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**Enhancing maintenance strategies: Implementing a Digital
Shadow for cost-effective solutions**

Készítette: Halász Gergely Lajos

Témavezető: Dr. Ruppert Tamás, Dr. Medvegy Tibor

Mérnöki Kar, Rendszermérnöki Intézeti Tanszék

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Contents

1	Introduction	2
1.1	The necessity of DT	3
1.2	Asset Administration shell as the enabler of DTs	5
2	Digital Twin enhanced maintenance strategies	6
3	The developed laboratory case study	9
3.1	The developed sensor network and information flow	10
3.2	The developed and integrated brownfield sensors	15
3.3	Demonstration study - maintenance scenario	19
4	Conclusions and further steps	23

Abstract

Maintenance represents a significant part of industrial companies. The vast majority of maintenance costs arise from inappropriate maintenance strategies. Choosing the right strategy and optimizing maintenance can significantly reduce both maintenance and production costs. However, achieving this goal is out of reach for most companies because they lack the appropriate technological systems. Currently, the cost of acquiring an adequate level of technology is so high that it is not worth the investment for smaller companies. This issue can be addressed through Brownfield Industry 4.0 developments or so-called retrofitting solutions, which provide a cost-effective way to integrate "not-smart" tools, machines, and equipment into the industrial network. This integration enables real-time monitoring of production parameters, allowing for the optimization of maintenance processes. For this purpose, a digital twin representation of the entire process would be the best option. However, a true digital twin is currently not feasible in a cost-effective manner. Therefore, we will propose a Digital Shadow for maintenance optimization. The aim of our research is to build a data acquisition unit (DAQ) that can provide a solution for mapping digital and analog signals on the shop floor in near real-time. The collected data will be used to create a Digital Shadow of the system, allowing us to examine the system's status in near real-time and dynamically manage the selection of the maintenance strategy based on its current condition.

Keywords: Digital Twin, Digital Shadow, Brownfield, Industry 4.0, data acquisition unit, maintenance

Chapter 1

Introduction

The issue of maintenance is of paramount importance to all industries and manufacturing facilities. It has a significant impact on the capacity of a plant and its ability to fulfil orders. Consequently, there is a constant drive to develop new studies and new methods to test the applicability of maintenance strategies. Since the 1970s, the literature has addressed various maintenance models that facilitate optimisation through fault detection and maintenance scheduling. Their application has been a continuous development in manufacturing to date. A significant advancement in their application is the online data collection, the Internet of Things (IoT), and the Digital Twin (DT), which facilitates the remote monitoring and examination of an object in real-time. This may encompass the entirety of a production line or a specific machine tool. However, it should be noted that this approach does have the disadvantage of requiring a high level of technological integration. A solution to this issue can be found in Brownfield Industry 4.0, which permits the retrofitting of existing machinery with alternative sensing technologies. This solution impedes the possibility of implementing a DT; however, it does permit the creation of a Digital Shadow (DS) for the system. In examining the existing research, it became evident that there is a lack of a comprehensive system solution which, in addition to providing a solution for a specific task, can also offer a general solution for equipping a production line, thereby facilitating maintenance operations. In order to address this gap in the literature, I intend to propose a solution in my research.

The research will be presented through a concrete hardware implementation, which is not only an implementation of an IoT data acquisition unit (DAQ) on the production line, but also a data collection and evaluation system. The DS that has been created is intended to provide support for maintenance activities by utilising the system informa-

tion. One aspect of this is that the system is designed to communicate in real-time with a Computerized Maintenance Management System (CMMS), which is intended to transmit directly to maintenance technicians any work requests and information required for maintenance. I created the main process and information model in a Business Process Model and Notation (BPMN) model.

1.1 The necessity of DT

In the context of Industry 4.0, the manufacturing sector is witnessing a shift towards the use of Cyber-Physical Production Systems (CPS) as the central component of production systems [1]. This development is driven by the necessity for DT, which facilitate the analysis and control of production processes through centralized monitoring and control. A DT can be defined as a digital model of a physical production system, created for the purposes of optimising the system, monitoring its performance, diagnosing any issues and forecasting future behaviour. This is achieved through the integration of artificial intelligence (AI), machine learning (ML) and software analytics with a substantial volume of data from the physical system itself [2]. In terms of its degree of integrability, the DT can be classified into three categories (Figure 1.1), as outlined below:

1. Digital Model: A Digital Model (DM) may be defined as a virtual representation of an existing or designed physical object, in which there is no automatic exchange of data between the physical object and the digital model. Consequently, any modifications to the physical object are not directly reflected in the digital model and vice versa. The model can describe the production line, the plant, etc. in varying degrees of detail. However, a potential disadvantage of this level is the slow flow of information. This limitation can be overcome by the following two levels of detail.
2. Digital Shadow: The DS incorporates all the features of the DM. However, in the case of the DS, there is an automatic flow of information between the physical object and the digital object, which flows from the direction of the physical object to the direction of the digital. The information flow in the opposite direction is also manual. That is, changes in the physical system are automatically reflected in the digital object.

3. Digital Twin: The DT represents the pinnacle of integration. At this level of integration, the flow of information is already automatic in both directions. Therefore, not only is the state of the physical object amenable to modification by the digital object, but likewise, modifying the digital object can also effect a change in the state of the physical object. This property allows for efficient testing of optimisation functions on a production line without interfering with the physical operation of the line. If the changes are successful, the physical object's operation can be directly reconfigured.

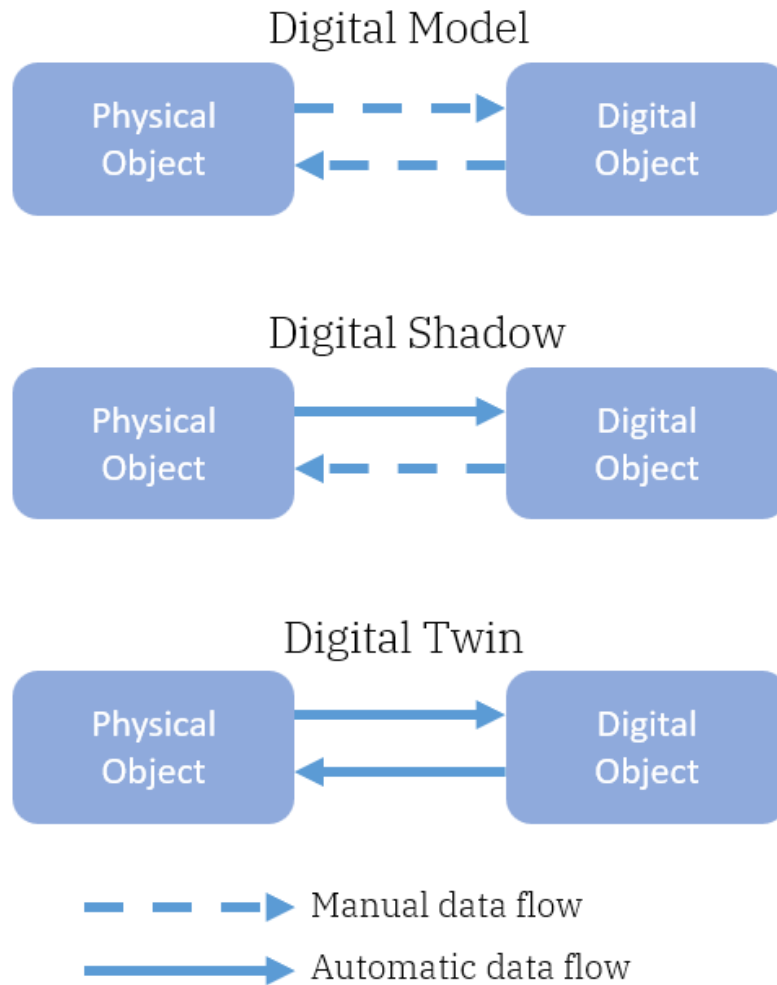


Figure 1.1: The levels of integration of DT

1.2 Asset Administration shell as the enabler of DTs

The Asset Administration Shell (AAS) is a digital representation of a device's DT, which serves as the foundation for the integration of industrial applications and is a pivotal component in the management of manufacturing systems. The AAS represents a digital structure comprising a number of submodels, each representing a specific aspect of the asset under consideration. These aspects include identification, communication, engineering, configuration, safety, lifecycle status, energy efficiency, health monitoring, and CAD model. Furthermore, the structure of the AAS allows the addressing of aspects such as access protection, data visibility, identity and privilege management, data security, and data integrity [3]. The submodels comprise structured properties that can refer to data and functions; the standardised format of these properties is defined according to the International Electrotechnical Commission (IEC) 61360-1 and the International Organization for Standardization (ISO) 13584-42 standards. Consequently, any definition of property values must adhere to the principles set forth in the International Organization for Standardization (ISO) 29002-10 and the International Electrotechnical Commission (IEC) 62832-2 standards.

While DTs offer significant potential benefits for organisations of all sizes, the use of this technology poses a considerable challenge, particularly for smaller and medium-sized companies. In essence, the applicability of the DT hinges on the establishment of communication channels between devices deployed on the shop floor, as well as the collection and tagging of data. However, the lack of an adequate hardware infrastructure prevents the integration of DT in such businesses [4]. In such cases, retrofitting represents a potential solution, in which IoT-based development occurs on the existing infrastructure. This development enables devices that lack communication or connectivity capabilities to deliver information through auxiliary units to the Enterprise Resource Planning (ERP) systems, the Manufacturing Execution System (MES), and other optimisation functions, such as maintenance optimisation [5].

Chapter 2

Digital Twin enhanced maintenance strategies

The significance of maintenance has led to a wealth of literature exploring the definition, implementation, and comparison of maintenance strategies. However, the absence of a universally accepted definition of these strategies has resulted in discrepancies in how they are conceptualised and categorised in different studies. Maintenance strategies can be classified into two main categories: pre-failure and post-failure [6]. The following sections will present a review of the strategies belonging to the aforementioned categories. This will include an examination of their definitions, costs, and applicability, as well as an analysis of their suitability when used in conjunction with a DT.

Reactive maintenance by DT: The category of post-fault maintenance encompasses a variety of approaches, including Reactive Maintenance (RM), which is sometimes referred to as corrective maintenance or breakdown maintenance. Reactive maintenance is typically used by industrial companies to meet orders deadlines. Provided that neither the product nor the manufacturing system fails, production will continue as planned under this maintenance strategy [7]. The greatest expenditure is in RM, which encompasses the cost of identifying the root cause of the failure, performing the repair and addressing the risk of unanticipated failures due to a lack of knowledge of the underlying issues. **Preventive maintenance by DT:** Preventive maintenance (PM) is the other method that is used most frequently in the industry, in conjunction with RM. It involves scheduled maintenance to prevent damaging and degrading impacts on the production system [8]. The plant policy, which specifies when the system must be avail-

able for as long as possible or not drop below a minimum reliability value, or when the time interval is to be determined without knowledge of the reliability of the system, is a significant factor in determining the interval between two maintenance operations [9]. The DT can be utilized in a similar manner for this maintenance plan, i.e., to conduct monitoring and information gathering functions or, in the event of a significant defect, to shut down the system and assist maintenance personnel in locating the fault.

Condition-based maintenance by DT: Real-time condition monitoring is the cornerstone of Condition-Based Maintenance (CBM) [10]. In addition to continuous monitoring, a well-defined optimization function is required to ensure that the strategy works properly, thus avoiding potential failure [11]. Using the system model and the data collected, the DT can predict the behavior of the system in the future and identify the location of a possible failure [12]. As a result, some literature considers it a subset of PM because CBM can be used to create maintenance plans cyclically [10] [13], while others classify it as Predictive Maintenance (PdM) due to the use of the system model [14] [15] [16]. **Predictive maintenance by DT:** PdM aims to predict when a component or system will fail to perform as intended. For this reason, two questions have been defined in the literature that PdM answers: 'When will it happen?' and 'Where will it happen?' [17]. Quantification of this prediction can be made using a remaining useful life (RUL) [18] or a Health Indicator [19] or equipment effectiveness [15]. With this prediction, the company can plan production capacity and maintenance downtime in advance. PdM uses a system model, which can be a physical model, a finite element model, a Monte Carlo method or even a numerical analysis [20]. These models can be incorporated into the DT so that the system can be controlled in real-time to match maintenance downtime with production capacity, order fulfillment, and reduce the risk of production downtime. **Prescriptive maintenance by DT:** Prescriptive maintenance (RxM) is the most advanced and complex maintenance strategy in the current literature [21] [22]. RxM is an answer to the question 'How can we control the occurrence of a given event?' [23]. To answer this question, the system must have a decision support solution that optimises the next maintenance process [24]. The implementation of this maintenance strategy in conjunction with a DT results in the creation of a system that is capable of aligning maintenance activities with production needs and deadlines, thereby optimising overall operational efficiency.

In examining the implementation of maintenance strategies, it became evident that there were seventeen noteworthy published studies that examined the potential integra-

tion of DT within a given strategy. In addition, a detailed investigation was carried out to assess the degree of application of AAS. The results of this analysis are presented in Table 2.1. It is evident that only one of the listed publications deals with AAS, while DT is mentioned in all the remaining studies. However, it should be noted that none of the studies adequately defined the level of integration. A review of the literature indicated that most publications applied the technology at the DS level. Furthermore, it was valuable in the context of this research to identify that only six publications provided more comprehensive information on the specific sensors and associated hardware systems they had developed.

It is of particular relevance to emphasize [12], in which the models in question are clearly defined in relation to the underlying causes of a ship's loss of speed. Furthermore, the Deep Learning techniques employed by these models may offer valuable insights for the subsequent stages of my research. Another notable publication was [27], which helped develop the data structure of the system to be constructed. The system they constructed is analogous to the application of AAS, in that they have decomposed their Entity Relationship Diagram into comparable assets as demanded by the application of AAS.

Table 2.1: Papers with the relevance of maintenance strategy, DT types and the considered aspects

Study	Maintenance strategy	Level of integration (DM/DS/DT)	Review paper	Considered aspects		
				Sensor technology	Data structure	AAS
[8]	PM	DS	No	0	0	0
[9]	PM	DS	No	0	2	0
[12]	CBM	DS	No	3	3	0
[13]	CBM	DS	No	0	3	0
[14]	CBM	DT	Yes	0	0	0
[15]	PdM	DS	No	2	1	0
[16]	PdM	DT	No	0	1	2
[17]	PdM	DT	Yes	0	0	0
[18]	PdM	DT	Yes	0	0	0
[19]	PdM	DS	No	0	2	0
[20]	PdM	DT	Yes	0	0	0
[21]	RxM	DM	No	0	0	0
[22]	RxM	DT	No	0	3	0
[25]	PdM	DS	No	1	2	0
[26]	RxM	DS	No	1	2	0
[27]	RxM	DS	No	3	3	0
[28]	CBM	DS	No	1	0	0

Chapter 3

The developed laboratory case study

In the food sector, manufacturers face significant challenges in adhering to food and manufacturing norms and standards. Due to these regulations, factories are required to set up strict internal policies and schedule maintenance appropriately. In their instance, even minor reactive maintenance might result in a significant financial impact because to the risks associated with product quality. Because of these additional costs, I tested my prepared system using the simpler procedure of a dairy facility. Two different product types are produced during the process and placed in similarly sized containers. The first item is milk in bottles. Yogurt, the second product, matures throughout the manufacturing process. In the following, I will describe the processes projected onto an existing Festo production line (Figure 3.1) in the Industry 5.0 laboratory for instructional reasons, where my prepared system was deployed.



Figure 3.1: Picture of the FESTO production line

3.1 The developed sensor network and information flow

To ensure comprehensive monitoring and control of the production line, all sensors and actuators within the physical system were thoroughly mapped. This mapping process served as the basis for creating the information model of the system (Figure 3.2), which visualizes how data flow throughout the production line and identifies key points of interaction between components. The production process can be divided into three main units: the cap transport, the bottle transport, and the product transport.

The cap transport: The initial step involves positioning the cap within a buffer container. Subsequently, it is transferred individually via a vacuum gripper to a conveyor. The conveyor can accommodate a maximum of four caps at any given time. The configuration is as follows: three are located in front of a dispensing arm, while the fourth occupies the terminal position on the conveyor. At this juncture, the caps are transported and sorted with a gripper. In the event that a cap is deemed to be of an incorrect dimension, the said cap will be sorted out and deposited in a designated reject receptacle by the aforementioned arm. In the event that the cap is deemed suitable, the arm will move it to the rotating disc, where the cap will be placed on the bottle.

The bottle transport: The production line is equipped with the capability to manufacture two distinct product types: those comprising a liquid fill and those containing a solid fill. After that, the aforementioned bottles are placed in an intermediate storage area which is determined by the product in question. It is essential to determine at the outset of the production process which products will be packaged in cans at the conclusion of production in a Human-Machine Interface (HMI). Consequently, the HMI transmits the pertinent parameters to the PLC, which is responsible for dispensing the bottles from the aforementioned buffer. The subsequent phase of the process involves the transfer of the bottles from the buffer to the relevant product dispenser.

The product transport: Once the products have been dispersed, the bottles are conveyed beneath the aforementioned cap transport arm, where the arm affixes the cap to the bottle. The subsequent stage in the process entails the utilisation of another arm, whereby the aforementioned cap is screwed onto the bottle. The completed products are transported by a conveyor for transfer to the packaging area. The final product warehouse is used for the distribution of empty containers that can hold up to six products. The products on the conveyor belt are transferred to the containers using a robot arm.

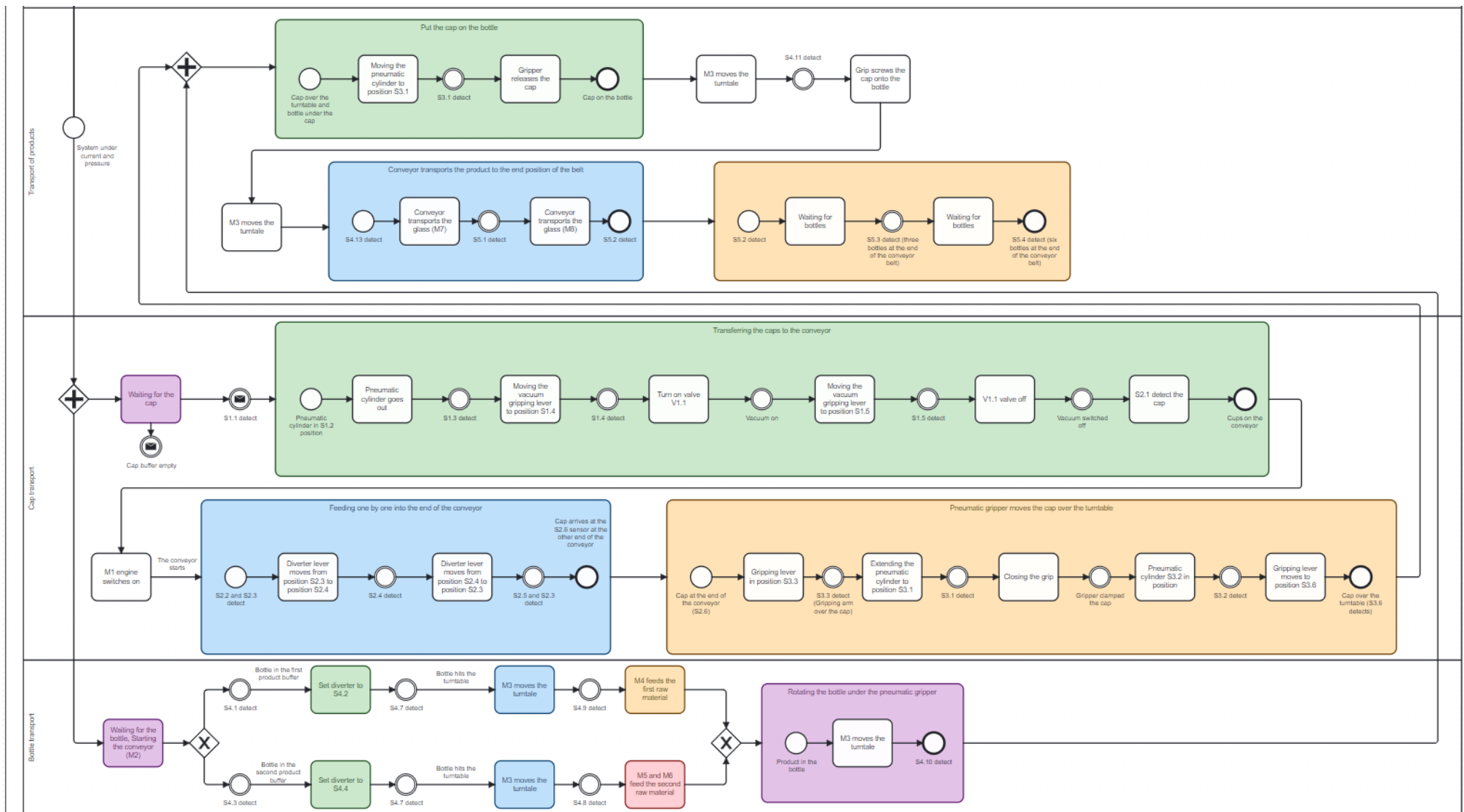


Figure 3.2: BPMN diagram of the production flow

The packaged products are placed either in an intermediate warehouse, which in the demonstration was considered to be a maturation warehouse, or in the warehouse for finished products. In addition to developing these diagrams, this stage also established several critical aspects of the production system:

- Types of devices in the system: A detailed inventory of all sensors, actuators, and machines involved in the process was compiled to understand their roles in the monitoring and execution of production tasks.
- Exact location of components in the production: The physical locations of each sensor and actuator were pinpointed, ensuring that every critical part of the production line was covered by the sensor network.
- Types of parts in production: The various materials and parts handled by the system, such as bottles, caps, and raw materials, were classified to better understand how they interact with the machinery and how sensors can track their movement and condition.
- Typical types of failure of each component: Potential failure modes for each piece of equipment were identified, such as motor failures, sensor malfunctions, or conveyor jams. This information is crucial for implementing the risk-based maintenance strategy.

By mapping the system, it is possible to guarantee that the sensor network is optimised for the capture of all the requisite data for real-time monitoring, fault detection, and the selection of the most appropriate maintenance strategy. This network forms the backbone of the DT, feeding critical information into the model to provide an accurate, real-time representation of the factory's operation.

In Table 3.1 the various sensors and their roles in the system are listed, showing how each contributes to the monitoring and maintenance of the production line. This setup enables continuous monitoring of equipment performance and product flow, identifying potential problems before they cause costly downtime or product defects. Utilising the pre-prepared spreadsheet, the database for the system was constructed. The production line was divided into eight sub-units, which were then used as the basis for the database tables. These sub-units were as follows: Distributing, Buffer, Handling, Rotating disc, Packager, Package carrier, Maturation warehouse and Final warehouse. Each table in

the database was assigned the sensors from the production line, in addition to other sensors that had already been installed at the site. These will be described in more detail at the next section. Furthermore, the most common causes of failure for each sensor were identified and assigned to the corresponding tables.

Name	Location	Type	Function	Potential Error
S1.1	Cup buffer (Distributing)	Optical gate	Detect cup in the buffer	Sensitive to pollution
S1.2-1.3	Cup buffer (Distributing)	Reed switch	Cap dispenser pneumatic cylinder detection	Switch burn-in
S1.4-1.5	Vacuum gripping arm (Distributing)	Switch	Detect arm position (cup/conveyor side)	Switch burn-in
V1.1	Vacuum gripping arm (Distributing)	Valve	Generate vacuum	Clogging
M1.1	Conveyor (Buffer)	Conveyor	Transport caps	Stretch of tape
S2.1	Conveyor start (Buffer)	Reflective optical gate	Detect cup start	Sensitive to pollution
S2.2-2.4	Conveyor (Buffer)	Reed switch /Optical gate	Detect cap and buffer arm position	Switch burn-in /Sensitive to pollution
S3.1-3.6	Gripping arm (Handling)	Reed switch	Detect arm cylinder/linear rail positions	Switch burn-in
M4.1	Bottle conveyor (Rotating disc)	Electric motor	Transport bottles	Stretch of tape
S4.1-4.6	Bottle conveyor (Rotating disc)	Reflective optical gate /Reed switch	Bottle/cap detection and arm position	Sensitive to pollution
M4.2-4.5	Rotating disc, Dispensers (Solid/Liquid)	Electric motor/Pump	Rotate disc, dose solid/liquid products	Bearing wear /Clogging
S5.1-5.4	Packaging conveyor (Packager)	Optical gate	Detect bottles at packaging stages	Sensitive to pollution
M5.1-5.2	Packaging conveyors	Electric motor	Transport bottles in packaging area	Stretch of tape
S6.1-6.30	Package carrier conveyor	Inductive sensor/ Optical gate	Position and package detection	Sensitive to pollution
S7.1	Cup buffer (Distributing)	Reflective optical gate	Detect multiple cups in buffer	Sensitive to pollution
S8.1-8.4	Packaged product buffer	Reflective optical gate	Detect buffer fill level	Sensitive to pollution

Table 3.1: Table to test captions and labels.

Figure 3.3 illustrates the final configuration of the developed system. The system can be subdivided into three principal sections: the DAQs and the sensors connected to them, the Message Queuing Telemetry Transport (MQTT) server, and the sections responsible for the processing, storage, and dissemination of the information that has been detected, according to user requirements. The following section will present an overview of the aforementioned components. The subsequent section will address the subject of brownfield tools in greater detail.

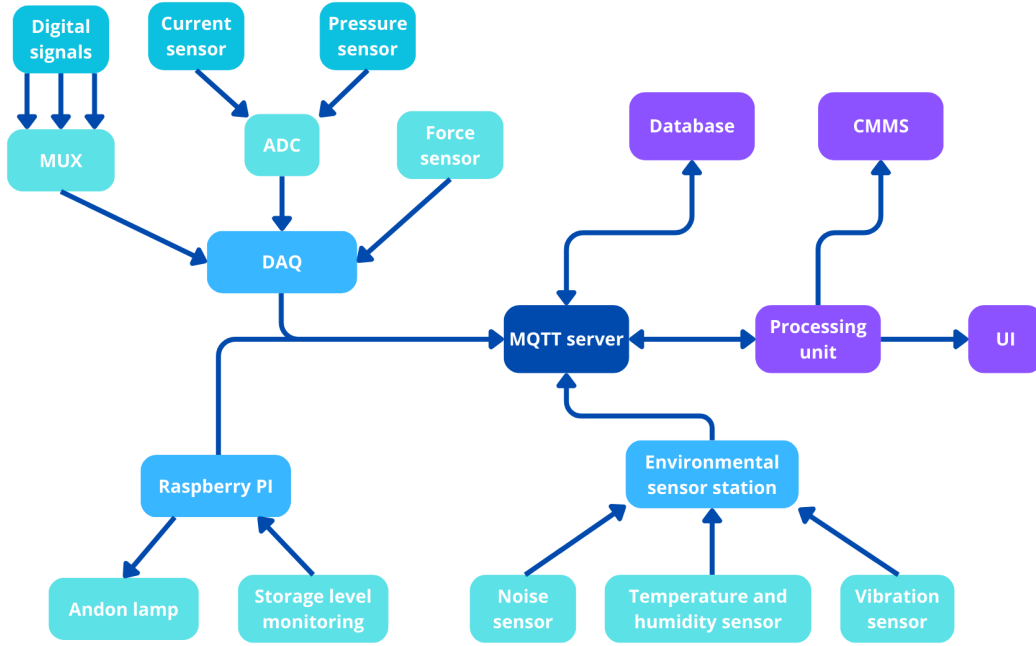


Figure 3.3: Architecture of the developed sensor network

The principal component of the system I have designed is the MQTT communication protocol. It is, in essence, a TCP/IP-based protocol, designed with the objective of minimising bandwidth and resource consumption. Furthermore, its open-source code facilitates a more straightforward setup and utilization in comparison to other analogous communication protocols. The protocol is based on the publish-subscribe pattern, which allows for the rapid and efficient transfer of data between a multitude of interconnected devices. In MQTT systems, the server is designated as a broker. The broker serves as an intermediary, relaying data between the publisher and the subscriber. The devices or clients transmit messages related to a specific topic to the broker, which then forwards them to the clients who have subscribed to that topic. In order to facilitate the accurate categorisation and filtering of the data, the signals from the various sensors have been

divided into discrete topics, with the exception of the digital signals collected by the DAQs, which have been consolidated into a single topic. However, a different label has been assigned to each sensor. Furthermore, the measured information is also assigned a unique timestamp prior to transmission to the server.

The data collection devices (DAQ, Raspberry Pi, Environmental sensor station) serve only as publishers within the system. In contrast, the processing unit will engage in two distinct yet complementary functions. Primarily, it will process the data from the specified time instant. Additionally, it will retrieve older states of the production line from the database. This approach will facilitate the development of more accurate maintenance models, as it allows for a deeper understanding of the production line's historical performance. It is accurate to conclude that, at this point in time, the sole function of the system is the collection of data. Data may be used to evaluate the viability of a prospective maintenance model prior to its incorporation into the system.

The processing unit is a Raspberry Pi, which is employed for the monitoring and filtering of sensor signals as well as for communication with the CMMS. The Node-RED programming language was employed for this implementation. Node-RED is a flow-based programming language based on Node.js. It offers the advantage of being open source, with numerous useful packages, as well as the possibility of building and testing programs over a network. For the aforementioned system, two packages were utilized: network operations and user interface interactions. Using the network package, sensor data stored on the MQTT server can be retrieved and subsequently processed before being sent to the database. Moreover, the processing unit can utilize this package to transfer maintenance information to the CMMS system via the REST API.

3.2 The developed and integrated brownfield sensors

In industrial environments, brownfield sensors refer to retrofit solutions designed to integrate with existing equipment and infrastructure, often without the need for significant modifications to the system. These sensors are added to monitor critical parameters in systems that were not originally built with advanced monitoring capabilities. By introducing brownfield sensors, I can collect and analyze valuable data in real-time, enabling better decision-making and more effective maintenance strategies. Together, these brownfield sensors form a robust sensor network that enhances the ability to monitor

the production line in real-time, predict potential failures, and implement maintenance models.

I developed a DAQ that can collect digital data from each stage of the manufacturing process. This DAQ can monitor multiple variables, such as power consumption and pressure levels at various points in the pneumatic system. When in use, this machine provides maintenance employees with a thorough understanding of the production line's performance, allowing them to spot inefficiencies or emerging issues before they lead to equipment failure or downtime.

The Figure 3.4 shows the PCB diagram of the DAQ. The central components include two CD74HC4051E multiplexers, which handle multiple inputs and allow communication between the connected components. An MCP3421 analog-to-digital converter is used to convert analog signals to digital and is complemented by an ACS758SM current sensor module and the pressure sensor. Additionally, a distinct I2C communication port has been integrated into the DAQ. I2C facilitates multi-master and multi-slave operations, which can be leveraged to increase the total number of sensors connected to the DAQ. An example of this would be a force sensor for monitoring dosage, which would be particularly useful in product dosage applications. Power is supplied by an LD1117 regulator, which provides a stable 3.3V supply to the system. The system is controlled by a NODEMCU microcontroller, which is responsible for data processing

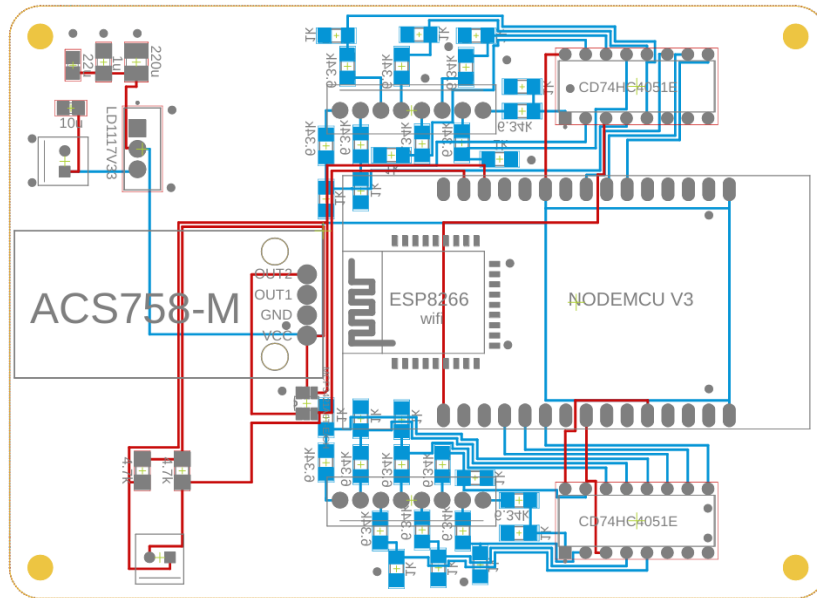


Figure 3.4: PCB plan of the DAQ

and communication via WiFi, enabling wireless data transfer.

I have implemented two Andon lamps (Figure 3.5) on the shop floor, each controlled by a Raspberry Pi 4B, to visually monitor and display the status of different parts of the production process. The role of the Andon system is to provide clear and immediate visual feedback on the state of the production line, allowing workers to quickly identify and respond to any issues. The Andon lamps use a three-color system:

- Green: Indicates normal operation.
- Yellow: Signals a warning, suggesting that an issue might be developing.
- Red: Indicates a serious problem that requires immediate intervention.

Figure 3.6 shows the operation of the two andon lamps. The upper part of the diagram shows the operation of the andon lamp in the end store, while the lower part shows the operation of the andon lamp at the cap buffer. In both cases, the process starts by initialising the program running on the Raspberry Pi. The Raspberry Pi then monitors the signals from the four sensors in the final warehouse (Figure 3.5a), which detects how

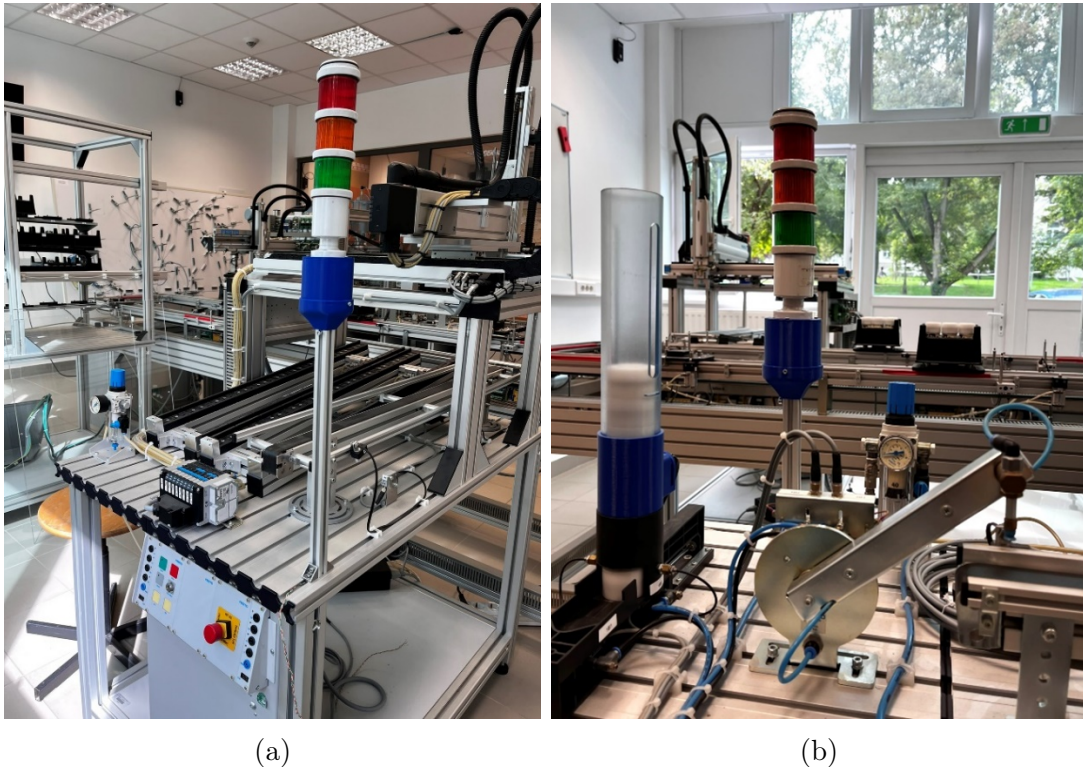


Figure 3.5: Andon lamps on the production line

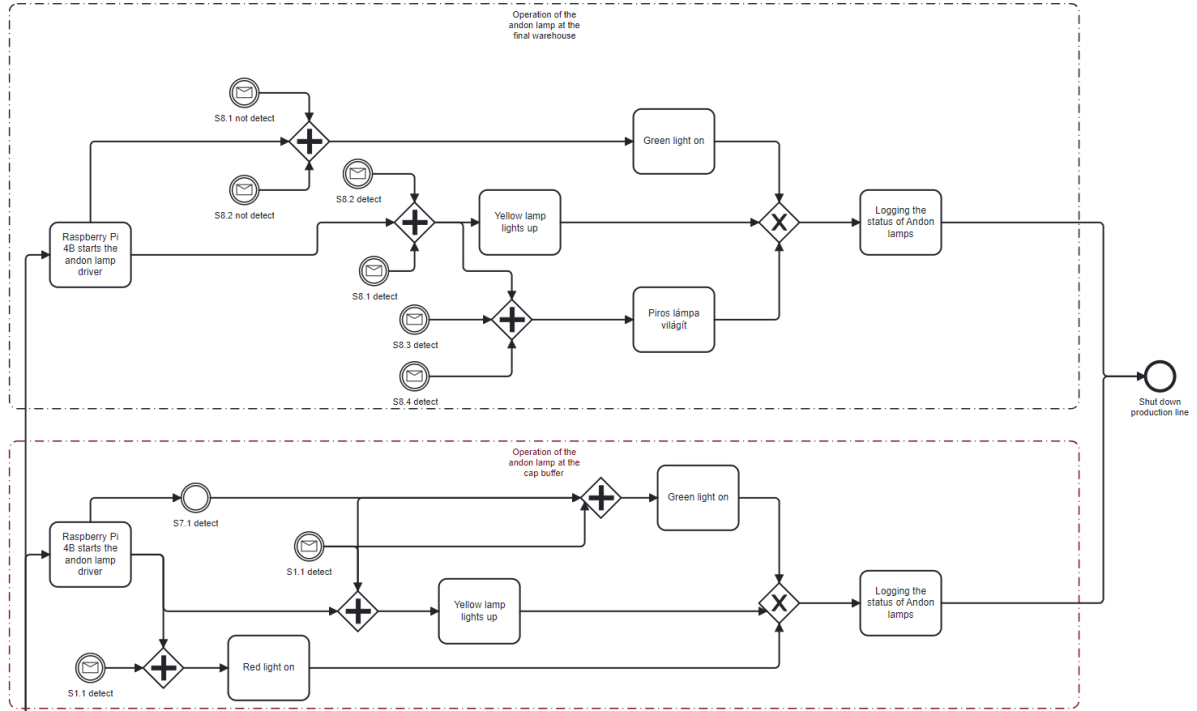


Figure 3.6: BPNM diagram describing the operation of Andon lamps

full the final warehouse is for a given type of product. Depending on the sensor signal, a green light will go on if the level is below a certain level, a yellow light will go on if the level of the crates holding the bottles is between two sensors, and a red light will go on if the final warehouse is fully saturated.

The Raspberry Pi on the cap buffer monitors two sensors during operation. These two sensors are located at the bottom and centre of the cylindrical storage tank shown in the Figure 3.5b. The light will be green when both sensors detect caps, the light will turn yellow as caps are consumed, the light will turn red when only the bottom sensor detects caps, and the light will turn red when the last cap is removed from the buffer. In addition, a custom environmental sensor station (Figure 3.7) has been constructed and installed, comprising instruments for measuring temperature, humidity, vibration, and noise. In order to assess the impact of vibration on the production line, the sensor station was strategically positioned at the location where vibration is of greatest consequence. This is the point at which the cap is transferred over the glass and placed on top.

The fundamental component of the sensor station is the MSP430G2553 microcontroller, which supervises the function of the sensors and disseminates the accumulated data through the UART protocol (Universal Asynchronous Receiver-Transmitter) to a

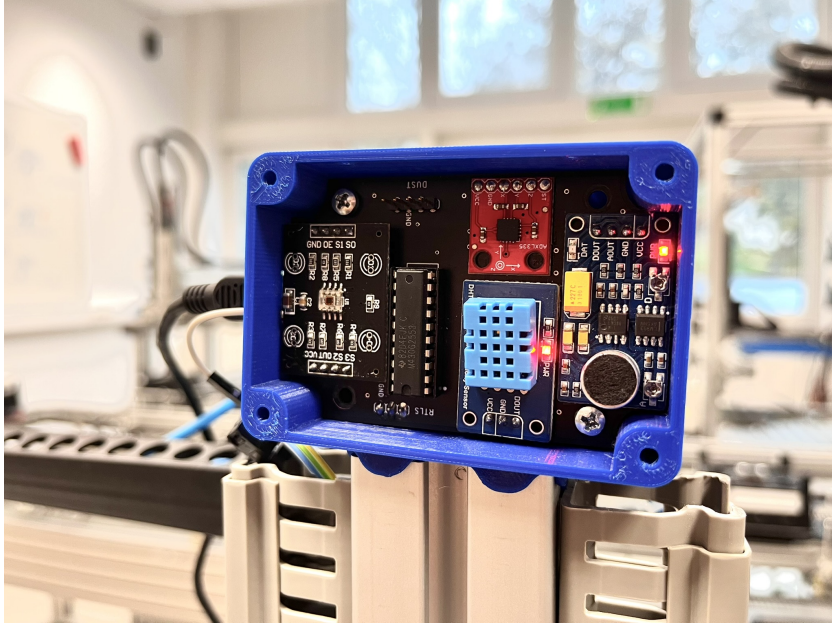


Figure 3.7: Environmental sensor station

NodeMCU microcontroller. The NodeMCU microcontroller subsequently transmits the data to the MQTT server.

3.3 Demonstration study - maintenance scenario

The time taken to complete maintenance operations is calculated from the moment the failure is reported until the system is restarted. The majority of the time spent on troubleshooting is dedicated to identifying the fault and preparing the necessary tools to rectify it. The use of CMMS can facilitate the dynamic management of time-based and state-based maintenance requirements for individual machines, thereby reducing the aforementioned time. However, the current approach to fault reporting in these systems remains based on the speed of employees. The next significant advance in reducing the duration of this process will be the implementation of a system whereby faults are reported directly by machinery, negating the need for human input into the CMMS.

The CMMS enables the transmission of discrete work requests to the user based on the sensor signals. As previously stated in Section 3.1, this communication is conducted via REST API. The JSON format message must contain the following parameters:

- requestedBy: the unique identifier of the notifier, in this case the processing unit

- subject: name of the work request
- productionStopped: maintenance necessitates a shutdown, which is defined as a Boolean operation.
- failureDate: date of failure in ISO8601 format
- description: description of work
- deadline: deadline in ISO8601 format
- assetId: equipment identification number

Figure 3.8 shows the Node-RED program that was used for the demonstration. The program initially obtains environmental data from another program. Then it checks whether the environmental data exceed the allowed limit. If this is the case, the program transmits the JSON message detailed above to the CMMS.

In response to the received message, the CMMS generates a work request. In order to utilise such systems in an effective manner, it is of paramount importance to define the constituent elements of the production process with sufficient granularity. The Figure 3.9 depicts a work request that alerts maintenance personnel to exceedances of the pre-defined vibration maximum at a specific point within the system. A work task may be created by a maintenance worker or an employee of an equivalent rank, based on the information provided in the work request.

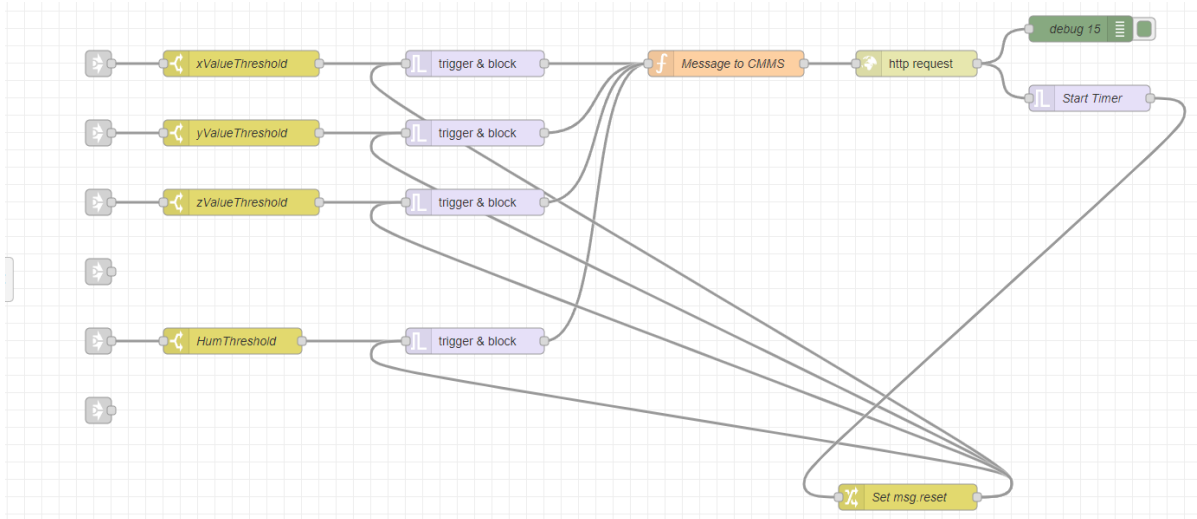


Figure 3.8: Node-RED program for communication with CMMS

MK000887 - Vibráció határértéken felüli.
Nyitott

Munkafeladathoz rendelés
Szerkesztés
Munkafeladat kiírása
Elutasítás

MUNKAKÉRELEM

Lokáció	I.5.0 Research lab.
Berendezés	Handling
Létrehozva	2024.09.27. 20:24
Meghibásodás kezdete	2024.09.27. 18:24
Határidő	2024.10.26. 08:00
Kategória	
Munka leírása	Berendezés túl nagy vibrációnak van kitéve. Vizsgálat szükséges.

KÉRVÉNYEZŐ

Monitoring name	
Név	Technikai felhasználó
Munkakör	
E-mail cím	
Telefonszám	

CSATOLMÁNYOK

Dokumentumok	
Képek	

Figure 3.9: Work request in the CMMS renderer

Another advantage of the CMMS system is that each user is required to enter an email address. The email address is used to distribute notifications upon receiving job requests for which the individual in question has been assigned (Figure 3.10). The email provides a concise overview of the essential details pertaining to the work request. Furthermore, this facilitates the expeditious rectification of any errors.

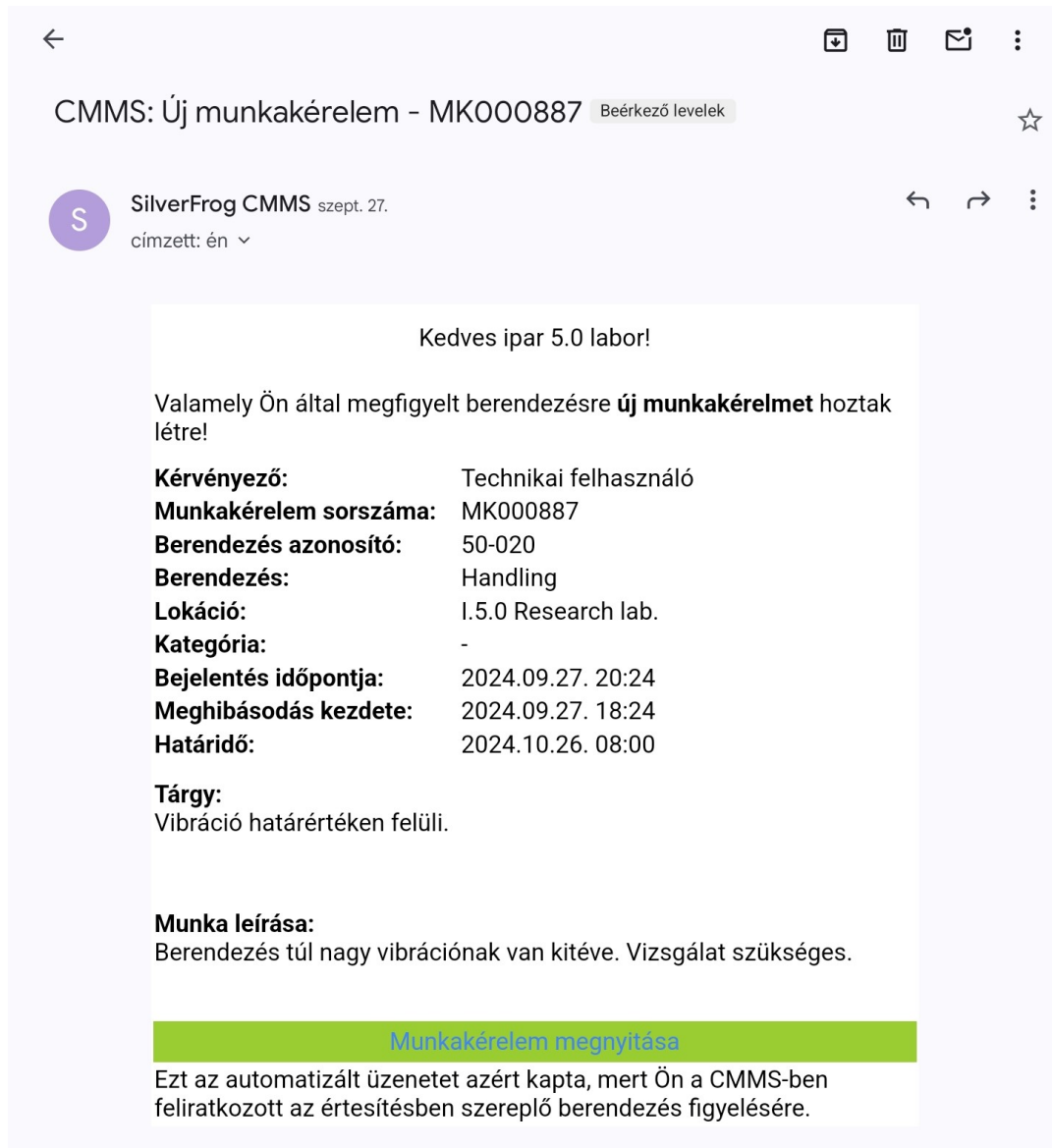


Figure 3.10: Email notification of work request

Chapter 4

Conclusions and further steps

The objective of my research was to develop a system that could serve as a foundation for my future research on the utilisation of digital assets and maintenance strategies. The resulting DS system is designed to be scalable so that it can be employed in actual production environments. The constructed system can be divided into three principal groups: data acquisition units, data transmission and storage systems, data processing units, and systems that communicate information to employees and maintenance personnel.

The system comprises three different types of data collection modules. The system comprises three types of data collection units. The first, DAQ, is responsible for gathering digital signals that regulate the production line process and the corresponding physical signals, such as motor current consumption or pneumatic system pressure. The second sensor station is tasked with measuring the environmental parameters of the shop floor and quantifying the vibration generated during production in a specified area of the production line. The third unit monitors the status of containers at a given time, either at one of the inputs to the production line or at the output of the production line.

To facilitate communication between the units of the system, an MQTT server was constructed, offering the benefit of straightforward data handling at scale. The data collection modules are linked to the server as publishers, while the database and the processing unit are connected as both publishers and subscribers. The database categorises the signals received from the server and stores them, subsequently transmitting the sensor states it has read to the processing unit.

The processing unit is currently engaged in the conversion of sensor signals into a format compatible with the user interface, with the objective of transmitting them to the

aforementioned interface. Additionally, the system monitors existing and potential faults on the production line and generates maintenance work requests for the CMMS. The user interface presents an overview of the current status of the shop floor environment. In the subsequent phase of my research, I intend to supplement this by utilising the accumulated sensor data to facilitate the user interface in visualising the production process.

The following step is to expand the functionality of the processing unit, in addition to that of the user interface. This will entail enabling the unit to perform not only error identification but also the discovery and communication of the data necessary for maintenance. This encompasses the choice of suitable maintenance strategies. Furthermore, it would be desirable to enhance the system's capability for error detection.

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