IDTA 02048
Predictive Maintenance

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SPECIFICATION

Submodel Template of the Asset Administration Shell

Submodel Template
IDTA approved
- 100% AAS compliant
- Consistent & interoperable
- Released by the AAS experts

Imprint

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Contents

Figures

Tables

1 General

1.1 About this document

This document is a part of a specification series. Each part specifies the contents of a Submodel template for the Asset Administration Shell (AAS). The AAS is described in [1], [2], [3] and [6]. First exemplary Submodel contents were described in [4], while the actual format of this document was derived by the "Administration Shell in Practice" [5]. The format aims to be very concise, giving only minimal necessary information for applying a Submodel template, while leaving deeper descriptions and specification of concepts, structures and mapping to the respective documents [1] to [6].

The target group of the specification are developers and editors of technical documentation and manufacturer information, which are describing assets in smart manufacturing by means of the Asset Administration Shell (AAS) and therefore need to create a Submodel instance with a hierarchy of SubmodelElements. This document especially details on the question, which SubmodelElements with which semantic identification shall be used for this purpose.

1.2 Scope of the Submodel

The Submodel Predictive Maintenance aims to standardize metadata and information from various sub-systems within highly automated production lines, that are required for developing and deploying predictive maintenance solutions (PdM solutions). This facilitates integration and interoperability of sub-systems of production lines into PdM solutions. In addition, their data can be evaluated in a more targeted manner in the context of the PdM application in order to reduce unplanned machine downtimes. Accordingly, the PdM solutions can in turn provide maintenance-relevant information via the AAS, e.g., on predicted remaining lifetime and/or the probability of failure.

In general PdM aims to predict the end of useful life of a specific device or component (asset). The remaining useful life (RUL) is the duration until this end of life is reached, and the asset must be replaced or a maintenance action must be performed. RUL can be measured in time or other wear relevant units such as a distance/length or numbers of process cycles. The scope of the Submodel is mainly on data related to PdM, not on the prediction model itself.

Thus, this Submodel does not contain the implementation details data-driven and AI-boosted models for PdM,. As a matter of fact, this Submodel is merely structuring the data attained from an algorithm or model (physical or mathematical) for better utilization in planning and maintaining physical assets in a shopfloor.

The Submodel Predictive Maintenance aims at interoperable provision of information describing PdM topics in regard to an asset. Central element is the provision of properties [7], ideally interoperable by the means of dictionaries such as ECLASS and IEC CDD (Common Data Dictionary). The purpose of this document is to make selected specifications of Submodels in such manner that information about assets can be exchanged in a meaningful way between partners in a value creation network. It targets components of machines or plant sections which are themselves sub-systems of factories or plants and predictive maintenance applications for these components and sub-systems.

The conception is based on existing norms, studies of common practices at enterprises, directives and standards so that a far-reaching acceptance can be achieved (see also section 1.3).

In the context of maintenance, it is important to understand that PdM for industrial applications is a niche but rapidly growing segment within the much broader field of maintenance use cases. Therefore, only functionalities which are directly enabled because of PdM, namely predicted remaining useful lifetime of an asset, are the main focus of this Submodel. Topics out of the scope of this Submodel are maintenance instructions and preparation, corrective maintenance, predetermined or condition-based maintenance. Figure 1 shows a schematic overview on types of maintenance adapted from DIN EN 13306. Appendix B provides a future vision for the embedding of PdM Submodel in the context of maintenance as a whole and its connections to other existing and potential Submodels

Furthermore, it is important to understand that the aforementioned predicted useful lifetime of an asset in the sense of predictive maintenance is not static. Rather it depends on the concrete use of the asset in a specific process environment. In that regard, this prediction is impacted by the constant changes of the process values, which cause wear and tear to the asset.

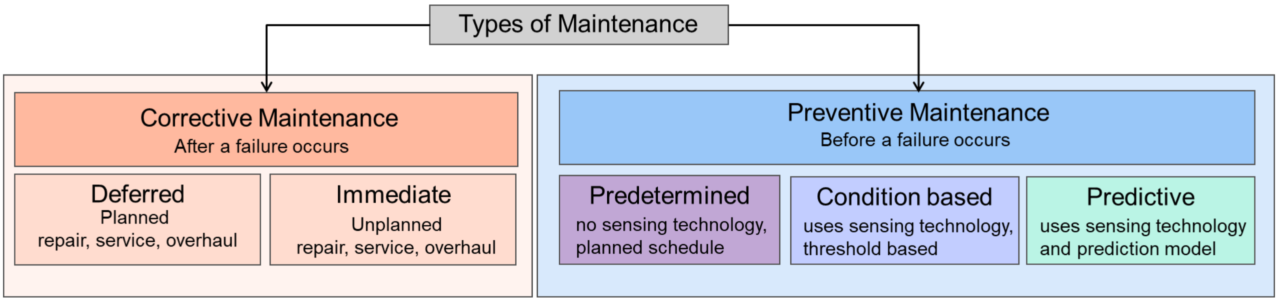

Figure 1: Schematic overview on types of maintenance adapted from DIN EN 13306.

1.3 Relevant standards for the Submodel template

According to [3], interoperable properties might be defined by standards, consortium specifications or manufacturer specifications. Useful standards providing sources of concepts are:

Table 1: List of standards defining interoperable properties

DIN EN IEC 63270	Industrial automation equipment and systems – Predictive maintenance [8]
VDI 2872	Lean production systems – Lean enterprise system – Introduction and fundamentals [9]

The definition of the AAS Submodel Predictive Maintenance is based on the standard DIN EN IEC 63270 Industrial automation equipment and systems – Predictive maintenance [8]. In this context PdM is a “form of preventive maintenance performed continuously or at intervals governed by observed conditions to monitor, diagnose or trend a structure, system or component’s condition indicators. Results indicate present and future functional ability or the nature of, and schedule for, planned maintenance”. Maintenance management is not in the scope of the Submodel Predictive Maintenance, but addressed by IDTA Submodel Maintenance Instructions [10].

The so called property dictionaries are used to identify information elements (see Terms and Definitions of [6]). Such property dictionaries include:

- ECLASS, see: https://www.eclasscontent.com/
- IEC CDD, see: https://cdd.iec.ch/cdd/iec61987/iec61987.nsf and https://cdd.iec.ch/cdd/iec62683/cdddev.nsf

In this document, properties are aimed to be described by ECLASS.

1.4 Use cases, requirements and design decisions

The intended use-case is the provision of a standardized property structure for PdM relevant information related to RUL prediction, which enables to integrate PdM easier on the shop floor level and in maintenance procedures. This integration enables PdM solutions to provide well-structured information about remaining useful lifetime, in order to reduce machine downtimes in manufacturing processes. The Submodel Predictive Maintenance helps to overcome the high level of effort required for integrating PdM solutions by providing a standardized way via the AAS. Furthermore, previously rigid maintenance intervals can be supplemented or replaced by dynamic need-based intervals using appropriate PdM solutions suitable for Industry 4.0.

This helps to reach the economic interest of companies with highly automated manufacturing processes (e.g., injection moulding or process industry) and process industry for avoiding unplanned machine downtimes. Likewise, manufacturers of machines, as well as suppliers of components have an interest in recognizing possible component failures and their causes at an early stage.

Possible causes for unplanned plant downtimes include but are not limited to:

- Wear and tear (e.g., of servo motors, increased friction/lubrication, joints, dirty fans which result in increased temperature of the servomotors, longer switching times, etc.)
- Machine component failures (servo motor, relay, converter, fan, etc.)
- Component failures, e.g., cooling system (temperatures, flow rate/leakage), handling (vacuum loss), conveyor belt (motor, slippage, etc.)

Factories and plants usually consist of numerous machines and components. The monitoring of process parameters based on different sensors, as a part of condition monitoring, e.g., using the OPC/UA standard, is common practice. To integrate data-driven PdM applications and PdM solutions in the maintenance procedures of the manufacturing and process industry, however, information on remaining useful life time and meta-information for its interpretation must be made available. The Submodel Predictive Maintenance therefore is designed not to replace OPC/UA machine-to-machine communication but to enhance it on the side of the AAS of the asset by providing essential information for monitoring the remaining useful life of the asset in an interoperable manner.

1.4.1 Typical approach of predictive maintenance

As mentioned above PdM in general aims to predict RUL which indicated the end of life of an asset and can be measured in time or other wear relevant units such as a distance/length or numbers of process cycles.

The end of useful life can be detected using some direct or indirect failure detection mechanism. A widespread indirect approach is based on condition monitoring by defining a threshold for one or more critical process indicators (KPI) which are defined by experience before the actual failure happens. In a condition-based maintenance scenario, the maintenance is triggered when the KPI reached this threshold. Figure 2 shows this principle. The lifetime of the asset varies depending on boundary conditions of other parameters or process indicators under which the asset is used, e.g., the temperature.

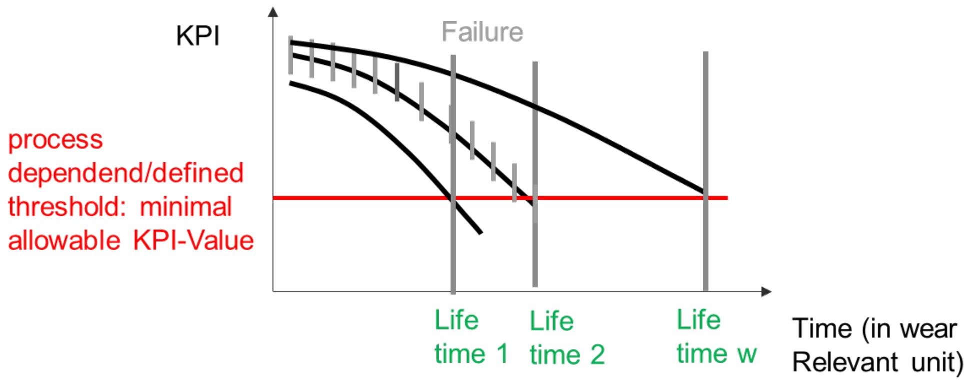

Figure 2: Different lifetimes of a component depending on process values, indirectly measured by a suitable KPI which reaches a certain threshold value to detect end of life.

An appropriate RUL prediction model predicts the time (in a wear-relevant unit) until the threshold, indicating the end of useful life is reached. Typically, this is done using a Machine Learning model (ML model), also called data driven model. Additionally, there are also use cases where physical models can be applied or a mixture of both, referred to as Hybrid Models [8]. An example of a hybrid model is illustrated in Figure 3. Input values to RUL prediction model can be material or asset properties, process values or process indicators which are impacting wear of the asset (model input values).

In case of data driven or hybrid models, these models are trained using historical or experimental data of the model input values and remaining useful life times (output of the model) for different boundary conditions of using the asset (e.g., with high and low temperatures). The performance measures used during model training provide information about model behaviour from which a confidence interval can be derived mathematically. A confidence interval in ML represents a range of values within which a model's prediction or estimated parameter is likely to fall, with a certain probability (typically 95%). It quantifies the uncertainty in model outputs and helps assess the reliability of predictions [11].

An additional criterion for assessing the reliability of predictions is to check if the values of the input indicators are within the range of values used during training (boundary conditions). If they are, the model is interpolating, and the confidence interval is valid. If they are outside this range, the model has the extrapolate, and the confidence interval might not be valid anymore. This topic can additionally be monitored using different data drift detection techniques. Data drift detection in machine learning refers to a metric or technique used to detect changes in data distribution over time, which can impact model performance [12]. Drift occurs when the statistical properties of input data or output values shift away from the training distribution, leading to model performance degradation.

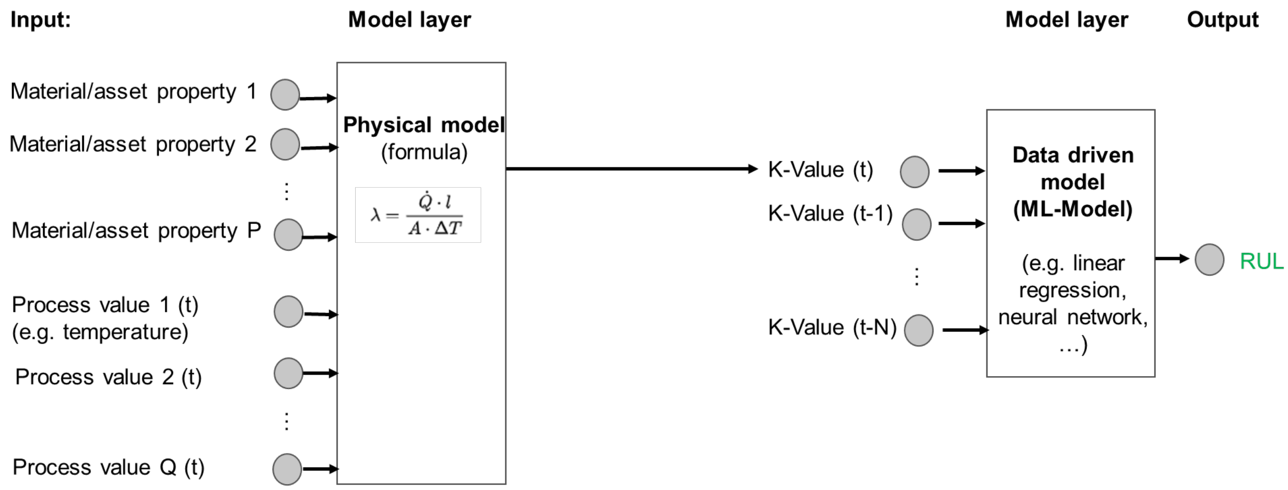

Figure 3: Example of a prediction model for the remaining useful life (RUL) with different input values such as material or asset properties and process values. Depicted is a hybrid model, which consists of physical and data driven model parts. In general, the model can be physical, data driven (using machine learning) or hybrid.

1.4.2 Design decisions

1.4.2.1 Focusing on Remaining Useful Life Information

The management of RUL-prediction models and their data is not part of the Submodel Predictive Maintennace, since there is a separate set of AAS Submodels for managing such models in general (Artificial Intelligence Dataset, Artificial Intelligence Model Nameplate, Artificial Intelligence Deployment [17]). Moreover, the models themselves are often Intellectuel Property (IP) of PdM solution providers and therefore in a majority of cases not directly accessible.

Data from condition monitoring and fault detection which are important for training the RUL-prediction models is not detected directly in the Submodel Predictive Maintenance, because the topics condition monitoring and fault diagnosis / detection are also required in other contexts. Therefore, for these topics, the development of separate AAS Submodels is recommended (see Appendix B).

In addition, the last maintenance events based of PdM model outputs should also be stored in a global list of upcoming and historical maintenance events, accompanied by maintenance events resulting from predetermined and condition based events, rather than in the Submodel Predictive Maintenance itself.

1.4.2.2 Levels of Implementation

To understand on which level(s) the Submodel Predictive Maintenance should be implemented, it is important to look at the hierarchical structure for managing and representing industrial assets using the concept of Asset Administration Shells (AAS), as illustrated in Figure 4.

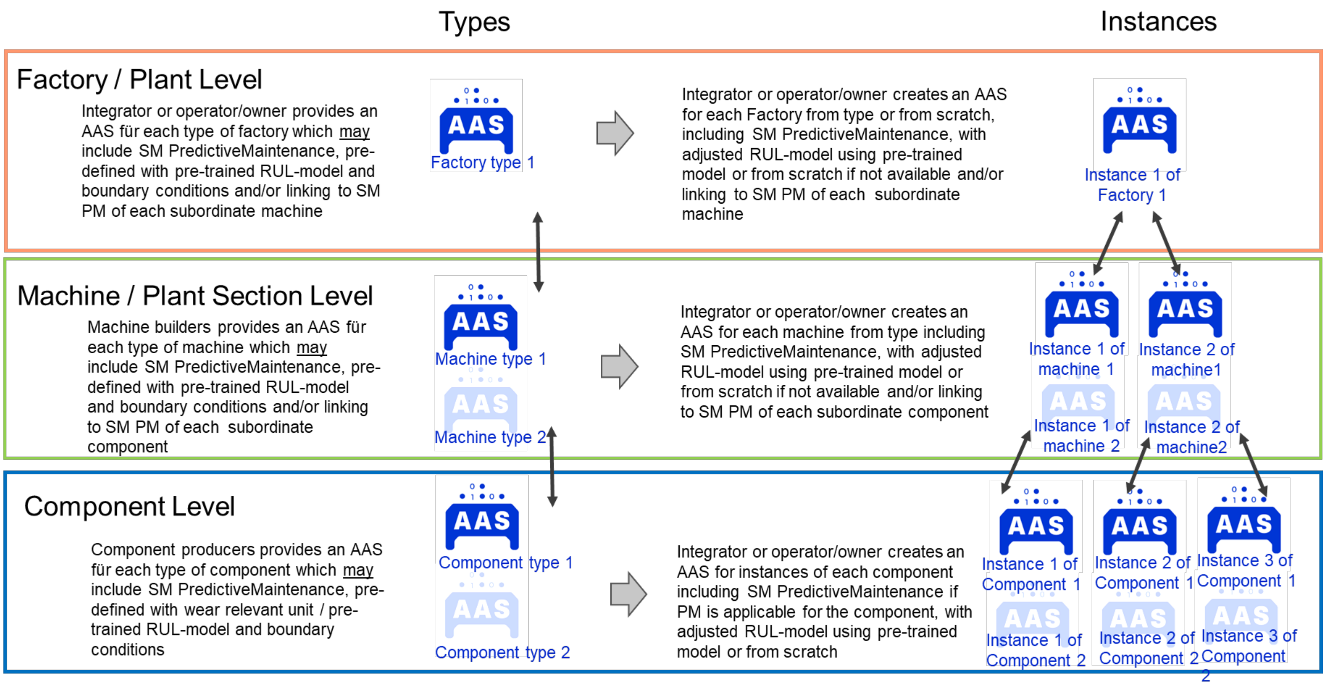

Figure 4: Schematic depiction of implementation levels of Submodel Predictive Maintenance

This structure is divided vertically into three levels: the factory level, the machine level, and the component level, emphasizing the relationship between types and instances at each layer. Horizontally, types and instances of the assets are considered.

1. **Factory / Plant Level**: At the top level, there is the Factory Type represented by an AAS. This type defines a generic representation or blueprint for a factory. Instances of this factory type are created to represent specific factories. These instances inherit the properties and attributes defined by the factory type, providing a digital twin for a particular real-world factory.
2. **Machine / Plant Section Level**: The next level focuses on machines within the factory or plant sections in process industry. It starts with Machine Types, represented by an AAS for each type of the machines. On this level, the type of a machine might be already equipment by the manufacturer of the machine with a Submodel Predictive Maintenance with information on a pretrained RUL-model, and corresponding boundary conditions, based on the historical data of this type of machines. Similar to the factory level, instances of these machine types are created to represent specific machines or plant sections working in different environments. These machine instances are connected to their corresponding type definitions, ensuring consistency in how machines are represented across the hierarchy, but contain their individual information depending on the environment they are running in. The AAS of these instances can have a Submodel Predictive Maintenance using the pre-trained RUL-model from the type or modified versions according to the individual data, or even their own RUL-models created from scratch, if not per-trained model is available in the type of the asset (See Figure 5).

3. **Component Level**: At the bottom level, individual types of components within machines are represented, each with their own AAS. The type of a component might be already equipped by the component provider with a Submodel Predictive Maintenance holding information on a pretrained RUL-model, and corresponding boundary conditions, based on historical data of machines of this type. Instances of these component types are created to represent specific components in the system running in different machines and environments. These instances are linked to their respective machine instances, illustrating the hierarchical and modular nature of the system. As on the machine level, the AAS of the instances of components can have a Submodel Predictive Maintenance using the pre-trained RUL-model from the type or modified versions according to the individual data, or even their own RUL-models created from scratch, if not per-trained model is available in the type of the asset. The integration of sub-systems into the PdM solution is simplified by providing semantic information of the sub-system in the AAS, without having to implement individual solutions for each sub-system. For the sub-system possible faults can be predefined semantically, and if a fault occurs corresponding information can be provided for the PdM solution.

The PdM solution can return information about the predicted remaining life time via the AAS to the asset, so that this information can be incorporated in the maintenance plan of the operator.

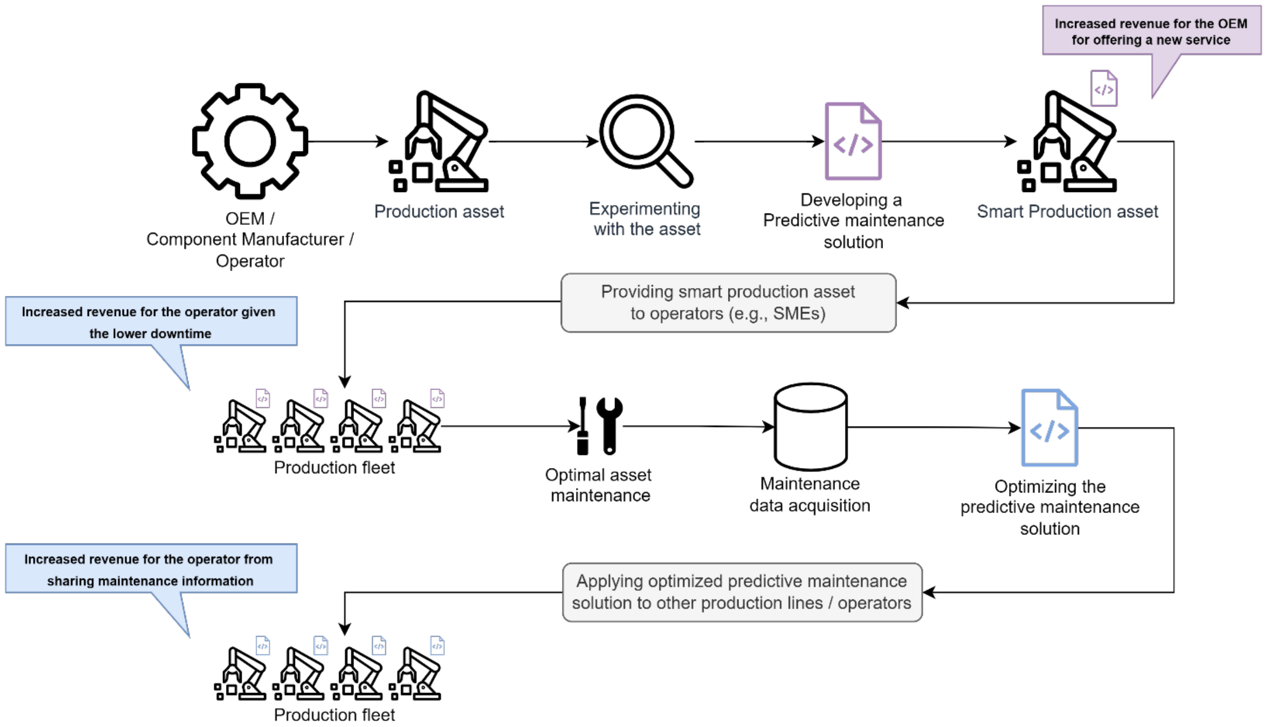

Figure 5: PdM as a service business model in smart production assets [13]

1.4.2.3 Concepts for describing the Remaining Useful Life (RUL)

The remaining useful life is defined as a value in wear relevant unit represented in the concept of Lifetime Model defined by the OPC Foundation [14]. This is a data model which allows to define a timespan expressed in a suitable unit, in the case of PdM a wear relevant unit (e.g. time, distance, cycle number), with additional meta information, such as the starting and end point of the time span.

1.4.3 Use case examples

1.4.3.1 Use case example 1: Predictive Maintenance for a temperature control unit in an injection molding production line

In injection molding, mold temperature control plays a crucial role in the stability of the manufacturing process and part quality. The corresponding temperature control devices are independent sub-systems of the injection molding machine and are therefore not necessarily integrated into the machine monitoring system. The unnoticed failure of a temperature control unit can result in expensive consequential damage to the tool, hot runner and machine. This might occur e.g., if the temperature control unit fails in a blind shift and the hot runner temperature is not reduced, the mold heats up to several hundred degrees Celsius (up to 300°C). In the worst case, this results in a tool defect, combined with financial damage of a five to six-digit amount in Euro.

Possible causes for a critical decrease in the cooling capacity or a failure of the temperature control unit are, for example, dirt and deposits in the lines, which lead to blockages over time.

By integrating the temperature control unit in the condition monitoring of the entire system, a corresponding failure can be detected at an early stage. The water flow or the decisive cooling capacity can be determined via the temperature difference at the inlet to the outlet of the temperature control unit and via the corresponding pressure difference. When monitoring a condition indicator based on these values, a warning can be triggered if the cooling capacity falls below a pre-set threshold. In addition, a data-driven model from historical data can be used to forecast the period or number of cycles until the threshold is reached and thus a Remaining Useful Life (RUL) can be predicted.

The staff can be warned beforehand about reaching the end of useful life by several pre-warning levels.

1.4.3.2 Use case example 2: Predictive Maintenance for a heat exchanger in process industry

In many industrial processes, heat exchangers play a crucial role in temperature regulation, ensuring stable operating conditions for machinery and production lines. One critical application is in industrial cooling systems used in sectors such as power plants, chemical processing, and food production. A failure or decline in performance of a heat exchanger can lead to overheating, process inefficiencies, and even costly equipment damage.

For instance, in chemical processing plants, cooling towers and heat exchangers regulate temperatures during exothermic reactions. A malfunctioning heat exchanger may cause excessive temperature buildup, potentially leading to safety hazards, production losses, or expensive damage to reactors.

The cooling efficiency of a heat exchanger can deteriorate over time due to several factors like

- Scaling and fouling: Accumulation of dirt, minerals, or biological growth reduces heat transfer efficiency.
- Blockages: Particles or debris in the cooling circuit can clog heat exchanger tubes.
- Corrosion: Internal degradation of the material impacts heat exchanger performance.
- Pump and flow issues: Reduced water or coolant flow affects heat dissipation.

One important KPI for monitoring the health status of a heat exchanger is thermal conductivity (K-Value). The K-Value tends to decrease over time by wear and the accumulation of dirt, minerals, etc.. If it reaches a certain threshold the heat exchanger should undergo maintenance or be replaced. Possible input indicators for a RUL-prediction model in this use case are temperature differences, heat flux, and material properties.

By implementing real-time monitoring and predictive maintenance for heat exchangers, industries can minimize downtime, prevent failures, and ensure stable and efficient operations. Integrating sensor data, condition-based alerts, and RUL prediction transforms traditional reactive maintenance into a proactive strategy, maximizing efficiency and reliability.

2 Submodel Predictive Maintenance

2.1 Approach

There are three main sections in which information is provided by the Submodel:

2.1.1 Remaining Useful Life (RUL) Time

The remaining useful life is defined as a value in wear relevant unit represented in the concept of Lifetime Model defined by the OPC Foundation [14], as a timespan expressed in a wear relevant engineering unit (e.g., time, distance, cycle number), with additional meta information, such as the starting point of the time span.

Applying this concept to the Remaining Useful Life (RUL) prediction means that the DurationValue is the (time)span until the remaining useful life is predicted to end, starting with the StartValue in the same engineering unit as a reference. The DurationValue and StartValue is updated each time when the model predicts a new value for the RUL. The StartValue may be updated when a maintenance action takes place (e.g., if a cycle counter is reset to zero during the maintenance action). E.g., if wear is depending on the number of production cycles of a machine the values StartValue=10,000, DurationValue=2,000 indicate that the RUL ends after 12,000 cycles. If for example the model updates its prediction after 200 cycles the next values are StartValue=10,200, DurationValue=1,800.

In addition a timestamp can be defined (property RemainingUsefulLifeDateTime), which describes at which date and time the useful life ends.

This RUL information is accomplished by a confidence interval of the model used for prediction.

2.1.2 Boundary Conditions

To understand how to interpret the calculated RUL it is also important to make information available on the boundary conditions for which the RUL prediction takes place (SMC ListRULBoundaryConditions). The boundary conditions are defined by value ranges for parameters which are used in the model for rule prediction and additional parameters.

2.1.3 Model information

The model used for RUL prediction can be described by model type as an enumerated list (property ModelType) with labels:

- ModelTypePhysical
- ModelTypeDataDriven
- ModelTypeHybrid

In addition a text description for the model can be provided.

2.1.4 Alerts

Pre-alerts can be defined before reaching end of useful life using the SMC ListPreAlerts. A pre-alert is characterized by an event (AlertEvent), a message (PreAlertMessage) and a value (PreAlertValue) which defines the duration when the alert is trigger before reaching end of useful life, in wear relevant units.

2.2 UML-Diagram of the Submodel Predictive Maintenance

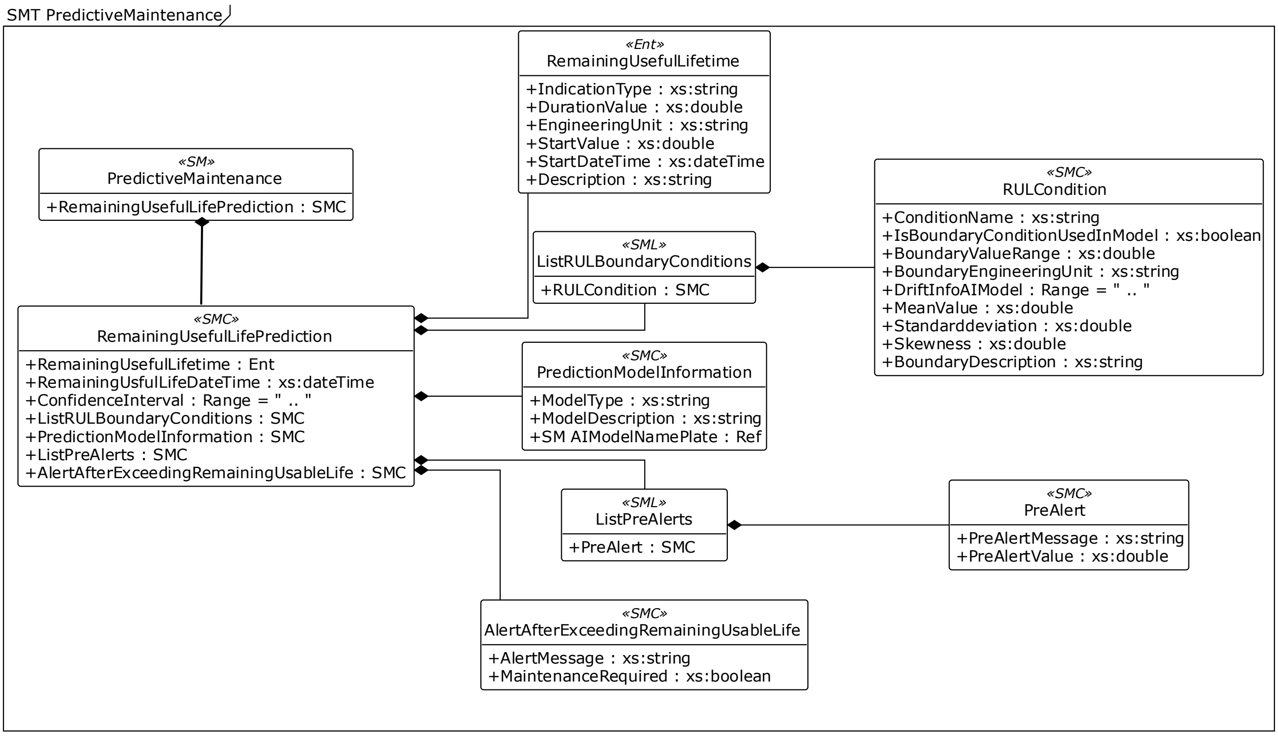

Figure 6: UML diagram of Submodel Predictive Maintenance

2.3 Elements of the Submodel Predictive Maintenance

Table 2 Elements of Submodel "Predictive Maintenance"

idShort:	PredictiveMaintenance		
Class:	Submodel (SM)		
semanticId:	[IRI] https://admin-shell.io/idta/SubmodelTemplate/PredictiveMaintenance/1/0		
Parent:	Asset Administration Shell, to which the predictive maintenance shall be associated to		
Explanation:	The Submodel Predictive Maintenance is a collection of properties to provide information for predictive maintenance use cases. It is intended to use this Submodel in sub-systems of production lines to describe predictive maintenance relevant topics for the asset, as well as to use this Submodel in predictive maintenance software applications.		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[SMC] RemainingUsefulLifePrediction	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/RemainingUsefulLifePrediction/1/0 Information about remaining useful life (RUL) prediction in the context of predictive maintenance	n/a	1

Table 3 Elements of SMC “RemainingUsefulLifePrediction”

idShort:	RemainingUsefulLifePrediction		
Class:	SubmodelElementCollection (SMC)		
semanticId:	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/RemainingUsefulLifePrediction/1/0		
Parent:	RemainingUsefulLifePrediction		
Explanation:	Information about remaining useful life (RUL) prediction in the context of predictive maintenance		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[Ent] RemainingUsefulLifetime	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/RemainingUsefulLifetime/1/0 Remaining useful life time, based on Lifetime model of OPC Foundation (https://reference.opcfoundation.org/DI/v104/docs/10)	[-] n/a	1
[Prop] RemainingUsfulLifeDateTime	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/RemainingUsfulLifeDateTime/1/0 mark attributed to an instant by means of a specified timescale, expressed as a date and a time.	[DateTime] 2025/05/14 20:46:00	0..1
[Range] ConfidenceInterval	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/ConfidenceInterval/1/0 confidence interval, measured in the unit of the predicted value	[-] 750 .. 850	1
[SML] ListRULBoundaryConditions	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/ListRULBoundaryConditions/1/0 List of boundary conditions for which remaining useful life has been predicted.	[-] n/a	1
[SMC] PredictionModelInformation	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/PredictionModelInformation/1/0 Information about the model for RUL prediction relevant in the context of predictive maintenance.	[-] n/a	1
[SML] ListPreAlerts	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/ListPreAlerts/1/0 List for defining pre-alerts which should be raised before remaining useful life is exceeded.	[-] n/a	0..1
[SMC] AlertAfterExceedingRemainingUsableLife	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/AlertAfterExceedingRemainingUsableLife/1/0	[-] n/a	0..1

	Alert information which should be triggered or displayed after exceeding remaining useful life.		

Table 4 Elements of the Entity "RemainingUsefulLifetime"

idShort:	RemainingUsefulLifetime		
Class:	Entity (ENT)		
semanticId:	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/RemainingUsefulLifetime/1/0		
Parent:	RemainingUsefulLifePrediction		
Explanation:	Remaining useful life time, based on Lifetime model of OPC Foundation (https://reference.opcfoundation.org/DI/v104/docs/10)		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[Prop] IndicationType	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/IndicationType/1/0 Type of wear-relevant duration, e.g. time, cycles, distance, etc.	[String] time	1
[Prop] DurationValue	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/DurationValue/1/0 Value of duration in the wear relevant unit, e.g. time, operation cycles, distance, etc.	[Double] 800	1
[Prop] EngineeringUnit	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/EngineeringUnit/1/0 Wear relevant physical unit, e.g. time, operation cycles, distance, etc.@en	[String] hour	1
[Prop] StartValue	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/StartValue/1/0 Starting value from which the duration is measured in the wear-relevant unit, e.g. time, cycles, distance, etc.	[Double] 2500	1
[Prop] StartDateTime	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/StartDateTime/1/0 Start date and time from which the duration is measured.	[DateTime] 2025/02/03 12:46:00	0..1
[Prop] Description	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/Description/1/0 Description of the wear duration information.	[String] operation time	0..1

Table 5 Elements of SML “ListRULBoundaryConditions”

idShort:	ListRULBoundaryConditions		
Class:	SubmodelElementList (SML)		
semanticId:	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/ListRULBoundaryConditions/1/0		
Parent:	RemainingUsefulLifePrediction		
Explanation:	List of boundary conditions for which remaining useful life has been predicted.		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[SMC] RULCondition	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/RULCondition/1/0 Boundary condition for which remaining useful life has been predicted.	[-] n/a	1

Table 6 Elements of SMC “RULCondition”

idShort:	RULCondition		
Class:	SubmodelElementCollection		
semanticId:	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/RULCondition/1/0		
Parent:	ListRULBoundaryConditions		
Explanation:	Boundary condition for which remaining useful life has been predicted.		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[Prop] ConditionName	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/ConditionName/1/0 Name of the indicator (process value, KPI, material property, asset property) describing a boundary condition for which RUL prediction is valid.	[String] fluid temperature 1	1
[Prop] IsBoundaryConditionUsedInModel	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/IsBoundaryConditionUsedInModel/1/0 If this boundary condition is used in the model for RUL prediction true, else false.	[Boolean] true	1
[Range] BoundaryValueRange	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/BoundaryValueRange/1/0 Value range of the indicator (process value, KPI, material property, asset property) describing a boundary condition for which RUL prediction is valid.	[Double] 40.5..55.4	1

[Prop] BoundaryEngineeringUnit	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/BoundaryEngineeringUnit/1/0 Engineering Unit of the boundary condition indicator,	[String] °C	1
[Prop] DriftInfoAIModel	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/DriftInfoAIModel/1/0 Drift information of AI model.	[Double] 0.62	0..1
[Prop] MeanValue	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/MeanValue/1/0 Mean value of the distribution of indicator values	[Double] 48.0	0..1
[Prop] Standarddeviation	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/Standarddeviation/1/0 Standard deviation of the distribution of indicator values	[Double] 3.4	0..1
[Prop] Skewness	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/Skewness/1/0 Skewness of the distribution of indicator values.	[Double] 1.2	0..1
[Prop] BoundaryDescription	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/BoundaryDescription/1/0 Description of the boundary of a RUL prediction condition.	[String] temperature data of the fluid in the heat exchanger	0..1

Table 7 Elements of SMC "PredictionModelInformation"

idShort:	PredictionModelInformation		
Class:	SubmodelElementCollection		
semanticId:	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/PredictionModelInformation/1/0		
Parent:	RemainingUsefulLifePrediction		
Explanation:	Information about the model for RUL prediction relevant in the context of predictive maintenance		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[Prop] ModelType	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/ModelType/1/0 Model type as an enumerated value: physical based methods, data-driven methods, hybrid methods.	[String] hybrid	1

[Prop] ModelDescription	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/ModelDescription/1/0 More detailed description of the model type used for RUL prediction (optional).	[String] Hybrid model with a physical model which calculates the thermal conductivity (K-Value) from the temperature difference, etc.	0..1
[Ref] SM AIModelNamePlate	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/SMAIModelNamePlate/1/0 Reference to AIModelNameplate.	[-] https://admin-shell.io/idta/AIModelTemplate/ids/cd/0085_9091_4032_5460	0..1

Table 8 Elements of SML “ListPreAlerts”

idShort:	ListPreAlerts		
Class:	SubmodelElementList (SML)		
semanticId:	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/ListPreAlerts/1/0		
Parent:	RemainingUsefulLifePrediction		
Explanation:	List for defining pre-alerts which should be raised before remaining useful life is exceeded		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[SMC] PreAlert_00	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/PreAlerts/1/0 Definition of a pre-alert which should be raised before remaining useful life is exceeded.	[-] n/a	0..*

Table 9 Elements of SMC “PreAlert”

idShort:	PreAlert		
Class:	SubmodelElementCollection		
semanticId:	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/PreAlerts/1/0		
Parent:	ListPreAlerts		
Explanation:	Definition of a pre-alert which should be raised before remaining useful life is exceeded.		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[Prop] PreAlertMessage	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/PreAlertMessage/1/0	[String] Alert one week	1

	Message to be displayed when alarm regarding predicted remaining useful life is raised.	before end of RUL	
[Prop] PreAlertValue	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/PreAlertValue/1/0 Pre-warning duration in wear relevant unit before remaining useful life is exceeded.	[Double] 168.0	1

Table 10 Elements of SMC "AlertAfterExceedingRemainingUsableLife"

idShort:	AlertAfterExceedingRemainingUsableLife		
Class:	SubmodelElementCollection		
semanticId:	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/AlertAfterExceedingRemainingUsableLife/1/0		
Parent:	RemainingUsefulLifePrediction		
Explanation:	Alert information which should be triggered or displayed after exceeding remaining useful life.		
[SME type]	**semanticId = [idType]value**	**[valueType]**	**card.**
idShort	**Description@en**	**example**	
[Prop] AlertMessage	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/AlertMessage/1/0 Message to be displayed when alarm regarding predicted remaining useful life is raised.	[String] End of RUL reached	1
[Prop] MaintenanceRequired	[IRI] https://admin-shell.io/idta/PredictiveMaintenance/MaintenanceRequired/1/0 Maintenance required@en,Wartung erforderlich@de	[Boolean] true	1

Annex A. Explanations on used table formats

1. General

The used tables in this document try to outline information as concise as possible. They do not convey all information on Submodels and SubmodelElements. For this purpose, the definitive definitions are given by a separate file in form of an AASX file of the Submodel template and its elements.

2. Tables on Submodels and SubmodelElements

For clarity and brevity, a set of rules is used for the tables for describing Submodels and SubmodelElements.

- The tables follow in principle the same conventions as in [5].
- The table heads abbreviate 'cardinality' with 'card'.
- The tables often place two informations in different rows of the same table cell. In this case, the first information is marked out by sharp brackets [] form the second information. A special case are the semanticIds, which are marked out by the format: (type)(local)[idType]value.
- The types of SubmodelElements are abbreviated:

SME type	SubmodelElement type
Property	Property
MLP	MultiLanguageProperty
Range	Range
File	File
Blob	Blob
Ref	ReferenceElement
Rel	RelationshipElement
SMC	SubmodelElementCollection

- If an idShort ends with '__00__', this indicates a suffix of the respective length (here: 2) of decimal digits, in order to make the idShort unique. A different idShort might be chosen, as long as it is unique in the parent's context.
- The Keys of semanticId in the main section feature only idType and value, such as: [IRI]https://admin-shell.io/vdi/2770/1/0/DocumentId/Id. The attributes "type" and "local" (typically "ConceptDescription" and "(local)" or "GlobalReference" and (no-local)") need to be set accordingly; see [6].
- If a table does not contain a column with "parent" heading, all represented attributes share the same parent. This parent is denoted in the head of the table.
- Multi-language strings are represented by the text value, followed by '@'-character and the ISO 639 language code: example@EN.
- The [valueType] is only given for Properties.

Annex B. Future Vision

The Predictive Maintenance Submodel is just one of several existing and potential Submodels within the broader field of maintenance. To establish a systematic overview and a future-oriented vision of asset maintenance within the context of the AAS, during IDTA Maintenance Expert Discussions a common understanding of how Predictive Maintenance fits among other maintenance types—such as Corrective, Predetermined, Preventive, and Condition-Based Maintenance has been developed.

This understanding is illustrated in Figure 3, with a focus on Predictive Maintenance, highlighting the integration of PdM and its connections to other Submodels. In the future, Submodels may also be developed for each of these maintenance types, if deemed suitable. Depicted is a potential variant of implementation, which considers an AI model.

In the preparation of maintenance, these Submodels can be provided with generalized data specific to asset types, in addition to Maintenance Instructions. These maintenance Submodels can then be assigned to individual asset instances, incorporating asset-specific maintenance information, such as Remaining Useful Life (RUL) data for Predictive Maintenance.

The various maintenance schedules that emerge from the different maintenance types can be organized and finalized within a potential Maintenance Plan Submodel, which would serve as a central point for managing and executing specific maintenance actions.

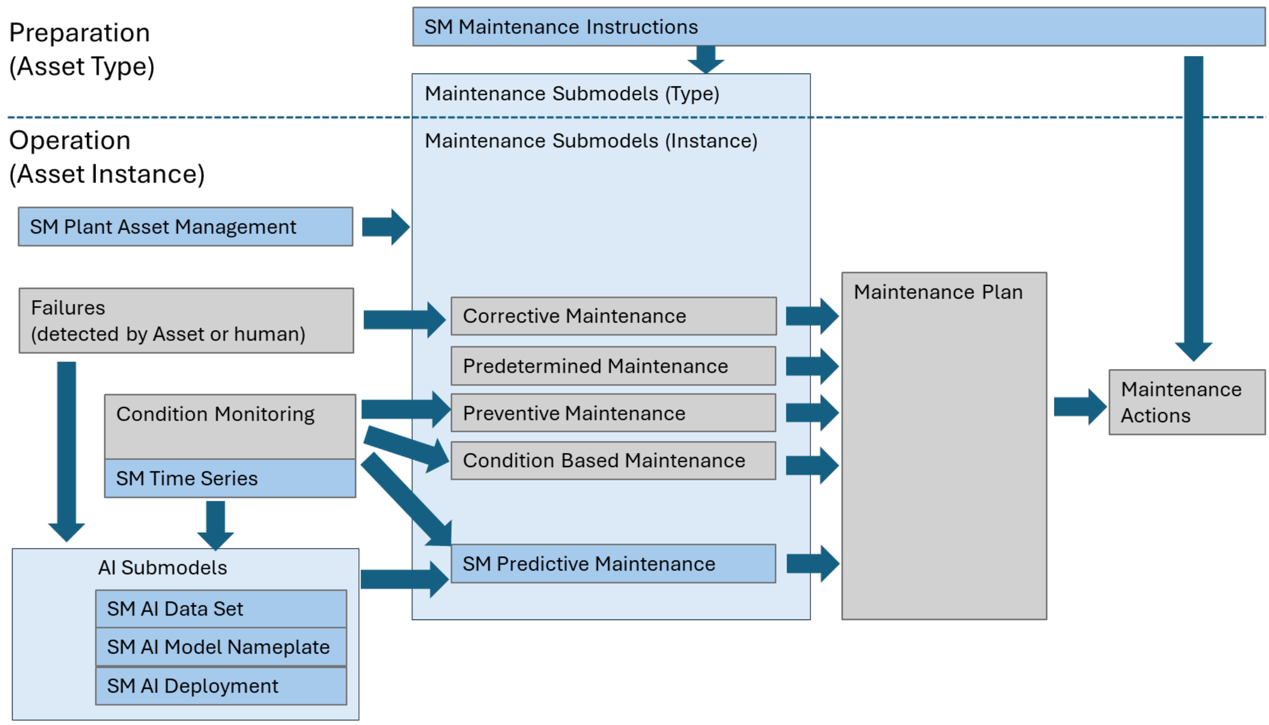

Figure 3: Schematic overview of a potential orchestration of Submodels in the context of Maintenance. Blue: existing Submodels [10, 15, 16, 17], Grey: potential future Submodels. The figure illustrates a subset of the maintenance landscape, highlighting connections between Submodels while acknowledging additional links to other Submodels.

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