DEVELOPMENT OF A HYBRID MODEL FOR LARGE-SCALE PLANT RUL PREDICTION BASED ON DATA AND PHYSICAL MODELS

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Abstract. *Large plants in the process industry are monitored and maintained at regular intervals and repeatedly maintenance is either too early or too late. This causes unnecessary costs due to technicians, spare parts procurement as well as delivery issues and to high downtime costs due to unexpected shutdowns. In this context, the Remaining Useful Life (RUL) plays a major role, as it is an indicator of how long a machine or component can run without breakdown, repair or replacement. By predicting RUL using predictive maintenance, maintenance can be better planned, operational efficiency optimized, and unplanned downtime avoided. Optimizing the prediction accuracy should therefore always be in the foreground and is therefore the topic of this paper.*

1 INTRODUCTION

Many industrial plants are now equipped with cyber-physical systems and are on the way to becoming smart factories in the sense of the future project Industry 4.0. The Internet of Things (IoT), predictive maintenance and big data are among the essential core elements of future industrial plants. The overarching goal is to create digital plant transparency - the so-called Digital Twin. This will not only improve maintenance and servicing, but also the availability of machines and components.

In this context, Remaining Useful Life (RUL) plays a major role, as an indicator of how long a machine or component can run without breakdown, repair or replacement. By predicting the RUL with the help of predictive maintenance, maintenance work can be better planned, operational efficiency optimised and unplanned downtime avoided. The optimisation of predictive accuracy should therefore always be in the foreground and is therefore also the topic of the publication. However, many companies do not fully exploit the potential of predictive

maintenance. For example, components are replaced after a defect, but the collected data is hardly used to improve RUL predictions. In addition, the data is often available as CSV or PDF files and/or as handwritten documentation, but cyber-physical systems are not used to generate data.

In the context of a successful use of Digital Twins, the new plant of the car manufacturer Audi in Mexico or the Siemens plant in Amberg are examples - the implementation of Digital Twins is a complex process and for a better implementation companies resort to different development models.

RUL prediction models do not simply predict the RUL, but must also specify a confidence level to this prediction. The confidence level helps to assess how reliable the prediction is. Predicting the RUL as precisely as possible with a confidence level is one of the most important topics for operators of large-scale plants, and one that still needs to be researched in the future. The relevance of the topic also results from a concrete occupational field: for example, the purchase of a plant also includes the maintenance concept by the service staff - in order to be able to better plan the maintenance intervals and the associated travel of the service staff and the on-site inspections. To shorten downtimes as well as to be able to produce and subsequently transport spare parts in time, the application of predictive maintenance concepts is necessary.

From the customer's or the plant operator's point of view, the reduction of downtimes and maintenance times becomes important in addition to an increase in plant reliability. This can be explained by the maintenance and repair costs incurred as well as by the loss of yield during a production outage - especially in the case of unscheduled outages, the loss of yield can be much greater than in the case of a planned shutdown. In those cases where there is also limited access to areas of operation, further delays can occur. The above illustrates the need for optimisation and efficient planning of maintenance intervals. Ensuring the reliable operation of a plant therefore requires the selection of a suitable holistic maintenance strategy that detects faults and anomalies in the operating behaviour at an early stage and can predict failures as precisely as possible.

2 SATE OF THE ARTS

Lei et al. [8], in a review on data acquisition to RUL prediction, emphasize that predicting the operational behavior of machinery and equipment is one of the major challenges in condition-based maintenance. According to the authors, such a prediction program consists of the following four technical processes: 1. data acquisition; 2. construction of the Health Indicator (HI) of machinery and equipment; 3. subdivision into different stages of the Health Stage (HS); and 4. RUL prediction.

In recent years, much research has been conducted in the four areas listed above, with RUL prediction in particular being the subject of numerous investigations. However, Lei et al [8] find fault with the fact that no systematic review has yet covered all four processes and therefore fill this research gap by providing an overview of machine and plant behaviour prediction starting from data acquisition to final RUL prediction.

There are different approaches from the field of artificial intelligence, physical modelling and data-based modelling - but they all have limitations in terms of RUL prediction. The hybrid approach combines the advantages of different approaches.

Lei et al. [8] show with the help of Fig. 1 that hybrid models have been considered relatively

rarely in the scientific literature compared to the other three categories.
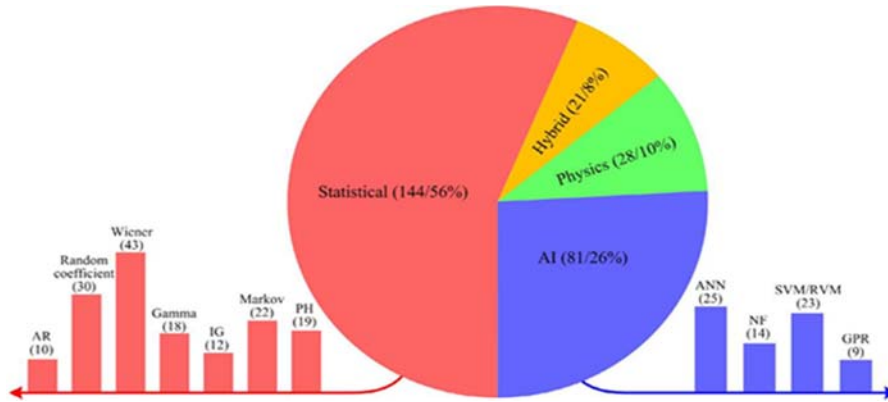

Figure 1: RUL prediction approaches [8] (Lei et al., 2018, p. 815).

The relevance of RUL prediction is also emphasised by Jimenez-Cortadi et al [11]; the authors dealt with the process of implementing data-driven predictive maintenance as part of their study. The focus of the investigations was not only on machine decision-making, but also on data acquisition and processing.

Analogous to Lei et al [8], Jimenez-Cortadi et al [11] list different approaches and techniques, but the main contribution is finding a solution to the prediction problem in real machine processes. To generate such a solution, the following different steps are required:

Figure 2: Steps to develop predictive maintenance [11] (Jimenez-Cortadi et al., 2019, p. 2).

The results show that preventive maintenance can be transformed into predictive maintenance. The goal of predictive maintenance is to extend the life of machines and equipment. Jimenez- Cortadi et al [11] used a CNC milling machine as a real example and used machine learning techniques to predict RUL. Within the scope of the study developed an application with the help of which the RUL could be visualised in a machine process. However, the authors emphasise that the complexity of the model made it difficult to implement in the production machine. In order to improve the accuracy of the RUL prediction, other signals should be included [11].

An approach to hybrid modelling can be found in Arias Chao et al [2]. The authors emphasise that physical and data-driven models for RUL prediction usually face two challenges that limit their application to real-world domains [2]:

1. Incompleteness of physical models
2. Lack of representativeness of the training data set for data-driven models

In order to combine the advantages of both models and to override some of their limitations, Arias Chao et al [2] propose a hybrid model, which on the one hand draws on the information

of physical models and on the other hand uses deep learning algorithms. In this way, complex safety-critical systems are to be predicted under realistic application scenarios. Fig. 3 below shows the structure of the hybrid model proposed by Arias Chao et al [2].
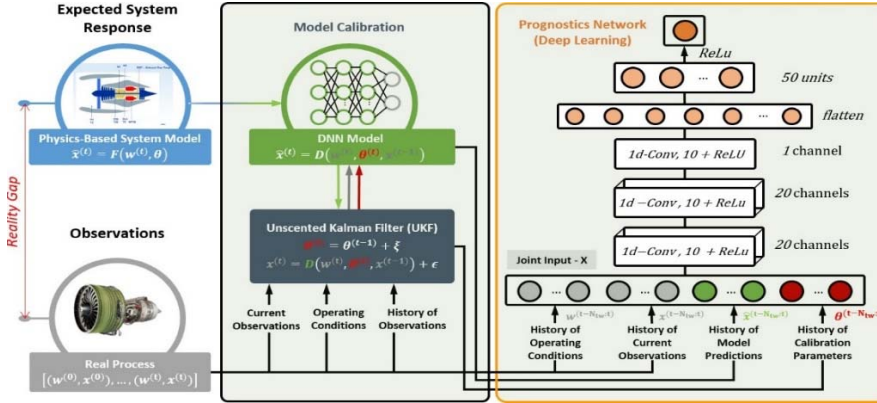

Figure 3: Hybrid model of physical and deep learning [2] (Arias Chao et al., 2020, p. 5.).

The proposed model incorporates physical performance models to tap into unobservable model parameters. These model parameters are related to the health of the system components and are used to solve the calibration problem shown in the center of Fig. 3 above.

The parameters are then combined with sensor readings and used as input to a deep learning network to generate a data-driven prediction model augmented with physical features. Arias Chao et al [2] tested the performance of this hybrid model and evaluated it through a comprehensive case study using nine turbofan engines under real flight conditions.

The results of the experiment show that the hybrid model outperforms purely data-driven models in terms of predictive power - the prediction horizon could be extended by about 127%. Furthermore, the hybrid model requires less training data and is less sensitive to the limited representativeness of the data set compared to purely data-driven approaches [2].

The previous remarks show that extensive data is required for modelling for RUL prediction of machinery and equipment. Janssens et al [10] dealt with fault detection for rotating machinery and emphasise that the analysis of vibrations is one of the proven techniques for condition monitoring of rotating machinery, after all, vibration patterns change depending on the type of fault or machine condition.

However, the particular challenge in using such features is that, on the one hand, the construction and, on the other hand, the interpretation require a great deal of human knowledge. Thus, in order to enable non-experts to perform vibration analysis to monitor an operating condition, the overall effort required to construct such features to detect faults must be reduced as much as possible. Janssens et al [10] therefore propose a learning model for such features to be able to monitor operating states using neural networks. The goal of this approach is to autonomously learn useful features from a database. The authors compare the learning model with a purely technical approach, using the same data to objectively quantify the performance of the models.

According to the results of Janssens et. al [10], the learning model based on a neural network exceeds the performance of the pure technical model. The application of the neural network to

the raw data could show that the network learns to transform the data so that it can be represented much better. In this way, less human knowledge is required and yet very good results can be achieved. However, further research should include other framework conditions in the analyses - it would also be possible to use an additional thermal camera as a sensor. After all, other empirical studies have already shown that thermal cameras can easily detect lubricant degradation, for example [10].

Machine learning classifiers were also used by Kolokas et al [13] to generate fault prediction algorithms - the authors refer in particular to the manufacturing industry and the equipment used there. To develop a prediction model, the authors use historical process data as input data. The goal is to correlate the anomalies found by the model as well as possible with future errors. Such a trained model can be of great importance for industrial real-time applications; after all, the anomalies identified by the model can enable predictive maintenance. Kolokas et al [13] applied the model to aluminum and plastics production - the results show that machine learning models are able to successfully predict future defects before they occur. However, the authors equally emphasise that the fundamental difficulty is to find useful information in the process data for fault prediction.

Tao et al [14] summaries that Prognostics Health Management (PHM) is essential in the field of product life cycle monitoring, but especially for complex equipment used in harsh environments. The emerging Digital Twin technology to improve the accuracy and efficiency of PHM is therefore proposed for complex equipment. The authors constructed a general digital twin for complex equipment and used a wind turbine as a use case to demonstrate the effectiveness of the constructed model. Fig. 4 below shows the flow of the Digital Twin model according to Tao et al [14]. The Digital Twin created is used to develop the PHM method shown - faults are classified by the model into creeping and abrupt faults. Creeping faults essentially result from component wear and tear and can therefore be predicted relatively well, whereas abrupt faults are unpredictable and result suddenly as a consequence of faults [14].

In the following Fig. 4 above shows that the Digital Twin model according to Tao et al [14] goes through seven different steps on three levels:

- Level 1 (Observation)
  Observation comprises the first three steps. Step 1 involves modelling and calibrating the Digital Twin for the complex equipment. If the virtual equipment differs from the physical equipment, it must be adjusted by changing the parameters using the least squares method. Step 2 involves model simulation and interaction, while Step 3 assesses the consistency of the model.
- Level 2 (Analysis)
  The analysis stage comprises steps four to six. Step 4 includes deviation detection: During operation, a performance deviation occurs, which the model detects with the help of defined indicators from the data. If some indicators exceed the limits, the component will wear out and a creeping fault will occur. Step 5 involves the assessment of inconsistency. Historical data from the physical model under the same conditions serves as a reference here. Step 6 identifies sources of error and predicts them, distinguishing between creeping and abrupt errors.

- Level 3 (Decision)
  The third stage comprises only the seventh step, the derivation of maintenance strategies. Depending on the source of the error, maintenance strategies are selected from various alternatives. The selected strategy is first executed on the Digital Twin in order to validate it. The strategy is then applied to the real component.
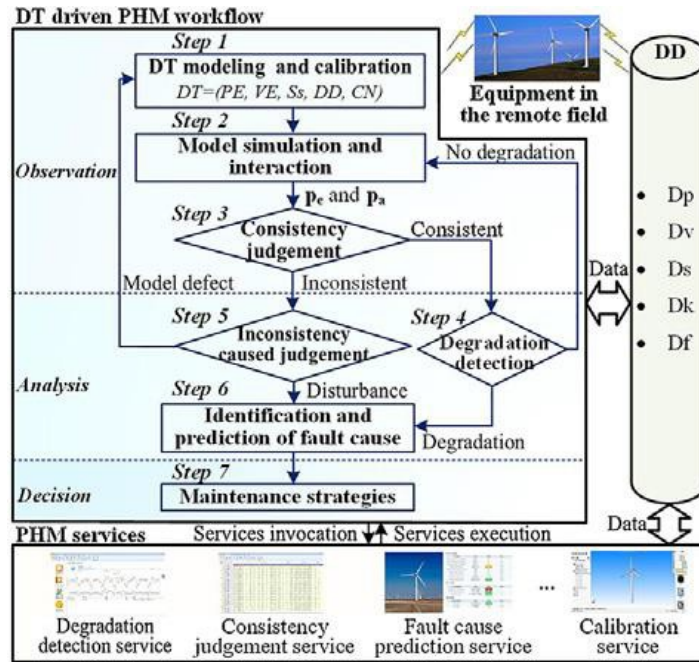

Figure 4: Digital Twin Model [14] (Tao et al., 2018, p. 171.)

The Tao et al. [14] model is characterised by numerous interactions, loops and communications, as shown in Fig. 4 above. The virtual and the real object are therefore constantly communicating with each other and the generated data is used to constantly improve the model, which in turn also increases the predictive power of the model or its accuracy.

The model was created for complex equipment, according to the authors it is suitable for monitoring high value equipment in a plant, but requires a certain amount of data. The particular challenges, according to Tao et al [14], are,

- to be able to reproduce complex equipment with different characteristics and behaviours with a high degree of fidelity,
- to be able to process the huge amounts of data of a Digital Twin and
- balance the costs and benefits of the Digital Twin.

According to the explanations in chapter 2, Lei et al. [8] already criticised that no scientific publication had yet dealt with all four processes from data collection to the definition of health states and the subdivision into different stages of the health state of machines and plants up to the final RUL prediction. The authors then wrote a systematic review - however, the publication was not based on an empirical survey or a run through of all four processes with concrete data from a use case. The planned research projects and the publication start at this point and include

all four processes in the investigation, whereby these processes are empirically analysed using a concrete example. Chapter 2 was also able to show that the scientific community has already recognised the great potential of hybrid prediction models and is engaged in the development of such models. For example, the current work by Arias Chao et al [2], which dates from 2020, shows the results of combining a physical model with a data-driven model in terms of RUL predictive power. However, Arias Chao et al [2] only focused on the analysis of a single hybrid model, but it can be assumed that the combination of further different models leads to better results in terms of RUL predictive power.

3   TARGETING AND RESEARCH GAP

3.1 Derivation of the research gap

The scientific publication by Lei et al [8] includes all four processes from data acquisition, the definition of health indicator / stage and the subdivision into different operating states of machines and plants to the final RUL prediction. A run through of all four processes with real data from a use case is missing. In a recommendation for further research, Lei et al. [8] state that various challenges exist in the areas of data acquisition, health indicator, health stage subdivision and RUL prediction. In summary, the following research gaps present themselves as starting points for further research:
1. To what extent can RUL prediction be carried out if only incomplete data can be generated in the area of data collection?
2. How can an error threshold be determined for newly constructed health indicators?
3. What influence does RUL prediction have on plant reliability?

Arias Chao et al [2] focused on the analysis of a single hybrid model; this results in the following research gaps:
1. Can the combination of further different models lead to an increase in RUL predictive power?
2. How much effort is required to combine the three models?

Furthermore, Arias Chao et al [2] emphasise in their study that the optimisation of RUL prediction models of complex systems often suffers from the fact that on the one hand the training data set is not representative and on the other hand the physical model is incomplete. In the context of this publication, the effects of limited physical models will be discussed in particular.

The publication starts with these research gaps and challenges and explicitly addresses the individual aspects in the following chapter 3.2 as part of the modelling.

3.2 Targeting

Against the background of the initial situation explained in chapter 2 and the research gap identified in section 3.1, the overall objective is to create a predictive maintenance model for large-scale plants with a digital twin as the basis. In addition to the research gaps described above, the following accompanying objectives and approaches will be addressed:

Table 1: Example of the the individual work packages and targets

Research gap	Targeting	Approach	WP
1.1	Data acquisition	Data Mining, Data Analytics	WP2
1.2.	Determine health indicator (HI)	Condition monitoring through Prognostics and Health Management PHM system (measured value: time stamp)	WP3
1.2.	Trends, Error and anomaly detection	Contextual anomalies: cluster procedures, collective anomalies:time series analysis, Outlier Detection, Unsupervised Learning, Grouping and Approximating the error	WP3
1.3.	Identify influencing factors	I. Operating Environment, etc. II.Damage cases, collateral and consequential damage; Weibull distribution, etc.	WP4
2.1. 2.2.	RUL prediction through learning hybrid models	Machine Learning, Go through four processes from Lei et al. Hybrid model Extension from Arias Chao et al. through experience-based model	WP5 WP6
	Validation	Execution of test cycles; transfer to real system and visualisation	WP7

3.3 Work plan

Within the framework of the planned research projects, a hybrid model for increasing the reliability of large-scale plants from the oil and gas industry is to be developed. The aim of the hybrid model is to develop a concept for the application of predictive maintenance, starting from data acquisition to RUL prediction.

WP1: Literature analysis:

Research and basics about RUL using hybrid model; on Health Indicator and Score and on failure scenarios and plant reliability.

WP2: Analysis of existing data and further data collection if necessary:

The first work package deals with "data collection" before data analysis - this includes the procurement and structured integration of data acquisition. Data acquisition includes all methods required to collect and store the outputs of sensors including relevant information (e.g. timestamp of a measured value, repair and damage reports, etc.). Subsequently, the recorded measurement data is processed for further evaluation. Data is collected from multiple sensors installed on the facility, stored and provided as a CSV file for further processing. Historical data collections may show some missing, inconsistent and noise values. The data quality has a great influence on the further work packages. Accordingly, the historical data are compared to answer the following questions: What happened? Why did something happen? With the aim of discovering useful information from existing data. This is to cleanse the data, understand it and determine what actions are needed to make the data useful for a particular context. This means discovering useful information, drawing conclusions and supporting the decision-making process/data mining. Using frequency counts, descriptive statistics such as mean, standard deviation, and normality histograms such as kurtosis and frequency can be used.

WP3: Data RUL model and anomaly detection:

Characteristic features are extracted mainly from data sources, e.g. several sensors, in order

to reflect the exact system behavior. To carry out WP3, the process steps from the Prognostics and Health Management PHM system of ISO 13374 are applied, from data acquisition, monitoring of the operating status by sensors to measurement data evaluation and fault diagnosis. Errors and malfunctions often manifest themselves as anomalies in the acquired data, when either the values are outside the expected ranges or at least the correlations between the data are disturbed. To detect the errors and anomalies in the data, all the information from the condition monitoring is gathered for evaluation. Subsequently, system information such as the current operating status (e.g. normal operation and/or test run after maintenance activity) or the reasons for shutting down the system (e.g. system operator request and/or limit values exceeded) are recorded, and the information evaluated from this is made available to the downstream data evaluation. In order to assess the current operating state and determine the healthy/normal operating state, abnormal and normal operating states are analyzed and identified using anomaly detection. Most of the data is only unmarked, which means that the data points are not marked as normal or abnormal. For this reason, the unsupervised learning method is used here. This method uses unlabeled data and assumes that normal condition is the most common pattern. This is followed by a second classification using the clustering method, which uses machine learning algorithms such as k-means to divide the data into groups. Operating states that are far away from all groups are identified as outliers. The relevant parameters and the data models used flow into statistical evaluations and train algorithms, which should then enable the prediction of future operating states. One of the decisive advantages of data-driven models is that they are also suitable for systems with complex behavior that can only be described with difficulty by physical or mathematical models. However, these are strongly dependent on the available historical and current data as well as the knowledge about the typical operating condition. This is also the disadvantage of data-based models.

WP4: Physical RUL model - decomposition of the system into individual components incl. consideration of collateral influences and operating conditions:

The basic questions are: Which system failed and when? What was defective and what was repaired? Which components fail most frequently? Which components have to be replaced or repaired at high cost? The prerequisite for this is service and repair data. With the help of the physical model, the wear and tear of the plant condition is assessed and prioritised under the given operating conditions and influences, and then the parameters are adjusted. The physical model describes a functional relationship between operational stress and service life. The remaining service life is finally predicted by determining whether and when the predicted parameters fulfil the failure criteria from the failure description. The task is to work out the technically essential aspects from the point of view of modelling mechanical components under the consideration of dynamic variables (finite element method) and simulation of a large industrial plant:

- Define system boundaries and divide the system into individual assemblies
- Modelling of the individual components (e.g. divide compressors into subgroups: impellers, shaft, bearings, etc.)
- Analyze components and their effects on the overall system
- Estimation of the load capacity and determination of influencing variables (geometry, environmental conditions, etc.)

- Calculate and analyze the service life of the components
- Presentation of life cycle models for relevant plant components with indication of uncertainty.

Random failures occur independently of the ageing process and are mostly due to operating errors or temporary overuse. Due to unavoidable, regular wear and tear of a system (e.g. due to wear, material fatigue or corrosion), the probability of a (age-related) failure increases with increasing service life. This is referred to as the reduction or degradation of the wear stock (see Fig. 5).
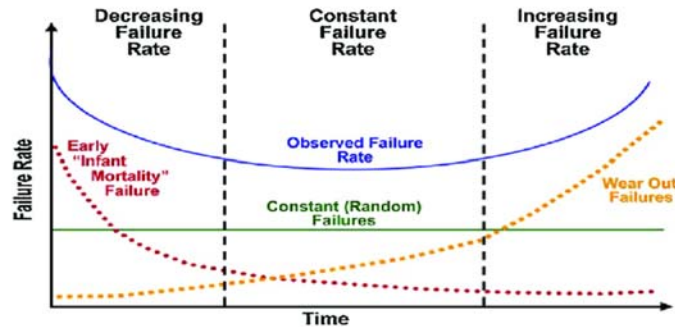

Figure 5: Illustration of the failure rate over the lifetime of a technical system and classification of the causes of failure into early, random and old-age failures [1] (Alcalde, 2000, p. 14).

In order to evaluate the influence of different damage events, the damage time model is built up and applied. In the damage time model, the time until damage occurs is mapped with a continuous probability distribution. This describes either the time from installation to the first damage or between two damages (damage time model type I) or the time from installation to the kth damage (type II). The Weibull distribution, the exponential distribution and the semi-parametric regression model are considered. The three damage time models will be evaluated against each other. A definitive selection of the methods can only be made after the collected data and the examination of damage reports.

WP5 Experience-based RUL model:

Experience-based modelling approaches include knowledge such as deductive and expert knowledge, but also empirical values. Here, it is important to check the availability of relevant plant data, which was already generated before operation, together with experts and to evaluate it accordingly. In addition, the existing expert knowledge can be used to interpret deviations. The model is based on a combination of mathematical algorithms and expert knowledge. Here, the two core competences, mathematical-statistical understanding and domain knowledge, must necessarily mesh and be combined via the cause-effect relationship.

WP6: Combined models and estimation of the predictive reliability for the different models:

The envisaged hybrid model will be a combination of data-based (a), physics-based (b) and experience-based (c) models. The following three models are developed for this purpose:

1. Data-based model (a)
2. Physics-based model (b)
3. Experience-based model (c).

Subsequently, the developed prediction models are combined to a hybrid model in such a way that the models are:
- (a) and (b)
- (a) and (c)
- (b) and (c) and
- (a), (b) and (c)

When using real operational data, RUL prediction "learns" from actual real-world experiences and events. These serve on the one hand to define the healthy system state / health indicator, and on the other hand as a reference to be able to detect deviations in the characteristics of faults and anomalies. If anomalies are detected, it is the task of selected algorithms to determine those features that have a significant influence on the abnormal system state.This fusion of real and digital system creates a digital twin. The hybrid modelling approach with sensor data transfer to the simulation tool can also be extended to include real-time operation. The RUL prediction is supplied directly and in real time with historical real data and additionally enriched with the realistic data generated in the simulation model - also in real time.

WP7: Validation and implementation:

The modelling approaches of RUL Prediction will be applied under real operating conditions. In the context of this case study, historical (raw) data as well as existing damage reports of the plant operator will be available.

4   CONCLUSION

The analysis of related work also leads to the conclusion that the detection of anomalies based solely on data-driven model and the physical behavior of a component can not predict 100 percent. Therefore, based on the current state of research, it is not possible to develop predictive models without using a combined model. In this context, the authors note from the publications [2,8,11] that the focus should be on exploring the division of tasks between human and machine workers. Specifically, this means that collaborative learning models, strategies, approaches, and innovative didactic approaches should be developed to achieve optimal collaboration between humans and intelligent systems in performing maintenance tasks.

In addition, taking into account the physical model and experience-based models contained information, the predictive accuracy of data-driven predictive models can support and improve. Suitable algorithms must be designed so that hybrid models can be used independently of industry partners.

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