Monitoring on a Shoestring: Low Cost Solutions for Digital Manufacturing

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Abstract

Digital transformation can provide a competitive edge for many manufacturers, however many smaller companies may not have the capabilities needed to embrace this opportunity and may be left behind. This paper reports on an approach which is attempting to alleviate this by creating a low-cost pathway to help manufacturing small and medium sized enterprises (SMEs) engage with digitalisation. This paper focuses on industrial monitoring and explores the potential for developing simple monitoring systems that solve real operation challenges in SMEs using low-cost, off-the-shelf technologies. A blueprint for developing such systems is presented and then exemplified through a case study system. The paper concludes that low-cost monitoring can be feasible given the right application and operating environment.

1. Introduction

Digital transformation is currently an important issue within the manufacturing sector and across the business spectrum. Many companies are eager to embrace the benefits that it is promised to offer such as improved efficiency and the potential for business growth (Lu 2017; Westerman et al., 2014; Ku et al., 2020; Siebel 2017). Consequently, there are a range of initiatives and approaches focussed on the digital transformation of manufacturing including Industry 4.0 (Lasi et al., 2014; Kumar et al., 2020), the Industrial Internet of Things (IIoT) (Sisinni et al., 2018; Koch and Knut, 2020) and Cyber-Physical Systems (CPS) (Jazdi, 2014; Sanchis et al., 2020). As these initiatives start to bear fruit there is potential for a “Digital Divide” between companies that are able to embraces these opportunities and those that are not (Horváth & Szabó, 2019; Hayriye & Fatma, 2020).

It has been noted that many small and medium sized manufacturers may not benefit from digital transformation to the same extent as larger companies (Horváth & Szabó, 2019; Stentoft et al., 2020; Peillon & Dubruc, 2019; Müller, Buliga & Voigt, 2018; Mittal et al., 2018; Matt, Modrák & Zsifkovits, 2020). For these companies, digitalisation is currently too complex, too expensive and/or overfitting (Masood & Sonntag, 2020). In other words, they don’t have the necessary skills, they can’t justify the capital to embark on an uncertain “digital journey” and many of the solutions available on the market are significantly more sophisticated than what they need.

In response, the authors have been involved in an approach which was launched in 2018 to address a common concern that recent developments in digital manufacturing are unlikely to be accessible to SMEs (McFarlane & Ratchev , 2018; Schönfuß et al., 2019; Hawkridge et al., 2019, de Silva et al., 2020). The project proposes an approach to the digital transformation for small and medium sized manufacturing companies that focusses on simple, low-cost, non-industrial solutions to industrial automation and information challenges.

This paper looks at industrial monitoring needs and the potential contribution of simple low-cost digital solutions in this area. Ordinarily, when digital transformation initiatives in large companies consider monitoring, the intention is generally widespread data acquisition with in-depth analysis, possibly leading to automated optimisation. These initiatives typically build on an existing foundation of monitoring, data gathering and analysis and seek to take it to the next level. However, when it comes to SMEs, there is seldom any active monitoring or data gathering, although many SMEs are seeking to improve in this regard.

The aim of this paper is to explore the potential for developing low-cost monitoring solutions for industrial equipment, to propose an extendable "blueprint" for a low-cost monitoring approach that will allow simple configuration changes, and to identify examples of suitable for low-cost candidate technologies for use in such solutions.

This paper begins with some background on what is required for a digital solution to be low cost, followed by an overview of monitoring in manufacturing and the relevant low-cost products and technologies that are available. Following this, the blueprint for low-cost monitoring is presented, and then applied through a case study. The implemented low-cost monitoring system is evaluated and conclusions are drawn.

2. Background

2.1. Low-Cost Digital Solutions

Low cost in the context of digital solutions refers to systems where the capital investment is low, the development cost is low, and the subsequent operational costs are also low. This informal definition draws on the definition provided in McFarlane et al. (2019), Schönfuß et al. (2019). Sometimes the term "low-cost monitoring" has been applied to the measurement device (or sensor) alone, however these components are of little use without the rest of the monitoring ecosystem. In this paper we consider the cost of a digital monitoring solution to include the entire monitoring system (sensors, communication technologies, computational devices, data management, analysis technologies and visualisation software) as well as the development, installation, and operation/maintenance costs.

What a company considers *low cost* is highly dependent on the particular circumstances of that company, even within the bracket of "SME" something low cost for a medium company (50 - 249 employees) could be out of reach for a micro company (<10 employees). Classifying a system as low cost also depends on the extent of the system, for example £5000 for a single monitoring node is very different to £5000 for ten monitoring nodes. Furthermore, there are cases (not just in SMEs) where low asset criticality or low asset value make it difficult to justify significant investment in monitoring for those assets.

In the context of this paper, a monitoring system is considered *low cost* if each component in the solution is less than £100 and the total system cost is less than £1,000. It is further assumed that the monitoring system in question is servicing between 1-5 pieces of equipment rather than an entire shop floor. This is in line with the idea that small and medium companies should embrace digital transformation incrementally rather than all at once.

A further consideration raised when discussing low-cost digital solutions is price to performance, with the argument presented (usually by vendors) that low-cost systems may not be the best value. There will likely be many scenarios for which this concern is entirely valid, however for this work the focus is unashamedly on low cost and not best value. The justification for this approach is that for many SMEs, particularly on the smaller side, the choice is between a low-cost approach or nothing at all since anything more expensive, even if it is a better value, is a "non-starter" if the company can't afford it.

2.2. The "Shoestring" approach to Digital Manufacturing

A low cost or "Shoestring" approach to digital manufacturing was coined in a programme initiated by University of Cambridge, involving Nottingham University and a significant number of industrial partners (McFarlane & Ratchev, 2018). It aims at incrementally increasing the digital capabilities of small manufacturers (SMEs) via a series of low-cost solutions. Low cost is ensured by using off-the-shelf, non-industrial components and software to address a company's (digital) solution needs one step at a time (McFarlane et al., 2019).

The Shoestring solution process has 3 main phases: *need identification*, *solution development,* and *solution deployment*. In the need identification phase, key stakeholders in an SME identify a "best next solution" for their company using a set of activities which include a catalogue of ~60 possible digital solutions (for more information on this process see Schönfuß et al., 2019). In the solution development phase, the SME models and then implements their chosen solution using a blueprint such as the one presented here. Once the solution has been implemented it moves to the operation phase where it is trialled and, if performance is satisfactory, transitions into day-to-day use.

In order to allow for the incremental addition of new Solutions, these "Shoestring" solutions use the same composition architecture; each solution is formed by a collection of reusable services and technology modules (McFarlane et al., 2019).

2.3. Monitoring in Manufacturing

Manufacturing systems tend to fail after a point of time in their deployment. The intensity of equipment failures is directly linked to the operational lifetime of the machine, the environment in which the machine is operated, part wear-and-tear, and operator errors. These unmonitored failures often lead to unprecedented downtimes, which is not only economically taxing for the industries, but may lead to domino effect of downtimes (especially in production lines).

Manufacturing industries can be classified based on their material inputs (Abbott (1990)). We further group some of the similar ones for ease of representation in Table 1. Typically, manufacturing industries fall into one of these nine types – 1) Metal, 2) Mining, 3) Petroleum, chemicals, and plastics, 4) Clothing and textiles, 5) Electronics and computers, 6) Food production, 7) Transportation and logistics, 8) Wood, leather, and paper, and 9) Pharmaceuticals (Dunne (1994)). The available literature on condition monitoring in manufacturing can be classified into one of these subdomains. By use of example, Table 1 illustrates recent monitoring efforts in various subdomains of manufacturing.

Table 1: Illustration of condition monitoring solutions in manufacturing

#	Manufacturing Subdomain	Purpose	Sensed Parameter(s)	Analysis Method	Reference
1	Metal Manufacturing	Monitoring for laser manufacturing	Thermal images	CNN*	Gonzalez-val (2019)
		Process Monitoring of Directed Energy Deposition in Additive Manufacturing	Thermal images	CNN*	Li (2020)
		Monitoring in ultrasonic additive manufacturing	Ultrasonic microscopy images	Empirical analysis	Nadimpalli (2020)
2	Mining	Seismic and aseismic rock deformation	Interferometric synthetic aperture radar (InSAR)	Empirical analysis	Yang (2019)
		Modelling vibration signals of sieving screens	Vibration	Clustering	Michalak (2021)

		Local damage detection in crusher bearings	Vibration, Tacho signals	Spectrogram	Wylomanska (2016)
3	Petroleum, Chemicals and Plastics	Nozzle condition monitoring in 3D printing	Vibration	Statistical analysis	Tlegenov (2018)
		3D Printing Remote Defect Detection	Visual images	Deep CNN	Paraskevoudis (2020)
		Monitoring of azimuth thrusters in drill ships and offshore rigs	Acceleration, shaft rotation speed	Linear regression	Nikula (2021)
4	Clothing and Textiles	Monitoring of manufacturing process and CFRP quality	Resistivity changes	Statistical analysis	Jeong (2020)
		Predictive maintenance of machinery in textile industries	Vibration	Frequency-domain analysis	Prutvi (2021)
5	Electronics and Computers	Tool Health Monitoring and Maintenance	Heat, pressure, voltage, flow-rate, position, RF	EWMA*, PLS*	Chein (2020)
		Monitoring of complex electronic laboratory setups	Voltage, flow-rate, temperature, magnetic field	Qualitative analysis	Chilcott (2021)
6	Food Production	Monitoring and control of production processes	Various sensors for various stages of production line	KPI*	Wohlers (2020)
		Remote monitoring of wind turbines	Current	Spectrum analysis	Peng (2021)
7	Transportation and logistics	Aerospace combustor health monitoring	Gas temperature, valve position	QFD* analysis	Mills (2020)
		Monitoring of high-speed railway turnouts	Laser-based lateral displacement	Qualitative analysis, FFT*	Jing (2021)
8	Wood, Leather and Paper	Dynamic Loads and Remaining Useful Life Prediction in Rolling Mills	Vibration	Statistical analysis	Krot (2020)
9	Pharmaceuticals	Manufacturing process monitoring of pharmaceutical solid dosage form	Halogen moisture analysis, Particle analysis, weight monitoring, spectrum analysis	PLS*	Roggo (2020)

*__CNN:__ Convolution Neural Networks, **KPI:** Key Performance Indicators, **EWMA:** Exponential Weighted Moving Average, **PLS:** Partial Least Squares, **QFD:** Quality Function Deployment, **FFT**: Fast Fourier Transform

It is interesting to note that a majority of the works that report on condition monitoring in manufacturing are from mining, metals and petroleum, indicating a popular acceptance of monitoring in these specific complex industries. The literature on monitoring in manufacturing is very broad. Here the authors simply highlight some developments relevant to this paper. The use of appropriate monitoring methods can enhance the profitability of manufacturing through real-time as well as predictive condition monitoring and health assessment. Some of the most common techniques used in the manufacturing sector are monitoring temperature, vibration, and acoustic emission (Rao, 1996). These three monitoring techniques have been used for various applications, equipment, and processes in manufacturing, such as additive manufacturing (Tlegenov et al., 2018), automated machinery (Engeler et al., 2017), conveyors (Liu et al., 2018), forging and casting (Behrens, 2016), electric motors (Nandi et al., 2005), injection moulding (Ogorodnyk & Martinsen, 2018), machine tools (Zhang et al., 2018). Further, from Table 1 and other recent literature, we observe that imaging and vibration-based monitoring are increasingly popular means of monitoring in many industries. This may be due to the ease of data acquisition, ease of setting-up the sensors, or even common availability of analytical tools and knowledgebase for the evaluation of data from these sensors.

One of the challenges in industrial sensing is that there may exist heterogeneous sensor types for the quantification of similar phenomena. For example, temperature can be measured using resistive temperature sensors, thermocouples, infrared cameras, and others (*ref. to* Table 2), all of which require different communication and energy interfaces and different data manipulation. Various industries have their proprietary, often sensor-specific condition monitoring frameworks. Industries such as Siemens[1], Analog Devices[2], and FLIR[3] are good examples of organizations that are taking-up condition monitoring as business opportunities. Despite the availability of a heterogeneous choice of sensors and rapidly increasing technology vendors, efforts are being made to standardize condition monitoring systems across industries. The Open System Architecture for Condition Based Maintenance (OSA-CBM) is one such example, which has major global organizations such as Boeing, Oceana Sensor Technologies, Rockwell Automation, and Caterpillar among its stakeholders[4]. The standard does not appear to have had much recent activity as its latest release (version 3.3.1) was in 2010, however it may see renewed interest with the advent of industrial IoT.

Owing to the complexity of tasks involved in monitoring and maintenance of manufacturing systems, the development of systems complying with a standardized condition monitoring and maintenance system is a very challenging task. As a result, industrial monitoring solutions that comply with a common specification are not yet accessible for a wide range of manufacturing companies. There is therefore benefit in examining low cost monitoring technologies, exploring their interfaces and evaluating the possibility of their implementation within the manufacturing environment.

In this section we have briefly reviewed different types of monitoring needs encountered in manufacturing and noted the OSA-CBM stack as a standard means of examining monitoring. In the next section we begin our examination of low-cost monitoring solutions for manufacturing.

3. Low-cost Technologies for Monitoring

Low-cost condition monitoring systems, either bespoke or universal, broadly require development of the following six “technology blocks”: 1) data collection, 2) computation, 3) communication, 4) analysis, 5) storage, and 6) visualization (Misra et al., 2018; Meng et al., 2018; Mohanraj et al., 2020). Figure 2 outlines a typical interconnection between the six technology blocks previously mentioned. These six blocks have been shown to be of fundamental importance to set-up a fully functional OSA-CBM stack for condition monitoring and maintenance (Bourezza et al., 2020; Hernandez et al., 2019). It is the authors’ view that systematically selecting low-cost components within the functional domain of each of these blocks, will lead to a sufficiently low-cost monitoring solution, which will be easy to develop from off-the-shelf components. When considering monitoring solutions for SMEs, these solutions could either be developed by technical employees within an SME using skills they have acquired during their schooling or through hobbies, by 3rd parties such as freelancers, or through student projects with local universities. These solutions would provide similar functionalities to some of the existing solutions and would be scalable and customizable for including updates and upgrades in a rolling manner. With this principle in mind, this paper evaluates the available low-cost solutions for each of these technology blocks in the subsequent sections of this manuscript.

[1] https://www.plm.automation.siemens.com/global/en/resource/remote-condition-monitoring/94020
[2] https://www.analog.com/en/design-center/evaluation-hardware-and-software/evaluation-development-platforms/condition-based-monitoring-development-platforms.html#
[3] https://www.flir.co.uk/instruments/condition-monitoring-solutions/
[4] https://www.mimosa.org/mimosa-osa-cbm/

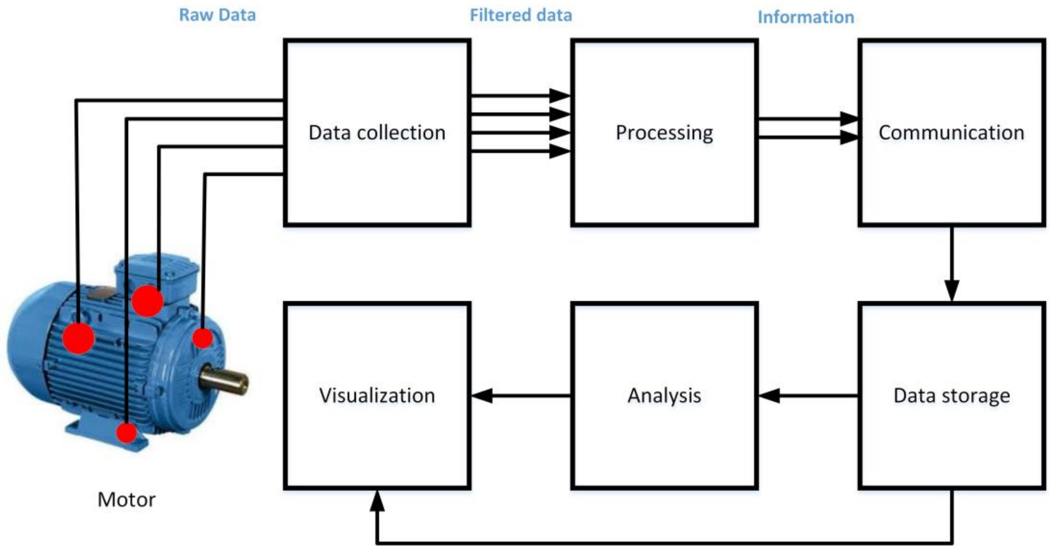

Fig. 1: A typical low-cost condition monitoring flow

In Table-2 we outline some of the Commercial-off-the-Shelf (COTS) component-based systems used in devising monitoring solutions for various application areas, including industrial, building management, power management, and other scenarios. We observe that condition monitoring systems across various application domains are witnessing the common use of COTS for rapid and cost-effective deployment of monitoring. Most of these initiatives are still lab-scale prototypes, but they all tend to have a common arrangement of functional blocks (similar to Fig. 2). Table 2 lists some low-cost monitoring technologies reported in various application studies, which reflect similar properties to a low-cost, "Shoestring" solution.

Table 2: Review of low-cost, off-the-shelf systems developed along the lines of Shoestring philosophy in various application domains.

#	Reference	Target	Computation	Communication	Sensing	Status
1	Xing et al. (2021)	Machine tool	MCont: ESP32	Wireless: IEEE 802.11	D/ Image: OV2640 2MP camera	Lab-based implementation
2	Hizarci et al. (2021)	Rotating machinery	MCont: STM32F429	Wired: Serial	A/ Accelerometer: PCB Piezoelectronics 352A76	Lab-based implementation
3	Alemayehu et al. (2021)	Transformer oil condition	MCont: Arduino MKR WiFi 1010	Wireless: IEEE 802.11	A/ Impedance: AD5933	Real-time deployment
4	Soto-Ocampo et al. (2020)	Rotating machinery	MComp: RPi+ADC	Wireless: IEEE 802.11	A/ MEMS Accelerometer: MEAS 805M1	Lab-based implementation
5	Pesch and Scavelli (2018)	Active magnetic bearings	MComp: RPi+ADC	Wired: Ethernet	A / Hall effect sensors	Lab-based implementation
6	Karami et al. (2018)	Building performance	MCont: Arduino Uno	Wireless: IEEE 802.15.4	*A* / Temp: Type K	Lab-based implementation
7	Basto et al. (2017)	Structural health	MCont: Arduino Uno	Wireless: IEEE 802.15.4, IEEE 802.15.1	*A* / Temp: LM35 D / Humidity; DHT22	Real-time deployment
8	Fuentes et al. (2014)	Monitoring of PV cells	MCont: Arduino Uno	Wired: Serial	*D* / Temp: DS18B20	6-month trial deployment

***RPi** – Raspberry Pi, **MCont** – microcontroller, **MComp** – microcomputer, **A** – analogue, **D** – digital, **ADC** – analogue to digital converter.*

In each case in Table 2, monitoring technologies were analysed in terms of their computation, communication, and sensing technologies. Microcontrollers, such as Arduino Uno, were used to obtain high sampling rates from analogue or digital sensing devices, but not performing the visualisation or analysis. On the other hand, microcomputers such as Raspberry Pi were used to obtain the signals from sensors, and then analyse, and visualise the data. Communication technologies varied depending on the application: wired for near board sensor locations, wireless for sensor locations on distance. Sensor output interfaces in literature were mainly of two types: analogue and digital. Previous works indicate that microcontrollers are suitable for analogue sensing interfaces and higher (>1 kSPS) sampling rates, and microcomputers, on their own, are suitable for digital sensing interfaces with lower sampling rates but with the possibility of data analysis and visualisation on the board. However, the recent rise in microcomputers' use as popular on-site data aggregation devices from sensor installations has led to the emergence of various strategies and dedicated hardware to handle analogue input signals. One of the most straightforward and low-cost strategies for enabling analogue signal handling on a microcomputer is the use of microcontrollers as analogue data acquisition interfaces. However, with increased circuitry stages and delays due to interfacing software, this approach has a limited sampling rate depending on the type of microcontroller used. A more robust alternative to the previous approach is dedicated Analog-to-Digital (ADC) chips and interfacing boards. Microcomputer interfacing boards are easy to handle, relatively simple to integrate, and have reasonable sampling rates (50 kSPS[5] to 100 kSPS[6]), sufficient for many applications. Further, although dedicated ADC chips require some minimal circuit assembly, ADC chips such as LTC2366 provide massive sampling rates of over 300 kSPS at a much lower cost than interfacing boards.

We now use the structure of Figure 2 to review low cost technological contributions in each relevant area.

3.1. Low-cost Data Collection

There are number of sensor types that monitoring can utilise in manufacturing such as: temperature, for monitoring heat generation; vibration, for detecting out of balance vibration; and acoustic emission, for material failure sound detection and regulation compliance.

Table 3: Examples of common low-cost sensing technologies for monitoring.

Sensed parameter	Sensor	Type	Output	Range	Accuracy H(L)	Resolution (R)/ Sensitivity(S)	Price range (USD)
Temperature	LM335	Transistor	A	-40°C ~ 100°C	±3°C (±5°C)	R=10mV/°C	1.4
	LMT01LPG	Transistor	D	-50°C ~ 150°C	±0.5°C (±0.6875°C)	R=0.0625°C	2.8
	MLX90614	IR	D	-70°C ~ 380°C	±0.5°C (±4°C)	R=16 bit	32
	NB-PTCO	RTD	A	-50°C ~ 600°C	±0.3°C	R=3850ppm/°C	1.8

[5] https://www.mccdaq.com/DAQ-HAT/MCC-172.aspx
[6] https://www.mccdaq.com/DAQ-HAT/MCC-118.aspx

	NTCLE100E3103JB0	NTC Thermistor	A	-40°C ~ 125°C	NA	NA	0.69
	TP29	K-type Thermocouple	A	-50 ~ 200°C	NA	NA	9.6
Vibration	PC420A	Piezoelectric	A	10 Hz - 1.0 kHz	NA	S=5%	330
	KX122	MEMS	D	6.25Hz ~ 12.8kHz	NA	S= ±2g ~ ±8g	1.83
Acoustic	CMA-4544PF	Electret	A	20 Hz ~ 20.0 kHz	SNR = 60dB	S=-44dB ±2dB	0.77
	SPU0410LR5H	MEMS	A	100 Hz ~ 80.0 kHz	SNR=63dB	S= -38dB ±3dB @ 94dB SPL	0.67
	PMO-4015PN	Magnetic	A	50 Hz ~ 12.0 kHz	SNR= 58dB	S= -42dB ±2dB @ 94dB SPL	1.58
Pressure	SDP31-500PA	Differential	D	-0.5kPa ~ 0.5kPa	±3%	R= 16 bit	30.69
	DP-101-N	Vented gauge	D	±100kPa	NA	NA	92
	24PCEFA6G	Compound	A	±3.45kPa	±1%	NA	27.27

**__IR__: Infrared, __RTD__: resistance Temperature Detector, __NTC__: Negative temperature Coefficient, __MEMS__: Micro Electro-Mechanical Systems, __A__: Analog, __D__: Digital, __SPL__: Sound Pressure Level, __PPM__: Parts per Million, __Hz__: Hertz, __Pa__: Pascal, __C__: Celsius*

Table 3 summarises some popular sensor types, typically low-cost, which are commonly found in monitoring solutions. We limited our selection of specific sensors to represent each type (preferably the cheapest) within each sensor category. When considering low-cost sensors, there is usually a compromise between a variety of factors. The cost of sensors is dictated by the sensing range, sensitivity to variable changes, and packaging. Typically, low-cost sensors have limited sensing range and sensitivity. However, the range and sensitivity offered by many non-industrial, off-the-shelf sensors are sufficient for most general monitoring applications, especially in SMEs. There will clearly be limits to what is possible using low-cost sensors due to lack of ruggedness, limited range, insufficient sensitivity, and/or higher levels of noise and this may preclude their use in a number of application scenarios or require a compromise between the cost and features of the solution. However there are still many less demanding applications within SMEs where monitoring that uses low-cost COTS sensors and systems for potentially simpler use cases can be of significant benefit (Lynn et al., 2017; Wu et al., 2017).

It is noted that the solutions reported here predominantly use data collection with “wired power” since there are several complications that arise from the use of “battery power”. These include optimisation of power usage which may not be feasible for low-cost development, and the operational procedures required to ensure that batteries remain charged which may require significant employee buy-in to overcome the additional hassle.

3.2. Low-cost Computation

Low cost monitoring solutions can use both microcomputers and microcontrollers to perform computation. Microcomputers are used as the primary edge devices and will therefore be the focus of this section. Since the objective of this paper is low cost, commercially available monitoring technologies, only single board microcomputers are evaluated.

Figure 3 summarises a market analysis of the popular single board microcomputers available at the time of writing. As pricing fluctuates, the costs are presented on a relative scale. These microcomputers were evaluated based on computing performance and connectivity, as these factors are core to their function within a monitoring system. Each microcomputer was given a computing performance score from 1-3 and a connectivity score from 1-3. The sum of these scores are presented as the combined score in the figure. The scores are determined as follows:

Computing performance:

1. **Low:** < 4 CPU cores; < 1.2 GHz; < 1 GB RAM
2. **Medium**: 4 CPU cores; 1.2 to 1.4 GHz; 1 to 2 GB RAM
3. **High**: > 4 CPU cores; > 1.4 GHz; > 2 GB RAM

Connectivity performance[7]: (All had Ethernet connectivity)

1. **Low**: has no Wi-Fi, Bluetooth or BLE
2. **Medium**: has either Wi-Fi, Bluetooth or BLE
3. **High**: has Wi-Fi, Bluetooth and BLE

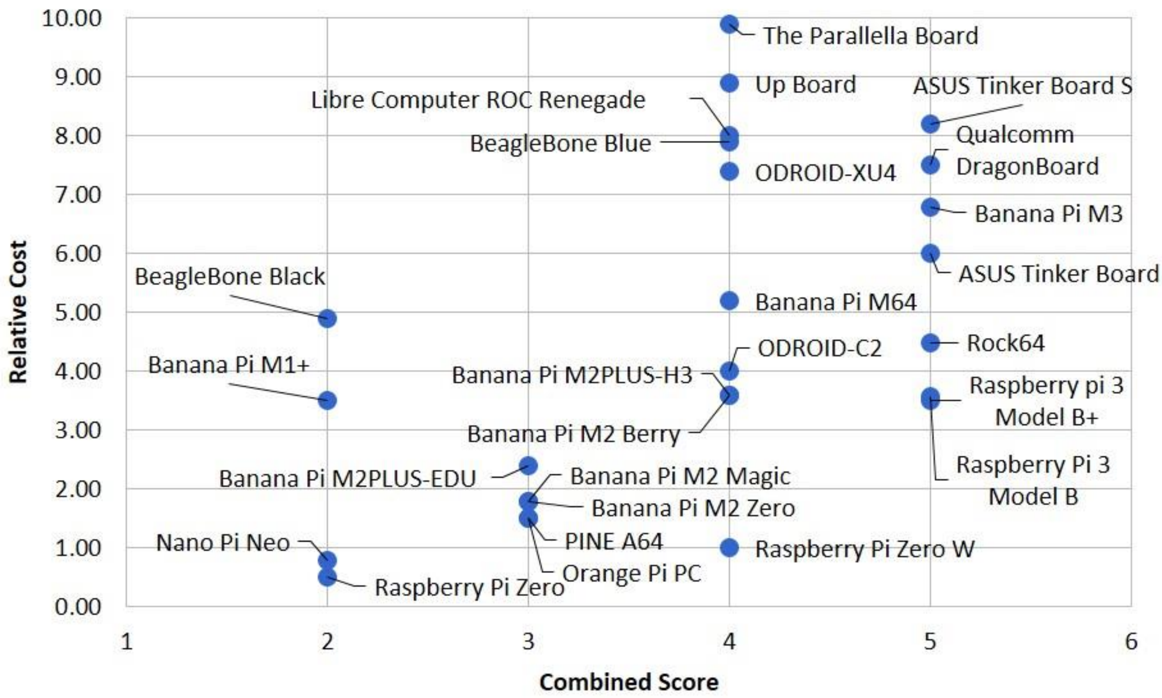

Fig. 2: Examples of low-cost single board microcomputers

The main message from Figure 3 is the relative abundance of low cost computational options, although other considerations such as interfacing, development environment, and industrial reliability are also important when selecting a computational option. It should further be noted that the results in Figure 3 represent a snapshot in time and it will therefore be important that readers

[7] It should be noted that the connectivity features of a microcomputer can often be expanded using low-cost adaptors.

intending to deploy a low-cost monitoring system examine their current low-cost computation landscape.

3.3. Low-cost Communication

There are wide range of communications networks to choose from when designing a connected digital manufacturing solution. These networks are based on a stack of protocols: sets of rules that allow electronic devices to communicate with one another. Portability is an important factor for many digital manufacturing applications and could easily be the primary reason to choose one communication over another. In Internet-of-Things (IoT) applications, for example, the hardware that is compact and portable is more beneficial. Using wireless communication is another good option for portability because the data acquisition can be portable while computing devices can remain stationary. As can be seen from Figure 4, Bluetooth Low Energy (BLE) and Wi-Fi wireless networks have the highest data transmission rates and are in the cheapest category. Many microcomputers comes with those technologies built-in, hence no additional hardware is required. External communication networks such as USB and Ethernet are also widely adopted for portable systems because of quick installation and compatibility with many devices.

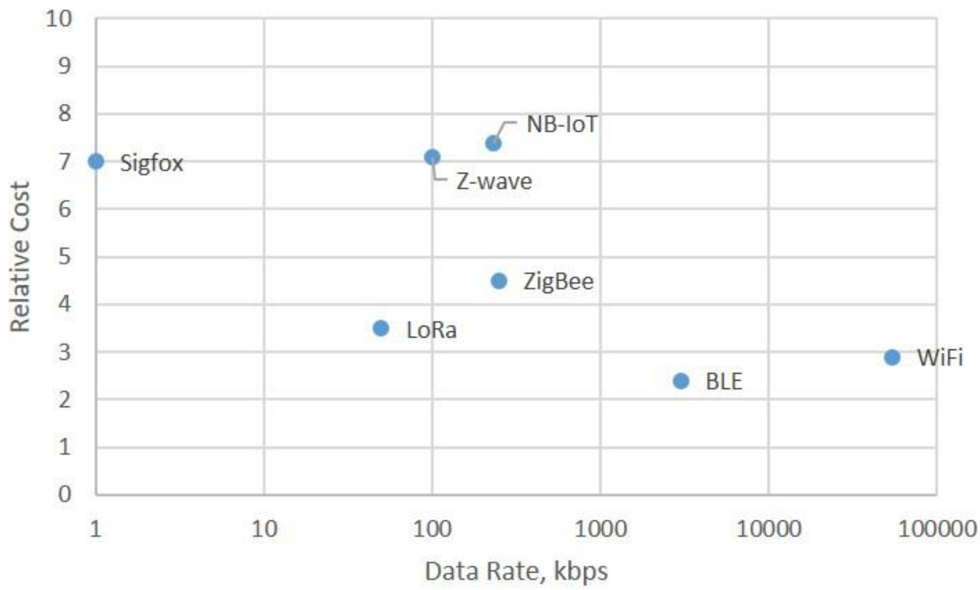

Fig. 3: Review of low-cost wireless communication technologies

Industrial applications often require real-time communications and high levels of robustness that are not easily achieved through wireless communications, rather wired communications are more suited to these needs. Popular industrial wired communications protocols include: EtherNet/IP, PROFINET IRT, EtherCAT, Powerlink, and SERCOS III. EtherCAT stands apart in terms of offering superior performance/price, as EtherCAT delivers determinism in a solution at the lowest cost, compared to the other protocols. EtherCAT data rates are over 100MBps and the shields for both Raspberry Pi and Arduino are available for £35 and £44 respectively, meaning this industrial grade technology can be implemented in a low-cost solution of comparable price to some of the low-cost wireless networks. It should be noted that there are additional factors to consider for a given application beyond the data rate of the connection such as range, reliability, and robustness. Additionally, the protocol layers used on top of the communication mechanism will also have an effect. The information presented in this section serves to indicate that there are a range of viable options within the low cost, commercial space. Finally we note that low data rate (typically high range) solutions are not relevant generally for production, but apply to the broader supply chain supporting smart manufacturing.

3.4. Low-cost Data Analysis Tools

Analysis approaches, from the point-of-view of their functionality and scope can be broadly classified into four categories:

1) ***Descriptive:*** it is the primary step of any data analysis chain. It focuses only on the "What" aspect of the data. In other words, a descriptive analytics tool would look into historical data trends for an observed phenomenon to identify the deviations and changes. In the context of condition monitoring, it would notify abnormal behaviour of monitored infrastructure based on previous data trends (Qiao et al., 2019).
2) ***Diagnostic:*** it is the subsequent step after descriptive analysis. It addresses the "Why" aspect of the data. Diagnostic analytics tools look into the causes driving the deviations from standard behaviour of an observed phenomenon. In the context of condition monitoring, it would focus on locating causes of abnormality of the incoming data from the monitored infrastructure (Wu, Zu & Wang, 2017).
3) ***Predictive***: it builds up on the diagnostic analysis. It focuses on the "Future" part of the data or forecasting. It builds up on historical trends and stored data signatures to forecast the behaviour of the monitored system (Wu et al., 2016).
4) ***Prescriptive***: it is considered as a frontier topic in data analysis. Rather than reporting trends and abnormalities, prescriptive analytics is expected to give solutions in the event of occurrence of such abnormalities (Vater et al., 2019). In other words, prescriptive analytics tools are expected to identify the best course of action identified from a set of possible outcomes based on predictive analytics of trends.

It must be noted that these four categories are not mutually exclusive. Rather, while going down the list, they build up on the outcomes of their predecessors. Interestingly, another approach of classifying data analysis method relies on the location of the analytics tool in an industry-wide or organization-wide data networking architecture. The classification of data analysis methods on the basis of the location of analytics operation is as follows:

1) ***Edge analytics:*** this method of analytics is performed at the site of the data collection, before it is pushed out of the data collection sensor network via a network gateway. The data streams from the sensors are analysed at the sensor node, another peripheral node, a switch, or the gateway. Typically, the devices in the data collection network are constrained in terms of computing resources, which necessitates the use of various computation offloading strategies or lean methodologies for performing analytics within the edge (Kufner et al. (2021)). Nowadays, specialized hardware[8] are being developed, which are capable of standalone edge analytics, even for high-speed, high-volume data streams. Edge analytics tools are generally used in situations, which are highly time-critical or/and have no recourse or budget for more powerful computation infrastructure such as clouds.
2) ***Federated analytics:*** this method aggregates decisions which are made on separate devices (often, edge devices), each running computations on their data locally. This peculiar arrangement for enabling data analytics uses distributed datasets on these different devices, which often have data from non-similar sensors, to draw a strong global conclusion. Aggour et al. (2019) demonstrated the use of federated learning on a platform for multimodal data storage and analytics in the domain of additive manufacturing.

[8] https://www.seeedstudio.com/sipeed

3) ***Distributed analytics:*** this method distributes a single computation task to multiple devices in its network, enabling each one of these devices to collectively contribute to the processing of a uniform dataset or data stream. Unlike federated learning, this method runs the same algorithm across multiple devices (often computationally constrained on their own), each working on a subset of a uniform dataset. This results in faster turnaround times for analytical operations. It is worthwhile to mention that not all devices in a distributed analytics framework will be equally configured, or even constrained. Pandiyan and Caesarendra (2020) provide good use-cases for distributed analytics for industrial robots ad abrasive finishing processes.
4) ***Cloud analytics:*** this method exploits the powerful features of a cloud computing infrastructure (scalability, elasticity, multi-tenancy, resource pooling, and on-demand self-service) to enable rapid analytics on data. The data from on-site sensors are transmitted to a public or a private cloud (typically, over the Internet), which hosts a suite of powerful analytical tools for a wide range of functional operations. Although, cloud-based analytical services are quite popular, they often become restrictive for SMEs with massive amounts of data to analyse and limited budget to do it on.
5) ***Fog analytics:*** this method extends the benefits of cloud analytics (elastic and on-demand resources) to a location much nearer to the site of data collection. Although considered as an intermediate stage between a data's transmission from the site of generation to the cloud, this approach reduces network latency between the data generating source and the site of actual analytics (Aazam (2018)). Typical configurations of fog computing architecture includes bulk of the high-volume, high-velocity data from various data sources processed at the fog, while only some specialized data streams are forwarded to the cloud. Considering the magnanimous amounts of data generated and transmitted over a network in an industry, this approach can significantly improve decision turn-around times and save costs in terms of reduced data sent to the cloud.

The choice of local on-site analytics or remote off-site analytics also determines the cost of the overall solution. Considering the above classification, the analysis of sensor data can be performed using a variety of open source analysis software and libraries such as Python Scikit, Python Pandas, PyBrain, Tensor Flow, Apache Spark, R, etc. Post-analysis, the alerting would typically require some form of integration into an existing management system. A simple form could be achieved using an SMTP library to send an alert email when the analysis software observes a particular condition.

3.5. Low-cost Data Storage

A robust monitoring system requires a versatile database management system (DBMS). The method of data storage depends on the type of data being collected, the speed at which the data is updated, and the end-user's requirements for visualization. Typically, condition monitoring and maintenance systems rely heavily on time series databases for managing the sensed information. However, a holistic approach to condition monitoring would also necessitate relational databases, especially for providing selective access rights to data. Figure 5 outlines the categorization of DBMS and some off-the-shelf solutions for the same.

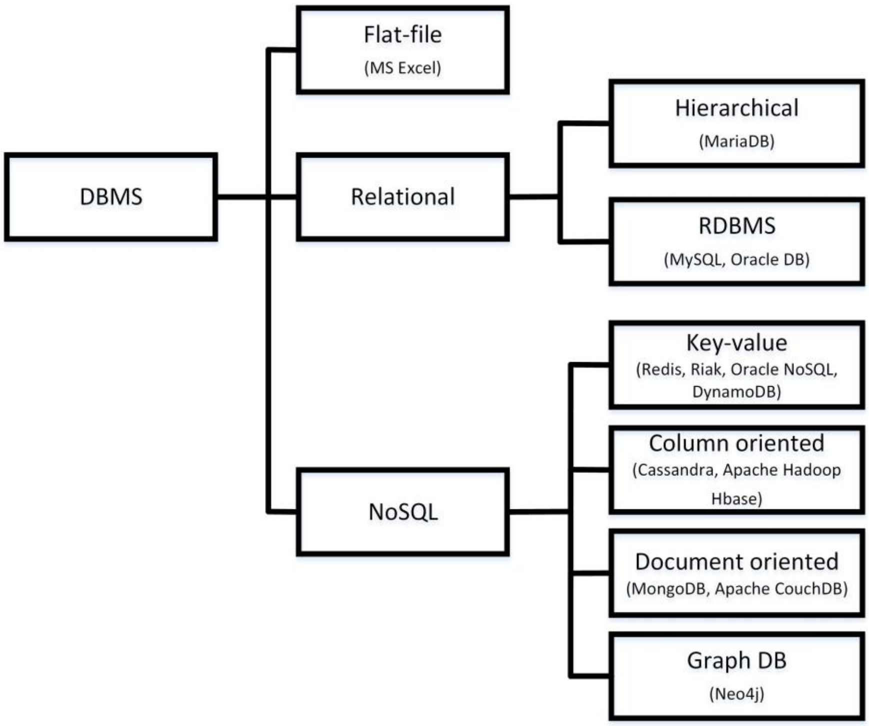

Fig. 4: Classification of data management solutions

The cost of data storage is interesting to quantify for local deployment because most of the DBMSs are available for free. Examples include MariaDB, CouchDB, Redis, etc. The cost of a local storage solution is therefore typically determined by the cost of the storage media. As a result the amount of data that needs to be stored can often be the determining factor in whether data storage is low cost or not. There are strategies that can be used to reduce or summarise the data that is stored in the long, however an SME may simply choose to only operate with live data, or to opt for a rolling overwrite strategy where new data overwrites the oldest data.

An alternative to local data management is to do it in the cloud. Cloud-based data storage is also an option and can be achieved using any of the major Database-as-a-service (DBaaS) providers such as Amazon DynamoDB, Microsoft Azure SQL Database, etc. However, the economics of cloud storage may be hard to justify as “low cost” unless large amounts of data need to be stored.

3.6. Low-cost Data Visualisation

Visualization is a crucial component that bridges machines and their human operators or maintenance crew. Traditional visualization systems made use of multi-coloured lights, dials, and LCD displays. However, modern-day visualization systems, especially in Industrial IoT, are expected to be omnipresent and accessible from anywhere. The visualization choice is often dictated by the complexity of the data to be visualized, specific requirements of SMEs, and cost constraints. For example, legacy factory floor devices relied on coloured lights and gauges for representing various states of the machinery to its operator. These were standalone systems, with no interaction between neighbouring machinery. This, however, made such systems quite economical to buy and maintain in comparison to a factory with connected machinery (say, with a Human-Machine Interface (HMI) at the end).

With time, the minimum basic expectations, in terms of visualization of information, have increased. Modern machine monitoring systems are expected to have a dedicated dashboard with multimodal data and output from various analytical tools, providing insights into some particular aspect of the gathered data. It is now cumbersome and infeasible to have on-site visualization of information with the machinery. Dashboards are nowadays popularly hosted on clouds or at a centralized remote server, which facilitates the visualization of data irrespective of location or time. Smartphone-based apps have become the cheaper yet attractive alternatives to web-based dashboards. This has led to the emergence of smartphone-based visualization tools, and web-based visualization frameworks. Visualisation is best performed using a web interface as it can be used to displayed data locally and over the network. Several packages are available for web-based visualisation such as Bokeh, Dash, Google Charts, Tableau, Grafana, etc.

3.7. Discussion

The development of low-cost monitoring solutions is constrained by the limited performance of inexpensive hardware and software, poor robustness of non-industrial components, potential integration issues with existing systems, and increased development effort. However, as technology advances, once expensive hardware and software become accessible and affordable to a broader range of users. This section has proposed preliminary findings on technologies that can contribute to low-cost industrial monitoring solutions. These results are part of ongoing work in developing an integrable solution that will support SMEs increasing digital capabilities. To ease development effort and integration issues, it is necessary to leverage the large communities surrounding many low-cost platforms and the wealth of libraries and tutorials they provide. The much fresher and current workforce are currently more skilled and technocrats in terms of exposure to the skills required to operate the basic hardware, software, and programming required for integrating some of the essential technologies covered in this section. This trend is primarily attributed to the modern school curriculum, the emergence of self-taught Do-It-Yourself (DIY) Internet forums, and the popular availability of online resources and tutorials. Leveraging this trend, the Shoestring initiative, outlined in the subsequent section, aims to provide self-explanatory and almost pre-packaged technical solutions/guidelines/templates that can be easily installed or replicated and customized for a specific task from low-cost COTS components by a moderately tech-savvy employee in an SME. This drives the Shoestring belief that operations peripheral to mainstream operations in the manufacturing industry can be easily deployed using COTS low-cost systems, without any need for specialized infrastructure or specialist human-resources

4. Blueprint for Low-Cost Monitoring

4.1. Overview

This section presents a blueprint for implementing a low-cost monitoring system using the low-cost technologies such as those discussed in Section 3. For a monitoring solution to be genuinely low cost its development and deployment must be low cost in addition to the underlying technologies. For this reason, a simple repeatable framework (or "blueprint") for solution development is critical, as it can provide a framework for implementing low-cost solutions that SME manufacturers with limited technical capabilities can use.

This section begins introducing some of the terminology associated with the proposed low cost or "Shoestring" monitoring solution. This is followed by a discussion of the requirements that a low-cost monitoring system can reasonably be expected to meet and then a description of a low-cost monitoring blueprint that has been developed to address these requirements.

In Section 2.2 we noted the concepts of services and technology modules as being central to developing low-cost "Shoestring" solutions and we use these notions again here in developing the blueprint for low-cost monitoring that is proposed here. Referring to Figure 6, we define two key elements:

- Service Module: an independent assembly of hardware and/or software that realises a fundamental digital manufacturing functionality (e.g. data collection, analysis, etc.). In other words, from a service-oriented architecture perspective, a Service Module provides a service. Service Modules provide and consume data using a service layer communication technology (e.g. REST[9], OPC-UA[10], MQTT[11] or MTConnect[12]) (Hawkridge et al., 2019). The rationale for modelling and developing solutions using Service Modules is that they provide a degree of decoupling that makes it easier to generalise the design as well as facilitating flexibility and extendibility for implementations of that design.
- Building Block: an element that embeds low-cost products/technologies to provide a basic function (e.g. image capture, temperature sensing, RMS analysis). The motivation for modelling and developing Service Modules using Building Blocks is that there is a plethora of readily available hardware and software components that can be used to develop low-cost systems and dealing with this array of options can be daunting for an end-user who just wants something that will work. The aim is that by grouping similar products/technologies and wrapping them in the same sets of interfaces, an end-user doesn't need to get bogged down in the compatibility details. In other words, if a user wants to measure temperature, they can simply select one of the temperature sensing Building Blocks.

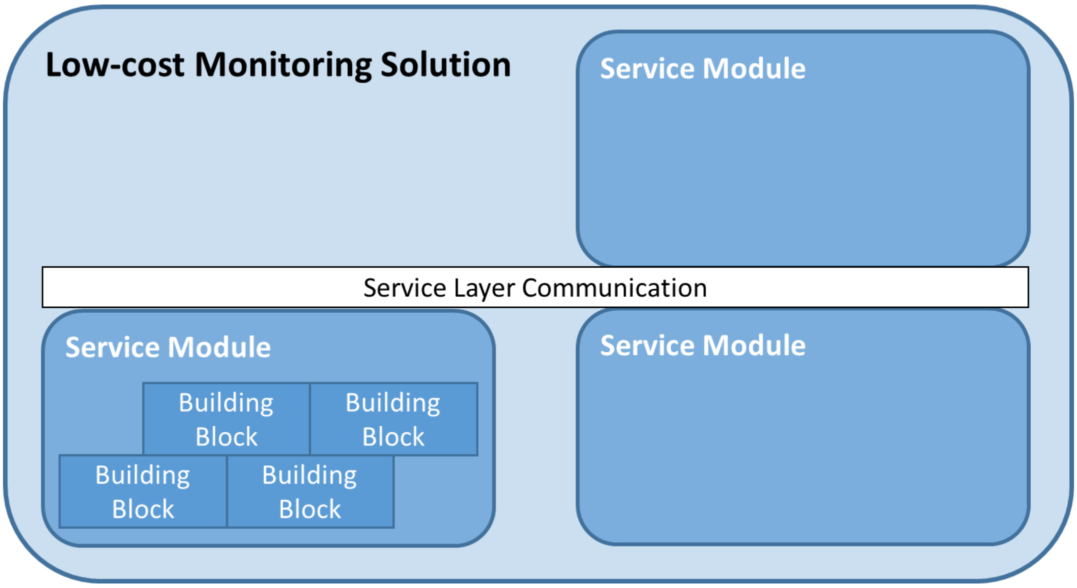

Fig. 6: Shoestring solution composition

4.2. Requirements for Low-Cost Monitoring Solution (for Manufacturing)

For a low-cost monitoring system to be useful to a manufacturer it needs to solve practical issues that they experience during day-to-day operations. For the majority of the SMEs interviewed during the course of this work, there was a common sentiment that their expectation from a monitoring system is for it to provide data (which is not currently available) that can then be manually processed and evaluated and used to inform employee decisions. Notably, these SMES do not seem

[9] https://www.ics.uci.edu/~fielding/pubs/dissertation/rest_arch_style.htm
[10] https://opcfoundation.org/about/opc-technologies/opc-ua/
[11] https://mqtt.org/
[12] https://www.mtconnect.org/

to be looking for systems that offer automatic diagnostics or prognostics using advanced analytics or machine learning, which is regularly what is marketed by commercial vendors. Desire for smart diagnostics and prognostics may come further along their digital journey, but to begin with SMEs want monitoring systems that help them reduce the opaqueness of their operational and production processes (Schönfuß et al., 2021). Some practical examples of this include:

- **Machine utilisation monitoring** – to help identify operational or capacity issues that are leading to bottlenecks
- **Monitoring key process variables** – to improve process visibility and facilitate continuous improvement
- **Monitoring environmental conditions** – such as humidity, temperature, vibration, emissions and/or noise which can influence quality, have an environmental impact, and/or affect working conditions
- **Energy and/or material usage monitoring** – to better attribute or estimate direct costs for parts or products

When it comes to developing these types of systems at low cost, there will clearly be compromises in terms of feature set, performance, and robustness. Furthermore, as low-cost monitoring is here considered to include the entire system cost, a system must be quick and simple to develop and deploy or else the labour costs can quickly push a system beyond the target budget. This is further motivation for the development of a blueprint as most of the design work is done once and can cover a range of deployments. To ensure the blueprint is functional and simple, the set of system target requirements in Table 4 were established. These requirements are not comprehensive but pragmatic in that this is sufficient to meet the needs of the majority of SMEs worked with.

Table 4: Monitoring blueprint target requirements

Criteria	Target
Data sources	The blueprint should be able to get data both from sensors and directly from equipment APIs
Sensing	The blueprint should support sensing commonly used variables (e.g. temperature, current, vibration, acoustic emissions)
Sample rates	The blueprint should support sample rates in the 10s of Hz by default with the option to add dedicated hardware for higher sample rates (e.g. up to 1kHz)
Data processing	The blueprint should facilitate basic pre-processing (e.g. filtering, FFT, RMS) and/or simple analysis (e.g. averaging, thresholding)
Ease of deployment	The blueprint should easily accommodate the distributed nature of monitoring in a shop floor environment and should not interfere with the functioning of the target system
Data access	The blueprint should make data available via an open API over a common protocol so that data can easily be extracted and leveraged by other systems if desired

4.3. A Blueprint for Low-Cost Monitoring in Manufacturing

Having established an approach for capturing monitoring requirements, this section presents the proposed blueprint for developing a low-cost monitoring solution in two parts; first it details the Service Modules used to form the solution and then describes how to develop each of those Service Modules using Building Blocks formed with selected technologies. We note that this two staged development has been developed with the notion of keeping development costs low and enabling the possibility of future reusability. After the blueprint is presented there is a brief discussion on how to convert it to an implementation using low-cost components.

4.3.1. Service Modules

Figure 7 shows the Service Modules in the monitoring blueprint. At a minimum, the blueprint requires a single Data Collection Service Module and a User Interface Service Module. In this most basic case, the system acquires data and presents it live to a user. If useful information needs to be extracted from the raw data, then an Analysis Service Module can be added. If historical data is needed for display in the user interface or for use by an algorithm, then a Data Management and Storage Service Module can be added. Additional Data Collection Service Modules can also be added to extend data collection across a wider physical area. Additional User Interface, Analysis and/or Data Management and Storage Service Modules could also be added, however that generally scales the solution beyond what can be considered a low-cost first step into monitoring.

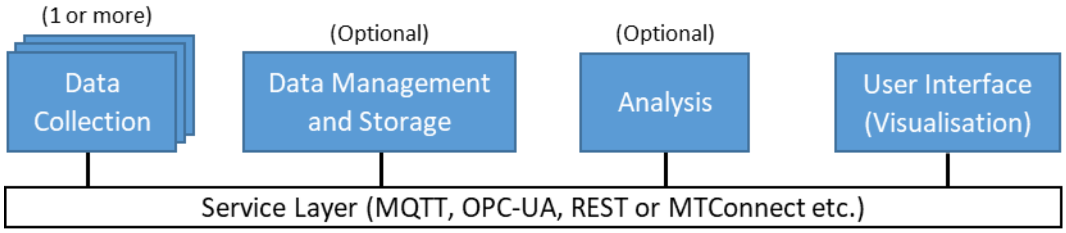

Fig. 7: Monitoring solution blueprint: Service Module schematic

4.3.2. Building Blocks

This section discusses the Building Blocks needed to develop each of the Service Modules as shown in Figure 8. Each of the Service Module schematics contains a computational hardware Building Block and a service layer interface Building Block; the *service layer interface* enables other Building Blocks to access data from and publish data to the service layer, and the *computational hardware* hosts the software components of the Service Module.

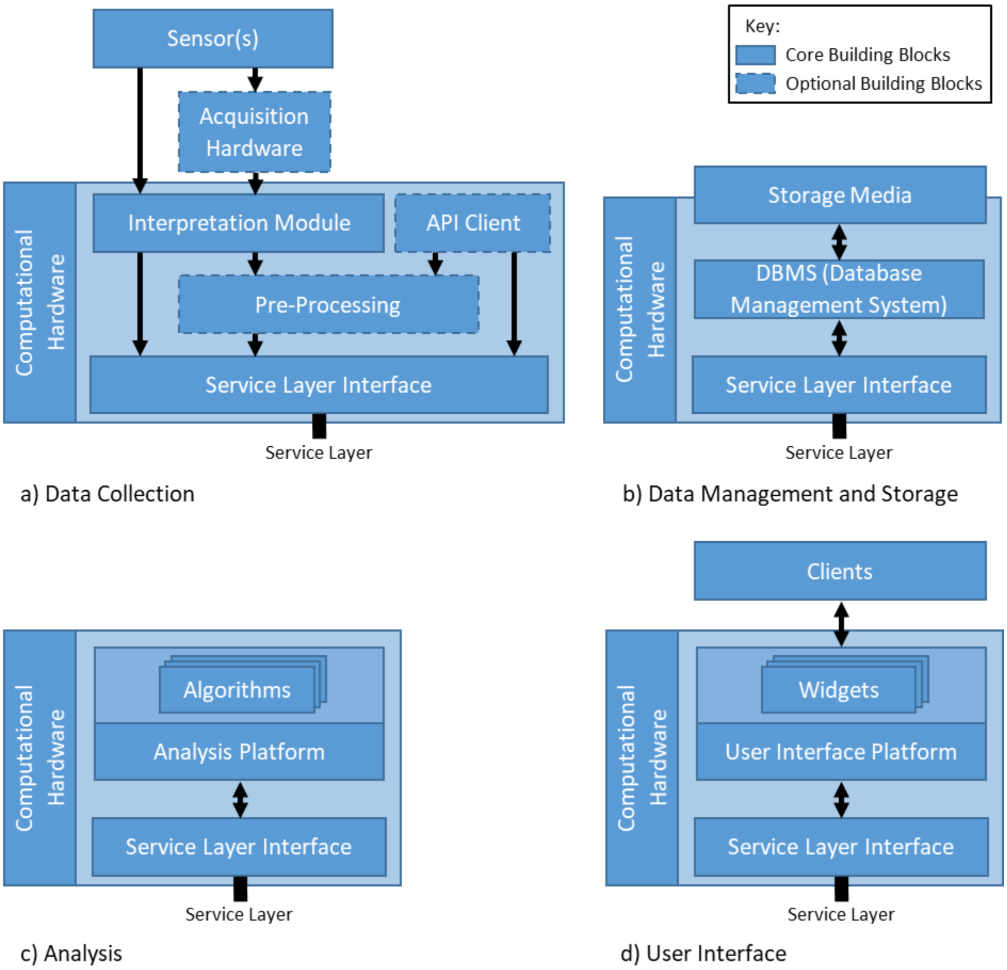

Fig. 8: Building block schematics for Service Modules

A schematic of the Building Blocks that are typically necessary to build a data collection Service Module is shown in Figure 8a. This Service Module has the potential to be the most complicated Service Module in a monitoring system because of the optional Building Blocks that can be added. In its simplest form (i.e. with only the core Building Blocks) a data collection Service Module consists of: *sensors* to obtain the required variables, an *interpretation module* to covert sensed variables from their binary representation to their decimal value (including any necessary calibration), as well as the service layer interface and computational hardware.

Depending on the application requirements, it may be necessary to add an *API client* to extract data directly from monitored equipment, *acquisition hardware* to perform high frequency deterministic sampling, and/or *pre-processing* to filter, aggregate or summarise data before publishing it to the service layer. Additional acquisition hardware may also be necessary if the selected computational hardware doesn't have the interface required for the selected sensors (e.g. analogue sensors with an all-digital microcomputer). It should also be noted that the degree of pre-processing that can be carried out may be limited by the computational abilities of the selected low-cost hardware.

A schematic of the Building Blocks necessary to develop a Data Management and Storage Service Module are shown in Figure 8b. In contrast to the Data Collection Service Module, the Data Management and Storage Service Module is significantly simpler. Besides the obligatory computational hardware and service layer interface, it contains *storage media* (e.g. hard drives) on which the data is stored and a database management system (DBMS) to manage the storage of the historic data.

The analysis Service Module schematic is shown in Figure 8c. It requires the following Building Blocks: *algorithms* to do the analysis, an *analysis platform* to execute the algorithms, the service layer interface and the computational hardware.

The user interface Service Module schematic is shown in Figure 8d. Alongside the service layer interface and the computational hardware, it requires a *user interface platform* to generate the user interface and *client devices* to display the user interface. Web-based visualisation is generally recommended as it facilitates the use of existing client devices within the company thereby reducing the system cost.

4.3.3. Blueprint Usage

In this section, the practical use of the blueprint is discussed. This section describes a three stage blueprint usage process conceptually and then it is exemplified in the case study in section 4. The three stages are:

- Stage 1: Service Module identification
- Stage 2: Building Block specification
- Stage 3: Technology specification

The first stage for an end-user wanting to use this blueprint is to identify which Service Modules are needed based on the Service Module schematic. One way of doing so is using a questionnaire like the one in Figure 9.

Q1. What data is needed?
- *a. How can it be obtained? (sensed or via an API)*
- *b. How many collection points are required?*
- *c. Are there cases where a single collection point can cover multiple data sources?*

Q2. Is pre-processing of data required before it is presented to a user? – e.g. moving average, threshold detection, frequency decomposition, etc.

Q3. Are historic records needed (for analysis, visualisation and/or record keeping)?

Q4. What information does the user need to see?
- *a. Which users require this information?*
- *b. What is the best way to present the data?*

Fig. 9: Service Module specification questionnaire

Q1 is used to identify how many data collection Service Modules are required. Q2 determines whether or not an analysis Service Module is needed, similarly Q3 determines whether a data management and storage Service Module is required. A user interface Service Module is always required, the answers to Q4 are used in the next stage.

Once the required Service Modules have been identified, the user moves to the second stage. In this stage they specify the Building Blocks required for each Service Module using the Service Module schematics. For the data collection Service Module, the answers to question 1 and its sub-questions can be used to identify which of the optional Building Blocks are required for each data collection Service Module (e.g. is an API client needed). They can also be used to specialise the sensor Building Blocks, i.e. change the generic “sensor” Building Block to “temperature sensor” if they are wanting to measure temperature. This procedure can similarly be carried out for the Building Blocks in the analysis and user interface Service Modules using their respective questions (e.g. specifying which algorithms and widgets are required).

Also as part of this stage it is necessary to decide where the Service Modules will execute; each Service Module schematic contains a computational device. In the implemented system, the Service Modules can have separate devices, be co-located on a single device, or a combination of separate and co-located execution (e.g. separate edge devices for the data collection Service Module and a single PC for the data management and storage, analysis, and user interface Service Modules). The authors have found that containerisation through Docker[13] can simplify the distribution of Service Modules across heterogeneous hardware, however this is not strictly necessary.

Further, in the case of monitoring, the management of data across Service Modules needs careful consideration. Issues such as filtering, buffering, error checking are included here.

In the third stage, the user instantiates their design by selecting Building Blocks that encompass low-cost products/technologies. To be a Building Block, the low-cost product or technology needs to meet a set of interface requirements. Some products inherently meet these requirements while others may require some wrapping (e.g. attaching a connector or adding a software adaptor). To begin with there is a limited set of Building Blocks that use a small selection of common interfaces. A prototype online tool is being developed that will streamline this process in order to simplify development for end-users. This tool would also allow us to extend the set of supported interfaces as compatibility could be ensured programmatically. The tool will also support users in the choices surrounding technology selection. In the case of monitoring systems, factors such as physical footprint, environmental protection, heat management, power requirements, etc. would also be considered.

After proceeding through these three stages, the user would have a fleshed out design for a low-cost monitoring system, as will be demonstrated in the next section.

4.4. Evaluation of the Low Cost Monitoring Blueprint

This section evaluates the blueprint approach to low-cost monitoring system development presented here. It reflects on the approach's ability to serve its targeted end-user as well as its limitations. It further comments on how the approach could be used in conjunction with IoT platforms and discusses the relationship between this approach and other architectures within the digital manufacturing space.

This blueprint approach is intended to provide a low-cost, low-risk method (particularly for SMEs) to implement industrial monitoring. This implementation may be to address a monitoring need that can only be justified at low cost, to meet an undemanding monitoring need, or as a trial to investigate a potential use case prior to further investment. The approach does this by providing a developer in an SME with a standard, understandable solution structure that can be filled out in a step by step manner as assisted by the provided questionnaire. This approach may come across as oversimplified when compared to state-of-the-art development approaches and architectures that have been developed as part of Industry 4.0 initiatives, however we would argue that the fact that these approaches are trying to address all the needs of all users leads to a necessary complexity which may have the unintentional side-effect of contributing to SME's belief that they don't have the skills required to embrace digitalisation (Horváth & Szabó, 2019; Mittal et al., 2020).

[13] https://www.docker.com/

In contrast the blueprint approach presented here is focused on providing a minimal architecture to cover most low-cost monitoring applications. This focus means that the blueprint approach may not work for all applications and will likely not satisfy more advanced applications. There is potential for this blueprint approach to lay the groundwork for adoption of more advanced architectures as the digitalisation level and skills of an SME increase. An example of this would be the Asset Administration Shell (AAS) as part of RAMI 4.0 (Reference Architecture Model Industry 4.0) (Schweichhart, 2016). An AAS is a "standardized digital representation of the asset" (Federal Ministry for Economic Affairs and Energy (BMWi), 2020) and forms an integral part of implementing a digital twin for the asset in question. The AAS provides an interface that enables data access and asset control in a neutral manner. Low-cost monitoring can form a precursor by ensuring that relevant data is available for integration. This is particularly relevant for assets where the manufacturer is unlikely to release an AAS implementation in the future (i.e. legacy assets).

A benefit of having a simple development approach is that it facilitates a low barrier to entry for SMEs with limited skills. However, even though this approach is simplified, there are likely many SMEs who do not have the requisite skills. One factor that can assist such SMEs is the increasing digital capabilities of new entrants to the workforce. Further, many SMEs may have employees that have developed skills through hobbies, etc. that could further encouraged by letting them attempt a low-cost project.

One possible criticism of this approach is that it is not readily clear how it could include one of the many IoT platforms available within the open source or commercial domains. Part of the challenge here is that different IoT platforms cover different extents of the monitoring chain. If a user wanted to use one of these platforms they could use it in place of the relevant portions of the blueprint, while still using the approach to fill out the rest of the solution. For example, the Kaa platform[14] is an end-to-end IoT platform. When mapped against the blueprints presented here, the Kaa platform covers the Data Management and Storage, Analysis, and User Interface service modules as well as the service layer interface of the Data Collection Service Module. To have a full system, filling out the remainder of the Data Collection Service Module is all that would be required. On the opposite end of the spectrum, the Macchina.io platform[15] provides an edge device software development platform that facilitates connecting devices one another or cloud platforms. When mapped against the blueprints presented here, the Macchina.io platform could provide the service layer interface for the Data Collection Service Module (and possibly others depending on how they are implemented) and would still require the rest of the blueprint to be filled out to get a functioning system.

In summary, the presented low-cost monitoring blueprint provides a simple mechanism that end users such as SMEs can use to implement monitoring solutions. As these solutions are low-cost they will clearly not be suitable for advanced applications, applications that are safety critical, or applications that require high levels of repeatability or reliability. Nevertheless it may help would-be solution developers with limited skills to address everyday needs within their organisation.

5. Case Study

5.1. System Description

In order to explore the effectiveness of the blueprint introduced in Section 3.4, a low-cost monitoring prototype was developed for a 3D printer system as shown in Figure 10. The objective for this monitoring system is to give an operator access to the temperature data that is usually kept

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[14] https://www.kaaproject.org

[15] https://macchina.io/

internal to the printer's control system and to augment this with data from additional bolt-on sensors. This is then extended with the addition of historic data storage for record keeping purposes in order to showcase the extendable nature of this approach to low-cost monitoring. Although this prototype monitoring system was developed for a 3D printer, the authors would like to emphasize that it could be applied to other forms of manufacturing machinery.

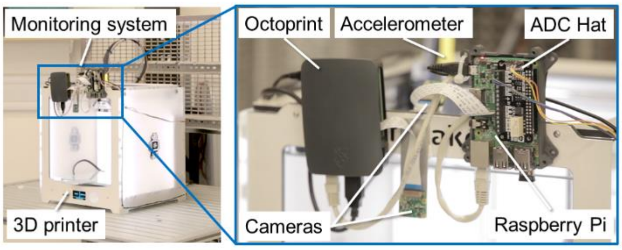

Fig. 10. Low cost monitoring system demonstrator

5.2. Monitoring Requirements

To meet its objective the monitoring system needs to be able to extract temperature readings and set points from the 3D printer's controller and augment that information with data from a bolt-on sensor. Vibration sensing was chosen as vibrations can cause phenomenon such as ringing which affect print quality and can further be used to identify other issues such as bearing wear. The temperature and vibration is to be made visually accessible to an operator via graphs. These requirements are summarised in Table 5.

Table 5: Requirements for case study system

Criteria	Target
Data sources	An API client to extract temperature readings and set points from the 3D printer's controller A bolt-on sensor on print head
Sensing	A vibration sensor is required
Sample rates	80 Hz for vibration sensing (aimed at low-frequency vibrations < 40Hz)
Data processing	The vibration readings should be pre-processed by applying a filtering algorithm
Ease of deployment	The installed hardware should not interfere with the functioning of the printer
Data access	The temperature and vibration data should be accessible by other systems over the network

5.3. Monitoring Solution Design

This section describes how the three stage procedure described in Section 4.3.3 was followed to design the monitoring system for the 3D printer in the case study system.

5.3.1. Phase 1: Service Modules

The Service Modules required for the case study system are shown in Figure 11. The system needs a single data collection Service Module and a user interface Service Module. It does not need the analysis or data management and storage Service Modules as it is simply and an "acquire and display" system which can be seen from the answers to the questionnaire in Figure 12.

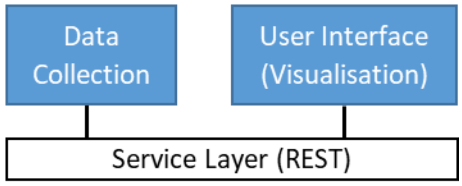

Fig. 11: Service module schematic for 3D printer monitoring system

Q1. *What data is needed?*
Temperature (readings and set points) and vibration
a. *How can it be obtained? (sensed or via an API)*
Temperature data can be extracted from the 3D printers API
Vibration data needs to be sensed
b. *How many collection points are required?*
One
c. *Are there cases where a single collection point can cover multiple data sources?*
N/A

Q2. *Is pre-processing of data required before it is presented to a user to make it useful? – e.g. moving average, threshold detection, frequency decomposition, etc.*
No

Q3. *Are historic records needed (for analysis, visualisation and/or record keeping)?*
No

Q4. *What information does the user need to see?*
Temperature readings and set points for the print head and print bed
A readout showing the vibration magnitudes
a. *Which users require this information?*
The print operator
b. *What is the best way to present the data?*
Line Graphs

Fig. 12: Completed questionnaire for case study system

5.3.2. Phase 2: Building Blocks

In this phase, the Building Blocks for each Service Module are identified. The final result is shown in Figure 13. For the data collection Service Module (Figure 13a), we can see that an API client is required and the sensor Building Block has been specialised to a vibration sensor as a result of the answers to question 1(a). For the user interface Service Module (Figure 13b), two line graph widgets have been specified based on the answers to question 4.

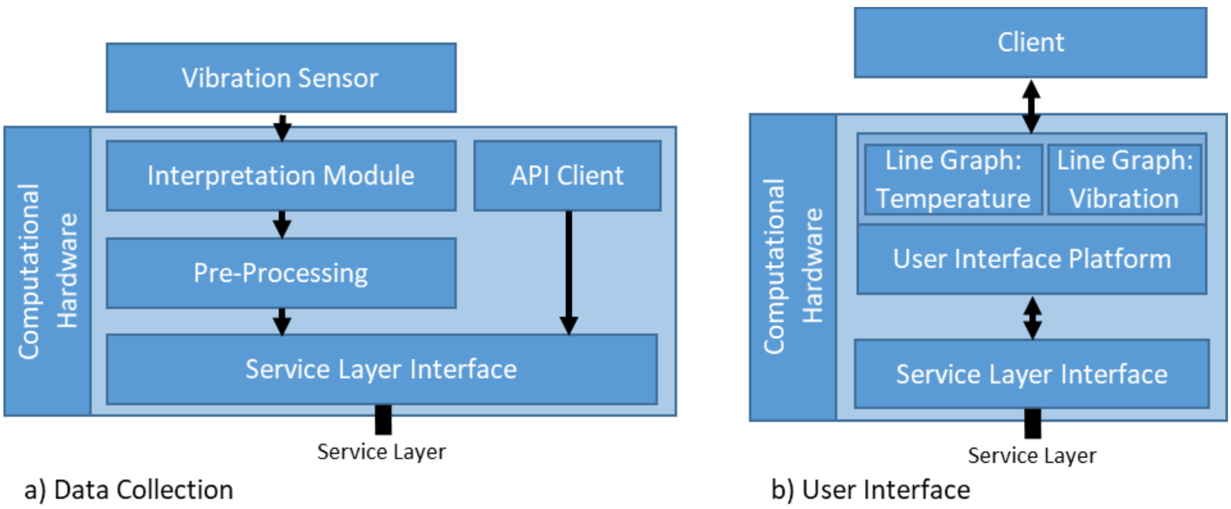

Fig. 13: Case study Service Module designs

5.3.3. Phase 3: Low-Cost Technology

Once the Building Blocks for each Service Module have been identified, the design process moves on to selecting low-cost technologies that can be used to instantiate those Building Blocks. The instantiated design is shown in Figure 14. Both Service Modules use the same computational device, a Raspberry Pi 3B+ and the Flask and Requests libraries were used to implement the REST-based service layer interface

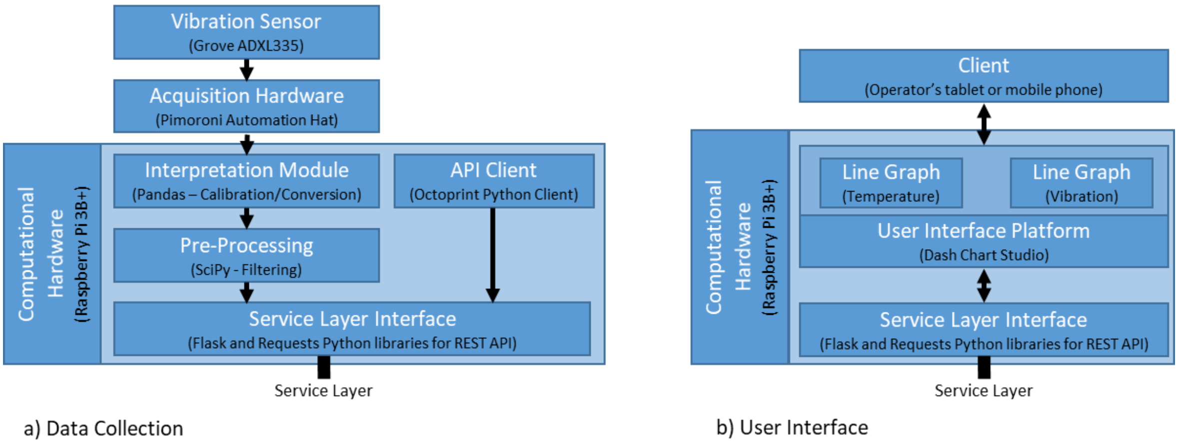

Fig. 14: Instantiated Service Module designs (selected technologies shown in black)

For the Data Collection Service Module (Figure 14a) the following technologies were selected. A Grove ADXL335 three axis analogue accelerometer was selected for the vibration sensor Building Block. As the Raspberry Pi does not have analogue inputs, acquisition hardware was added in the form of a Pimoroni Automation pHAT analogue-to-digital converter. The calibration and conversion equations in the interpretation module were implemented using the Pandas library in Python and filtering was done using SciPy for the pre-processing Building Block. The Octoprint Python Client was used to access the temperature data.

In the User Interface Service Module (Figure 14b), data visualisation was done using Dash Chart Studio Cloud as the user interface platform which was accessed using the operators tablet or mobile phone (assumed to already be present in the target company). Dash Chart Studio Cloud was configured to present the data as a set of line graphs as shown in Figure 15. Dash Chart Studio Cloud is a web-based tool so the interface code it provides which forwards data to the cloud platform runs on the Raspberry Pi rather than the tool itself.

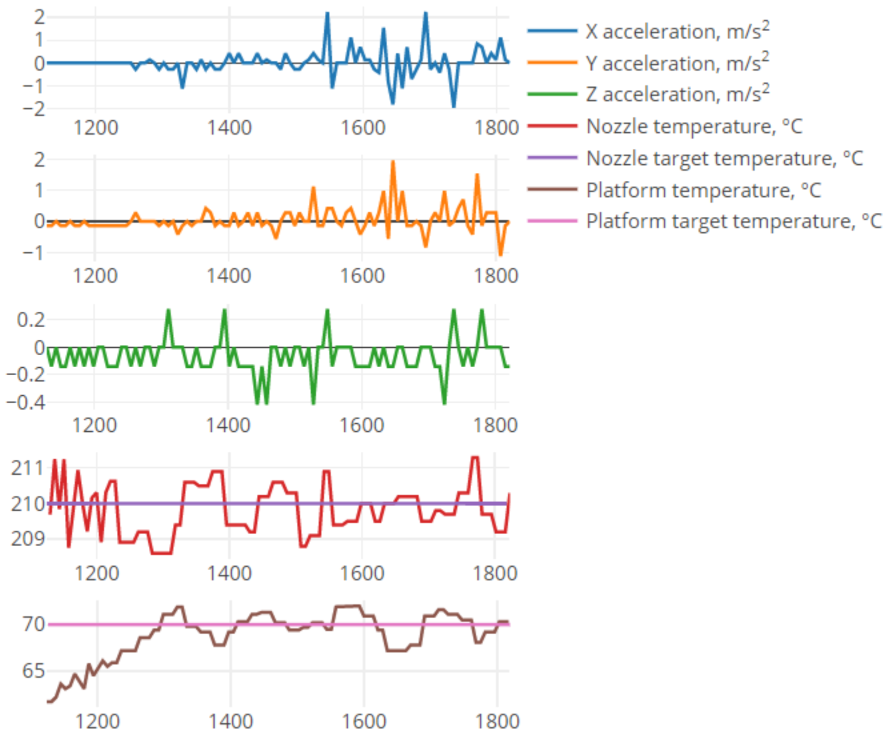

Fig. 15. Sensor data streaming from low cost monitoring system demonstrator

5.3.4. Solution Extension: Data Management and Storage

To demonstrate the expandability of the proposed blueprint consider the case where, after a period of operation, the end-user decides it is necessary to have a historic record of the temperature and vibration data so that they can correlate it with any failed prints or rejects. To add these historic records, a data management and storage Service Module would need to be added as shown in Figure 16. This Service Module would attach to the data streams coming from the data collection Service Module and persist them. The Building Blocks schematic for the new data management and storage Service Module can be seen in Figure 17; it uses MySQL to persist the required data on a SD card. It is noted that there is a limitation to the amount of data that can be stored on an SD card, however should more extensive, or longer term data storage be required, the storage media Building Block could be replaced with an alternative with larger capacity such as a hard drive.

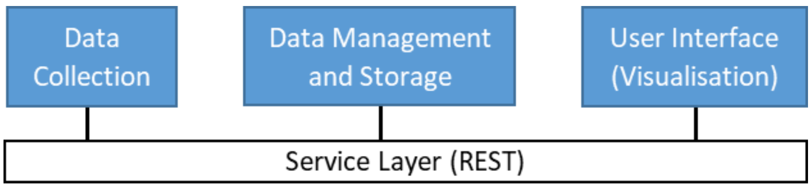

Fig. 16: Case study design extended with data management and storage

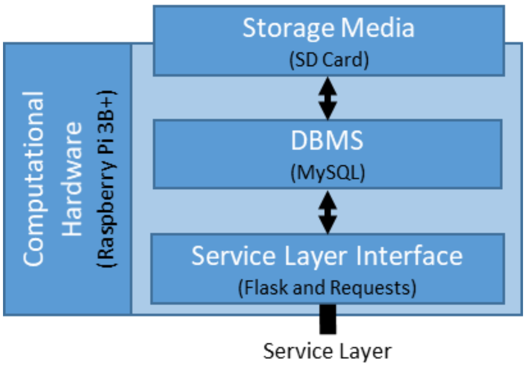

Fig. 17: Data management and storage Service Module

5.4. Case Study Design Evaluation

This section evaluates the design and implementation of the case study monitoring system. It begins by assessing whether the system meets its objective and then discusses some of the limitations imposed by the low-cost components that are used. Finally it discusses ways in which the system could be further extended.

The developed case study monitoring system is able to get the temperature and vibration data from the 3D printer and present it to the user (As shown in Figure 15) and therefore satisfies its overall objective. The hardware costs for the system are presented in Table 6 and at a total of £85 it falls well within the boundaries of low cost. However, component costs are not the only costs in a monitoring system, there are also development and installation costs.

Table 6: Bill of materials with component costs

Building Block	Technology	Cost
Computational Device	Raspberry Pi 3B+	£50 (Incl. case, power supply)
Service Layer Interface	Flask and Requests Libraries	£0 (Open Source)
Vibration Sensor	Grove ADXL335	£12
Acquisition Hardware	Pimoroni Automation pHAT	£13
Interpretation Module	Pandas	£0 (Open Source)
Pre-processing	SciPy	£0 (Open Source)
API Client	Octoprint Client	£0 (Open Source)
User Interface Platform	Dash Chart Studio Cloud	£0 (Free Tier Account)
Storage Media	Sandisk Ultra 32GB SD Card	£10
DBMS	MySQL	£0 (Open Source)
	Total:	£85

We now provide an indication of time and cost associated with the development of the case study system - from the perspective of an end user. We assume that the end-user developer would have technical capabilities in several areas, expertise in these areas is ranked on a scale of novice, beginner, competent, proficient, and expert in line with the Dreyfus model (Dreyfus & Dreyfus, 1980). The expected areas of expertise are as follows: software coding (competent), software configuration (competent), digital system design (competent), and hardware integration (beginner). (It is noted that part of the ongoing research is to reduce the “entry level” capabilities for future developers.) Given access to the ready-made Building Blocks, it is estimated that development of this system would take no more than 12 hours for an end user. Since this was a demonstration system it didn’t require installation to the same extent as would be typical for an industrial deployment, it is therefore estimated that if this were deployed industrially it would require a maximum of 3 hours. At an average labour cost of £25 per hour (Office for National Statistics, 2020), the 15 hours for development and deployment come to a total of £375. This shows the significance of labour costs and validates the authors' views on total system cost rather than component costs when considering low-cost monitoring.

The approximate total system cost is £460 (which satisfies the notional upper-limit of £1000 discussed in section 2.1). Admittedly, the case study is for a very simple monitoring system that can execute on a single microcomputer, however it supports the idea that monitoring is possible using low-cost, off-the-shelf technologies given an appropriate scenario. Even with additional time expenditure for testing and validation (which should be relatively low for this system) and additional costs for ruggedisation of the hardware, the total system cost is unlikely to exceed £1000.

There are limitations arising from the use of low-cost technologies. A good example of this is the cloud visualisation platform that was selected, using the free tier limits the frequency at which data can be sent. Furthermore, being cloud-based adds additional delay between when the data is sensed and when it is displayed, this was less significant in the case study system, but that may not be the case in other applications.

The robustness of the components may also be a significant issue, particularly since certain parts of manufacturing operations can be rather harsh. This was not a consideration for the case study system as it is used as a demonstrator in a relatively controlled environment (as is evidenced by the deliberately exposed components in Figure 10). With a little additional effort the robustness of the system could be improved, for example by housing sensitive parts in a protective enclosure. Additionally, it would be necessary to consider whether the chosen sensors are suitable for the target environment and may necessitate that they be replaced with an alternative, or that the sensing be done in an alternate way so that the sensor can be placed in a less harsh location. But even with this added protection there are no guarantees about the lifespan of components. Some of the SMEs that the authors have spoken to have raised the point that if the components are this cheap, then why not buy a few backups and have them ready to be swapped in if something breaks. This is a valid point however the significance of that downtime should be considered, in many cases it may be negligible, but it should be considered nonetheless.

Beyond outright breakages, there is further risk around the continued accuracy of a system due to factors such as sensor drift or operating temperature sensitivity that may be more pronounced in low-cost components. This risk suggests that if an application requires a higher level of trust then the monitoring system's correct operation should be regularly verified, or perhaps a low-cost approach is not justified for that application. It is also important to consider the security implications of using low cost technologies, however a discussion on this is beyond the scope of this paper.

This case study showed that the initial system could be easily extended with the addition of a data management and storage Service Module. It could also be further extended with an analysis Service Module which could use the temperature data to assess print quality, or calculate and log pre-heat times so that they could be reduces to improve productivity in a continuous production scenario. Furthermore, the head vibrations could be analysed and prompt the user to check for bearing wear. Alternatively, the system could be extended to monitor multiple printers using additional data collection Service Modules.

6. Conclusions

This paper evaluates the potential for low-cost monitoring of industrial equipment, and suggests that low-cost monitoring could be used for the following non-critical industrial scenarios. First, for simple applications where system visibility can improve operator decision making. Second, for important, yet inexpensive assets, where the cost of typical monitoring systems cannot be justified. Third, for the quick deployment of proof-of-concept, prototype systems when the return on investment is yet to be determined. There is a potential forth application in the form of temporary installations for troubleshooting, diagnostics and/or integration testing, however this was not discussed.

A blueprint was presented using the Building Blocks and Service Module composition model of the Digital Manufacturing on a Shoestring Project. This blueprint can be used by an end-user to facilitate the development of a low-cost monitoring system that meets their needs. The blueprint specifically focussed on a solution that is within the price range of a small to medium sized manufacturer. The blueprint is exemplified through a case study system which shows how a set of low-cost technologies is used to implement a simple, functional monitoring system.

This work shows that, given the right application, low-cost off-the-shelf technologies can be used to help companies take a first step towards digital transformation and present a pathway for this process. Future work within the Digital Manufacturing on a Shoestring programme includes applying the composition model to other application areas, piloting the process and developed systems with SME manufacturers, and investigating ways to further simplify development through the use of an online tool.

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References

Aazam, M., Zeadally, S. and Harras, K.A., 2018. Deploying fog computing in industrial internet of things and industry 4.0. *IEEE Transactions on Industrial Informatics*, *14*(10), pp.4674-4682.

Abbott, T.A. and Andrews, S.H., 1990. *The Classification of Manufacturing Industries: An Input-based Clustering of Activity*. US Department of Commerce, Bureau of the Census.

Abraham, S. and Li, X., 2014. A cost-effective wireless sensor network system for indoor air quality monitoring applications. Procedia Computer Science, 34, pp.165-171.

Aggour, K.S., Kumar, V.S., Cuddihy, P., Williams, J.W., Gupta, V., Dial, L., Hanlon, T., Gambone, J. and Vinciquerra, J., 2019, December. Federated Multimodal Big Data Storage & Analytics Platform for Additive Manufacturing. In *2019 IEEE International Conference on Big Data (Big Data)* (pp. 1729-1738). IEEE.

Alemayehu, B., Kota, A., Neidhard-Doll, A., Chodavarapu, V. and Subramanyam, G., 2021. Cloud-connected real-time oil condition monitoring of utility transformers using impedance spectroscopy. *Instrumentation Science & Technology*, pp.1-12.

Basto, C., Pelà, L. and Chacón, R., 2017. *Open-source digital technologies for low-cost monitoring of historical constructions*. Journal of Cultural Heritage, 25, pp.31-40.

Behrens, B.A., Bouguecha, A., Buse, C., Wölki, K. and Santangelo, A., 2016. *Potentials of in situ monitoring of aluminum alloy forging by acoustic emission*. Archives of Civil and Mechanical Engineering, 16(4), pp.724-733.

Bourezza, El Mehdi, and Ahmed Mousrij. "Towards a Platform to Implement an Intelligent and Predictive Maintenance in the Context of Industry 4.0." In International Conference on Artificial Intelligence & Industrial Applications, pp. 33-44. Springer, Cham, 2020.

Chilcott, M. and Kjærgaard, N., 2021. Low-cost wireless condition monitoring system for an ultracold atom machine. *Internet of Things*, *13*, p.100345.

De Silva, L., Hawkridge, G., Terrazas, G., Perez Hernandez, M., Thorne, A., McFarlane, D. and Tlegenov, Y., 2020, March. *An Application of HRI in Low-Cost Digital Manufacturing*. In Companion of the 2020 ACM/IEEE International Conference on Human-Robot Interaction pp.71-71.

Dreyfus, S.E. and Dreyfus, H.L., 1980. *A five-stage model of the mental activities involved in directed skill acquisition*. California Univ Berkeley Operations Research Center.

Dunne, T., 1994. Plant age and technology use in US manufacturing industries. *The RAND Journal of Economics*, pp.488-499.

Engeler, M., Elmiger, A., Kunz, A., Zogg, D. and Wegener, K., 2017. *Online condition monitoring tool for automated machinery*. Procedia CIRP, 58, pp.323-328.

Federal Ministry for Economic Affairs and Energy (BMWi), 2020, November. *Details of the Asset Administration Shell - Part 1- The exchange of information between partners in the value chain of Industrie 4.0 (Version 3.0RC01)*, Berlin, available: https://www.plattform-i40.de/PI40/Redaktion/EN/Downloads/Publikation/Details_of_the_Asset_Administration_Shell_Part1_V3.pdf (Accessed 20 March 2021)

Fraden, J., 2016. *Handbook of modern sensors: physics, designs, and applications*. 5th ed. Springer Science & Business Media.

Fuentes, M., Vivar, M., Burgos, J.M., Aguilera, J. and Vacas, J.A., 2014. Design of an accurate, low-cost autonomous data logger for PV system monitoring using Arduino™ that complies with IEC standards. Solar Energy Materials and Solar Cells, 130, pp.529-543.

Garbhapu, V.V. and Gopalan, S., 2017. *IoT based low cost single sensor node remote health monitoring system*. Procedia computer science, 113, pp.408-415.

Gonzalez-Val, Carlos, Adrian Pallas, Veronica Panadeiro, and Alvaro Rodriguez. "A convolutional approach to quality monitoring for laser manufacturing." Journal of Intelligent Manufacturing 31, no. 3 (2020): 789-795.

Hawkridge, G., Hernandez, M.P., De Silva, L., Terrazas, G., Tlegenov, Y., McFarlane, D. and Thorne, A., 2019, September. Tying Together Solutions for Digital Manufacturing: Assessment of Connectivity Technologies & Approaches. In 2019 24th IEEE International

Conference on Emerging Technologies and Factory Automation (ETFA) (pp. 1383-1387). IEEE.

Hayriye, A. T. İ. K., and Ü. N. L. Ü. Fatma. "Industry 4.0-Related Digital Divide in Enterprises: An Analysis for The European Union-28." Sosyoekonomi 28, no. 45 (2020): 225-244.

Hernandez, Luis, Mark Walker, and Al Salour. "White Paper: Determining When and Where PHM Should be Integrated into Manufacturing Operations." 2019

Hızarcı, B., Ümütlü, R.C., Kıral, Z. and Öztürk, H., 2021. Fault severity detection of a worm gearbox based on several feature extraction methods through a developed condition monitoring system. *SN Applied Sciences*, *3*(1), pp.1-12.

Horváth, D. and Szabó, R.Z., 2019. Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?. Technological Forecasting and Social Change, 146, pp.119-132.

Jazdi, N., 2014, May. Cyber physical systems in the context of Industry 4.0. In 2014 IEEE international conference on automation, quality and testing, robotics (pp. 1-4). IEEE.

Jeong, Changyoon, Tae Hee Lee, Seung Man Noh, and Young-Bin Park. "Real-time in situ monitoring of manufacturing process and CFRP quality by relative resistance change measurement." Polymer Testing 85 (2020): 106416.

Jing, G., Siahkouhi, M., Qian, K. and Wang, S., 2021. Development of a field condition monitoring system in high speed railway turnout. *Measurement*, *169*, p.108358.

Karami, M., McMorrow, G.V. and Wang, L., 2018. *Continuous monitoring of indoor environmental quality using an Arduino-based data acquisition system*. Journal of Building Engineering, 19, pp.412-419.

Koch, Claudia, and Knut Blind. "Towards Agile Standardization: Testbeds in Support of Standardization for the IIoT." IEEE Transactions on Engineering Management (2020).

Krot, Pavlo, Ihor Prykhodko, Valentin Raznosilin, and Radoslaw Zimroz. "Model Based Monitoring of Dynamic Loads and Remaining Useful Life Prediction in Rolling Mills and Heavy Machinery." In Advances in Asset Management and Condition Monitoring, pp. 399-416. Springer, Cham, 2020.

Ku, Chien-Chun, Chen-Fu Chien, and Kang-Ting Ma. "Digital transformation to empower smart production for Industry 3.5 and an empirical study for textile dyeing." Computers & Industrial Engineering 142 (2020): 106297.
Küfner, T., Schönig, S., Jasinski, R. and Ermer, A., 2021. Vertical data continuity with lean edge analytics for industry 4.0 production. *Computers in Industry*, *125*, p.103389.

Kumar, Ravinder, Rajesh Kr Singh, and Yogesh Kr Dwivedi. "Application of industry 4.0 technologies in SMEs for ethical and sustainable operations: Analysis of challenges." Journal of cleaner production 275 (2020): 124063.

Lasi, H., Fettke, P., Kemper, H.G., Feld, T. and Hoffmann, M., 2014. Industry 4.0. Business & information systems engineering, 6(4), pp.239-242.

Lewis, A.J., Campbell, M. and Stavroulakis, P., 2016. *Performance evaluation of a cheap, open source, digital environmental monitor based on the Raspberry Pi*. Measurement, 87, pp.228-235.

Li, Xiang, Shahin Siahpour, Jay Lee, Yachao Wang, and Jing Shi. "Deep learning-based intelligent process monitoring of directed energy deposition in additive manufacturing with thermal images." Procedia Manufacturing 48 (2020): 643-649.

Liu, X., Pang, Y., Lodewijks, G. and He, D., 2018. *Experimental research on condition monitoring of belt conveyor idlers*. Measurement, 127, pp.277-282.

Lu, Y., 2017. Industry 4.0: A survey on technologies, applications and open research issues. Journal of industrial information integration, 6, pp.1-10.

Lynn, R., Louhichi, W., Parto, M., Wescoat, E. and Kurfess, T., 2017, June. Rapidly deployable MTConnect-based machine tool monitoring systems. In *International Manufacturing Science and Engineering Conference* (Vol. 50749, p. V003T04A046). American Society of Mechanical Engineers.

Masood, T. and Sonntag, P., 2020. Industry 4.0: Adoption challenges and benefits for SMEs. Computers in Industry, 121, p.103261.

Matt, D.T., Modrák, V. and Zsifkovits, H., 2020. *Industry 4.0 for SMEs: Challenges, opportunities and requirements* (p. 412). Springer Nature.

McFarlane, D., Ratchev, S., 2018, *Digital Manufacturing on a Shoestring*, UK Engineering & Physical Sciences Research Council, Research Grant EP/ R032777/1

McFarlane, D., Ratchev, S., Thorne, A., Parlikad, A.K., De Silva, L., Schönfuß, B., Hawkridge, G., Terrazas, G. and Tlegenov, Y., 2019, October. *Digital manufacturing on a shoestring: low cost digital solutions for SMEs*. In International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing (pp. 40-51). Springer, Cham.

Meng, Kai, Xiaoming Qian, Peihuang Lou, and Jiong Zhang. "Smart recovery decision-making of used industrial equipment for sustainable manufacturing: belt lifter case study." Journal of Intelligent Manufacturing 31, no. 1 (2020): 183-197.

Michalak, A., Wodecki, J., Drozda, M., Wyłomańska, A. and Zimroz, R., 2021. Model of the Vibration Signal of the Vibrating Sieving Screen Suspension for Condition Monitoring Purposes. *Sensors*, *21*(1), p.213.

Mills, Andrew Robert, and Visakan Kadirkamanathan. "Sensing for aerospace combustor health monitoring." Aircraft Engineering and Aerospace Technology (2020).

Misra, Sudip, Anandarup Mukherjee, and Arijit Roy. "Knowledge discovery for enabling smart Internet of Things: A survey." Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 8, no. 6 (2018): e1276.

Mittal, S., Khan, M.A., Purohit, J.K., Menon, K., Romero, D. and Wuest, T., 2020. A smart manufacturing adoption framework for SMEs. *International Journal of Production Research, 58*(5), pp.1555-1573.

Mittal, S., Khan, M.A., Romero, D. and Wuest, T., 2018. A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs). *Journal of manufacturing systems*, *49*, pp.194-214.

Mohanraj, T., S. Shankar, R. Rajasekar, N. R. Sakthivel, and Alokesh Pramanik. "Tool condition monitoring techniques in milling process—A review." Journal of Materials Research and Technology 9, no. 1 (2020): 1032-1042.

Müller, J.M., Buliga, O. and Voigt, K.I., 2018. Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. Technological Forecasting and Social Change, 132, pp.2-17.

Nadimpalli, Venkata Karthik, G. M. Karthik, G. D. Janakiram, and Peter B. Nagy. "Monitoring and repair of defects in ultrasonic additive manufacturing." International Journal of Advanced Manufacturing Technology (2020).

Nandi, S., Toliyat, H.A. and Li, X., 2005. *Condition monitoring and fault diagnosis of electrical motors—A review*. IEEE transactions on energy conversion, 20(4), pp.719-729.

Nikula, R.P., Ruusunen, M., Keski-Rahkonen, J., Saarinen, L. and Fagerholm, F., 2021. Probabilistic Condition Monitoring of Azimuth Thrusters Based on Acceleration Measurements. Machines 2021, 9, 39.

Oberloier, S. and Pearce, J.M., 2018. *Open source low-cost power monitoring system*. HardwareX, 4, p.e00044.

Office of National Statistics, 2020. “Index of Labour Costs per Hour, UK: April to June 2020” Available Online: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/indexoflabourcostsperhourilch/apriltojune2020 [Accessed 02/12/2020]

Ogorodnyk, O. and Martinsen, K., 2018. *Monitoring and control for thermoplastics injection molding a review*. Procedia CIRP, 67, pp.380-385.

Pandiyan, V. and Caesarendra, W., 2020. Distributed Analytics Framework for Integrating Brownfield Systems to Establish Intelligent Manufacturing Architecture. *Industry 4.0: Current Status and Future Trends*, p.103.

Paraskevoudis, Konstantinos, Panagiotis Karayannis, and Elias P. Koumoulos. "Real-Time 3D Printing Remote Defect Detection (Stringing) with Computer Vision and Artificial Intelligence." Processes 8, no. 11 (2020): 1464.

Peillon, S. and Dubruc, N., 2019. Barriers to digital servitization in French manufacturing SMEs. Procedia CIRP, 83, pp.146-150.

Peng, Y., Qiao, W. and Qu, L., 2021. Compressive Sensing-Based Missing-Data-Tolerant Fault Detection for Remote Condition Monitoring of Wind Turbines. *IEEE Transactions on Industrial Electronics*.

Pereira, R.I., Dupont, I.M., Carvalho, P.C. and Jucá, S.C., 2018. *IoT embedded linux system based on Raspberry Pi applied to real-time cloud monitoring of a decentralized photovoltaic plant*. Measurement, 114, pp.286-297.

Perumal, V.S.A., Baskaran, K. and Rai, S.K., 2017. *Implementation of effective and low-cost building monitoring system (BMS) using Raspberry PI*. Energy Procedia, 143, pp.179-185.

Pesch, A.H. and Scavelli, P.N., 2019, March. Condition monitoring of active magnetic bearings on the internet of things. In *Actuators* (Vol. 8, No. 1, p. 17). Multidisciplinary Digital Publishing Institute.

Prutvi, S.H., Meti, S., Bhat, K.U. and Gupta, D., 2021. Triboelectric effect based self-powered compact vibration sensor for predictive maintenance of industrial machineries. *Measurement Science and Technology*.

Qiao, Qianzhe, Jinjiang Wang, Lunkuan Ye, and Robert X. Gao. "Digital Twin for machining tool condition prediction." Procedia CIRP 81 (2019): 1388-1393.

Rao, B.K.N. ed., 1996. *Handbook of condition monitoring*. Elsevier.

Roggo, Yves, Victoria Pauli, Morgane Jelsch, Laurent Pellegatti, Frantz Elbaz, Simon Ensslin, Peter Kleinebudde, and Markus Krumme. "Continuous manufacturing process monitoring of pharmaceutical solid dosage form: A case study." Journal of pharmaceutical and biomedical analysis 179 (2020): 112971.

Sanchis, Raquel, Óscar García-Perales, Francisco Fraile, and Raul Poler. "Low-Code as Enabler of Digital Transformation in Manufacturing Industry." Applied Sciences 10, no. 1 (2020): 12.

Schönfuß, B., McFarlane, D., Athanassopoulou, N., Salter, L., De Silva, L. and Ratchev, S., 2019, October. *Prioritising low cost digital solutions required by manufacturing SMEs: a shoestring approach*. In International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing (pp. 290-300). Springer, Cham.

Schönfuß, B., McFarlane, D., Hawkridge, G., Salter, L., Athanassopoulou, N., de Silva, L., 2021. *A Catalogue of Digital Solution Areas for Prioritising the Needs of Manufacturing SMEs.* Submitted to Computers in industry.

Schweichhart, K., 2016. Reference architectural model industrie 4.0 (rami 4.0). *An Introduction. Available online: https://www. plattform-i40. de I, 40*.

Siebel, T.M., 2017. Why digital transformation is now on the CEO's shoulders. McKinsey Quarterly, 4(3), pp.1-7.

Sisinni, E., Saifullah, A., Han, S., Jennehag, U. and Gidlund, M., 2018. Industrial internet of things: Challenges, opportunities, and directions. IEEE Transactions on Industrial Informatics, 14(11), pp.4724-4734.

Soto-Ocampo, C.R., Mera, J.M., Cano-Moreno, J.D. and Garcia-Bernardo, J.L., 2020. Low-Cost, High-Frequency, Data Acquisition System for Condition Monitoring of Rotating Machinery through Vibration Analysis-Case Study. *Sensors*, *20*(12), p.3493.

Stentoft, J., Adsbøll Wickstrøm,Philipsen, K. and Haug, A., 2020. Drivers and barriers for Industry 4.0 readiness and practice: empirical evidence from small and medium-sized manufacturers. Production Planning & Control, pp.1-18.

Tlegenov, Yedige, Geok Soon Hong, and Wen Feng Lu. "Nozzle condition monitoring in 3D printing." Robotics and Computer-Integrated Manufacturing 54 (2018): 45-55.

Vater, Johannes, Lars Harscheidt, and Alois Knoll. "Smart manufacturing with prescriptive analytics." In 2019 8th International Conference on Industrial Technology and Management (ICITM), pp. 224-228. IEEE, 2019.

Westerman, G., Bonnet, D. and McAfee, A., 2014. The nine elements of digital transformation. MIT Sloan Management Review, 55(3), pp.1-6.

Wohlers, Benedict, Stefan Dziwok, Faruk Pasic, Andre Lipsmeier, and Matthias Becker. "Monitoring and control of production processes based on key performance indicators for mechatronic systems." International Journal of Production Economics 220 (2020): 107452.

Wu, Dazhong, Connor Jennings, Janis Terpenny, and Soundar Kumara. "Cloud-based machine learning for predictive analytics: Tool wear prediction in milling." In 2016 IEEE International Conference on Big Data (Big Data), pp. 2062-2069. IEEE, 2016.

Wu, D., Liu, S., Zhang, L., Terpenny, J., Gao, R.X., Kurfess, T. and Guzzo, J.A., 2017. A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing. *Journal of Manufacturing Systems*, *43*, pp.25-34.

Wu, Haixi, Zhonghua Yu, and Yan Wang. "Real-time FDM machine condition monitoring and diagnosis based on acoustic emission and hidden semi-Markov model." The International Journal of Advanced Manufacturing Technology 90, no. 5-8 (2017): 2027-2036.

Wyłomańska, A., Zimroz, R., Janczura, J. and Obuchowski, J., 2016. Impulsive noise cancellation method for copper ore crusher vibration signals enhancement. *IEEE Transactions on Industrial Electronics*, *63*(9), pp.5612-5621.

Xing, K., Liu, X., Liu, Z., Mayer, J.R.R. and Achiche, S., 2021. Low-Cost Precision Monitoring System of Machine Tools for SMEs. *Procedia CIRP*, *96*, pp.347-352

Yang, Zefa, Zhiwei Li, Jianjun Zhu, Yuedong Wang, and Lixin Wu. "Use of SAR/InSAR in Mining Deformation Monitoring, Parameter Inversion, and Forward Predictions: A Review." IEEE Geoscience and Remote Sensing Magazine 8, no. 1 (2020): 71-90.

Zhang, X.Y., Lu, X., Wang, S., Wang, W. and Li, W.D., 2018. *A multi-sensor based online tool condition monitoring system for milling process*. Procedia CIRP, 72, pp.1136-1141.

Ziegelaar, A.J., Travaglione, B.C. and Hodkiewicz, M.R., 2020. Sensing system for low cost condition monitoring of remote assets. *IFAC-PapersOnLine*, *53*(3), pp.60-65.