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EXPLORING DATA ACQUISITION AND REAL-TIME ANALYSIS ALGORITHMS IN SMART MANUFACTURING WITH A FOCUS ON AUTOMATION AND INSPECTION TECHNOLOGIES

ZHENSHAN CHEN*, HANJUN ZHENG† AND JINYAN LIN‡

Abstract. The conducted research project is based on the process followed in the smart manufacturing method. It has been observed that there are different types of methods that have been used in the smart manufacturing process and among these methods most of the methods are directly associated with different modern technology and artificial intelligence as well. Along with the inclusion of automation systems in the smart manufacturing process, the incorporation of inspection technologies is also observed in the case of performing smart manufacturing systems. In association with these, the usage of an acquisition system and real-time analysis process is also observed as well. Independent steps are present inside the phases of production process of the smart manufacturing methods. The incorporation of automation processes significantly enhances the performance of individual phases within the smart manufacturing process, thereby raising the overall production standards. Automation minimizes the likelihood of human errors, data misplacement, and mishandling. Moreover, it proves highly advantageous in the data acquisition process, ensuring error-free data transfer through automated systems.

Key words: Data acquisition software system, Transducer sensor, Superlinear algorithm, Smart manufacturing process

1. Introduction. The term smart manufacturing process refers to the production process where Artificial Intelligence has been used. The smart manufacturing process is capable of performing the production process by following the automation system with the help of AI-based technology. Therefore, a smart manufacturing system is an independent method of producing an item and does not depend on manpower and other human-based factors to produce any item. Due to the presence of such beneficial items, different business sectors all over the world are adopting this technology of smart manufacturing in association with AI. Along with the inclusion of automation systems in the smart manufacturing process, the incorporation of inspection technologies is also observed in the case of performing smart manufacturing systems. Apart from this the conducted project also highlights the application of both the data acquisition process and the real-time analysis algorithms in the smart manufacturing process. Data acquisition involves outperforming an important role in terms of transferring the data in the smart manufacturing process. Moreover, all kinds of algorithm-based statistical and numerical data are further analyzed by real-time data analysis systems. Therefore these two technologies played an important role in the improvement and better performance of the smart manufacturing system.

Smart manufacturing represents a paradigm shift in the way industries operate, leveraging cutting-edge technologies to maximize efficiency and product quality. Automation, driven by artificial intelligence, robotics, and the Internet of Things (IoT), plays a pivotal role in orchestrating an integrated, data-driven production environment. The application of automation technologies not only enhances the performance of individual manufacturing phases but also raises the overall standards of production. With the reduction of human errors, improved data accuracy, and greater precision, automation stands as a cornerstone in the quest for manufacturing excellence.

Simultaneously, inspection technologies have undergone significant advancements, contributing to the real-time assessment of product quality and process performance. These technologies facilitate the constant monitoring of production processes, enabling prompt corrective actions and quality control.

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2. Objectives. The primary objectives of the project are illustrated in the following section.

1. To describe the overview of the data acquisition system
2. To identify the role of data acquisition system in the smart manufacturing process
3. To understand techniques used in the real-time analyzing process of algorithms
4. To find out the application of automation process in different aspects of the smart manufacturing system
5. To recognize different types of methods that are used under the inspection technologies of the smart manufacturing process

The incorporation of automation systems and inspection technologies within the smart manufacturing framework emerges as a key focal point, showcasing how these technologies optimize various phases of the production process. Moreover, this research sheds light on the pivotal role of data acquisition systems and real-time analysis methods in this context, emphasizing their impact on enhancing manufacturing efficiency. By elucidating the individual steps within the production phases, this study underlines the transformative potential of automation, which significantly elevates production standards while reducing the likelihood of human errors and data mishandling. Additionally, the error-free data transfer facilitated by automated systems represents a noteworthy advancement in the smart manufacturing landscape. This research makes a valuable contribution to the understanding and implementation of smart manufacturing processes, setting the stage for more efficient, accurate, and technologically-driven production methodologies.

3. Methodology. Different information based on the smart manufacturing process is discussed in this project. Among different data mostly secondary types of data have been used in this project. With the help of secondary information from other writers about the manufacturing process and the other technology and technical gadgets used in the smart manufacturing process illustrated in this project and by this secondary type information, the final result of the project can also be developed [1]. Hence secondary data is collected for developing the final outcome of the project and this step is a clear indication of performing the qualitative methods in order to collect information for the completion of the project.

Data acquisition systems begin with sensors and transducers that capture physical parameters such as temperature, pressure, voltage, current, or other environmental conditions. These sensors convert physical measurements into electrical signals. In many cases, the raw electrical signals from sensors need to be conditioned to ensure accuracy and compatibility with the data acquisition system. Signal conditioning may include amplification, filtering, analog-to-digital conversion, and other adjustments to the signal.

3.1. Overview of the Data Acquision System. The data acquisition system contains software and different devices as well. This software and devices are involved in measuring the data while transferring the data from one system to another. The application of the sensor system is also observed in the data acquisition system [2]. With the help of a sensor system, the data acquisition system develops the ability to sense the data and its transfer process as well. Moreover, it has been observed that the data acquisition software is involved in performing different functions as well. Acquiring the data, and storing the data in different devices all are performed by a data acquisition software system. Moreover visualizing the data on the device screens are also performed by the software of the data acquisition system [3]. In addition to that the software system is also capable of processing data and modifying the data making it ready for further utilization of the data by the users. In association with understanding the electrical wave, the data acquisition system is capable of transferring the data from one end of the device to the other end of the device as well [23].

The concerned diagram of the above section highlights the different sections of the Data Acquisition system [22]. In order to transfer data from one computer to another the data has to pass by four different phases. Each phase of the data transferring process is involved in processing the data and making the data ready for transferring to another device. The four different phases are the "physical system, transducer sensor, signal conditioning, and the analog-digital converter" [5]. In all four phases of the data acquisition system different signals are developed and by accepting these signals the device of another end of the transferring process can be able to accept the data.

3.2. Utilization of Data Acquisition System in the Smart Manufacturing Process. The application of the data acquisition system is involved in the inclusion of the automation system in the data transferring

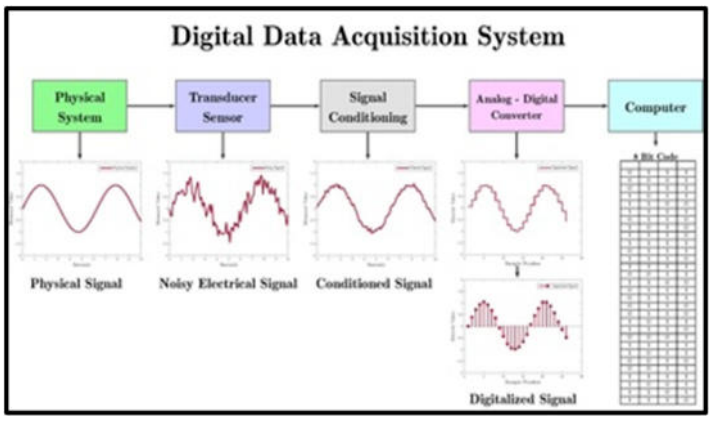

Fig. 3.1: Digital Data Acquisition System

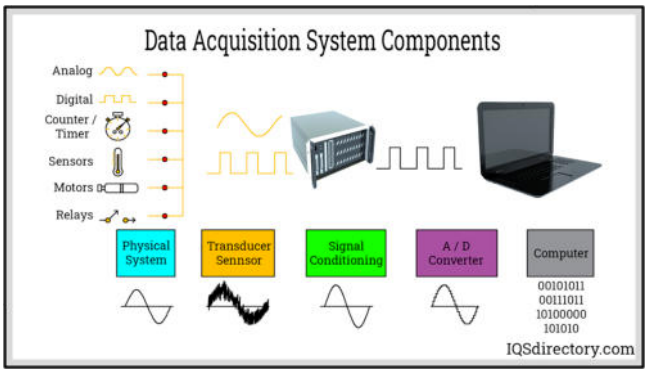

Fig. 3.2: Utilization of data acquisition system

and in the data managing system. The utilization of the data acquisition system is involved in lowering manual errors. Moreover, it has been observed that when the data processing, data managing, and data transferring system is performed by the different software applications [4]. This lowers the participation of any manual recess and furthermore, this also lowers the occurrence of any kind of human error as well. Furthermore, in the case of using this system in the smart manufacturing process, it also benefited by lowering the incidents of any kind of misplacing and misconducting the data. By reducing the misplacing of the data the rate of the accuracy of the transferred data is increased to a high level [6].

Moreover, it has been observed that the usage of digital data acquisition systems is also involved in reducing the overall charges of the data acquisition process that is performed under smart manufacturing procedures [21]. When the methodology and the techniques of the data acquisition process shifted from a manual process to a digital process. In this shifting procedure, the charges of performing different types of physical data managing and data acquisition steps are removed which helps lower the overall estimated costs of the data acquisition process [7]. In addition to that, the inclusion of a digital data acquisition system is also beneficial in terms of performing the retrieval process of the data.

3.3. Techniques followed in Real-time Analysis Algorithms. There are three different techniques that have been observed which are involved in performing the real-time analysis process of algorithms. These three techniques are based on the three different designs of the algorithm structures. Therefore three different algorithm designs are “divide-and-conquer, dynamic programming, and greedy heuristics”. Apart from three different algorithm designs, different examples of the real-time analysis of algorithms are “Linear algorithm

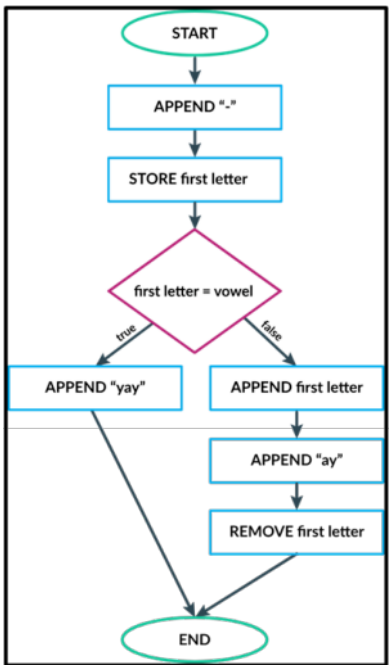

Fig. 3.3: Flow chart of an algorithm analysis

– O(n) and Superlinear algorithm – O(nlogn), Polynomial algorithm – O(n∧c), and Exponential algorithm – O(c∧n)" [8].

This above-developed flow chart fig. 3.3 contains different steps which are involved in developing the visualization of the whole steps that are involved in completing the analysis of different algorithms. In this flowchart, the application of natural language has been observed and as a result of this, these steps involved process also can be performed naturally as well [9]. With the help of using natural languages, this flowchart can be able to connect maximum numbers of users by its easy programming capacity. Apart from that it has been observed that the application of natural languages is also associated with different limitations such as the application of natural languages in the algorithm analysis process causing the presence of difficulties in the whole structure of the process [10].

4. Role of Automation in Smart Manufacturing. The inclusion of an automation system in the smart manufacturing process is involved in creating a fully autonomous production process. Moreover, the automation system in the smart manufacturing process is also capable to develop an interconnection between the steps that are performed in the supply chain process under the smart manufacturing system [11]. The automation process allows the application of different types of robotics, AI, and different other software applications in order to make the smart manufacturing process a fully autonomous [production process.

The inclusion of an automation system in the smart manufacturing process is directly involved in offering different types of benefits. These benefits are further involved in enhancing the efficiency of the smart manufacturing process. Cost-effectiveness is one of the most important benefits that the smart manufacturing process can have after the inclusion of the automation system [12]. Moreover, the inclusion of an automation system is helpful for improving the worker's safety and lowering any kinds of hazardous risks in the manufacturing process as well.

4.1. Types of Inspection Technology. There is a wide range of technologies available which are helpful for performing the inspection process. These inspection technologies are involved in checking the quality of the final products and also give the declaration of the high-quality product. In the case of the smart manufacturing process, the application of Automated inspection technology (AIS) has been observed in the

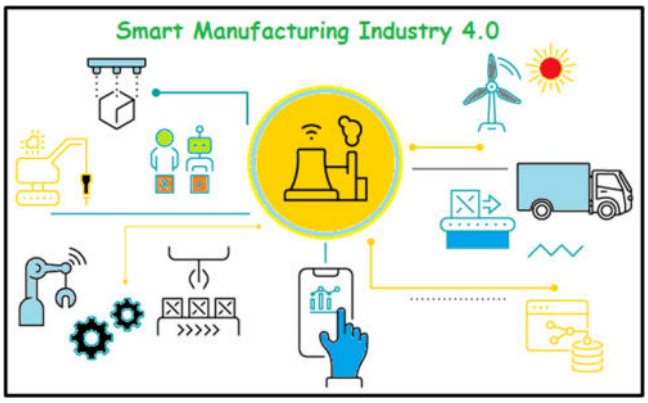

Fig. 4.1: Role of Automation in Smart Manufacturing

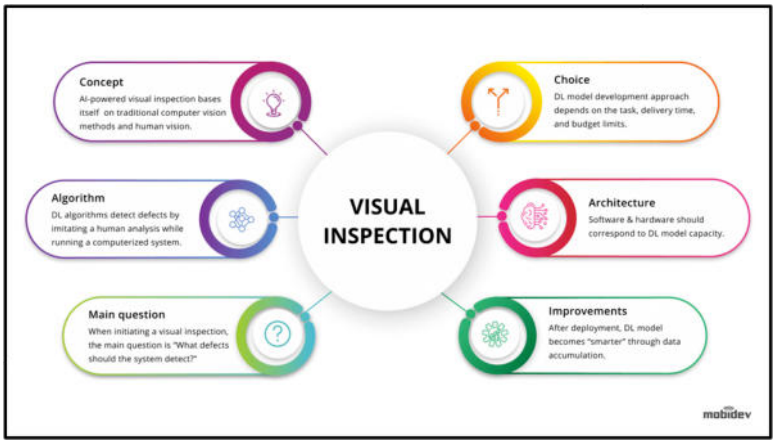

Fig. 4.2: Visual inspection

largest amount [13]. The application of this AIS is involved in improving the quality of the product to a high level. Apart from this method, it has been observed that there are different methods that also contributed to the develop,emy of inspection technologies. Hence the different other technologies that can also be used as examples of inspection technologies are "nondestructive testing, radiography, magnetic particle inspection, automated optical inspection, ultrasound, acoustic emission, visual inspection, and thermography" [14].

Apart from this technology in the smart manufacturing process mainly four different methods are observed which are involved in the inspection process of the quality control process. The four different methods that are performed under the manufacturing process are "pre-production inspection (PPI), first article inspection (FAI), during production inspection (DPI), pre-shipment inspection (PSI), container loading inspection (CLI)" [15]. Proceeding with all these technologies and steps is helpful for enhancing the overall effectiveness of the smart manufacturing process.

5. Results. The result of the project is based on the data and information discussed in the previous section. It has been observed that the inclusion of different automated software applications is considered one of the most important steps in order to maximize the output of the smart manufacturing process [16]. It has been observed that with the help of the automated system, the users of the smart manufacturing process can be able to add an autonomous strategy of performing different steps of the production recess. This helps to increase the rate of production even in the least amount of time. Due to its transferring into an autonomous

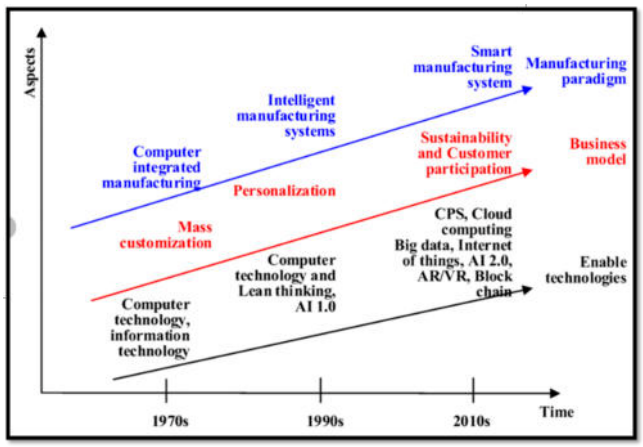

Fig. 5.1: Application of SMART manufacturing process

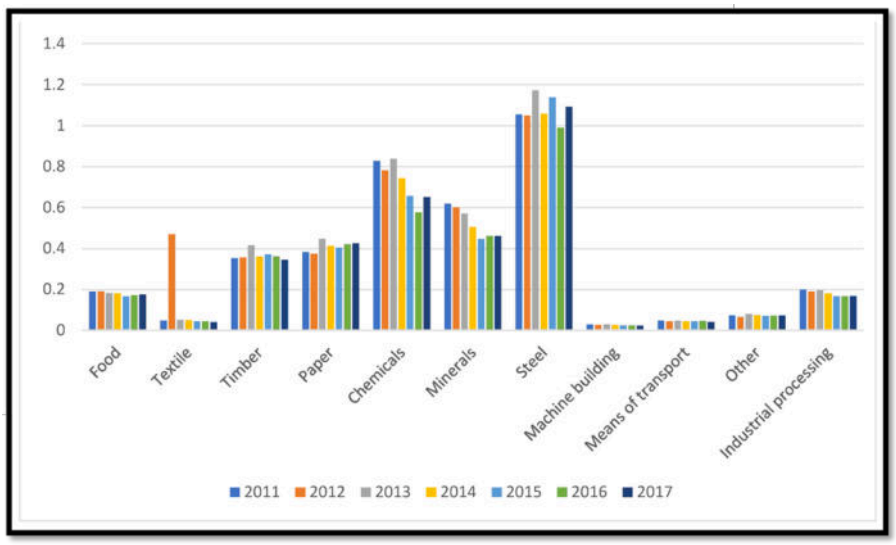

Fig. 5.2: SMART manufacturing process in different business industries

process, the time required to produce a product becomes reduced than the usual one [17].

Moreover, it has been observed that the inclusion of the digital data acquisition system is also involved in enhancing the quality of the data management and the data transferring process. By enhancing the data transferring process the utilization of the data can be also enhanced in the smart manufacturing system [18]. When the utilization of the data becomes better than the final output that is developed by the utilization of the data it also gets better.

The betterment of the data acquisition process is also considered beneficial for analyzing the algorithm data as well. It has been observed that due to the improvement of the algorithm, the data management process of the smart manufacturing system is getting better than the existing one [19]. Apart from that inspection technology is further involved in enhancing the overall quality of the manufacturing process that is totally based on smart technology and autonomous artificial intelligence as well. Therefore it can be stated that the application of all four different technologies finally impacted the positive development of the smart manufacturing system [20].

6. Conclusion. Thus it can be concluded that the concerned project highlights the smart manufacturing process and different technologies that are available and can be included in the process of smart manufacturing. It has to be observed that the inclusion of an automation system is considered one of the most effective software applications that can increase the accuracy rate of the smart manufacturing system and are also involved in improving the steps that are performed under the autonomous production process as well. Apart from this, the data acquisition system is also involved in improving the data-transferring process of the smart manufacturing process. Furthermore, the implementation of a data acquisition system plays a pivotal role in optimizing data transfer processes within the smart manufacturing landscape. The harmonious amalgamation of these technologies goes beyond just optimizing production; it elevates the overall quality, efficiency, and precision of the smart manufacturing process. As a result, this research illuminates the transformative potential of these technologies, charting a path towards more advanced, efficient, and high-quality smart manufacturing practices.

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