Predictive Maintenance for the elevator and escalator industry
Smart Services enabled by Industrial Analytics
Let's connect.

Whitepaper

Abstract

Words like Smart Elevator, Big Data, Predictive Maintenance etc. are currently inspiring many elevator and escalator manufacturers. Based on predictive maintenance, guaranteed machine uptime is projected to deliver added value to new systems in the future. But more and more companies are realizing that the expansion of data-based services provide them with real business advantage and such future-proof business models are set to leverage long-term customer loyalty. The methods employed by Industrial Analytics help to achieve this. Machine learning and artificial intelligence techniques allow machine behaviors of an elevator or escalator to be better understood by the manufacturer thereby revealing structures and patterns and providing new insight into data relationships. But the path to go need to be a well-organized process. Weidmüller shows how to describe the use case and to establish a proof of concept, while the project team run through the traditional stages of data capture, integration, preparation, analysis, implementation and finally evaluate the economic benefit.

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1. Introduction
Advantages of model-based monitoring methodologies

Technological developments of automation systems towards digitalization bring many advantages and opportunities, such as flexibility, economic production of small lot sizes, and optimization of production processes. Besides that, there are also big challenges to increase equipment reliability and uptime, especially for elevator and escalator companies. A further challenge is the realization of more efficient maintenance strategies, while reducing costs.

Nowadays, rule-based monitoring systems are well established among elevator systems, mainly because of the simplicity of such approach, where boundaries for individual signals (e.g., sensor values) are setup by application experts. If, for example, a motor needs to be monitored, limit values for specific fault-indicators are defined (e.g. temperature, current consumption). If any of the monitored signals goes beyond the defined boundaries, an alarm can be generated. For simple applications, rule-based approaches are well suited. However, if for the application at hand dynamic transitions of many signals are relevant for fault detection, this task becomes too complex for a rule-based approach. Furthermore, changes in the signal behavior, which occur between the boundaries defined by rule-based monitoring systems, are not detectable, as shown in Figure 1.
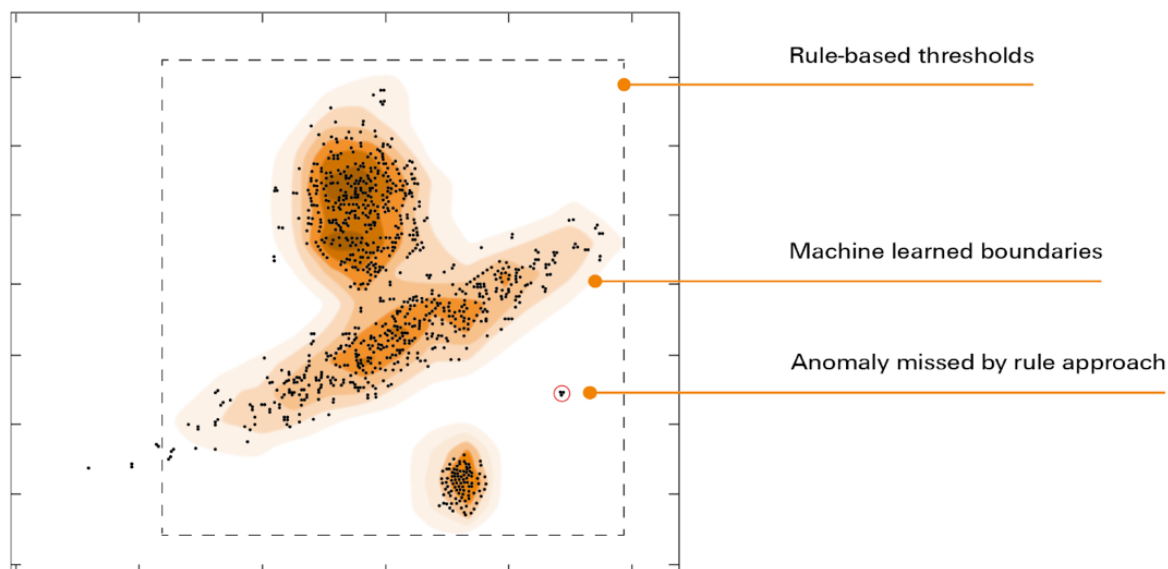
Figure 1: Rule-based monitoring vs. model-based approach

A model-based approach can be used to improve the performance of a monitoring system. A model can represent several dimensions simultaneously so that machine states are well identifiable. The development of an adequate model can be very demanding and requires highly skilled human resources. However, by using Industrial Analytics methods (e.g. machine learning algorithms) and process data to derive a machine model the complexity of the implementation of a monitoring function can be significantly reduced [1]. Furthermore, the monitoring quality is improved as more complex faults, which are not identifiable with a rule-based system, can be detected.

2. Industrial Analytics Workflow
From data acquisition to visualisation

Industrial Analytics functions are typically composed of different tasks, as shown in Figure 2. The figure shows the typical workflow of an Industrial Analytics application, where data from the different devices are first consolidated in a single data source (data storage). The next step is to pre-process the data as preparation for the learning process (pre-processing). In this step, relevant features are extracted from the raw data signals, involving the combination of statistical methods with domain-knowledge to select meaningful features.
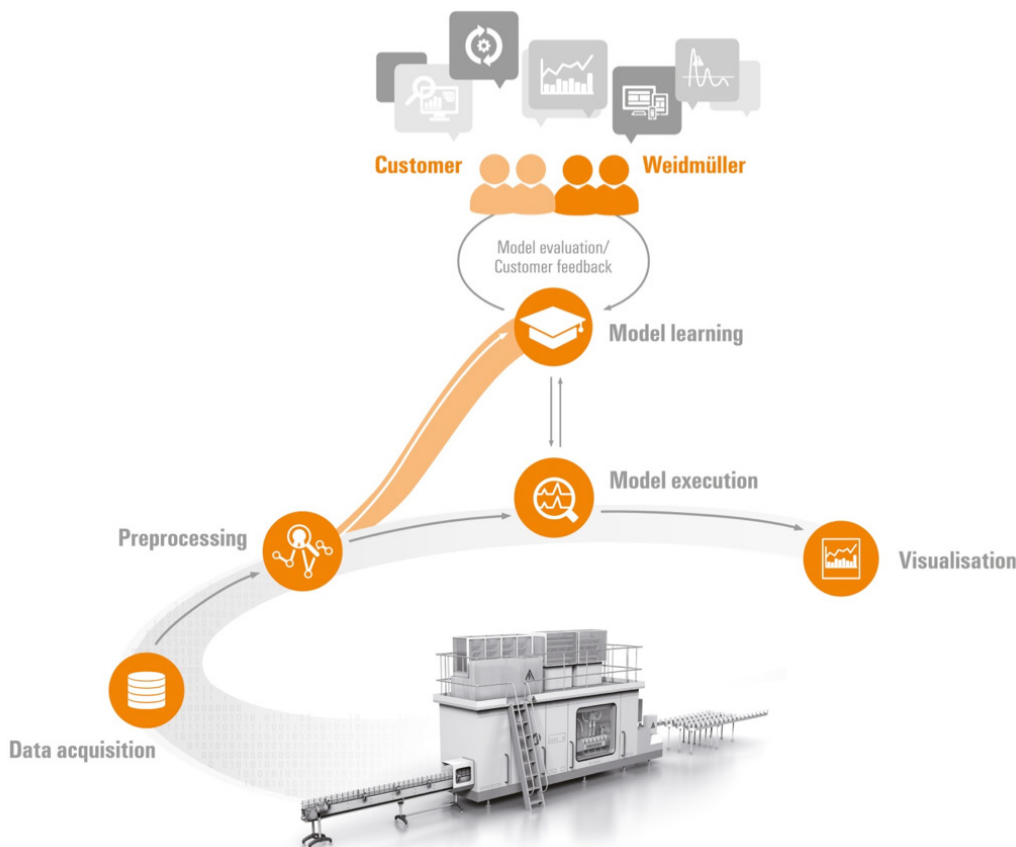

Figure 2: Typical workflow of an Industrial Analytics application

The next step is the selection, training and tuning of machine learning algorithms in order to derive a model from the selected features (model learning). Again, the combination of analytics expertise and domain knowledge is key to develop an efficient model. Once developed, the model can be used at runtime to monitor the machine or process (model execution). To be useful the results need to be properly visualized (visualization). The kind of visualization should be selected according to the role of the person who shall use this information, e.g. the building owner, the facility or maintenance manager, etc. The integration of an Industrial Analytics function in an automation system can be done at different levels, for instance at the machine, or using a cloud platform. These possibilities are explored in the next section.

3. Topology for the realization of Industrial Analytics
From sensor to cloud

The realization of the basic operations of analytics function (data storage, pre-processing, model learning, model scoring, and visualization) can be done at different levels, e.g. to collect data at component level (drive, car, doors) and at field level, e.g. using a sensor kit and collecting signals with a remote I/O system. Since data sources can be heterogeneous there is the requirement to transform the data into a unified format for further analytics processing. Depending on the given application and on the prerequisites of the user application, data can be stored either locally on premise, e.g. by using the main controller or an IoT gateway, or in the cloud using suitable storage cloud services, as shown in Figure 3. The analytics processing can be performed on various devices or platforms or using software as a service in cloud platforms. While automation components are primarily used for process control, they might qualify for implementing analytics processing functionality if a suitable amount of resources is left.
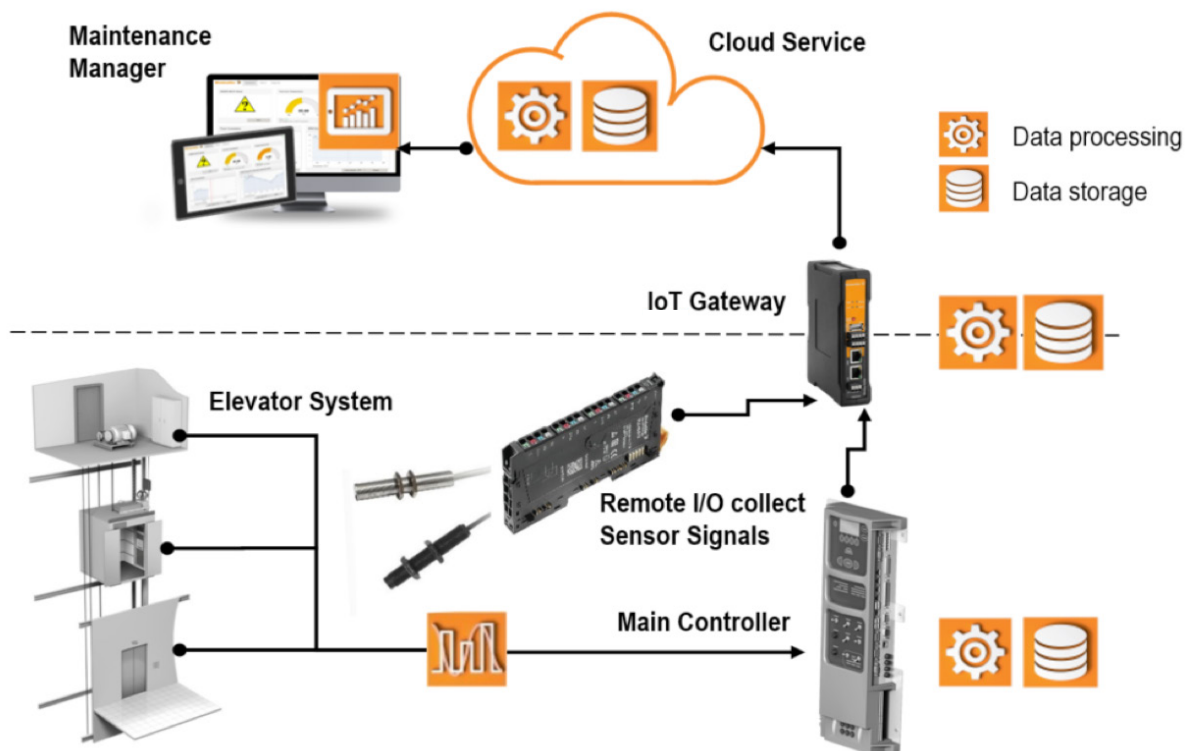

Figure 3: Possible topology to collect data at component and field level

Besides the given hardware resources, processing and memory requirements vary according to the task to be performed. Especially, deriving a machine model often requires significantly more resources than executing that model. There are various architectural options for storing and processing data, and the selected implementation is subject to constraints, such as the given architecture, the processing needs, data rates, and storage complexity. There is a need for flexibility in the realization of analytics functions to address the various industry applications. For elevator applications, data sets are mainly generated from controller in real time. The applied algorithms need to show low latency, and the data sets are typically of small volume and are highly correlated to each other. Therefore, an implementation of Industrial Analytics functions using edge devices (e.g. IoT gateway) can bring many advantages, such as short reaction times and decreasing network traffic.

4. Typical phases of an analytics project
From target definition towards deployment

The path to go for an analytics project need to be a well-organized workflow of typically five phases, as shown in Figure 4. At the beginning stands the problem analysis and target definition, e.g. what particular failures should be predictable. During the phase of data exploration, the quality of the generated data will be verified, if the defined faults can be detected, or more data quality is needed. During proof of concept, the technical and economic proof of feasibility will be checked (offline analysis). In the pilot phase, a functional prototype will run on a pilot application (online analytics). Finally, in the last phase, the pilot-proofed analytics solutions will be developed and deployed.

| 1. Target definition | 2. Data Exlporation | 3. Proof of consept | 4. Pilot | 5. Development and Deployment |
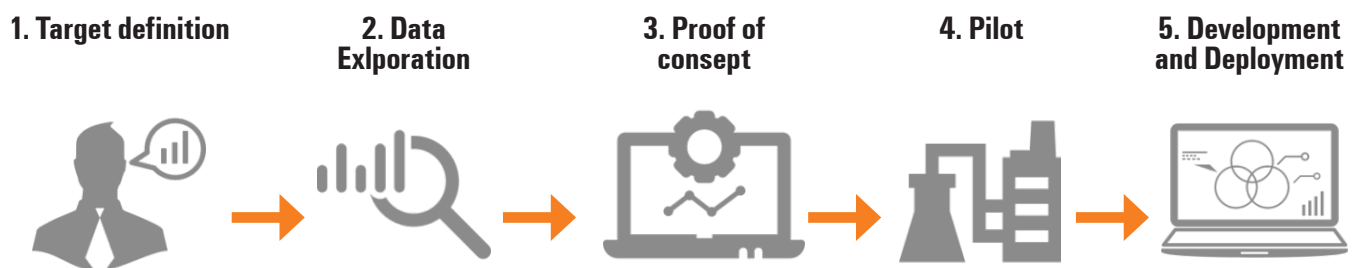
4.1 Offline analysis

Applying data analytics on machine data typically starts with its offline exploration. Sample data from few machines for a selected representative time frame are retrieved and then analyzed offline by data scientists. They explore the data by applying various data analytics methods to find out which methods provide the best actionable insights. Companies who offer such services differentiate by their ability to perform offline analytics in an efficient way. We, for instance, have built over time an extensive data science and machine learning toolbox that allows assessing sample data in short time frame.

4.2 Online analytics for predictive maintenance

For the purpose of predictive maintenance, the machine data needs to be continuously monitored. From the acquired data, the machine state is assessed, abnormal events and failure indicators are detected and used to identify required maintenance. Then, recommendations for maintenance activities are provided to building owner, facility or maintenance managers. Depending on the nature of the physical conditions that lead to machine failures, it may be necessary to process data in near-real-time with sub-second latency on the one side, or in a daily or weekly test on the other end of the spectrum. Online analytics systems should be flexible to handle this variety of timing requirements.

We currently consider three different categories of analytics that generate information for machine monitoring and predictive maintenance systems: direct calculations, machine state and activity recognition, and anomaly detection.

Direct calculations take sensor data from a machine as input and compute for example the wear of a machine part.

Machine state recognition algorithms as input consume machine sensor readings or process data to identify the state of the machine at a given point in time. We use machine learning technologies to classify machine states and machine activities based on models learned in a designated training phase before [2]. The obtained machine states and activities are useful for predictive maintenance when further processing and reasoning is performed.

Anomaly detection [3] is another very helpful technique for finding failure indicators and assess maintenance need. When in normal operation, the sensor signals usually lie within certain value ranges or exhibit particular normal patterns. Obviously, we are interested in capturing deviation from normal behavior. A single detected anomaly can already be indicative for a failure and used to trigger an action. Often it is the case that a single anomaly is actually not sufficient, and only an increasing number of anomalies over the course of time will provide sufficient indication that the machine is not working optimally or developing a condition that needs to be addressed by personnel. Furthermore, there are many reasons why anomalies can be detected in machinery sensor data, and plenty of these might actually not be related to any problems, but caused by other influence factors. For instance, operator interaction or change of parameter settings can have an impact on the sensor measurements. An important feature of a predictive maintenance solution is to understand the context of measurements, and to assess which anomalies are relevant to predict maintenance needs.

5. Conclusion

In this paper, we have outlined the workflow and topology for Industrial Analytics functions and described the five phases of a typical analytics project. The offline and online approach to realize predictive maintenance were discussed, showing the key advantage of combining data science with domain specific know-how.

Machine data generated from elevators and escalators combined with data from the maintenance organization are turned into powerful insights when Industrial Analytics functions are applied. These data can turn into actionable outcome like predictive maintenance, e.g. to predictively identify, analyze and resolve possible service issues before they occur. This finally results in reduction or elimination of downtime.

Weidmüller can partnering in joint realization of Industrial Analytics solutions, step-by-step from the idea to scalable, smart services, and in the development of innovative data driven business models. Tailored analytics solutions are provided, that deliver the best possible performance for the costumer's needs. We act platform independent and can realize on premise, cloud, or hybrid deployment, regardless of specific cloud platforms. Our analytics solutions work vendor independent, regardless of the underlying automation or control system.

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Rami Aro
Global Segment Manager Elevators & Escalators

Born in 1979, Rami Aro did an apprentice in electronics and holds a degree in Bachelor of Business Administration from the HWZ in Zurich. Since 2001 he has been working in the Weidmüller Group, holding positions of increasing responsibility in Product Management, Sales Management and Industry Management. Since 2017 he is responsible for worldwide market development in Elevator and Escalator segment.

Weidmüller Schweiz AG, Switzerland
Contact: rami.aro@weidmuelller.com

Dr.-Ing. Carlos Paiz Gatica
Product Manager Industrial Analytics Solutions

Born in 1977, Carlos Paiz Gatica studied electrical engineering at the Instituto Tecnológico de Querétaro, Mexico. He then completed a Master's degree in Complex Adaptive Systems at Chalmers University in Gothenburg, Sweden. In 2011, he received his doctorate at the University of Bielefeld, Germany, in the field of resource-optimized use of reconfigurable hardware for implementing adaptive control algorithms. Since then he has been with the Weidmüller Group, where he led research and development projects in the area of Industry 4.0. Currently is Dr. Paiz Gatica responsible for product management of Industrial Analytics solutions.

Weidmüller Interface GmbH & Co. KG, Germany
Contact: carlos.paizgatica@weidmueller.com