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Teaching Predictive Maintenance using Industrial AI Tools

Ihor Savchenko*, Herbert Fleck, Peter Novotny, Helmut Ropin

Abstract: A new concept of an educational tool using predictive maintenance techniques is proposed. The tool is a part of a larger 'learning and research factory' that aims to enhance the current educational processes for industrial engineering students. The factory is organized as close as possible to the real business situation, so the students "learn by doing", gaining both theoretical knowledge and practical skills. Two use cases presented by the authors intended to effectively teach the principles of predictive maintenance. Basic elements of data science, machine learning and statistical analysis are used to prognose possible anomalies in the production process and react actively before a harmful event occurs. The authors outline ways for further development of the tool, including using it for other educational purposes.

Keywords: AI; anomalies; digital twin; machine learning; predictive maintenance

1 THEORETICAL OVERVIEW
1.1 AI in Education

Over the last decade, the artificial intelligence (AI) industry experiences an unprecedented boom. There is a multitude of various definitions of the AI term, such as "a branch of computer science devoted to developing data processing systems that perform functions normally associated with human intelligence, such as reasoning, learning, and self-improvement" [1], "a framework deployed with the objective of building intelligent systems that can creatively solve a given problem" [2] or "a paradigm that endows machines with intelligence, aiming to teach them how to work, react, and learn like humans" [3]. Most of these definitions clearly present the core of the idea: a machine able to "think like a human".

Rapid development of AI-related techniques and tools in almost all traditional areas of human life allowed many scientists and specialists to speak about the "AI revolution" starting as early as in 2017 [4-6]. The education is not an exception. Being a key element of a well-functioning society, the education as a process of passing and enhancing knowledge and skills through generations has been already deeply influenced by AI, with new ideas and theories appearing every day. In the first months of 2024 only, the concepts of using AI in healthcare education [7], language learning [8], social studies [9] and mathematics education [10] have been proposed and reviewed in multiple papers. The effectiveness of AI tools has been shown both on school [11] and college/university levels [12], as well as in different forms of adult (continuing) education [13]. Most researchers agree that correctly chosen AI tools greatly enhance the traditional learning process and will become an irreplaceable element of general education in the nearest future. Still, the reckless use of AI raises many ethical concerns [14], especially in areas like education, which has for thousands of years been an example of "human – human" interaction.

1.2 Predictive Maintenance

The concept of maintenance can be as old as the civilization itself, but after the onset of the Industrial revolution it gained a truly scientific meaning as a set of processes to avoid machine failures and to improve a machine's health condition [15].

With further industrial development the theories of maintenance became more complex, until the new digital revolution of the 21st century introduced the so-called "Industry 4.0" and specific maintenance techniques related to it. Achouch et al. defined predictive maintenance as "an approach that consists of improving the performance and efficiency of the manufacturing process by… offering the possibility of interventions through the prediction of failures" [16]. They regarded this approach as the most effective and developed compared with traditional ways like reactive (post-failure) and preventive (scheduled) maintenance. Cakir et al., by applying machine learning algorithms to predictive maintenance, postulated that this approach provides the longest life and highest reliability of equipment, as well as the most environmentally sound and cost-effective solutions [17]. In the Fig. 1, a standard predictive maintenance workflow is shown.

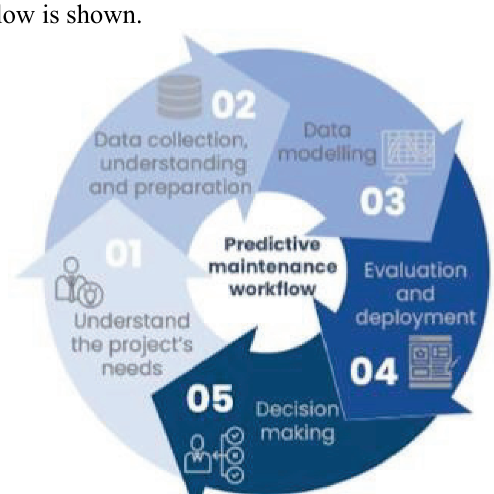

Figure 1 Predictive maintenance workflow [16]

Unlike the older approaches, predictive maintenance uses proactive methods to reduce cost and increase machine uptime. Predictive maintenance aims to foresee when a component or system will no longer fulfill its function. A key indicator in such a prediction is a remaining useful life (RUL), showing the amount of time during which the equipment is supposed to work normally before the need for repair/replacement occurs. Various AI techniques can be helpful in making such forecasts. In the systematic literature review provided by Van Dinter at al., the importance of digital twins (precise digital replicas of physical equipment) in predictive maintenance models was summarized and underlined. [15]

In the same paper, most popular statistical methods applied in predictive maintenance models were listed:

- probability distribution functions;
- Kalman and particle filters;
- Monte Carlo methods;
- Principal Component Analysis (PCA).

At the same time, several authors pointed out the challenges in applying predictive maintenance approaches as well as downsides of the model itself [18, 19]. The main issues can be divided into four categories:

- financial and organizational;
- data source;
- repair activities;
- deployment limits.

It has been specifically noted that the integration, support and updating of predictive maintenance techniques can be too expensive and not economically efficient for smaller industries and areas of work [20].

2 EDUCATIONAL TOOL

In this paper, the authors, representing a team of researchers affiliated with FH Joanneum (Austria) and FESTO (Germany), present a specific case: using a system of AI tools for teaching the basics of predictive maintenance for business engineering students on a bachelor/master level. The AI system consists of three main elements, integrated into a wider data generation and analysis system. The system architecture is presented in Fig. 2, while the three main elements are described below.

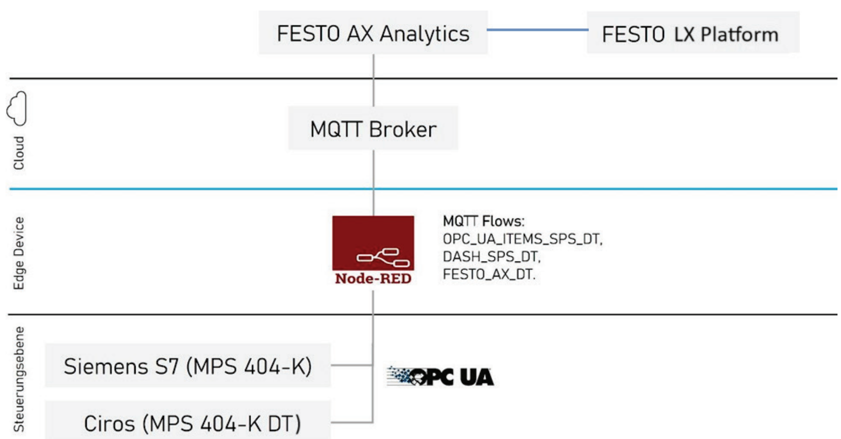

Figure 2 System architecture

2.1 Working Station

The working station is a simplified model of a real-life production equipment and a data generator at the same time. The station exists in two forms: a physical one (FESTO modular production system, or MPS) and its digital twin, created with CIROS virtual reality simulation tool. MPS consists of four consecutive stations simulating typical operations of the Conveyor Belt Production Process: distribution of source materials, measuring, assembling (joining two materials) and sorting the production by quality. This is an intuitively understandable, but hardly transportable learning appliance, driven electrically and by compressed air. On the other hand, CIROS simulation tool requires almost no maintenance and allows to process large productional quantities in short time without any manual effort. The digital twin in question was developed and implemented during the COVID-19 pandemic and continues to be used because of its effectiveness in distance learning. Both physical and virtual stations regularly produce the streams of data related to the different aspects of the micro factory in use. These data (e.g. speed of conveyor belt or time required to eject an element out of a cylinder) are recorded and stored for comparison and later statistical analysis. More details on the physical station and the CIROS digital twin are provided in the previous work of the authors. [21]

The working station used in the workshop is a part of a larger MPS 404-K learning factory developed by FESTO and designed to address economic topics in a production simulation. It provides a comprehensive understanding of an industrial production process, starting from the sensor technology through to the ERP system.

With MPS, the students have the opportunity to learn key performance indicators such as availability and efficiency and get a realistic impression of industrial processes.

The data generated by MPS are captured by its sensors and transferred to the middleware level by OPC UA specification. Then the data are processed and filtered by the Node-RED middleware. When only the relevant data are left, they are transferred further using MQTT – a standard protocol for communication between "internet of things" devices and other computers. OPC UA and MQTT brokers play crucial roles in transferring data between the learning factory and the FESTO AX software. FESTO AX analyses the obtained data and displays results in a dashboard.

2.2 FESTO AX

FESTO Automation Experience (AX) is an industrial AI- and machine learning (ML)-based solution designed to gain valuable insights from the system data. By analyzing live data in real time, FESTO AX enables quick identification of anomalies that can lead to reduction in productivity, quality problems or high-energy costs.

For the purpose of predictive maintenance, this means that through real-time analysis of data FESTO AX can early identify possible anomalies. This enables proactive (i.e. predictive) maintenance instead of reactive one.

FESTO AX applies ML to the collected data to recognize specific patterns and relations. Specifically, it uses k-means clustering, an unsupervised, easy-to-perform ML algorithm, to group the generated data into clusters based on their characteristics. K-means clustering is often used for anomalies detection and similar tasks. Here are the basic steps of this algorithm:

- Define the number of clusters K.
- Position the starting cluster centroids. This can be done by arbitrarily separating the data points into K clusters, then computing their centroids.
- Iterate over all data points and calculate the distances to the centroids of all clusters. In our example, the most common Euclidean distance was used. Then each data point was assigned to the cluster with the nearest centroid.
- Recalculate the centroids of new clusters.
- Repeat step 3 until the centroids remain stable.

For the workshop's purposes, a simplified clustering model was chosen with three expected clusters:

- "no anomalies"
- "conveyor belt attrition"
- "membrane tear in valve".

In addition, there were only two data features:

- "conveyor belt movement time"
- "suction cup active time".

Before the k-means procedure, features' data were normalized.

After the k-means calculation, the schematical results can be displayed as in the Fig. 3. In this case, three definitive clusters were formed based on two types of anomalies. In both cases, anomalies were caused by imperfect equipment parts (conveyor belt and valve membrane) and, as a result, slower operational times of these parts. Data points related to the normal settings are marked with blue, to the damaged conveyor belt – with red and to the damaged valve – with orange. Average distance between clusters was in the range of 30-40 ms for the belt and 40-50 ms for the valve.

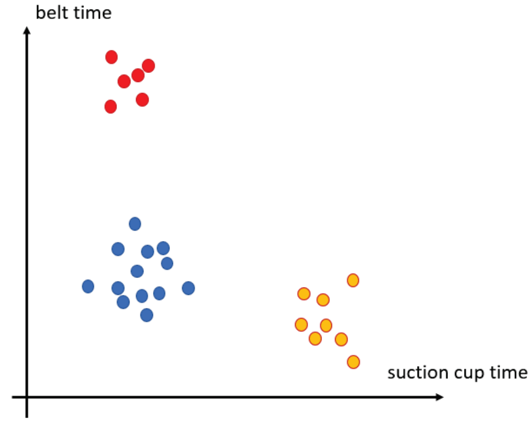

Figure 3 k-means algorithm results

The groups situated too far from the predefined normal criteria are marked as potentially dangerous (causing anomalies). For example, the system still functions with a slower conveyor belt or a damaged vacuum membrane, but without necessary measures, these states can result in a station crash. By identifying problems early and solving them users can reduce unplanned downtime and extend the service life of equipment. This leads to higher availability and efficiency indicators.

For anomaly detection and classification FESTO AX uses a practice-oriented "Human in the Loop" approach. This means that data are recorded, models are trained and anomalies are detected in real time, during the production process. The user helps the model to "learn" by confirming the fact of anomaly and classifying the anomalies. When there is a match, the anomaly is detected and the corresponding safety measure is proposed.

The results of system health monitoring in the form of "health scores" are displayed in FESTO AX user interface. It consists of following screens:

- Dashboards containing various widgets for data visualization, e. g. in a live chart form;
- Assets containing information about various machines and its components, e. g. conveyor belt or vacuum suction cup;
- Infrastructure providing connection between assets and dashboards;
- Data for different quantitative values collected by system sensors, e. g. duration of a suction cup movement;
- Models for various ML models based on collected data;
- Analytics where the user can choose an analysis object, define its features and the aim of analysis, assign the data, choose the model type and the visualization parameters.

2.3 FESTO LX

FESTO Learning Experience (LX) is a digital learning platform from FESTO that initially enabled companies and employees to expand their knowledge in the fields of automation technology, electrical engineering and pneumatics. The platform can be expanded to other topics, providing a wide range of online courses for beginners as well as for advanced learners. FESTO LX allows each user to study at their own preferred pace.

Main elements of the platform are learning paths and nuggets. A learning path is an interactive didactic module with a clear "begin to end" structure, helping to establish long-term knowledge and skills by practical problem solving. In this path, students learn theoretical basics, after that they gain skills and apply them in practice step by step. A learning path can contain different learning methods and media, such as online courses, e-learning modules, interactive simulations, videos, audio and text files as well as practical exercises. It can convey both theoretical and practical knowledge and help to improve or expand learners' skills in specific areas.

Nuggets can be defined as compact learning units in FESTO LX, each of which is dedicated to a specific topic and usually only last a few minutes. They are designed to teach a specific concept or skill in a short time. Nuggets allows for more personalization and flexibility in the learning process. It is important to note that nuggets are not simple "building blocks" of a specific learning path. They can be used independently, or be included in different paths at the same time.

Main types of nuggets are Task, Info, and Question-nuggets.

- Task-nuggets consist of series of tasks to perform using physical or digital equipment. They are usually accompanied by instructions, motivation explanations and list of helpful materials.
- Info-nuggets provide general theoretical information on the subject learned in the module.
- Question-nuggets serve to assess the users' skills and knowledge after performing the tasks. The proposed questions can be of various types, e.g. single-choice and multiple-choice tests, fill-the-gap and match-pair exercises, etc.

The learning path in question, named "FESTO AX and Predictive maintenance at the MPS station", was divided into three modules. In the first module, the theoretical foundations of the learning path were laid down. This is followed in the second module by practical implementation of these fundamentals with examples from FESTO AX, such as the creating analysis objects, models and dashboards. The last module presents use cases in which the content learned can be applied again on a physical station.

An example of a task nugget page, instructing the user (in German) to find pre-defined system features, is shown in Fig. 4.

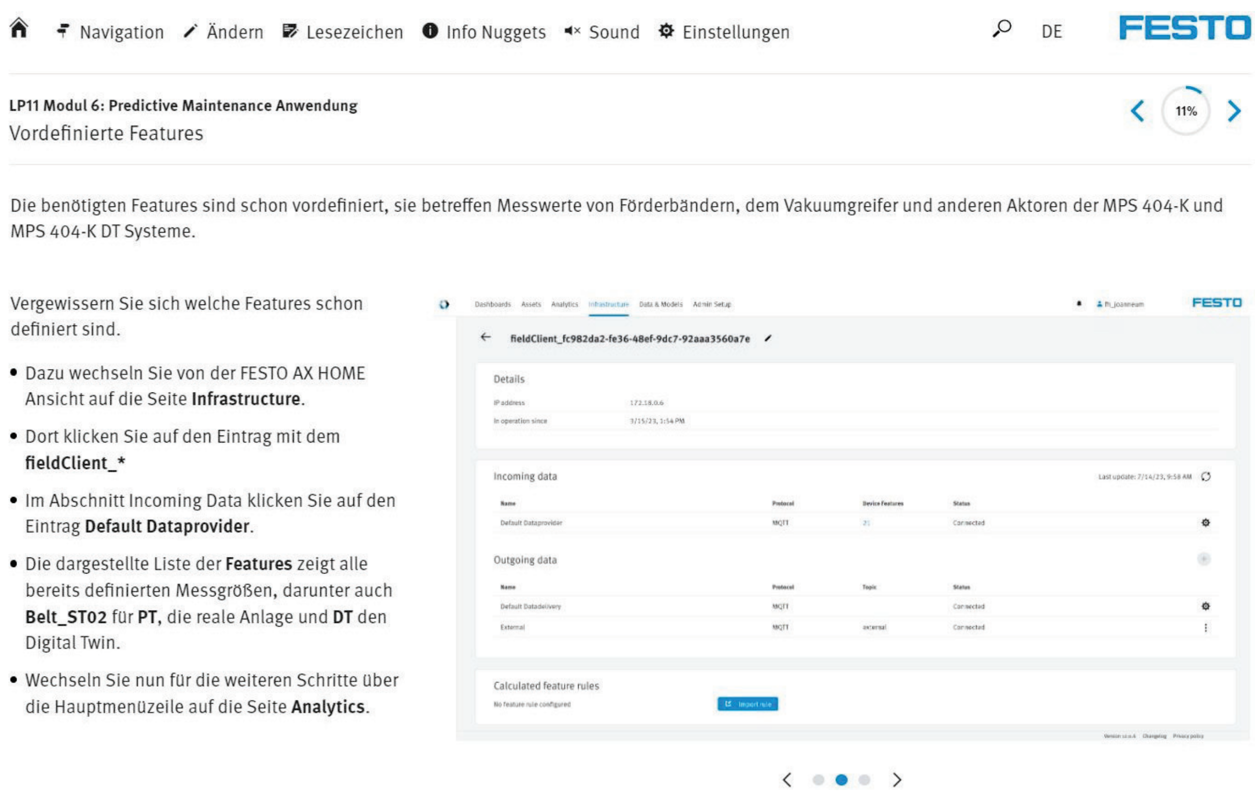

Figure 4 FESTO LX page outlook (task nugget)

2.4 Use Cases

Within the frame of the authors' workshop, two use cases for business engineering students were prepared.

First, one related to the presumed attrition of conveyor belt elements of the station 2 "Measuring". The effect of attrition was simulated by a potentiometer with a control knob installed at the front panel of the station. By turning the knob, users can regulate voltage at the electrical motor driving the conveyor belt, thus influencing the belt's speed.

In the course of the workshop, students first created a new analysis object with a feature related to the speed of the conveyor belt. Then, a model was created and configured using previously collected speed data for training. The model was assigned to the analysis object in the Analytics screen of AX. At the end of preparation, a dashboard was created with a gauge widget for displaying the health score of the analyzed object. and a chart widget displaying the data in real time. After that, three tests were conducted: without changing the motor voltage, with changing it to 70% of an optimum (simulating the attrition) and back with full voltage (simulating the situation after repairs). The health score was over 90% after the first and the third tests, while the slowing down of the conveyor belt resulted in the health score between 40% and 60%. The dashboard displaying the optimal situation is presented in Fig. 5.

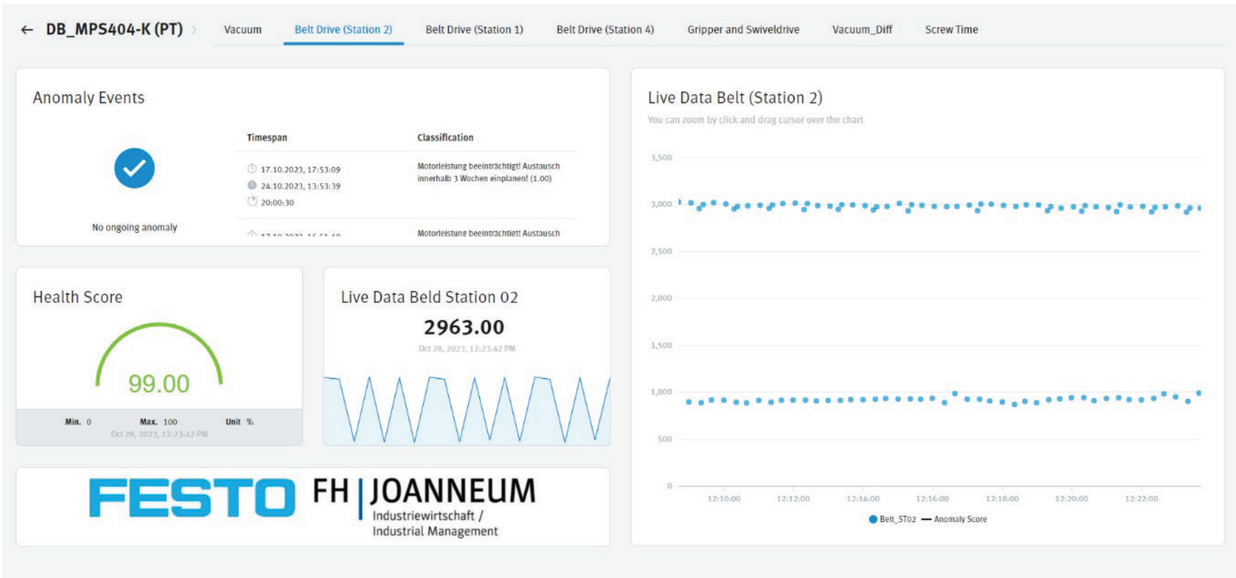

Figure 5 FESTO AX dashboard (use case 1 "Conveyor belt", optimal state)

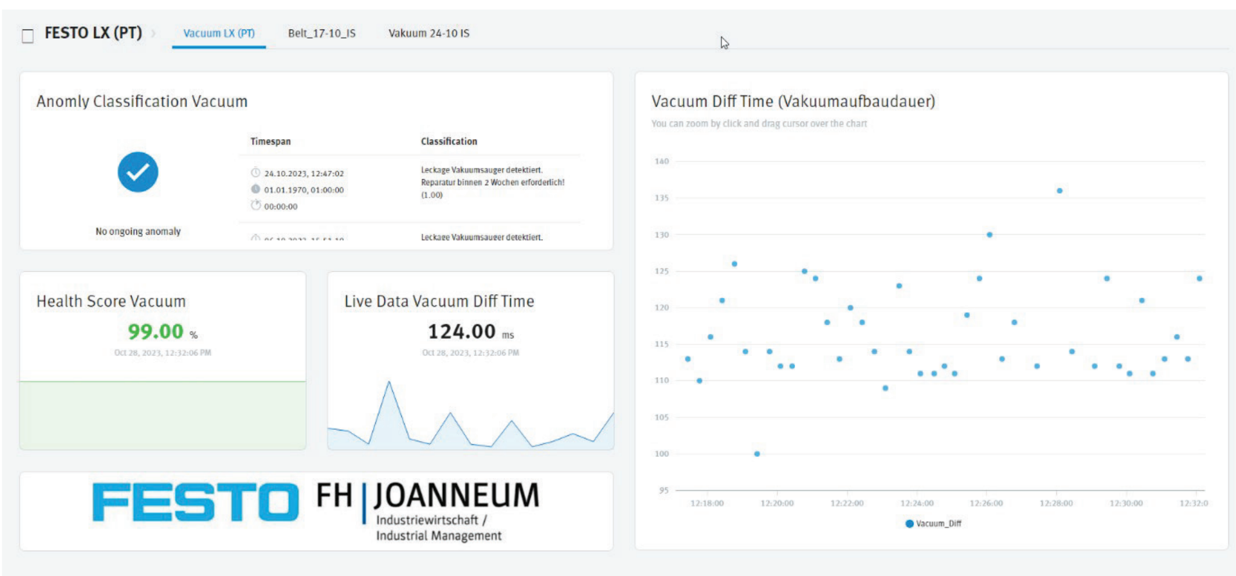

Figure 6 FESTO AX dashboard (use case 2 "Vacuum suction cup", optimal state)

In the second use case, the possible effects of vacuum suction cup attrition at the station 3 "Joining" were studied. The students prepared the AX tools in a similar procedure, this time choosing the suction cup as the feature of the analysis object. The problems of the suction cup were simulated by installing a throttle valve and a valve bypassing the throttle valve in line to the tube providing compressed air for the suction cup. By closing and then opening the bypassing valve, the students observed differences in the health score – first falling below 50%, then returning to normal values. The dashboard displaying the optimal situation is presented in Fig. 6.

Combined with theoretical information and control questions provided in corresponding nuggets, the students demonstrated high level of mastery of the predictive maintenance basics.

3 CONCLUSION

In the course of the proposed workshop, a concept for using a three-faceted industrial learning tool was described and tested. By combining a physical production station / learning factory, an AI interactive solution (AX) and a digital learning platform (LX), the high level of student involvement and skills transfer was reached.

To conduct the experiment, the physical station was enhanced by adding two components allowing for better simulation of anomalies and subsequent learning of predictive maintenance methods: a speed regulator of the conveyor belt and an air throttle valve for vacuum at the joining station. Both elements are intuitively understandable and easy to use. Later they were programmed to the digital twin model as well.

Based on the workshop, a learning path dedicated to predictive maintenance was created. The path, contains both theoretical part and a set of practical tasks regarding two use cases (slow conveyor belt and lack of air pressure), with corresponding questions for students. Both use cases are adjusted for a physical twin as well as for the digital one, allowing to combine the educational approaches. The workshop results further expanded the findings of authors presented in the 2021-2023 papers on business process modeling and learning factory simulation.

Main parameters like anomaly detection limits and model smoothness are set and justified, the results are visualized with dashboards and Excel tables.

4 FUTURE USE

By its nature, the learning concept described in this paper can be used not exclusively for teaching predictive analytics, but for other, broader educational purposes, for example:

- machine learning basics, especially k-means algorithm
- Node-RED coding
- Data visualization in Grafana or Snowflake
- data transfer by OPC-UA and MQTT
- Technical skills like computer-added design, rapid prototyping and managing electrical and pneumatical components using programmable controllers.

Possible future steps in using FESTO AX as well as positive experience based on the workshop are depicted in Fig. 7.

Regarding predictive maintenance itself, authors plan to use additional AI platforms like DataRobot to share ideas and concepts with other specialists in the field. Any dataset stored on AI platforms can be shared with the scientific community, furthering the authors' ideas. After more workshops and tests at FH Joanneum, the authors plan to cooperate with other technical schools and universities, in Austria as well as abroad.

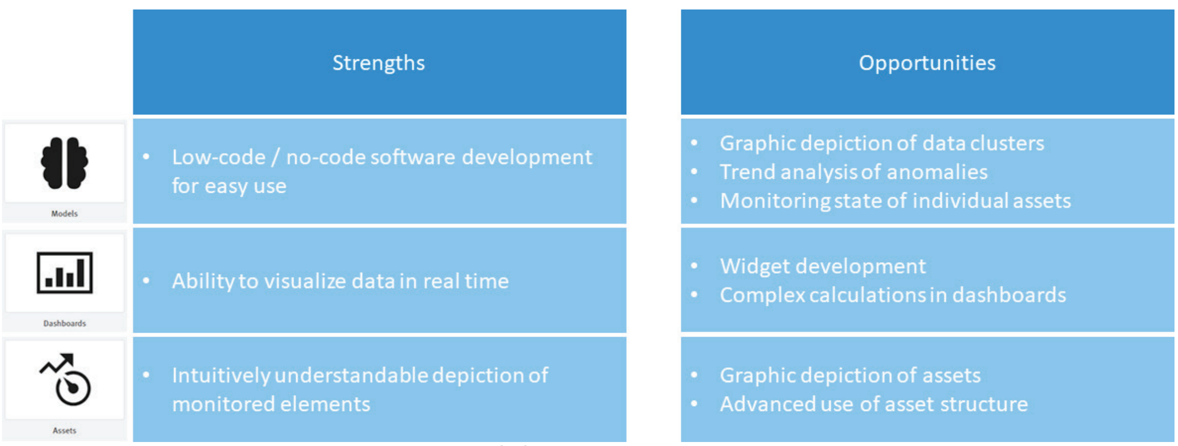

Figure 7 FESTO AX strengths and opportunities

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Authors' contacts:

Ihor Savchenko, BSc
(Corresponding author)
FH Joanneum,
Werk-VI-Straße 46, 8605 Kapfenberg, Austria
+4367762527133, igor.savchenko@tavr.at

Herbert Fleck, DI
HITEL GmbH,
Redtenbachergasse 25/1/12, 1160 Vienna, Austria
herbert.fleck@hitel.at

Peter Novotny
FH Joanneum,
Werk-VI-Straße 46, 8605 Kapfenberg, Austria
peter.novotny@tavr.at

Helmut Ropin, DI
FH Joanneum,
Werk-VI-Straße 46, 8605 Kapfenberg, Austria
helmut.ropin@fh-joanneum.at