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ARTICLE

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Shop floor to cloud connect for live monitoring the production data of CNC machines

Prathima B A[a], Sudha P N[a] and Suresh P M[b]

[a]Electronics and Communication Engineering Department, K S Institute of Technology, Visvesvaraya Technological University, Belagavi, Karnataka, India; [b]Mechanical Engineering, ACS College of Engineering, Visvesvaraya Technological University, Belagavi, Karnataka, India

ABSTRACT

Manufacturing industry is at its most exciting times with digital revolution. Man, machine, material and tools have to co-ordinate with each other seamlessly to maximize efficiency in a mass production environment. Various theoretical models are in practice to measure efficiency of equipment, gauging, services, maintenance, etc. While all the theoretical models are quite accurate in their approach to measuring the activities, they lagging behind in the process of data collection. The data collection methods are manual and not accurate. In this paper, a model is arrived at to collect live data of production, rejection and idle time in a machine tool with the help of electronic sensors. Effort is made to enhance operator engagement by compelling the operator to feed data so that the data collection becomes closed loop. As all data are digital in nature, meaningful information is sent to the management through an Internet of Things platform. This paper focuses on the digital data flow from the shop floor to management through the Cyber Physical System, enabling smart manufacturing in a mass production environment. The proposed model has been implemented and validated in a mass production set-up, engaged in manufacturing plug shell components.

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KEYWORDS
Industry 4.0; cyber physical systems; production data monitoring system CNC machine; overall equipment efficiency

1. Introduction

Manufacturing activities are highly critical areas of a manufacturing enterprise. In the entire value chain, effort is required to make manufacturing activities easy and simple. Measurement results of any activity are the major source of information to identify the lagging areas. The activity that is not measured in quantifiable form is not improvable. Measurement of an activity in a quantifiable form brings focus. It makes the people involved aware of their position and status in the activity's value chain by bringing them accountability.

In the proposed method, a portion of the measurement results is calculated locally in a Programmable Logic Controller (PLC). The measured results are displayed near each machining system through a Human Machine Interface (HMI) system. Suitable electronic sensors are provided at strategic locations of the machining systems to track production data, rejection data, rejection reasons, idle time data, idle time reasons, performance shortfall reasons, etc. This shows the live data of the production, rejection and idle time to the operator. This develops accountability in the operator and improves involvement. Employee involvement is a powerful tool for enhancing operational efficiency.

The data hence collected and partially treated in the local PLC are sent to the Cyber Physical System (CPS), where several such data from various machining systems are gathered and converted into meaningful and useful data for the management. The required hardware and software have been developed which are contemporary to the new era of Industry 4.0.

With the above efforts, the proposed monitoring method collects live and active data from the shop floor and allows the management, having decision support capabilities, to make accurate decisions. An old and conventional data collection model enables passive data and results in reactive decisions, whereas in the new digital era, live data and active data enable the decision maker to take proactive decisions. Proactive decisions based on active data are bound to result in efficient manufacturing operations.

The structure of the paper is designed as follows: Section 2 carries literature review, covering technology components used for live monitoring of shop floor data and the importance of digitalization to

CONTACT Prathima B A prathimaholla75@gmail.com Electronics and Communication Engineering Department, K S Institute of Technology, Visvesvaraya Technological University, Belagavi, Karnataka, India
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improve operator involvement and accountability. Section 3 defines the problems faced by the industry, and the motivation to carry out this work. Section 4 takes the reader through the Hardware and Software architecture of production data monitoring system and connectivity with the cloud server. The whole cycle has been tested and validated through an Indian Small and Medium Enterprise (SME) and the results are annexed in Section 5. The scope of this paper is limited to the production data collection and its cloud connects. However, the researcher intends to use the proposed model to other areas of manufacturing operations viz. gauging, maintenance, process control, energy monitoring, etc., in the future. A roadmap for future work is tabled in Section 6, correlating the virtual print of the physical factory to theoretical models. Section 7 concludes the paper followed by references.

2. Literature review

This section covers the key enabling technologies used in the proposed production monitoring systems. Cyber Physical Systems and Cyber Physical Production Systems, Internet of Things and Industrial Internet of Things, various protocols and methods followed for live machine monitoring in the industry and significance of digitalization to improve the operator engagement are reviewed.

2.1. *Cyber Physical Systems (CPS) and Cyber Physical Production Systems (CPPS)*

Manufacturing industry is seeing a new era of Industry 4.0. In the past, the manufacturing industry passed through the first, the second and the third revolutions, being mechanical production facilities, electrically operated mass production machines, automation using electronics and information science, respectively (Monostori 2014). The 4th revolution is all about reducing the gap between physical systems like machines, factories, people, manufacturing activities and the virtual activities carried out in computers, automation to form altogether a new way of manufacturing with minimum human intervention. The introduction of the Cyber Physical System can be envisaged as the starting point of the 4th industrial revolution (Stock and Seliger 2016).

Cyber Physical Systems monitor the physical systems and processes to draw a virtual copy of the physical system. The virtual copy of the physical system produced has enormous data whether it is required or not. This is called Bigdata. This data contains several useful and unuseful data which have to be processed through algorithms and analytics to articulate meaningful information that is of use. Such articulated data can throw light on several visible and invisible issues of the physical systems. This is how the cyber system creates a virtual print of the physical systems, and through analytics and algorithms effective decisions are made (Mourtzis, Milas, and Vlachou 2018; Alcácer and Cruz-Machado 2019).

Electronic sensors sense the data and connect these digital data through networks to the cloud which will compute and analyze the data in cyber systems to create a meaningful content having a correlation with the data, which can be shared in a personalized form to a community which will finally create a value in this collaboration. Physical systems in a virtual landscape with contents that are meaningful to a community will make the 'issues' obvious and visible. Once the issues become obvious and visible, solutions find their way. In brief, CPS can be mathematically represented as the function of Sense, Connect, Content and Share.

$$\begin{aligned} &\textit{Cyber Physical System} \\ &\quad = f\,(\textit{Sense},\ \textit{Connect},\ \textit{Content},\ \textit{Share}) \end{aligned}$$

In general, there are a few key technology components of CPS which form a strong basis for Industry 4.0 platform. They are, Bigdata, Cloud computing, Internet of Things, Simulation, Autonomous robots, Augmented reality, Cyber Security, System Integration and Additive manufacturing. One or more technology components are augmented together to form an ecosystem which is specific to manufacturing, to evolve the specific subset of Cyber Physical System called Cyber Physical Production System (Monostori 2014; Stock and Seliger 2016; Fatorachian and Kazemi 2018).

5c architecture for implementation of CPS (Lee, Bagheri, and Kao 2015) is discussed on multiple occasions. 5C architecture specifies general guidelines for implementation of CPS for any given application. It explains the salient features of an ideal Cyber Physical System implementation. If these steps are taken care of while designing any Cyber Physical System or Cyber

Physical Production System, then there are less chances of committing any mistake in the system design. This is generic in nature and is adaptable to any functional model so as to reach highest maturity levels of Industry 4.0 model. 5C architecture explains about Connect, Conversion, Cyber, Cognition and Configuration layers, which systematically unfold the eco-system for CPS implementation (Rossit, Tohmé, and Frutos 2019).

2.2. *Internet of Things (IoT) and Industrial Internet of Things (IIoT)*

Internet of Things is an important and primary technology component of Cyber Physical System (Mourtzis, Milas, and Vlachou 2018). A Physical device embedded with an electronic sensor which can connect, collect and exchange data with the world of computer systems, facilitating improvement of efficiency and economic development can be referred to as IoT-enabled devices. The expectation of the virtual world is that every 'thing' is made capable to connect to 'Internet' so that the 'Things' can speak to each other or such similar IoT-enabled devices. This will reduce human intervention in the functioning of the devices. This will facilitate more predictive behaviors of the devices and they speak for themselves, resulting in better efficiencies of the operations. Ever since the industrial age started, manufacturing industry has been busy with innovations within the arena of manufacturing operations. However, during the third industrial revolution, computers and the communication systems influenced the manufacturing systems to a large extent to go digital. This digital revolution encouraged researchers and industries to empower various manufacturing devices, inspection devices, measurement devices and machine elements to get equipped with IoT (Zhong et al. 2017). This created a subset of IoT called IIoT: Industrial Internet of Things.

2.3. *Connectivity with the intra and internets*

Interconnectivity is the key factor of the Cyber Physical Production Systems. It is a challenge to make CNC Machines IIoT ready, as many of them are invariably very old legacy machines. Communication is difficult with most of the communication protocols available in the present day. But these old legacy machines are functioning machines and replacing them with the new generation machines is not economically feasible. Manufacturing industry needs significant research in the integration of physical facilities using information and communication technologies (ICT), to gain insights into accurate and real-time information on the production processes (José Álvares, Oliveira, and Ferreira 2018).

Most of the machines are equipped with RS 232 serial port for data communication. Data can be sent out through the CNC machine's RS232 serial port whenever there is a cycle start/end, spindle on/off, etc. Machine's RS232 serial port is connected to a server via serial-to-LAN converters, over wired or Wi-Fi network. Data is sent to the server, reports are visible on PCs on the local network. However, it calls for IT infrastructure like LAN and cables. Many old generation machines may not have Macros enabled in the CNC System. Next-generation machines have Ethernet connectivity along with RS232. Ethernet port is connected to a server via serial-LAN converters, over wired or Wi-Fi network on shop floor. Data is sent to the server, reports are visible on PCs on the local network. MTConnect is a data exchange protocol that allows various devices of manufacturing systems to share data seamlessly in a common format enabling very good interoperability (Vijayaraghavan et al. 2008). Sunny, Liu, and Shahriar (2017), has developed an agent-adapter-based communication method for exchanging manufacturing services over the internet in the cyber physical manufacturing cloud based on MTConnect and HTTP. In Siemens controller machines, data acquisition is realized based on OPC specification (Wang et al. 2016). But this is specific to Siemens controller machines. Recent studies show that the status of signals at the machine's relays is monitored through a sensor that tracks digital signal lines from the CNC machine's PLC. These data can be sent directly to cloud using TCP/IP protocols using Mobile network. José Álvares, Oliveira, and Ferreira (2018) have developed a framework in the form of an internet-based client-server model, for monitoring and teleoperation of CNC machine tools, which has attributes compliant with Industry 4.0.

2.4. *Shop floor monitoring system*

There is a hunt for live and active data in the new era of manufacturing. Passive data have no prominence in the digital life. Shop floor data collection and usage has happened mostly in the machine maintenance area. Probably it is an easy winner for data sensing, connecting, collecting and sharing (Lee et al. 2013). Predictive maintenance systems are showing trends of next-generation production systems. The machine elements are made IoT enabled and are able to sense the fatigue factors and the ageing of the elements by appropriately calibrating the power consumption and precisely estimating expected remaining life span of the elements. The systems are able to self-aware, self-compare and self-configure to maintain themselves and trigger the alarms well before their expected life comes to an end. Thus, preventive maintenance schedules can be affected and the breakdowns can be eliminated (Lee, Kao, and Yang 2014; Lee, Bagheri, and Kao 2015; Bagheri et al. 2015).

These predictive maintenance capabilities are leading to a new phase of the service industry. Generally, the service industry suffers from lack of data on the causes of failure. They will get to know that the machine has failed, without any clue on the reasons for failure. The advent of CPS has equipped the service industry with new technological capabilities through IoT-enabled devices, so as to know precisely the cause of failure (Herterich, Uebernickel, and Brenner 2015; Jay Lee et al., 2015). This will change the perspective of the service industry by making Predictive Maintenance more feasible. Spindle current consumption and Axes current consumption monitoring are calibrated to get a feel of the health of the machining process (Mourtzis, Milas, and Vlachou 2018). Several researches have happened in the area of Design of industrial elements and the manufacture of them using CAD/CAM/CAE/PLM software. They are in their smart stage. The need for Industry 4.0 era is that the design solutions and manufacturing solutions have to be smarter than their smart days. Smarter means connectivity with larger area in the value chain through enabled IoT (Ivezic and Srinivasan 2016). Once almost all the activities get connected to each other in a factory, it's time to connect multiple factories, multiple vendors for efficient co-ordination (Weyer et al. 2015).

The literature review evidences the progress in predictive maintenance, servicing of machines, machining parameter monitoring, engineering services, smart factory environment, etc. An important area of manufacturing operation is production data monitoring. Some efforts are made to monitor real-time production data monitoring in (Staniszewski, Legutko, and Raos 2014; Prasetyo, Sugiarto, and Rosyidi 2018). Caggiano (2018) proposed a three-layered approach for cloud-based manufacturing process monitoring. Physical resources like machines and accessories equipped with multiple sensors are treated as the first layer. Local servers with database servers are treated as the second layer wherein the data are processed partially or fully. Both first and second layers are within the factory premises. With the cloud server as the third layer, the whole model gets eligibility to connect multiple machines from multiple geographical locations and matches very closely the Industry 4.0 framework.

2.5. *Significance of operator engagement*

Employee involvement is a powerful tool for enhancing operational efficiency. Mohanty and Choudhury (2018) carried out an extensive review which reveals that both productivity and employee engagement drivers are closely linked and have impact on each other. Markos and Sridevi (2010), in his employee engagement strategies, envisage that two-way communication between the management and the employee builds self-efficiency and commitment towards the work. Further, Osborne and Hammoud (2017) strongly recommend that the leadership team should be creative enough to find innovative ways to improve communication between the management and employees.

Hannola et al. (2018) presented a conceptual framework opening that empowering production workers with digitally facilitated knowledge presents that the skills, flexibility and efficiency of the shop floor workers are decisive factors in ensuring accurate product specifications, meeting deadlines and keeping the machines running, in order to meet global market competition and increasing diversity of customer demands. To substantiate the above, Orellana and Torres (2019), proves through a case study that the digital transition of a factory with legacy machines to a smart factory reduces considerable human errors and records improvement in the key performance indicators like quality, energy consumption and maintenance.

3. Problem description and motivation

The Literature review reveals that in the current production environments, increasing of knowledge building, decision-making skills and social interaction among team members on the shop floor is a major topic which is not yet supported by digital technologies. To stimulate interaction across workers, teams and production machines, new modes using digital technologies will be required. The transformational ability of digital technologies to knowledge-intensive production environments is expected to be one of the advancements in the human centric manufacturing of companies to improve efficiency and productivity, in order to survive competitive markets (Hannola et al. 2018). In hugely populated countries like China and India, where most of the MSMEs are not well equipped with the emerging technologies, production monitoring is mostly manual in nature (Singh, Mahanty, and Tiwari 2018). Digitalization has penetrated deep into the general public, but the same to penetrate into the manufacturing scenario needs intensive study and research. This aspect is the motivation for the subject research.

The current method of data collection in manufacturing machine shops is manual, inaccurate and open loop in nature. Typically, the data collection happens in the following manner:

3.1. *The whole process is manual*

Companies have different formats designed to capture the production data. The formats have to be filled with data like the component being produced, component name, target per shift, name of the operator, etc., by the operator at the beginning of the shift. The operator is also expected to write the output per hour at the end of each hour. The format has provisions to identify the idle time reasons which need to be filled up by the operator. Some companies have provisions to calculate the utilization, performance and quality parameters and calculate the OEE the end of the shift.

3.2. *The data collected could be inaccurate*

The operator is expected to enter the production numbers, rejection numbers and idle time data at the end of each hour. But practically, it may not be possible due to various reasons like the operator's hands are oily, blank format is not available and pen not available. He tends to write these data at the end of the shift or at his convenience. This can lead to erroneous data entry. Though the reasons look small or insignificant, the amount of error it generates at the end of the day is quite significant. The compilation of these data is also time consuming and can lead to errors.

3.3. *Data processing is open-loop in nature*

The data hence collected are processed by manual compilation using excel or any other equivalent spreadsheets. The compilation happens remotely by a supervisor and it may not reach back to the operator or it may reach him on the next day. This makes the whole system open loop, creating a significant mismatch between the machine and the operator. The operator, who is an important stakeholder in the whole production process, is not 'aware' of his own performance. Not knowing one's own performance will lead to lower-than-expected involvement, less knowledge transfer, finally resulting in reduced productivity.

3.4. *Isolated from digital revolution*

The data is in the handwritten form. Manual intervention is required to compile the data of various machines and consolidate them on a spread sheet. This system is conventional and not dynamic in nature. It results in reactive decisions and slow actions. This has a significant impact on production, resulting in production losses, OEE reduction and finally affecting Quality, Cost and Delivery. Instantaneous information is essential in the present day so that the actions are in tune with the present-day speed. The current method does not support such a spirit.

These are the issues which need the support of digitalization to make the process free of manual intervention, accurate, closed loop and cloud enabled so that the data collected are reliable, and meaningful objectives and actions can be derived out of the same.

4. Shop floor to cloud connect production data monitoring system

This section explains the theoretical model of OEE, development of hardware architecture and algorithm used for shop floor to cloud connect production data monitoring system.

4.1. *The theoretical model of OEE (Overall Equipment Efficiency)*

Every industry will have some or other method of theoretical models and key performance indicators for evaluation of performance. In case of a manufacturing industry, this theoretical model is called Overall

Equipment Efficiency (OEE). In a production shop, there could be several issues such as human behaviors, machine performance, accuracy and precision, productivity, quality defects, loss of productive time, measurement errors, energy consumption, probability of failures, preventive maintenance cycles, operator fatigue, material non-availability and so on. Significant amount of activities are captured in the theoretical model of OEE (Nakajima 1988).

In the proposed work, OEE is calculated by using production and rejection data from shop floor CNC machines. With the Production part count, Rejection part count and Machine idle data, the OEE is calculated as follows:

$$\textbf{OEE} = \textbf{Availability x Performance x Quality}$$

Availability gives unplanned machine downtime losses. It is equal to the ratio of actual machine running time to total available time. Planned downtime such as lunch breaks and tea breaks do not affect the OEE evaluation.

$$\text{Availability (\%)} = ((\text{Total available time} - \text{Machine idle time}) / (\text{Total available time})) \times 100$$

Performance gives the speed loss. It is equal to the ratio of the number of components produced over the measurement period (shift, day, etc.) to the theoretical maximum number of components that could be produced if the machine runs at its maximum possible speed.

$$\text{Performance (\%)} = ((\text{Total part count} / \text{Target part count}) \times 100$$

Quality is the ratio of good parts to total parts produced.

$$\text{Quality (\%)} = ((\text{Total part count} - \text{rejection count}) / \text{Total part count}) \times 100$$

The complete Data Acquisition System (DAQ) and analysis to calculate OEE are described in the flow chart shown in Figure 2.

4.2. Hardware architecture

The proposed CNC machine's production data monitoring system is described in the architecture diagram as shown in Figure 1. The CNC machine tool is the production system. The production system can be with any CNC system which is a globally available brand like Fanuc, Siemens, Fagor, Mitsubishi, etc. Though the recent generation machines are equipped with communication ports for communicating with the CNC System, the proposed work uses independent electronic sensors used in production output locations. By this strategy, the intervention with the CNC System is eliminated. This simplifies the system integration which requires expert interventions. The end of the CNC program cycle will be

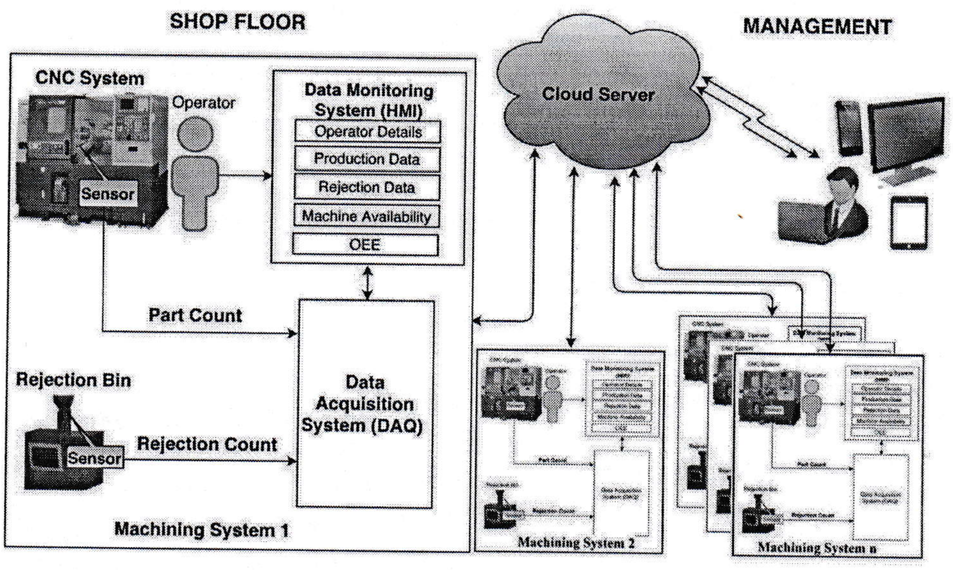


Figure 1. Hardware architecture of shop floor to cloud connect production data monitoring system.

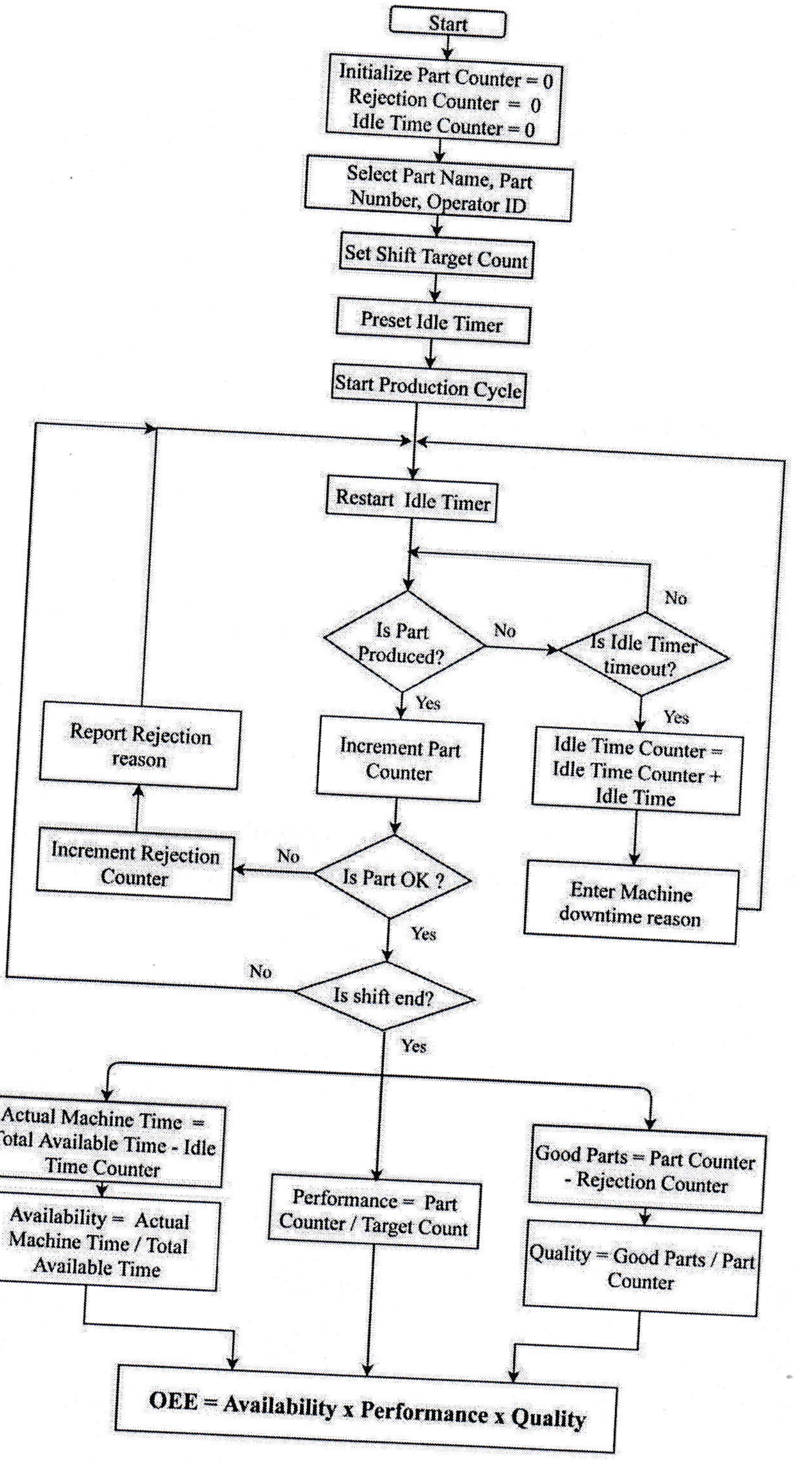


Figure 2. Workflow of data acquisition and OEE calculation.

sensed by the sensor and it will send the signal to the data acquisition system by incrementing the production quantity. Similarly, electronic sensors are used in the entry of the one-way red rejection bin which monitors the entry of the rejected component into the bin. Any entry of the component to the red bin will be sensed by the sensor and the rejection count will be incremented by one. The algorithms are built into the DAQ to sense no activity and the same is recorded as idle time. This arrangement enables real-time data collection of production, rejection and idle time in a CNC Production Machine. The hardware contains sensors fitted into the

CNC machine and the rejection bin. It also includes the PLC and an IoT-enabled HMI. Computational capabilities of PLC and the IoT capabilities of the HMI are used effectively to sense, analyze, display and connect to cloud, using the above explained architecture. The several data from various CNC machines are consolidated and converted into meaningful and useful forms by using intelligent data management systems in cyberspace and information is fed back to management.

4.2.1. Data Acquisition System (DAQ)

The DAQ in the proposed hardware architecture consists of electronic proximity sensors and PLC. This electronic proximity sensor contains a transistor output and is polarity sensitive. A source type (PNP) proximity sensor can only interface with sink type PLC input channel and vice-versa. The non-invasive inductive type proximity sensors are used to detect the presence of nearby metallic objects without any contact. So, the current sourcing (PNP) inductive proximity sensors are selected and placed in appropriate positions to detect the production parts and rejection parts (Kuphaldt 2008; Lamb 2013).

Programmable Logic Controller (PLC) is an industrial digital computer used for many different types of process control applications. They are fast and designed for the rugged industrial environment. The PLC consists of CPU, Memory, Input/Output, Power supply unit and communication interfaces. Programs are written on the computer and downloaded into the PLC using its communication interface. These loaded programs are stored in the non-volatile memory of the PLC. In the proposed work, ABB's AC500-eCo PM554-ETH CPU is used for data computations. The ABB automation builder development tool and CodeSys automation software is used for software development. The software is developed using the Ladder Diagram programming Language. This application software so developed is downloaded into the PC using MODBUS TCP/IP network protocol.

Figure 2 explains the developed algorithm, through a flow chart, the various steps involved, from the data collection to analysis to calculate the OEE, by taking into account the factors of idle time, performance and quality.

The PLC receives signal from the sensor whenever a part is produced from the CNC machine. This signal is given to the part counter to get the total part count produced per shift. Similarly, the part rejected, due to various reasons, is put into a rejection bin to avoid mixing of the good parts with the bad ones. Each time when the part is rejected, the operator is made to enter the rejection reason in the HMI and also the sensor will give a signal to the PLC and the rejection count per shift is calculated in the rejection counter. The data analysis algorithm is developed in the PLC to give live information about the total part produced, total parts rejected, percentage of target count achieved, by taking the data collected from the sensor and the target count input from the HMI by the supervisor.

The machine downtime called idle time calculation algorithm is developed by using the retentive timers of PLC. By tracking the part production time, the unplanned machine downtime is calculated and each time when the machine is down more than the predefined time, the operator is made to enter the reason for downtime through HMI and also the timer will calculate the accumulated time.

4.2.2. Data monitoring system (HMI)

In the proposed work, the data monitoring system is built using Human Machine Interface (HMI). An HMI is a user interface or dashboard that connects an operator to a machine for an industrial system. In industrial applications, HMI is used to display the data visually, to monitor machine input and output, to track production time, trends and tags, etc. HMI can replace hundreds of push buttons, selectors, lights and so on.

EXOR eSmart07M IoT-enabled HMI is used in the proposed work for data monitoring and connecting to cloud. This has a 7-inch TFT display and an ARM Cortex-A8 CPU. The communication between PLC and HMI is carried out by using TCP/IP protocol (Exor 2019).

In the proposed work the supervisors are given control to enter the Component name, Part number, Operator ID and Target count per shift. Target part count is fed to the DAQ from the HMI. The outputs of DAQ such as total part count, rejection count, percentage target achievement, OEE and trends are displayed on the HMI and can be monitored in real time. At any given point of time, the production rate with reference to the target output can be checked by the operator or the supervisor or the management on the HMI screen.

4.2.3. Connectivity with the cloud server

In the proposed work, EXOR eSmart07M IoT-enabled HMI is used to establish a connection between the shop floor and the cloud server. The HMI cloud enabler application is used to configure HMI and to connect the

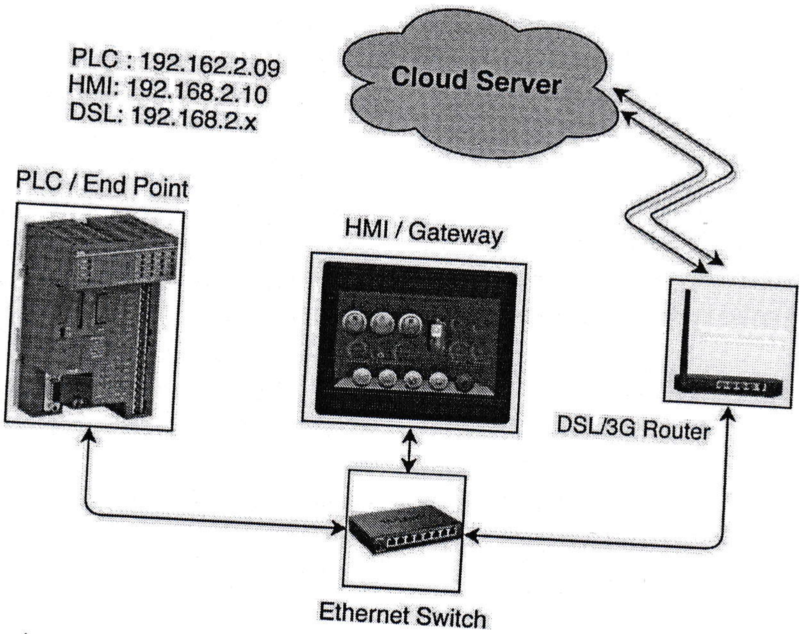


Figure 3. Shop floor to cloud connect framework.

Corvina cloud. Corvina cloud is a software platform design for connecting users and machines through a global network like the internet. Corvina cloud is a VPN-based solution that allows to remotely manage divers remote devices connected to a centralized server through gateways (Corvina Cloud 2019). Corvina cloud app is used to monitor the real-time data on a laptop, a mobile or a tab. The shop floor to cloud connection is established as shown in Figure 3.

5. Case study results

The developed production data monitoring system was implemented in an Indian SME (Small and Medium Enterprise) which is engaged in mass production of plug shell components. Plug Shells are the steel housing of spark plugs inside which the electrode is housed and is bound by a ceramic insulator. As spark plugs are used in automotive OEMs and also in the spare market, the requirement is large in number. The Indian SME which is engaged in manufacturing of these parts produces 10,000 components per day using four CNC Machines. The CNC Machines are equipped with Siemens 802D CNC System. The Cycle time per component is 29 seconds. The operator is engaged most of the time in component inspection and filling up the inspection reports. It was observed that the operator missed capturing the correct data about production, idle time and the rejection. It was an invitation to apply the live production data monitoring system in the subject's production set-up. The above live data monitoring system was applied in the machining set-up, which systematically solved the issues faced by the conventional data collection method explained in Section 3.

The proposed work focused on how to collect data automatically without the intervention of the operator and the supervisor. The work contributed to the processing of the data on real-time basis. It also made the operator 'Aware' of his own performance at any point of time during the shift through a digitally compiled summary. The work addressed how to transfer these real-time data to the management in a compiled manner using the IIoT platform. The CNC machine with cloud-based live production data monitoring system implementation is shown in Figure 4.

Eventually, the proposed method became automatic, accurate and closed loop in nature through the support of the digitalization. The results observed after the implementation are explained in the following sections:

5.1. *The whole process became automatic*

The manufacturing shop removed all the manual formats and the data collection became completely

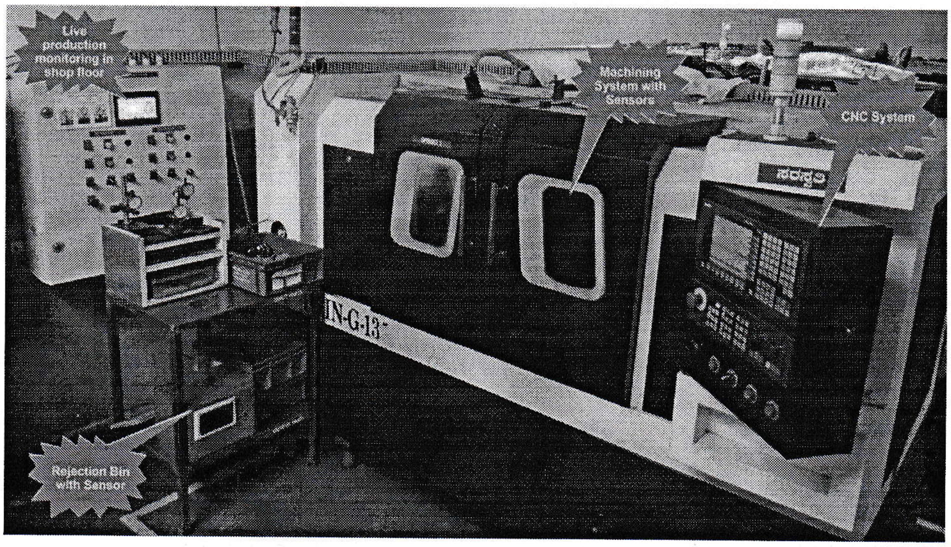
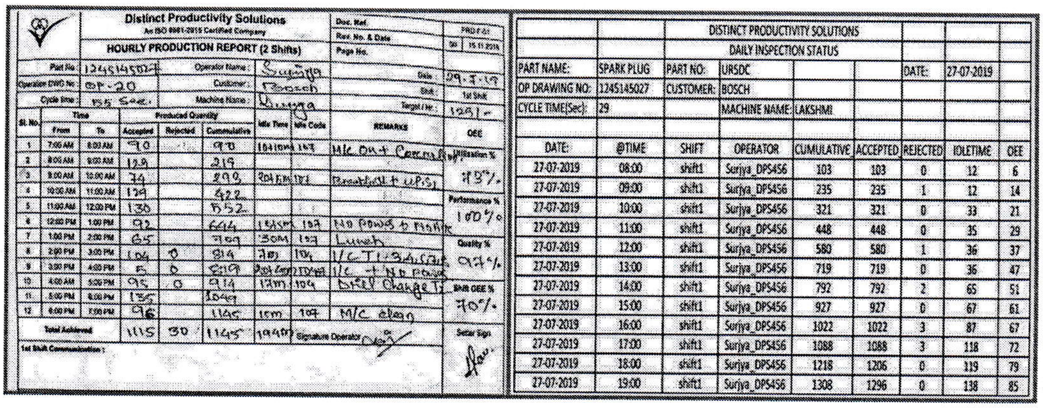


Figure 4. The CNC machine with cloud-based live production data monitoring system.



Distinct Productivity Solutions
HOURLY PRODUCTION REPORT (2 Shifts)

		DISTINCT PRODUCTIVITY SOLUTIONS						
		DAILY INSPECTION STATUS						
PART NAME:	SPARK PLUG	PART NO:	URSDC			DATE:	27-07-2019	
OP DRAWING NO:	1245145027	CUSTOMER:	BOSCH					
CYCLE TIME(Sec):	29		MACHINE NAME:	LAKSHMI				
DATE:	@TIME	SHIFT	OPERATOR	CUMULATIVE	ACCEPTED	REJECTED	IDLETIME	OEE
27-07-2019	08:00	shift1	Surjya_DPS456	103	103	0	12	6
27-07-2019	09:00	shift1	Surjya_DPS456	235	235	1	12	14
27-07-2019	10:00	shift1	Surjya_DPS456	321	321	0	33	21
27-07-2019	11:00	shift1	Surjya_DPS456	448	448	0	35	29
27-07-2019	12:00	shift1	Surjya_DPS456	580	580	1	36	37
27-07-2019	13:00	shift1	Surjya_DPS456	719	719	0	36	47
27-07-2019	14:00	shift1	Surjya_DPS456	792	792	2	65	51
27-07-2019	15:00	shift1	Surjya_DPS456	927	927	0	67	61
27-07-2019	16:00	shift1	Surjya_DPS456	1022	1022	3	87	67
27-07-2019	17:00	shift1	Surjya_DPS456	1088	1088	3	118	72
27-07-2019	18:00	shift1	Surjya_DPS456	1218	1206	0	119	79
27-07-2019	19:00	shift1	Surjya_DPS456	1308	1296	0	138	85

Figure 5. Manual and auto-generated production report.

automatic by use of sensors. Minimum manual intervention was required by the supervisor to set the shift target, operator name, component name, etc. The operator would only enter the rejection reason and the idle time reason. The OEE, which considers availability, quality and performance parameters, is automatically calculated. The manual and auto-generated production reports are shown in Figure 5.

This type of automatic data collection without the intervention of the operator resulted in the saving of operation time. Prior to the implementation of this proposed method, management had allotted the last 30 min of the shift for OEE calculations, writing rejection report, production report, idle time report, etc. As the data capturing became automatic, the time saved was found to be 30 min per shift. This is taken as the average time saved over a sampling period of 25 working days on 4 machines. Based on this, the net improvement in the production clocked is 4.17% per machine. The detailed calculations are shown in Table 1.

5.2. *The data collected are accurate*

Data collected are very accurate due to the following reasons:

- The shift production count is not dependent on the part count feature of the CNC system. It is incremented at the end of each cycle after ensuring that the component is produced, by capturing the signal from the electronic sensor.
- The rejection is accounted for accurately, as the part is dropped into a sensor-enabled one-way

Table 1. Increase in production due to implementation of automatic report generation.

Description	Values
Time saved per shift by elimination of writing of the physical report	30 min
Number of shifts per day	2
Time saved per day	60 min
Number of working days in a month	25
Time saved per month	1500 min
Cycle time per component/part	0.48 min
Total number of extra parts produced per month	3103 Parts
OEE applied	85%
Actual increase in production per months	2638 Parts
Current production rate per day	2979 Parts
Total number of parts produced per month	74,483 Parts
Total number of parts produced after OEE	63,310 Parts
Percentage increase in production due to automatic report generation.	4.17%

rejection bin. Poka-yoke are built into the system to ensure that the system does not start unless the rejection reason is entered in the HMI through an easy way of reason selection method.

- If no machining activity is felt by the sensor beyond a certain specified time, then the system locks and it treats such time as idle time. The system does not allow proceeding further unless the idle time reason is selected through the HMI.

The production, rejection and idle time data captured along with rejection and idle time data entry screen are shown in Figure 6.

Accuracy of data capture improved considerably as the different types of idle time are authentically captured on the above screen. Probable causes of idle time and probable causes of rejection are already built into the system, enabling a broad framework to the operators. This helped the data flow in a structured manner, which improved operator involvement through the data entry into the HMI. It was not possible for the operator to fill up the data unless he knew the type of defect enlisted in the HMI screen. The expected time saving, after a study of about 6 months of implementation, is found to be an average of 20 min per shift, subject to standard operating conditions. The calculation of increase in production due to the accuracy in the idle time computation is indicated in Table 2.

5.3. *Data processing is closed loop in nature*

The data hence collected are processed instantaneously through a local server. The operator was made aware of his own performance against the set target, which was made visible to him through a digital display. Other relevant information, like operator photo, production target per shift, production/rejection count at any point of time, was shown in a graphical display form. These processed data of the operator's own performance will create a 'Self-Aware' in the production worker and will have a positive impact in the form of improved OEE. In the given case, the operator engaged in the work with more enthusiasm which increased his accountability and involvement. The operator Self-Aware screen is shown in Figure 7.

As a part of validation of the results, 3 operators from the team were assessed by their supervisors on 10 different working parameters related to technical aspects, motivational factors and engagement issues. These 10 parameters were rated on a scale of 1–5, one being the least skill and 5 being the highest level of skill and 0 being not applicable. The results were further validated by demonstration of the specified tasks and the method study by a cross-functional team. It was collectively felt by the operators and the supervisors, after this exercise, that the operators are more confident

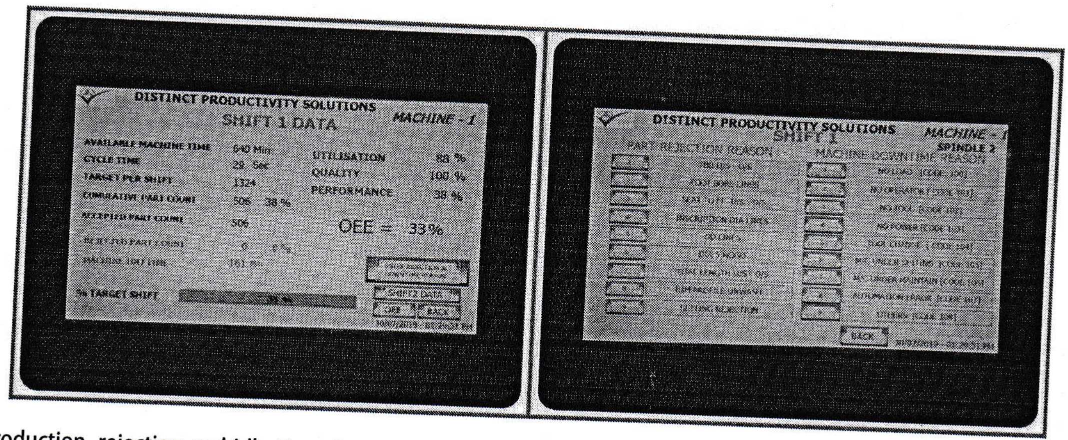


Figure 6. Production, rejection and idle time data.

Table 2. Increase in production due to accuracy in the idle time computation.

Description	Values
Time saved per shift by system integration of idle time tracking	20 min
Number of shifts per day	2
Time saved per day	40 min
Number of working days in a month	25
Time saved per month	1000 min
Cycle time per component/part	0.48 min
Total number of extra parts produced per month	2069 Parts
OEE applied	85%
Actual increase in production per months	1759 Parts
Current production rate per day	2979 Parts
Total number of parts produced per month	74,483 Parts
Total number of parts produced after OEE	63,310 Parts
Percentage increase in production due to accuracy in the idle time computation	2.78%

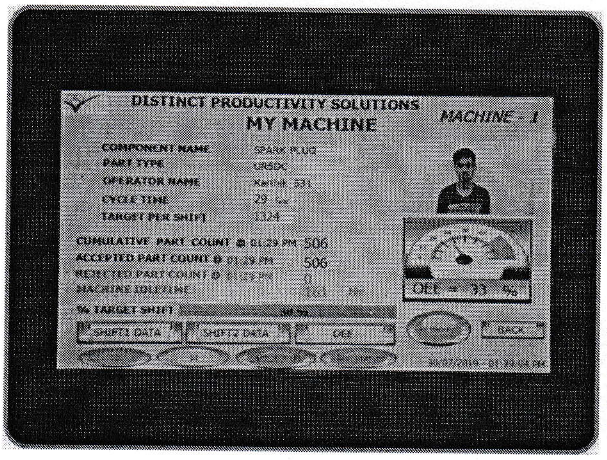


Figure 7. Self-aware screen.

and more oriented towards their targets on the quality and quantity front. The survey report is tabulated in Table 3.

The survey has indicated that there are positive improvements in Sl. No.1, 2, 3, 4, 6, 8, 9, 10. New learnings happened in Sl. No.5 and certain routine works, like Sl. No.7, are eliminated from the day-to-day work and transferred to the new system. Improvement in major working areas and elimination of manual routine work has resulted in positive improvement in the results.

5.4. *Data is cloud enabled*

As the information flow of the operator and the machining systems' performance is transmitted to the management through cloud, it makes the complete process closed loop. Directions for the production system can be given remotely. Due to cloud-enabled solutions, the results can be compiled for any number of machining systems. The compiled data can be seen on Laptops, mobile phones, smart Televisions, etc. at any geographical location as shown in Figures 8 and 9. It forms a perfect eco-system for implementation for Industry 4.0.

The stoppages are escalated to the authorities concerned, irrespective of the geographical locations, through multiple modes of communication. The status will show 'Red Alert' in case of any stoppage. The stoppage reasons, if known to the operator, can feed the same in the idle time report card. If not, they get autonomously escalated to the next level. This is possible as the whole system is cloud enabled. The escalation of the machine status through cloud connect is shown in Figure 10.

For instance, in Figure 10, it is evident that out of 4 machines, only 3 are working and one machine has stopped working. This signals escalations to the teams concerned to take immediate actions. Twenty-eight hours of production time was recorded to have been saved, over a study period of a month's duration, due to the quick attending to of break downs or stoppages, by the supervisor. Management interventions also became more prominent as the issues

Table 3. Results of the assessment of operators before and after implementation.

Sl. No.	Parameters	Operator-1		Operator-2		Operator-3	
		Before	After	Before	After	Before	After
1	Ability to check critical parameters	3	4	2	4	3	4
2	Availability of time for deburring	2	5	3	5	2	5
3	Ability to identify variants in the component	4	5	3	5	4	5
4	Ability to identify the types of defects	3	5	4	5	3	5
5	Ability to operate HMI Screen	0	5	0	4	0	4
6	Ability to give tool offsets	2	4	3	3	2	4
7	Ability to carry out OEE computation	3	0	4	0	3	0
8	Attitude towards achieving production targets	3	5	3	4	3	5
9	Competitive spirit between operators	2	5	2	5	2	5
10	Confidence level of the operator	2	5	3	4	2	5

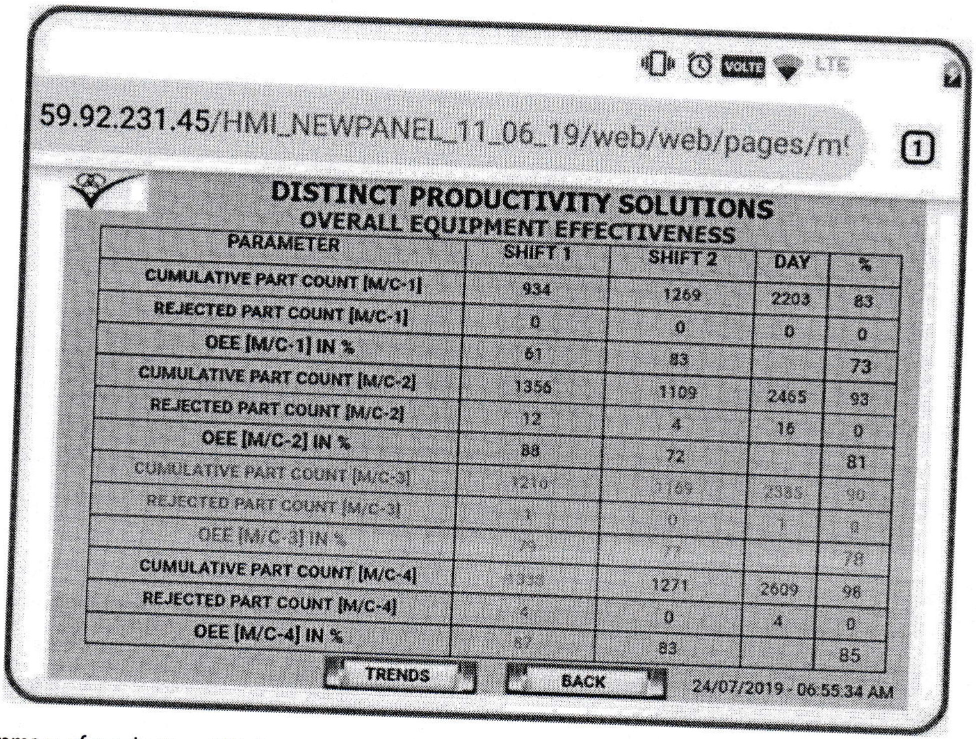


Figure 8. The summary of production OEE for multiple CNC machines captured.

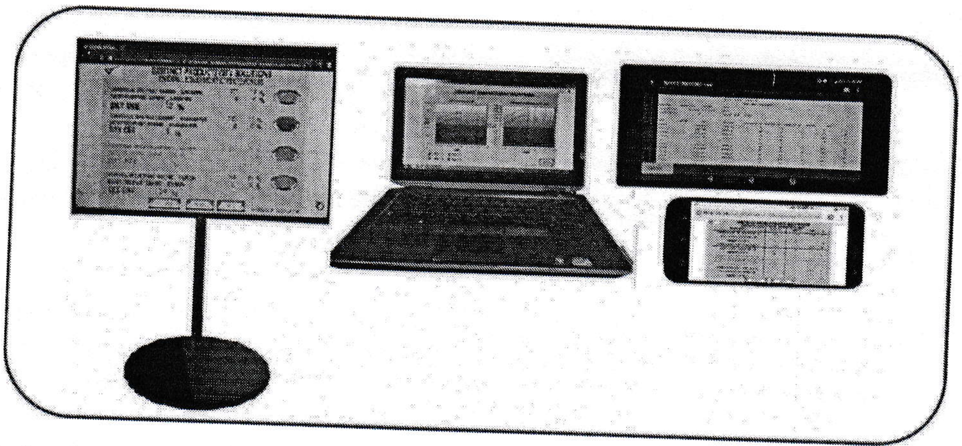


Figure 9. User interface for real-time cloud connect of production data.

started showing up on the screen, as and when they passed beyond the stipulated time frames set by the organization. An increase in production to the tune of 5.15% was recorded due to the prompt and timely attention to the issues, as indicated in Table 4.

The quantified savings from various sections of improvements are shown in Figure 11.

A summary of the features of the proposed work is drawn in Table 5 which tabulates the characteristics of the previous works with the proposed new methodology.

The validation of the above characteristics was carried out in the case study and it is observed that competitive spirit between the operators increased. The digital environment created excitement in the workplace. The management and the operators shared the common data, which enhanced transparency. These factors improved the accountability of the operator. An incremental growth of about 12% in production quantity and OEE was recorded. The results over the period of implementation are shown in Figure 12 with the milestones achieved by the implementation.

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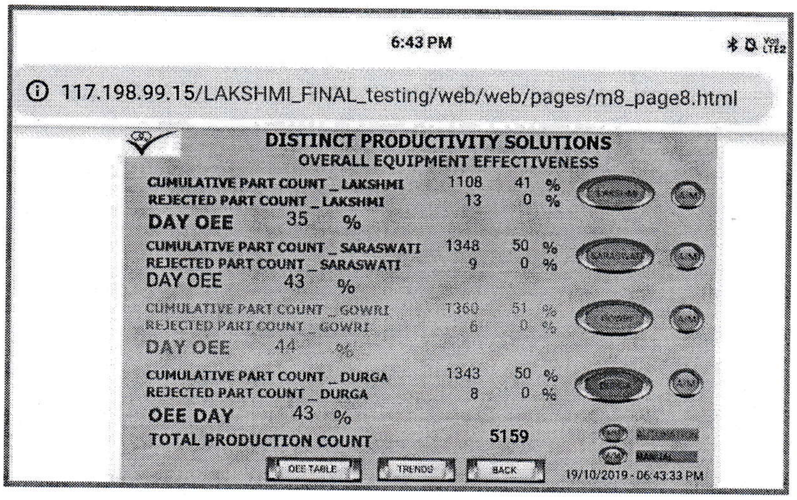

Figure 10. The escalation of the machine status through cloud connect.

Table 4. Increase in production due to the prompt attending to of the issues.

Description	Values
Time saved in a month	28 h
Cycle Time per component	0.48 min
Total number of extra parts produced per month	3476 Parts
OEE applied	85%
Actual increase in production per month	2954 Parts
Current production rate per day	2700 Parts
Total number of parts produced per month	67,500 Parts
Total Number of parts produced after OEE	57,375 Parts
Percentage increase in production due to the prompt attending to of the issues	5.15%

6. Scope of the present work and scope for future expansion

The scope of the present work is limited to live production data monitoring and management decisions supported by the information provided by the analytics. The developed model can be used in other areas of manufacturing like Quality, Maintenance, Machine Performance, Inspection, Instrument performance, Energy consumption, etc. All functional areas of the physical factory can be brought under the umbrella of the proposed model. Table 6 annexes the functions and their attributes for future work.

Future work can lay stress on creating similar structures in other functional areas. Closed loop inspection systems (Prathima, Sudha, and Suresh 2015) and Predictive maintenance systems are the major focus areas for researchers in the future. When all the above functions are integrated, the manufacturing industry can reach very good maturity levels of Industry 4.0 scenario.

7. Conclusions

This paper is a contribution towards collecting live data from the shop floor with IIoT enabling the production devices. Once the devices became IIoT enabled, they

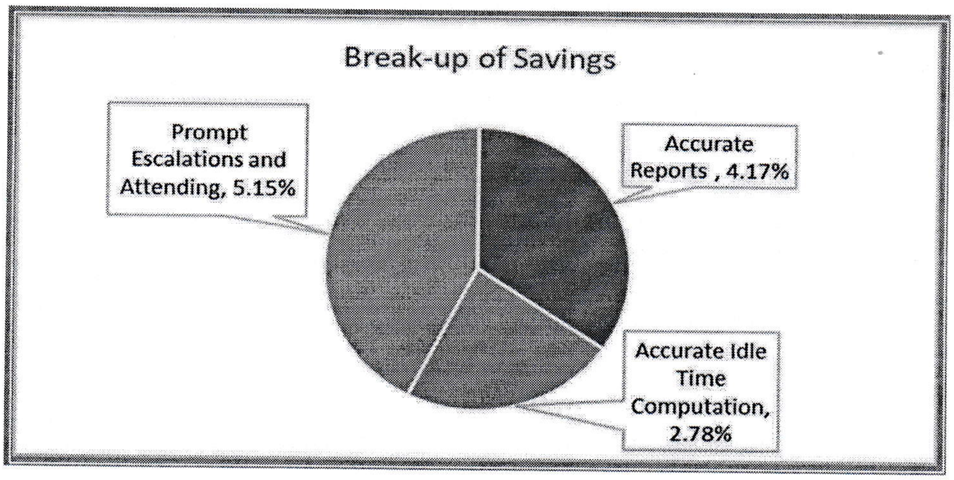

Figure 11. Break-up of the savings as quantified.

Table 5. Comparison of previous works with the proposed methodology.

Publications	Functional area	Data collection method	Data accuracy	Closed loop	Cloud enabled	Operator engagement
Staniszewski, Legutko, and Raos (2014)	Production monitoring in a small machine shop with primitive monitoring system	Through sensor	Medium	No	No	Requires dependable staff
Lee, Kao, and Yang (2014)	Provides implementation guidelines of an ideal CPS	Through sensor	High	Yes	Yes	Feature can be built into the system
Jay Lee et al., 2015	Predictive maintenance by self-maintenance feature	Through sensor	High	Yes	Yes	Feature can be built into the system
Bagheri et al. (2015)	Provides implementation guidelines of an ideal CPS through Self-Aware machine	Through sensor	High	Yes	Yes	Feature can be built into the system
Herterich, Uebernickel, and Brenner (2015)	Implementation of CPS in Service Industry	Through sensor	High	Yes	Yes	Not attempted
Mourtzis, Milas, and Vlachou (2018)	CPS-based machine process condition monitoring between machines	Through sensor	High	Yes	Yes	Not addressed
Ivezic and Srinivasan (2016)	Engineering services from smart to smarter	Analytics	High	Yes	Yes	Not applicable
Weyer et al. (2015)	Supply chain management	Analytics	High	Yes	Yes	Not applicable
Prasetyo, Sugiarto, and Rosyidi (2018)	Production monitoring system using RFID	Through sensor	High	Yes	No	Attempted
Caggiano (2018)	Tool wear pattern monitoring	Through sensor	High	Yes	Yes	Not attempted
Existing method at SME	Production monitoring in SME	Manual	Low	No	No	No
Proposed method	Live production monitoring in SME	Through sensor	High	Yes	Yes	Yes

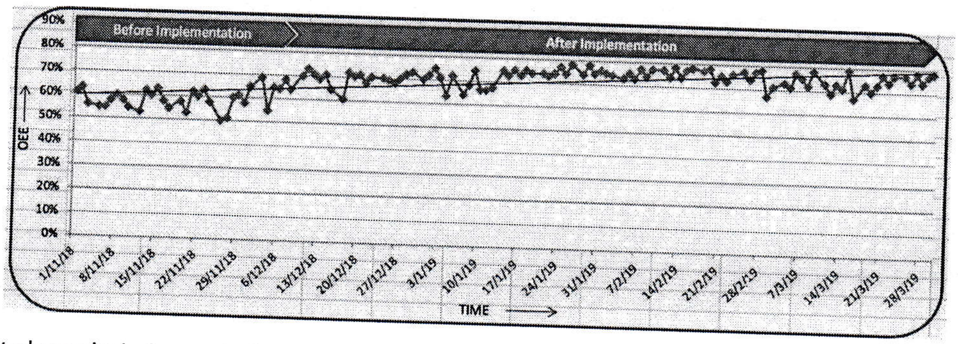

Figure 12. Case study results before and after implementation of the proposed method.

Table 6. The list of manufacturing functions and attributes.

Sl. No.	Functional area	Activity	Performance parameter	Areas covered
1	Production	Live Production Data Monitoring	Overall Equipment Efficiency (OEE)	Idle Time detection, Performance Indication, Rejection data in closed loop
2	Quality	Live monitoring of Processing Stability	Process Capability & Process Capability Index (Cp/CpK)	Stability of process, Repeatability of the machining parameters.
3	Machines	Live Monitoring of Machine Performance	Machine Capability and Machine Capability Index (Cm/CmK)	Machine's capability to Repeat, Machine accuracy
4	Inspection	Live Monitoring of Gauge Performance	Gauge Capability/Gauge Capability Index (Cg/CgK)	Gauge Repeatability and Reproducibility
5	Maintenance	Live Monitoring of Maintenance of Machines	Mean Time Between Failure and Mean Time to Repair (MTBF/MTTR)	Maintainability of the Equipment and its history
6	Power Energy	Consumption Consumption of the equipment	Live Capture of Power conservations	Kilo Watt Hour (KWH)

gained capability to form a virtual print of the whole production system. Once the data were available in digital form, it was convertible to information by the computational capabilities of the embedded systems. Using computational capabilities, data could be molded to the theoretical model of OEE which is in practice in the industry. Analytics and computational capabilities of cyber level could compare and conclude the results and the performances of various such production systems, to the management level. The operator's own performance was shown to him while it was shared with his superiors. The developed model can be used in the multi-functions of various manufacturing operations, to make the manufacturing operations efficient and economically profitable by converting data collection, analysis and deployment of actions, from manual to automatic, from error prone to error free, from open loop to closed loop and finally from digital disability to digitally enabled scenario. This work created a 'self-aware' feature through the HMI screen, which created accountability in the operator who is an important stake holder in the production process. The case study results recorded an incremental improvement in productivity after implementation. This work is a significant contribution towards implementation of Industry 4.0 concepts in developing countries and SME sectors.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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