Industrial Internet of Things (IIoT) Based Job Shop Scheduler Monitoring System

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DECLARATION

I certify that this research work titled "Industrial Internet of Things (IIoT) Based Job Shop Scheduler Monitoring System" is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged / referred.

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LANGUAGE CORRECTNESS CERTIFICATE

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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I am thankful to Allah Almighty for His countless blessings bestowed upon me and the knowledge that He granted me.

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DEDICATION

I dedicate this thesis to my mother and sister who have always encouraged me to reach out for the stars, to never settle for the second best and to unleash the hidden potential that is still untapped with in me.

ABSTRACT

The manufacturing industry has now started the 4th revolution; also referred to as Industry 4.0, powered by the Industrial Internet of Things (IIoT) technology. In this context factories are now being transformed into smart industries by automation of the Shop Floors. Automation comprises of scheduling and monitoring cycles. To implement the true essence of Industry 4.0, a number of different techniques have been applied to schedule the shop floor tasks, while a gap persists in monitoring the job shop scheduler. The aim is to present an optimized IIoT based Job Shop Scheduler Monitoring System that tracks the tasks being performed by the machines, thus completing the closed loop feedback path, enabling automatic detection of completion time of a job and based on that, dynamic rescheduling. The task being performed by the machines on the shop floor are monitored in real time making current profiles via industrial current sensors network. These current profiles are compared with all the current profiles already stored in the database providing a vivid picture of the lead or lag in the tasks being performed, judged by the current variations. This novel automation improves the efficiency of the whole shop floor and ultimately resulting in the optimal management of the resources and time at enterprise level. The monitoring system was tested in an actual shop floor setting and results verify the practicability in improving performance of the shop floor.

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CHAPTER: 1 INTRODUCTION

Industries have acted as the core reason for many nations in the world, to rise up and become the economic and technical giants of twenty first century enabling the industrial revolutions periodically throughout the history. These revolutions have brought peace and sustenance to these leading nations. Industrial revolutions have had two fold effects whenever it unravels. Charles Austin Beard an American historian and professor at Columbia University, famously states this effects as:

"The Industrial Revolution has two phases: one material, the other social; one concerning the making of things, the other concerning the making of men."

Today the world at large is technology dependent come it be agriculture or the processing end such as the Industries. Previously the focus of scientists and engineers was more towards the implementation of technology that enables quick and abundant production. The trend has now inclined towards the quality with quick production, the new concept of customized products as implemented by Tesla Factory in Fremont, California, operated by Tesla, Inc. The need for feedback monitoring has grown more so with the establishment of this new trend of customized industries.

1.1 Subject Overview

The past few centuries have seen many revolutions of the manufacturing industry, from its birth in 18th century also known as Industry 1.0 (I 1.0) which is the transition from hand made to machine made by the use of steam power. Later transitioning into Industry 2.0 (I 2.0) which has its story lit up by the presence of electricity allowing modern production lines in factories. The third industrial revolution or Industry 3.0 (I 3.0) is marked by the emerging of the computational technology on the global landscape. Finally to the present era where factories are overhauled into Industry 4.0 (I 4.0). Today it will not presumptuous to say that industry today has grown out from being Willy Wonka's Chocolate Factory transforming into VIKI's USR as in iRobot. Figure 3 gives a glimpse of the journey from I 1.0 to I 4.0.

The recent urge to make every process automated leads to research and development, enabling the enterprises to become much advanced as compared to the production level. Factories are still dwelling in the past hindering the organization's necessity for a shorter production life cycle, more automated Shop Floors (SF) and enhanced monitoring capabilities. Realizing this huge gap, enterprise is ready to invest additional resources and technology on production level to synchronize it with the enterprise level growth.

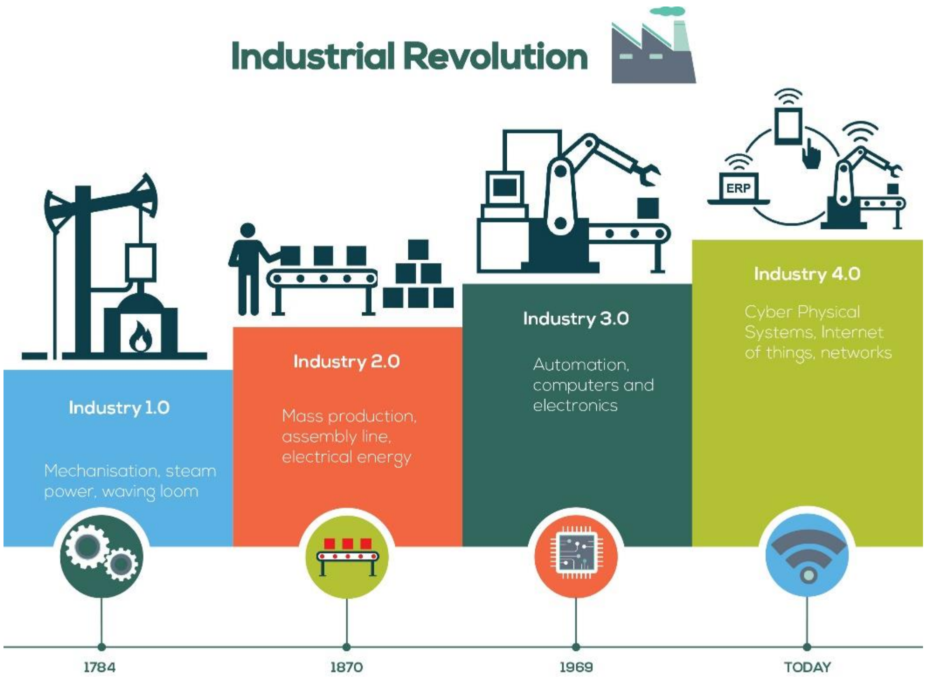


Figure 1 The Industrial Revolution

This is enabling the human race to witness the 4th industrial revolution, empowering manufacturing systems to be transformed into digital environments [1].

The fourth industrial revolution was first projected in 2011 as the goal for developing the German economy [2]. I 4.0 is reliant on the use of communication of sensors and devices with one another to enable decision making autonomous and de-centralized providing increased industrial efficiency, productivity, safety, and transparency. The I 4.0 paradigm promotes the interconnection of sensors, devices and enterprise assets, not only to each other but also to the Internet [3]. This revolution is defined as a new level of organization and control over the entire production life cycle increasingly individualized customer requirements [4].

I 4.0 is still evolving and the corner stones of this revolution are technologies like Internet of Things (IoT), Industrial Internet of Things (IIoT), Smart Manufacturing, Cloud based manufacturing and Cyber Physical Spaces (CPS) [5]. The modern literature has discussed several definitions, applications and integrational architectures of these constituent. However, this paper focuses on the use of IIoT to monitor the Job Shop Scheduler (JSS) for the manufacturing industry, enhancing the efficiency of the whole SF.

The ability of the machines to perform tasks with least human assistance is considered as a general definition of automation today. This leads to the need of converting the machine already installed in the factory, into self-aware and self-learning machines to improve the performance and enabling automated maintenance [6]. This conversion has been made possible by the integration and communication of a few sensors forming IIoT. This technology allows factories to become more intelligent, flexible and dynamic by equipping SF with sensors, actors and autonomous systems [7]. Accordingly, machines and equipment will achieve high levels of self-optimization and automation [8], enabling industry to become smart industry and automation is the key.

This thesis puts forward a design for monitoring the machines on the SF, which has been fed the schedule generated by JSS. The proposed Monitoring System is able to record and monitor the activity on the SF using the space-age technology of IIoT, completing the feedback cycle and enabling JSS to finely tune the existing schedule. Monitoring of production system can be done in two ways: manually or automatically. Manual production monitoring is done by recording the production data by means of paper sheets. This method is prone to errors [9]. Meanwhile, the automatic production monitoring system requires sensors and algorithms analyzing the input data, providing transparency on the shop floor and improves manufacturing competitiveness [10].

Deep dive into literature [11] provides enlightenment on how to build real time SF monitoring system. It was found that an effective monitoring system should comprises of five key elements: collection, display, analysis, prognoses and data storage [9]. Automatic production monitoring systems requires appropriate sensor technology along with the right method used for data acquisition [12].

There are two primary methods of data monitoring: direct monitoring and indirect monitoring. Direct monitoring is a method of using sensors capable of directly measuring the quantities that emerge during the machining process. For example the use of laser, optical and ultrasonic sensors to measure the wear and tear rate of cutting tools on the machining process. The indirect monitoring method uses sensors that can indirectly measure the physical quantities such as the use of force, vibration and electric current and power drawn. This method is more efficient than direct monitoring but requires a more complex modeling for processing the signal [9]. In this thesis we are using indirect method to collect data for electrical current drawn by the machines using sensors as the IIoT. This collected data is then analyzed and the results prove the considerably improved productivity at SF ultimately leading to a better JSS.

1.2 The Motivation

The automation process comprises of two part, the feed forward and feedback loop or in other words, the process of automation of factory SF consists of the Scheduling Cycle and the Monitoring Cycle. Currently, SF are being operated either manually or by scheduled tasks performed by machines but monitored by the humans. This implies that not only the automation of feed forward loop must be done but also the feedback loop. Presently, the JSS are only automating SF via feeding the schedule to the machines on the floor enabling the automation. The feedback from the machines to the JSS is still not discussed extensively in literature. Therefore, a gap exists in this domain, making it the prime objective of our research. This gap became the motivation for pursuing this novel research and development based idea in hope to make it an industry based tested and implemented technology.

1.3 Scope of Work

The work represented in this thesis puts forward a design for monitoring the machines on the SF, which has been fed the schedule generated by JSS. The proposed Monitoring System can monitor and record the activity on the SF using the space-age technology of IIoT, completing the feedback cycle, enabling JSS to finely tune the existing schedule. Production monitoring system can be done in two ways: manually or automatically. Manual production monitoring system is done by recording the production data by means of paper sheets. This method is very vulnerable to errors. [9]. Meanwhile, the automatic production monitoring system provides transparency on the shop floor and improves manufacturing competitiveness [10].

Deep dive into literature [11] provides simple and clear explanation on how to build real time production monitoring system. It is also found that an effective monitoring system should comprise of five elements: collection, display, analysis, prognoses and data storage [9]. Automatic production monitoring systems also require appropriate sensor technology. According to [12], there are two primary methods of sensor measurement: direct monitoring and indirect monitoring. Direct monitoring is a method of using sensors capable of directly measuring the quantities of physics that emerge during the machining process. For example, the use of laser, optical and ultrasonic sensors to measure the wear rate of cutting tools on the machining process. The indirect monitoring method uses sensors that can indirectly measure the physical quantities. For example, the use of force, vibration and electric current sensors. This method is more efficient than direct monitoring but requires a more complex modeling for processing the signal [9].

1.4 Contributions

In this research, we are using electrical current sensors as the IIoT that is one of the indirect monitoring methods. Variation in electrical current sensors gives us current profiles of task being performed. Real time data is collected from these electrical sensors and current profiles are saved in database (DB). These current profiles are used to schedule the jobs on shop floor. This research focuses on these current profiles to monitor the JSS to provide the automated solution of re-scheduling the job shop floor. A Robust technique is implemented in this research work, which monitor the deviation in proposed scheduling with real time schedule and automatically re-schedule the JSS. This method is tested successfully in industry that reaffirms the importance of I 4.0.

1.5 Organization

The rest of the thesis is organized in the following manner. Chapter 2 provides the detailed theoretical background of the whole system along with the back ground knowledge needed to understand the system. Chapter 3 provides the detailed literature review. Chapter 4 discusses the methodology carried out in this research to enabling IIoT based JSS Monitoring System to perform the monitoring as intended. Chapter 5 provides the factory tested results and analysis of the system under discussion. Chapter 6 concludes the overall performance and give some future perspective in this field respectively.

CHAPTER: 2 THEORACTICAL BACKGROUND

2.1 What is IoT

The next steam engine for the evolution of human technology is interconnectivity. To understand the basic concept imagine an everyday object can communicate via a medium to all the other objects around it just like our laptops talk to the machines in next continent. The medium is the Internet. This connectivity of everyday devices or things over internet creates a space known as Cyber Physical Space (CPS). These CPS can be remotely monitored and controlled. This whole ecosystem gives birth to the Internet of Things (IoTs). No doubt IoTs have evolved as a result of convergence of various technologies, analyzing data in real-time, application of machine learning algorithms, integration of multiple sensors and embedded systems. Similarly the core fields of embedded systems, wireless sensor networks, control systems, automation (including home and building automation), and others all contribute to enabling the Internet of things.

The term "Internet of things" was likely coined by Kevin Ashton of Procter & Gamble, later MIT's Auto-ID Center, in 1999, [1] though he prefers the phrase "Internet for things". Initially Radio-frequency identification (RFID) was considered the most essential element to the Internet of things, which would allow computers to manage all individual things. The widespread applications for IoTs devices is often divided into consumer, commercial, industrial, and infrastructure spaces.

The IoTs are considered by many researchers as the natural extension of SCADA (Supervisory Control And Data Acquisition), a category of software application program for process control, the gathering of data in real time from remote locations to control equipment and conditions. SCADA systems include hardware and software components. The hardware gathers and feeds data into a computer that has SCADA software installed, where it is then processed and presented it in a timely manner. The evolution of SCADA is such that late-generation SCADA systems developed into first-generation IoT systems.

A growing portion of IoT devices are created for consumer use, including connected vehicles, home automation, wearable technology (as part of Internet of Wearable Things (IoWT)), connected health, and appliances with remote monitoring capabilities.

The IoT for medical and health related purposes, data collection and analysis for research, and monitoring. Along with assistance in the integration of communications, control, and information processing across various transportation systems can be categorized as the commercial application of IoTs. The vehicular communication systems, vehicle-to-everything communication (V2X) is also an example of the commercial applications of IoTs. IoT devices can be used to monitor and control the mechanical, electrical and electronic systems used in various types of buildings (e.g., public and private, industrial, institutions, or residential) in home automation and building automation systems.

Monitoring and controlling operations of sustainable urban and rural infrastructures like bridges, railway tracks and on- and offshore wind-farms is a key infrastructure application of the IoT.

The industrial internet of things (IIoT) refers to interconnected sensors, instruments, and other devices networked together with computers' industrial applications, including manufacturing and energy management. This connectivity allows for data collection, exchange, and analysis, potentially facilitating improvements in productivity and efficiency as well as other economic benefits. The IIoT is an evolution of a Distributed Control System (DCS) that allows for a higher degree of automation by using cloud computing to refine and optimize the process controls.

2.2 IIoT Technology

This thesis revolves around the Industrial Internet of things (IIoT). This technology is refered to as interconnected sensors, instruments, and other devices networked together with computers' industrial applications, including manufacturing and energy management. This connectivity allows for data collection, exchange, and analysis, potentially facilitating improvements in productivity and efficiency as well as other economic benefits. The IIoT is an evolution of a distributed control system (DCS) that allows for a higher degree of automation by using cloud computing to refine and optimize the process controls.

The IIoT is the use of smart sensors and actuators to enhance manufacturing and industrial processes. Also known as the industrial internet or Industry 4.0 (I 4.0), IIoT leverages the power of smart machines and real-time analytics to take advantage of the data that dumb machines have produced in industrial settings for years. The driving philosophy behind IIoT is that smart machines are not only better than humans at capturing and analyzing data in real time, they are better at communicating important information that can be used to drive business decisions faster and more accurately.

Five of the most important ones are described below:

- **Cyber-physical systems (CPS)**: the basic technology platform for IoT and IIoT and therefore the main enabler to connect physical machines that were previously disconnected. CPS integrates the dynamics of the physical process with those of software and communication, providing abstractions and modeling, design, and analysis techniques for integrated the whole.
- **Cloud computing**: With cloud computing IT services can be delivered in which resources are retrieved from the Internet as opposed to direct connection to a server. Files can be kept on cloud-based storage systems rather than on local storage devices.
- **Edge computing**: A distributed computing paradigm which brings computer data storage closer to the location where it is needed. In contrast to cloud computing, edge computing refers to decentralized data processing at the edge of the network. The industrial internet requires more of an edge-plus-cloud architecture rather than one based on purely centralized cloud; in order to transform productivity, products and services in the industrial world.
- **Big data analytics**: Big data analytics is the process of examining large and varied data sets, or big data.
- **Artificial intelligence and machine learning**: Artificial intelligence (AI) is a field within computer science in which intelligent machines are created that work and react like humans. Machine learning is a core part of AI, allows the software to become more accurate with predicting outcomes without explicitly being programmed.

2.3 Enterprise Level

Enterprise means Big Organization and Enterprise solutions means the software they use in their organization to secure and manage their work operation. Their IT admin has total control over the devices, apps, and content used by their employees. Services provided by enterprise software are typically business-oriented tools.

By definition Enterprise Software is a collection of computer programs that have common business applications, tools for modelling how the entire organization works, and development tools for building applications unique to the organization. The software is intended to solve an enterprise-wide problem, rather than a departmental problem. Enterprise level software aims to improve the enterprise's productivity and efficiency by providing business logic support functionality.

Enterprise systems (ES) are large-scale enterprise software packages that support business processes, information flows, reporting, and data analytics in complex organizations. Types of enterprise systems include:

- enterprise resources planning (ERP) systems,
- enterprise planning systems, and
- customer relationship management software

Although data warehousing or business intelligence systems are enterprise-wide packaged application software often sold by ES vendors, since they do not directly support execution of business processes, they are often excluded from the term.

2.4 Production Levels and Factory Shop Floors

The enterprise level is at the top of the architecture scheme and the ground work to this scheme is the production level, where actual manufacturing happens. The factory Shop Floor (SF) are the atomic unit of the production level. Effective management of SF acts as the optimization catalyst for the production level and ultimately enterprise level leading to the efficient material handling and low-waste low-cost production at factory SF. This represents the current scenario at the production level where human intervention is necessary. The SF consists of the machines such as Milling, CNC, and Lathe etc. which need human operators and human supervision. Figure 2 shows an illustration of SF at the production level. In traditional SF the tasks on every machine is done manually and is prone to error along with being in contradiction to the concept of I 4.0.

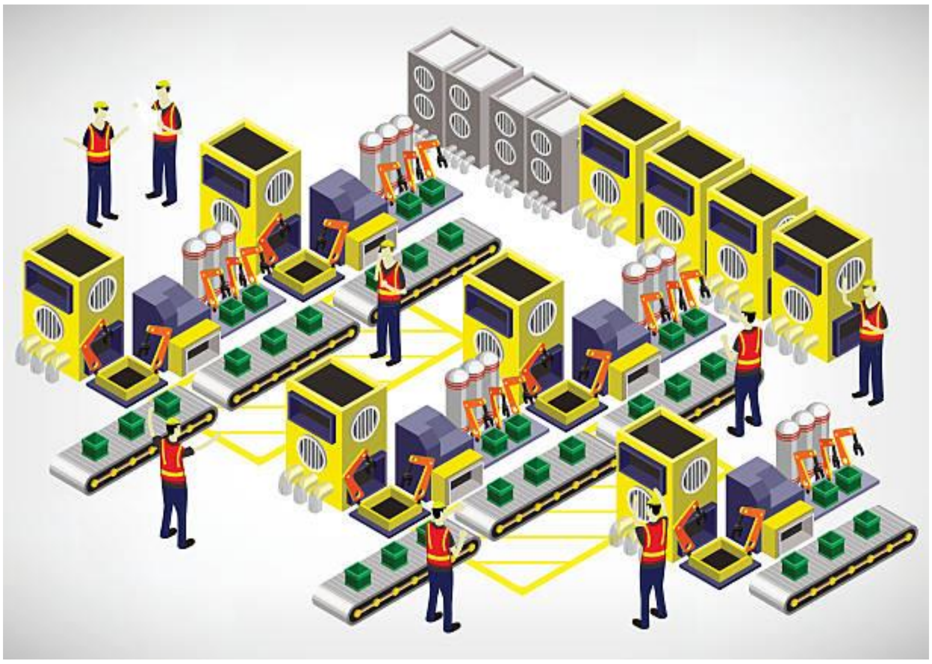


Figure 2 Shop Floor Illustration

2.5 Job Shops and Job Shop Scheduler

Scheduling tasks for a SF to optimize the resources, can be done in a number of ways and via variety of tools. At production level (Factory level) it can be done manually using paper for layman or by digital illustration in a manager's office. In literature scheduling schemes are illustrated by Gantt charts and the Disjunctive graphs. However since here our approach is more of practical nature hence Gantt charts are discussed. They are widely used in highly efficient factories such as Aircraft Manufacturing Industry, enabling workers and manager to plan using software like Microsoft Project or Oracle Primavera P6. They providing a pictorial overview standing true to the saying "a picture is worth a thousand words". Figure 3 show a rudimentary Gantt chart for the scheduled tasks.

ID	Task Name	Predecessors	Duration
1	Start		0 days
2	a	1	4 days
3	b	1	5.33 days
4	c	2	5.17 days
5	d	2	6.33 days
6	e	3,4	5.17 days
7	f	5	4.5 days
8	g	6	5.17 days
9	Finish	7,8	0 days

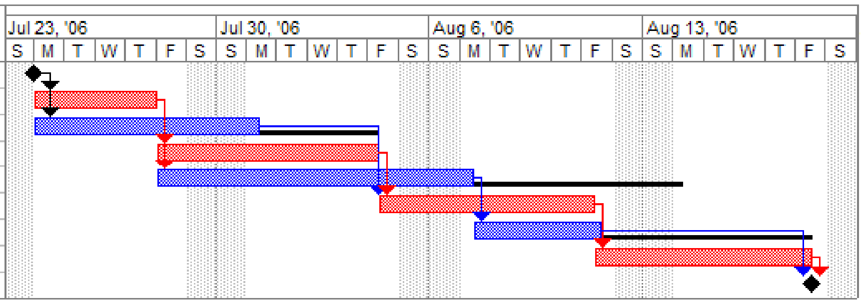


Figure 3 Gantt chart representing tasks and the unit time

There are a number of factors that need to be taken into consideration before scheduling tasks for a shop floor. For instance the duration required for completion of a task, the order in which tasks are to be performed on a particular machine, the availability of the machines, the duration for which a machine may be used, the time for which machine stays idle in the whole day, the total time needed to complete all the tasks and many more. For example a nut has to be made from cylindrical aluminum piece. Crudely speaking the aluminum raw material should be first drilled in its center then thread should be made, followed by the surfacing of its outer edges. Hence there are three tasks that are to be scheduled on the three available machines on the shop floor. Now suppose a screw is to be manufactured on shop floor as well. The aluminum cylinder will first be trimmed on the outer surface followed by threading and in the last grooved. These three tasks will also be processed by the same machines but in different order, at different time and in different time period. Figure 4 represents this arrangement. Here the question arises, is this the ideal arrangement for best resource management?

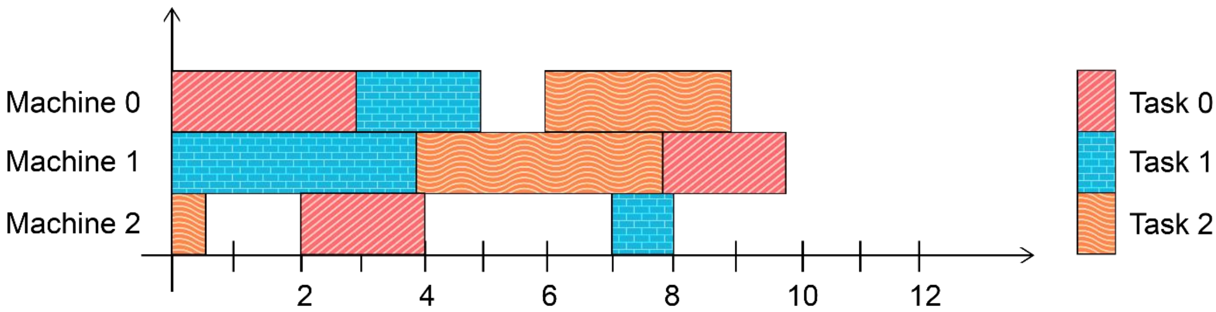


Figure 4 Division of three tasks for every machine

Classical Job Shop Problem (JSP) has its own jargon for these factors. The number of machines $(\boldsymbol{M_0}, \boldsymbol{M_1}, \dots \dots \dots \boldsymbol{M_m})$ available on the SF is considered as the first factor. Machines now require the tasks that are to be processed called Jobs $(\boldsymbol{J_0}, \boldsymbol{J_1}, \dots \dots \dots \boldsymbol{J_j})$ that are to be scheduled on machines $\boldsymbol{M_m}$. The matrix X represents a case of three jobs and two machines every machine must process every job only once.

$$X_{jm} = \begin{bmatrix} J_0 & J_1 \\ J_1 & J_2 \\ J_2 & J_0 \end{bmatrix} \dots \dots \dots (1)$$

Third factor to determine is whether the jobs can further be broken down in to operations $(\boldsymbol{O_{0j}}, \boldsymbol{O_{1j}}, \dots \dots \dots \boldsymbol{O_{ij}})$ or they are the atomic level jobs $(\boldsymbol{J_a})$. Let's say J_1 is to make an aluminum nut as in example given above, hence this job can be broken down into 3 sub parts or operations and can be represented as $J_1 = \{\boldsymbol{O_{01}}, \boldsymbol{O_{11}}, \boldsymbol{O_{21}}\}$. Similarly there are other jobs which have a specific number of operations as well. For simplicity let's consider three jobs having three operations each. The columns in the following matrix denotes the jobs while the operation number is represented by the rows.

$$\boldsymbol{O_{ij}} = \begin{bmatrix} \boldsymbol{O_{00}} & \boldsymbol{O_{01}} & \boldsymbol{O_{02}} \\ \boldsymbol{O_{10}} & \boldsymbol{O_{11}} & \boldsymbol{O_{12}} \\ \boldsymbol{O_{20}} & \boldsymbol{O_{21}} & \boldsymbol{O_{22}} \end{bmatrix} \dots\dots\dots\dots (2)$$

Next it is considered that every machine has to be occupied for a limited period of time, referred to as the processing time ($\boldsymbol{P_{ij}}$) required for the completion of each $\boldsymbol{O_{ij}}$ along with a start time ($\boldsymbol{t_{ij}}$) at which operation must begin for the smooth flow and timely completion of the jobs. The total time period that encompasses $\boldsymbol{P_{ij}}$ and $\boldsymbol{t_{ij}}$ is known as make span ($\boldsymbol{S}$) as represented by equation 3.

$$\boldsymbol{S_{max}} = \mathbf{max}\{\boldsymbol{t_{ij}} + \boldsymbol{P_{ij}}\} \dots\dots\dots. (3)$$

Every operation $\boldsymbol{O_{ij}}$ corresponds to an Ordered Pair ($\boldsymbol{M_m}$, $\boldsymbol{P_{ij}}$): operation $\boldsymbol{O_{ij}}$ need to be processed on $\boldsymbol{M_m}$ machine for a period of $\boldsymbol{P_{ij}}$. Hence the ordered pair is the breakdown of $\boldsymbol{O_{ij}}$ and represented finally as equation 4 below.

$$O_{ij} = \begin{bmatrix} (\boldsymbol{M_1}, \boldsymbol{P_{00}}) & (\boldsymbol{M_1}, \boldsymbol{P_{01}}) & (\boldsymbol{M_3}, \boldsymbol{P_{02}}) \\ (\boldsymbol{M_1}, \boldsymbol{P_{10}}) & (\boldsymbol{M_0}, \boldsymbol{P_{11}}) & (\boldsymbol{M_0}, \boldsymbol{P_{12}}) \\ (\boldsymbol{M_1}, \boldsymbol{P_{20}}) & (\boldsymbol{M_0}, \boldsymbol{P_{21}}) & (\boldsymbol{M_2}, \boldsymbol{P_{22}}) \end{bmatrix} \dots\dots\dots. (4)$$

$$O_{ij} = \begin{bmatrix} (\mathbf{1}, \mathbf{2}) & (\mathbf{1}, \mathbf{2}) & (\mathbf{3}, \mathbf{7}) \\ (\mathbf{1}, \mathbf{2}) & (\mathbf{0}, \mathbf{4}) & (\mathbf{0}, \mathbf{10}) \\ (\mathbf{1}, \mathbf{2}) & (\mathbf{0}, \mathbf{5}) & (\mathbf{2}, \mathbf{5}) \end{bmatrix} \dots\dots\dots. (5)$$

Matrix in equation 5 can be represented in Gantt chart in Figure 5**Error! Reference source ot found.** and vice versa. For instance the ordered pairs (0, 4) is operationO_{11} which is the first operation to be performed for job no. 1. This must be processed on machine zero (the first machine on shop floor) for a unit time of 4 days. Thus for J_1 to be marked as complete all of the operations $J_1 = \{\boldsymbol{O_{01}}, \boldsymbol{O_{11}}, \boldsymbol{O_{21}}\}$ must also be completed which will take 11 days as per our scenario. Here it is worth mentioning that start time $t_{01} = 15\ Nov$ 2018 for O_{01} but to calculate the make span for the whole schedule $S_{max} = \max\{t_{23} + P_{40}\}$ is being used. Here $S_{max} = 40\ days$. The objective is to reduce make span as far as possible keeping in view the expense of other key resources such as machines or human resources. Less the make span more optimized is the JSS. Since we are working on the JSS Monitoring System that will ultimately act as the input for the JSS hence firm understanding is necessary.

So far it is understood how the augmented manual scheduling is done. The scheduled jobs are displayed as Gantt chart and can be represented as a matrix as well.

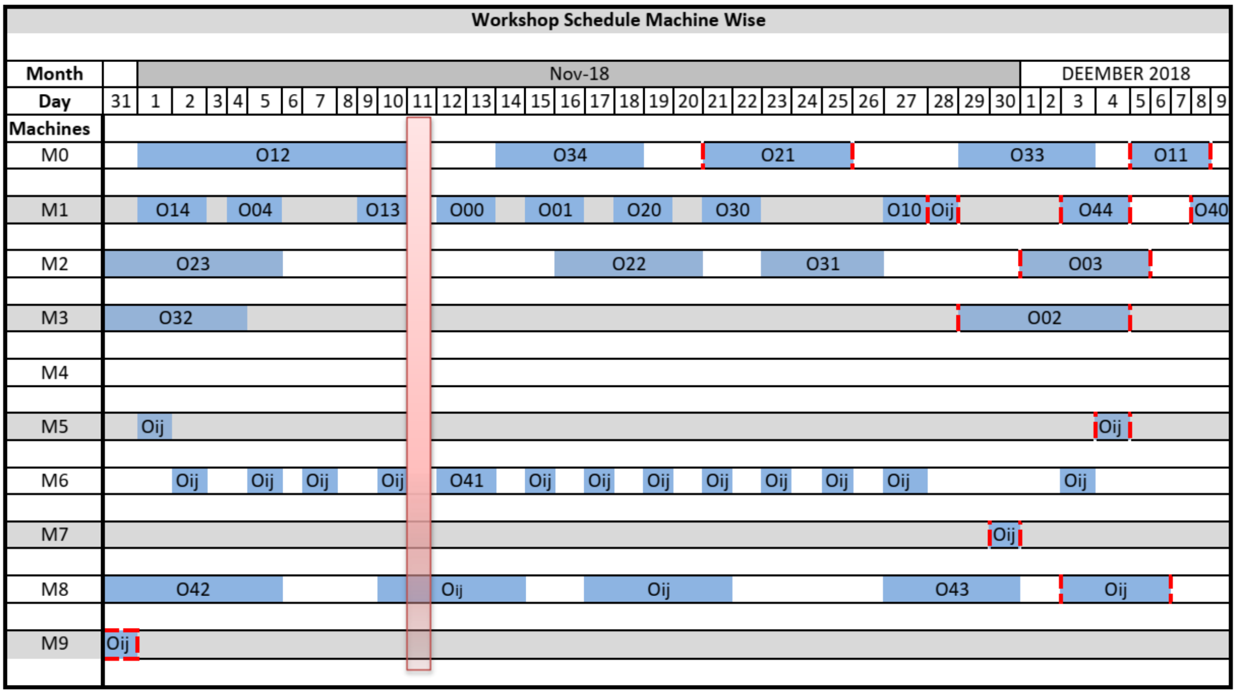


Figure 5 Gantt chart representation of the Job Shop Schedule.

The schedules can also be generated by using a number of algorithms. For example a heuristic algorithm, Johnson's algorithm is used to solve the case of $M_m = 2$ machines and $J_j = j$ problem when all jobs are to be processed in the same order. Yet another example is the Genetic Algorithm (GA). Since JSP falls under category of "Combinational Optimization" exhaustive search is not tractable and GA's tendency to converge towards local optima or even arbitrary points rather than the global optimum, makes it viable only for non-exponential increase in search space size. Another promising algorithm is the Tabu Search Optimization Technique, a Global Optimization algorithm and a Metaheuristic or Meta-strategy for controlling an embedded heuristic technique. It takes a potential solution to a problem and check its immediate neighbors (that is, solutions that are similar except for very few minor details) in the hope of finding an improved solution. Local search methods have a tendency to become stuck in suboptimal regions or on plateaus where many solutions are equally fit.

2.6 Monitoring Job Shop Scheduler

The SF work in accordance to the schedule produced by JSS. The monitoring of SF is done by the line mangers mostly manually using paper based method. This cause a considerable delay and is prone to errors. The monitoring enable floor managers to optimize JSS according to the information received by the line manager. This is the scenario representing a normal routine SF activities where every machine works in accordance to the schedule but what happens if a priority based job comes? This will take a human based monitoring to readjust the whole schedule just to the extent where the priority task is done and then JSS plan is executed on SF.

The question arises how does the human based monitoring happens? Traditionally the monitoring was done by two primary methods of data monitoring: direct monitoring and indirect monitoring. Direct monitoring is a method of using sensors capable of directly measuring the quantities that emerge during the machining process. For example the use of laser, optical and ultrasonic sensors to measure the wear and tear rate of cutting tools on the machining process. The indirect monitoring method uses sensors that can indirectly measure the physical quantities such as the use of force, vibration and electric current and power drawn. This method is more efficient than direct monitoring but requires a more complex modeling for processing the signal [2]. In this thesis we are using indirect method to collect data for electrical current drawn by the machines using sensors as the IIoT. Thanks to the development of IIoT technology measuring the variable factors such as the electric current and the power drawn is relatively easier, more accurate and customizable as per our requirement.

CHAPTER: 3 LITERATURE REVIEW

Machining workshop also known as the SF consumes a lot of energy and an effective method of monitoring is missing. The monitoring system proposed here [3] is based on IoT technology and hence potential energy efficiency can be achieved by the proposed solution. Potential for energy savings in the manufacturing sector lies not only in optimizing production process for energy, but also in developing novel energy monitoring approach [4].

The study presented in this paper [5] is an IoT based monitoring system. The components of this system are DAQs, wireless sensor networks and a cloud server. The system consists of three layers i.e., the DAQs with the sensors in the machine-tools, the microcomputer gateway with the local database, and the central cloud server. Moreover, a wireless sensor network is implemented to transfer from the sensor nodes to the microcomputer coordinator. The developed framework provides automatically reports on the tasks performed in a SF, which is a procedure that up until now included a lot of manual work. This provides new capabilities for manufacturing companies to advance into the digital era and harvest the benefits that arise. [2]

Similarly this paper [5] also provides us with a framework that enables manufacturing systems to be transformed into digital ecosystems. In this transformation, the internet of things (IoT) and other emerging technologies pose a major role. To shift manufacturing companies toward IoT, smart sensor systems are required to connect their resources into the digital world. To address this issue, the proposed work presents a monitoring system for shopfloor control following the IoT paradigm. The proposed monitoring system consists of a data acquisition device (DAQ) capable of capturing quickly and efficiently the data from the machine tools, and transmits these data to a cloud gateway via a wireless sensor topology.

The developed system follows the loT paradigm in terms of connecting the physical with the cyber world and offering integration capabilities with existing industrial systems. In addition, the open platform communication—unified architecture (OPC-UA) standard is employed to support the connectivity of the proposed monitoring system with other IT tools in an enterprise.

[2] Every production process requires monitoring system, so the desired efficiency and productivity can be monitored at any time. This system is also needed in the job shop type of manufacturing which is mainly influenced by the manufacturing lead time. Processing time is one of the factors that affect the manufacturing lead time. In a conventional company, the recording of processing time is done manually by the operator on a sheet of paper. This method is prone to errors. This paper aims to overcome this problem by creating a system which is able to record and monitor the processing time automatically. The solution is realized by utilizing electric current sensor, barcode, RFID, wireless network and windows-based application. An automatic monitoring device is attached to the production machine. It is equipped with a touch screen-LCD so that the operator can use it easily. Operator identity is recorded through RFID which is embedded in his ID card. The workpiece data are collected from the database by scanning the barcode listed on its monitoring sheet. A sensor is mounted on the machine to measure the actual machining time. The system's outputs are actual processing time and machine's capacity information. This system is connected wirelessly to a workshop planning application belongs to the firm. Test results indicated that all functions of the system can run properly. This system successfully enables supervisors, PPIC or higher level management staffs to monitor the processing time quickly with a better accuracy.

Nowadays, a large amount of energy is consumed by buildings in the city. Among them, industrial energy consumption accounts for a large proportion due to the high power of manufacturing devices in the job-shop. To achieve higher energy-efficiency, lots of scheduling methods in the job-shop are developed. However, most of the current scheduling method is based on the prior-experimental data and the schedule of the production cycle cannot be adjusted according to energy status of manufacturing devices.

Thus a dynamic scheduling system based on the cyber-physical energy monitoring system is proposed to improve the energy efficiency of the job-shop. First, a novel process of ''scheduling-monitoring-updating optimizing'' is implemented in the proposed system. In the scheduling model, tool aging condition is considered along with the geometry information of the work-piece to estimate energy consumption of the manufacturing process. At last, a modified genetic algorithm with multi-layer coding is applied to generate an energy-efficient schedule. The proposed system is implemented in a production cycle which contains 36 operations of six work-pieces and ten machine tools to prove its validity.

Zhou et al. [12] made a comprehensive review of the existing energy consumption models and pointed out that the energy efficiency of a machining process is highly dominated by its Material Remove Rate (MRR), which is determined by a series of cutting parameters, such as feed rate, cutting force and scallop height requirement, etc. Aramcharoen and Mativenga [13] calibrated the energy consumption model for three feed axis and found that the feed rate influences the driving power linearly. Hence, zig-zag and spiral tool path generation method with no unnecessary air-cuts could lead to a significant promotion of energy efficiency. Besides, feed rate is also an important distributor which is highly proportional to the other machining parameters and impacts the total energy cost.

Since lots of machining parameters of machining are highly coupled, many researchers focus their attention on optimizing series of parameters simultaneously to minimize the energy consumption. Li et al. [14] presented an integrated approach of process planning and cutting parameter optimization for energy-aware CNC machining to achieve minimum energy consumption and balance of machine workloads. Sato et al. [15] constructed an energy consumption model of feed-drive system based on the machine tool configuration, including the masses, sizes, velocities and moments of inertia, etc. Kant and Sangwan [16] proposed an accurate predictive model of energy consumption using ANN, and analyzed the impacts of spindle speed, feed rate, cutting depth, cutting stripe width on the cutting energy consumption. Some researchers, such as Mouzon et al. [17] and Hu et al. [18], proposed methods which optimized the whole machining process which contains milling, turning, grinding, etc. Besides, plenty of heuristic algorithms are applied to optimize the working process in the job-shop.

CHAPTER: 4 RESEARCH METHODOLOGY

To be able to produce a resource efficient schedule is half the battle. Without monitoring the SF in real time, it is not possible to ensure the productivity of the schedule generated by JSS. This section discusses the approaches taken to monitor the schedules to estimate the difference between the scheduled jobs and actual developments at the SF.

4.1 The Esplanade

There are a number of ways in which machine schedule can be monitored on a SF. The jobs performed by the machines are analyzed by “current profiles” or “machine energy signatures”. In order to profile machines’ current, the energy consumed while performing different operations needs to be recorded. Therefore it is indispensable to measure the electric current drawn by them during different stages of the machining processes. For this instance a number of approaches can be applied e.g. a visual inspection via watt meters to collect data manually but this approach is not feasible due to larger time constraint and higher error rate. Therefore two approaches were tested, pulling data from the Programmable Logic Controllers (PLC) and Supervisory Control and Data Acquisition (SCADA) embedded in the SF machines or to use new IIoTs. Keeping in view our specific design requirements IIoTs were pursued further and the reason to select this technology over other approaches is also discussed in the following sections.

4.1.1 MT Connect

Many of the contemporary SF machines have in-built features of operation monitoring, data acquisition and data storage automatically. This is done via the use of PLC and SCADA technology. In [13] researchers have exploited these features by developing Web-based Remote Machine Monitoring System for several types and brands of machines. The system provides data collection, analysis and machine event notification for the SF managers enabling him to improve efficiency of the entire SF. Moreover, the proposed system was accessible remotely via internet. The type of the machines used were compliant to MTConnect, a manufacturing communications protocol standard. This protocol retrieve information in form of data log from the PLC and SCADA embedded in machines. Unfortunately, many of the machines still operating on SF now a days are old version of machines, which are unequipped with MTConnect technology.

The purpose of industrial automation is to re-engineer SF machines in a manner to provide computerization as an add-on also known as plug and play scheme. This decision is made keeping in view a known fact, that the commercial machine-tools have the life span of the 30 years or more [1] hence, old machinery often does not have the required capabilities for connectivity. Therefore, efforts were focused towards the IIoT device relying on plug and play abilities.

4.1.2 Onset® HOBO® ZW Series Wireless Sensors

The IIoTs studied next for the current profiling are Onset® HOBO® ZW Series Wireless Sensors. The current profiling was done by placing the current sensor between the sockets and the machines as shown in Figure 6 below.

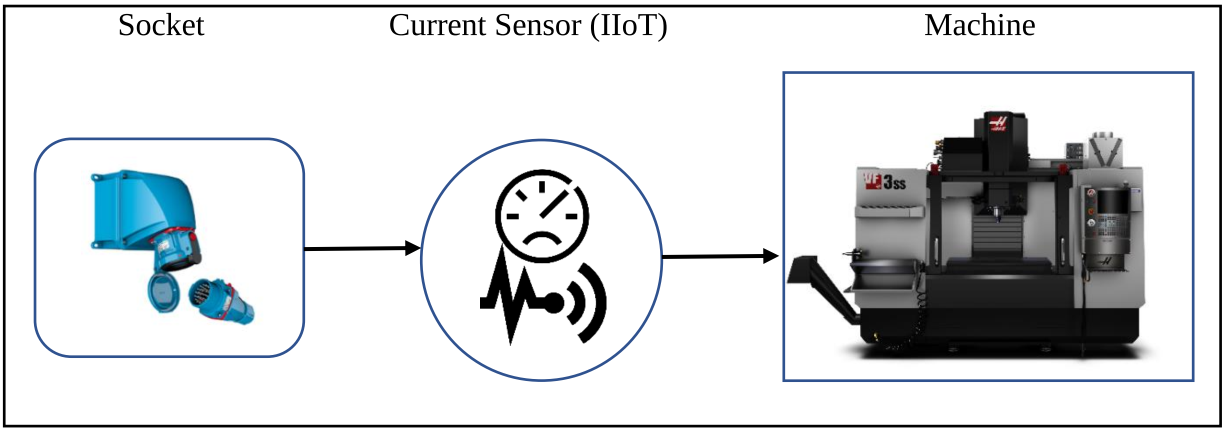


Figure 6 Current IIoT placed between the power socket and the shop floor machine

These sensors have a number of features that may or may not be of use depending on the level of analysis required and the style of communication on SF. Table 1 gives an overview of the features and the set elements that were required for our particular design and the features that were not suitable.

Table 1 ONSET HOBO ZW FEATURES

Supporting Features	Non-Supporting Features
Real-time centralized data collection within a facility	Data logging interval either 30 sec or 1 min

Scales up to a network of 100 nodes	Per node price expensive for PKR economy, ranging between $241 to $329 per node
Self-healing network to overcome obstructions in communication paths	Nodes difficult to integrate when forming network for the first time
Proprietary software for organizing and viewing data	Software generates only the MS Excel sheet for logged data externally, else all the data manipulation is done only in the software
wireless network	Our SF requirements were to use wired sensors

In designing any SF monitoring system, it is emphasized that the important design aspects are kept in mind such as being economical, accurate and easy to set up on a production line. Although Onset® HOBO® ZW Series Wireless Sensors are excellent IIoTs, but we had to drop these mainly due to the high cost due PKR vs US$ exchange rate and secondly due to strict client requirement of wired IIoT network.

4.1.3 Our very own Current IIoT

Keeping aforementioned point of view, we designed our own IIoT based on Arduino-computing platform, Ethernet and current sensor. It is capable of collecting 5 readings per second saved in a database (DB) as the value of current and futher converted in to Root Mean Square Values ("I" _"RMS"). Its worthy to mention here that the data pulling frequency is reconfigurable. This data can be pulled from the DB in .CSV format to be further processed and analyzed in the proposed Job Shop Scheduler Monitoring System. These IIoTs were placed in the same fashion as in Fig 1 above, on 20 SF machines for the starters and the current profiles were saved in DB. Although for this specific paper we are going to stipulate a defined set of operations on the SF machines so that data acquisition, analysis and results are easier to understand for the readers.

4.2 The Data Acquisition

The current profiles of one milling machine but different operations are generated for this paper specifically. Keeping the machine constant provides us with the ability to consider “jobs, operations and tasks” as the varying factor. The data acquisition is done to make the current profile of the milling machine while performing different tasks. The Table 2 below provides the milling operations along with their tasks breakdown, performed for the current profiling.

Table 2 FIVE OPERATIONS REPRESENTING THEIR TASKS

Milling Operations	Task-1 along x-axis	Task-2 along y-axis	Task-3 along z-axis
CASE-I	10	10	1
CASE-II	15	10	1
CASE-III	15	15	1
CASE-IV	20	15	1
CASE-V	20	20	1

For example CASE-I represents a single milling operation which is a part of a job and is further divided into three tasks i.e. milling along x-axis, y-axis and the z-axis in a unit length. Similarly in CASE-V milling is done 20 unit lengths in x-axis followed by 20 unit length in y-axis and 1 unit length in z-axis. These tasks cause the milling machine on our SF to draw different current values. It is understood that in CASE-I the current drawn will be less as compared to the CASE-V. These raw current readings are measured by the IIoT and values are placed in DB. This raw data is of no use as is until these values are further processed into I_{RMS} using (1).

$$I_{RMS} = I/\sqrt{2} \qquad (1)$$

The data set in I_{RMS} is now used to make the current profiles of each machine on the SF, which is ultimately used in the monitoring system of the JSS. Figure 7 A look inside DB having I_RMS values saved .CSV fileshows the values for I_{RMS} is arranged in a .CSV file. While each column represents I_RMS values for each machine performing different operation. Hence each column in actual is one current profile.

	A	B	C	D
1	1.31	1.46	1.31	1.36
2	1.33	1.3	1.31	1.313333
3	1.31	1.32	1.33	1.32
4	1.33	1.31	1.35	1.33
5	1.35	1.31	1.44	1.366667
6	1.33	1.32	1.53	1.393333
7	1.34	1.42	1.62	1.46
8	1.35	1.87	1.83	1.683333
9	1.34	3.2	2.52	2.353333
10	1.32	2.85	3.16	2.443333
11	1.34	3.2	3.16	2.566667
12	1.33	3.22	4.12	2.89

4.3 The Data Analysis

The objective of the proposed JSS monitoring system is to monitor the real time situation on the SF and to provide the feedback to the JSS for re-adjustment of the machining schedule if need be. This data acquired via IIoT is used to generate the current profiles. These profiles are saved in DB as pre-generated current profiles for the machines. They are then compared to the real time current profiles also produced in real time by the IIoTs and analyzed by the JSS monitoring system.

4.3.1 The Current Profiles

The current profile of the operation for the above mentioned milling machine i.e. CASE-I is shown in the Figure 8 M_1 implementing CASE-I below. The graph represents variation of I_RMS across time, performing the tasks by Machine-1(M_1). When JSS gives out the schedule to SF, the machines start working in the set pattern. JSS monitoring system reads the real time scenario on the SF via IIoT. This enables a real time M_1 current profile to be generated and saved in DB. Figure 9 Saved Current profile vs Real-time Current Profile for CASE-I represents the predicted vs actual current profiles where the time delay is evident; leading to rescheduling of JSS. The fluctuations may not only be in terms of time delay but also in the values of I_RMS due to the real time scenario while milling for CASE-I.

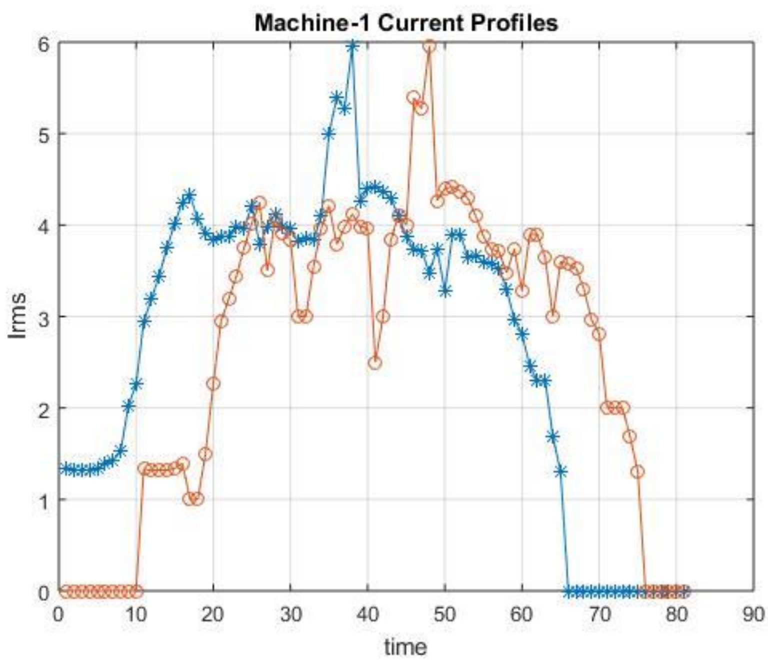


Figure 8 M_1 implementing CASE-I

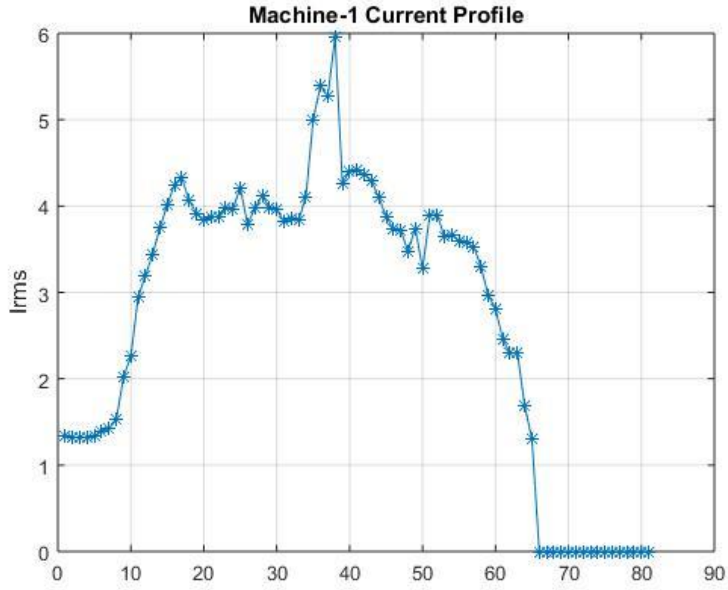


Figure 9 Saved Current profile vs Real-time Current Profile for CASE-I
Figure 9 M_1 implementing CASE-I

Now the question arises how the proposed JSS monitoring system will judge the fluctuation of real vs predefined schedule via current profiles? Since the JSS is reliant on the time line being followed, hence the change in time is the key factor. The correlation coefficient provides us with the factor that can decide the behavior of our JSS monitoring system.

4.3.2 Finding Correlation

The scheduled current profiles generated by JSS and the real time current profiles being read by IIoT are compared by correlation. In doing so, the concepts of auto-correlation, cross-correlation and the correlation coefficient are key factors. The proposed JSS monitoring system uses Pearson Correlation Coefficient to be specific, which is stated in (2).

$$\rho(A,B)=\frac{1}{N-1}\sum_{i=1}^{N}\left(\overline{\frac{A_i-\mu_A}{\sigma_A}}\right)-\left(\frac{B_i-\mu_B}{\sigma_B}\right) \qquad (2)$$

Where "μ" _"A" and σ_A are the mean and standard deviation of column vector A respectively, and μ_B and σ_B are the mean and standard deviation of vector B. This deduces that ρ(A,B) calculates the correlation coefficient for vector A and B, which are the real-time and predicted current profiles from M_1 performing CASE-I on the SF. The correlation is said to be a cross-correlation, if the vector A and B have considerable different values. But in case both the vectors have considerable similar values it is said to be auto-correlation. While finding the correlation between the two current profiles, the greater chances are of cross-correlation because of the differences in profiles.

In our case the actual and predicted current profiles (or vector A and vector B) are computed and the results are analyzed to determine whether the SF machines are running according to schedule or are in the state of lead or lag. The results of these correlations and their analysis are discussed in detail in section III. The proposed JSS monitoring system uses correlation coefficient, to compare the current profiles and providing the feedback to the JSS to readjust the schedule for the SF and the machines performing operations. The following section provides the details of the JSS monitoring system algorithm.

4.4 The Algorithm governing JSS Monitoring System

In this research paper, a particular case of SF schedule was generated and machines on SF were then allowed to operate in accordance to it. The real-time current signature were generated using our IIoT and correlated to determine the need for feedback to the JSS, completing the closed loop feedback path, enabling automatic detection of completion time of a job and based on that, dynamic rescheduling. Figure 10 represents the schedule generated by JSS. In this schedule, the machines are represented by M_k, where k represents the machine number on the SF. O_ij is the operations being performed, i represents the operation number while j represents the job number in terms of JSS terminology. Time line in which the operation O_ij must complete is represented along the x-axis at the top of the schedule Figure 10.

The current profiles that are being produced by the IIoT in real time on the SF can have three possible outcomes. Either the real-time current profiles are leading in time unit that is greater than the desired threshold level or are in a lag. The third scenario can be the ideal case were JSS provided schedule and the real-time current profiles match exactly. For further understanding let's take operation O_23 as an example, shown in Figure 11 Operation O_23 needs to be completed in 6 days. Although for every JSS the time unit can vary from days to minutes, as per factory requirements.

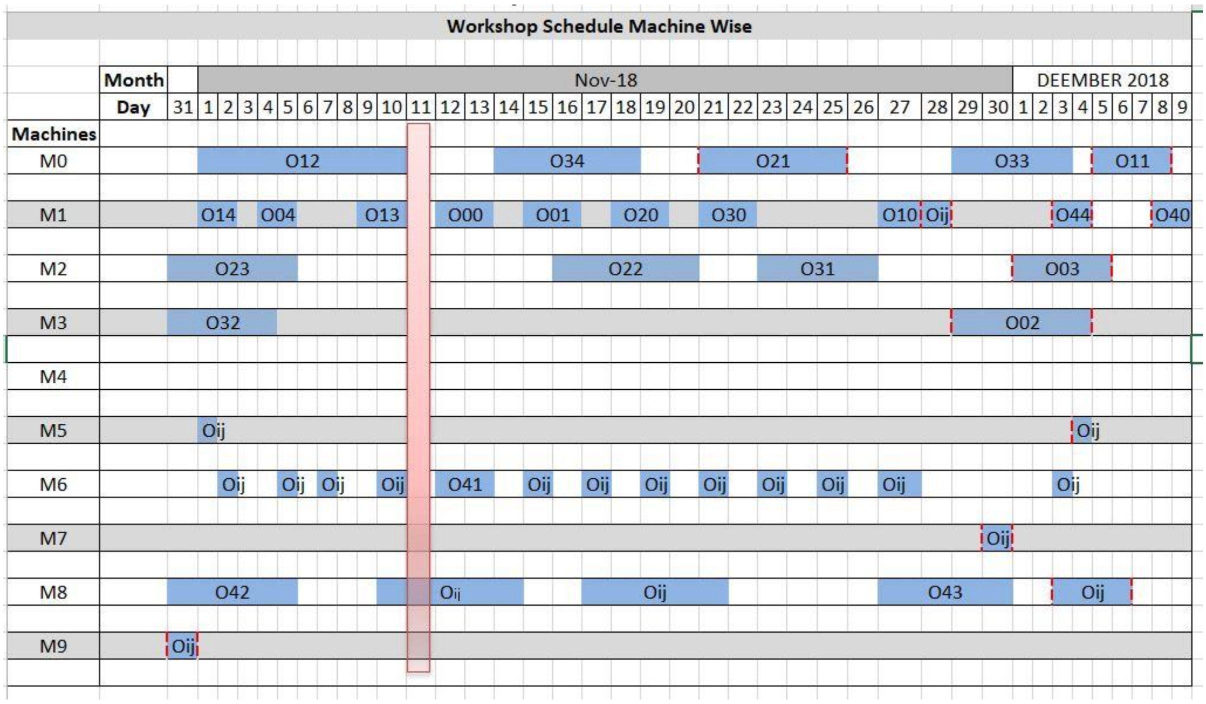


Figure 10 Schedule generated by the JSS

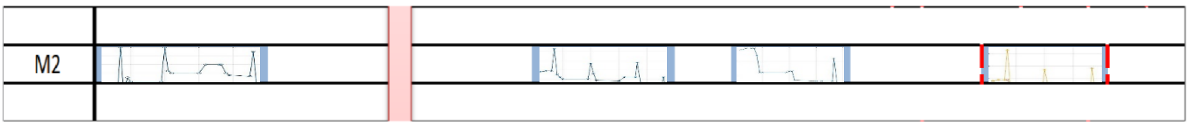


Figure 11 Current profiles per operation saved in DB

Once M_2 starts working on the operation in real time the current profiles received may be different. Fig. 7 provides the flow of the algorithm for JSS monitoring system. The current IIoT receives the current signature for O_23 at a certain time. This comparison is done by performing the correlation between the current profiles for M_2 saved in DB and the real-time current profile. Next the result of this correlation is analyzed. The greater correlation between current profiles of M_2, indicates the case of schedule matching. Now the next check will be whether there is a time delay or not. In case there is no time delay the operation e.g. O_23 is being performed as scheduled. In case there is delay greater than a certain threshold, the JSS must reschedule O_23 along with all the operations dependent on it. Acceptable threshold limit is determined by iteration and analysis of the operations over a long time period and by input from SF manager also known as the actor.

It is assumed here that threshold is set manually by the choice of the manager in our particular case.

If the correlation or matching between the current profiles is near to zero, JSS monitoring system searches the DB for any profile similar to the current profile being received from IIoT. In case there is a match available the operation is classified as that certain operation e.g. O_22 and doesn't not prompt any rescheduling. But if there is no match found, JSS monitoring system prompts the machine operator to enter the operation being performed. This may be a new process or a high priority urgent task, which must become the part of the job shop scheduler and the data base. The action will trigger the rescheduling on JSS.

In this manner the monitoring system is not only updating the DB for JSS but also keeps an eye on vagaries in the SF operations, raising flags for human intervention and optimizing the resource utilization.

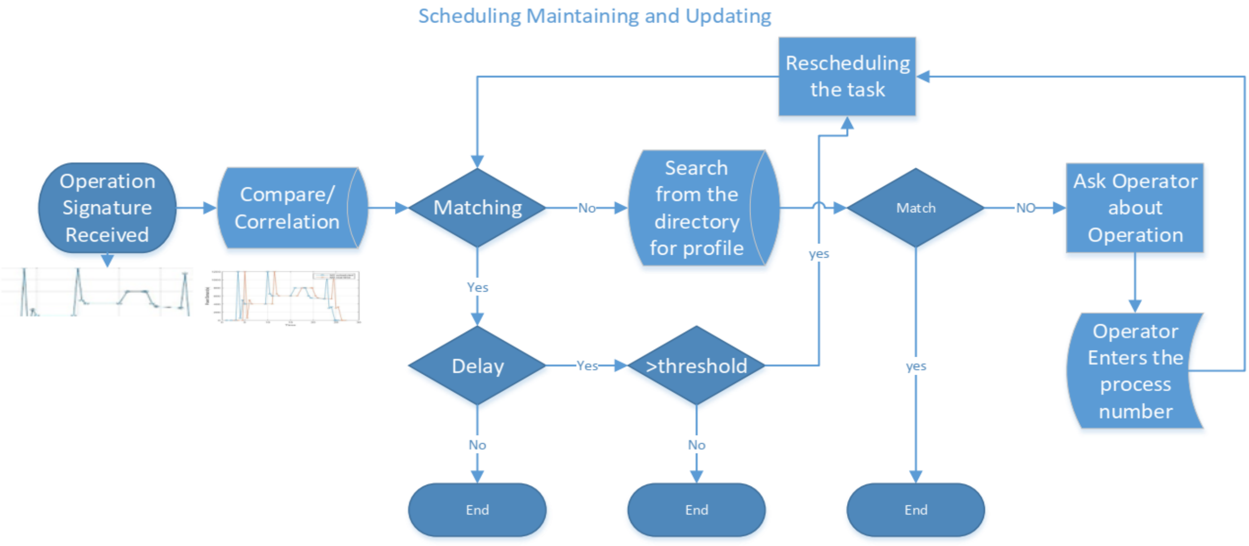


Figure 12 JSS Monitoring System Algorithm

CHAPTER: 5 RESULTS AND ANALYSIS

This section presents graphs showing the importance of the current profiles, their comparison via correlation, correlation coefficient and rescheduled JSS. The example of machine M_2 performing operation O_23 as mentioned previously, has the following current profiles as shown in the Fig. 8. The time delay is evident and JSS monitoring system senses this delay by performing correlation on the two current profiles and analyzing the value of correlation coefficient.

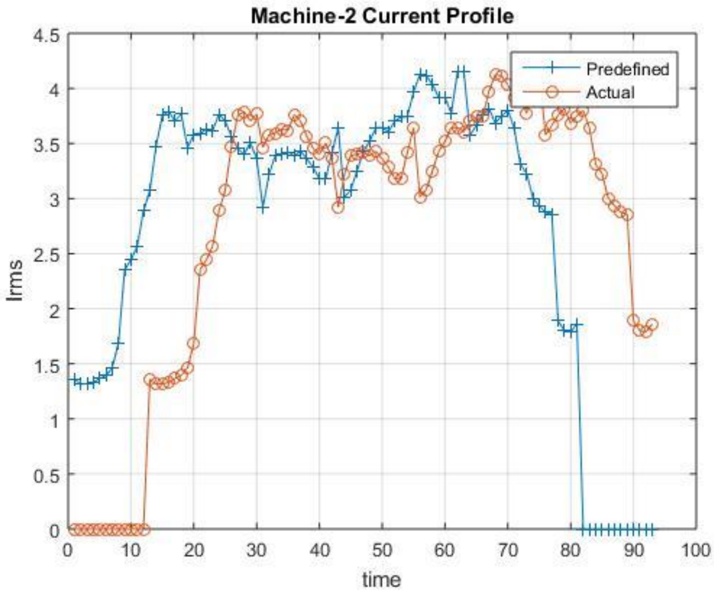


Figure 13 predicted vs actual Current profiles for Machine 2

The closer the results of the correlation coefficient are to the value of 1, the two signals are strongly correlated. In terms of correlation graph in Fig. 9, the whole curve is shifted towards right of zero, indicating the lead of actual current profile. But this shift in actual indicates delay in start of operation on SF. The correlation coefficient matrix for M_2 is shown below. The value of 0.3272 shows lesser correlation between the two current profiles, along with being below threshold limit and hence the JSS rescheduled the operation O_23.

$$\begin{bmatrix} 1.0000 & 0.3272 \\ 0.3272 & 1.0000 \end{bmatrix}$$

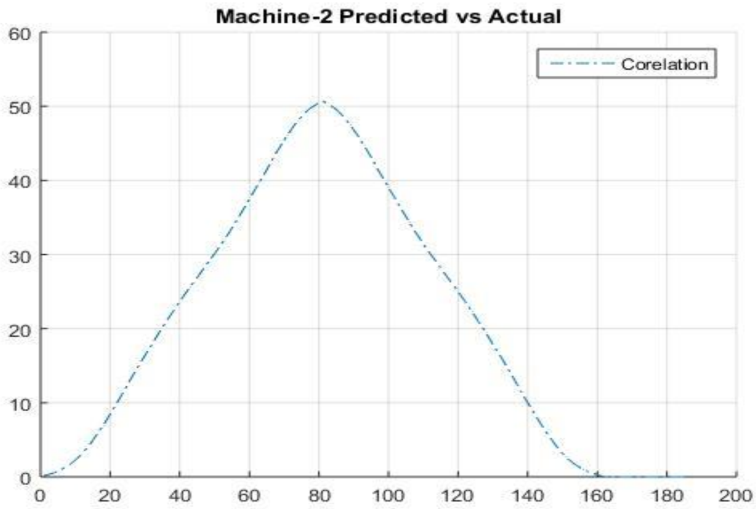


Figure 14 Fig. 9. Correlation curve for the current profiles for M_2

In the similar manner, the correlation coefficient matrix and correlation curve for the operations performed by M_1, as discussed in previous section, are shown in the Fig. 10 below. The value 0.6676 in comparison to the M_2 is much closer to 1, thus we can deduce there is similarity between the actual and predicted current profiles. In this case JSS checked the threshold limit set as per algorithm and the value of 0.6676 is below the rescheduling limit. Hence JSS will not be prompted.

$$\begin{bmatrix} 1.0000 & 0.6676 \\ 0.6676 & 1.0000 \end{bmatrix}$$

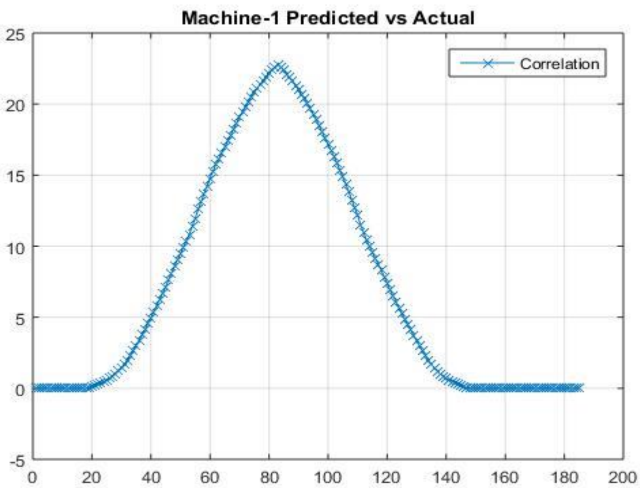


Figure 15 Correlation curve for M_1

In Fig. 11 correlation curves for current profiles are compared for the operation O_23. It is evident for this graph that peak value of M_2 is way below the threshold limit of 0.6 as compared to M_1. Also the lag between the both machines is almost same as the peak values lies at 83 and 81 for M1 and M2 respectively. This shows the elements of the current profiles directly correlate or match exactly to themselves at these peak values. The JSS monitoring system triggered JSS to reschedule for M_2 and the schedule shown in Fig. 5 is now updated. Since there is idle machine time available next to O_23, the JSS will readjust this operation in a manner to optimize the resource utilization via optimal operations readjustment. Fig. 12 represents the new optimized rescheduling.

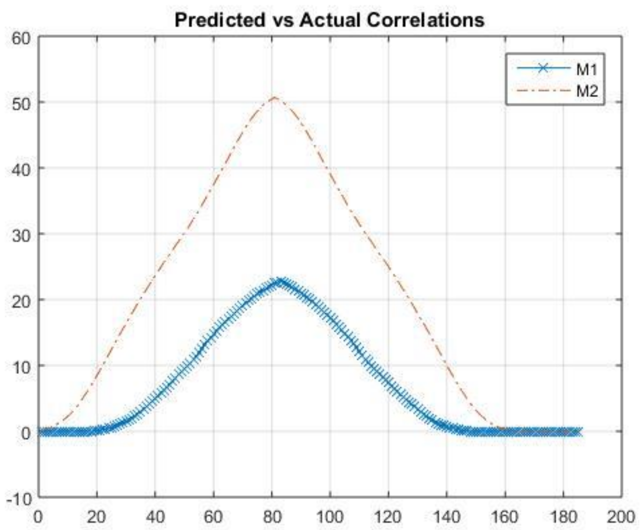
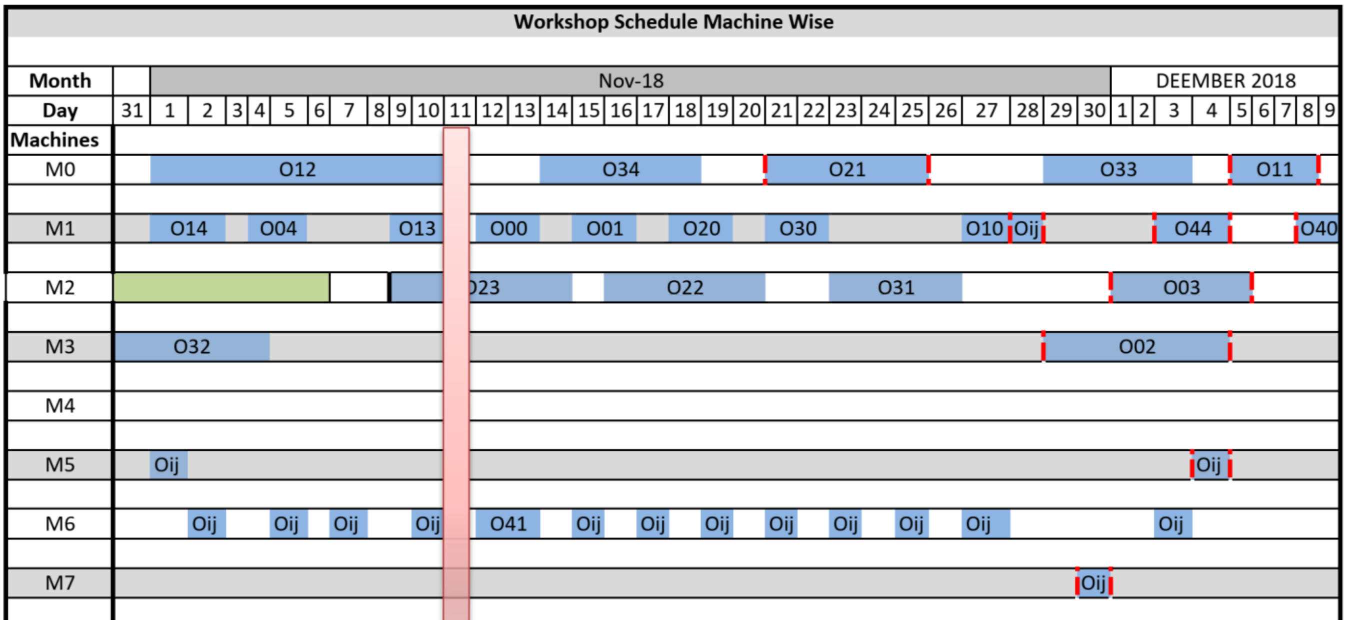


Figure 16 Comparison of correlations for M_1 and M_2



CHAPTER: 6 CONCLUSION AND FUTURE WORK

I 4.0 let us to the idea of the automated Shop Floors using IIoTs. In this paper we have discussed JSS monitoring algorithm which, depending on lead, lag or perfect match triggers rescheduling of the jobs, operations and tasks. The results obtained by practical SF performance discussed in previous section, confirms the efficiency of proposed algorithm in real factory settings. The proposed JSS monitoring system is not limited to the factory setup only but can be modified for the automation of other indoor spaces such as the smart offices, homes and hospitals. Also, adaptive or signal processing algorithms can be applied to adapt the threshold value to maximize the efficiency of shop floors.

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