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Industrial IoT system for laser-wire direct energy deposition: data collection and visualization of manufacturing process signals

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Abstract. Industry 4.0, also known as the Fourth Industrial Revolution, is a term used to describe the current trend of automation and data exchange in manufacturing and other industries. The Internet of Things (IoT) plays a crucial role in Industry 4.0 by connecting devices, machines, and products to the Internet and enabling real-time data exchange. Moreover, additive manufacturing is a key developing manufacturing technology in Industry 4.0. New technologies such as data analysis with Artificial Intelligence and machine vision are widely used in optimization. However, in a lab environment, these technologies depend on the data collected from the process. For such work, the researchers should be able to focus on their core research rather than on the development of infrastructure to collect and analyse the data. This research presents an open software and hardware IoT solution to monitor a laser wire direct energy deposition system installed in a cartesian type 3-axis machine tool. The IoT solution adopts three open-source tools for core issues, such as 1) interoperability, flexibility, and availability; 2) data storage; and 3) data visualization of sensor data and manufacturing process signals. The system architecture is based on one or more edge devices connected to sensors and forwarding their data toward a local API endpoint. The endpoint is created with Node-RED, an open-source visual flow-based development tool for IoT data. Node-RED forwards the data to an open-source InfluxDB database. Finally, the data is visualized with an open-source Grafana application. The system is prototyped, designed, implemented, and tested in a lab environment to monitor a laser-wire direct energy deposition process. The significance of such a flexible IoT data collection system for research and development projects can be integral. Thus, providing savings in time and money can substantially speed up the development of new technologies where the value arises from the sensor data and its analysis.

Keywords: Internet of Things, Additive Manufacturing, Manufacturing process monitoring, open source

1. Introduction

Metal 3D printing, also known as metal additive manufacturing, is one of the most relevant technologies in Industry 4.0. This is because it offers several benefits that are highly relevant to modern manufacturing, such as the ability to produce complex geometries [1], improve part performance, and reduce the cost and lead time [1] associated with traditional manufacturing methods [2]. By fine-tuning the printing parameters, such as laser power, travel speed, and wire feed rate, manufacturers can achieve better control over the properties of the printed parts [3]. This can result in better control of the part geometry and improve mechanical properties, such as strength, hardness, and ductility [4], [5].

A laser wire direct energy deposition system is an additive manufacturing technology that uses a laser to melt a wire feedstock material as it is deposited onto a substrate. The process involves feeding a wire into the melt pool created by the laser and depositing it layer by layer to build up a 3D object. The laser melts the wire and fuses it with the substrate, creating a strong and precise bond. This technology can create complex geometries and repair damaged or worn parts, making it useful in aerospace, automotive, and medical [2].

Optimizing the printing process can also help to reduce defects and improve the quality of the printed parts [6]. For example, by predicting the temperature and stress distributions during the printing process, manufacturers can identify potential defects and adjust the printing parameters to prevent them [7], [8]. Additionally, in-situ monitoring techniques, such as infrared cameras and acoustic sensors, can help detect defects in real time and enable corrective actions to be taken during printing [9]. Through the optimization of the printing process, manufacturers can achieve greater control over the properties of the printed parts and improve the quality of the final product.

Data collection is an integral part of the research, as it serves as the foundation for generating accurate and reliable findings [10]. It enables researchers to gather information and evidence that helps in answering research questions, testing hypotheses, and drawing conclusions [10]. Furthermore, this work presents an affordable and flexible solution for data collection from the laser wire direct energy deposition system used in the lab. Moreover, user-friendly visualization tools make it easier for researchers to get firsthand knowledge from the process in real time. Further, the system is tested, and its performance is evaluated.

Research questions are defined as follows:

1. *How to collect data from various sensors to monitor the 3D printing process.*
2. *How to make the collected data easily available for the researchers.*

IoT-related research work often centers around the challenge of achieving efficient and affordable data collection. Researchers at the University of Iowa have highlighted the need for a data acquisition infrastructure that can enable them to focus on research and scholarship rather than being bogged down with hardware and software development [11] This is also reflected in a survey conducted in 2015, which identified the need for tools to facilitate the development of various IoT applications and services [12].

1.1. Context

Here the aim is to optimize the laser-wire direct energy process for additive manufacturing by monitoring the process using a suite of sensors. However, the system's architecture has yet to be discovered, and new sensors may be added in the future. The current plan is to include the following sensors.

Firstly, the energy consumption of the laser, wire feed, and the movement of the printing head and table are monitored. This information can be used to optimize the energy consumption and reduce the environmental impacts of the additive manufacturing.

A Cavitar camera can be used to capture high-speed footage of the laser-wire interaction, providing detailed insight into the process and allowing researchers to identify areas for improvement or optimization. For example, the camera can capture the formation of the molten pool, the size and shape of the deposited material, and the behavior of the wire feed and laser during the deposition process. [13]

A pyrometer is an infrared thermometer used to measure the temperature of an object from a distance. In a laser-wire direct energy process, pyrometers can be used to measure the temperature of the material being processed, as well as the temperature of the laser itself. This information can be used to control the laser power and maintain the desired processing temperature [14], [15]

Laser distance sensors can be used to monitor the distance between the laser and the material being processed [16]. This information can be used to adjust the focus of the laser and ensure that the material is being processed at the desired depth. In addition, laser distance sensors can be used to measure the height of the printing head and the position of the table, providing additional information for controlling the process.

Acoustic sensors can be used to monitor the printing process and detect any potential defects. These sensors can detect acoustic emissions generated by the process, such as the sound of wire feeding, laser melting, and the movement of the printing head and table. By analyzing the acoustic signals, it is possible to detect anomalies such as wire breakage, improper melting, and movement irregularities [17], [18]

A profile scanner can generate a high-resolution 3D model of the object, which can be used to monitor the quality of the printing process and detect any defects or deviations from the desired shape. The profile scanner can also be used to adjust the printing process in real-time, for example by adjusting the position or power of the laser or the speed of the printing head, to ensure that the object is built to the desired specifications. [19]

In conclusion, the integration of a suite of sensors in a laser-wire direct energy process for additive manufacturing has the potential to optimize the process and improve the quality of the final product. The combination of energy monitoring, high-speed camera footage, temperature measurement, laser distance sensing, acoustic sensing, and profile scanning can provide comprehensive insights into the process and enable researchers to identify areas for improvement. Furthermore, the real-time feedback provided by the sensors can be used to adjust the process parameters and improve the overall quality and efficiency of the additive manufacturing process. I.e., optimize the process parameters such as the laser power, wire feed rate, and the speed of the printing head and table.

As such, the development of such a sensor suite represents an important step forward in the advancement of additive manufacturing and could have significant implications for a range of industries.

1.2. Literature and prior works

This section presents an overview of some related studies and their developed systems in the realm of IoT-based data acquisition, storage, processing, and visualization. The aim is to provide a foundation for understanding the current state of the art in this field and to identify potential areas for future research and development.

The Iowa Quantified (IQ) infrastructure, developed by researchers at the University of Iowa, provides an end-to-end solution for sensor deployment and data collection based on Amazon Web Services (AWS), MQTT, and Jupyter notebooks. The infrastructure focuses on enabling researchers to concentrate on their work by offering wireless sensors, a cloud-based toolkit, and a web-accessible portal for real-time and offline data processing and visualization. [1]

An integrated data collection platform designed for smart grid and microclimate research combines wired energy subsystems and wireless climate and heating subsystems, using LoRaWAN technology. The platform employs custom scripts and MQTT protocol to send data to the IoT platform ThingsBoard. The ThingsBoard platform is used for visualization, enabling the monitoring of sensor data, climate sensor mapping, and displaying energy disaggregation algorithm results. [20]

A performance evaluation and resource monitoring system for heterogeneous edge devices was developed using open-source software like Docker, Kubernetes, Prometheus, Grafana, and Node

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Exporter. This system creates a containerized environment and edge computing-based cluster, allowing for streamlined management, deployment, and real-time monitoring and analysis of CPU and memory usage. The system is designed for practical utility in deep learning models, big data analysis, distributed systems, and parallel computing applications. [21]

A study focused on creating a data acquisition system for solar power systems, collecting battery voltage, room temperature, and humidity data through an IoT platform. The system employed an ESP8266 Node Micro-Controller Unit with a DHT11 sensor for data sensing, and a Raspberry Pi for data access, processing, and visualization. The MQTT protocol, Grafana, and InfluxDB were used for messaging and data visualization. Implemented through Docker containers, the system allowed for seamless migration to other platforms, flexibility in mounting locations, and the potential for future adaptation to cloud-based servers for database replication. [22]

While each system serves a distinct purpose, they collectively demonstrate the potential of open-source IoT platforms in addressing various data collection and analysis challenges.

2. Materials and Methods

The ultimate goal of the work with laser-wire printing is to control the printing process in real time using a feedback loop from the sensor data.

"Keep It Simple Stupid" (KISS) principle suggests that developers should choose the simplest system or tool that can meet their needs rather than selecting a more complex tool that may have additional features that are not necessary [23]. Moreover, the definition of "best" may vary depending on the specific application, with some prioritizing reliability, speed of implementation, ease of use, and so on [23]. However, ultimately the best solution is one that is cost-effective and provides value for money [23]. In the context of this work the aim for simplicity is based on lowering the requirements of the system performance and focusing on the interoperability and usability. Which does not actually lead to the selection of simplest tool, but rather on the selection of most flexible and easiest tools.

Subsequently, the development of a fast and optimized real-time control system will be deferred. Moreover, it is important to note that the definition of 'real-time' may vary depending on the context in which it is applied [24]. This approach later allows to narrow down the development of the real-time control system to specific sensors and gives more information to define its minimum requirements. I.e., the real-time control can be developed once enough data and knowledge is gathered to develop models to control the process. After further analysis of the collected data from the process, it could be also possible to better define what real-time means in the context of laser-wire direct energy process.

The system architecture can be divided into separate tasks, adopting the idea of IoT platform classification [25]. Consequently, the architecture should consist of three main parts: A) data flow handling, B) data storage, and C) visualization. The design focuses on extensibility, interoperability, performance, and low cost. The use of open-source tools is prioritized, and the system should not be reliant on any individual application [26]. Edge processing is adopted to handle vast amounts of data and reduce the load on the data collection system [27]–[29]. Edge processing becomes crucial when working with high-frequency data, and helps ensure accurate timestamps [30]. It is also more suitable for developing real-time control with less latency [31].

Consequently, with edge processing, the requirements for the data handling system are lowered. The main requirements for the system are extensibility, interoperability, and low cost. The next three chapters introduce different options for the main parts of the system architecture. The remainder of the paper is organized as follows: Sections 2.1. , 2.2. , and 2.3. present possible tools for each part in the system. Section 3 presents the developed system and its architecture, and other technical choices. Section 4 discusses the implications, proposes future improvements, concludes the paper, and summarizes the results.

During the preparation of this work the authors used ChatGPT versions 3.5 and 4 to refine the narrative, improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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2.1. Data flow handling
Node-RED is an open-source visual programming tool built on Node.js, enabling users to create complex workflows and automate tasks using a drag-and-drop interface. Node-RED offers a library of pre-built nodes for interacting with various devices and services [32]. Crosser.io, an edge computing platform, provides a visual programming interface for building and deploying real-time data processing applications, featuring pre-built modules, debugging tools, and deployment support [33]. Apache NiFi, an open-source data integration platform, allows for managing data flows, connecting data sources, and processing data in real-time. It is designed for handling large data volumes and offers a visual interface, data transformation tools, and monitoring, security, and scalability features [34].

2.2. Databases
InfluxDB is a time-series database designed for storing and querying time-stamped data, suitable for IoT data storage due to its ability to handle large volumes and built-in downsampling and retention policies [35]. Prometheus is a monitoring and alerting system with a time-series database, ideal for IoT data collection and storage, offering powerful query and visualization tools and a push-based data model [36]. Elasticsearch is a distributed search and analytics engine with built-in support for time-series data, handling large volumes of data and providing powerful search and visualization capabilities, as well as real-time data ingest [37]. Cassandra is a distributed NoSQL database designed for handling large data volumes, with column-based storage and support for replication and fault tolerance, suitable for IoT environments requiring high availability [38]. PostgreSQL is a scalable relational database suitable for IoT data storage, offering powerful indexing and querying capabilities, as well as data replication and high availability support [39].

2.3. Visualization
Grafana is an open-source platform for collecting, storing, and visualizing data from various sources, including IoT devices. It supports over 50 data sources, powerful visualization tools, and is compatible with time-series databases like InfluxDB, MySQL, and PostgreSQL [40]. Kibana, an open-source analytics and visualization platform, works with Elasticsearch and is suitable for IoT data collection and visualization [41]. ThingsBoard, an open-source IoT platform, offers data collection, processing, and visualization with support for multiple data sources and databases, and features a built-in visualization engine [42]. Prometheus, an open-source monitoring and alerting system, is ideal for IoT data collection and visualization, supporting time-series data and numerous data sources, including custom exporters for IoT devices [36].

3. Results
The Node-RED flow editor is chosen for its open-source nature, ease of use, local execution, and compatibility with various devices and APIs. As a popular visual programming tool for creating IoT applications, Node-RED can integrate with methods like MQTT, CoAP, and HTTP REST [43]. MQTT, a lightweight protocol designed for IoT applications with low overhead [44], is selected as the primary protocol for sending data from edge to Node-RED, while still allowing flexibility for other protocols if needed. CoAP, a lightweight protocol for constrained devices and networks [45], and REST, a widely used architecture for web services and APIs [45], [46], are also considered.

According to the methodology the system is set up in the most profitable manner, i.e., using the easiest tools. Grafana, an open-source option known for its flexibility, scalability, and community support, supports a wide range of data sources and is compatible with various databases and IoT platforms. Its intuitive interface and extensive visualization options make it an attractive choice for users with different technical backgrounds. InfluxDB is often preferred over other databases for use with Grafana due to its specific design for handling time-series data, making it a highly efficient and scalable option for data storage and retrieval [35]. The simplified system architecture in the Figure 1 shows the main parts and selected tools and their connections.

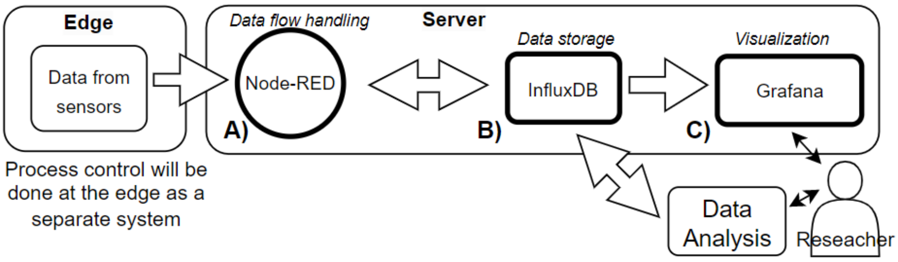

Figure 1. The system architecture.

After the data collection system is set up, the focus is on collecting the data from sensors. The data collection is primarily done with PLCs and computers at the IoT edge, but also microcontrollers as edge devices could be used. Consequently, the system consists of one or more edge devices with sensors connected to them. These edge devices are further connected to the server through Ethernet. Moreover, these edge devices must be programmed for their tasks to collect and transmit their data which sets another challenge for the researchers. In addition, if using multiple computers on the same network, it is important to ensure that the clocks on all the devices are synchronized to the same time source. Timestamps and synchronization are especially critical in IoT edge devices that require time-sensitive data collection such as acoustic sensor data [47]. This can be achieved for example, through the use of software tools such as Chrony or NTP to synchronize the system clock with a common time server [48], [49]. The more detailed architecture in the Figure 2 shows the complete system with various sensors. The system is designed to be expandable for real-time, closed-loop control to optimize the process, and potentially enable data backup and sharing via cloud databases.

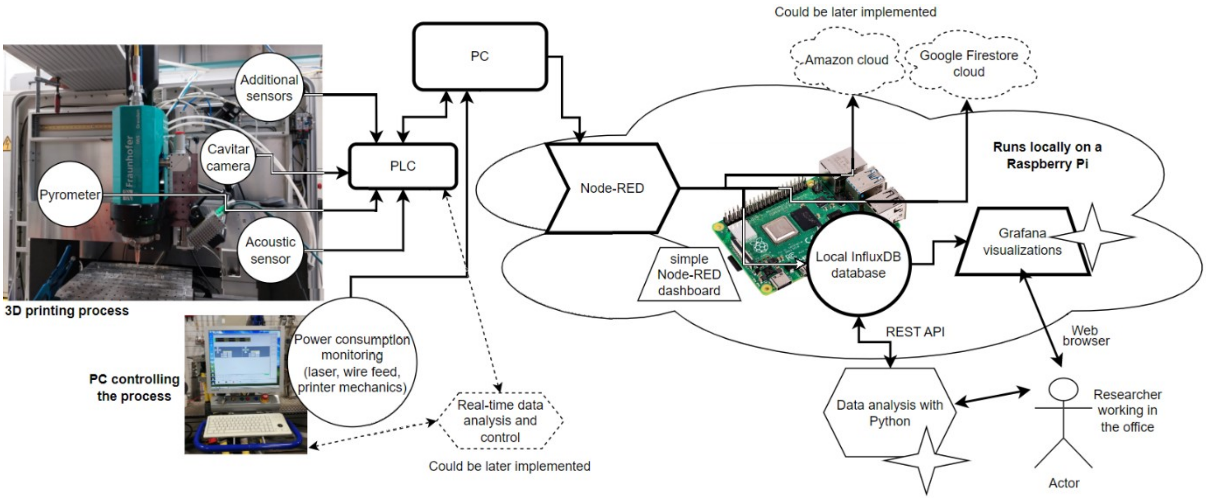

Figure 2. Detailed illustrative architecture of the system in the lab.

The deployment of an outdated Windows XP computer, which controls the laser-wire direct energy deposition and gathers system data sets additional challenges to system architecture. Firstly, it poses a security risk due to its discontinued support and potential vulnerabilities. To mitigate these risks, a segregated lab network is established without internet access. This is facilitated through a dedicated router and switch, connecting all necessary devices. Moreover, older operating systems without built-in support for modern time synchronization protocols may pose further challenges in data collection.

Figure 3 illustrates the wire direct energy deposition system under observation, along with data obtained from various sensors. The system has been performing as anticipated. Existing Grafana plugins facilitate the visualization of images captured by the Cavitar camera as seen in the figure. Real-time visualizations enable operators to oversee the details of the printing process from a safe distance, allowing them to respond as necessary. Creating new dashboards featuring data from a selection of sensors is effortless, and the wide range of plugins, coupled with community support, greatly expands the available possibilities.

The system is straightforward to configure, and, importantly, incorporating a new sensor into the system is relatively simple as the biggest changes are done on the edge. Presently, all sensor data is transmitted to the cloud from a single PC which can be later replaced with a PLC. This setup is effectively addressing the majority of synchronization challenges. However, servo and power consumption data from an older Windows XP machine can only be integrated into the system after the printing process. This limitation arises because the data file is reserved by another process and cannot be accessed until the process is complete. In this instance, synchronization is achieved by identifying the corresponding timestamp from the acoustic sensor data and adjusting the timestamps accordingly.

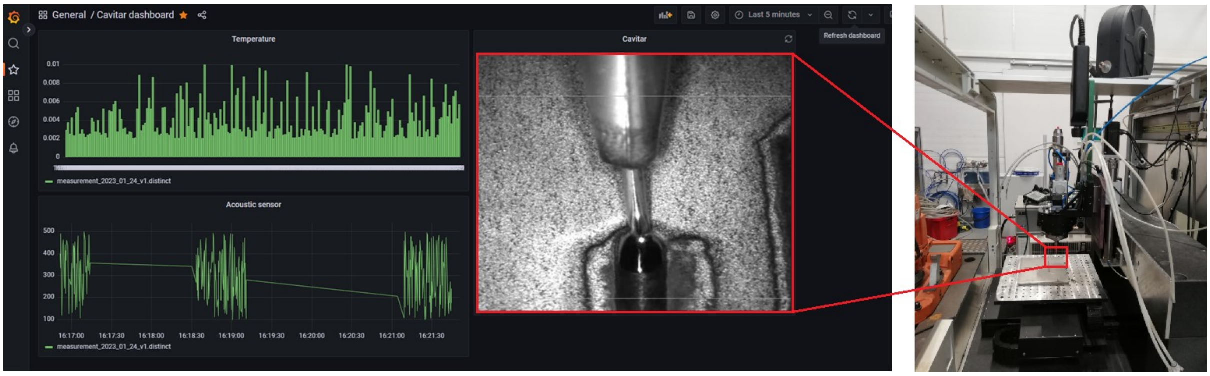

Figure 3. Hardware and data visualization.

From the perspective of researchers conducting data analysis, the system offers numerous advantages. Data can be accessed remotely via the internet, and Grafana's visualization tools enable preliminary analysis before employing more sophisticated techniques. Animations of recorded datasets can be created with tools such as grafanimate [50]. For advanced analysis, researchers primarily utilize Python. Consequently, the InfluxDB-Python library is recommended for extracting data from InfluxDB using Python, as it provides a Python API to interface with InfluxDB. However, the ease of data access presents potential risks to the system's data integrity. Consequently, higher privileges are necessary for altering data stored in the cloud. Finally, data retrieval templates are provided and shared among the researchers. These include scripts for example for extracting and storing requested data in both Pandas DataFrames and CSV files.

4. Conclusions

In conclusion, the presented open-source tools based IoT solution offers an open software and hardware approach for real-time data collection and visualization from a laser-wire direct energy deposition system. It consists of three main components: data flow handling, data storage, and data visualization. Node-RED, InfluxDB, and Grafana are employed due to their flexibility, efficiency, and ease of use. This solution aligns with the Industry 4.0 paradigm and enables researchers to focus on their core research. Real-time monitoring and data collection can facilitate process optimization, improve quality control, and reduce energy consumption.

The proposed system architecture based on edge devices and API endpoints handled with Node-RED makes it easy to add new sensors and expand the system's functionality. The collected data is easily accessible to researchers through the use of Grafana, which offers a user-friendly interface and a variety of visualization options. Additionally, the use of InfluxDB-Python library provides an easy-to-use Python API for data retrieval for analysis. This allows researchers to easily import data into their preferred data analysis tools, such as Pandas and NumPy. Overall, the combination of user-friendly visualization tools and flexible data retrieval options makes it easy for researchers to access and analyze the collected data in a meaningful way.

The developed system offers a flexible, cost-effective solution for efficient data collection and analysis. Future directions involve process optimization on edge and integration of additional sensors or data sources. More comprehensive comparative analysis of different tools for similar systems can also be explored, testing system performance and modifiability.

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