A Solution Architecture for Energy Monitoring and Visualisation in Smart Factories with Robotic Automation

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Abstract. In today's manufacturing landscape, digital twin-enabled smart factories are revolutionising traditional practises by leveraging cutting-edge technologies such as Internet of Things (IoT) devices, advanced analytics, machine learning, and artificial intelligence (AI). These factories create virtual replicas, or digital twins, of their physical counterparts, enabling real-time monitoring, analysis, and control of manufacturing operations. One area of innovation within smart factories is the role of energy condition monitoring and data analytics, which has gained significant attention due to the challenges of interoperability in industrial environments and the emerging need for sustainable manufacturing systems. This paper proposes an energy monitoring and visualisation solution architecture and example data visualisation dashboards at multiple user levels. The proposed solution architecture is deployed on a case study that included robotic material handling, and the results showed that the proposed solution can provide valuable insights to the users regarding the energy consumption of shop-floor components and provide a cost-efficient solution for energy analytics that can be used within SMEs.

Keywords: Industry 4.0; Big Data Analytics; Energy Analytics; Industrial Robotics; Data Visualisation; OPC-UA; InfluxDB; Grafana.

1 Introduction

Smart factories are at the forefront of modern manufacturing, leveraging cutting-edge technologies to integrate physical and digital systems for optimised production processes. These factories digitally transform their physical counterparts, enabling real-time monitoring, analysis, and control of manufacturing operations. By doing so, smart factories can achieve unprecedented levels of operational efficiency, predictive maintenance, and product quality [1]. Enabled by a wide array of technologies, including Internet of Things (IoT) devices, advanced analytics, machine learning, and artificial intelligence (AI), to enable data-driven decision-making and automation [2]. This transformative approach is reshaping the manufacturing landscape, driving innovation, and revolutionising traditional manufacturing practises towards wide adoption Industry 4.0.

In the context of Industry 4.0, energy condition monitoring and data analytics are areas of innovation that have gained significant attention due to the challenges of interoperability in industrial environments and the increasing need for sustainable manufacturing systems [3]. Resman et al. [4] propose a five-step approach for data-driven digital twins (DT) in discrete assembly scenarios. Their effective use of digital models and shadows allows for inline process monitoring at different time intervals for each state of the physical system, enabling communication of adapted processes from the DT to the physical world. This approach facilitates targeted monitoring of energy-related data through levels of integration. Franceschi et al. [5] aim to implement a DT for flexible coordination between workers and machines. Their proof-of-concept assembly of an aircraft fuselage's interior includes Human Machine Interface (HMI) dashboards that extend to mobile and Mixed Reality (MR) systems, enabling close monitoring of processes and task allocations for workers and machines. This work emphasizes the importance of interoperability between workers and systems. Dall'Ora et al. [6] further highlight the need for interconnected and interoperable ecosystems within smart factories for effective data analytics. Their DT-enabled power consumption condition monitoring of a production line identifies network design as a key enabler for strategic decision-making and real-time monitoring. Their DT implementation aims to detect discrepancies between real-time data and digital twin data for early intervention in maintenance.

Rocha et al. [7], address challenges of interoperability and propose an event-driven ecosystem for energy consumption management. Using a message broker system with Apache Kafka, the solution integrates tools from different vendors and technologies. Tested in automotive industry robotic cells, it stores energy consumption data in a Postgres database with a user-friendly interface. Promising results demonstrate the potential for sustainable operations and advanced solutions like production scheduling for energy optimisation. Further technical aspects of energy condition monitoring can be seen [8], where further key issues of data establishment and aggregation, data processing and analysis, scalability and performance, and further applications of data-driven energy management are addressed. Alternatively, Zhong et al. [9], introduce an IoT-enabled real-time machine status monitoring approach for Cloud Manufacturing (CMfg) with the aim of achieving ultimate service sharing and circulation among different manufacturing parties. The contributions of this research include presenting a SOA architecture for organising a CMfg shop floor, demonstrating a systematic deployment scheme for IoT facilities in a typical manufacturing shop floor, and presenting re-engineered and rationalised production operations in a CMfg environment. However, their approach to multi-level analytics revolves around the use of RFID and specialised handheld monitoring devices, which may provide limitations in terms of deployment and usage efficiencies.

However, introducing such solutions are generally expensive, with requirements for compatible or updated infrastructure to work alongside energy condition monitoring and data analytics platforms. Therefore, the need for low-cost and lightweight solutions are apparent for digital transformations, especially with small and medium-sized enterprises (SMEs) [10]. This paper proposes an interoperable n-tier energy monitoring and visualisation solution architecture and example dashboards at multiple user levels, providing insights from the process of data acquisition to visualisation. The boundaries of the scope of this study are carefully defined as being limited to the monitoring and visualisation of data pertaining to energy. However, network gateways and data analytics, which are included in the proposed solution architecture, were considered out of scope for this study. Therefore, this study can serve as a tangible demonstration of the potential insights that can be gained from granular and real-time data, with a key emphasis on data visualisation.

2 The Implementation of the Proposed Architecture

2.1 An overview of the approach

Within the scope of this study, a proposed n-tier solution architecture and implementation are discussed in relation to energy monitoring and analytics within industrial robotic assembly. **Figure 1** displays a high-level overview of an n-tier solution architecture used within industrial robotic assembly. The proposed solution architecture is primarily designed to aid machine-level energy monitoring and analytics in SMEs. Within the proposed architecture, the information flow starts with acquiring raw-process data from shop floor components such as robots and conveyors. Next, the acquired data are organised and managed through a network gateway to ensure data integrity while being transferred. After being passed through the network gateway, data management and storage are needed for adequate time series data collection and identification. The final two layers are aimed at data analytics and visualisation. Gaining valuable insights from the collected data and visualising them in a manner that is usable and useful is where the value of this solution architecture can be seen.

In the following sub-sections, we will explain the implementation of the proposed architecture through the use of a case study that includes a small scale collaborative robotics system for low-volume high variety discrete assembly processes.

2.2 Test set-up

To demonstrate the proposed data-driven energy monitoring and visualisation solution architecture, a brief overview of the information flow and test bed is set up. **Figure 2** shows the information flow and technologies used to acquire and visualise energy-related information. In the test setup, real-time energy consumption data was collected from a simple pick and place operation from a collaborative robot, i.e., the Niryo Ned robot. **Figure 3** displays the performed operation where the robot was in an idle position before and after (4 mins each) the pick and place operation, lasting 18 minutes in total.

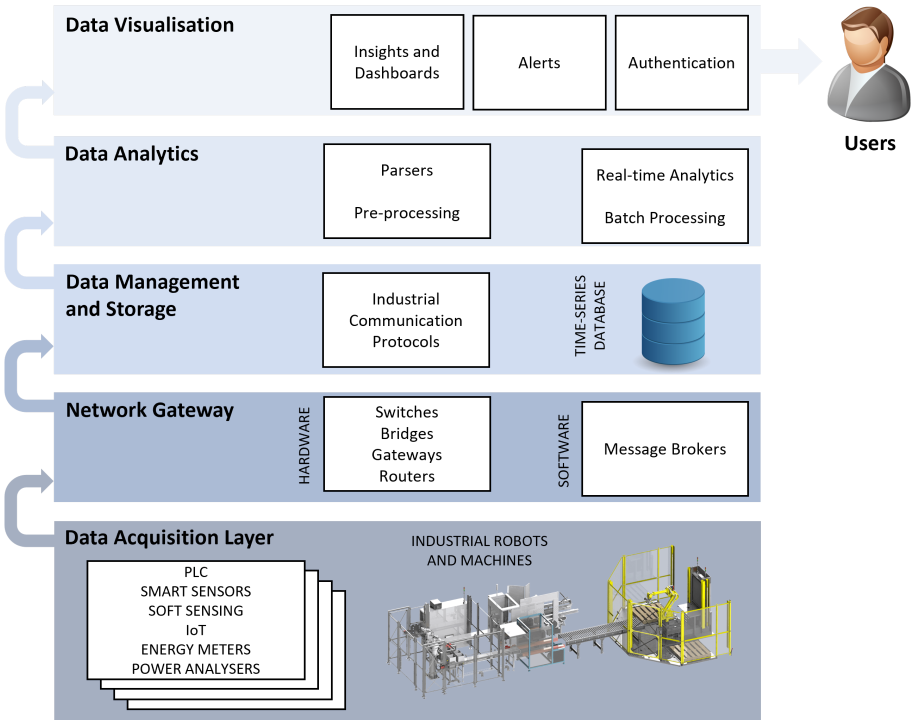

Fig. 1: The proposed architecture for industrial robotic assembly.

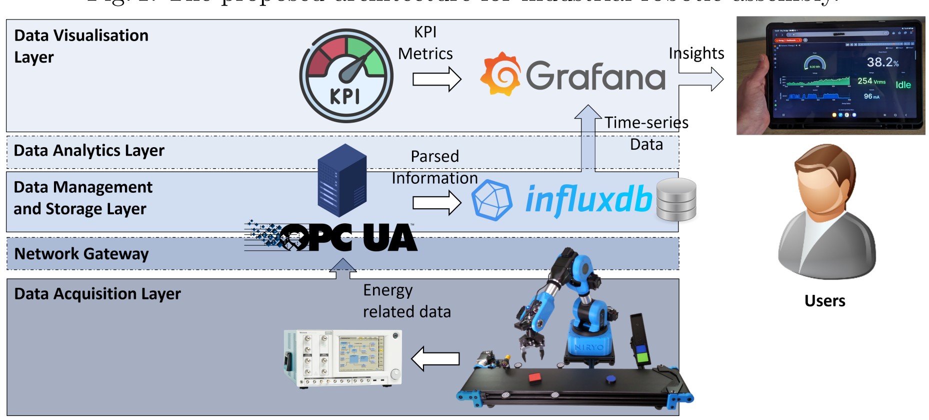

Fig. 2: Energy-related information flow and implemented technologies (Layers that are outlined with a dashed line are not considered within the scope of this study.).

2.3 Data Acquisition Layer

To acquire real-time energy data from the robotic manipulator, a power analyser was used. The analyzer sits in between mains power and the robot's PSU, thus

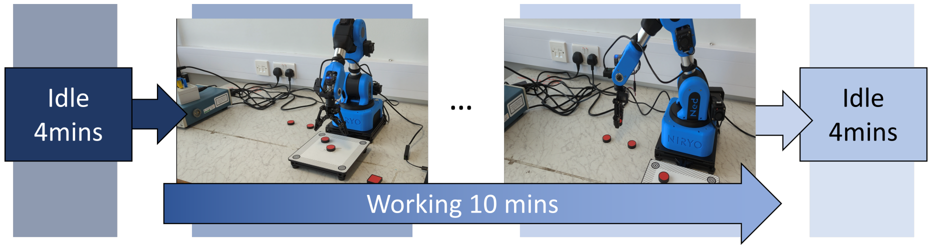

Fig. 3: The experimented material handling operations.

measuring total power. Acquired data consists of V_{rms} (V), A_{rms} (mA), power (W), and power factor (%).

2.4 Network Gateway

The network gateway acts as a central communication hub that enables connectivity between different devices and protocols. It serves as an interface between the robot manipulator, connected via hotspot, and the power analyzer, connected via Ethernet. The network gateway facilitates data exchange and communication between these devices using OPC-UA (Open Platform Communications - Unified Architecture) server, which is a widely used industrial communication protocol for interoperability in industrial automation and control systems.

The network gateway plays a critical role in aggregating, processing, and routing data between the robot manipulator, power analyser, OPC-UA server, database, and visualisation tool. It ensures that data from the robot manipulator and power analyser is securely transmitted throughout architecture. The network gateway may also handle protocol conversions, data filtering, and data transformation tasks to ensure seamless integration and interoperability among the different components of the energy monitoring and visualisation system.

2.5 Data Storage and Management Layer

The energy analytics and visualisation require a proper data management and storage approach and platform. Within industrial scenarios, the ability to acquire multiple sources of data while storing the timestamp of their measurements can provide valuable insights into production processes, leading to data-driven decisions. In this research work, the combination of OPC-UA and InfluxDB was used to address the requirements for data storage and management.

OPC-UA is a widely used protocol for industrial communication and data exchange. It allows for the exchange of data between different devices and systems in an industrial environment, regardless of the manufacturer or platform. InfluxDB, on the other hand, is a time-series database that is designed to handle large volumes of time-stamped data. It provides a scalable and efficient way to store and retrieve time-series data, making it well-suited for industrial scenarios where data is generated at a high frequency.

Within this study, a custom OPC-UA server was developed in Python to facilitate interoperability between the power analyser and Niryo Ned Modbus interface. To continue, each node within OPC-UA can be given a namespace and identifier. As this study is primarily focusing on monitoring energy consumption, all energy measurements are labelled within the same namespace with separate identifiers. The server then stores all OPC-UA nodes within an InfluxDB through a Telegraf plugin. The Telegraf plugin allows further management between OPC-UA and InfluxDB, where a data sampling rate of 100 ms was configured.

2.6 Data Analytics Layer

This layer is where the actual analysis of the data takes place. It involves using machine learning/deep learning algorithms and statistical techniques to extract meaningful insights from the operational data. The analysis may involve identifying trends, anomalies, or patterns in the energy consumption data that can aid in the optimisation of the robotic assembly system's energy usage [11]. For real-time analysis, Apache Flink or Apache Spark can be used for analysing the data as it arrives, enabling the response of anomalies and events quickly. For batch processing, Apache Hadoop can be used to process large volumes of data in parallel, enabling complex analyses that lead to deeper insights [12].

2.7 Data Visualisation Layer

The final tier within the proposed architecture visualises all the stored and processed energy-related data. Depending on the target user, multiple dashboards with modular displays can be utilised to view different KPIs and metrics throughout the value chain and product life cycles. Within this study, the Grafana data visualisation platform was used to display energy-related data conditions targeted towards manufacturing technicians. Grafana allows creating custom dashboards that display the energy consumption data in various forms, such as charts, graphs, tables, and gauges, which can be useful for identifying trends, anomalies, and patterns in the data. Alerting features can also be used in Grafana to receive notifications when energy consumption levels exceed a certain threshold or when anomalies are detected. The configuration of Grafana was conducted in a way that interfaces with InfluxDB, allows viewing the dashboard remotely or within a handheld device, and uses OAuth2 to securely authenticate users. To continue, the Grafana dashboards were designed with interactive features to improve the user experience. Users could filter the data by selecting specific time periods. Zooming and panning functionalities were implemented in the line charts to allow users to focus on specific time intervals or data points of interest. Drill-down capabilities were also provided, allowing users to click on specific elements in the visualisations to access detailed information. These interactive features were designed to enable users to explore the data and gain insights more effectively.

2.8 Information Flow between Layers

Figure 4 further highlights the information flow within the use case of this study. The diagram shows the high level functions and data from data acquisition to visualisation, further supporting the previous subsections. The key enabler of within this architecture is the OPC-UA server acquiring, mapping, and sending the energy data. Then, within the storage and visualisation layers, appropriate queries are needed to display and convert into metrics and Key Performance Indicators (KPIs).

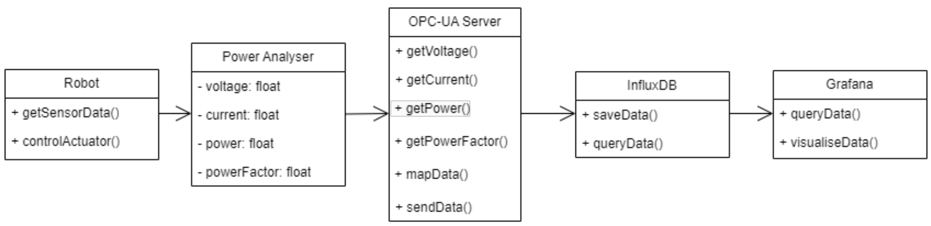

Fig. 4: High level system information flow.

3 Energy-related Data Visualisation

This section provides insights into the dashboards presented for monitoring and managing the energy performance of the robotic manipulator under consideration. The section discusses the usefulness and benefits of these dashboards, including the dashboard designed for real-time data and alerts to technicians and the dashboard offering managerial-level insights and visuals for informed decision-making by managers. The customisation features, alerts, and comprehensive approach towards energy management are highlighted, showcasing how these dashboards serve as valuable tools for optimising energy usage, improving operational efficiency, and promoting sustainability in the assembly line operations.

3.1 Key Performance Indicators and Metrics

Energy-related KPIs are essential to properly gauging the most useful data visualisations that will be used by the users. The first dashboard design in this study is a shop-floor condition monitoring dashboard that can be most useful for maintenance technicians and shop-floor engineers. This dashboard consists of the following: RMS voltage and current measurement provides an indication of the quality of the electrical supply and helps in identifying any voltage and current fluctuations or deviations from standard levels. These measurements are important to ensure that the manufacturing cell is receiving a stable and reliable electrical supply. Power (Watts) measurement is a key parameter that provides information about the amount of electrical energy being used by the manufacturing cell. Monitoring power consumption is important to identify areas where energy efficiency can be improved or to detect any abnormal or unexpected power usage. Power factor measurement is also important for electricity condition monitoring. The power factor indicates how efficiently the manufacturing cell/component is using the electrical power supplied to it. A low power factor indicates that the cell/component is drawing more power than required, which can lead to higher energy costs and the inefficient use of electrical power. However, these KPIs may not be appropriate for higher-level energy consumption insights. Zimmerman [13] provides a comprehensive list of KPIs and metrics used within robot performance and manufacturing processes. Utilising their proposed distinctions between metrics and KPIs, with hierarchical considerations, the second design will include further KPI metrics.

For a dashboard to be useful at the managerial level, it is necessary to include additional energy-related KPIs and metrics in order to provide additional economic and sustainability insights. These particular KPI metrics have been selected to be included in this dashboard:

- Current power (W): Raw value in Watts.
- Total power usage (Wh): At each time interval, the power value is multiplied by the total time, $E = \overline{W} \cdot t$.
- Current energy cost (£): power conversion to kWh then multiplied by the current UK energy cost per kWh, $W/1000 \times 0.34$.
- Utilisation (%): The percentage of power consumption from current power measurement, against the max power rating, $W/66.6$
- Carbon footprint(kgCO2/kWh): The total power and time are multiplied by the UK carbon intensity, $kgCO2/kWh = (KW_{\text{total}} \times T_{\text{total}}) \times carbonIntestiy$.

3.2 Dashboard Designs

The first dashboard presented is targeted towards maintenance technicians and shop-floor engineers who would need to quickly and easily identify energy-related fluctuations as they monitor the field-devices on the shop floor. **Figure 5** displays the metrics of power (W), represented as a gauge, with colour coded power thresholds. The power factor is represented as a percentage. Voltage and current (V_{rms} & mA_{rms}), represented both over time, within a graph, and as a single value from the latest measurement, **Figure 5** further illustrates the clear identification between the robots working and idle conditions by looking at the current and power visualisations. Further state and alert indicators are presented to easily display the state of the machine and if any energy spikes have been identified. The alerts can be communicated via email or SMS and are displayed within the same dashboard, indicating the date and time of the occurrence. Finally, a key deployment requirement was to display this dashboard on a handheld device, as displayed in **Figure 6**.

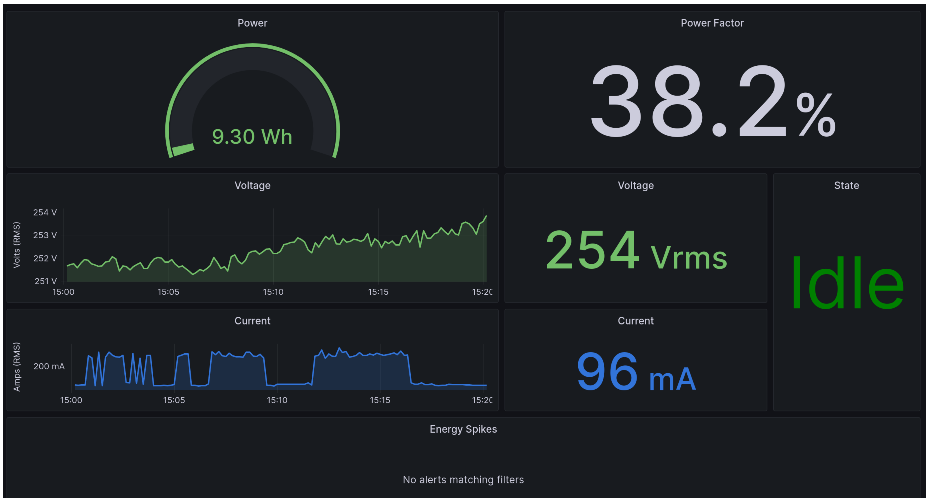

Fig. 5: Energy-related data monitoring and visualisation dashboard for shop-floor engineers and maintenance technicians.

Fig. 6: Energy-related data monitoring and visualisation dashboard on a hand-held device.

The second dashboard that was presented aims for higher level insights and allows managerial roles to view additional KPI metrics. The strategy that was implemented to address this issue consisted of providing visualisations for the purpose of forecasting energy consumption from the shop floor.

Figure 7 displays a proposed concept of some managerial insights, utilising the same acquired data, within an alternative higher level dashboard. By providing visualisations of real-time data on current power consumption, power

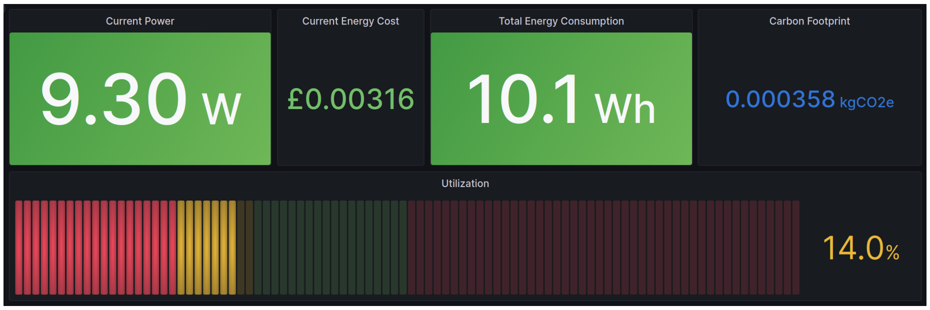

Fig. 7: Energy-related data monitoring and visualisation dashboard for managerial decision-making.

usage, carbon footprint, and utilisation, the dashboard enables a comprehensive overview of the energy performance of the robotic manipulator. The combination of these energy KPIs across the shop-floor decisions enables informed decision-making regarding the optimisation of energy usage, the identification and resolution of potential energy inefficiencies, and the reduction of the carbon footprint caused by the assembly line operations.

4 Discussions

The presented dashboards offer benefits for monitoring and managing the energy performance of field devices in manufacturing systems. They can facilitate proactive energy management and help optimise energy performance, leading to improved operational efficiency and reduced energy costs. Furthermore, the state and alert indicators on energy dashboards allow for timely notifications of energy spikes or abnormal conditions. This enables maintenance engineers and technicians to quickly respond and take the necessary actions to mitigate any energy-related issues, minimising downtime and optimising energy usage. The handheld device deployment also offers mobility, allowing technicians to monitor energy performance while on the go, providing convenience and flexibility in managing energy resources. The energy dashboards that are designed to offer higher-level insights and visualisations for managers allow making informed decisions on energy optimisation strategies, identify potential energy inefficiencies, and reduce the carbon footprint of the assembly line operations. This promotes sustainable practises and aligns with eco-friendly initiatives, contributing to the overall environmental sustainability goals of the organisation. The ability to customise the dashboards according to the specific requirements and preferences of the users further enhances their usability. The alerts and notifications feature ensures that operators and managers are promptly informed of any energy-related issues, enabling timely response and action. The comprehensive approach to energy management offered by the dashboards, covering multiple energy metrics, provides a holistic view of the energy performance of the robotic manipulator, allowing for effective energy resource utilisation and cost savings.

To further gauge the effectiveness of the proposed platform and visualisation implementations, comparative approaches are also discussed. Zheng et al., [14], proposed a platform that incorporates acquisition of a multitude of devices, controllers, machines, and sensors towards AR-based visibility and real-time machine status visualisations. Their approach does consider multiple ways of gaining valuable insights towards the energy conditions of each system, however efforts towards the interoperability of such a platform was not widely addressed. Saqlain et al., [15], propose a IIoT-based management and monitoring approach, with similar complexity in terms of data acquisition and management, but include cost considerations. Their justification towards the feasibility is from a perspective forecasting of the decrease in IIoT infrastructure cost and potential growths within organisations that use such platforms. However, the comparison of speculation and complexity being viewed by SMEs with costs and interoperability may deter the prospect of implementing and operating such platforms within their own organisations. Thus, the platform proposed within this study aims to appeal towards SMEs by adhering to industrial communication protocols and open source custom client-servers and data visualisations tools, that targets the overall cost and interoperability of such ecosystems. In conclusion, there are some limitations that need to be addressed in this study's comparison. Firstly, the scalability compatibility issue may arise when implementing this architecture in larger scale manufacturing shop floors. Despite proposing an interoperable solution, the performance and capability of the OPC-UA server may not yield the same results with data mapping and real-time data transfer in the same infrastructure. Secondly, cost considerations need to be taken into account, as the increased volume of sampled data will require additional bandwidth, storage, and computational resources for a big data platform, building on the previous point.

5 Conclusion and Future Works

This study proposed an n-tier energy-related data monitoring and visualisation solution architecture. With the implementation of dashboards, real-time energy-related data was collected, analysed, and visualised in a series of user-friendly interfaces. The proposed solution architecture facilitated real-time monitoring, analysis, and visualisation of energy consumption data, providing manufacturers with the information needed to optimise their operations and make data-driven decisions.In future works, efforts can be directed towards integrating advanced data analytics techniques, such as machine learning algorithms and deep learning techniques, to enable predictive analytics, anomaly detection, and the optimisation of energy consumption in real-time. Furthermore, the network layer of the proposed solution architecture will be further developed to support efficient and secure data communication between the different tiers of the architecture. Also, further benchmarking and performance analytics will be conducted to forecast the potential of scaling this architecture within further smart manufacturing scenarios.

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