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Frequent and Automatic Monitoring of Resource Data via the Internet of Things

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Abstract. The Internet of Things (IoT) offers potential for developing an intelligent and sustainable manufacturing system, allowing for better and more informed decisions that increase efficiency and cut down waste in production processes. The insights are generated from automatically collected data coming from machines and devices. While process data are already reported and support a close to real-time monitoring and evaluation of process efficiencies, data about resource consumption in manufacturing environments is more scarce but crucial for becoming more resource efficient. Through connected hardware and software applications, data from resource consumption of energy, water, and waste can be automatically collected. To achieve this, this study presents an IoT framework for monitoring resource efficiency in an automatic and frequent manner. Thus, the eco-efficiency and productivity of the process can be measured and integrated into the decision-making processes by sharing the data with shop floor and production management personnel via dashboards.

Keywords. Data-driven, Eco-efficiency, Manufacturing, Internet of Things

1. Introduction

In recent years, the concept of Industry 4.0 has become increasingly important, characterized by technologies such as Internet of Things (IoT), big data, and cyber-physical systems (CPS), which are used to achieve productivity gains and higher profits [1, 2, 3]. The aim is an intelligent system, integrated vertically from machine to internet as well as horizontally from machine to machine along the value chain [4], that can predict and act on potential problems arising in production processes in real time [2]. Monitoring and coordination are possible via analysing information sourced from machines, embedded sensors, and actuators [4], while data collection and transmission between the devices are enabled through IoT [1, 3, 5].

Another major trend in the industry, accelerated by the sustainability crisis [6], is the growing attention to sustainable manufacturing through resource efficiency, providing advantages such as cost savings, independence of volatile resource prices, reputational improvements, and adaptations to consumer preferences [5]. Sustainable manufacturing (SM) is defined as the procedure of creating products and services through economically sound processes that minimize negative environmental impacts

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while conserving energy and natural resources [7]. While scholars called for corporate environmentalism as early as 25 years ago [8], its relevance today is expressed by new regulations and international agreements. This is, among other things, highlighted by the European Union's Green New Deal, promoting the development towards a green and digital industry with low-emission technologies and sustainable processes, and the United Nation member countries' agreement on the Sustainable Development Goals (SDGs) [9, 10]. Numbers 9 and 12 of the SDGs concern "inclusive and sustainable industrialization" and "responsible consumption and production", formulating the target of achieving "sustainable management and efficient use of natural resources" by 2030. The goal is to improve resource efficiency as well as tracking and reporting on energy, water, and material consumption via the reporting guidelines developed by the UN [11], thereby establishing a common way to collect, share, and report data about progress towards the SDGs.

Despite its importance, few case studies so far focused on the application of emerging industrial technologies for eco-efficiency gains in production processes. Despite its potential, many companies struggle with inefficient, costly and time-consuming data collection practices. This study aims to provide a framework on how to efficiently collect and integrate resource parameters such as energy, water, and waste from production processes into the decision-making process. in order to collect and use data on resource parameters such as energy, water and waste.

2. Frame of Reference

Recently, research has grown at the intersection of the two major trends of data-driven technologies and sustainable manufacturing development [1, 3, 12, 13], spurring the widening of the purpose of Industry 4.0. Having so far focused on data-driven technologies, the concept has recently been supplemented and extended by principles of social fairness and sustainability, called Industry 5.0. The new concept still aims to deploy the mentioned technologies to increase automation and flexibility, while developing these solutions in a human-centered way that adapts to the worker instead of the other way around, and deploying them for circularity and sustainability [14].

Conducting a systematic literature review, Jamwal et al. [13] found that technological solutions such as big data from shop-floor activities, IoT solutions such as connected sensors and machines that communicate data between systems through the internet, and machine learning to analyse and act on the large amounts of collected data, have become significant factors for achieving sustainable manufacturing [13]. This is supported by a literature study conducted by Andronie et al. [15], finding a great potential in similar technological developments, however stating a lack of practical applications of analytics of real-time data from IoT devices. Both studies suggest that optimization techniques through the stated means could help develop models for efficient shop-floor management, picturing a future state in which autonomous and self-optimizing actuators can steer production processes based on real-time analysis. Shrouf & Miragliotta [5] suggested a high-level framework for working with IoT to collect energy data from production processes, finding six achievable benefits from applying IoT. Jagtap et al. [16] found similar issues in the food industry regarding lack of data on resource use and waste generation on production-line level and introduced a practical framework for using IoT solutions to support real-time monitoring of waste, energy, and water in food production.

Despite previous research suggesting that Industry 4.0 holds great importance for sustainable manufacturing and pointing at shop-floor management to act as the crucial element for achieving eco-efficiency in manufacturing, case studies from the automotive industry are lacking and many challenges still unresolved. On the one hand, machines already constantly report productivity data about the process, as in the cycle time that it takes the machine to produce a task including operative and idle time, and throughput, specifying the number of products that a machine turns out in a certain amount of time. This is shared and used in an organization for, among other things, production planning and maintenance. On the other hand, several problems arise regarding information on resource consumption:

- First, reports on resource consumption are only created a few times a year on a high factory level, leading to a lack of awareness of resource consumption and waste generation and thus of resource management practices [5, 16].
- Second, it is time-consuming to collect the information on resource consumption of various parameters, among others energy, water, and waste, in manufacturing processes at machine and process level. The operational technology (OT) was often introduced several decades ago and is proprietary, making it harder and costlier to collect the information.
- Third, even where information exists, it is often stored in different locations and hence difficult to access and is not digitally visualized to all employees who could draw insights from the data in order to affect resource consumption of processes.

Consequently, despite companies from across the industry being already concerned with collecting data on resource consumption, its mostly used once at the end of the month for billing purposes, while its usability for precise process improvements on eco-efficiency is low. In this context, IoT solutions can support frequent collection and monitoring of resource consumption in manufacturing environments [16]. This study aims to contribute to the area of data-driven sustainable manufacturing through a case study applied in the heavy duty and off-road (HDOR) industry. While the case company's ambition towards more resource-efficient processes follows the global trend and aims to reduce energy, waste, and water consumption in all industrial operations, as shown in the study by Jagtap et al. applied in food manufacturing [16], other companies might have different parameters to investigate. Through the deployment of connected IoT hard- and software, so far mostly in use for maintenance purposes such as monitoring machines by streaming production data and hence not utilized to its full potential, a flexible setup can guarantee the collection of different parameters.

To achieve this, this study presents and discusses an IoT framework for monitoring and visualizing resource efficiency, in this case on water, energy, and waste, in an automatic and frequent manner. This allows measuring and integrating eco-efficiency with the productivity data of the process into the decision-making support, by sharing the data with shop floor and production management personnel via dashboards.

3. Method

The study's methodological approach follows the Design Science Research, addressing research through the building and evaluation of artifacts designed to meet the business need [17]. Through this, an appropriate and effective solution, e.g. a hardware or software framework, can be designed to solve the identified problem.

This study stems from a cooperation project between the case company, in the following referred to as 'the company', in the HDOR industry and the academy, using inductive reasoning due to a scarcity of previous studies. Both quality engineers and environmental coordinators from the company took part in project discussions and helped define the status quo in the company. The innovation arena Smart Factory Lab was used in the case company to develop and test new frameworks, avoiding the risk of having to interfere with production-critical processes. The use case in the lab comprises a process that includes the parameters energy (kWh), water (l), and waste (kg). The environmental data were collected by applying smart sensors and devices designed to interact with gateways and servers to network with an IoT framework that decodes, forwards, and stores the data signals. The developed framework can then, once evaluated, be implemented at other processes in the production environment.

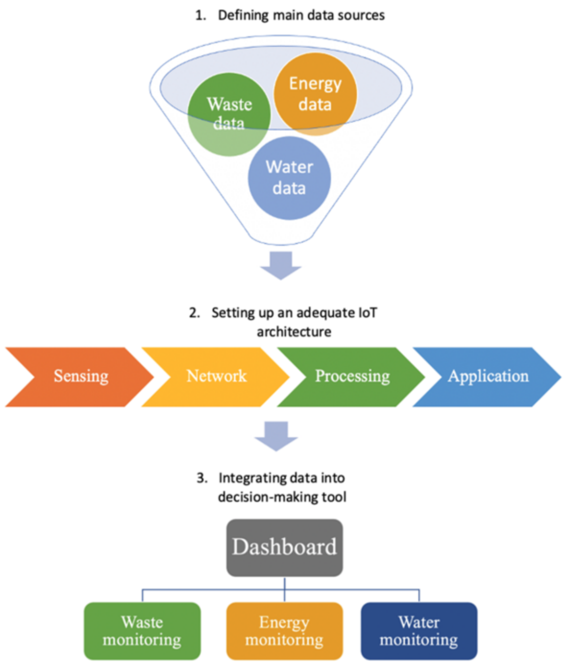

Figure 1: IoT-enabled framework for monitoring resource efficiency in manufacturing (inspired by Jagtap et al. [16]).

3.1. Data collection

Data about consumption of the three parameters energy, waste, and water served as the main data source. Since most machines today lack the ability to report data on resource consumption, this required the integration of measuring alternatives. By adding specific sensors tailored to the process, the existing operational technologies were retrofitted to report missing data. Meter-Bus (M-Bus) sensors reported data on a building level, while LoRaWAN energy sensors from the company mcf88 together with a gateway that links the end devices to the network server collected data every minute on a machine level. To measure the waste consumption at the source, the following components were selected: an industrial floor waste scale from the company Elicom Electronic, highly stressable and spacious for industrial recycling containers, and a RaspberryPi used as a gateway. Regarding water metering, wireless LoRaWAN water meters from the company Quandify communicating via a LoRaWAN protocol to the gateway were chosen and mounted onto the lab's pipe.

3.2. IoT architecture

Several software systems were needed to continuously and automatically collect the signals generated by the hardware and report them to the gateways. The chosen software setup includes open-source IoT solutions, namely Node-RED, InfluxDB, and Grafana, after both open-source and commercial IoT frameworks with Amazon Web Services (AWS) had been tested. The IoT platform Node-RED supports the connectivity of the sensing devices with its various protocols and networks and processes the data. The generated data were stored in the database InfluxDB, and the dashboarding tool Grafana was used to retrieve the stored data and visualize them in a user interface (UI). Furthermore, the dashboard can analyse and share the data to all employees involved, to pass on data based on the users' needs.

3.3. Integration for decision-making support

With the sensing solution and IoT architecture in place, resource consumption can be monitored, improved, and taken into account during the continual improvement processes. Solution processes in production today are often based on visual reports from engineers summarizing production data. The environmental dimension outlined in this paper was visualized in a dashboard, receiving automatic and regular data updates and showing trends of resource consumption over time.

4. Case study result

4.1. IoT architecture

Several different IoT architectures consisting of three, four, or five layers are frequently outlined in literature [18, 19]. At the physical level, a device or perception layer uses smart sensors to translate information from the physical environment into computational form in the shape of data signals, communicating the data to the local server via gateways. The gateways are part of a network layer providing the network through which the sensor data are transferred in a specific format. From there, the data go to a service or processing layer that is able to store, analyse and process high quantities of data, based on user requests. A content or application layer then gives feedback to the user mostly in the form of visualizations or calculations. For this study, an IoT architecture based on four layers is used: sensing, network, processing, and application layers.

Node-RED is an open-source browser-based IDE (Integrated Development Environment), using pre-built modules to achieve connections from operational technologies such as PLCs and sensors to information technologies (IT) such as the outlined softwares like InfluxDB. This OT/IT connection is made by using different IoT protocols such as MQTT and LoRaWAN. The flow nodes can parse the data from one format into another, more usable one. From there, the messages are forwarded and stored in InfluxDB, a time-series database suited for large and time-stamped IoT data. The dashboarding part is done with Grafana, a browser-based data visualization application that offers several advantages. First, it can connect to different databases. Second, it allows the user self-service functions such as filtering, aggregating, analysing, and visualizing as well as automatic updates on the dashboards in regular intervals.

This setup (Figure 2) removes the need for manual data collection and updates and is flexible to allow user-based designs, not overwhelming the user with unnecessary information. To ensure a secure connection, all applications are hosted on an on-premises server in the case company.

4.2. Energy monitoring

The energy data packages regarding the building's energy consumption are generated by a Meter-Bus (M-Bus) energy meter connecting to a M-Bus converter that sends the data over a TCP protocol to a server forwarding it to a proprietary SQL database. Node-RED connects to the SQL database to receive hourly energy consumption values in kWh and forwards them to InfluxDB. On the other hand, the LoRaWAN energy meters attached to the machines in the assembly line can report data every minute. Linked via the LoRaWAN gateway to a network server, where its connectivity is managed and an Application Programming Interface (API)) exposed, the sensor signals can be queried from Node-RED. There the data are decoded from hexadecimal into Base64 format and forwarded to InfluxDB.

4.3. Water monitoring

The architecture for the LoRaWAN water meters is similar to the LoRaWAN energy meters, where the gateway connects the end devices to a network server that receives the data packages. At the server side, an API is exposed and allows for backhaul connectivity for data processing through Node-RED. In contrast to the energy meters, the water meters aggregate data and forward hourly values to the server in order to reduce battery drain.

4.4. Waste monitoring

Waste data are streamed from the scale via cabled RS232 serial communication to a single-board computer (SBC), in this case a RaspberryPi. In the SBC, a python script runs as a TCP server that connects with and listens to a socket and receives the waste data. From there, the received messages are parsed and published via MQTT to a broker to which Node-RED can subscribe and continue the data processing.

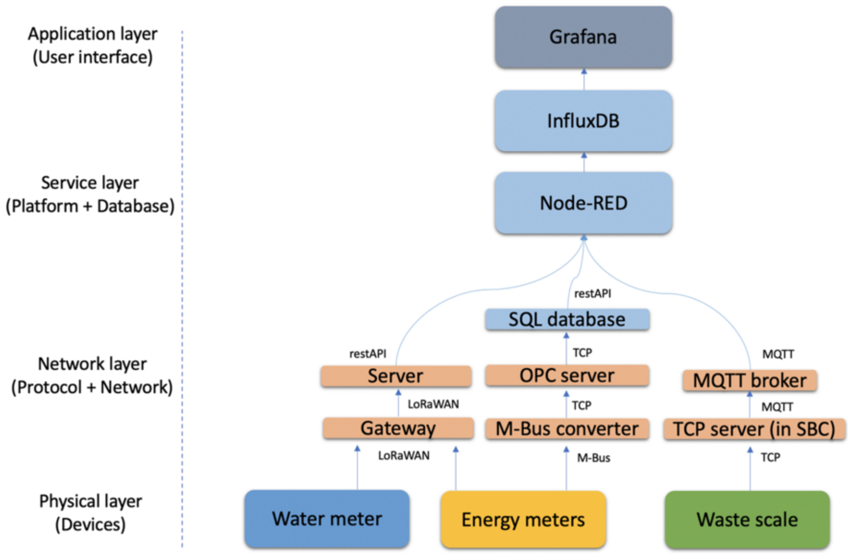

Figure 2. Four-layered IoT architecture used for gathering resource data.

4.5. Integration into decision-making tool

The resulting dashboard comprises the parameters energy, water, and waste, visualized in line graphs over time to reveal consumption trends (Figure 3). Energy from a machine level and waste get updated every minute, while energy on building level and water data are aggregated and reported on an hourly basis due to the suppliers' sensor solution. The data can be visualized in different graphs and periods, depending on the user's needs. This allows for trend analysis to understand how many resources a given machine or station consumes in a certain time. Aggregated values (such as total energy consumption) can complement the dashboard, to show concise information for gross assessments.

5. Discussion

Previous research as well as technological developments have highlighted the potential of using IoT solutions for sustainable manufacturing [13, 15], however there are scarce studies linking the two and evaluating the outcome in practice. While Jagtap et al. [16] studied a similar problem applied to food manufacturing, no studies were found in the automotive industry. This paper is one of the first to present a framework that allows manufacturing companies to collect resource parameters and use it in their decision-making, through the means of IoT technologies.

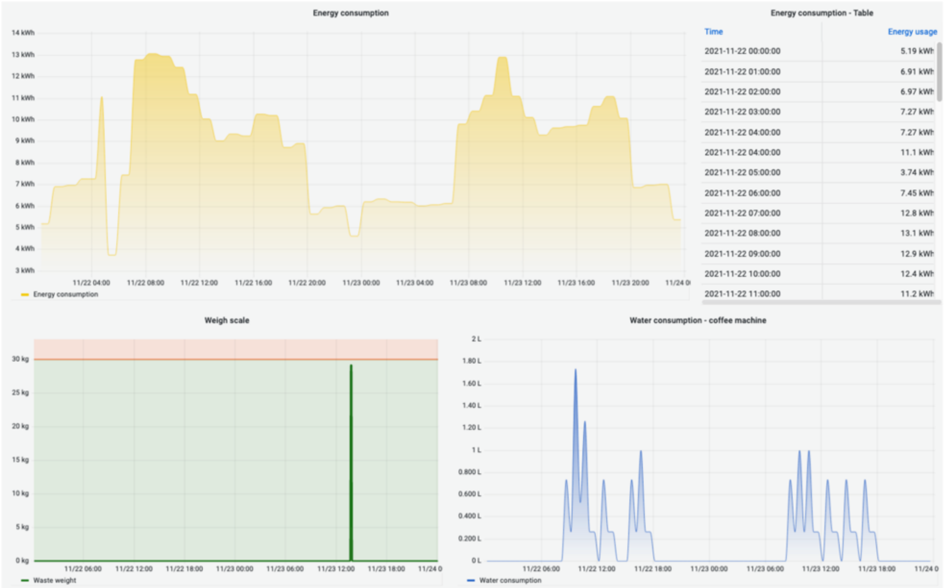

Figure 3. Dashboard including energy, waste, and water data collected during two days.dd

5.1. *Discussion of results*

Preliminary results show the strengths of IoT solutions for achieving eco-efficiency evaluations in industrial decision-making processes. While energy is measured today on a building level every hour, water and waste data are more scarcely collected at the company. The outlined IoT framework allows for automatic and more frequent data collection of these parameters, based on the needs of the users. This way of automatic data gathering is time-saving and eliminates the need for manual collection. The resource data can be obtained both from a detailed machine level and from an aggregated factory level, allowing for the identification of main consumers in processes. In a subsequent step, the environmental data can be combined with productivity parameters to create the link between production output and resource consumption. This will result in decision making taking both productivity and environmental information into account. The data collection and analysis over time can provide understanding of normal and abnormal behaviour of the process. This information allows the production personnel to take better informed decisions and manually optimize production processes.

However, monitoring resource efficiency is not effortless. New and wireless IoT technologies such as LoRa are constantly emerging, rendering the search for adequate hardware time-consuming. Each alternative promises unique advantages, yet testing and evaluation need to be done to understand the implications of each technology for the company and the use case. The protocols and networks offered show differing properties that need to be weighted depending on the usage. For example, the used water and energy meters communicate through the LoRa network, advantageous with its wide area network coverage and economic and wireless hardware, but inconvenient with its low bandwidth restricting frequent data trafficking. On the other hand, MQTT is an easy-to-use, light protocol with fast delivery time but showing drawbacks in scalability. Also, the hardware configurations can differ from supplier to supplier, as in this study’s case one supplier programming the water meters for hourly reporting, another the energy sensors for every minute.

Since several sensor solutions deployed in this project are found to communicate in different data formats, through different protocols, and at different granularities, this compatibility issue required the development of a suitable data integration framework. The framework needs to allow connections from all kinds of existing OT, such as described sensors and programmable logic computers (PLCs), to a common platform, database, and dashboard. To do this, numerous open-source solutions are available and prove a viable option for industrial usage. Here, flexible integration with other tools and free use are main advantages while on the downside some functions and documentation as well as service support are found sparse or lacking. For example, tools such as Grafana allow for flexible dashboard customization and basic statistical calculations that provide deeper insights into consumption patterns, while the user experience (UX) part is improvable. The commercial platform AWS, on the other hand, was found to be an advanced and versatile tool also able to connect different equipment and to analyse and visualize the information. However, costs and user-friendliness are downsides, since the device onboarding and the IoT setup need to be done by personnel with AWS and at least basic programming knowledge.

For these reasons, it is good to set measurable criteria for the hardware as well as the software choices, based on the needs of the company and the use case. For the purpose of this study, the hardware was chosen based on several criteria: quick setup, low maintenance, high reliability, low cost, wireless connectivity, and customizability. Regarding software, easy device onboarding by the user, cyber and data security, low maintenance, good integration with other software, and customizable user interface were the criteria. This led to the use of low-cost hardware and free software that allow companies to test the proposed solutions without having to invest large amounts of money and time. Additionally, the three software tools Node-RED, InfluxDB, and Grafana can be regarded as building blocks, permitting for substitutions of each of these tools. Commercial solutions offering full-stack frameworks like AWS or Microsoft Azure, on the other hand, restrict companies while demanding more effort and higher investment. Hence, the outlined framework is specific to the case company's needs, but allows for easy testing for varying applications within different companies.

Finally, case studies like the one presented stand or fall with the support from different employees in the company. Especially during the problem definition phase at the beginning of the project, support and knowledge sharing from employees is crucial. The company studied had already certain roles defined that were predestined to offer support for this study, however other companies might not own these resources or employees might show more reluctance. Furthermore, the laboratory used for testing the framework has helped in accelerating the testing and development process of this study. Companies needing to test on 'real' production will face additional complications.

5.2. Discussion of method

The proposed IoT framework consisting of different sensors and free software solutions was chosen on the basis of the listed criteria. These tools depict only a popular fraction of the available solutions, as the market for IoT hard- and software is vast and a comparison between all the alternatives would be interminable. Since each of the proposed layers can be substituted, other types of solutions may be chosen and compared to the results of this study.

5.3. Discussion of future research

Once consumption behaviour is better understood, a subsequent step could be to merge resource and productivity information into one decision-making tool for the user. With defined KPIs on both resource and process efficiency, alerting features in software such as Grafana can be used to notify when deviations occur. Having said that, the data visualization side poses challenges, where more and more data introduced to the user (who is already concerned with large amounts of data) need to provide insights that are intuitive to understand. For this, a UX study investigating how the information is best displayed could follow. In a later stage, the systematic collection and data processing could allow for using mathematical or metaheuristic optimization methods in order to improve both of the seemingly contradictory goals of productivity and resource efficiency.

6. Conclusion

In the course of this paper an IoT framework has been developed that allows for flexible and automatic collection of resource data from production processes. Further, the integration of data on energy, water, and waste into a decision-making tool for production personnel is presented. The developed IoT framework can lead to a better understanding of the processes, in order to allow manual optimization. The newly collected and processed data can be analysed to generate key performance indicators (KPIs) through which better production planning can be realized. With the sensing solution and IoT architecture in place, the KPIs can be monitored, improved, and taken into account during the continuous improvement process. This will expand the traditional decision-making process into a combination of productivity and environmental KPIs and support organizational reporting and learning on resource efficiency.

To achieve this, the integration of data signals from hardware to software in the IoT framework of this study requires customized solutions, and choosing the right configuration is vital. An integral part of IoT technologies, there are multiple different IoT protocols available, each one showing different advantages and capabilities suitable for various needs based on the IoT deployment. Equally important is the deployment of adaptable software that allows the wiring together of the different hardware devices. This IoT framework can be established as one of the first standards for companies where traditional process efficiency is aimed to be combined with resource efficiency.

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