# Applying Prognostics and Health Management to Optimize Safety and Sustainability at the First Adaptive High-Rise Structure

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## Abstract

Prognostics and Health Management (PHM) offers the potential to increase the acceptance of adaptive structures and to operate them in an optimal way. With suitable design and proper operation, adaptive high-rise structures enable significant increases in sustainability and service life extensions compared to passive high-rise buildings. The control loop for PHM provides a systematic overview of the contents related to PHM and their sequence. However, a framework is required for application to a complex adaptive system. Such a framework is presented in this paper. The framework is divided into the areas of system analysis and modeling as well as the PHM solution. A systematic approach is used to analyze the system and create the basis for full integration of all functional domains. This is then used in modeling to develop an adapted model structure. Finally, the PHM solution looks at the details of the approaches for diagnosis, prognosis, and health management.

## 1. Motivation

The construction industry consumes significant resources and is responsible for a considerable proportion of $CO_2$ emissions (Thibaut Abergel & Dulac, 2018; OECD, 2015). Traditional load-bearing structures are typically designed for infrequent critical load cases. Additionally, there are numerous uncertainties, which are compensated in the design by safety factors. As a result, the load-bearing structure is often significantly oversized for most of its service life, which leads to increased resource demands and $CO_2$ emissions (Efinger et al., 2022). Actuators can be used to induce displacements, homogenize stresses in structures, and actively dampen vibrations. This enables the structural mass of such adaptive load-bearing structures to be reduced compared to passive structures by targeted reduction of cross-sections. In addition, the actuators need to be integrated into the structure and complemented by associated systems – including measurement systems, control systems and energy supply. Adaptive load-bearing structures offer the potential to save structural mass and – through suitable operation – to be more sustainable than conventional passive load-bearing structures (Efinger et al., 2022). At the same time, ensuring sustainability should not come at the expense of safety or serviceability. On the other hand, unnecessarily frequent maintenance measures need to be avoided for both sustainability and economic reasons. However, in addition to the parameter space for maintenance, there is also the parameter space for adaptivity control. This includes determining when which actuators exert how much force on the system and in what combination. As a result, stiffness and damping are controlled locally at the individual points, but also globally in the load-bearing structure. Depending on this, static and dynamic effects develop under the respective load, and more or less damage occurs in the individual elements of the structure. For both operation and maintenance, short, medium, and long-term objectives must also be considered and balanced. This high-dimensional problem cannot be solved with conventional methods for operating or maintenance strategies.

Prognostics and Health Management (PHM) offers the potential to improve the reliability and availability of technically complex systems in line with requirements. A comprehensive understanding of the application of PHM is crucial, especially when it comes to developing customized PHM solutions for complex systems.

The challenge in developing a universally applicable PHM solution lies in the high complexity and variability of the systems. Henß (Henß, 2021) highlights this problem and proposes a PHM control loop that offers a general approach to implementing PHM. However, this still needs to be embedded in the system for the application itself. To that end, this paper provides a framework that enables the practical implementation of the PHM solution and provides a structured approach for applying PHM to the complex system of an adaptive high-rise building.

To do this, a framework is presented that is specifically designed to apply PHM to complex systems. This framework serves as both a method and a framework to enable effective implementation of PHM strategies. It is divided into two main parts: *System analysis and modeling* as well as *PHM-solution*.

In order to achieve this objective, section 2 – **basics** – initially introduces adaptive systems, the high-rise structure that serves as an example, and the PHM control loop.

Section 3, **system analysis and modeling**, focuses on understanding and modeling the specific features and behavior of the system under consideration. This phase is fundamental for the development of accurate predictive models and for the identification of relevant system parameters that are important for condition assessment and prediction.

This is followed by the **PHM-solution** in section 4, which comprises the development and implementation of solutions based on the findings and models of the system analysis. Specific techniques and procedures are used to implement system prognostic and the optimization of the system based on this.

Finally, section 5 gives a **summary**.

## 2. Basics

This section introduces relevant basics for the adaptive system and introduces the PHM control loop.

### 2.1. Adaptive Systems

Systems that actively change with the help of sensors and actuators are referred to as adaptive systems. The system interacts with the environment and manipulates loads, for example, in such a way that load peaks are avoided (Sobek, Haase, & Teuffel, 2000). Adaptivity is enabled by a control process, whereby the input signals are fed into the system through sensors.

### 2.2. The D1244

The world's first adaptive high-rise building is called D1244. D1244 is a multi-functional experimental platform and is located on the campus of the University of Stuttgart. The load-bearing structure is activated by hydraulic actuators. Hydraulic pressure accumulators close to the cylinders ensure homogenization of the system pressure and minimize the switching requirements for the hydraulic pump. A central control unit and several module control units are available to control the hydraulic actuators, which are actuated by electro-hydraulic valves. Various sensors provide the controls with information on the load-bearing structure, the actuator system, and the ambient conditions. There are strain gauges for strain measurement in a redundant arrangement on the pillars and diagonals. LEDs mounted on the outer shell in the transition between the modules of the load-bearing structure serve as measuring points for an optical measuring system that uses cameras on two sides to record relative displacements and deformations of the load-bearing structure. The change in displacement of the actuators is recorded using displacement measuring systems on the hydraulic cylinders. There is a weather station on the roof of the building that records wind speed and wind direction.

### 2.3. Control of the Adaptive Structure D1244

The control loop contains the physical system, from which relevant variables such as stresses, deflection and other measured variables are recorded, a Kalman filter (KF) for condition monitoring and a linear-quadratic regulator (LQR) for controlling the adaptive components. Using the KF as an observer and estimator, the current system state $\hat{x}$ is estimated and iteratively transferred to the controller by a feedback loop. This allows unknown system variables to be determined and the system to self-adapt (Ostertag, 2021). Finite element models are used to investigate the equation of motion of the mechanical structure. The finite element method is used for the dynamic analysis of structures and the equation of motion of the structure. The discretization of the FE model at the nodal points results in the equation of motion according to (Ostertag, 2021; Gienger, Schaut, Sawodny, & Tarin, 2020):

$$M\ddot{q} + D\dot{q} + Kq = F_u u_{act} + F_\nu(\nu) \tag{1}$$

with the following boundary conditions:

$$\dot{q}(0) = \dot{q}_0, \;\; q(0) = q_0. \tag{2}$$

### 2.4. PHM Control Loop

The PHM control loop, as introduced by Henß (Henß, 2021), represents a systematic approach to optimizing the operation and maintenance of technically complex systems. Central to the control loop is the continuous interaction between the system and its optimization based on data from measurements, diagnosis, and prognosis. The optimization is fed directly back into the system, creating a closed loop that leads to continuous improvement.

The control loop can be abstractly divided into three main areas:

1. **Condition assessment:** This includes collecting data and analyzing it to determine the current system status.
2. **Forecast approaches:** Based on the condition assessment, a prediction is made about the future condition of the system.
3. **Optimization approach:** The results of the condition assessment and forecast are used to define and implement measures to improve the system.

Figure 1, based on (Henß, 2021), illustrates the PHM control loop including the three main areas formed. This illus-

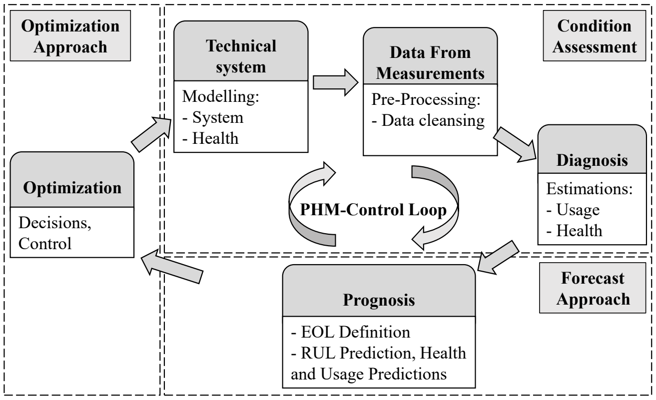


Figure 1. PHM control loop with its three main areas.

tration demonstrates the dynamic and cyclical nature of the PHM approach, which is based on continuous improvement and adaptation.

The condition assessment includes the evaluation of the system (system and health modeling), the evaluation of the data (data collection and cleansing) and the diagnosis (state estimation). This classification enables a precise assessment of the system and health statuses, based on which estimates can be made for the current state. Based on the estimates determined from the diagnosis, the predicted range within the condition forecast is determined. The downtime or, if an end-of-life definition has been selected, the remaining useful life (RUL) can be calculated. The basis for this is, among other things, the history to date. If information on future changes is available, these can also be considered. During optimization, the adjustable system settings are adjusted so that the objective function is as optimal as possible within the scope of the observation horizon. The information from the condition assessment and condition forecast is used for optimization. This holistic approach enables proactive maintenance and the optimization of operating processes, which leads to an extension of the service life and an increase in the efficiency of systems.

## 3. System Analysis and Modeling

This paper is built around the D1244 system, which offers ideal conditions for the application of PHM due to its complexity and adaptive capabilities. The special feature of the D1244 lies in the large number of influencing variables and the associated uncertainties. This makes the implementation of PHM a challenging task.

For a comprehensive integration of PHM into a complex system – such as an adaptive high-rise structure – a systematic approach is required. This is dealt with as part of the framework in this section. It is further subdivided into the steps of system analysis and modeling. During the system analysis in subsection 3.1, all aspects relevant for modeling the PHM application are determined. The models and their interrelationships are then built on this basis in subsection 3.2.

### 3.1. System Analysis

This subsection develops the content to create models for state estimation, prediction, and health management. A comprehensive system analysis is carried out for this purpose. This begins with the overall objective, which also provides target parameters, followed by the system description. In addition, the requirements and boundary conditions for operation and its optimization are extracted. From this, the dimensions of the system are derived and supplemented by further conditions. Influencing factors are then identified on this basis. Lastly, uncertainties for the target parameters and the boundary conditions can be derived from the target parameters and influencing factors.

Once these steps have been completed, all areas are available for developing models for the PHM application.

#### 3.1.1. Objective

The objective of the PHM control loop according to Henß (Henß, 2021) is to operate and maintain the system in such a way that the target parameter is maximized, and the existing boundary conditions are met. A target parameter describes a measurable or countable variable from the objective. For the use case of the adaptive high-rise system this means:

Firstly, the environmental impact should be as low as possible, with the $CO_2$ equivalent being assessed. Secondly, increasing the service life of the system beyond a certain level may also be a further goal. Thirdly, this needs to be done in compliance with the requirements and boundary conditions.

There is now a conflict of interest between the goals of lowest possible $CO_2$ equivalence and increased service life. The lowest possible $CO_2$ equivalent would be achieved with the shortest possible service life and an increase in service life would presumably require additional $CO_2$ expenditure. For this reason, the $CO_2$ equivalent is used as a reference for its opposing benefit – i.e., the service life. This means that the $CO_2$ equivalent is normalized to the useful life. Nevertheless, it is possible that the target parameters compete. Therefore, an individual objective function needs to be formed for each use case from the existing target parameters and boundary conditions for multi-criteria optimization. This is implemented as part of the modeling in subsection 3.2.1.

#### 3.1.2. System Description

Now that the objective is set, it is important to clearly define what it applies to. The system description serves to make the system and its components tangible and to separate the area under investigation from the environment through a defined system boundary. In addition to a physical and a signal-related system boundary, the system boundary also includes a temporal dimension. For the example under investigation, this means:

The system of interest is the entire system of the adaptive high-rise structure, described in subsection 2.2. In addition to the load-bearing structure, this also include the functional domains of the actuators, various sensors, physical control, and transmission elements, the software control and the energy supply. Furthermore, maintenance with all its domains – including spare parts stocking, capacity planning, etc. – is also included in the system scope. Figure 2 shows the domains of the adaptive structure schematically and indicates their allocation. The temporal consideration starts from the beginning of the building usage until the end of the service life. The manner in which the adaptation function is carried out by the components of the adaptive system corresponds to the description in subsections 2.1 and 2.3. To do this, a functional adaptation function is required. If the adaptation function is to be performed and it is not functional, the adaptation function fails.

#### 3.1.3. Requirements and Boundary Conditions

The first question that arises for a defined system or its optimization is that of the general requirements and boundary conditions. They are set externally or internally and need to be fulfilled. There are elementary requirements for a structure such as a high-rise building. These include the fact that they have to enable their intended use and that they have to have a certain geometrical shape. Standards such as the Eurocodes formulate further requirements. There are also project-specific, definable requirements that the building has to fulfill. The probability of partial or total failure of the structure or its function is of central importance. Suitable measures must be taken to ensure that the probability of occurrence is lower than the limit values defined as acceptable. Typical design measures for this are redundancies in the functional structure or the oversizing of relevant structural components. The limit values to be fulfilled are, on the one hand, limit values for the designed service life and, on the other hand, limit values for failure at any time. The Eurocodes typically work with two different safety levels for buildings. The stricter one deals with the risk of structural failure. Whereas the less stringent one concerns, for example, the occurrence of non-failure-critical cracks or the occurrence of building vibrations that could potentially be perceived as unpleasant by users. While the stiffness – and therefore the vibration behavior – of passive load-bearing structures cannot be actively changed, this is possible with adaptive structures. This means that compliance with building vibrations defined for user comfort could be linked to the presence of users in the building. In this way, the limit value would change over time – if there were people in the building, it would take effect, if there are no people in the building, it could be raised.

#### 3.1.4. Dimensions

The existing dimensions can be developed based on the requirements and can be further enhanced based on the objective and the boundary conditions. To fulfill the requirements, the system has to perform functions, but these are not always requested in the same way.

For the D1244, this gives rise to the three existing dimensions – the function request dimension, the function availability dimension, and the temporal dimension. These are supplemented by additional criteria from the objective and the boundary conditions. From the objective, this are the target parameter of $CO_2$ equivalent and the extension of the service life. The boundary conditions provide the time-variable risk limit for the failure of the adaptation function.

The dimensions can be examined in more detail. The aspects to be found there can influence each other within the dimension as well as between the dimensions or are dependent on each other. For example, the temporal dimensions consist of endless gradations between the past, the present and the future. The dimension of function request is composed of the aspects of building usage, external influences such as wind and weather as well as the limits of safety levels.

However, the most comprehensive dimension is that of function availability. It can be divided into the physical system, non-adjustable and adjustable system properties, and system monitoring. The following lists show some of the contents.

Physical system:

- *Load-bearing structure:* Load capacity; Statics; Dynamics; Health
- *Actuators:* Dynamics; Fault; Failure; Health
- *Sensors:* Fault; Failure; Health
- *Physical control elements:* Dynamics; Fault; Failure; Health
- *Physical transmission elements:* Fault; Failure; Health
- *Energy supply:* Fault; Failure; Health

Non-adjustable system properties:

- *Function structure:* Redundancy; Compensation possibilities
- *Failure behavior individual elements:* Reliability; Health; Damage factor; Failure behavior

Adjustable system properties:

- *Control options:* Control limits; Control models; Actuators; Ph. control el.; Energy supply
- *Maintenance:* All physical domains; Spare parts; Tools; Personnel; Measures

System monitoring:

- *State detection:* Position; Force; Stress; Pressure; Motion; Acceleration; Control; Health; Maintenance; Usage; External influences; function request

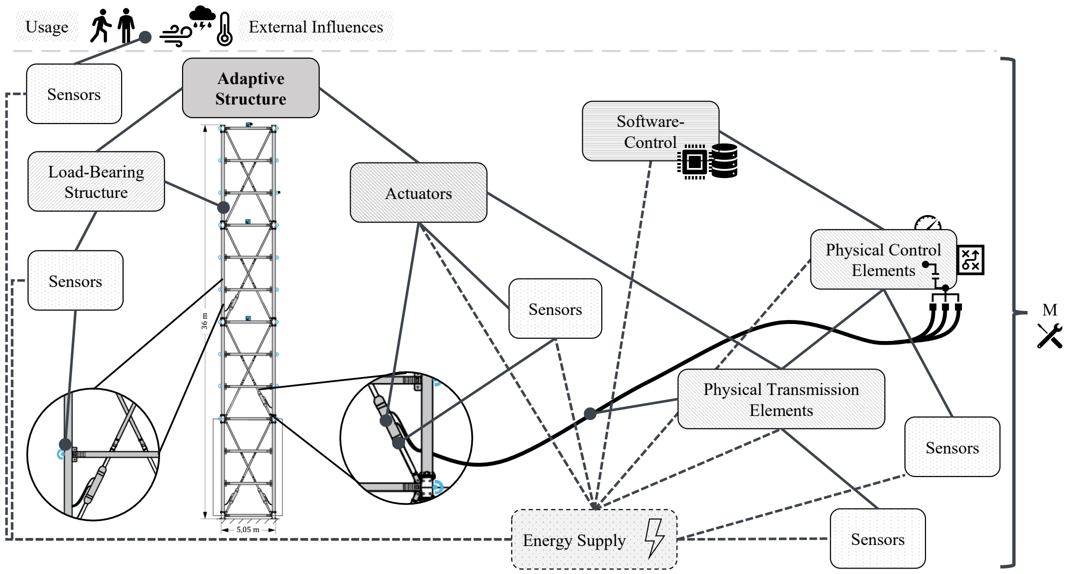


Figure 2. Schematic illustration of the system.

- *Fault detection:* All physical domains with exception of load-bearing structure; Control
- *Failure detection:* All physical domains; Control

Using the dimensions, the subsequent steps of the system analysis can be systematically examined for all existing aspects of the system. The dimensions can also be used to systematize the interconnection of aspects and dependencies in the functions for subsequent modeling. Aspects with identical themes can therefore be found in different dimensions.

### 3.1.5. Influencing Factors

This step collects all existing influencing factors. Influencing factor is anything that influences the fulfillment of the requirements, the boundary conditions, or the objective at any point in time. For the PHM application, the influencing factors needs to be divided into those that cannot be adjusted during operation, those that can only be adjusted indirectly and those that can be adjusted directly by PHM.

### 3.1.6. Uncertainties

Uncertainties describe a lack of or imprecise knowledge about something. To utilize the existing knowledge, it is necessary to quantify the uncertainty. Otherwise, unknown risks would be taken. These can be of an economic, social, or ethical nature. Uncertainties can be determined from the combination of target parameter and influencing factor as well as their relationship and classification in the existing dimensions.

Generalized uncertainties of the respective influencing factors from the following areas have to be taken into account. This applies to each measurement and model level and influences dependent model and system areas.

- Measurement uncertainties: Measurement errors, measurement data noise, etc.
- Model uncertainties: Model errors, model inaccuracies, etc.
- Stochastic effects
- Time

From the levels of the measured variables to the sub-models and the models, more influences of uncertainties are added. Some of these can be reduced using appropriate models to reduce uncertainties. An example of this is checking for measurement errors from sensor signals using a model that checks several sensor signals for plausibility and can perform error identification.

The temporal dimension plays a crucial role in uncertainties. In a present state, uncertainties from the areas of measurement uncertainty and model uncertainty can be present. If the corresponding data is available for the past, the situation is the same there. When considering future points in time, however, the uncertainty from the temporal development is always added. Figure 3 shows an uncertainty space that spans the areas of measurement and model uncertainties and the temporal dimension. There is no temporal uncertainty for the past and the present, provided that the data from the past is still fully available. For the future, however, the temporal uncertainty increases more with increasing temporal distance. The measurement uncertainty and the model uncertainty do not have a generalizable function from lower to greater uncertainty. They must be estimated individually for each case under consideration.

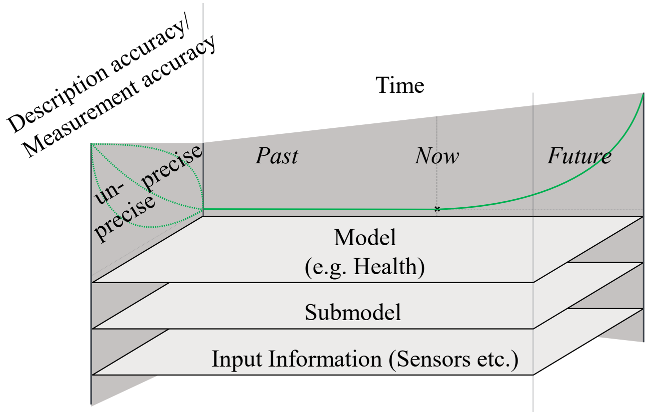


Figure 3. Illustration of a dimension model with dimensions of uncertainties.

### 3.2. Modeling

Subsection 3.2.1 establishes the target space and objective function based on results, requirements, and boundary conditions. The creation and interconnection of model structures across various levels are detailed in 3.2.2. System integration for the structural control of an adaptive high-rise structure is discussed in 3.2.3.

#### 3.2.1. Target Space and the Objective Function

The target space represents the scope in which all specifications and requirements are met. It therefore describes permissible solutions. The objective function defines the weighting of the target parameters in relation to each other. Permissible solutions fulfill all requirements, the best possible solutions achieve the highest values for the objective function. In concrete terms, this means that the probabilities of partial or total failure of the structure or its function must be always kept below the limit values and for the entire planned service life of the structure. Some of the limit values can change over time, depending on factors such as building occupancy. At the same time, the overriding objective is to achieve the lowest possible $CO_2$ equivalent and possibly an increase in the service life of the building. The weighting of the two target parameters needs to be described by way of a relationship. Further boundary conditions and target parameters are possible and could be added in the same way. The optimization of such an objective function is not trivially solvable for such a complex system. Therefore, the use of fuzzy logic is proposed in section 4 in order to enable an assessment of all influencing factors based on the information about the system using the hybrid approach described there.

#### 3.2.2. Model Structure

The development of the model structure relates to two designations of models and their structure. On the one hand, it is about the dimensional models and their interconnections. On the other hand, it is about functional models and their interaction.

**Function Models** The function models are divided into the three areas of condition assessment, forecast assessment and optimization approach introduced in subsection 2.4. Figure 4 also shows an overview of the structure of some function models for the PHM solution of the adaptive high-rise building. In accordance with the PHM control loop according to Henß and figure 1, the diagnosis in the condition assessment provides input for the prognosis in the forecast assessment and this for the optimization. Optimization continues until an accepted condition forecast is reached, for which the instruction to adjust the relevant influencing factors is given. In addition to these optimized adjustment instructions described above, there are also system variables that are also provided externally by the condition assessment from the PHM solution. The adjustment instructions contain parameters with different change behavior over time. For example, the instruction of a maintenance measure after several years of operation and with an execution time of several days or weeks. But also, the current state of stress on an element of the load-bearing structure or the pressure in one of the actuators.

- The **diagnostics** includes function models for the detection, determination or estimation of
  - Failures: for example of individual actuators, sensors, valves or load-bearing elements
  - Faults: for example in the measurements of sensors, the control behavior of valves or the control instructions of the control system
    For example, (Stiefelmaier, Böhm, Sawodny, & Tarín, 2023) provides a concept for detecting sensor or actuator faults that can be integrated.
  - System states: for example, for the individual parts of the load-bearing structure, actuators, sensors, feed and control systems, or maintenance processes in relation to their positions, mechanical or electrical stresses or hydraulic pressure, the dynamic state or the state of damage
- The **prognostics** contains function models for forecasting all states of the condition assessment. It is fed with information from the diagnostics. External predictions are also included. These include forecasts for wind and weather, personnel capacity, spare parts capacity and, if applicable, utilization and the planned remaining service life.
- **Optimization** takes place in Health Management. Function models are available to evaluate the optimized solution and to optimize the adjustable influencing factors.

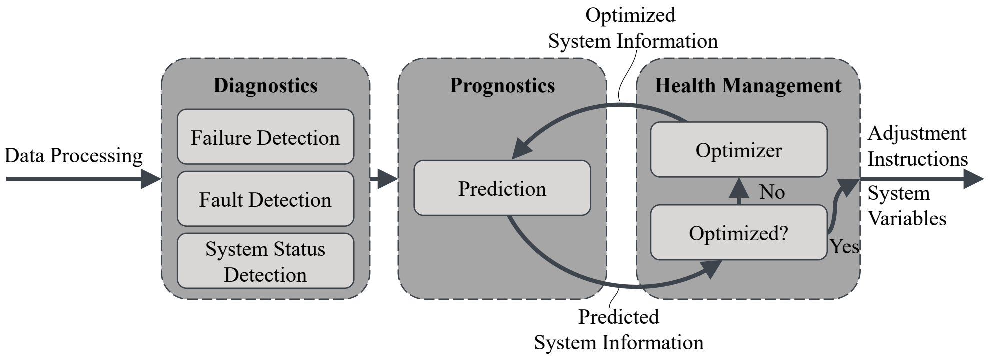


Figure 4. Some feature models of the PHM-solution.

**Dimension Models** The dimensional models or models of dimension aspects form different layers on top of the function models. They interact with each other and with the function models. Figure 3 shows such a dimension model using the example of health and taking the temporal dimension into account. The dimension model uses various input information, which is prepared and processed in sub-models before being merged in the dimension model.

The correlations can be illustrated using a simple example of a fault in the measured value of a sensor. In the case of fault detection in the measured value of a sensor, the function model for the fault detection is used to handle an influence from the dimension aspect of sensors. To assess whether or with which other sensor information an evaluation is possible, the model for the dimension aspect of function structure is used to work on redundancies or compensation options. These may be reduced in number by the results of the function model for failure detection. The temporal dimension may also be used to detect changes in the data history.

### 3.2.3. System Integration on the Example of Structural Control

This subsection uses the example of structure control to describe how system integration can be carried out with the PHM solution. To do this, we refer back to Figure 4 in the previous subsection. The PHM solution provides adjustment instructions. These must then be processed – for structural control in the control of the actuators. The system integration for structural control can be divided into two higher-level subareas if this is abstracted:

- Intelligent control model
- Intelligent monitoring and assessment model

The conventional approach from subsection 2.3 for controlling the high-rise demonstrator involves using a linear-quadratic controller in a closed control loop with feedback and a Kalman filter as an observer. This means that only a limited adaptation of the control behavior is possible.

In (Dakova, Heidingsfeld, Böhm, & Sawodny, 2022) the authors present an agent-based fatigue level controller through the use of a model predictive control (MPC) and the use of a cost function for the damage in the elements. This controller is adopted for structural control as a so-called score MPC. The PHM solution provides it with the control difference $e(t)$ and the optimized scores for each actuator as adjustment instructions. In this way, the PHM solution defines the intensity of the control and the distribution between the actuators in the system. The block diagram for the control loop is shown in Figure 5. The score MPC thus forms the intelligent control model, and the PHM solution forms the intelligent condition monitoring and evaluation model.

## 4. PHM-Solution

This section covers the diagnostics and prognostics approach, detailing the use of a hybrid model and a health management agent that utilizes optimized system information for improved control behavior. It also introduces a data-driven strategy employing fuzzy neural networks (FNN) to manage the complexity of the D1244 system. This method facilitates the efficient analysis of extensive, multi-layered data, enhancing decision-making in maintenance and operations. Fuzzy neural networks enable the PHM solution to adapt and refine predictions, crucial for addressing challenges in complex systems like the D12444.

### 4.1. Diagnostics and Prognostics Approach

The effective assessment and prediction of the health of complex systems have requirements that cannot be met by conventional approaches. As described by Kim et al. (Kim, An, & Choi, 2017), Goebel et al. (Goebel et al., 2017), and Si et al. (Si, Zhang, & Hu, 2017), hybrid approaches offer a promising solution. These approaches combine data-driven algorithms with physical degradation models to improve the accuracy of condition assessment and prediction.

Such a hybrid approach is made up of various sub-models, each of which depicts individual dimensions of the system,

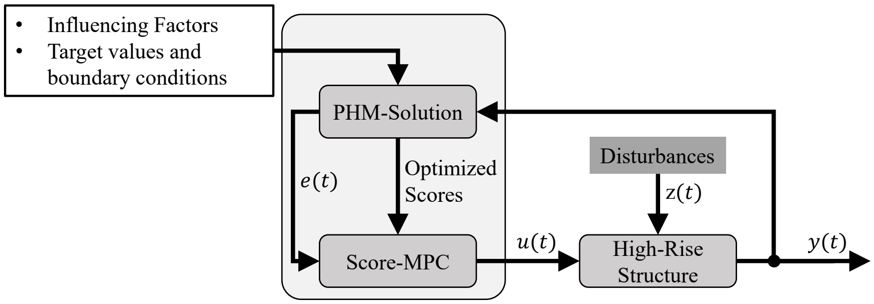


Figure 5. Control loop for the D1244 optimized for PHM application.

and which are linked together. Training and experience data are essential for the development and refinement of these approaches. This data includes not only the current measured values recorded by sensors, but also historical data that is used to calibrate and train the algorithms.

#### 4.1.1. Design of the Hybrid Approach

The hybrid approach combines data-driven and physically based models to enable a comprehensive analysis of the failure behavior of system components. Pure data-driven models based on mathematical functions can only approximate reality without taking underlying physical models into account. The integration of a physical model, on the other hand, enables a deeper insight into the behavior of the system. This combination not only increases the accuracy of the predictions, but also expands the database for training the algorithms and promotes a holistic understanding of the overall system.

A schematic setup for the application of such an hybrid approach to a complex adaptive system, such as the D1244, is shown in Figure 6. Data- and physics-based methods are used to both estimate the current state and predict the future state.

A degradation model forms the basis for making valid statements about the system based on sensor data and minimizing inaccuracies. The combination of data-driven findings and physical models provides a robust basis for the reliable evaluation and prediction of system performance.

To optimize the informative value of this approach, continuously recorded training data is integrated into the prediction models over the system's service life. This enables a flexible and effective response to unexpected system changes.

This approach distinguishes between two sub-models, which are discussed in detail in the following sections. These submodels are the state estimation and the state prediction.

#### 4.1.2. State Estimation

The state estimation serves as the basis and data foundation for the forecasting approaches. For this purpose, system and condition modeling is carried out and data from the technical system is recorded by sensors. The degradation model plays a key role here, as it provides a basis for the estimates. Degradation modeling is conducted using damage mechanisms on the components or estimates of the system modeling, for example using KF. The assessment of the condition takes place in the diagnosis: Through data, states that affect the use and health of a technical system are estimated in diagnostics based on collected information.

#### 4.1.3. State Prediction

In addition to current sensor data, the hybrid approach can also incorporate training data from past measurements for the state prediction. This allows the forecast to be improved. This therefore represents a continuously learning process.

### 4.2. Health Management Agent

During optimization, the predicted system information is finally optimized iteratively, and a decision is made for the system. Optimization goals such as fault tolerance, sustainability and fault prevention are considered, for example to enable proactive and environmentally friendly maintenance planning. Based on the optimized system information, the control behavior of the system can be adapted and improved.

Calculating the score is therefore one of the most important tasks of optimization and can be achieved by using fuzzy methods in combination with NN. The use of FNN has the advantage that a more precise classification and assignment of the optimized system variables is possible and thus a more precise score calculation can be realized for the respective actuators.

#### 4.2.1. Optimization of System Information

The optimization of the predicted system information as part of health management aims to improve the service life and added value over the entire life cycle by integrating optimization factors. This strategic adjustment affects both maintenance planning and the efficiency of use of the system components. Through targeted control, component functions can be adapted not only to extend the service life but also to

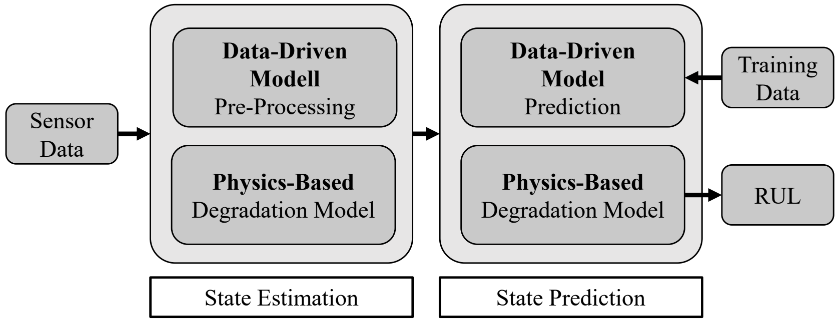


Figure 6. Schematic setup of the hybrid approach for a complex system.

prevent premature failures. The process is iterative and is based on the continuous analysis of the remaining useful life (RUL), which considers both risk factors and life cycle analysis (LCA) factors. This comprehensive approach enables dynamic adaptation of maintenance strategies and a flexible response to changing operating conditions or new findings about the condition of the components. By integrating both data-driven insights and physical model assumptions, a more precise forecast and thus more effective planning and control of maintenance measures is achieved.

The continuous improvement of the management system through this iterative approach not only supports an extended service life and increased reliability of the system components, but also helps to reduce maintenance costs and increase overall efficiency. This methodical approach is therefore an essential part of strategic maintenance and operational management, creating a balance between preventive maintenance and operational flexibility.

#### 4.2.2. AI-Supported Optimization Using Fuzzy Neural Networks

At the core of the Prognostics and Health Management solution is the implementation of fuzzy neural networks, which use the hybrid approach to make adaptive decisions regarding the system components and adjust the control behavior accordingly. Embedding fuzzy logic (FL) in neural networks enhances their ability to precisely interpret and process complex system states and dynamics. FL mimics human thinking by making it possible to represent complex relationships in an understandable form. In addition, the use of FL enables a sophisticated analysis of uncertainties and ambiguities within the system data, allowing FNNs to make efficient decisions even in the presence of incomplete or fuzzy information. Fuzzy sets and rules are directly integrated into the structure of the neural networks, resulting in a synergetic architecture of fuzzy neural networks (de Campos Souza, 2020; Mishra, Sahoo, & Mishra, 2019).

The special feature of this approach lies in the improved interpretability of complex systems and the effective handling of data uncertainty. The use of FNNs enables a deep understanding and clear interpretability of system dynamics and state evaluations, which is crucial for the optimization of PHM solutions (de Campos Souza, Lughofer, & Guimaraes, 2021).

### 4.3. Fuzzy-Based Score Calculation

The interface between the PHM solution and the controller from 2.3 requires a control difference to be defined and transferred to the control system. For this purpose, a PHM solution is added to the control system, which calculates a score value for the individual actuators using extended optimization. The score calculation can be performed using various methods, including simple weighting or the application of complex logical operations using fuzzy rules in fuzzy neural networks (FNNs). The objective function from subsection 3.2.1 and the influencing factors from subsection 3.1.5 are included in the calculation of the score. For example, deferring maintenance to reduce $CO_2$ emissions can increase the risk of failure. All of these factors needs to be considered as part of an iterative optimization, as illustrated in Figure 4. The influencing factors can be integrated into a calculation function as weights. One implementation option is the formulation of fuzzy rules, whereby the weighting of the individual factors within the FNN is included in the evaluation. This allows complex logical relationships based on the data to be considered and the result to be interpreted as a score value.

The main objective of using an FNN is to make the score calculation for adaptive control efficient and effective. By integrating fuzzy rules, the various influencing factors are categorized and evaluated by fuzzification layers in the network. This allows not only a specific weighting of the factors, but also a flexible adjustment of these weightings within the layers. Training data from previous calculations or empirical values can also be used to train the network. A particular advantage of fuzzy networks is that they do not require an explicit model and that they can simplify the score calculation despite complex mathematical relationships through fuzzification.

#### 4.3.1. Design of a Fuzzy Network

A fuzzy-based neural network consists of several core components. These are:

- **Fuzzy logic:** Enables the processing of uncertainties and ambiguities through the use of fuzzy sets and fuzzy operators.
- **Membership Functions:** Each fuzzy set is represented by a membership function, which specifies the degree to which an input value belongs to a set.
- **Fuzzy Rules:** Fuzzy rules, formulated as "IF-THEN" statements, define how input values should be processed based on their membership of different fuzzy sets.
- **General neural network structure:** Similar to traditional neural networks, including layers of neurons that are interconnected by weighted connections.

#### 4.3.2. Definition of Fuzzy Rules

As the decisions of the adaptive system are based on the fuzzy rules, it is important to define the most precise boundaries possible when recording the rules. The rules should represent the characteristics of the training data sets as accurately as possible. To define precise fuzzy rules, approaches such as the improved Wand-Mendel method can be used. This tool makes it possible to determine fuzzy rules directly from the data sets. However, as this leads to further uncertainties, it is important to determine the fuzzy rules iteratively to keep the uncertainties as low as possible. And use methods such as the WM method as an additional option.

Since the determination of fuzzy rules is a continuous process, it is essential that the fuzzy rules within this framework can be adapted flexibly and adaptively to changes to be able to react effectively to modifications of the underlying rules.

#### 4.3.3. Example Use Case of Fuzzy Neural Network

To demonstrate the practical application and effectiveness of FNNs across various adaptive control systems, we explore an example using the D1244. This use case illustrates how FNNs can be seamlessly integrated into complex environments to manage and improve system responses dynamically.

**FNN Implementation:** The FNN architecture in this scenario consists of several key layers, each tailored to handle the specifics of sensor data interpretation and decision-making in a fuzzy context:

- **Input Layer:** Directs raw sensor data into the network.
- **Fuzzification Layer:** Converts numeric sensor inputs into fuzzy values using membership functions. These functions define linguistic terms such as low, medium, high, which are easier to handle in rule-based logic processing.
- **Inference Layer:** Implements fuzzy logic rules that determine the control responses based on the fuzzy inputs. This layer combines the fuzzy terms using logical operators and forms the backbone of decision-making within the network.
- **Defuzzification Layer:** Converts the fuzzy conclusions back into precise control outputs, such as adjustment levels for actuators.

**Input:** The FNN receives real-time input from the sensor array, which is continuously monitoring the process variables:

- **Temperature sensors** provide data that are vital for preventing overheating and ensuring chemical processes proceed at optimal rates.
- **Pressure sensors** monitor the integrity of containment vessels and pipelines, preventing leaks and ruptures.

These inputs are sampled at a frequency high enough to allow real-time responses from the control system.

**Results Interpretation:** The outputs from the FNN directly influence the operational controls of the D1244. They are interpreted as follows:

- **Control actions:** Adjustments made by the control system based on FNN outputs are implemented immediately to optimize processes and reduce energy consumption.
- **Operational efficiency:** By continuously adapting to changing conditions, the D1244 maintains optimal performance with minimal waste of resources.
- **Safety:** The system enhances safety by maintaining all process variables within safe operational limits, reducing the risk of accidents.

All these features are summarized in a score value, which can be managed in the PHM solution for the prediction of future states.

#### 4.3.4. Advantages and Future Prospects of Fuzzy Neural Networks

FNNs represent a significant advancement over traditional NNs in that they provide interpretable relationships despite the increased complexity of systems and data. This capability makes FNNs particularly valuable for modeling and controlling complex systems. The score generated by FNNs enables a simplified yet comprehensive representation of system states and interactions, which are summarized in a value that can be interpreted by the controller. This not only reduces complexity, but also lays the foundations for improved decision-making and system control.

The combination of the adaptability of fuzzy logic and the learning capacity of neural networks allows FNNs to process imprecise and uncertain information effectively. This is particularly advantageous in decision-making processes where traditional methods reach their limits. FNNs show their strengths especially in scenarios characterized by high uncertainty and fuzziness and offer a robust solution to the challenges of the real world.

The future of FNNs in application methodology aims to achieve real-time data processing and interpretability. The further development of these technologies will enable even more precise decision-making, which will significantly improve the adaptivity and autonomy of the system components. This direction of development promises to increase efficiency and effectiveness in the processing of complex data structures and at the same time create the basis for innovative control and monitoring systems that are able to react dynamically to changes and make proactive decisions (Talpur et al., 2022).

The integration of FNNs with advanced data processing techniques, such as Long Short-Term Memory (LSTM), could further enhance the ability to analyze and adapt to newly added information in real time. This not only increases system performance, but also lays the foundation for extensive use of FNNs in a variety of applications, from predictive maintenance to optimization of operations (Wang, Shao, & Jumahong, 2023).

## 5. Conclusion

This paper provides a framework for the comprehensive realization of Prognostics and Health Management for a complex system of an adaptive high-rise building. This includes not only the load-bearing structure, but all domains involved in the system such as actuators, sensors, the control system as well as maintenance with all sub-domains such as spare parts stocking and maintenance resources.

Adaptive load-bearing structures offer the potential to increase the sustainability and service life of high-rise buildings. However, this integrates many other functional domains into the system that can fail and whose optimal use may require regular adjustments. Prognostics and Health Management offers the potential to reduce uncertainties about the current state of the system and to optimize it for use.

The PHM control loop consisting of five modeling elements – system, data, diagnosis, prognosis, and optimization – is used as the basis for the structure in the application of PHM. However, since embedding in a system is required for implementation, a framework is introduced here that does this under the requirements of the complex system of an adaptive structure.

The framework is divided into the areas of system analysis and modeling and the description of the PHM solution. The comprehensive nature of the framework and the systematic approach support the consideration and accurate integration of all functional areas of the adaptive structure into the PHM.

The system analysis consists of six sub-steps. First, the system is described, and the relevant system scopes are defined. On this basis, existing dimensions are identified. With the help of the dimensions and the system description, specifications, boundary conditions are determined. The target parameters for operation and its optimization are defined on the same basis. This is followed by the derivation of influencing factors on the target parameters and for compliance with boundary conditions. At the end of the system analysis, uncertainties are identified for compliance with the boundary conditions and optimization of the target parameters.

Modeling begins with the development of the target space and objective function. The target space describes all permissible solutions, as the boundary conditions are met. The objective function weights the individual target parameters in relation to each other if there are several target parameters. The next step is to develop the model structure. Here, the results of the system analysis are used again to map and link all the necessary functions. Finally, system integration is presented using the example of structural control for an adaptive high-rise building.

The PHM solution section covers details of the approaches for diagnosis, prognosis, and health management. A hybrid approach of physically based and data-driven models is recommended for diagnosis and prognosis to meet the requirements of the complex system. For the health management agent, the use of fuzzy neural networks is discussed to enable precise interpretation and processing of complex system states and dynamics.

Through the presented content, the paper provides, besides the framework for the implementation, the structure in terms of system sizes and models for the application of PHM to the complex system of the first adaptive high-rise building.

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