed] | Factor Value[VB] |
|---|---|---|---|---|---|---|---|
| Spec-0 | KC710 | 483 | mm | | D:\time\Run_01.csv | D:\CS\Run_01.csv | D:\VB\Run_01.csv |
| Spec-14 | KC710 | 483 | mm | | D:\time\Run_15.csv | D:\CS\Run_15.csv | D:\VB\Run_15.csv |
| Spec-13 | KC710 | 483 | mm | | D:\time\Run_14.csv | D:\CS\Run_14.csv | D:\VB\Run_14.csv |
| Spec-12 | KC710 | 483 | mm | | D:\time\Run_13.csv | D:\CS\Run_13.csv | D:\VB\Run_13.csv |
| Spec-11 | KC710 | 483 | mm | | D:\time\Run_12.csv | D:\CS\Run_12.csv | D:\VB\Run_12.csv |

*b)*

Figure 5. Examples (partly) of Study in ISA-Tab format: a) diagnostic test; b) prognostic test with multiple runs.


```
"studies": [
    {
        "filename": "s01.txt",
        "identifier": "",
        "title": "BPFO Fault Severity 1 100%",
        "description": "BPFO Fault Severity 1 at 100%",
        "submissionDate": "2023-10-26 00:00:00",
        "publicReleaseDate": "2023-12-17 00:00:00",
        "publications": [],
        "people": [],
        "comments": [],
        "studyDesignDescriptors": [],
        "protocols": [
            {
                "@id": "#protocol/23449578-6944-425f-8d50-f77d182883e3",
                "name": "Experiment preparation",
                "description": "",
```


Figure 6. Example of (part of) ISA-JSON file.

In principle, the ISA-Tab files can be created manually, but that requires thorough knowledge of the underlying ISA standard, and is a tedious job. Therefore, software tools have been developed by the ISA community to support this process. However, the generic ISA tools use the generic naming of the entities, which make it challenging for experts from the PHM field to use them. Therefore, specifically for ISA-PHM, new tools have been developed, like a new easy-to-use wizard to support the translation of PHM test results into the ISA-PHM data model, as will be discussed in section 5. The next section will first demonstrate the process of storing several existing (public) datasets in ISA-PHM format.

## 4. APPLICATION OF ISA-PHM TO EXISTING DATASETS

This section will demonstrate how three well-known datasets, two experimental and one simulated, as well as a real failure from a fielded system, can be documented in ISA-PHM format. Also a discussion on the benefits will be presented.

### 4.1. Diagnostic Test

The centrifugal pump test dataset (NLN-EMP) published by Bruinsma et al. (2024) is used as a first example to demonstrate the ISA-PHM data model. This is a diagnostic test, where well-defined faults are introduced in the set-up (e.g. in bearings or impeller), see Figure 7, and the response

Figure 7. Test-setup used to generate the NLN-EMP dataset.

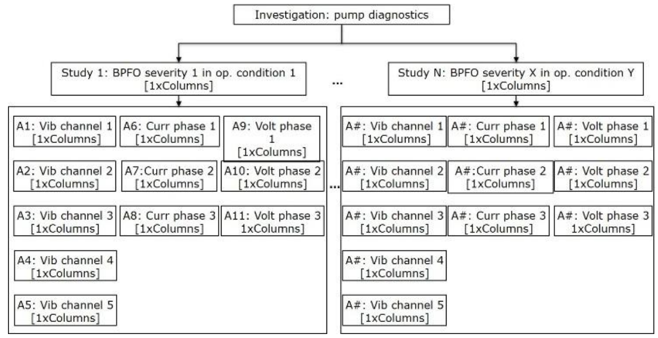



Figure 8. Representation of (part of) the NLN-EMP dataset in ISA-PHM structure.

of that fault is measured with vibration monitoring and motor current signature analysis (MCSA). This yields multiple files with (raw and processed) measurement data for several sensors (location, orientation), fault types and operating conditions (rpm, flow). In this case, the data structure and definitions of faults and operating conditions are described in the accompanying publication. However, to prepare the data, for example, for training and testing a classification algorithm for bearing faults, the meta data for each individual test must be described (e.g. fault type, severity, motor rpm). To enhance that process, the meta data of the full NLN-EMP test program has been transformed to the ISA-PHM data model:

- One Investigation is created, containing an overview of the test program details (location, set-up, studies and assays). When available in an accessible format in the future (see section 5.2.3), this allows to quickly select tests at the required conditions (e.g. bearing faults at specific rpm);
- A Study is created for each entry in the test matrix. With 20 different faults and four different motor speeds, around 80 experiments have been executed, for which the measurement time series have been split in five subsets of 12 s duration each. This yields a total of 400 Studies describing individual tests. In each Study, the fault details and operating condition are unambiguously defined through Study Factor Values. Also the Measurement and Processing Protocols are defined in each Study, specifying the details of the measurements and data processing methods applied in the various Assays;
- An Assay is created for each individual measurement in a Study. For example, a vibration measurement in radial direction at location 4 is one Assay belonging to Study 1, but a similar Assay has been created for Study 2 with a different fault severity. With 5 vibration channels and 6 MCSA channels, each Study contains 11 Assays. For the complete test program, this adds up to 4400 Assays. Each Assay contains the measurement and signal processing details (as Parameter Values for the Protocol Parameters), and refers to one unique raw data file and one unique processed data file;

In this way, the documentation of the NLN-EMP dataset described in Bruinsma et al. (2024) is fully translated to the ISA-PHM format. A schematic representation of a small part of the meta-data (2 Studies) is shown in Figure 8. As the Assays require a link to a two-column data file, as was discussed in 3.2.4, the multi-column storage of vibration and MCSA data adopted in the NLN-EMP dataset needed to be adapted. All individual measurements have therefore been extracted from the original files, and stored in separate two-column files. The complete ISA-PHM representation of meta-data for this dataset is provided as supplementary information for this paper.

### 4.2. Prognostic Test

The process for a prognostic test will be demonstrated with the NASA milling dataset (Agogino & Goebel, 2007). In this experimental test program, the wear of a milling tool insert (see Figure 9) is monitored under a range of operating conditions. The dataset contains 16 different cases, varying in depth of cut, feed, and machined material, each consisting of multiple runs (using the same tool insert). The tool wear ($VB$) cannot be measured continuously, so values are only available after completion of (some of) the runs. In addition, spindle motor current, vibration and acoustic emission measurements are performed during the runs.

The ISA-PHM representation of this test program is as follows:

- One Investigation is created, containing an overview of the milling test program details (location, machine type, studies and assays). When available in an accessible format in the future (see section 5.2.3), this allows to quickly select tests at the required conditions (e.g. all runs for case 04, or all 1$^{st}$ runs in each case);
- A Study is created for each entry in the test matrix. In this case, only one degradation mechanism, i.e. tool wear, is considered. Although this is a prognostic test, in

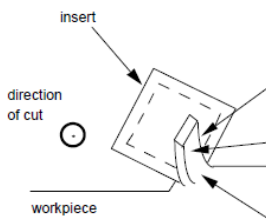



Figure 9. Tool insert removing material on the work piece (Agogino & Goebel, 2007).

which the fault severity (VB) evolves over time, the degradation is only measured at the end of each machine run (as it requires removing the tool from the machine). Therefore, it is registered as a fixed value for each run in a Study in the Study Factor 'fault severity'. Further, 16 different operating conditions (cases) are tested, so in total 16 experiments have to be documented in 16 Studies. However, each experiment contains multiple runs with the same tool insert, so each Study contains up to 23 rows specifying the individual runs. In each of these rows, the fault details (i.e. wear status) and (constant) operating condition (depth of cut, feed, machined material) are unambiguously defined through Study Factor Values by entering the values;

- An Assay is created for each individual measurement in a Study. In this case, six measurements (2 x spindle motor current, 2 x vibration and 2 x acoustic emission) are performed in all cases, so for the 16 Studies this yields 96 Assays. Moreover, in each Assay, all the runs are represented, so up to 23 rows are created. Each Assay contains the measurement and signal processing details (i.e. amplification, LP/HP filter, rms), defined through Protocol Parameter Values, and refers to one unique processed data file. For this experiment, no raw data files are included;

In this way, the documentation of the milling dataset is fully translated to the ISA-PHM data model. Also in this case the data was not directly available in the required single file format (section 3.2.4). The 1x167 Matlab struct array must therefore be transformed into a set of separate files to allow proper linking within the ISA-PHM format. However, this has to be done once, and after that the data is available in exactly the same format as other datasets, which significantly simplifies processing the data during model development.

### 4.3. Prognostic Simulation

While the previous two datasets were generated with an experimental set-up, the ISA-PHM format can also be used for simulated datasets, as will be shown for the NASA CMAPSS dataset (Saxena et al., 2008), generated by a simulation code of an aircraft engine (Figure 10). In this numerical experiment, four datasets (FD001 – FD004) have

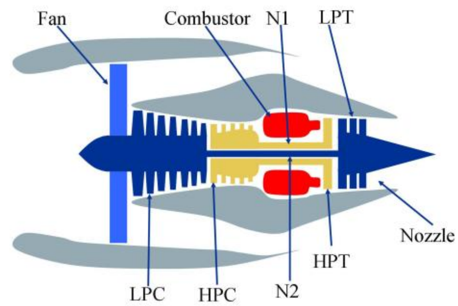



Figure 10. Schematic representation of the simulated engine used for the CMAPSS dataset (Saxena et al., 2008).

been created for a fleet of up to 260 aircraft engines. Each engine has a slightly different starting state (due to manufacturing variations), and develops a fault at some point during operation. The fault then grows in magnitude until system failure. Operating conditions during each cycle (flight) are constant, and are defined as a combination of three parameters: flight altitude, Mach number and throttle position (TRA). During a complete run-to-failure trajectory, operating conditions may be constant (data sets FD001, FD003), or switch per cycle between six predefined operating conditions (FD002, FD004).

Moreover, two types of degradation have been used in the simulations, both effecting the performance of the engine: High-Pressure Compressor (HPC) Degradation and Fan Degradation. The severity of the degradation changes over time, which is achieved by changing flow and efficiency modifiers for the considered component (HPC or fan) with an exponential function in the simulation. Note that the details of the simulated degradation, i.e. the parameters in the exponential function, are not included in the dataset, nor specified in the accompanying description. This means that no direct condition measurement is available, and the system health may only be derived from indirect measurements (e.g. temperature, flow). However, since complete run-to-failure trajectories have been simulated, the ground truth of remaining useful life at any moment in time is available (after completion of the simulation). Therefore, for each engine the RUL value is available in the datasets.

Finally, the dataset contains for each engine trajectory the time series of 21 sensor outputs, like in- and outlet temperatures and pressures of various engine components, rotational speeds, fuel flow and cooling air flow.

The ISA-PHM representation of CMAPSS training dataset FD004 is as follows:

- One Investigation is created, containing an overview of the CMAPSS (simulated) test program details (simulation model, engine configuration, studies and assays). When available in an accessible format in the future (see section 5.2.3), this allows to quickly select simulations at the required conditions (e.g. all trajectories with HPC degradation, or all trajectories at Sea Level operating conditions);

- A Study is created for each entry in the test matrix. In dataset FD004 (training) two simultaneously occurring degradation mechanisms, i.e. HPC and fan degradation, are considered (which are specified in the Study Factor 'fault type'). As in any prognostic test, the fault severity (degradation) evolves over time, and should therefore be registered as an output file, to be linked in the Study to the Study Factor 'fault severity'. However, details on the degradation level are not made available for this experiment. Instead, for each trajectory the time to failure (i.e. 'useful life', but labeled as RUL) is provided. However, this allows to calculate the evolution of the RUL (see section 3.2.2), which will be considered here as a measure of the degradation severity. Further, random sequences of six different operating conditions (combinations of altitude, Mach and TRA) are tested, and the simulation is repeated for 248 (slightly different) engines. So in total 248 experiments have to be documented in 248 Studies. In each of these Studies, the degradation details (indirectly expressed by the RUL) and (time-varying) operating conditions are unambiguously defined through Study Factor Values, all by referring to a file describing the time series of RUL, altitude, Mach and TRA;
- An Assay is created for each individual measurement in a Study. In this case, 21 measurements are performed in all cases, so for the 248 Studies this yields 5208 Assays. Each Assay contains the measurement details (i.e. sample rate, accuracy) defined through Protocol Parameter Values, and the values of a simulation output (virtual sensor) by referring to one unique data file. In this case, no signal processing is performed, so no processed data files are included;

In this way, the documentation of the CMAPSS dataset is fully translated to the ISA-PHM data model. The raw data was provided in multi-column text files per dataset (FD001-FD004), each containing 100 – 260 engine simulations. This can easily be transformed to the ISA-PHM required format of single file per engine and per sensor.

More recently an updated version, the N-CMAPSS dataset (Arias Chao, Kulkarni, Goebel, & Fink, 2021) has been created. In this new dataset, real operating conditions (as measured in a commercial jet) are used in the simulations, which make them more realistic. For the ISA-PHM representation this makes no difference, as the operating conditions (altitude, Mach and TRA) were anyhow specified by a time-series (in a separate file), which now only will show much more variation (and has one additional operating condition, i.e. fan inlet temperature).

But more importantly, the N-CMAPSS dataset contains ten *model health parameters*, that specify how the degradation of the engine components is introduced in the simulation. This important piece of information was missing in the original CMAPSS dataset, where only the RUL was available as indirect condition parameter. In the ISA-PHM representation, the values of these model health parameters would be stored in the Study Factor 'fault severity', while the considered fault is stored in the Study Factor 'fault type'.

### 4.4. Failure in Fielded Systems

The previous three examples in this section have demonstrated how ISA-PHM is applied for documenting (physical or numerical) experiments, intended to generate failure data. However, ISA-PHM can also be used to document failures that occur in real systems in practice, and to link it to the associated (sensor) data. As was mentioned in the introduction, this context information (labeling) is often lacking in practical cases, so proper registration would facilitate the use of the data for training, testing and validating models and algorithms.

The example used here is a crank shaft bearing in a diesel engine on board of a vessel, see Figure 11. After a combination of prolonged operation and imperfect maintenance (e.g. lubricant contamination), friction in the journal bearing may increase, which leads to wear of the bearing parts and an increase in bearing (and lubricant) temperature. Ultimately, this process may lead to seizure of the bearing and associated failure of the complete engine.

The engine control system typically monitors the lubricant temperature close to each of the seven bearings ($T$ symbols in Figure 11). This implies that a sudden increase in one of those temperatures might give an indication of an upcoming bearing seizure (although also other circumstances may lead to such a temperature increase). In addition, the engine control system also contains around 15 other sensors that characterize the engine operational condition, like fuel flow, rpm, turbocharger rpm and pressure, inlet and cooling air temperature and pressure, etc. In the considered case, all these parameters are monitored and stored with a sample frequency of 0.2 – 1 Hz.

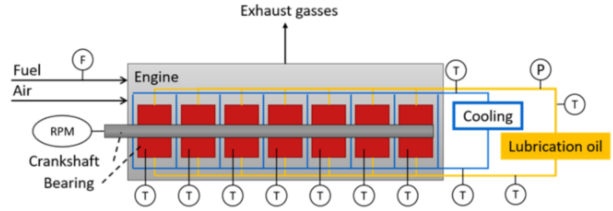



Figure 11. Schematic representation of the crank shaft bearings in a 12-cylinder marine diesel engine.

Despite the potential warning from the increasing oil temperature, in practice not all bearing seizures can be prevented. These real failures would be very interesting for diagnostic or prognostic model development, but this requires proper documentation (what fault exactly happened?) and saving of the preceding operating history and sensor readings of the engine. This is what ISA-PHM can be used for. So in this case, after a careful root cause analysis that ensured that the crank shaft bearing seizure was the actual failure mode, the following ISA-PHM representation was constructed:

- One Investigation is created, containing a general description of the observed failure and associated system (engine type and configuration, failure mode description: bearing seizure), as well as the associated studies and assays. When available in an accessible format in the future (see section 5.2.3), this allows to quickly select similar failures from a database when creating diagnostic and prognostic models;
- One Study is created for this observed failure. While real failures only occur occasionally (distributed over time), and operating conditions cannot be varied (but just are as they occurred in practice) an ISA-PHM entry of this type typically contains only one Study. The observed failure is specified in the Study Factor 'fault type'. Then it has to be decided whether the fault is to be registered as a diagnostic or prognostic entry. This depends on the purpose of documenting the fault and on the estimated quality of the associated (sensor) data. In case of doubt, it should be registered as a prognostic 'test', as that requires the most extensive documentation (and can also be used for diagnostic purposes). The (evolution of the) fault severity (i.e. magnitude of bearing wear) has in this case not been measured directly. However, as the moment of failure is known, the evolution of the (calculated) RUL is registered here as a measure of the degradation severity (as was done in the CMAPSS case in 4.3). The RUL values, stored in a separate file, are referenced in the Study Factor 'fault severity'. Finally, the parameters defining the operating conditions of the engine have to be selected from the 15 monitored parameters (like rpm, fuel flow, turbocharger rpm and pressure, etc.). In this case of a marine diesel engine, the independent parameters are the engine speed (rpm) and engine power (kW). All other parameters are a response (dependent variables) to the settings of these two parameters. The time series of these two independent parameters are stored in separate files, and referenced in the associated Study Factor Values;
- An Assay is created for each individual measurement in the Study. In this case, nine 'condition measurements' and 15 engine performance measurements are recorded. This implies that the single Study yields 18 Assays. The condition measurements are all indirect measurements: the lubricant temperature monitoring data (for both the failed bearing and the six other bearings) and the results of two dedicated condition monitoring techniques, i.e. oil monitoring and vibration monitoring. The oil and vibration monitoring results are only obtained periodically (typically every 4 months, or 100-500 operating hours), resulting in a time series with a much lower sampling rate than the temperature (every 5 seconds). Each Assay now contains the values of a single measured (sensor) output, and refers to one unique data file. In this case, no signal processing is performed, so no processed data files are included;

In this way, the documentation of the observed bearing seizure is fully translated to the ISA-PHM format.

### 4.5. Benefits of Using ISA-PHM

Putting all this effort in transforming experiment results and descriptions into ISA-PHM format only makes sense when it yields clear benefits. For a single test or dataset, the effort of structuring the meta-data and especially creating many Assays (up to 2100, see CMAPSS example) is typically not worth the effort. The real benefits appear when multiple tests or datasets have to be used (multiple times) in model development processes.

In those cases, interpreting the different experiments and transforming the case-specific data formats to a usable form takes a large effort. This is also a challenging task for many data scientists (developing the PHM algorithms), as they typically lack the engineering and system knowledge associated to the executed experiments. At the same time, test executers are not (always) familiar with the requirements that data scientists set to the data they are using. The proposed ISA-PHM data model closes this gap, by prescribing to test executers what needs to be documented, and offering this info in an accessible format to the data scientists. Therefore, the ISA-PHM format has advantages for three types of users: database builders, PHM model developers, and test executers, as will be discussed next.

First, it should be noted that ISA-PHM only prescribes the structure and format of the (meta)data, and not its representation. However, the latter largely determines the mentioned accessibility of the data: processing thousands of separate files is not very convenient, but accessing a database containing all that data would be much more practical. Therefore, in section 5 the creation of a database with many different (PHM related) datasets will be discussed. It will be shown that having the data and metadata available in a common format, in this case the ISA-PHM format, considerably simplifies the building and filling of such a generic database.

Second, for PHM model developers, having the data available in ISA-PHM format offers the following advantages:

- they do not need to understand the test details, but just get meta-data like fault types, operating conditions (independent variables) and (sensor) responses delivered in a known format;
- they do not need to understand the structure in which the measurement data is stored, but just get the appropriate subsets (of sensor data) delivered upon request;
- data signatures or trajectories from different experiments or simulations (with possibly similar fault types) can easily be combined;

Third, for parties executing the experiments or simulations, the ISA-PHM format offers the following advantages:

- the ISA-PHM template exactly prescribes them what information should be collected and documented to make their experiments useable for PHM algorithm development. As an example, the missing condition info in the CMAPSS dataset (see section 4.3) would be detected when completing the template;
- by delivering test or simulation results in ISA-PHM format, the usability of their data is increased, which will enhance the visibility and impact;

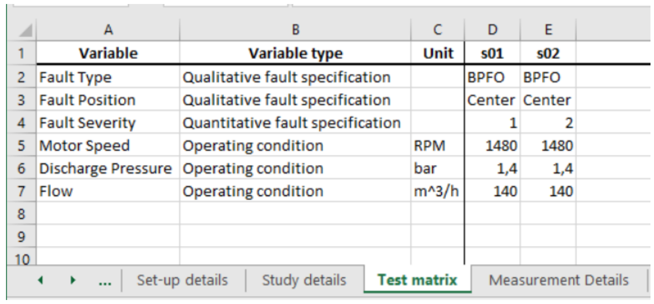
With the four examples discussed in this section, and the benefits illustrated in the final subsection, the value of ISA-PHM has been demonstrated. In the next section, the implementation of this standard in some practical software tools will be discussed.

## 5. IMPLEMENTATION

### 5.1. User Interface

Directly entering all the entities for a specific test into an ISA-Tab or ISA-JSON file would be tedious and error-prone. Therefore, an Excel template (see Figure 12) and a user-friendly input wizard (Figure 13) have been created to facilitate this process. In the Excel template, 10 separate worksheets are used to collect the required inputs. For example, in the worksheet 'Set-up details' all specifications of the used set-up (e.g. location, type of machine, sensors and control system details, etc.) have to be provided. Figure 12 shows the worksheet 'Test matrix', that collects the details of all individual experiments executed in the considered test program (or simulation). Each combination of fault (type, location, severity) and operating conditions yields a unique experiment (later to be stored as Study in ISA-PHM), and is defined as a separate column in the template.

As the template guides a user to complete all fields in the 10 worksheets, a complete documentation (i.e. aspects 1 to 4 as defined in 3.2.1 and 3.2.2) of the considered test program is ensured. After the completion of the template, a Python script is used to translate all entries in the template to the proper entity in the ISA-PHM format, yielding both an ISA-Tab and



| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | Variable | Variable type | Unit | s01 | s02 |
| 2 | Fault Type | Qualitative fault specification | | BPFO | BPFO |
| 3 | Fault Position | Qualitative fault specification | | Center | Center |
| 4 | Fault Severity | Quantitative fault specification | | 1 | 2 |
| 5 | Motor Speed | Operating condition | RPM | 1480 | 1480 |
| 6 | Discharge Pressure | Operating condition | bar | 1,4 | 1,4 |
| 7 | Flow | Operating condition | m^3/h | 140 | 140 |
| 8 | | | | | |
| 9 | | | | | |
| 10 | | | | | |

... Set-up details | Study details | Test matrix | Measurement Details

Figure 12. Screen dump of the ISA-PHM Excel template.

ISA-JSON output file. To further enhance the user-friendliness of creating the ISA-PHM output files, also an input wizard has been developed (Figure 13). While in the Excel template all the entries are text-based, the wizard simplifies several of the input processes. For example, it allows to select filenames from a file-explorer, which eases the process and prevents typing errors in file names. Also the wizard has multiple screens that have to completed consecutively, and after completing the final screen, the ISA-PHM output files are created.

By having a user completing the input template or wizard, all required info is obtained in a logical manner. Also, checks can be included for the presence of obligatory inputs. The underlying software then processes this input data and stores it at the right location in the ISA structure. In that way, the person entering the test data does not have to bother about the details of the ISA-PHM standard, while the person using the data for modeling purposes always receives the right data and meta-data. A demo version of the wizard is available in the supplementary material for this paper.

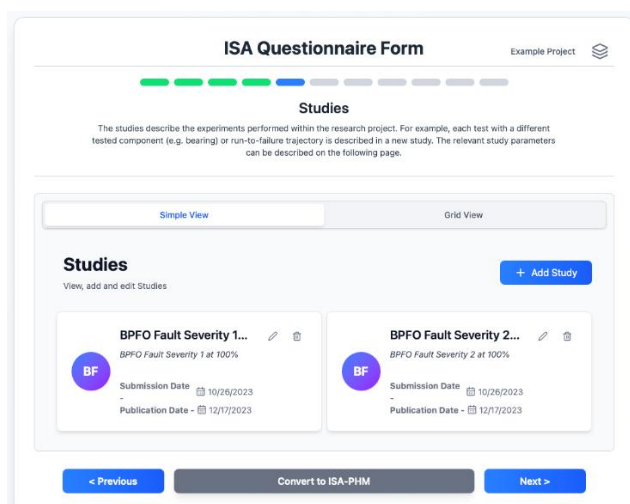



Figure 13. Screen dump of the ISA-PHM input wizard.

### 5.2. Future Extensions

With the definition of the ISA-PHM standard (section 3), and the creation of the input tools (previous subsection), the basic ingredients for ISA-PHM are now ready. However, to harvest its full potential, some additional developments are planned for the near future, including a generic database, software code to access the data and a joint testing program to extend the amount of relevant data.

#### 5.2.1. Using External Ontologies

ISA offers the use of references to external ontologies for common entities, e.g. a well-documented sampling procedure or a name of a biological substance. This is possible for the PHM community as well. For example, using standardized descriptions of equipment classifications (e.g. ISO14224, 2016) or failure modes and mechanisms will considerably increase the sharing and exchange potential of data sets from different sources. Moreover, making use of such ontologies reduces the need for descriptions in text.

#### 5.2.2. Database

As was mentioned before, working with a large number of separate files containing the measurement data is not convenient. Therefore, a database will be created that contains all the data, but also contains the associated metadata. In that way, subsets of the data can easily be accessed or retrieved for algorithm development.

The design of the database must be such that every individual measurement data point (and its time stamp) is properly linked to its metadata. This is ensured by the ISA-PHM format: each measurement value is stored in a data file, fully specified by a 'datafile_id' and a filename. Moreover, each data file is uniquely associated to an Investigation (with its id, name and url) through its Studies and Assays. Therefore, the relations shown in Figure 14 provide the required links in the database.

Once a database with these relations has been built, and datasets have been added, it can be queried to retrieve certain subsets of the data. For example, when the time series data of a specific sensor for a specific fault at given operating condition is needed for algorithm training or testing, the Investigation defines which Assay and associated data file contains that data. All data points with that specific datafile_id will then be retrieved from the database. These data points can be either raw measurement data or processed data points. Software tools to select the specific subsets in the data, obtain the data file ids from the ISA-JSON, and make the data available in appropriate data frames for further processing will be discussed in the next subsection.

#### 5.2.3. Software Tools

To further enhance the usability of the ISA-PHM format and (to be developed) database, several software tools are now

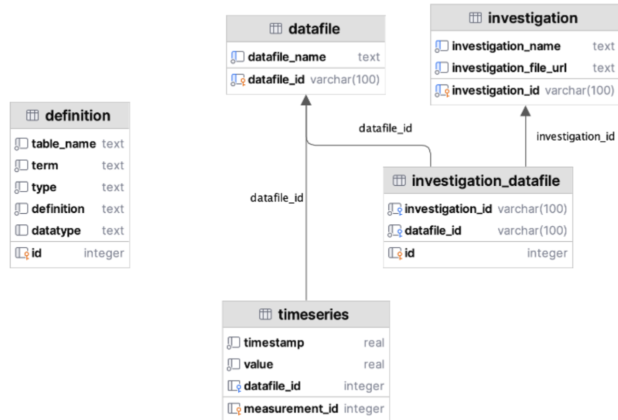



Figure 14. Entity relation diagram to link measurement data to associated metadata.

under development:

- **Dataset explorer**: it will be possible to view the content of (datasets in) the ISA-PHM database. With this tool the defined metadata is used to provide a generic summary of the datasets. This allows to quickly check which faults, operating conditions and sensors are available in all datasets. The standardized documentation allows easy comparison of datasets from different sources;
- **Subset selection**: it will be possible to select subsets of the data for retrieval. This solves one of the problems with current datasets, where often the complete dataset (of typically several GBs) needs to be downloaded before specific subsets can be accessed. Using the overview created by the previous tool, subsets of the data for specific combinations of faults, operating conditions and sensors can be selected;
- **Wrappers**: tools will be developed that facilitate accessing the database for submitting or retrieving specific subsets of the data. For example, when the previous tool is used to select a specific subset of the data, a wrapper needs to read the associated ISA-JSON, find out which Study and Assay(s) are concerned, and which measurement data points (through datafile_id) should be retrieved. Also, tooling wil be developed to deliver the data retrieved from the database in various formats to data scientists (e.g. specific data frames in Python). Finally, also wrappers will be developed to submit new datasets to the database (again using the ISA-JSON file);

When all these tools are available, a data scientists can very easily select and retrieve specific test results from the database, in a convenient format, and without downloading large datasets completely. This will considerably enhance PHM algorithm development.

#### 5.2.4. Distributed Testing and Data Sharing

The final step in getting access to useful and properly labeled data is the actual generation and sharing of the data. The preparation and execution of a test program, especially if it concerns physical experiments, is time consuming and expensive. For that reason, the number of publicly available well-documented diagnostic and prognostic experiments is rather limited. However, by 'ISA-fying' these tests, i.e. transforming the (meta)data to the ISA-PHM format, it will be much easier for data scientists to use this data.

In addition, the authors aim to generate new data through the concept of distributed testing. This implies that a group of seven (research) organizations with experimental test set-ups will join forces in executing tests and sharing the generated data. Currently bearing, e-motor and pump, battery, valves, and cooling system set-ups are available, in which a range of faults can be introduced for the generation of diagnostic test data. It is also planned to perform (long-term) degradation tests that can be used for prognostic model development.

The generated data will be shared amongst the participating organizations through the ISA-PHM database. In addition, mechanisms will be developed to also share the data with other interested parties, and enable others to submit their data (in verified ISA-PHM format) to the database.

## 6. CONCLUSION

In this work the ISA-PHM standard has been proposed for unambiguously documenting diagnostic and prognostic tests. By structuring and standardizing the metadata needed for using the measurement data for diagnostic and prognostic algorithm development, and storing this in the entities from the ISA ontology, a unambiguous representation of a test is obtained. Application of the proposed standard to four different datasets has demonstrated:

- that the use of ISA-PHM leads to a consistent and transparent storage and interpretation of (test) data;
- that ISA-PHM can be used for documenting the three envisioned use cases, i.e. laboratory testing, numerical simulations and real failure data from fielded systems;
- that the use of ISA-PHM enforces test executers to completely document their tests, leading to more useful test data;

With the (to be) developed database and software tools, this allows data scientists to easily and quickly use subsets from the data for training and testing algorithms.

## SUPPLEMENTARY MATERIAL

More information on the ISA-PHM standard, as well as worked examples for the treated datasets, and the input wizard can be found on the website ISA-PHM.com. More info on distributed testing can be found on NL-prognostics.nl

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## APPENDIX A

The interpretation of the original ISA entities are defined in Table 1. Their equivalents in ISA-PHM (as far as different from ISA), are defined in Table 2 for diagnostic tests, and in Table 3 for prognostic tests.

| ISA entity | original ISA interpretation |
|---|---|
| **Investigation** | Complete test program description, e.g. aim, persons, publications |
| Source | Source of (biological) material that is investigated |
| Sample | Specific sample that is taken from the source to be given a specific treatment. Typically many samples are taken from one source |
| Characteristics | Details of the *Sample*, like size, extraction method |
| **Study** | Single experiment, defined as combination of *Sample* and applied treatment, defined by *Study Factors* |
| Protocol(s) | Experiment preparation;<br>Measurement, Processing; |
| Parameter(s) | Required details of *Protocols*. Values are provided in Assay |
| Study Factor(s) | Independent variables (*X*) |
| Factor Value | Values of *Study Factors* (different for each *Study*) |
| **Assay** | Output of one single measurement (dependent variable *Y*) for one specific *Study* |
| Parameter Value | Values of the *Parameters* (different for each measurement) in the Protocol(s) |
| Data file | Link to file containing the raw or processed data |

Table 1. Interpretation of original ISA entities.

| ISA entity | ISA-PHM interpretation |
|---|---|
| **Investigation** | Complete test program description, e.g. aim, persons, publications |
| Source | Generic test set-up or machine name, location, and lab name |
| Sample | Specific configuration of the generic test set-up or machine (e.g. with specific components) |
| Characteristics | Details of the configured set-up (*Sample*), like type, brand, control system, to be tested component(s) |
| **Study** | Single experiment, defined as combination of configured test set-up (*Sample*), introduced fault and operating conditions (*Study Factors*) |
| Protocol(s) | Experiment preparation (*description or link to document describing the details of fault introduction*);<br>Measurement, Processing (*describing additional details, stored in Parameters or in separate file*) |
| Parameter(s) | Required details of measurements / sensors (e.g. location, orientation, sample rate) or processing (e.g. filter type, scaling). Values are provided in Assay |
| Study Factor(s) | Independent variables: fault type + severity + location & operating condi-tion(s) |
| Factor Value | Values of Study Factors tested in the experiment (different for each *Study*) |
| **Assay** | Output of one single sensor / measurement for one specific experiment (*Study*) |
| Parameter Value | Values of the Parameters (different for each sensor) in the Measurement and Processing Protocol(s) |
| Data file | Link to file containing the raw / processed data |

Table 2. Interpretation of (deviating) ISA entities in ISA-PHM for diagnostic tests.

| ISA entity | ISA-PHM interpretation |
|---|---|
| **Investigation** | Complete test program description, e.g. aim, persons, publications |
| Source | Generic test set-up or machine name, location or lab name |
| Sample | Specific configuration of the generic test set-up or machine (e.g. with specific components) |
| Characteristics | Details of the configured set-up (*Sample*), like type, brand, control system, to be tested component(s) |
| **Study** | Single experiment, possibly consisting of multiple *Runs*, each defined as combination of configured test set-up (*Sample*), evolution of the fault over time and time-varying operating conditions (*Study Factors*) |
| Protocol(s) | Experiment preparation (*description or link to document describing the details of fault introduction and evolution*); Measurement, Processing (*describing additional details, stored in Parameters or in separate file*) |
| Parameter(s) | Required details of measurements / sensors (e.g. location, orientation, sample rate) or processing (e.g. filter type, scaling). Values are provided in Assay |
| Study Factor(s) | Independent variables, defined per *Run*: fault type + location + time evolution of the severity & time-varying operating condition(s) |
| Factor Value | Refers to separate file containing time series of Values of Study Factors tested in the experiment (may be different for each *Run* in a *Study*) |
| **Assay** | Output of one single sensor / measurement for one specific experiment (*Study*), possibly containing multiple *Runs* |
| Parameter Value | Values of the Parameters (different for each sensor) in the Measurement and Processing Protocol(s) |
| Data file | Link to file containing the raw / processed data |

Table 3. Interpretation of ISA entities in ISA-PHM for prognostic tests.

## BIOGRAPHY

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