Application of Machine Learning Techniques to the Reconfiguration of Automated Manufacturing System

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DOI: 10.56201/ijcsmt.v9.no5.2023.pg150.159

Abstract
The aim of this research is to apply machine learning techniques to the reconfiguration of automated manufacturing system, the objective is to provide a model for fast decision making in automation processes in the manufacturing industry, to use the dataset in product reconfiguration to predict a product, to design an intelligent model that could provide an easy and faster reconfiguration of products in a manufacturing industry. The motivation towards this work is caused by the high rate of delay in the production processes caused by the disturbance, taking proper corrective actions to complete the production orders on time and to minimize the impact of the disturbances. Humans can break down during product production leading to reduction and delay in product production, there is need for an intelligent model that does not require human effort, the model would be able to take decision, automate processes and facilitate production processes. The data which is on the production of semi-conductors in an industry will be analyzed with R and R-Studio platform sourced from UCI machine learning repository. The methodology adopted in this project was SEMMA which stands for Sample Explore Modify Model Access which focuses on the main modeling tasks in the project without venturing into the business understanding and deployment according to oreilly.com. The expected result after the experiment is to develop an intelligent model for the reconfiguration of product in a manufacturing company and also facilitate production and decision making in the company using the dataset on the production of semi-conductor as a use case.

Keywords: *Machine Learning, Manufacturing System, Customer, Information System*

Introduction

The rise of the global economy has generated a greater competition for the manufacturing enterprise from every part of the globe. Nowadays, to be competitive, manufacturers must not only produce low-priced products with high quality, but also manufacture products that need to be customized according to the customer's personal preferences. Consequently, these requirements take the reasonability of increasing the product variants and decreasing the product life cycles. The consequences of these trends create a need of building more efficient, flexible and agile manufacturing systems that can adapt new and changing requirements or changes in the manufacturing environment. These systems will allow manufacturers to produce multiple variations of customized products at the price of standardized mass products offerings (Leitão, 2004). A reconfigurable manufacturing system (RMS) is defined as "a system designed at the outset for rapid change in structure, as well as in hardware and software components, in order to quickly adjust production capacity and functionality within a part family" (Koren et al., 1999).

The RMS concept of living and evolving factories, that quickly adapt new products and changing market demands, was introduced at Engineering Research Centre of the University of Michigan (UM) in the mid-1990s. Subsequently, RMS enabling technologies were developed at both the UM and in Europe and Canada. RMS is being recognized today as a necessary tool for increasing productivity and sustaining profit despite abrupt global market changes. The RMS is designed to have the best of both worlds the high throughput of dedicated manufacturing lines (DML) and the flexibility of flexible manufacturing systems (FMS). It is intended to handle changes in production capacity and manufacturing requirements. Many approaches have been proposed in the academic literature to deal with the reconfiguration manufacturing paradigm. The well-known approaches are biological manufacturing systems (BMS) (Ueda *et al,* 1997) and holonic manufacturing systems (HMS) (Vancza, and Monosstori, 1996). A biological manufacturing system is a distributed manufacturing system, in which each part tries to achieve its own goals and each machine tries to attract them for processing. It has the capability of learning and healing itself when problems appear in various work stations and it is structured from the bottom up in a self-organized manner. BMS focuses on self-organizing and evolution since it is the major strength of biological organism to keep cells alive. A holonic manufacturing system is based on the concept of holon. A holon is an autonomous and cooperative building block of a manufacturing system for transforming, transporting, storing and/or validating information and physical objects. It consists of two parts: an information processing part and physical processing part. It can be part of another holon and has the ability to create and control the execution of its own plan and/or strategies. HMS is considered a system of holons that co-operate to achieve a goal or objective and integrates the entire range of manufacturing activities from order booking through design, production, and marketing. The application of machine learning techniques in the reconfiguration of automated manufacturing system is the basis of this study, by adopting a branch of artificial intelligence called machine learning to assist in the advance automation in the manufacturing industry. Machine learning (ML) is an application of AI that enables systems to learn and improve from experience without being explicitly programmed. Machine learning focuses on developing computer programs that can access data and use it to learn for themselves (Selig, 2022). Artificial intelligence (AI) is about the evolution of machines into smart machines. In other words, machines that can do more than simply input or output data and respond to process algorithms, they can leverage the data from various sources to provide an 'intelligent, almost human,' response. The machine is, in effect, replicating human behavior in terms of decision making and other tasks. With AI, machines can learn. In the reconfiguration of products in the manufacturing industry is an area that needs these AI machines, in a business model steeped in legacy technology and age-old production processes, finding ways to grow, improve product quality, limit unplanned downtime and innovate with short lead times for customer satisfaction are not easy goals to achieve. That is, until the advent of machine learning and AI, hence the need to implement an AI system into manufacturing system is highly required and should be seriously looked into.

The aim of this study is to apply machine learning techniques to the reconfiguration of automated manufacturing system.

The objectives are:

1. To provide a model for fast decision making in automation processes in the manufacturing industry
2. To use the dataset in product reconfiguration to predict a product
3. To design an intelligent model that could provide an easy and faster reconfiguration of products in a manufacturing industry.

AUTOMATED MANUFACTURING SYSTEM (AMS)

The Automated Manufacturing System (AMS) is a method or process of automatically manufacturing products under the direction or instruction of a computerized production or control system. According to (Swamidass, 2000) automated manufacturing system exhibits flexibility in parts routing, part processing, part handling, and tool changing. Additionally, an automated manufacturing system exhibits the following characteristics:

i. High degree of automation: This is a level of automation that doesn't require the management of people. This is a stage where all processes and managements of automation are being automated itself, without the help of human or manual systems, that is the use of machines to manage other machines without human intervention

ii. High degree of flexibility: This is the ability for an automated system through programming to produce various products in a short time frame or to be able to create products of varying models and lifespan.

iii. High degree of integration: This is a level whereby the automated manufacturing systems results in smoother and more efficient production process. All these characteristics are needed for an automated manufacturing system to process and efficiently provide adequate and accurate system for manufacturing companies to adopt to using information systems.

TYPES OF AUTOMATED MANUFACTURING SYSTEM (AMS)

One of the most important areas for the use of automated manufacturing system is in production, being able to produce various parts and perform varying complex algorithms needed for the easy and smoother workflow of the production system. In this case, automated manufacturing system can be classifying into three basic types;

i. Fixed Automation: Fixed automation or hard automation is a system in which the sequence of processing or assembly operations is fixed by the equipment configuration. These programmed commands are imbibed into the machine in the forms of wires, cams, gears and other machine components. In this way the product styles are difficult to change. This form of automation is characterized by high initial investment and high production rates. It is therefore suitable for products that are made in large volumes. Examples of fixed automation include machining transfer lines found in the automotive industry, automatic assembly machines, and certain chemical processes (Groover, 2019).

ii. Programmable automation: The programmable automation is created with the order of operations to produce products in sets and also to accommodate varying product elements or combinations. Production rates in programmable automation are inherently lower than in fixed automation, because the equipment is designed to accommodate product changeover rather than for a fixed product (Groover, 2019)

iii. Flexible automation: Flexible automation is an enlarged scope of programmable automation. It avoids the time wasted in the programmable automation for reprogramming and change-over, that means it is capable of producing parts ranging from one to another without the need for reprogramming or change-overs. Advances in Technological systems are precisely the main reason for this programming ability in flexible automation. Changing the physical setup between parts is accomplished by making the changeover off-line and then moving it into place simultaneously as the next part comes into position for processing.

COMPUTER INTEGRATED MANUFACTURING (CIM)

The comprehensive use of computers is known as computer-integrated manufacturing (CIM). since the 1970s there have been a growing tendency for manufacturing industries to use computers to carry out many of the complex functions related to designing and production. The use of Computer Aided Design (CAD) and Computer Aided Manufacturing (CAM) technologies has also been widely associated with these tendencies and it is also recognized that the scope of applying computer technologies must be extended beyond designing and production to add in the business functions of the industry (Groover, 2019). The implementation of CAD/CAM not only involves the automation of the manufacturing operations but also the automation of elements in the entire design-and-manufacturing procedure. In a manufacturing industry, the physical activities related to production that take place in the factory can be distinguished from the information-processing activities. The physical activities include all of the manufacturing processing, assembly, materials handling and inspections that are performed on the product. Computer aided design (CAD) is any type of design activity, that involves the use of computer systems to assist, in the development, creation, modification, analysis and optimization of an engineering design. The CAD systems in implementation now are based on interactive computer graphics (ICG) which denotes a user-oriented system whereby the computer is used to create, display and transform data in the form of symbols and pictures. (Sakar*et al*., 2008). Computer aided manufacturing (CAM) involves the use of computer systems to assist in the planning, control, and management of production operations. This is accomplished by either direct or indirect connections between the computer and production operations. CAM system is able to generate program for computer numerical control (CNC) machine tools to manufacture a component. (Sakar*et al*., 2008). The related based goal of modern factories is computer integrated manufacturing (CIM). CIM indicates the data-driven automation that affects all parts of the manufacturing industry; design and development engineering, manufacturing, marketing and sales, field support and services (Alavudeen & Venkateshwaran, 2008).

MACHINE LEARNING TECHNIQUES

Machine learning technique which is a sub-field of artificial intelligence (AI) can be said to be the use and development of computer systems that are able to automatically learn and adapt, by using algorithms and statistical models to analyses and draw inferences from patterns in data and make predictions with minimal human intervention or instruction. It is the capability of a machine or computer to imitate intelligent human behavior. Machine learning gets useful information from very large volumes of data by making use of algorithms to predict, identify patterns and learn in an iterative process. New developments in certain domains like mathematics and computer science (e.g. statistical learning) and availability of easy-to-use, often freely available (software) tools offer great potential to transform the manufacturing domain and their grasp on the increased manufacturing data repositories sustainably. One of the most exciting developments is in the area of machine learning (incl. data mining (DM), artificial intelligence (AI) etc.). However, the field of machine learning is very diverse and many different algorithms, theories, and patterns are readily made available. For many manufacturing industries, this represents a barrier regarding the adoption of these powerful tools and thus may bar the effective utilization of the large amounts of data increasingly being available (Wuest*et al.*, 2016).

REVIEW OF RELATED WORKS

Leng *et al.* (2020) carried a study on digital twin-driven rapid reconfiguration of the automated manufacturing system via an open architecture model. The scholars carried this study by increasing individualization demands in products call for high flexibility in the manufacturing systems to adapt changes. Their research proposes a novel digital twin-driven approach for rapid reconfiguration of automated manufacturing systems. The digital twin comprises two parts, the semi-physical simulation that maps data of the system and provides input data to the second part, which is optimization. The findings of the proposed system of the optimization part are fed back to the semi-physical simulation for verification. Open-architecture machine tool (OAMT) is defined and developed as a new class of machine tools comprising a fixed standard platform and various individualized modules that can be added and rapidly swapped. The study enables engineers to flexibly reconfigure the manufacturing system for catering to process planning by integrating personalized modules into its OAMTs. Their study also was able to produce a physical implementation which was used to verify the effectiveness of the proposed approach and enable the achievement to be improved on the system performance while minimizing the overheads of the reconfiguration process by automating and rapidly optimizing it. Renna (2017) reviewed a study on reconfigurable manufacturing systems (RMSs) which was first proposed by the Engineering Research Center of the University of Michigan in 1999. Alsafi and Vyatkin, (2010) also approved that these systems will allow manufacturers to produce multiple variations of customized products at the price of standardized mass products. A significant breakthrough in RMS theory research and engineering application was possible after two decades of development. Leng *et al.,* (2020) machine level reconfiguration capability is the foundation of RMS for achieving functionality. Their study defined the open architecture in both the mechanical and software system of machine tools for supporting the rapid reconfiguration with more reusability and fewer time costs. Their research also explicitly shows that the modeling of RMS is detailed as a basis for bi-level programming. Furthermore, their research proposed that for a multi-dimensional optimization variables and constraints, a systematic reconfiguring method for rapid reconfiguration of RMS was included. Their study proposed to use a system-level bi-level programming of upper-level productivity re-balancing and lower-level reconfiguration cost for obtaining an optimal reconfiguration solution. Their research proposed the use of a novel digital twin-driven approach for rapid reconfiguration of automated manufacturing systems. This approach contributed to the open architecture of machine tools (OAMT) in both the mechanical and software system for supporting the rapid reconfiguration with more re-usability and fewer time costs. Morgan *et al.* (2021) defined RMS as "reconfigurable manufacturing system which is designed for rapid adjustment of production capacity and functionality, in response to new circumstances, by rearrangement or change of its components." Changing components can include machines in a system, or modules and mechanisms in individual machines, such as tools, actuators and fixtures (hardware), functions, programs, services (software). New circumstances can include changing product demand (capacity), and new product family variety (capability). Further clarification was given to Dedicated Manufacturing Lines (DML), which are typically designed to produce a single part at a high production rate, achievable by fixed simultaneously operations. Flexible manufacturing systems (FMSs) can produce a variety of products, with changeable volume and mix, on the same system. However, FMS typically utilize general purpose technology, which have a range of operational flexibility, but at lower throughput speeds due to sequential operations (Morgan *et al.* 2021). Hatami *et al.* (2019) study on the state-of-the-art review on the applicability of AI methods to automated construction manufacturing shows that productivity in the U.S. construction industry has stagnated over the past 50 years, whereas manufacturing industries have about doubled productivity levels. Their study shows that the adaption of smart manufacturing with construction has challenges to achieving efficiency in a factory environment. Construction projects are one-off designs with little replication in the configuration of components. The ability to reconfigure factory production and network optimization performance help smart manufacturing systems. Artificial intelligence (AI) is well suited to this problem. Their research gave an in-depth review of AI methods and how the technology is to be applied to automated construction manufacturing systems. It started with a state-of-the-practice review of AI applications within construction manufacturing, followed by an identification of the AI needs of construction manufacturing systems. Finally, their research reviewed the state-of-the-art of artificial neural networks (ANNs) (e.g. deep learning and transfer learning) from the domains of manufacturing and industrial engineering, and discussed the potential for application to construction manufacturing. Their research helped to identify the path for future research and development in this field. Morgan *et al.* (2021) conducted a research study on Reconfigurable

Manufacturing Systems (RMS), which also explores the state-of-the-art in distributed and decentralized machine control and machine intelligence. Their study drew objective answers to two related given research questions, which are; reconfigurable design and industry adoption and enabling present and future state technology. Their research also assessed key areas such as; RMS fundamentals, design rational, economic benefits, needs and challenges; Machine Control modern operational technology, vertical and horizontal system integration, advanced distributed and decentralized control; and Machine Intelligence distributed and decentralized paradigms, technology landscape, smart machine modelling, simulation, and smart reconfigurable synergy. The scholars approached, their research in an exclusive way that establishes a vision for next-generation Industry 4.0 manufacturing machines, and also exhibit extraordinary Smart and Reconfigurable (SR) capabilities. The wide range developments of RMS to-date spans different research streams focusing on reconfigurable level assessment, analysis of features and performances, applied research and field applications, and the alignment with Industry 4.0 goals as reviewed by Bortolini*et al.*, (2018). The recent emergence of tangible state-of-the-art RMS solutions demonstrates a maturity, or “golden age”, of the research field, which is in line with the new “smart manufacturing” era. Adamietz *et al.*, (2018) realized the prototype of a container-integrated RMS, that was well in-line with the ‘micro/movable/fractal’ factory concept. Key design attributes can be seen in the encapsulation of the RMS in a mobile container, with a unified automaton platform, modular production units, and plug-and-produce control system. The study carried out on the container-integrated format enabled the transportation of the system to provide on-site manufacturing, enabling the benefits of localized service delivery without duplication of equipment at multiple locations. Nikolakis*et al.*, (2020) made a review of an end-to-end approach for RMS dynamic planning and control, in-line with Cyber-Physical Production System (CPPS) research. Their review proposed a containerized software framework for high-level planning and low-level execution. Specifically, the Docker software container environment, Python (high level) programming language, and IEC61499 industrial standard for function block (low level) programming of distributed field devices. Their study carried out High-level management of manufacturing operations on a centralized node in which the data was processed and executed control was handled at the network edge. Runtime events were generated at the edge and in smart connected devices via means of a variant of IEC61499 function blocks. Software containers manage the deployment and low-level orchestration of FBs at the edge devices. All aspects of the proposed solution were carried out on a software framework and applied in a small scale CPPS coming from the automotive industry. Park *et al.*, (2020) defined an intersected framework for RMS, which pivoted around a central robot with modular stations positioned in an octagon formation, for personal production in a “micro factory” setting. The reviewed solution was an intersected framework of several technologies and research paradigms, including CPPS, Digital Twin (DT), and the P4R information model. Intelligent manufacturing systems rely on the ability to adapt and evolve to face the volatility of dynamic markets, (Rodrigues *et al*., 2018). The complexity of these systems increases with the demand of more customized and quality products, which requires more agile and flexible methods to support the dynamic and on-the-fly system reconfiguration aiming to respond quickly to product changes, by offering more efficient services. In this service-oriented manufacturing context, where process functionalities are modelled as services (e.g., quality control, welding and transportation), the dynamic reconfiguration of the services structure (e.g., in terms of quality, processing time and provided features) assumes a critical role to achieve the referred requirements. Despite the current research efforts, the service reconfiguration approaches usually use reactive event triggers, with decisions coming from a centralized decision-maker and performed manually. This means a lack of dynamic and run-time reconfiguration flexibility by discovering opportunities and needs to change, and, thus, exploring possible actions leading to new and appropriate system configurations. Rodrigues *et al.*, (2018) research study rectified the above-mentioned issues, by essentially to providing solutions that answer to when and how to reconfigure a manufacturing system in an integrated, automatic and dynamic manner. Their study introduced an agent-based approach for service reconfiguration in manufacturing systems that allows the identification of opportunities in a pro-active and dynamic manner, and the on-the-fly implementation of new configuration solutions leading to a better production efficiency. The scholars' experimental findings, using a flexible manufacturing system case study, allowed to verify the feasibility and benefits of the proposed agent-based service reconfiguration solution for competitive and collaborative industrial automation scenarios.

CONCLUSION

This paper has succeeded in the design and implementation of Automated Manufacturing System. This will enhance the speed at which product is been processed and also maximize profit for the company. The automation system is a very important aspect of running the manufacturing company since it is concerned with learning, training and certification of company workers. Hence this research work will provide enhanced ways of database security and will ensure that accurate and consistent production outputs are well managed. But considering the benefit which will be accrued from implementing the new system, one would agree with me that the investment after all worth it.

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