A Taxonomy for Complexity Estimation of Machine Data in Machine Health Applications

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Keywords: Predictive Maintenance, Condition Monitoring, Complexity, Taxonomy, Product Automation Systems.

Abstract: The *Machine Health* (MH) sector—which includes, for example, Predictive Maintenance, Prognostics and Health Management, and Condition Monitoring—has the potential to improve efficiency and reduce costs for maintenance and machine operation. This is achieved by data-driven analytics applications, utilising the vast amount of data collected by sensors during machine runtime. While there are numerous possible fields of application, the overall complexity of machines and applications in scientific publications is still low, preventing MH technologies from being implemented in many real-world scenarios. This may be the result of a diffuse understanding of the term *complexity* in the publications of this field, which results in a lack of focus towards the core problems of real-world MH applications. This article introduces a new way of discerning complexity in data-driven MH applications, enabling an effective discussion and analysis of present and future MH applications. This is achieved by creating a new taxonomy based on observations from relevant literature and substantial domain knowledge. Using this newly introduced taxonomy, we categorise recent applications of MH to demonstrate the usefulness of our approach and illustrate a still-prevalent research gap based on our findings.

1 INTRODUCTION

The sector of *Machine Health* (MH), whose more prominent elements are, for example, *Predictive Maintenance* (PdM), *Prognostics and Health Management*, and *Condition Monitoring*, has the potential to revolutionise modern machinery-related applications. In theory, MH technologies, such as estimating a machine's Remaining Useful Lifetime (RUL), are able to reduce downtime, cost, and resource consumption of maintenance and can improve overall machine efficiency by using data that is continuously collected and analysed (Serradilla et al., 2022).

However, as current surveys repeatedly find, there are still numerous open challenges and research gaps in the domain, preventing its technologies from being widespread and commonplace (Nunes et al., 2023)(Gashi and Thalmann, 2020)(Serradilla et al., 2022). Most important, there is a lack of generalisation in current research, with each research project being a solution to the specific machine at hand (Nunes et al., 2023). Applications that are reported in scientific literature are not as diverse as they could be; published articles are still mostly staying at the level of system components (Gashi and Thalmann, 2020). The overall complexity of actual MH applications is often said to be low, while—at the same time—there is a lack of common understanding of the term complexity in MH.

For the scope of this article, a first definition of *complex* applications references applications, that are hard or impossible to implement using existing standard components and algorithms. To aid future research on implementing this type of applications, the aim of this article is to further refine this definition, and describe what exactly makes an application complex. This refined definition is presented and introduced as a new taxonomy in Section 4.

This taxonomy allows identifying and addressing the parts of an application that introduce the most complexity, thereby guiding the research field towards removing the most relevant barriers to the adoption of MH methods in practice.

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Meitz, L., Heider, M., Schöler, T. and Hähner, J.
A Taxonomy for Complexity Estimation of Machine Data in Machine Health Applications.
DOI: 10.5220/0012994900003822

In *Proceedings of the 21st International Conference on Informatics in Control, Automation and Robotics (ICINCO 2024) - Volume 1*, pages 341-350
ISBN: 978-989-758-717-7; ISSN: 2184-2809

The contributions of this article are:

- Collection of related articles dealing with complexity
- Introduction of a taxonomy for the term complexity
- Categorisation of multiple applications using this taxonomy
- Discussion of current applications, their complexity level and research gaps

The structure of this work is the following: In Section 2 the foundations for the remainder of this article are introduced to enable an effective discussion. Section 3 comprises a review of how the term complexity has been used in recent applications, and summarises the building blocks of related work. Afterwards, the proposed taxonomy is explained in detail in Section 4 and used to classify multiple recent applications and illustrate the findings in Section 5. Lastly, a discussion about the selected applications and the usage of the taxonomy is provided in Section 6 followed by an outlook to future research.

2 FOUNDATIONS AND PROBLEM DEFINITION

An application is a concrete implementation of a paradigm, such as Predictive Maintenance, for a given machine. Applications differ from machines in that different applications are possible for one machine. One application of MH for CNC Mill's might be RUL estimation of the used tool. Another application may be the monitoring of vibrations from the same CNC mill's spindle. As can be seen from this, application complexity is related not only to a machine, but to each specific application.

In the context of this paper, we define *Machine Data* as data that is created by or related to the operation of machinery. This not only encompasses production machinery, but any type of machine that is subject to continuous monitoring. Mostly, this data is gathered by connected sensors attached to or built into the machine or by logging signals that control the machine or parts of it. However, different additional sources of information can be present in an MH application, such as meta-information about the operation of the machinery. The data usually takes the form of time series, as samples are recorded periodically from sensors and other information sources.

We assume that the collection of data follows a purpose beyond purely internal use, e.g. for control systems: Engineers and/or Data Scientists want to use that data for a variety of applications. Here, extracting machine-related information from the collected data is the main goal of MH. We can distinguish between direct consumption by humans, e.g. for remote condition monitoring, dashboarding, or remote control, and (semi-)intelligent data-driven applications, such as Prognostics and Health Management, which is often also known under the term Predictive Maintenance and the main type of application we focus on in this study.

To give an intuitive understanding of the problem found in recent literature, we give a short example of what complexity encompasses. One prominent application example in the MH domain is fault detection on ball bearings of rotating machinery. This can be a straightforward affair and has seen exhaustive attention in recent publications, which are summarised for example in (Farooq et al., 2024). The vibration data in form of time series, generated by the ball bearing in operation, can be analysed using off-the-shelf models. However, implementing the same fault detection application is not as straightforward for more *complex* machinery. Take the example of a robotic arm, which consists of multiple jointed components monitored by sensors. This setup is generating multiple different time series with additional dependencies, in contrast to the ball bearings application. Naturally, providing the same fault detection mechanism for such an arm is much more difficult and comes with more challenges than in the simple ball-bearing application. In other words, the robotic arm application is more *complex*, but the way in which it is more complex is not properly defined.

This lack of specific understanding of complexity leads to problems for implementing Predictive Maintenance for sophisticated machinery. Solving the example application with existing off-the-shelf solutions is unlikely but of course highly desired. In recent literature every application needed its own research for finding suitable methods, as there is no detailed description of the problem of complexity at hand and comparison of different machines is not trivial.

In this context, the consideration of data properties is an important aspect, as we presume that it will aid further research. Considering the sources and type of complexity of an application can be used to estimate the complexity of an application, help focus on the core problems for implementation, and enables the comparison of different settings. This in turn lends an idea of what models or modelling approaches and pipelines are applicable for any specific use case. To achieve all this, we propose the creation of a new taxonomy that enables a mapping of complexity levels to ways to process and model data.

3 DISCUSSION OF THE TERM COMPLEXITY

Complexity is a term regularly used in multiple publications, especially to characterise systems that cannot be easily described. In consequence, there are varying definitions of the term *complex* in the context of MH. To shed some light and give an overview of popular definitions, we dive into the relevant literature based on a short survey we performed.

3.1 Usage in Related Literature

In their work, Gashi et al. (Gashi and Thalmann, 2020) state that recent PdM applications mostly consists of single-component-system solutions, which neglect the dependency of components on each other and therefore lacking complexity. The authors coint the term multi-component systems (MCS) and give four types of component interdependence, in order to communicate which type of complexity could be part of future research. Some publications use the term complexity without explicit definition, such as Fossier et al. (Fossier and Robic, 2017) and Dai et al. (Dai et al., 2008), missing out on the opportunity to clarify the exact challenges faced in their work.

In contrast to these, there are articles which explicitly deal with the term complexity and establish isolated descriptions. Miller and Dubrawski (Miller and Dubrawski, 2020) for example give an overview of multiple different applications and group them by similarity, which is useful for illustrating the range of different implementations. As an additional result of their work, they analyse research gaps regarding the complexity of current scenarios. To better communicate their findings, they introduce the terms component-level and system-level Predictive Maintenance, referring to the scope of implementations. They find two gaps: First, in component-level scenarios, there is mostly two distinct states of operation, which are *faulty* and *healthy*. Second, most of the more elaborate applications do not incorporate the interdependence of components into their analysis and fail to observe the system as a whole. Their terminology using component-level and system-level gives a solid starting point to where complexity might be introduced in applications.

Nguyen et al. (Nguyen et al., 2015) set the focus of their article on a decision policy rather than data analysis. They introduce their own description of system complexity as being inter-dependencies of different kinds for a MCS.

Van Horenbeek et al. (Van Horenbeek and Pintelon, 2013) similarly introduce complexity in the form of MCS with different kinds of dependencies between components. They further state that there are stochastic, structural and economic dependencies between components of one machine. In their paper, they address the problem of modelling such types of dependencies and choosing a maintenance strategy suited for a given system.

The approach of considering component dependencies is adapted in a clear definition by Ahmed et al. (Ahmed et al., 2021). They describe complex systems as systems with multiple components with dependencies that are either unknown or hard to incorporate into a model. As examples of domains containing complex applications they mention aerospace, automotive, oil and gas, as well as industrial applications.

3.2 Basic Aspects of Complexity in Applications

There are multiple publications that describe small aspects of complexity in the context of MH, whose insights form a solid basis for discussion. To understand their impact onto the proposed taxonomy, they are referenced and described shortly.

Klein et al. (Klein and Bergmann, 2019) worked on the subject of complexity in machines from the perspective of data. Their publication tackles the problem of complex data generation for PdM applications, with complexity being defined as multivariability. They give an overview of datasets that are commonly used for benchmark purposes, describe their attributes and finally introduce their own method of generating multivariate time series data based on a Fischertechnik factory model. The main aspect of complexity they introduced is the use of multivariate time series, which is considered an important attribute in the further scope this article.

Blancke and Combette (Blancke et al., 2019) use the term complex to mean that there are many possible modes of failure for the equipment being monitored. They used expert knowledge to create a causal graph of failure causes and symptoms in order to implement PdM. They intuitively refer to complexity as a high variance of possible machine states, but do not give a formal definition. We, too, incorporate the amount and difference in possible failure modes into our taxonomy.

Lee and Pan (Lee and Pan, 2017) published a way of implementing PdM for complex systems with probabilistic dependencies. They list publications addressing PdM for multi-component machines and single-component applications, and give a possible implementation of PdM. While their dataset does not consist of time series data and is quite outdated, they do define their understanding of a complex system explicitly: They characterise it as multi-leveled hierarchical system with multiple components and unknown component dependencies. These dependencies are another way of introducing complexity to a multi-component system, which will be relevant in the course of this article as well.

Züfle et al. (Züfle et al., 2021) also deal with the complexity of data, but do not explicitly explain their understanding of it. They introduce a workflow for anomaly detection on machine tool data. Instead of relying on benchmark datasets, they use real-world data collected from a machining centre and process it in order to implement supervised anomaly detection. To achieve this, they used a segmentation approach on the complex real-world data to make it suitable for the anomaly detection task. Their publication introduces a conception of especially relevant in real-world PdM applications, which is variance in form of multiple steps in a process.

As can be seen, all named publications implicitly or explicitly deal with data complexity, but they lack a common understanding in their applications. The majority only take the mechanical properties of a machine into account when referring to complexity, making them too specific for comparison among different MH applications. However, as stated in the foundations section, different applications can be implemented for a given machine, introducing complexity in a second field: the *process* being executed by the machine.

There is still a lack of sophisticated applications, as stated for example by (Züfle et al., 2021) or (Gashi and Thalmann, 2020). We think this is a direct result of the research gap at hand, which is the matter of clearly describing complexity in MH. In order to fill this research gap, our article will further characterise the term complexity and provide a way of estimating and comparing application complexity by introducing a novel taxonomy that can be used for all types of MH applications.

3.3 Challenges of Complexity

Complexity influences not only the feasibility of implementation for some applications, but also the necessary steps for properly working with the data. More complexity in the data generally means models might not perform well or at all. More complexity in terms of machine hardware will introduce more feature dimensions, data types, component dependencies and general data heterogeneity. Higher complexity in the observed process also leads to longer time series, possible deviations in length, more possible machine states, different types of machine states and more possible environmental influences. Increased complexity in either attribute means more states and variance to consider, with only a small part of the data relevant to maintenance decisions, bringing off-the-shelf models to their performance limit. Most models cannot work well with high amounts of variance, as they are only trained to learn one specific function or classification, not a combination of multiple ones. The taxonomy, which will be now introduced, can be used for a categorisation of an application in terms of its complexity, and therefore help with selecting the proper operations for actual data preprocessing and models for the implementation, mitigating some of these challenges.

4 A NOVEL TAXONOMY FOR COMPLEXITY

Essentially, the previously mentioned publications referring to complexity describe attributes like volume and variance in the application's data. This is already a common understanding in the domain of big data, where the five Vs (Volume, Velocity, Veracity, Variety, and Value) are often addressed as the main challenges (Naeem et al., 2022).

However, in contrast to the specific definitions of our related work, the definition given in Big Data publications is too general for the subject of Machine Health. There is no deeper look at where the volume or variance is introduced, missing out on the possibility of solving problems at their core. The core problem of complex applications is handling or reducing the complexity in/to a form that existing models can handle. To successfully achieve this, the source and type of complexity needs to be found and dealt with in the implementation.

When looking at the data recorded from Machines, two major factors contribute to an application's complexity: *the machine* and *the process being implemented*. The first factor solely describes the hardware aspect of an application, while the second one focuses on the technical process that is implemented by the machine.

To illustrate this, we get back to the previously introduced example of Section 2. By being a machine consisting of more than one component, the robot arm introduces more volume of data, simply by needing

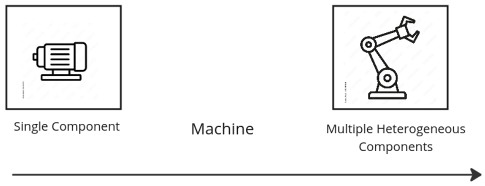

Figure 1: Machine Complexity Illustration.

more sensors to monitor all of its components. Additionally, the robot arm can perform tasks that are more complicated or inherently different from each other, which increases the variance in recordings for each process. While this is intuitively understood, a definition of the two factors machine and process will help in aiding the discussion about complexity.

4.1 Machine-Induced Complexity

By looking at the hardware part of an application, complexity can be found in the number and type of components that are the building blocks of the machine or system. With more components, there are more possible interactions and dependencies. Additionally, with many different components there are a wider variety of observable properties. Different types of sensors create heterogeneous time series data, with multiple observations that have to be treated differently. This increases volume and variance of the recorded data, creating the aforementioned challenges.

Depending on the application setup, a single machine or a batch of machines can be subject to the approach. For a single machine, an observation of operating condition over time is the only way to implement monitoring. This way, degradation and trends over time can be extracted from the observations. For multiple machines, deviations from the behaviour of the bulk of machines can be the mode for detection. This enables detection of failures without trend or degradation attributes, as there is no need to compare a history of observations.

Another factor to consider is that machine degradation is not always linear. Components can fail spontaneously or degrade exponentially, among other possibilities, which may not be easily modelled. Different components may fail differently, all inside of one machine, which makes the task of failure detection and diagnosis even harder for complex machines. For this taxonomy, the type of degradation is not among the properties for complexity estimation, as the interactions of components are considered the prime cause for complexity.

The scale of machine complexity ranges from a single component to a system of multiple different interdependent components, with single component machines being the least complex type of applications. This scale is further defined in Table 1 and is illustrated in Figure 1.

Machine complexity in PdM applications is crucial to incorporate into preprocessing. As machine complexity increases, so does the possible dependence and interaction of the components. With high machine complexity, components may not be able to be monitored separately, but need to be seen as a whole system. In addition, some models may not be able to learn the complexity of circular dependencies.

The complexity of the monitored machine is the main focus of relevant publications. While this is one big aspect of complexity, there is another important factor which has not seen too much attention in recent research.

4.2 Process-Induced Complexity

In addition to the machine complexity, the implemented process itself has significant impact on data complexity and needs to be considered as an additional source of complexity in applications. The main influence on process complexity is the number of machine states that can be observed in the data.

Simple processes can range from stamping or pressing a part to driving a shaft or tool. For these cases, only a single state is enough to define the normal operating conditions of the process. However, in most real-world applications the processes have more than one or two states. For example, the manufacturing of a complicated shape from a piece of stock involves manipulating material in a sequence of different operations. For sequences with multiple steps, there are multiple different states for each one, resulting in turn in a higher complexity of the application.

In recording or monitoring, the process can have an influence on the form of data. Some processes or segments can deviate in their length, making direct instance comparison infeasible. Processes can, depending on their nature, produce periodic and non-periodic data. For some algorithms or models, non-periodicity can be a problem during learning or inference.

Control signals recorded in the time series data, can be beneficial and enable more sophisticated analysis approaches. In the absence control signals, a black box approach is used, where measurements, or observations, depict to the machine condition. With the presence of control signals a grey-box approach can be implemented, in which the desired machine state can (partially) be extracted from control signals and more precise assumptions about the normality are possible. However, another form of information/data

Table 1: Scale of complexity for the Machine Part.

Low Complexity	**Medium Complexity**	**High Complexity**
Single Component	Multiple Independent Components	Many inter-dependent Components
Single Sensor	Multiple Sensors	Many Heterogeneous Sensors
Single Machine	Multiple similar Machines	Multiple Machines w/ Environmental Influences

Table 2: Scale of complexity for the Process Part.

Low Complexity	**Medium Complexity**	**High Complexity**
Single State	Multiple known States	Many Unknown States
Uniform Length	Uniform Length	Non-Uniform Length
Periodic Data	Periodic and Non-Periodic	Non-Periodic

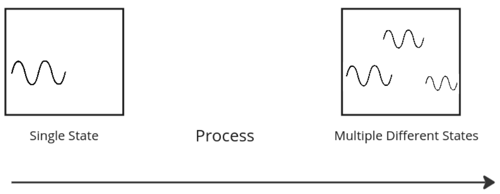

Figure 2: Process Complexity Illustration

introduces even further complexity to the application.

The levels of process complexity range from a single-state, continuous process up to a multi-state sequenced process containing multiple modes of failure. The summary of these levels can be found in Table 2 and are illustrated in Figure 2.

Process-attributes contribute a lot to the overall complexity of an application, but has not seen attention in related publications. By considering this second aspect as an important one, our taxonomy presents a new and effective way of describing the overall complexity of a MH application.

5 USING THE PROPOSED TAXONOMY

After introducing and explaining the two types of complexity sources, this section will demonstrate the usage of the taxonomy on different published applications to give a brief overview over recent research efforts. By using it to categorise and compare multiple data sets, a better overview of the current complexity of applications can be given for the set of selected applications.

5.1 Literature Search for Applications

The next goal of this article is to give an overview of some of the existing applications and categorise them using the proposed taxonomy. In order to give an unbiased image, a structured literature search for application publications is needed to create a dataset that can be used as a basis for the demonstration.

One method of looking for applications is to apply numerous keyword-searches to scientific search engines. However there are existing surveys that collect applications in PdM or CM in order to give an overview of the recent advances. For the purpose of this article, taking a collection of applications from an already published survey-paper is sufficient.

In the following, the findings of Mallioris et al. (Mallioris et al., 2024) will be used for further discussion. Using the proposed approach, a set of applications has been collected from their survey and will be described in the following subsection. As there were multiple similar listings in their overview tables, representative examples have been selected to be included in this illustration of our taxonomy.

Table 3 gives an overview of all the selected applications for the scope of this article. On the first column of the table, the referenced application is named and cited. In the next column, the used features are presented to give an impression of the application scope.

For the application of our taxonomy, one column per feature is present in the table. The estimations were retrieved by comparing the authors description in the publications with our introduced scales for machine- and process-induced complexity. The first aspect, machine complexity, is described by the *Machine Setup* column. Here, a brief description of the selected machine components and used sensors are given, followed by an estimation of the complexity based on these attributes. Process complexity is presented in another dedicated column named *Process Setup*. Here, the type of process is described briefly, how many different states it involves and if it is continuous or periodic. This column also contains the complexity estimation for the given process.

Table 3: Overview of the selected applications with the taxonomy applied. The Machine Setup and Process Setup columns describe and categorise the two complexity sources.

Machine Type	Data Features	Machine Setup	Process Setup
Pressing Machine (Serradilla et al., 2021)	Rotational Speed, Power Consumption, Force, Position	Motor Connected over Gearbox to friction clutch; Multiple Sensors of different kind; **Medium Complexity**	Stamping a Part in one Motor Rotation; Non-periodic time series and Single Normal State; **Low Complexity**
Centrifugal Fan (Lis et al., 2021)	Vibration	Single Motor driving a Fan; Single Component and Sensor; **Low Complexity**	Turning a Fan at constant RPM; Single Normal State of a constant signal; **Low Complexity**
Conveyor Belt (Elahi et al., 2022)	Power Consumption	Single Motor driving a conveyor belt with tensioning mechanism; Single Component and Measurement; **Low Complexity**	Turning a Conveyor Belt at constant speed; **Low Complexity**
Hydraulic Machinery (Roosefert Mohan et al., 2023)	Vibration, Oil Pressure, Contamination	Motor Driving hydraulic Pump Single Measurement and Autoregression; **Low Complexity**	Hydraulic system monitoring (e.g. oil pressure); Single healthy state with degradation; **Low Complexity**
CNC Milling Machine (Züfle et al., 2021)	Vibration, movements, temperature, speed, torque, power, acoustics	3 Axis CNC Machine with one spindle; Monitoring Sensor with multiple different signals; incorporation of control signals; **Medium Complexity**	Manufacturing Process with multiple steps; multiple possible states; **Medium to High Complexity**
CNC Spindle (Hesser and Markert, 2019)	Vibration	CNC Machine Spindle; Single vibration sensor; **Low Complexity**	Test Process with single healthy state; **Low Complexity**
Industrial Robot Joint (Izagirre et al., 2020)	Torque Signal	Robot arm with multiple Joints; Torque Readings from Two joints; **Low to Medium Complexity**	Fixed test trajectory on the same Machine; Non-periodic time series; **Medium Complexity**
Nasa Turbofan (Wang and Zhao, 2022)	Temperature, pressure, ratio flow, fan speed, coolant bleed	Turbofan Engine with many components Multiple heterogeneous sensor signals; **High Complexity**	Continuous usage in varying conditions; Single Healthy State with Degradation and RUL; **Low to Medium Complexity**
CFRP Drilling Machine (Domínguez-Monferrer et al., 2022)	Energy Consumption, Cutting Time	Drill with different Tool inserts; Power Consumption and Statistical Features; **Low to Medium Complexity**	Drilling Operation with 4 Phases; Non-Periodic Time Series; **Medium Complexity**

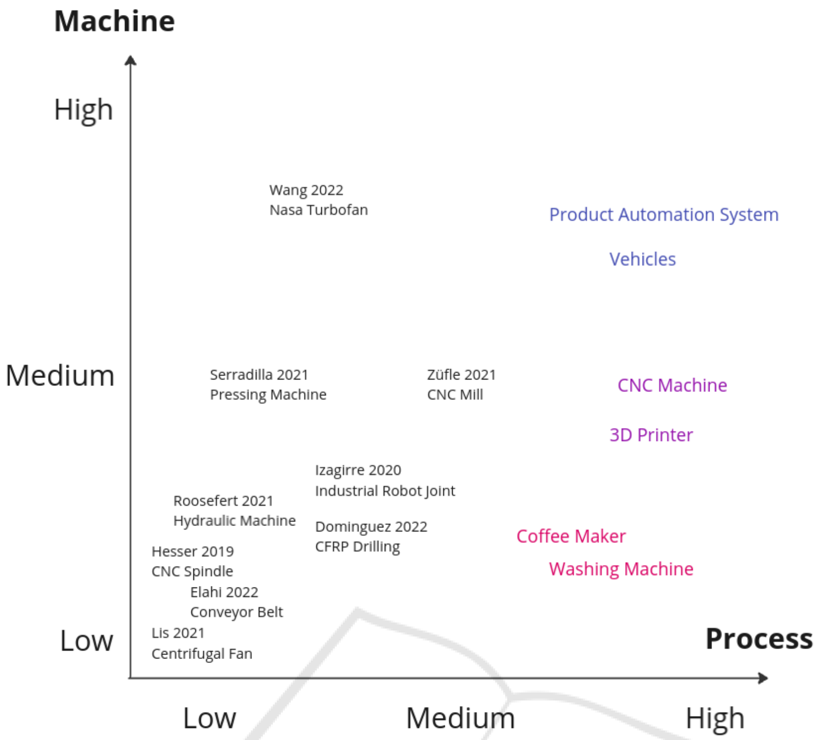

Figure 3: Complexity of related applications.

5.2 Illustration of the Dataset

In order to get a comprehensive illustration of the complexity of different applications, it is useful to combine the two introduced factors, machine and process, into a *two-dimensional plot*. When applied to multiple data points, this creates an illustrative way of comparing complexity among the given applications.

For each application, an estimate of relative complexity in Machine and Process has been made. These data points have been placed in a graph displaying the machine complexity in its X-axis and process complexity in its Y-axis. Figure 3 shows the plot of the selected and classified applications. Applications from the list of selected publications are shown in black. Additionally, there are coloured data points, which are examples of possible future applications and will be introduced in the following discussion.

6 DISCUSSION

The illustration of our proposed taxonomy yields interesting insights into the current application spectrum as given by (Mallioris et al., 2024). In this section, a discussion of the findings will be presented, as well as a discussion of the approach itself.

6.1 Observations from the Taxonomy

When looking at Figure 3, two conclusions can be drawn from the illustration: 1. Clusters of similarly complex applications can be established, and 2. There is a lack of applications with high process complexity. These two observations are an important subject for further discussion.

First, by using the taxonomy on a set of applications, clusters of similar complexity have been created. This enables the observer, or an interested enterprise, to find similar solutions to their own problem, based on the characteristics of the application. It therefore aids the development of real-world implementations by giving a starting point to look for when it comes to preprocessing techniques and model selection.

Second, evident through a lack of data points on the right side of the graph, process complexity in the observed applications is still low. This means that the currently published types of solutions are only suitable for simple processes or kept simple for ease of implementation. Processes of such type have only few known states or a single healthy state, which is distinctly different to most real-world scenarios.

Figure 3 illustrates the complexity of selected applications in black. In addition to those points, there are coloured instances, which are examples of possible applications that could be implemented to fit those complexity. These can be summarised as a specific type of machinery, called *Product Automation Systems (PAS)*. PAS automate a technical process for manufacturing or production of goods in a single machine. As can be seen in the illustration, this can be simple machines such as a washing machine or a coffee maker, but is also true for 3d printers and CNC machines. What these machines introduce by automating a complicated technical process is a high complexity in the process-axis. The difference of the examples in the illustration to existing research is the scope of the application, which often does not consider all of the possible process-induced complexity.

6.2 Identified Research Gap and Relevance

The main research gap that can be observed by applying the proposed taxonomy to recent implementations in the MH setting is a *lack of process-induced complexity*.

A possible cause of this could be the lack of process-complex datasets in the field. Benchmark datasets are popular and seen as a solid way to compare performance over different models. However, these benchmark datasets are neither optimised to be as close as possible to real scenarios, nor complex enough to make current algorithms struggle, as has been demonstrated for the case of time series anomaly detection (Wu and Keogh, 2022). Without readily available datasets only industry-partnered projects have access to complex data, which are then often restricted by NDA policies. The result of such a lack in complex datasets is a lack of research concerning process complexity. Exactly this complexity is an essential part and challenge of using MH technology in real-world scenarios. Without being able to research this field, complex applications will ultimately stay out of reach for the MH community, and applications will stay on the component level of machinery.

In order to mitigate this scarcity, some preliminary steps should be taken. First, industrial co-operations should be able to publish and share their data in a scope that allows researchers from different institutions to work together and compare their results, or to develop methods for dealing with complex applications. Second, the creation of synthetic data based on real-world applications should be researched to create publicly available benchmark datasets that contain various aspects process complexity. Third, the effort to implement MH applications for PAS machinery should be increased. This type of machine is widespread and not only reserved for big industrial partnerships. Small machines such as CNC machines, 3d printers or coffee makers are available for consumers and can build an important foundation for research applications. Improvements in these areas would foster the efforts of dealing with the process-induced complexity and aid future efforts of implementing sophisticated real-world applications.

6.3 Limits of the Proposed Approach

There are some fields of machinery, where this taxonomy is more suitable than for others. Industrial machinery, especially PAS are now part of the discussion in MH. Overall, the taxonomy can be used for comparing most applications that can be found in the domain of Machine Health, as it is general enough to encompass not only industrial machines.

Additionally, unsupervised learning is the mode of operation for most applications. For supervised learning, the complexity of the application is not the first consideration. When labels are present, most of the issues that arise through complexity become less important.

One limitation of our taxonomy is that there is no exact numerical quantification of complexity, but more of a continuous scale that can vary slightly depending on the observer. This makes it hard to give a precise estimation for some applications, which can however be resolved in discussions.

7 CONCLUSION

This article introduced a novel way of characterising machine data in the context of Machine Health applications, which was described in detail as a two-feature taxonomy containing machine- and process-induced complexity. Using this taxonomy, selected applications from a well-crafted survey article have been classified and illustrated using a two-dimensional plot.

Based on observations from the plot, two important topics have been identified and discussed: The possibility to find clusters of similar applications in the illustration, as well as the lack of high-complexity processes in recent publications. The type of machines and research that could fill this gap in the future have been introduced as *Product Automation Systems*.

The introduced taxonomy is an important step towards fostering the discussion about complex, real-world Machine Health applications. Using this well-defined baseline for discussion, two improvements to the state of the art are now possible. First, comparing existing applications to another and to planned implementations of MH. Second, applications with previously unsolved challenges can be identified as such and targeted specifically in future research. Implementation can focus on core sources of complexity for tackling future problems.

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