A Systems Approach to Digitalizing a Traditional Manufacturing SME: Implementing Low-Cost Industry 4.0 Solution for a Hand Press Machine.

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Abstract: The traditional manufacturing industry, often reliant on paper-based manual processes, must digitalize to remain competitive in an era where artificial intelligence drives everyday processes. Accurate and realistic production planning and control are crucial for the success of small and medium-sized manufacturing enterprises (SMEs), and data is key to these processes. However, legacy machines in traditional manufacturing make data collection challenging. This work presents a data acquisition approach for collecting real-time production data, such as daily production volumes and downtime from a hand press machine.

In this study, as a demonstration, a hand press machine in a manufacturing industry[1] was digitalized by installing electronic hardware, including an inductive proximity sensor and an ESP8266 microcontroller with an optocoupler relay. The Arduino IDE environment was used for coding, and the Tdslite open-source library facilitated the transmission of sensor data from the microcontroller to the Microsoft Structured Query Language (MSSQL) Server Management Studio, which also served as a database to store live data. The processed data was then visualized using a Power BI dashboard, enabling the monitoring of hourly production rates and downtime. To measure the effectiveness of digitalization in business growth, KPI benchmarking was established for all relevant departments in the SME. This demonstration highlighted the potential of digitalization and showed how data acquisition and visualization help monitor and implement data-driven decision-making processes in production planning.

1. Introduction

Industry 4.0 is changing the way manufacturing works by bringing in new digital technologies that improve productivity, quality control, and resource management. However, small, and medium-sized enterprises (SMEs) often struggle to adopt these technologies due to high costs, complexity, and lack of technical skills.

In many traditional manufacturing settings, companies still use manual methods to collect and monitor production data. These old-fashioned ways can lead to errors and inefficiencies. Accurate data collection and real-time monitoring are essential for effective production planning and control, but SMEs need a solution that is affordable and easy to implement.

This paper presents a practical approach to digitalizing a hand press machine, which is a common piece of equipment in many SMEs. We used low-cost hardware like an inductive proximity sensor, Arduino UNO, and NodeMCU ESP8266, along with free software tools. Our system captures real-time production data, stores it in a Microsoft SQL Server database, and visualizes it using Power BI dashboards.

2. Background

Digital transformation begins with identifying the current stage of digital maturity within an organization [1]. As shown in Figure 1, the ISA-95 framework serves as a benchmark to map the digital maturity of Protaform Springs & Pressings. The levels of digitalization are represented on the Y-axis, while the pillars of transformation are depicted on the X-axis.

In the company, some digital systems support key pillars at higher levels, such as Levels 4 and 5 (e.g., the SAGE 200 ERP system). However, there is a lack of systems at the lower and mid-levels, particularly at Level 1, which focuses on process sensing. Currently, there is no existing system at this level, and the input from Level 1 is directly linked to activities at higher levels. For example, live production monitoring is crucial for guiding business activities at Levels 3 and 4. E.g., such as to achieve effective production planning and control., real-time information on existing capacity, unplanned downtime and machine utilization etc. Therefore, while designing the future digital maturity stage of Protaform, retrofit sensors have been highlighted as a critical pillar at Level 1. Various machine monitoring solutions are available in the industry as an alternative solution, and for a small-to-medium-sized manufacturing firm with 48 machines, the total cost of ownership over five years can range from £13,400 to £216,000. This cost includes both hardware and software components. For the details, please refer to Figure 9 in the

[1] Protaform Springs and Pressings Ltd

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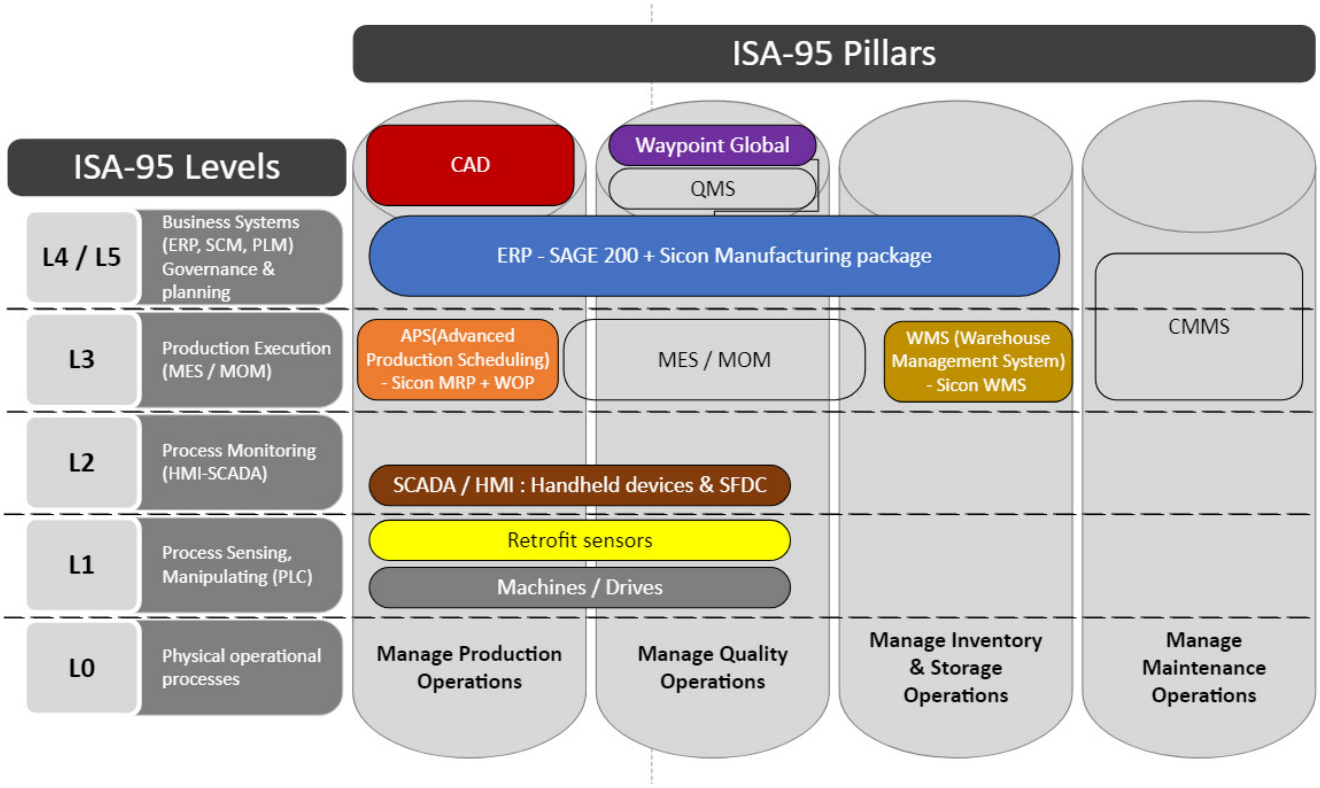

Figure 1. Current stage digital maturity mapping of the organisation using ISA 95 framework (Source: MTC, Coventry).

appendices. Financial constraints are a significant barrier for SMEs in adopting these solutions. Additionally, these organizations often lack digital champions who can assess the current state of digital maturity, gather requirements from key stakeholders, and develop a future state map based on the stakeholders' vision. The absence of internal digital champions forces organizations to rely on third-party vendors who may not be familiar with the existing technology stack [2]. Integrating solutions from multiple vendors can become a complex challenge. Therefore, this study focuses on assessing the current state of digital maturity and implementing low-cost solutions at Level 1, specifically for machine monitoring.

3. Methodology

3.1. Machine Selection

3.1.1. Value Stream mapping

Value Stream Mapping (VSM) was employed to identify key process inefficiencies [3][4] and the location of data points within the operation of the hand press machine that could benefit from digitalization. The pin-forming machine was selected for analysis due to existing inefficiencies noted by the production team, which affected the timely delivery of orders. VSM helped visualize the current state of operations, highlighting inefficiencies and pinpointing areas where data acquisition could help the production team enhance production planning and control related to this specific pin-forming machine.

The value stream map in Figure 2 shows a total of four such machines (jig 1, jig 2, jig 3, and jig 4), with jig 1 and jig 2 performing identical operations for process 1, and jig 3 and jig 4 intended for process 2. Ideally, all four jigs should be operational when there are orders for two types of pins - jig 1 and jig 2 for process 1, and jig 3 and jig 4 for process 2. The takt time was calculated based on machine availability and the promised delivery date, while the cycle time was measured manually using a stopwatch. Five readings were taken for two different operators to finish the operation on each jig, and the average was considered the final cycle time.

A significant lead time was observed for process 2, primarily because each machine requires an individual pneumatic control circuit to operate manually. However, only two pneumatic circuits are available for the four machines, meaning that only two jigs can be operational at any given time. This limitation causes substantial waiting time for the second type of jig, as the pneumatic controls must be transferred to jig 3 and jig 4 after jig 1 and jig 2 have completed their operations. This bottleneck was reported to top management for resolution.

3.2 Data Architecture

The data acquisition system designed for this study involved multiple components working together to collect, transmit, and visualize production data in real time. The architecture was built to be low-cost and easily replicable for other small and medium-sized enterprises (SMEs). As shown in Figure 3 the data was collected at the machine level using an inductive proximity sensor, which was processed by a NodeMCU and then transmitted to an SQL server using the Tdslite library for

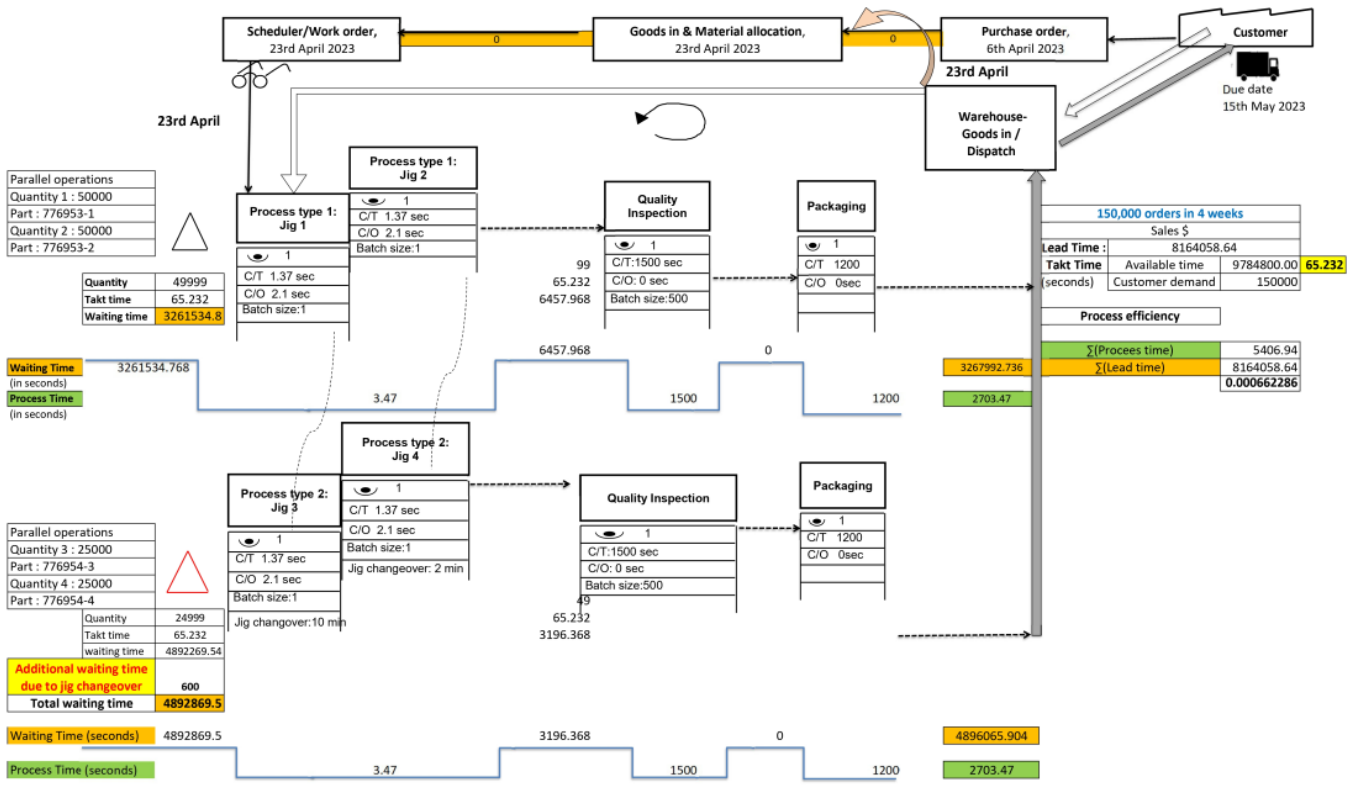

Figure 2. Value stream mapping of pin-forming machines for measuring the process efficiency.

data storage. Data operations were managed in Microsoft SQL Server Management Studio, where two views were created: the first stores the machine number, DateTime, and count, while the second stores additional information about the downtime between two successive counts. These views were loaded into Power BI using the Direct Query option. As per the production manager's requirement, the data needs to be updated hourly hence the page auto-refresh frequency was set to hourly in the Power BI dashboard setting. The Production Quantity and machine downtime were displayed on the Power BI dashboard after each update. The core system components included hardware (sensors and microcontrollers), a data transmission library (Tdslite), a database (MSSQL server), and a data visualization tool (Power BI). It's also shown in Figure 7.

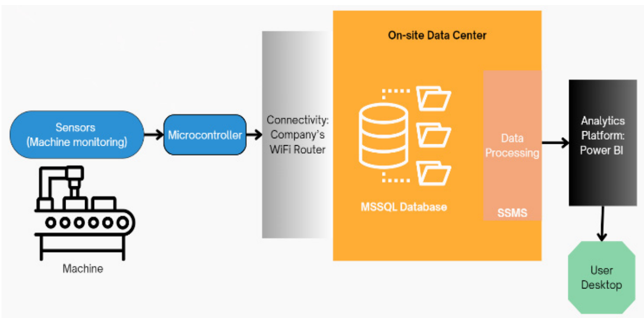

Figure 3. Data Architecture diagram (MSSQL – Microsoft SQL server, SSMS – SQL server management studio)

3.2.1 Flow Chart for Counting the production volume:

The flow diagram is shown in Figure 4. The process begins with the initialization phase, where the system starts by initializing the inductive proximity sensor and the NodeMCU ESP8266 microcontroller. Once the hardware is set up, the NodeMCU connects to the specified Wi-Fi network, establishing a wireless communication link necessary for data transmission. Following the hardware setup, the NodeMCU attempts to connect to the Microsoft SQL Server Management Studio (MSSQL) database. During this database initialization phase, the program checks for the existence of the required table in the database. If the table does not exist, the program creates it, ensuring that the data schema is correctly set up to store incoming sensor data. The system then enters the main loop, a continuous cycle where the sensor's output is monitored in real-time. The NodeMCU reads data from the inductive proximity sensor, which is designed to detect metal objects. Each time the metal object is detected the proximity sensor generates the voltage which is then converted as a digital output signal and the timestamp is registered when the output is detected. If the sensor does not detect an object, the program continues to loop.

3.3 Implementation

3.3.1 Sensor selection:

An inductive proximity sensor was chosen for its reliability and effectiveness in detecting metal objects as shown in Figure 5. (Model number: NBB5-F9-E0) This sensor type is well-suited for industrial environments where metal detection is crucial. To ensure that no false counts were detected due to the presence of other metal parts, the inductive proximity sensor was mounted beneath the hole where the pin was inserted for the forming operation. As shown in Figure 5, the pin faces the sensor, and the in-built LED is illuminated,

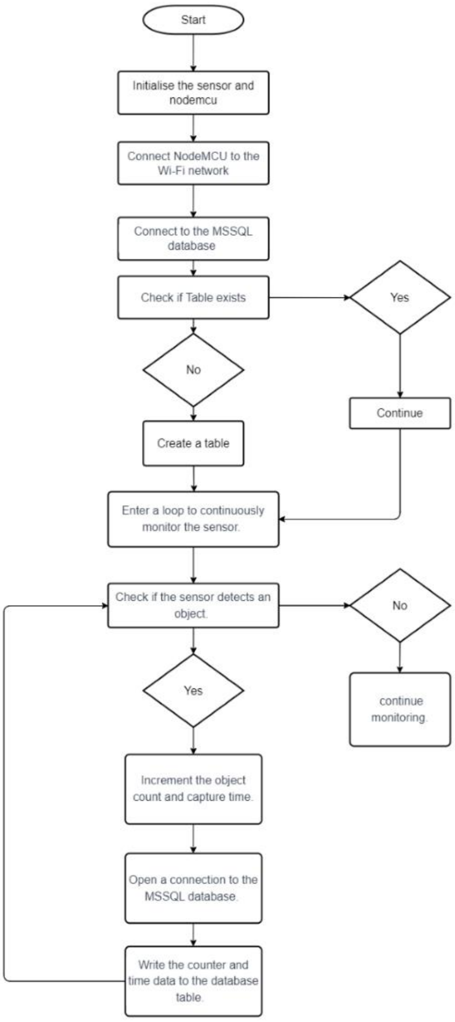

Figure 4. Flow diagram for the code used to program the NodeMCU using Arduino IDE to visualise the production count.

Figure 5. An inductive proximity sensor detects the pin placed in front of its detecting face.

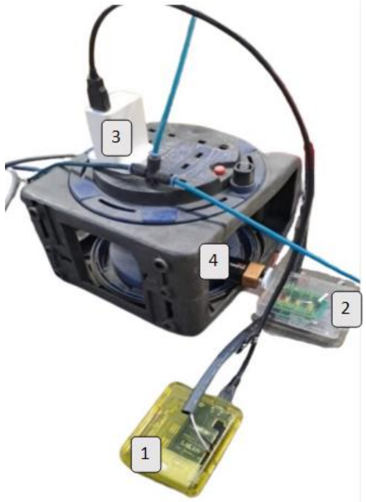

Figure 6. Hardware connections used on the machine for machine monitoring: 1) Microcontroller (NodeMCU), 2) Optocoupler Relay, 3) Power supply from the AC power socket outlet to the NodeMCU, 4) Power supply from the 9V battery to the proximity sensor.

indicating the presence of the pin. Along with this, the timestamp is also stored. The signal
generated by the sensor is used as a count and the timestamp is analysed such as hourly production quantity and downtime leading to measure the machine utilisation. The connection for the wiring of the components is as shown in Figure 6: Inductive Proximity Sensor, which is wired to the digital input pin D2 of the NodeMCu. Power Supply: the sensor is powered using a 9V battery and NodeMCU is powered by the standard micro-USB charger from the AC power socket.

3.3.2 Data Storage – MSSQL:

The Microsoft SQL Server Management Studio (MSSQL) was used as the central repository for all collected data. The SQL server provided robust data management capabilities, allowing for the storage, retrieval, and querying of real-time production data [5]. The data schema was designed to accommodate various data points, including production counts, downtime events, and timestamps. The full source code will be available upon request.

3.3.3 Data Processing &Visualisation:

Power BI was employed for data visualization due to its powerful analytical capabilities and user-friendly interface. The data stored in MSSQL was processed and visualized using Power BI dashboards. The table data from the database was queried using the direct query method in Power BI. These dashboards enabled the monitoring of hourly production rates, downtime, and other key performance indicators (KPIs). The visualization provided actionable insights, helping the manufacturing enterprise make data-driven decisions to optimize production efficiency.

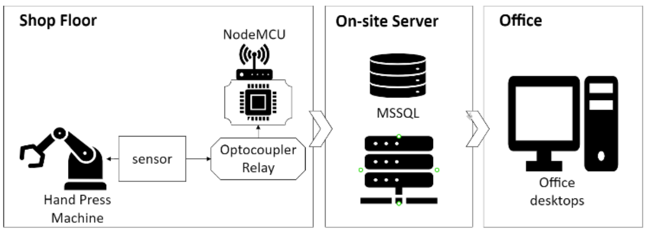

Figure 7. Schematics of data flow from the machine level to the organisation level.

Table 1 Direct Cost of components involved.

Component	Quantity	Cost in £
Proximity sensor	1	50.3
NodeMCU	1	4
Optocoupler - relay	1	3.5
Cables	Pack	17
Casing & mounting accessory	Pack	11
Battery	2	7
Total		**92.8**

4. Results

4.1 Key Performance Indicators (KPIs) Visualisation

4.1.1. Production Volume:

Production volume was calculated based on the detected counts. For the production manager, the data is updated every hour. On the dashboard, the hourly counts of the produced parts are updated and displayed automatically. It is shown in Figure 8 a) & b).

4.1.2. Production Downtime:

The company's break times are as follows: a morning break from 10:00 AM to 10:15 AM and a lunch break from 1:00 PM to 1:30 PM, with total machine availability for the given shift from 7:30 AM to 4:30 PM. Based on the production team's experience, it was noted that the hand press machines require minimal maintenance, as they do not have many heavy electrical or mechanical moving parts that could fail quickly. Therefore, unplanned downtime due to maintenance issues was considered negligible. To measure downtime using the timestamp and count, the following condition is applied: if the time interval between two successive counts exceeds 2 minutes and falls outside the scheduled break times, it is recorded as downtime. The 2-minute interval was chosen to account for the cycle time plus a few seconds of tolerance for the operators. Any intervals meeting these criteria are classified as downtime.

The in-process quality checks with the help of gauges have to be conducted at the machine and it takes less than 2 minutes so again that is considered. As per the machine and the part, the in-process checks vary, where in some cases operator has to physically move from the workstation to the Quality department and carry out the inspection using the machines in the Quality department. In that case, it needs to be considered as time allocated for quality inspection and excluded from downtime.

In such cases the machine monitoring kit along with the sensor can have the push button and the operator can press it when they have to conduct the quality check and that push button input will be counted towards the quality inspection check.

Figure 8. a) Production KPIs visualised on the Power BI dashboard on the office laptop.

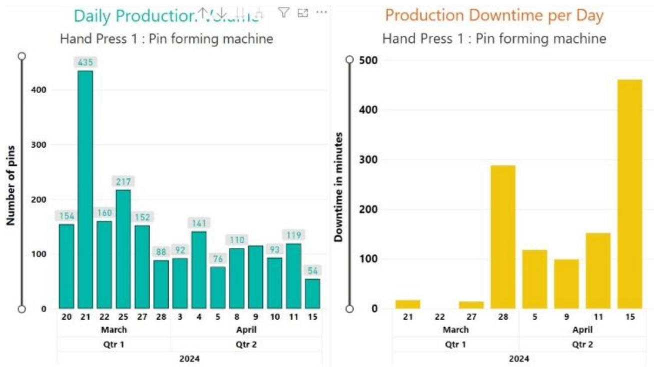

Figure 8. b) Report page from Power BI displaying the production KPIs in detail.

5. Discussion

5.1. Cost-effectiveness

The total direct cost of the hardware used in the project is £93, as detailed in the table below. The software for coding, Arduino IDE, is open source, as is the TDSLite library [6] used to connect the NodeMCU to the MSSQL database. Data was stored on an on-site server using Microsoft SQL Server Management Studio. We utilized the free license of Microsoft Power BI for data visualization. The cost of R&D and human resources involved in the project amounted to £10,400. This is still less than the lowest price quoted by the commercial vendors for machine monitoring solutions.

5.2. Limitations of the low-cost solutions

The low-cost solution adopted in this study is effective; however, the longevity of the NodeMCU hardware board is a concern. The lack of a troubleshooting guide or comprehensive documentation from the manufacturer or designer makes long-term maintenance challenging. Although the TDSlite library [6] used supports communication with an MSSQL server, the database structure needs to be redefined when more than one sensor is connected to a single NodeMCU, particularly when scaling up to multiple machines. Consequently, the limited processing power of the NodeMCU may be a significant limitation for complex data collection and processing applications. For more demanding tasks involving complex data collection, processing, and storage, the Raspberry Pi 3B+ could be a more suitable alternative.

5.3. Improved shop floor visibility

Before digitalization, there was a lack of shop floor data visibility. The primary requirement received from the production team was capacity planning. For this, there are 3 main things needed which are machine, labour, and material. The machine availability data needed to be captured hence the machine monitoring solution was selected as the project scope at the beginning to display the hourly production volume and downtime. The ERP system used in the company has features for stock management. There is a 3rd party system for workforce management. With the implementation of a live machine monitoring solution, the live machine capacity is known which help to plan the capacity. This improvement allows for precise prediction of delivery dates, eliminating the need for guesswork.

The secondary goal of the long-term digitalization project is to enhance Overall Equipment Effectiveness (OEE) by reducing unplanned downtimes and accurately estimating lead times based on production capacity. To measure OEE, three critical factors are required: Availability, Quality, and Performance. This study focused on visualizing Production Volume and Production Downtime, with machine availability directly measured, while quality and performance were assumed based on available data. To accurately reflect true OEE, it is essential to account separately for scrap quantities and the time allocated to quality checks and maintenance operations. Integrating these factors with the order management system can further refine the estimation of production lead times. The KPIs identified for the business should guide the digital transformation strategy and system selection.

5.4. Change management

In traditional manufacturing setups, the absence of machine monitoring and live shop floor data capture systems presents significant challenges for adopting Industry 4.0 technologies. These challenges are not only financial and technical but also involve integrating new infrastructure and addressing employee scepticism. Shop floor employees may perceive the technology as a threat, especially when manual hand machine outputs are monitored. This is being overcome using a soft systems change management methodology known as the PrOH (Process Oriented Holonic) Modelling methodology [7][8][9][10]; see prohmodeller.org [11].

For a successful digital transformation, it is crucial for top management to clearly articulate the organization's vision and objectives to the mid-level and shop floor teams, emphasizing the tangible benefits to secure their buy-in and foster a collaborative implementation environment.

Additionally, conducting training and engagement workshops can significantly increase awareness and acceptance among all involved teams, from shop floor workers to administrative staff. These initiatives foster a better understanding of digitalization's advantages, ultimately driving a smoother transition and greater buy-in from employees, and will be done partly by using PrOH Modelling

6. Conclusion

In this study, we explored the digital transformation of small to medium-sized enterprises (SMEs) within the manufacturing sector, focusing on the implementation of low-cost machine monitoring solutions. Using the ISA-95 framework, we assessed the digital maturity of Protaform Springs & Pressings and identified Level 1 process sensing as a crucial area for improvement.

Our implementation of an inductive proximity sensor and ESP8266 microcontroller demonstrated that it is possible to collect real-time production data cost-effectively. The data acquisition system successfully transmitted information to an MSSQL database, which was then visualized using Power BI. This setup provides a robust foundation for data-driven decision-making, enabling SMEs to improve their production planning and control.

Financial constraints and the lack of internal digital champions are significant barriers for SMEs in adopting digital solutions. However, our study shows that with careful planning and the use of affordable technology, these barriers can be overcome. The success of our low-cost implementation highlights the potential for similar approaches in other SMEs, facilitating their journey towards Industry 4.0.

Future research should focus on scaling this approach to other levels of the ISA-95 framework, exploring levels of systems thinking (e.g., strategic, tactical, and operational), and exploring additional low-cost technologies that can further enhance digital maturity. Collaboration with technology vendors and industry experts can also help SMEs navigate the complexities of digital transformation more effectively.

By embracing digitalization, SMEs can not only improve their operational efficiency but also enhance their competitiveness in an increasingly digital world. Our study serves as a practical guide for other SMEs looking to embark on their digital transformation journey, proving that significant improvements can be achieved without substantial financial investment.

7. Acknowledgments

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9. Appendices

Vendor	Location	No. of Machines	No. of nodes reqd	Price pe Unit - Node	No. of Gateways required	Price pe Unit - Gateway	Hardware price (5 yrs)	Software Price	Total software cost (5 yrs)	5 yr Total cost of ownership
Vendor A	UK	48	48	NA	48	NA	0	£3600/month	£216,000.00	£216,000.00
Vendor B	UK	48	NA	NA	3	£1,295	£3,885	£1696/month	£101,760.00	£105,645.00
Vendor C	USA	48	48	£549	1	£799	£27,151	£2000 (OTC)	£2,000.00	£29,151.00
Vendor D	UK	48	48	£195	6	£600	£12,960	£81.26/Yr	£406.30	£13,366.30

Figure 9. Detailed total cost of ownership of the machine monitoring solutions for 48 machines.

The cost analysis presented in Figure 9 considers electrically powered machines with an electrical signal. The shortlisted solutions aim to monitor machines for hourly production volume, downtime, and Overall Equipment Effectiveness (OEE). As per the vendor's claim and demo, this data is monitored through the custom dashboard designed for the users and the reports can also be downloaded. The cost assessment is based on 48 machines, as some vendors offer discounts at this number; with fewer machines, the per-machine cost may be slightly higher due to different pricing models.

The solutions vary in terms of connection types and architectures:

1. Vendor A provides a set that includes a current sensor, a wireless gateway, and a tablet for operators to input data on stop reasons and quality inspections. The current sensor has a way to detect the machine working based on the difference in power consumption. For 48 machines, there are 48 such sets, with data stored on the vendor's cloud and accessed via a monthly subscription model.
2. Vendor B offers hardware that connects to the machine's power inlet cable to monitor activity. This data is transmitted to the vendor's cloud through an Ethernet connection, which is suitable for facilities with existing Ethernet support. This solution also operates on a monthly subscription basis.
3. Vendor C employs a system architecture with one node per machine. These nodes detect digital output from sensors (e.g., photoelectric, proximity) and communicate with a gateway that can connect to 60 nodes. Data from these nodes is accessible to the client and can be processed or manipulated as needed. Vendor C's solution involves a one-time cost for hardware and software without ongoing subscription fees.
4. Vendor D provides a package that includes sensors, nodes, and gateways, with data access offered through a monthly subscription model.

Each vendor supports different configurations, such as Ethernet connections or wireless options, and offers various combinations of hardware and data transmission methods. Depending on the specific requirements and existing infrastructure, the cost-effectiveness and suitability of each vendor's solution may vary. These vendors were selected for this study because they offer a wide variety of solutions tailored to the different needs of SMEs, considering factors such as machine age, operating principles, and specific monitoring requirements.