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Acquisition and presentation system for Energy Management - design and implementation

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***Abstract*—Energy Management (EMS) is understood as the effort to minimize energy consumption in industrial facilities through a continuous improvement approach. Decentralized Control Systems (DCS) concentrated on optimizing energy consumption in small and medium enterprises (SMEs) are still rarely used. The practical application of the continuous improvement approach relies on a Deming-like cycle, utilizing data gathered through Data Acquisition and Presentation Systems. The article addresses the issue of designing and implementing such type of systems as foundation of Energy Management in SMEs.**

***Keywords*—Data acquisition and presentation systems, IIoT systems, EDGE computing, Cloud computing, Energy management**

I. Introduction

ENERGY management is crucial, not only from a financial perspective, but also in light of the growing problem of climate warming. This challenge requires significant changes for companies [1], that have not previously prioritized energy consumption reduction. This transformation demands an unavoidable investment, which must be carefully planned and gradually implemented to avoid disrupting ongoing operations [2]. The paper presents the entire process of designing and implementing a data acquisition and presentation system. This system, in combination with a Deming-like cycle approach, will support companies in reducing their energy consumption.

The paper provides information on high-level business goals and both functional and non-functional requirements. Furthermore, it offers detailed insights into the architectural aspects of the infrastructure and software, as well as the algorithms that support efficient data analysis [3]. Additionally, the article discusses the most significant issues related to selected non-functional requirements [4]. The final section delves into the matter of further system development, addressing some of the problems mentioned in the preceding sections.

This article presents two alternative options: a straightforward architecture centred around an RPI computer, and a more sophisticated solution built upon IIoT infrastructure. In the following steps, authors provide a comprehensive description of all the details and issues that arose during the implementation phase, with a primary focus on those related to non-functional requirements. This article addresses challenges pertaining to Big Data topics and considers solutions within this domain. Additionally, authors explore Edge computing as a potential solution to address a significant portion of these issues. Some of the algorithms that support users in gaining a better understanding of energy consumption structure are presented along with references. Additionally, a compound method of data analysis is proposed.

All the primary issues encountered during the implementation phase are outlined, and some potential solutions are suggested for the further development of the presented system. In summary, the results of the proof of concept (PoC) and real-world business cases are provided to demonstrate the effectiveness of such solutions in practical situations.

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II. Energy Management

A. Deming-like Cycle

In many cases, particularly in SMEs, modifying Decentralized Control Systems (DCS) to prioritize energy management is a challenging task that requires significant time, effort, and cost to be fully implemented. However, a much simpler approach can be considered for temporary use to understand the nature and structure of energy consumption in the company. This approach is based on a Deming-like cycle, as shown in Figure 1.

This approach consists of a few simple steps outlined below.

1) Measure: collect data from sensors (e.g., energy, gas, flow, environmental meters, etc.).
2) Analyse: analyse collected data in order to find opportunities for improvements.
3) Prepare: use the identified opportunists to define an action plan on how to reduce energy consumption.
4) Act: implement the plan either by introduction of manual, structural changes or by implementation of control theory.

B. Selected capabilities

The previous section describes the general approach based on continuous improvement that can be used to address energy leakage. The steps in this approach (a Deming-like cycle) must then be translated into a list of capabilities that address all the needs in the energy management area. A list of selected capabilities with brief descriptions can be found below.

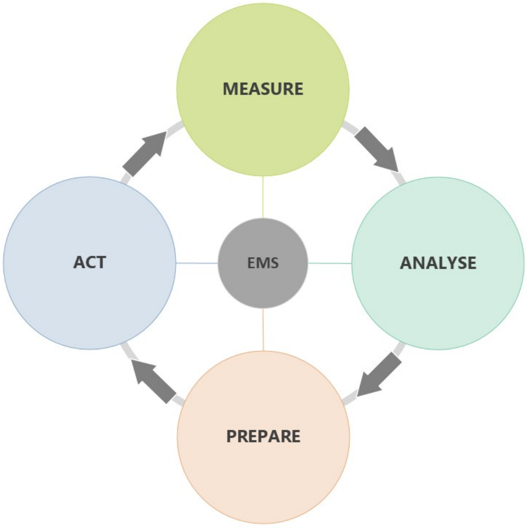

Fig. 1. Deming-like cycle in Energy Management in SMEs.

- Real-Time Monitoring – energy monitoring to track usage patterns and identified area for improvements.
- Energy Analytics – analysing of data to gain insights into usage trends, relations and patterns.
- Energy Auditing – conducting energy audits to identify opportunities for energy savings.
- Forecasting and Planning – predicting future energy demand and plan energy consumption accordingly.
- Fault Detection and Diagnostics – detecting malfunctions and providing tools to address issues promptly.
- Reporting and Visualization – generating reports and visualisation to communicate energy performance.
- Compliance Management – ensuring compliance with regulatory requirements and standards.
- Remote Monitoring and Control – enabling remote access and control allowing real-time adjustments.
- Renewable Energy Integration – integrating renewable sources into energy mix to optimize their usage.
- User Engagement – involving and educating end-users in energy-saving practices.

The final point is particularly interesting because it actively engages employees in the company's energy-saving efforts.

III. Requirements

Based on the capabilities defined for energy management and the functionalities listed for Energy Management Systems, a list of functional and non-functional requirements can be established. Below one can find some selected aspects of both areas (functional and non-functional).

A. Functional Requirements

In order to build fully functional Energy Management System above capabilities should be broken down to functionaries. A list of selected once can be found below.

- User Authentication and Security – authenticate users and devices accessing EMS, protect sensitive data.
- Automated Metering Infrastructure – remote control of energy meters allowing data collection.
- Data Acquisition and Monitoring – collecting real-time and archive data from energy meters.
- Data Aggregation – data aggregation in time and space to achieve high view on emery performance.
- Data Mining – utilizing data analytics tools to unveil data consumptions trends and patterns.
- Process Mining – utilizing results of data mining to improve processes to gain energy savings.
- Alarms and Notifications – communicating occurrence of defining situations to be able to react promptly.
- Reporting and Dashboards – reports and figures presenting energy consumption, savings and performance.
- Compliance and Regulatory Reporting – reports regarding compliance with standards and regulations.
- Accessibility and Scalability – enable remote monitoring and management of energy data (big data).
- Gamification – utilization of gaming approach to convince employees to pay attention to energy consumption.

The lasts point could be effective, as it may increase employee engagement in energy management through a gamification approach

B. Non-Functional Requirements

The importance of non-functional requirements can be illustrated with the following example. Assume the energy management infrastructure consists of ten energy meters, each with only one channel. If data from these meters is read once per minute and stored in a database, this results in 14400 records collected and stored daily, and over 5000000 records annually. Considering that real use cases are much more complex, involving 500 to 1000 devices measuring more than four channels each, non-functional requirements become a significant challenge. These challenges need to be addressed from the very beginning, as we are dealing with Big Data issues even in relatively small systems.

IV. Concept

The general concept of the system is visible in the Fig. 2.

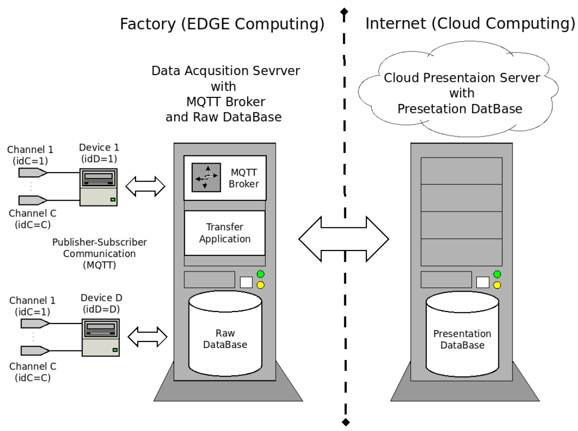

Fig. 2. The general concept of the Energy Management System.

In order to fulfil non-functional requirements, this concept relies on both edge and cloud computing environments. The raw data should be stored locally within the factory, with the edge computing system responsible for aggregating it and transferring only selected aggregated data to the cloud. Otherwise, the cost of storing all data in the cloud would increase indefinitely without significant improvements in system functionality. This approach assumes the connection of numerous multi-channel measuring devices that will be read at configurable intervals (e.g., every minute). Communication with these meters will be implemented using their specific protocols (e.g., Modbus), which will then be converted to a universal protocol commonly used in Industrial Internet of Things (IIoT) systems (e.g., MQTT). Additional converters will be necessary to translate the meters' protocols to MQTT. The edge system will house raw databases, including some aggregated data, while the cloud server will store only the aggregated data. Ensuring secure communication between both environments is crucial and must be carefully considered before implementation. The cloud environment will provide high-level capabilities, allowing users to access prepared data and draw conclusions related to energy consumption.s

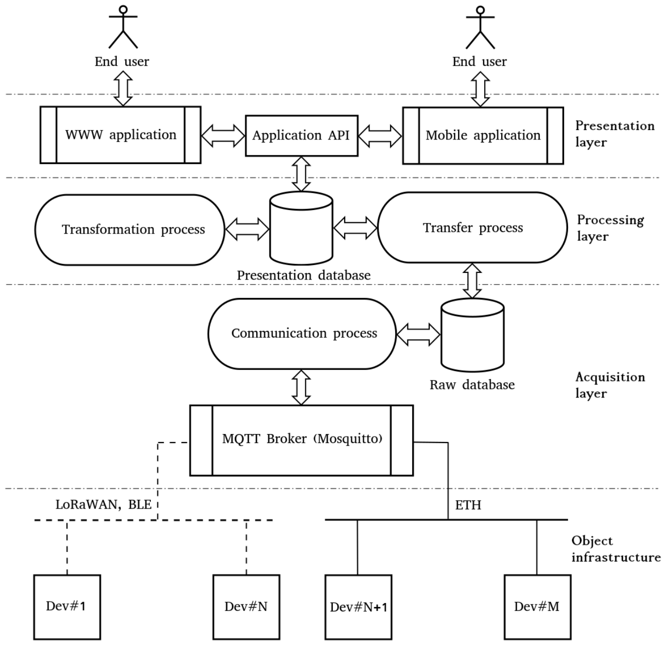

Fig. 3. The general architecture of the Energy Management System.

V. Architecture

In the next step of the design process, the architecture of the system needs to be proposed. Figure 3 presents the high-level architecture of the system that will meet most of the previously mentioned requirements. This architecture is divided into four layers: infrastructure, acquisition, processing, and presentation.

The first layer ensures communication with the metering infrastructure to enable real-time monitoring. In this solution, two commonly used approaches are considered: a classic cable network using Ethernet or a radio connection using LoRaWAN or BLE. Assuming small communication packets with measuring devices, the MQTT protocol can be considered for communication. MQTT is a simple IoT/IIoT protocol based on a producer-subscriber communication model.

The acquisition layer consists of three main components: an MQTT broker, which serves as the central point for data exchange, and a communication process responsible for transferring data between the broker and the raw database used to store the original data collected from the meters. This layer secures data acquisition and monitoring.

The processing layer is responsible for data aggregation and transformation. It manages the transfer of data from the raw database to the presentation database and implements all necessary data transformations. This layer can be complex and includes the following capabilities: energy analytics, forecasting and planning, fault detection and diagnostics, and preparing data for complex reporting and visualizations. Having two database in the system provides redundancy.

The final layer, the presentation layer, ensures communication with end users. For maximum flexibility, there should be a single, unified application API available for desktop, mobile, and web applications. The API facilitates communication between front-end solutions and the presentation database. This layer can be built using various, multi-level technologies and can use different protocols for communication between the API and the different user interfaces. Some examples will be discussed in the following sections.

In summary, this simple architecture addresses most of the capabilities related to data acquisition and presentation part in Energy Management Systems. It gives high flexibility and ensures scalability. However, it worth to mention that implementing this architecture requires significant effort and resources to create a distributed, real-time, multi-layer system.

VI. Implementation

A. *Use case 1*

Figure 4 illustrates a straightforward data acquisition and presentation system designed to test communication with specific energy meters. This system also encompasses some of the foundational capabilities discussed in the preceding section. The system was built using the industrial version of the popular minicomputer, the Raspberry Pi Compute Module 4. Equipped with an RS-485 module, the Raspberry Pi established connections with the energy meters. Communication between the measuring devices and the computer was implemented using the Modus ASCII protocol.

Additionally, several IT components were installed on the Raspberry Pi Compute Module 4. Notably, a Python solution was developed to collect data from the energy meters and store it in a MySQL database. This database was designed to house both configuration data and measurements. To present data to end users, a simple web-based system was created using Java Spring Boot technology and ReactJS. The combination of these widely used technologies enabled the efficient creation of an application that allows users to define basic system configurations and view data through reports and figures.

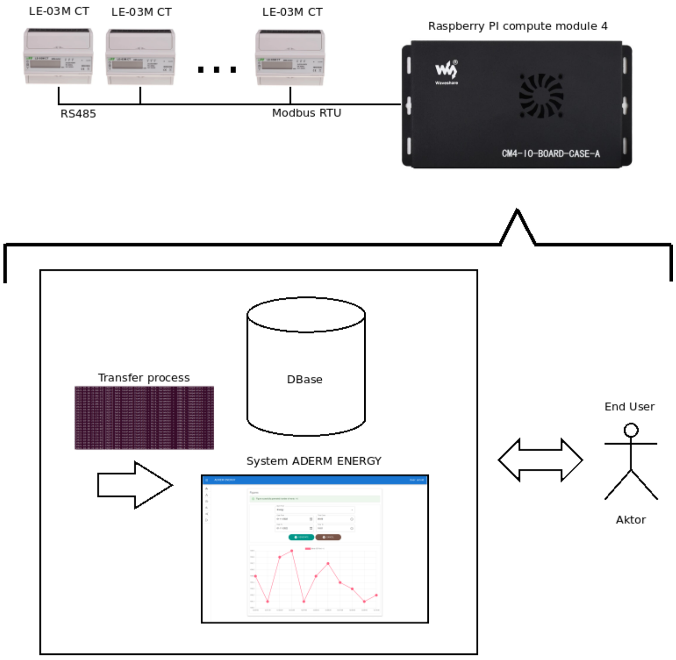

Fig. 4. Simple EMS system implemented based on RPI CM 4.

Throughout the testing phase, this system was linked to the factory network, allowing employees to monitor energy consumption across various segments of the energy infrastructure. Additionally, it was feasible to activate the Wi-Fi hotspot on the Raspberry Pi (RPI) computer, enabling direct connections to the system from mobile devices or local computers.

B. Use case 2

The second approach, as depicted in Figure 5, was proposed to enhance the security and scalability of the system within a real factory setting. This solution leveraged the Industrial Internet of Things (IIoT) concept [5], utilizing some off-the-shelf devices produced by RAK company.

At the core of this system was a gateway responsible for securing communication with both the measuring devices (via LoRaWAN) and the presentation layer (via Wi-Fi/LTE). This gateway is equipped with an MQTT broker, enabling unified communication across the entire system using the MQTT protocol. In this specific use case, the MQTT broker was installed on the presentation server.

The communication between the energy meters and the gateway was established using Modbus-LoRaWAN converters. These devices facilitate the collection of data from multiple devices using the Modbus ASCII protocol, following configurable routines. The collected data is then transmitted via LoRaWAN to the gateway.

In the subsequent step, the gathered data is sent to the presentation server using a Wi-Fi connection and the MQTT protocol. To ensure security, a transfer application subscribes to defined MQTT topics and sends the data to the presentation database (MySQL).

The final application, developed using Java Spring Boot and ReactJS technologies, implements various presentation functionalities, allowing end users to track energy consumption through reports and figures.

In general, this simple system has met most of the expectations outlined in the previous sections. However, there are some issues that require correction in future versions of this solution.

One of the issues involves the non-deterministic behavior of converters collecting data from energy meters and sending it to the gateway. Even though the data measurement cycle and the schedule for reading each meter were precisely defined, the timestamps of the data fluctuated. Since LoRaWAN is a low-energy protocol that sends small data packets and is designed to minimize energy consumption, the meters were probably not read on time, resulting in delays or early data readiness. This issue can be easily resolved by replacing the simple meters with slightly more advanced ones that have the capability to store archived data.

The second issue, which was anticipated during the design phase, relates to the large volume of data being collected. Unfortunately, this has a significant impact on the stability of the database, which is a critical component of this solution. There have been several instances where tables and indexes in the database were corrupted due to the substantial number of processes working with them simultaneously and the large dataset. While these issues are easy to fix when they occur, it is important to find a systemic solution to prevent them from happening in the first place.

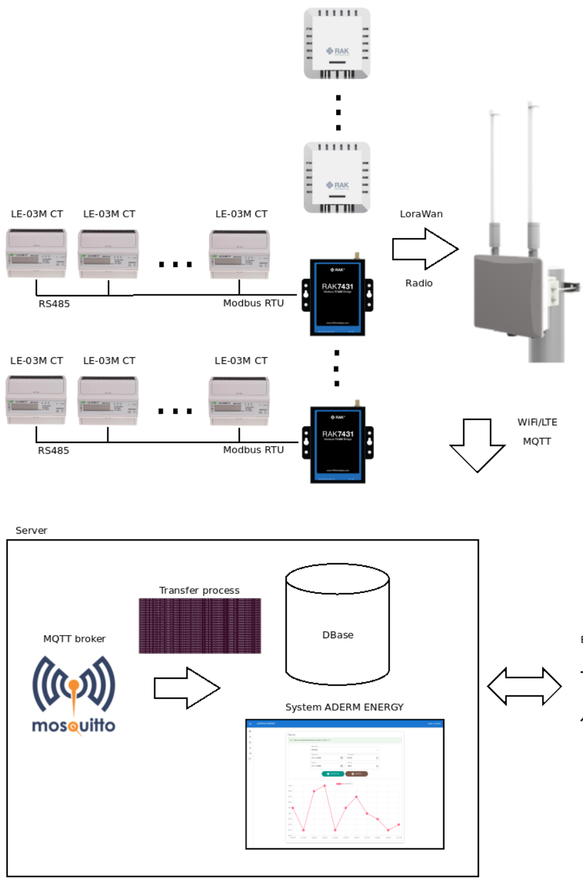

Fig. 5. Simple EMS system implemented based on RPI CM 4.

One solution is to introduce full redundancy in the system by separating the acquisition servers (inc. databases) from the presentation servers. The next level of redundancy involves duplicating the acquisition and presentation servers, thereby creating two redundant channels. To maintain data consistency, one can use the replication algorithm available in MySQL. This ensures that if one database goes down and then comes back online, all data will be copied from the properly functioning database to the affected one.

Unfortunately, it's not possible to use similar functionality to copy data from the acquisition servers to the presentation servers because the types of data stored in the two databases are different. To address this issue, an additional, customized process needs to be introduced.

The final system setup for acquisition and presentation servers and databases, which addresses all the issues encountered during the entire process, is shown in Figure 6.

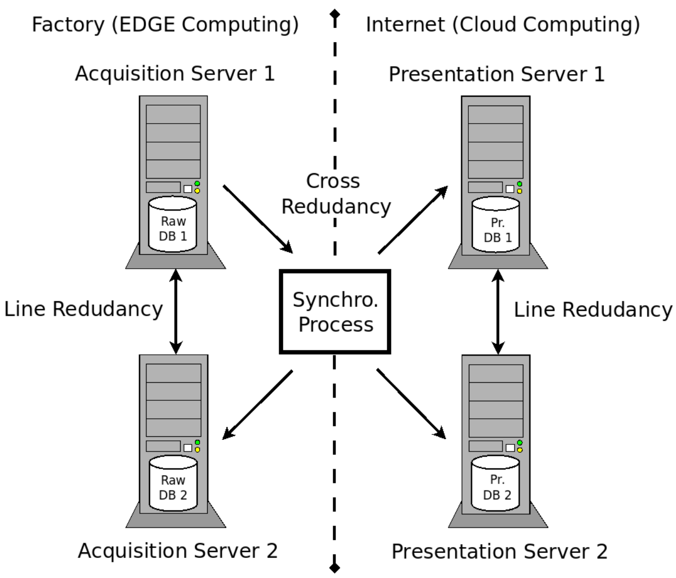

Fig. 6. Cross and line redundancy in the acquisition and presentation system.

The introduction of additional servers, databases, and other components increases the cost of the infrastructure but, on the other hand, enhances the stability, security, and scalability of the system, making it more advanced and ready for further development.

VII. Data Mining

The steps described in the previous section of this paper aimed to secure foundational processes such as data acquisition and presentation. This section is devoted to fulfilling some of the expectations related to data analysis and mining. Several interesting algorithms that aid in understanding behaviour represented in data can be found in the following papers: [3] and [6]. The ultimate goal is to provide methods that allow users to identify patterns and opportunities for improvement. Even more advanced function is to implement data prediction capabilities, which are crucial in advanced Energy Management Systems. To implement these types of functions in the system, it is necessary to first prepare the data sets.

A. Matrix notation

To organize the data collected from the factory's meter network in an easy-to-use form, it is beneficial to consider both the time and space dimensions. The matrix notation can be used and defined as follows:

- let $n \in (1, \ldots, N)$ denote he number of single-channel energy meters in the existing infrastructure,
- assume $t \in (1, \ldots, T)$ represents a point in time (the same for all energy meters),
- considering the above assumptions, one measurement in time and space can be denoted as $m_{(n,t)}$,
- the set of measurements can also be presented as a matrix $M_{[N\times T]}$ in the form of:

$$M_{[N\times T]} = \begin{bmatrix} m_{(1,1)} & \ldots & m_{(1,T)} \\ \vdots & \ddots & \vdots \\ m_{(N,1)} & \ldots & m_{(N,T)} \end{bmatrix} \quad (1)$$

.

Formulating the set of measurements as a matrix allows us to consider the relationships between different elements in both time and space. In practice, this means that in addition to examining the natural temporal relationships of the measurements, one can also analyse the relationships between measurements from different machines in the factory.

B. Correlation invariants

One important aspect of the collected data series is their interdependence. In practice, this means that the correlation between data from different meters might be crucial for understanding infrastructure behaviours that may not be immediately evident. There are two simple factors that can be used to reveal these relationships based on the analysis of previously defined matrix $M_{[N\times T]}$. Let's begin by defining the linear correlation function for two time series:

- let assume two times series given by $s_i = (m_{1,1}, m_{1,2}, \ldots, m_{1,T})$ and $q_i = m_{2,1}, m_{2,2}, \ldots, m_{2,T})$
- Linear Correlation Function (LCF) is given by the equation:

$$C_{s,q} = \frac{\sum_{i=1}^{I}(s_i - \overline{s})(q_i - \overline{q})}{\sqrt{\sum_{i=1}^{I}(s_i - \overline{s})^2 \sum_{i=1}^{I}(q_i - \overline{q})^2}} \quad (2)$$

,

The Linear Correlation Function (LCF) can be easily transformed into the Linear Autocorrelation Function (LAF) for a single time series. This transformation allows us to identify the following situations:

- a positive autocorrelation indicates that similar patterns tend to repeat at regular intervals,
- a negative autocorrelation suggests that opposite patterns occur with a certain periodicity,
- a zero autocorrelation implies no linear relationship between the observations at different time points.

Understanding autocorrelation helps to uncover hidden patterns in time series data, which is essential for making reliable predictions.

The second indicator unveiling even more sophisticated correlations in the data set is based on the Information Theory. Assuming similar notation of time series as above, Mutual Information coefficient can be defined as follows:

$$\overline{I_{s,q}} = \sum_{i,j} P_{s,q}(s_i, q_i) \log_2 \left[\frac{P_{s,q}(s_i, q_j)}{P_s(s_i) P_q(q_i)} \right] \tag{3}$$

,

Unfortunately, the Mutual information is much more difficult to be calculated in practice, however there are at least two algorithms available in the literature, which describes how to do that. One of the is based on adaptive histograms [7] and second one is bases on kernel density estimation [8].

VIII. Industrialization

A. Use case 1 - infrastructure

To assess the efficiency of system implementation and its scalability, both use cases described in the previous sections were validated with real-world examples. The first use case, implemented based on the RPI CM 4, is depicted in Figure 7 on the right side. This system is equipped with an LCD screen that allows users to monitor the current state of the system and verify whether it's operational. The user interface provides information such as date and time, device temperature, energy consumption from the meter, and the total amount of data collected so far.

In the same image, on the left side, one can see the electric cabinet where this simple system was deployed. End users found this solution convenient because, in addition to centralized data gathering, they could connect to the device using their mobile phones to check the system status and analyse the collected data.

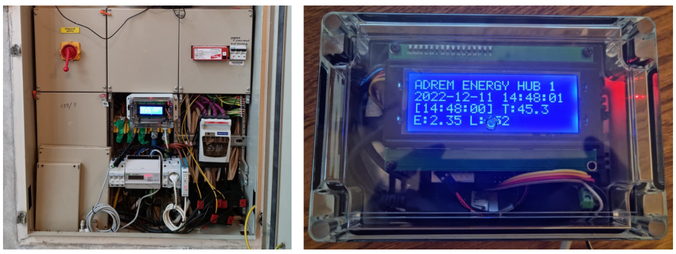

Fig. 7. Simple EMS system implemented based on RPI CM 4.

The implementation of the second example followed the concept presented in Figure 5. Utilizing ready-to-use, out-of-the-box devices significantly simplifies the process and accelerates achieving the final results. However, there may be requirements that are not straightforward to implement and necessitate customizations, which always carry some risk (both in terms of time and implementation costs).

In this specific case, the primary challenge was configuring the system to transfer data from energy meters every minute, precisely at the same second. Unfortunately, with the devices

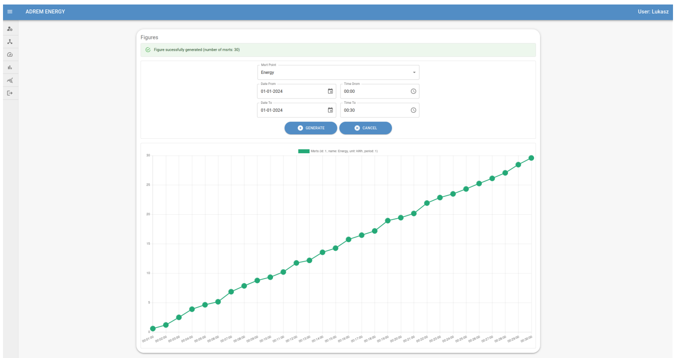

Fig. 8. Simple EMS system implemented based on RPI CM 4.

selected for this project, achieving this level of precision was not feasible. However, this limitation is not critical in practice. A straightforward solution would be to replace the energy meters with ones that have an internal data buffer, allowing them to store data temporarily.

Despite this challenge, the system operated effectively, and the chosen equipment offered a wide range of possibilities.

IX. Conclusions

To summarize the various aspects considered in this paper, several conclusions can be drawn:

- optimal control algorithms that prioritize minimizing total energy consumption during the production process are rarely utilized in small and medium-sized enterprises (SMEs) at the moment,
- in the past, energy costs were not a significant concern because production revenue far exceeded these expenses,
- the situation has changed - energy costs have risen significantly in recent months, posing a substantial challenge for SMEs,
- the current solution involves collecting data from sensors placed at different locations within the factory to measure energy consumption,
- by adopting a continuous improvement approach, the goal is to systematically eliminate or minimize energy wastage,
- modern data collection and presentation systems, leveraging IoT technologies and statistical methods, play a crucial role in addressing this challenge,
- data mining and process mining can serve as efficient tools for identifying energy wastage and proposing targeted improvements.

In addition to these general conclusions, it's worth to mention that there is significant potential in data mining and process mining, which can now be implemented using modern AI approaches. Furthermore, the implementation of such systems can leverage the capabilities of edge and cloud computing. By combining these technologies with a big data approach, they can offer numerous benefits for Small and Medium Enterprises (SMEs). Furthermore, assuming that a significant portion of energy consumption in factories can be influenced by employees, it is crucial to persuade them to pay close attention to this issue. An effective approach to achieve this is by implementing various gamification strategies, similar to those used in IT companies, to enhance overall efficiency.

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