Conversion of a Manufacturing Lab as a Learning Factory to Educate Factories of the Future Concept

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Abstract. The demand for enhancing the flexibility and efficiency of the manufacturing industry has rapidly increased over the years due to mass customization to cater to the needs of society. The conventional manufacturing industry could not survive these rapid changes. Though, the manufacturing sector is the forerunner to embrace technological paradigm shift, which paves the way for Industry 4.0 or the 4th industrial revolution. With Industry 4.0, now many world leaders are moving towards a new concept called "Factories of the Future" (FoF), which predominantly engages with the cyber-physical world to digitalize manufacturing while maintaining a strong link between hardware and the cyber-physical world. To perform any manufacturing, engineering teaching/learning programs should introduce these concepts with some practical exposure, which will enable students to contribute to the manufacturing industry all around the world. Therefore, this study focuses on converting an old manufacturing lab into a learning factory to promote FoF concept. This is achieved by enabling existing manufacturing machines to be digitally connected via Industry 4.0 while creating connections with the other machines to create flexible manufacturing systems (FMS). Competencies in integrated scheduling of machine centers and autonomous material handling systems were also explored. Furthermore, the study suggested that the conversion of the manufacturing lab needs to be done in many different integration platforms.

Keywords: Learning Factory · Factories of the Future (FoF) · Industry 4.0 · Internet of Things (IOT) · Flexible Manufacturing System · Integrated Scheduling

1 Introduction

The manufacturing sector currently contributes 16% to the global GDP [1], which makes it one of the essential factors contributing to the imports and exports of any country. Given the importance of manufacturing as a source of revenue for any country, fostering excellence has become a strategic priority which makes the manufacturing industries more competitive and demanding. To cope with this highly competitive environment,

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the manufacturing industry needs to be more flexible and more efficient. This furtherance in the manufacturing environment requires a technological paradigm shift that paves the way for the Factories of the Future (FoF) concept, which is enabled by Industry 4.0 or the 4th industrial revolution. The FoF concept encourages future-oriented manufacturing that implements intelligent and sustainable processes using cutting-edge digital technologies [2]. It makes creative, efficient, and optimized use of resources and energy. Industry 4.0 refers to the present trend in both professional and academic fields of industrial technology automation and data sharing, which includes cyber-physical systems, the Internet of Things (IoT), cloud computing, and cognitive computing, as well as the creation of the smart factory [3].

Industry 4.0 is based on the use of digital technology to collect and analyze data in real-time, delivering important data to the manufacturing system [4]. When it comes to developing nations, it is very difficult to acquire these state-of-the-art manufacturing facilities due to the lack of funding. As a solution to this problem, consideration was taken place to use a few old conventional manufacturing machines for this study. However, to accommodate the 4th industrial revolution and its technologies, the old manufacturing machines need to be digitalized to a certain extent for data collection and data analysis.

Before considering a full-fledged industry, to perform any manufacturing, the education sector needs to adapt and expose these cutting-edge technologies to the students for them to be able to contribute to the manufacturing industry all around the world. Therefore, the educational paradigm needs to address the emerging challenges of the manufacturing sector by practicing in an industry-relevant environment with more modern and realistic manufacturing practices called the learning factory (LF), which has facilities to learn multidisciplinary abilities, skills to synthesize, and adaptability to a variety of situations [5–8]. Even though there are many studies on the usage of industry 4.0, there are no significant studies on the conversion of old conventional manufacturing machines using Industry 4.0 technologies, especially in an LF. Therefore, this study paid particular attention to LF to educate of FoF concept.

This study also explored Flexible Manufacturing Systems (FMS), competencies of integrated scheduling of machine centers, and material handling systems in a learning factory. A flexible manufacturing system facilitates flexibility of the system to improve productivity and lower the work-in-process inventory [9, 10]. Integrated scheduling in production involves scheduling, batching, and coordination of delivery decisions to achieve optimization in operational performance [11].

2 Methodology

2.1 Conversion of Conventional Manufacturing Machines to Smart Factory Using IoT

In order to convert old conventional manufacturing machines to accommodate industry 4.0 technologies, the machines should be connected to four tangible layers: the physical resource layer, industrial network layer, cloud layer, and supervisory control terminal layer [12]. These layers can be further categorized into different integration platforms such as the resource platform, sensing platform, network and service platform, administration platform, and application platform. This system architecture is illustrated in Fig. 1.

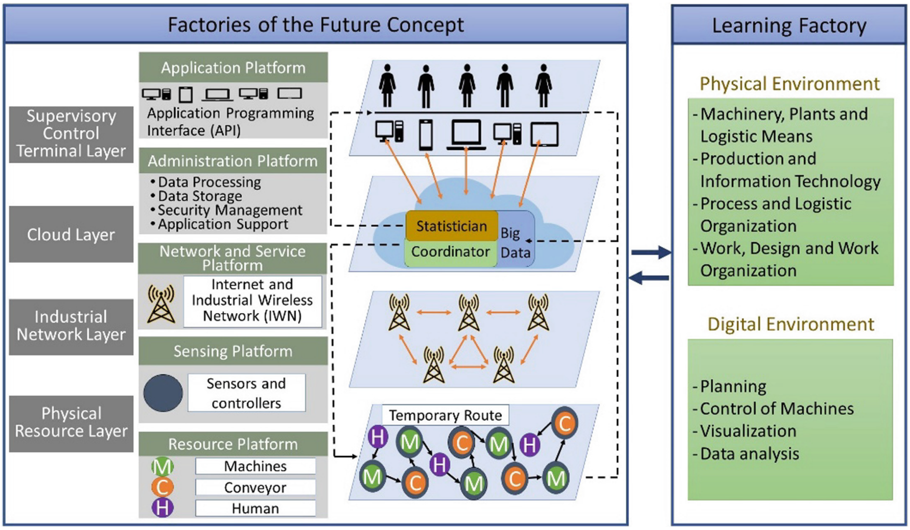

Fig. 1. Framework of a smart factory in a learning factory

Ideally, the resource platform will in include both human resources and machinery resources. The human resources include the students, operators, and instructors, while the machinery resources include the learning factory setups, equipment, appliances, and machines.

The sensing platform, that interconnects sensors and controllers to the industrial network layer, consists common interface module, communication module, and control module. The control module is capable of connecting sensors, and controllers via a common connection protocol. This layer should be able to self-configure and self-adapt, which are considered the main features of the sensing layer.

The network and service platform consists of the backbone networks along with resource and administration platforms. The backbone network includes 3G, 4G networks, optical fiber networks, and Ethernet networks.

The administration platform provides means for data processing, data storage, security management, and application support. This fosters specific IoT support capabilities as in any telecommunication network layer, such as authentication, authorization, mobility management, services, applications, users, and developers.

The application platform provides a common function and an open application programming interface (API). With the aid of the API, users could publish information to the application platforms.

For a digitalization process, information transparency is important. The available data needs to be identified and then convert into accessible data with the aid of sensors and measurement devices. Furthermore, the data needs to be converted into active data, which is real-time data. The final step is to transform data into action-oriented data, which can be used in optimization algorithms, deep learning, and big data analysis.

During the process of transforming accessible data into active data, sensors will be connected to a network through interfacing devices. Then, a visualization method will be implemented to access the data. Next, a further transformation of accessible data into active data will be done by enabling real-time monitoring through the visualization method. When using these data for performance optimization, efficiency improvement, extending capabilities, reducing downtime and machine lifetime widening these data will become actionable data.

2.2 Flexible Manufacturing System (FMS) and Material Handling System

An FMS can have different forms of flexibility, such as process flexibility, material handling flexibility, machine flexibility, operation flexibility, product flexibility, routing flexibility, volume flexibility, expansion flexibility, production flexibility, and control program flexibility [10]. For an FMS setup, to accommodate any of these flexibilities, all the machines need to be able to communicate with each other. The common information that is needed to implement these flexibilities is the status of the machine processing. Using the smart factory approach, sensors can be installed to get the status of the machining process. To communicate this information with the other machines, IoT-enabled hardware needs to be installed to create a wireless sensor network. This can be done with wireless sensor network hardware and technology such as Zigbee and Xbee. With its low power, low data rate, low cost, and short time delay characteristics, Zigbee is one of the most widely used Wireless Sensor Network standards. It is also easy to develop and deploy, offers strong security, and has high data reliability. Xbee is a module that uses a radio communication transceiver and receiver which supports Zigbee protocol. It has a source/destination addressing feature with unicast and broadcast communication support which supports point-to-point, point-to-multipoint, peer-to-peer, etc. communication topologies.

The mismanagement of the materials and logistics can reduce productivity and efficiency. Therefore, good material management should be implemented, which involves planning and controlling the quantity of the materials, punctuality of the placement of materials and equipment, and delivery of the right quantity. To manage the material handling system, an automatic guided vehicle (AGV) can be used. The AGV also should be able to access the machine process status information. Therefore, the AGV should have a communication protocol method to be able to receive the information from the wireless sensor network. This communication can be established using serial communication or through software applications such as Robot Operating System (ROS). ROS is an open-source framework that helps researchers and developers in creating and reusing code for robotics applications such as an AGV.

3 Case Study

So far, the work presented focuses on concept definition. Concept implementation will be part of an ongoing and future collaborative project work. The implementation approach is shortly discussed in the following paragraphs.

The Department of Manufacturing and Industrial Engineering (DMIE), University of Peradeniya, Sri Lanka, has a few old conventional manufacturing machines which needed to be digitalized and IoT enabled to create a smart factory and a learning factory. In addition, due to the Covid-19 pandemic, globally, there was a paradigm shift in the method of education. All the classes and practical sessions were obliged to be conducted online. Due to this reason, there was a need for the academic staff and the students to access and control the machines remotely. Therefore, the conversion of the conventional manufacturing machines to a smart factory concept was implemented in a Computer Integrated Manufacturing (CIM) center, which consists of an RH-M2 Mitsubishi robotic arm.

The controller of the robot arm was connected to a control PC via an RS232 interface. A Wi-Fi module (ESP 8266) was connected to the PC via a USB port, and then it was interconnected to the PC and the cloud database through the network layer. Values updated in the real-time database were sent to the control PC via network layer using ESB 8266. With the aid of real-time data, commands were obtained, and the robot arm was controlled online. A camera is installed to view the movements of the robot arm. The connection of the robotic arm is illustrated in Fig. 2.

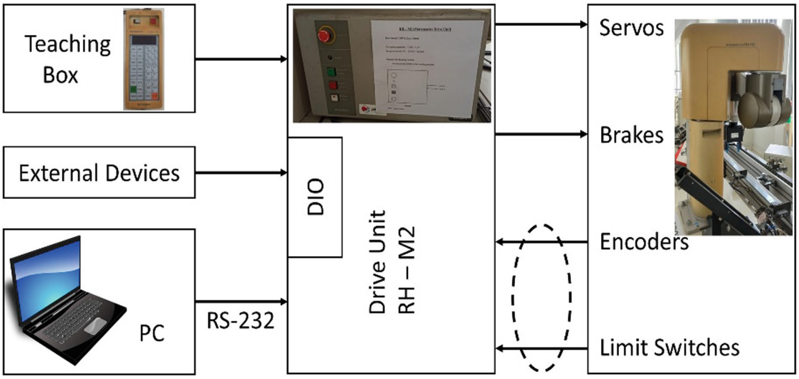

Fig. 2. Connection of the robotic arm to obtain the real-time data.

To interact, code, control, and view the movements of the robotic arms in the CIM center, a dashboard was created named ‘Smart DMIE’, which was named after the Department of Manufacturing and Industrial Engineering (DMIE). The Smart DMIE interface enabled the students and the instructors to conduct laboratory sessions online in real-time without physical participation. The dashboard programming panel allows students to remotely write programs and execute them to control machinery and button controllers (see Fig. 3). The dashboard also displayed the collected data on a graph to analyze the data conveniently.

To create the Smart DMIE dashboard, web-based applications and languages were used. To handle the request from the user, a back-end JavaScript runtime environment, ‘Node.js’, was used. Node.js is an open-source, cross-platform, and executes JavaScript code outside of a web browser. It helps to create scalable network applications. In this

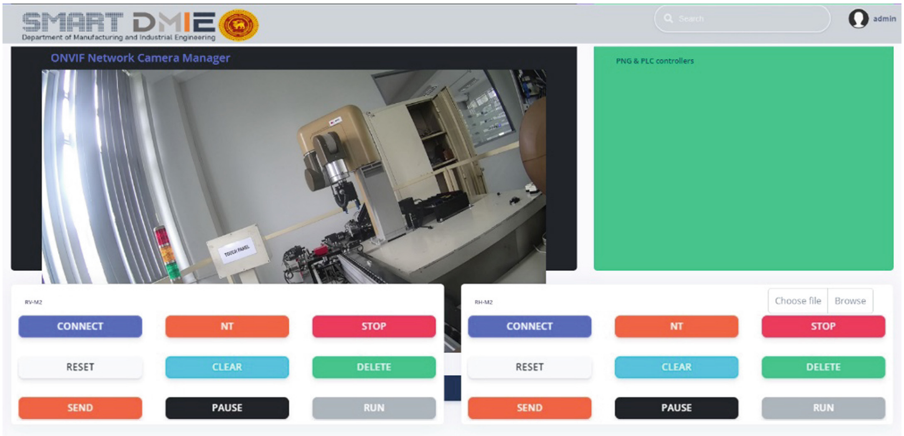

Fig. 3. 'Smart DMIE' online dashboard.

case, Node.js controls the server and collects data asynchronously which makes it a faster connection. To define, manipulate, retrieve, and manage data, 'PostgreSQL' was used as a database. PostgreSQL, also known as Postgres, is an open-source object-relational database system that utilizes and extends the SQL language to safely store and manage complex data workloads. To bridge Node.js and Postgres database, 'Express.js' was used. Express.js is an open-source web application framework for Node.js which can program web apps that can be launched using a web browser. It is mainly used to design and construct web applications quickly and easily. Figure 4 illustrates the software architecture that was used to create the Smart DMIE dashboard.

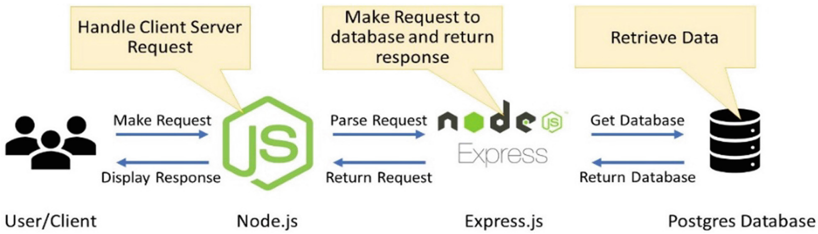

Fig. 4. 'Smart DMIE' dashboard web-based application and language architecture

Comparing the case study and the conceptual framework of a smart factory in an LF, the human interaction and the robot are considered the resource platform. The camera that is fixed to view the robot movements and the servos and encoders in the robot comes under the sensing platform. The usage of the Wi-Fi module (ESP 8266) connects the set-up to the network and service platform. The usage of the Postgres database is considered the administration platform. Finally, the usage of Node.js and Express.js acts as the application platform. Since the Smart DMIE dashboard was implemented in an academic environment with many ongoing research and education on realistic manufacturing, it supports the learning factory concept. It is evident that industry 4.0 technologies have been used by introducing the Smart DMIE dashboard that uses cutting-edge technologies to revolutionize and improve manufacturing capabilities. Not only that, the Smart DMIE supports future-oriented manufacturing that uses advanced technologies such as IoT, cloud computing, cognitive computing, and real-time virtualization. Based on this preliminary assessment, and the acquisition of high-quality and relevant manufacturing data from the Smart DMIE dashboard project, it has been identified that the implementation of the conceptual framework is successful.

The future work of this project is to develop the digital twin (DT) enabled dashboard or to create a realistic 3D visualization approach to demonstrate DT. The conversion of the conventional machines can be implemented in all the other machines in the learning factory to enable FMS and AGV-enabled material handling systems.

4 Results and Discussion

After the conversion of the conventional manufacturing lab using the help of the four tangible layers and five integration platforms, to a certain extent, the machines can be used to perform advanced and latest manufacturing techniques in a classroom environment which makes it an LF. Implementing these layers and platforms uses the technologies such as cyber-physical systems, IoT, cloud computing, and cognitive computing therefore, it makes it an industry 4.0-enabled environment. Not to mention, the usage of these cutting-edge technologies and implementation of FMS and integrated scheduling allows it to perform futuristic manufacturing which promotes the FoF concept.

5 Conclusion

This study focused on the conversion of traditional manufacturing machines to a learning factory to promote factories of the future concept. This is achieved by enabling existing manufacturing machines to be digitally connected via industry 4.0 and by creating a flexible manufacturing system.

In this paper, the concept of how to convert conventional manufacturing machines to a smart factory using IoT and the concept of creating an FMS with AGV enabled material handling system was explored. The study suggested that the conversion can be done in five different integration platforms: resource platform, sensing platform, network and service platform, administration platform, and application platform. To create an FMS, many machines can be digitalized and enable IoT to communicate through a wireless sensor network. To create a material handling system, AGV can be connected to all the machines using serial connections or communication software such as ROS.

An ongoing project at a learning factory at the Department of Manufacturing and Industrial Engineering (DMIE), University of Peradeniya, Sri Lanka, proved that the conversion of the conventional manufacturing machine to a smart factory was successfully implemented. It is also noted that there can be some limitations to the project presented in the paper. Since the machines enable to be controlled online, security can a threat to this system. Not only that, the sensor that needs to be installed at the sensing platform varies from machine to machine. Also, the sensors need to be calibrated and once again, the calibration can vary from machine to machine. Therefore, a generic method of implementation of the sensors and sensor calibration cannot be obtained. Though, this study also proved to have advantages such as conducting the laboratory classes remotely. Using existing manufacturing machines to implement futuristic technologies makes it sustainable manufacturing. Even though there are a few drawbacks to the study, ultimately, the implementation of the suggested framework and the subsequent validation of the expected benefits will be part of future work.

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