Fleet Knowledge for Prognostics and Health Management – Identifying Fleet Dimensions and Characteristics for the Categorization of Fleets

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Abstract

Current prognostics and health management approaches are often not able to meet expectations due to their limited ability to accurately detect abnormal machine conditions, identify failures and estimate the remaining useful life. This is in many cases attributed to the lack of real data and knowledge about the component or machine under consideration. Instead, experimental data is often used for algorithm training, which is not able to reflect the complexity of real-world systems. To improve prognostics and health management approaches condition data from fleets of machines rather than single units can be taken into consideration. Therefor machine conditions are assessed against situations encountered by machines in the same fleet and knowledge is transferred to allow algorithms to intelligently learn and improve their capabilities.

Several approaches have recently been presented in the literature, which make use of the fleet knowledge for condition-based maintenance. These approaches are designed for specific fleet compositions and characteristics. Therefore, in order to incorporate fleet knowledge into diagnostic and prognostic approaches the fleet under consideration and resulting requirements have to be analyzed. With this information, it is possible to determine whether fleet-based approaches are applicable in general to the specific case as well as facilitate the selection of a suitable fleet-based approach. Three types of fleets are distinguished in the literature, namely identical, homogeneous and heterogeneous fleets. This distinction makes reference to the structural dimension of fleets. For fleet-based approaches, however additional dimensions should be taken into account. These include among others the operating condition in the fleet (e.g. identical, different, or dynamically changing) and the type of available data (e.g. sensor reading, context data, textual description). This paper aims at identifying and analyzing different dimensions and respective characteristics of fleets to be considered in the context of prognostics and health management. The results are synthesized in a classification structure to support the categorization of fleets.

1. Introduction

Prognostics and Health Management (PHM) is a field of research which addresses the detection of incipient failures, the assessment of the current machine health as well as the prediction of the remaining useful life (Lee et al., 2014). It facilitates the planning of required maintenance activities and spare parts demand before the actual machine breakdown. PHM consists of two important elements, the detection and identification of the type of failure (diagnostics) as well as the estimation of the remaining useful life (prognostics) (Jardine, Lin, & Banjevic, 2006). Approaches for diagnostics and prognostics are either physics-based (physics models describing the behavior) or data-driven (models are build using available data) (Al-Dahidi, Di Maio, Baraldi, & Zio, 2016). Due to the increasing amount of available data and complexity of the machinery, data-driven models are gaining in importance.

Current PHM approaches mainly focus on the development of specific models for individual machines. However, data from identical or similar machines forming a fleet can be used to improve data availability and by thus the accuracy of diagnostic and prognostic approaches. When considering data from a fleet of machines, the specific characteristics of the units and the composition of the fleet has to be taken into account. For this reason, approaches designed for individual machines are often not able to handle the challenges imposed by the multitude of different components within a fleet (Krause et al., 2010; Léger & Iung, 2012). Instead, comparable units and situations are identified in the fleet in order to intelligently learn from already existing knowledge (Monnin, Abichou, Voisin, & Mozzati, 2011). An additional benefit of fleet-based PHM is the availability of data to assess new units in the fleet (Leone, Cristaldi, & Turrin, 2017).

Most of the existing fleet-based PHM approaches are designed for specific fleet compositions and characteristics. For this reason, in order to identify appropriate approaches for a fleet under consideration, the specific characteristics of the fleet have to be matched against the properties of the different techniques. To facilitate the specification of fleets, this work will present different dimensions and fleet characteristics describing fleets in the context of PHM. Those characteristics are obtained by means of a literature review. Based on these results, a fleet classification structure will be developed. The classification structure allows the comparison between the different fleets. If fleets are comparable with regard to the identified characteristics, approaches are likely to be transferable as well. By this, both the accurate description of the fleet under consideration is facilitated as well as characteristics to delimitate fleets are provided. The contribution of this paper comprises a detailed evaluation of the research field of fleet PHM as well as the an investigation of fleet dimensions and characteristics used in existing literature.

The paper is structured as follows: chapter 2 provides an introduction into fleet-based diagnostics and prognostics including an investigation of different fleet definitions as well as existing fleet classifications in the context of PHM. In chapter 3, different fleet dimensions and corresponding characteristics for the specification of fleets are presented which are relevant for fleet-based prognostics and health management. This is followed in chapter 4 by the presentation of a fleet classification structure and its exemplary application to the data set of the PHM data challenge 2008.

2. FLEET-BASED PHM

Fleet-based PHM refers to the assessment (diagnostics and prognostics) of an individual unit using data and knowledge available from a group of similar units. In this respect, it refers to the prediction method *Type IV* (Data Analytics based prediction), which allows the prediction model to learn from units in the fleet to improve the individual prediction (Saxena, Sankararaman, & Goebel, 2014). The overview of different prediction method classes is shown in Tab. 1. This type of prediction method only recently gained in importance, which can be seen by the increased number of publications dealing with fleet-based PHM in recent years.

In order to perform fleet-based diagnostics and prognostics, different steps have to be implemented which are dependent on the specific characteristics of the fleet. Fig. 1 depicts the general fleet-based PHM process. In a first step, the characteristics of the fleet are analyzed in order to identify the peculiarities and challenges, which are taken into consideration by the subsequent steps. This step is crucial for the selection of a suitable fleet-based PHM approach. Algorithms designed for specific fleet characteristics will perform poorly when used for fleets having different characteristics because relevant aspects are not considered (e.g. customized units, data availability) (Monnin, Abichou et al., 2011). In a subsequent step, data is prepared and transformed into a format suitable for diagnostics and prognostics. Depending on the fleet characteristics, it might be necessary to reduce the fleets to identical or similar sub-fleets, which present the basis for data acquisition. This is followed by the selection of a suitable approach with regard to the identified fleet characteristics. The requirements of the specific fleet, respectively the fleet characteristics, are matched against the properties of existing fleet-based approaches. With regard to the benefits and drawbacks of each approach, the most appropriate technique should be chosen and adapted to fit the problem best. In the last step, the performance of the selected approach is evaluated considering several criteria. In case the performance is not within the defined limits, previous steps are reconsidered and the approach is adjusted. This publication will target the first step (*fleet characteristics*) of the presented process by highlighting different dimensions and possible characteristics, which enables a specification of the fleet at hand in order to improve the selection of suitable fleet-based PHM approaches. In order to gain a deeper understanding of the notion fleet in the context of PHM, the following sub-

Table 1. Classification of Prediction Methods cf. (Saxena et al. 2014)

Prediction Method	Prediction Model	Applicability
Type I (Reliability analysis based prediction)	Population-based statistics data from experiments or usage history data	Predict mean life of a component. Prediction for a fleet in general, and not for an individual unit
Type II (Damage accumulation model based prediction)	Unit specific load history data + population based damage accumulation model	Predict remaining life of an individual unit based on population model
Type III (Condition based predictions – Prognostics)	Unit specific degradation model (data-driven or physics based), load history, and condition monitoring data.	Predictions customized for individual unit by learning specific individual behavior
Type IV (Data Analytics based predictions – Predictive analytics)	Rich set of data from multiple units in a variety of operating conditions + analytical data model for pattern matching	Predictions for individual unit based on rich operational history data

chapters survey existing fleet definitions and fleet classifications.

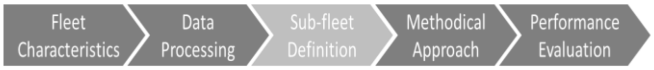

Figure 1. Fleet-Based PHM Process

2.1. Fleet Definition

The word *fleet* is a term widely used and acquainted in different areas. Nevertheless, no common and concise understanding is available in the literature. This is mainly attributed to the different contexts it is applied in. In most cases, the term fleet is associated with a specific type of fleets having unique characteristics. While fleet in fleet management mainly refers to managing the transportation fleet (e.g. vehicle/ ship) of a company, fleets can also arise in other contexts like industrial systems (Monnin, Abichou et al., 2011). Depending on the specific context, the fleet can have different characteristics and features.

Common dictionaries define the term fleet as a group "*operated under unified control*" (Merriam-Webster) or "*engaged in the same activity*" (Oxford Dictionaries). These definitions are rather vague and mainly focus on fleets of ships. With regard to Prognostics and Health Management, the term fleet is often used without a detailed description mainly presenting the fleet dimension as an additional data source (e.g (Saxena, Goebel, Simon, & Eklund, 2008), (Fan, Nowaczyk, & Rögnvaldsson, 2015)) and generally referring to the fleet as similar components (e.g. (Al-Dahidi, Di Maio, Baraldi, & Zio, 2017)). Only few publications provide a detailed specification of their understanding and the composition of the units within the fleet.

From these publications, two different predominant definitions can be deduced. On the one hand, a fleet is referred to as a *set of units* (either systems, sub-systems or equipment), which are grouped together for a *specific purpose*, a *given time* and *share some characteristics* (Monnin, Abichou et al., 2011). In this case, fleets depict the whole units (or a subset) belonging to one owner (Medina-Oliva et al. 2012). On the other hand, a fleet is regarded as a set of *homogeneous units* covering the *same functionalities* (Leone et al., 2017). The fleet's units are clustered forming different *groups of interest* (Cristaldi, Leone, Ottoboni, Subbiah, & Turrin, 2016). While the first definition provides a rather general view on fleets, the second definition is more restrictive by limiting fleets to homogeneous units.

Besides these two definitions, further fleet characteristics are presented in the literature which group units based on the same critical components (Gebraeel, 2010), sequential sets of missions (Schneider & Cassady, 2004) and similar utilization and maintenance records (Bonissone & Varma, 2005). An overview of these different fleet understandings is provided in Tab. 2. Taking all descriptions and definitions into account and aligning them, a fleet can be described as a set of units, which are linked with regard to similar characteristics. In the context of PHM, the fleet definition has to be further complemented by the aspect that units in the fleet (or a subset of the fleet) are assumed to have similar failure indicators, types and/ or degradation behaviors. If this is not the case, knowledge cannot be transferred between the different units of the same fleet.

Table 2. Fleet Understanding in the Literature

Fleet Understanding	References
set of objects (systems, sub-systems, equipment); specific purpose; given time; subset of owner; shared characteristics; similar context, similar individuals	(Monnin et al. 2011) (Voisin et al. 2013) (Medina-Oliva et al. 2012)
set of homogeneous products; intended function; clustered following different criteria	(Leone et al. 2017) (Cristaldi et al. 2016)
data source	(Saxena et al. 2008) (Agarwal et al. 2015) (Fan et al. 2015)
similar/identical components; availability of data; working condition	(Al-Dahidi et al. 2017a)
identical units; same critical components	(Gebraeel 2010)
sequential sets of mission	(Schneider, Cassady 2004)
similar utilization, similar maintenance records	(Bonissone, Varma 2005)

2.2. Fleet Classifications

Fleets can consist of a variety of different compositions, each of these compositions having specific requirements and challenges for PHM algorithms. In order to describe the heterogeneity of units within the fleet, three different types of fleets are distinguished in the literature, namely identical, homogeneous (similar) and heterogeneous fleets (Medina-Oliva, Voisin, Monnin, Peysson, & Léger, 2012). In this classification, fleets are grouped based on the similarity of the technical features as well as their operating conditions (Al-Dahidi et al., 2016):

- *Identical fleets*: have identical features and usage and work in the same operating conditions
- *Homogeneous fleets*: share some technical features and work in similar operating conditions, but show differences either on some features or on their usage
- *Heterogeneous fleets:* have different and/or similar technical features, but undergo different usage with different operating conditions

The majority of the fleet-based approaches consider identical and homogeneous fleets, while heterogeneous fleets are seldom addressed (Al-Dahidi et al., 2016).

A further concept introduced for fleet–based PHM, which is mainly relevant for heterogeneous fleets, is the identification of similar or identical *sub-fleets*. In this context, a sub-fleet is defined a set of units (subset of the fleet) to be used as target population for fleet-based diagnostic or prognostic approaches (Medina-Oliva et al., 2012). Sub-fleets are built in order to identify similar units either based on technical machine characteristics (Monnin, Abichou et al., 2011) or similar degradation patterns (Leone et al., 2017) as well as with respect to common semantics (Medina-Oliva, Voisin, Monnin, & Léger, 2014) or categories of interest (Cristaldi et al., 2016), depending on the available data and the purpose of the investigation.

3. FLEET DIMENSIONS AND CHARACTERISTICS FOR PHM

In order to analyze and classify different fleets (step *fleet characteristics* in the presented process), fleet characteristics for PHM are obtained by systematically analyzing existing literature on fleet PHM. Even though the composition of the fleet as well as the fleet characteristics are often not directly specified in the corresponding publications, properties of the different methods and described challenges are considered in this publication to extract relevant information.

The developed ontology by Medina-Oliva et al. (2014) and Monnin, Voisin, Léger, and Iung (2011) is used as a foundation for the identification of fleet dimensions. The ontology enables the classification of units within a fleet with regard to six different contexts, namely technical, service, operational, performance, dysfunctional and application context (Medina-Oliva et al., 2014; Monnin, Voisin et al., 2011). These contexts are modified, amended and further refined using categories and corresponding characteristics provided in the literature. Due to the high importance of the available data for PHM approaches, the data dimension is additionally included. Therefore, in total five fleet dimensions are identified.

3.1. Purpose

The first dimension for fleet characterization depicts the purpose or performance context of the fleet. PHM approaches designed for fleets serving the same or similar purposes are likely to fit the fleet under investigation. Fleets having the same objectives will exhibit similar characteristics and challenges. With regard to existing literature, three clusters can be distinguished (cf. Tab. 3), fleets aiming at transportation, power generation as well as industrial fleets. Though, fleet-based PHM is not limited to these clusters, further clusters could be e.g. agricultural machinery, medical instruments and electronic devices, which however have not been subject by research in this area yet.

Table 3. Purpose

	System/ Component	**References**
Transportation	Automotive vehicles	(Saxena et al. 2005) (Al-Dahidi et al. 2016)
	Locomotive	(Bonissone, Varma 2005)
	Bus (cooling system, air compressor)	(Byttner et al. 2011) (Fan et al. 2015)
	Helicopter (drive train bearing)	(Patrick et al. 2010)
	Aircraft (different types of engines)	(Zaidan et al. 2016) (Xue et al. 2008) (Gebraeel 2010)
	Ships	(Medina-Oliva et al. 2014) (Léger, Iung 2012)
	Railways (railways, point machines)	(Jin et al. 2015) (Guepie, Lecoeuche 2015)
Power Generation	Nuclear Power Plants (transformer insulation, pneumatic valve, electric cables, accelerator drive)	(Agarwal et al. 2015) (Liu, Zio 2016) (Zio, Di Maio 2010) (Shumaker et al. 2013)
	Wind Turbines	(Lapira 2012)
Industry	Industrial Robots (welding)	(Lapira 2012)
	Milling	(Le, Geramifard 2014)
	Electric Valve	(Zuccolotto et al. 2015)
	Circuit Breaker	(Subbiah, Turrin 2015)

3.2. Contextual Information

The contextual information dimension depicts information to describe the general structure of the fleet without details regarding the fleet composition. By this, it facilitates the identification of fleets with similar structures. The different characteristics specifying the contextual information dimension are:

Unit: System (Monnin, Voisin et al., 2011) | Sub-System (Monnin, Voisin et al., 2011) | Component (Monnin, Voisin et al., 2011) | Equipment (Monnin, Abichou et al., 2011)

Size: Small (0-50) | Medium (50-200) | Large (> 200)

Age Structure: Identical | Different | Dynamic (Krause et al., 2010)

Remaining-Useful-Life: Short (Agarwal, Lybeck, Pham, Bickford, & Rusaw, 2015) | Medium | Long

Distribution: Location (Agarwal, Lybeck, Pham, Rusaw, & Bickford, 2012) | Region (Leone et al., 2017; Subbiah & Turrin, 2015) | Geographically Distributed (Leone et al., 2017)

Maintenance Responsibility: Owner | Service Provider

Maintenance Activity: Never | Seldom | Regular | Similar (Bonissone & Varma, 2005)

3.3. Fleet Composition

The fleet composition dimension is strongly linked to the presented fleet classification. While some publications describe fleets either as similar or heterogeneous, the degree of similarity or heterogeneity is often neglected. Besides that, the distinction between the different fleet types is often not fully understood. Therefore, in order to specify the fleet composition, further criteria are considered with respect to the technical and functional characteristics of the units:

System Design: Identical (Byttner, Rögnvaldsson, & Svensson, 2011) | Variations (Byttner et al., 2011) | Variants (Byttner et al., 2011) | Customized (Medina-Oliva et al., 2014)

Nature of Heterogeneity: Mechanical (Léger & Iung, 2012)| Electrical (Léger & Iung, 2012) | Electronic (Léger & Iung, 2012) | Software (Léger & Iung, 2012)

Critical Components: Identical (Gebraeel, 2010) | Non-Identical

Units: Dependent | Independent (Schneider & Cassady, 2004)

Manufacturer: Same | Different (Krause et al., 2010)

Functioning: Identical (Medina-Oliva et al., 2012) | Non-Identical (Medina-Oliva et al., 2012)

3.4. Operating Condition

The operating condition refers to the environment the fleet is exposed to. It has a large influence on the degradation behavior. Identical units will exhibit unique characteristics under different operating conditions. Even though most publications refer to the operating condition as one concept, the operating condition comprises of the usage (time), the load/ stress as well as the environmental conditions (with regard to climatic conditions and the physical environment (Ghodrati, 2005)). These information are available for the historical data, however future conditions are unknown in general. For this reason, it is assumed that the operating conditions remain similar to the current condition (Leone et al., 2017). Due to different operating conditions, peer units can change dynamically (Bonissone, Varma, & Aggour, 2005). In order to specify the operating conditions of individual units within the fleet, the following characteristics can be used to describe the operating condition dimension:

Usage: Identical (Lapira, 2012) | Stationary | Changing | Individual (Byttner et al., 2011)

Load/ Stress: Identical | Stationary | Changing (Agarwal et al., 2012) | Individual

Environment: Identical | Stationary | Changing (Agarwal et al., 2015; Liu & Zio, 2016) | Individual (Byttner et al., 2011)

Working regimes: Identical (Bagheri, Siegel, Zhao, & Lee, 2015) | Individual (Bagheri et al., 2015)

Missions: Identical (Schneider & Cassady, 2004) | Different (Medina-Oliva et al., 2014)

3.5. Data

The data dimension describes and analyzes the available data for fleet-based PHM. Depending on the specific data characteristics, approaches might differ significantly from each other. In general, three areas for data analysis can be distinguished, namely data description, data properties and data transmission. Data description refers to the structural description of the data values, while data properties specify the contextual information of the data. Lastly, data transmission determines when data becomes available for analysis.

The different characteristics for the data dimension are as follows:

<u>Data Description</u>

Structure: Unstructured | Semi-structured | Structured (Agarwal et al., 2012)

Values: Continuous | Discrete | Textual (Saxena, Wu, & Vachtsevanos, 2005)

Dimension: Single | Multiple (Al-Dahidi et al., 2016)

Stationarity: Stationary | Non-Stationary (Liu, Djurdjanovic, Ni, Casoetto, & Lee, 2007)

Types: Raw Signals (Monnin, Abichou et al., 2011) | Process Information (Agarwal et al., 2012; Monnin, Abichou et al., 2011)

<u>Data Properties</u>

Generation: Simulation (Byttner et al., 2011) | Experiment | Real (Byttner et al., 2011)

Run-to-Failure: Incomplete (Al-Dahidi et al., 2016) | Complete (Al-Dahidi et al., 2016; Bagheri et al., 2015; Leone et al., 2017)

Acquisition Time: Cycle (Guepie & Lecoeuche, 2015) | Time varying (Guepie & Lecoeuche, 2015)

<u>Data Transmission</u>

Transmission: Real-time (Fang, Hongfu, & Shuhong, 2010) | Online (Agarwal et al., 2012; Fang et al., 2010) | Offline (Agarwal et al., 2012; Byttner et al., 2011)

3.6. Assessment of Dimensions

The five different dimensions, purpose, contextual information, fleet composition, operating condition and data, are identified to describe and categorize fleets in the context of PHM. The first two dimensions, purpose and contextual information, describe the general fleet characteristics setting the basis for comparison. However, not all categories have to be defined in order to specify the fleet. This includes among others the age structure and maintenance responsibility. The dimensions fleet composition and operating condition depict the categories most frequently described in the literature. In several cases, a classification into the different types of fleets (identical, homogeneous or heterogeneous) are stated without specifying the concrete characteristics. Different categories are developed to determine the concrete fleet structure, include the system design, usage and load of the units. The data dimension represent the characterization of the available data which is crucial for the application of fleet-based PHM approaches. An overview of the developed categories and the corresponding assessment is presented in Tab. 4. The assessment is based on the author's personal estimate, which is based on the characteristics included in existing fleet-based diagnostic and prognostic approaches as well as the analysis of described data sets in the literature. The evaluated importance depict a general perspective, which could differ depending on the actual fleet setting and peculiarities.

Even though fleets might exhibit similar characteristics, in case where statistical data similarity is not provided no or little information can be obtained from the fleet. Fleets have to be designed in a way that indicators are transferable among units (anomaly detection), the same types of failures occur (diagnostics) or degradation profiles are comparable (prognostics). If this is not the case, the inclusion of fleet data into diagnostic and prognostic approaches will lead to worse results. This applies especially for prognostics in cases with different underlying data distributions. In these cases, data similarity is not provided.

Table 4. Assessment of Categories

Dimension	Category	Importance
Purpose	Purpose	Medium
Contextual Information	Unit	High
	Size	Medium
	Age Structure	Low
	Remaining-Useful-Life	Medium
	Distribution	Medium
	Maintenance Responsibility	Low
	Maintenance Activity	Medium
Fleet Composition	System Design	High
	Nature of Heterogeneity	Medium
	Critical Components	Medium
	Units	Medium
	Manufacturer	Low
	Functioning	Medium
	Usage	High
Operating Condition	Load/ Stress	High
	Working Regimes	Medium
	Missions	Medium
Data	Structure	Medium
	Values	High
	Dimension	Medium
	Stationarity	Medium
	Types	High
	Generation	Medium
	Run-to-Failure	High
	Acquisition Time	Low
	Transmission	Medium

4. FLEET CLASSIFICATION STRUCTURE

The results of the literature research with regard to different fleet dimensions and characteristics conducted in the previous chapter enable the development of a classification structure to support the description of different types of fleets. Results are synthesized to build a fleet classification structure for fleet-based PHM.

4.1. Fleet Classification Structure

The developed fleet classification structure can be used to describe and categorize different types of fleets. It supports the comparison of different fleets as well as the selection of appropriate fleet-based PHM approaches. In cases where fleets exhibit similar characteristics with regard to the identified dimensions and categories, approaches are likely to be transferable. When describing the fleet under consideration using the developed classification structure, not all categories can and have to be specified in all cases. This is attributed to missing knowledge or limited relevance of the category for the specific case under consideration. Therefore, depending on the importance (cf. 3.6) some categories might be omitted. Tab. 5 depicts the developed fleet classification structure. It depicts all possible categories as well as available characteristics to be used for each category.

Table 5. Fleet Classification Structure

Dimension	Category	Characteristics
Purpose	Purpose	Transportation, Power Generation, Industry
Contextual Information	Unit	System, Sub-System, Component, Equipment
	Size	Small, Medium, Large
	Age Structure	Identical, Different, Dynamic
	Remaining-Useful-Life	Short, Medium, Long
	Distribution	Location, Region, Geographically Distributed

	Maintenance Responsibility	Owner, Service Provider
	Maintenance Activity	Never, Seldom, Regular, Similar
Fleet Composition	System Design	Identical, Variations, Variants, Customized
	Nature of Heterogeneity	Mechanical, Electrical, Electric, Software
	Critical Components	Identical, Non-Identical
	Units	Dependent, Independent
	Manufacturer	Same, Different
	Functioning	Identical, Non-Identical
Operating Condition	Usage	Identical, Stationary, Changing, Individual
	Load/ Stress	Identical, Stationary, Changing, Individual
	Working Regimes	Identical, Individual
	Missions	Identical, Different
Data	Structure	Unstructured, Semi-Structured, Structured
	Values	Continuous, Discrete, Textual
	Dimension	Single, Multiple
	Stationarity	Stationary, Non-Stationary
	Types	Raw Signals, Process Information
	Generation	Simulation, Experiment, Real
	Run-to-Failure	Incomplete, Complete
	Acquisition Time	Cycle, Time varying
	Transmission	Real-time, Online, Offline

4.2. Example Application

In order to show the application of the developed fleet classification structure, the PHM data challenge 2008 data set is used as an exemplary case, which simulates a fleet of different turbofan engine degradations (Saxena et al., 2008; Saxena & Goebel, 2008). This data set is used widely in fleet-based PHM research. Since data is simulated, some categories are omitted for which information are not available. Tab. 6 depicts the results of the fleet classification for the simulated turbofan engine degradation data set. Characteristics are assigned for all categories where information is available in the literature as well as by analyzing the available data set and its description. The identified characteristics demonstrate the key properties to be considered when implementing a diagnostic or prognostic approach applicable for the PHM 2008 data set.

Table 6. Fleet Classification of the PHM Data Challenge 2008

Dimension	Category	Characteristics
Purpose	Purpose	Transportation (Aviation)
Contextual Information	Unit	Component (Engine)
	Size	Large (438)
	RUL	Medium
Fleet Composition	System Design	Variations
	Nature of Heterogeneity	Unknown
	Units	Independent
	Functioning	Identical
Operating Condition	Load/ Stress	Changing
	Working Regimes	Identical
Data	Structure	Structured
	Values	Continuous
	Dimension	Multiple
	Stationarity	Non-Stationary
	Types	Raw Signals
	Generation	Simulation
	Run-to-Failure	Complete
	Acquisition Time	Cycles

5. CONCLUSION

This study presents an investigation of relevant fleet characteristics for the specification of fleets in the context of prognostics and health management. Five dimensions are identified by means of a literature review, namely purpose, contextual information, fleet composition, operating condition and data. In order to describe the fleet, the heterogeneity of the fleet (fleet composition) as well as the operating condition are widely used in the literature, however without specifying the degree of heterogeneity and the characteristics of the operating condition. By presenting different categories and respective characteristics, the categorization of fleets are substantiated with concrete attributes facilitating the description of the fleet under consideration as well as the comparison with and delimitation from other fleets. Besides the general fleet description dimensions, the data dimension characterizes the available data for fleet-based PHM. This is especially relevant since diagnostic and prognostic approaches are designed with regard to the specific data characteristics. The developed fleet classification structure is subsequently applied to the PHM data challenge 2008 data set to show an exemplary application using a well-known case study.

Future research will target in-depth investigation and research of existing fleet-based diagnostic and prognostic approaches. Identified approaches are analyzed with regard to their applicability to the presented fleet characteristics. By this, the identification of suitable PHM approaches can be facilitated, supporting the application of fleet-based PHM.

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