The Scientific Temper
Vol. 13, No. 2, July-December, 2022:pp 317-326
ISSN 0976-8653, E-ISSN 2231-6396
A Web of Science Journal
DOI: https://doi.org/10.58414/SCIENTIFICTEMPER.13.2.2022.317-326
Doc ID: https://connectjournals.com/03960.2022.13.2.317

Reconfiguration of Automated Manufacturing Systems Using Gated Graph Neural Networks

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ABSTRACT

To deal with the unpredictability of dynamic markets, automated manufacturing systems rely on their capacity to adapt and change. With the need for more personalized and high-quality goods, the complexity of these systems evolves, prompting more agile and adaptable techniques. To enable dynamic as well as on systems reconfiguration aimed at responding swiftly to product changes by providing more efficient services. To increase production in response to market demand and meet the referred requirements, this proposed study employs Machine Learning Techniques for the Reconfiguration of Automated Manufacturing Systems. Gated Graph Neural Network (GGNN) based prediction model is generated using graph instances as input, and the prediction model provides a result for each graph instance, as well as activity level relevance and ratings for the relevant needs such as model accuracy and validation. For better use of the model effectiveness by the proposed methodology for the final model is validated for cost, time, and productivity.

Keywords: Machine Learning, Reconfiguration, Computer numerical control (CNC), Gated Graph Neural Network (GGNN), Automat Manufacturing Systems, Dedicated Manufacturing lines.

INTRODUCTION

An Automated Manufacturing System (AMS) is a good example of a discrete event system (Hu, Yihui, Ziyue Ma, and Zhiwu Li.,2020). It enables different product types to introduce the different times by sharing resources such as machines, automated operated vehicles, robots, and tools during concurrent or asynchronous processes. There is a need to make speedy alterations to the hardware and software to stay up with the rapid developments. Traditional automated production systems can supply the demand for unreasonably expensive products. The shortcomings of traditional automated production systems are being addressed by reconfigurable manufacturing systems (Mehrabi, Mostafa G., A. Galip Ulsoy, and Yoram Koren, 2020).

There is a new kind of manufacturing system that is configured in the field at random and dynamically in real-time. Setups, failures, and processing rework, as well as machines, new goods, and handling equipment, are all examples of such configurations. In reconfigurable manufacturing systems, the set of system assets is utilized to the process element under the process series. Resolving the impasse problem is critical for reconfigurable production systems (Patel, Ravi, Anil Gojiya, and Dipankar Deb,2019). A Reconfigurable Manufacture System (RMS) changes the manufacturing of one component or product into another within the same product effectively by modifying its configuration (Huang, Aihua, Fazleena Badurdeen, and Ibrahim S. Jawahir, 2018). In exchange for services, and RMS offers to manufacture the specific production capacity and capabilities that they require at any given time. The supervisory control system is an important component of an RMS because it enables the production system to react to changes in product demand quickly and adaptively. Therefore, the growing need for reconfigurability in industrial supervisory control systems has garnered a lot of attention lately. The manufacturing area is under pressure from global market expansion, which producers should be able to respond quickly and cost-effectively such as product customization, delivery timeliness, and quality change. There are taking all the variables into account and keeping up with Industry 4.0, Internet of Services, built on Cyber-Physical Systems (CPS), supplemented with other emerging information and communications technology (Henning, Kagermann, 2013). For example, cloud computing, big data, and data analytics are seen as critical to the distribution of more robust, flexible, reconfigurable systems, responsive, and interoperable. The development of Service-Oriented Architecture (SOA) based solutions necessitates the deployment of many characteristics, including registration, reconfiguration, composition, and service discovery. Service reconfiguration is critical for responding to condition alterations that occur in unexpected settings by constantly adapting and improving the capabilities extracted by the provided services (Rodrigues, Nelson, Paulo Leitão, and Eugénio Oliveira, 2016).

There is a requirement to establish proper communication between the different sectors of the manufacturing process with the help of various multipath routing protocols (Khan, Nikhat Raza, C. D. Kumawat, and Sanjay Sharma, 2018) the communication between the different manufacturing sectors is done to eliminate unnecessary chaos.

Typically, service reconfiguration is carried out to deal with unanticipated situation shifts, enhance system competitiveness, and react to different business plans. In manufacturing systems, services are functions supplied by a system or device, such as welding activities or pick-and-place performed by inspection or robot operations offered by quality control location. There can reconfigure quickly to keep up with the mass customization trend, existing and future production systems. Reconfiguration aims to enable a production system to switch from one configuration to another rapidly and cost-effectively without taking it down. There are preserving systems to effectiveness and unexpected events such as malfunctions and interruptions occur. To shorten the time, it takes to launch new systems, it is also vital to swiftly integrate technology and functionality into existing systems. Reconfigurable manufacturing was recognized as one of the six major manufacturing issues for the year 2020 in research conducted by the National Research Council. However, the inflexible nature and limited adaptability of today's production systems, which are hierarchical control structures, centralized restrict the capacity to react quickly and effectively to dynamic changes (Lepuschitz, Wilfried, Alois Zoitl, Mathieu Vallée, and Munir Merdan, 2010).

In this manner, sophisticated manufacturing systems need to properly address economic factors to engineering aspects. There cannot acquire a fair proportion of the competitive market to justify the investments. Modular manufacturing systems are designed to rapidly produce various product families in the quickest time and at the lowest cost without compromising quality. The most important characteristic of the systems is termed reconfigurability, which is the ability to reorganize and alter production components targeted at adapting to new environmental and technological developments. A modularity-based structure must be a goal in the layout design stage allowing reconfiguration manufacturing systems to create product variations. This feature enables production systems to generate significant product diversity. Therefore, reconfiguration manufacturing systems must be upgradeable in process technology with new operational needs and able to change capacity quickly when it's changing product kinds. The same machines are arranged in different ways in different system throughputs, and even within the same layout, the choice of machine types and numbers affects the efficiency of the production system. By adjusting the configuration, configurable systems may adapt and change operational conditions for varied functional requirements. RMS is remarkable in that it adjusts the setup and ensures that the capability is maintained. It is preferable to reconfigure when demand changes to minimize the amount of idle capacity and functionality (Krishna, Mr. Braj, and S. C. Jayswal, 2012).

Anomaly detection is used in resource maintenance to use machine learning. However, machine learning based on Reconfiguration of Automated Manufacturing Systems is employed for manufacturing control and real-time optimization of production plans at the collection horizon (Luo, Jian, Tao Hong, and Meng Yue, 2018). There are 3 techniques of machine learning; reinforcement, supervised, and unsupervised learning. These techniques are applied for the reconfiguration of automated manufacturing systems. Expert and intelligent systems must perform a complicated and time-consuming categorization process. The influence of new different classifiers that improve accuracy or actual positive levels on automated manufacturing systems. Every criterion has a distinct weight or benefit in respect to each choice. Each set is divided into two parts: a set of criteria and a collection of alternatives to evaluate. The major aim is to enhance the reconfiguration of automated manufacturing systems. Several prior experiments have hampered algorithmic feature selection. Machine learning methods are used to identify traits (Shailaja, K., B. Seetharamulu, and M. A. Jabbar, 2018).

Type of Manufacturing Systems

Many manufacturing industries use a variety of dedicated flexible manufacturing systems for the production of the products (Rahman, AA Abdul, and Nor Rizan Mohamad, 2016).

a) Dedicated Manufacturing Lines (DML)

There are based on mass-producing the company's main products or components using low-cost fixed automation. One component (i.e., line rigidity) is manufactured at high rates by employing multiple tools simultaneously at machine stations on each devoted dedicated line (called "gang drilling"). There is high demand for a product price per component. DML demand outnumbers supply is cost-effective if it can operate at full capacity. When the global competition heats up and overcapacity is built all over the world which dedicated lines are operating at full capacity.

b) Flexible Manufacturing Systems (FMS)

It can use the same technique, a variety of products in different quantities and combinations may be generated. FMSs are made up of high-priced "Computer numerical control (CNC)" machines and other general-purpose programmed automation. Because FMS throughput is lower than DML throughput the CNC machines utilize a single tool. The cost per piece is extremely high because of the high cost of the equipment and the restricted output. As a result, the FMS has a lower production capacity than specialized lines, and its beginning costs are higher, as indicated.

RELATED WORK

There is various work given by the different authors which are given below:

(Zan, Xin, Zepeng Wu, Cheng Guo, and Zhenhua Yu, 2020) studied that focuses on multi-objective development challenges in automated production systems. The impasse is possible to the flexibility and limited resources of work processing pathways in such an automated manufacturing system. It is coping with a scheduling problem to avoid a stalemate and optimize performance. The new Pareto-based evolutionary process is resolving the multi-objective planning difficulties of reconfiguration manufacturing systems. In automated factories, planning not just specifies the routing of each work, but it is specifying a viable workflow. Possible solutions are expressed as the operation sequence of all positions and individuals containing information of processing routes. The possibility of individuals is confirmed by the Petri net model of an automated manufacturing system and deadlock controller assess people's feasibility, and infeasible people are converted into viable ones. The techniques have been tested with various variants, and they have been compared to modified non-dominated sorting machine learning.

(Moghaddam, Shokraneh K., Mahmoud Houshmand, Kazuhiro Saitou, and Omid Fatahi Valilai, 2020) stated that manufacturing systems are forced to adapt and react rapidly to market variations due to strong global rivalry, dynamic product variations, and rapid technological advancements. The issue of the configuration model for ascendable reconfigurable manufacturing systems that generate various component family products is addressed in the study. RMS setups must vary to manage demand variations in goods over the lifecycles at a low cost.

(Kim, D-Y., J-W. Park, Sujeong Baek, K-B. Park, H-R. Kim, J-I. Park, H-S. Kim et al, 2020) state that mass customization and personalization are recent manufacturing trends that necessitate factories to be efficient to customer requirements and respond quickly. There are using adjust operational parameters to account for system failures product quality issues, resiliently retool machinery, and retrofit old systems with upcoming innovative technologies. Product lifecycles are growing quicker because of customer expectations for unlimited and unexpected flexibility, requiring reconfigurable and flexible production infrastructure to enable the basic building blocks of smart factories. This study provides a flexible manufacturing testbed by using a distributed shop floor control architecture. Self-layout recognition, inter-layer data distribution, quick workstation reprogramming, and customized software for observing are all elements of fast industrial transformation. The testbed is being used to develop and verify these technologies or methods.

(Morariu, Cristina, Octavian Morariu, Silviu Răileanu, and Theodor Borangiu, 2020) state that the making digital processes in manufacturing companies, integration of progressively complex equipment and software control systems. It has increased dramatically the number of data points available in the manufacturing system. The capacity of companies to gain value from extract and big data processing valuable understandings is essential when it comes to establishing rules that maximize production while also safeguarding resources. In recent years, the application of big data technologies and machine learning has increased in particular areas such as logistics and production control. The ability to utilize these technologies in real-time via cloud manufacturing reduces installation and implementation expenses. Therefore, the suggests a cloud-based machine learning technique for identifying and optimizing a situation's reality. The major subjects of the study are predictive maintenance and predictive production planning. There was wanting to develop a hybrid control resolution that analyses real-time data streams in large industrial systems using both machine learning techniques and big data with a focus on energy usage aggregated at many levels. The control architecture is distributed to allow for data gathering and format change on the shop floor. An artificial neural network is qualified and utilized to variations and detect anomalies from the typical designs of energy utilization at every layer. There are real-time long or short-term memory deep learning and neural networks are utilized to correctly predict energy consumption patterns during production to allow for resource reallocation.

(Kaid, Husam, Abdulrahman Al-Ahmari, Zhiwu Li, and Reggie Davidrajuh, 2020) stated that the architecture of a system is changed while it is running. Many factors may lead to this reconfiguration failures, processing rework, adding additional equipment, and adding new goods. In RMSs, resource sharing may cause deadlocks, resulting in certain operations being left unfinished. The author offers a new two-step method for fast and accurate regulatory control reconfiguration for deadlock management in RMSs with dynamic modifications.

(Battaïa, Olga, Lyes Benyoucef, Xavier Delorme, Alexandre Dolgui, and Simon Thevenin, 2020) stated that RMS isn't only a new manufacturing paradigm that allows for customization. They also serve as a foundation for the development of a new generation of sustainable manufacturing systems. The model and intense improvement of reconfigurable manufacturing systems are the potential paths toward sustainable production. The goal is to extend the life cycle, address end-of-life issues, and reduce energy use and emissions.

(Prasad, Durga, and S. C. Jayswal, 2019) state that the industrial environment is fraught with ambiguity and change. It is distinguished by shorter product and technology life cycles, faster delivery times, a higher degree of customization at the price of a conventional product. There is more product kind of the unpredictability of demand, quality, and fierce global rivalry. These are distinguishing features. Academics and practitioners anticipate that uncertainty was a rise in the coming years. There are required reconfigurable at a low cost to address market difficulties as demand and production capacity vary manufacturing system. This kind of system is known as a reconfigurable manufacturing system. There are some associated with specialized manufacturing methods, while others view it as a more adaptable approach. There have been debates on the growth of mixed families and the challenges to reconfiguration. This study attempts to conceptually systematize reconfigurable manufacturing systems and reconfigurability via the synthesis of the vast material available after a comprehensive examination.

(Brahimi, Nadjib, Alexandre Dolgui, Evgeny Gurevsky and Abdelkrim R. Yelles-Chaouche, 2019) conducted a detailed examination of the major components and kinds of RMS that have been addressed in the literature. The author explained how optimization plays a role in the design and function of the systems. The author does so by first describing the most important objective functions for assessing and evaluating the performance of an RMS, and then recommending a categorization of optimization issues and methods for solving them.

(Koren, Yoram, Xi Gu, and Weihong Guo, 2018) state that the challenges presented by globalization, "reconfigurable manufacturing systems (RMS)" were developed in the mid-1990s. RMS combines the advantages of committed sequential lines with flexible production methods. The main aim of an RMS is to improve the capacity of the production system to respond to unanticipated differences in customer demand. RMSs are more cost-effective which increases productivity while simultaneously prolonging the total system lifetime. However, RMS's experience over the last two decades indicates that in-line inspection stations are an aid in maintaining excellent product quality. There is a cutting-edge overview of the design and operation techniques utilized in real-world implementations using RMSs. More study was conducted to determine how current advancements in intelligent manufacturing technologies enhance RMS operations and design.

(Puik, Erik, Daniel Telgen, Leo van Moergestel, and Darek Ceglarek, 2017) state that the manufacturers are creating reconfigurable manufacturing equipment to go through the increasing need for new responsive output. The use of agile manufacturing technology, which allows for a fast market launch for large-scale production to increase a company's turnover. There are systems known as reconfigurable production systems that utilised modular reconfiguration which is described as changing the configuration of the machine. There are allow for greater product diversity on a single production system. When it comes to RMS quality and the resources required for reliable production to reconfiguration process must be finished as soon as possible. It was providing a method for comparing various approaches to reconfiguration. There are three kinds of reconfiguration to each with a unique impact. The approach utilizes a newly designed index mechanism based on the axiomatic design methodology to construct RMS process modules. The lead time of the reconfiguration process are determined using weighing criteria and resources. There was using the method early in the development phase provides for a quick assessment of many alternatives. A 3D measuring probe manufacturing process demonstrated that the method was effective.

Table 1: Summary of the literature review

S. no.	Authors [Reference no.]	Years	Outcome
1	Zan et al., [15]	2020	Compared to modified non-dominated sorting machine learning
2	Moghaddam et al., [16]	2020	Variations in goods over the lifecycles at a low cost
4	Kim et al., [17]	2020	Develop and verify these technologies or methods
5	Morariu et al., [18]	2020	Predict energy consumption patterns during production to allow for resource reallocation
6	Kaid et al., [19]	2020	Deadlock management in RMSs with dynamic modifications
7	Battaia et al., [20]	2020	The goal is to extend the life cycle, address end-of-life issues, and reduce energy use and emissions
8	Prasad et al., [21]	2019	Synthesis of the vast material available after a comprehensive examination
9	Brahimi et al., [22]	2019	Recommending a categorization of optimization issues and methods for solving them
10	Koren [23]	2018	Current advancements in intelligent manufacturing technologies enhance RMS operations and design
11	Puik et al., [24]	2017	Method early in the development phase provides for a quick assessment of many alternatives

BACKGROUND STUDY

To deal with the unpredictability of dynamic markets, intelligent manufacturing systems depend on the capacity to adjust and develop. With the need for more personalized and high-quality goods, the complexity of these systems grows, necessitating more agile and adaptable ways to enable dynamic and on-the-fly method reconfiguration to react rapidly to produce alterations with providing new economical facilities. Reactive event triggers are often utilized in service reconfiguration techniques, notwithstanding current research efforts, with decisions made by an implemented manually and centralized decision-maker. This translates to the lack of run-time reconfiguration flexibility and dynamics in terms of identifying possibilities. There are requirements for change and investigating potential actions that new lead and suitable system designs. There are required to address the problems, which resolutions the address when reconfiguring a production system in a combined, automated, and dynamic way. The dynamic service reconfiguration procedure is a popular subject in intelligent manufacturing systems. Yet, an analysis of the literature in the area revealed that service reconfiguration is often done manually, offline, and centralized, failing to meet the criteria for genuinely automated service reconfiguration (Rodrigues, Nelson, Eugenio Oliveira, and Paulo Leitão, 2018).

PROBLEM FORMULATION

The manufacturing paradigm has altered from mass production to set manufacture and newly to "batch size one production" for a condition over time like diverse customer requirements, supply-demand reversal, and shortening products life cycles. Cost, reactivity, variety, and quality are only a few of the new concerns and goals of production that have developed since the industrial environment changed. A production system must be changed to:

- React rapidly to customer demands.
- Retool equipment and modify operating parameters in the event of an unforced system breakdown or product quality issue.
- Retrofit existing systems with emerging new technology.

The current work presented a manufacturing configuration model, and the model goes for the reconfiguration based on certain parameters. The model initially works for defining the optimized manufacturing model based on communication levels between various stages. Based on data flow managed in the task table Gated Graph Neural Network (GGNN) is utilized to produce an initial current model utilizing data flow after the learning process. The final model is validated for cost, time, and productivity. On any change desired as compute or partial the model reinitiates and reconfigure the manufacturing process flow.

RESEARCH OBJECTIVES

a) To increase the production concerning demand occur in the market.

b) To determine the best-optimized path to reduce the cost and time of the model.

c) To reconfiguration of the model for better output and as per demands.

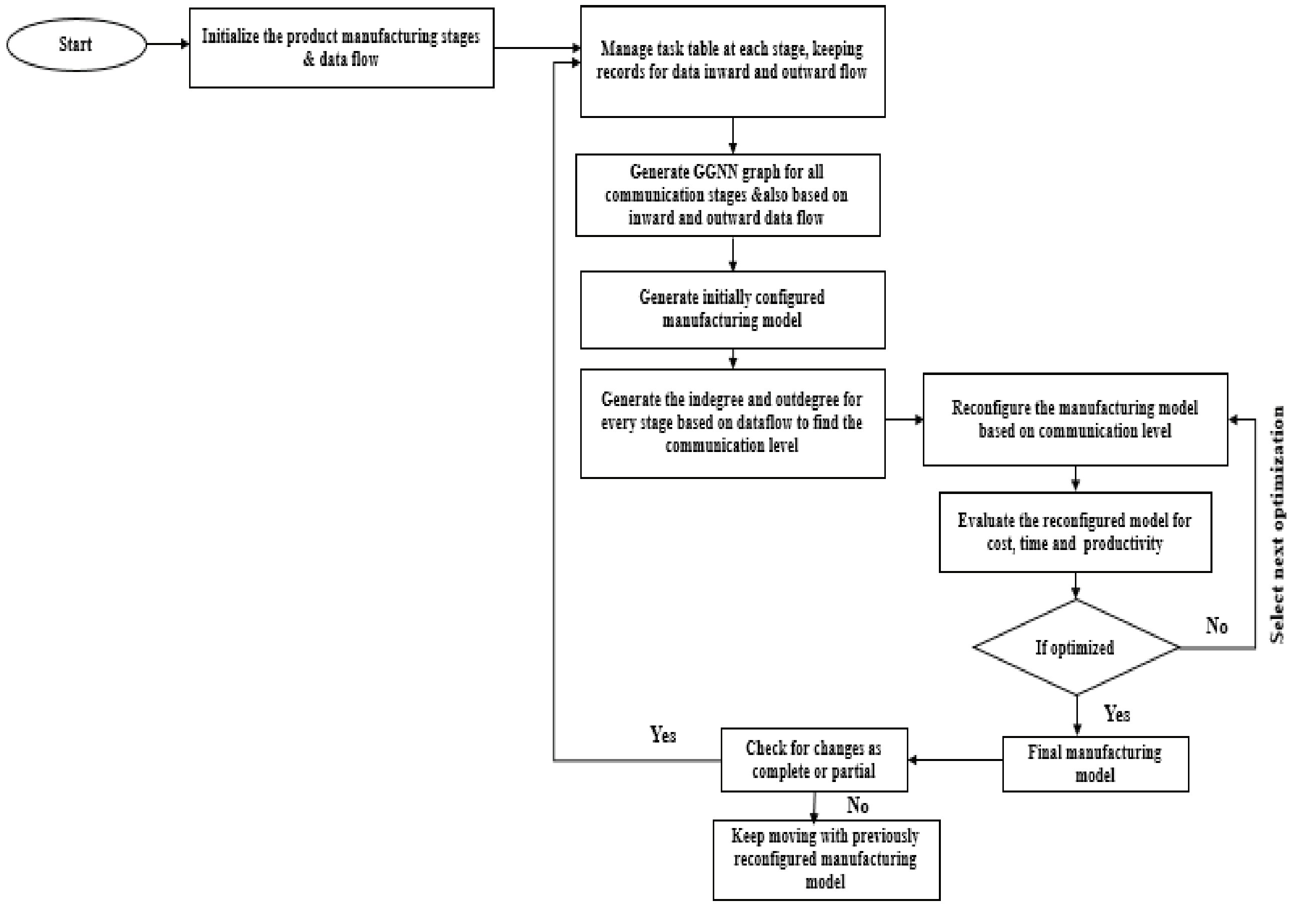

Figure 1 Proposed Methodology

$$G = \{V, \varepsilon, L_V, L_\varepsilon\} \quad (1)$$

Where V is a set of nodes (v, l_v), is a set of edges, and L_V and L_E are respectively vocabularies for nodes and edges, from which node and edge labels (l_v and l_e) are defined.

d) To meet or react to demands rapidly as much as possible through the model.

e) To find the model accuracy and validation for better use of the model.

RESEARCH METHODOLOGY

In the proposed methodology, firstly there is an initialization of various stages through which data flows in the proposed model. In this model, various department and their tasks are evaluated at the initial level. After that, a task table at each step is created which contains the flow of data in an inward and outward direction. Based on these inward and outward data the GGNN is created. After that, generate an initially configured manufacturing model and generate the indegree and outdegree for every stage based on data flow to find the communication level. After this step, there is a reconfiguration of the manufacturing based on the communication level and evaluating the cost, time, and productivity. If the model is optimized, then the final manufacturing model is created else select the next optimization. At last, if the final manufacturing model has completed or partial change then generate GGNN graph for all stages again else keep moving with the previously reconfigured manufacturing model. Figure 1 shows the proposed methodology.

Gated-Graph-Neural-Networks (GGNNs)

There are based on the graph cases obtained as input in the earlier phase, a GGNN-based prediction model is built. The prediction model generates a result prediction for each graph instance as well as activity-level relevance ratings concerning the outcome prediction. The method converts the data representation of the event log into a format suitable for subsequent usage by the GGNN in equation 1 (Harl, Maximilian, Sven Weinzierl, Mathias Stierle, and Martin Matzner, 2020).

TOOL FOR IMPLEMENTATION/ SIMULATION

To verify the effectiveness of the proposed approach, set out using a python implementation.

Python

It is an actively semantic, object-oriented high-level, construed language. Its built-in high-level data structures, merged by dynamic linking and dynamic typing, produce this ideal for quick Implementation Development as a scripting language for connecting current elements. Python's simple-to-learn structure stresses readability that lowers software maintenance costs. Packages and modules are endorsed by Python that enables code reuse and software modularity. The Python interpreter and its complete standard library are available to download and distribute in source or binary form for each general platform.

8. Implementation Results

Result 1: In the proposed study the workflow as shown in figure 2 are in various steps in which designing a model in the first stage, then manufacturing it in the second stage, assembling it in the second third stage, then trying to control it in the fourth stage and finally deliver it in the final step.

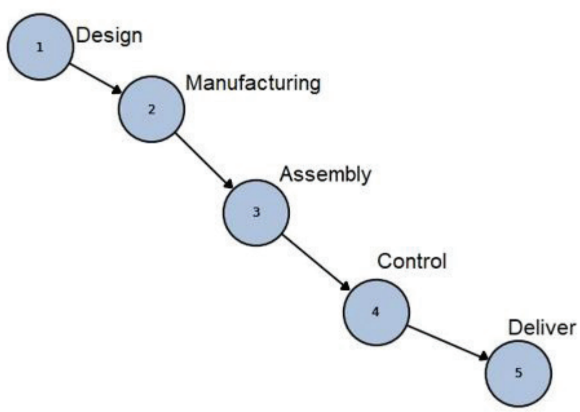

Figure 2 Workflow process from design to deliver

For case 1

Result 2: As shown in figure 3, In the first stage designing a model, after which will conduct the first step. If Test 1 does not pass, then revise the design and repeat process 1. After that, move on to the next stage which is model manufacturing. After manufacturing Test 2 will perform if the manufactured model does not pass from Test 2 then perform manufacturing again after that assembly of the model in the fifth stage.

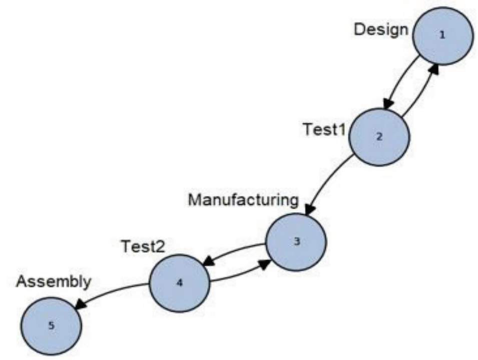

Figure 3 Workflow process from design to Assembly with two tests

Result 3: In the first stage, design a model, then execute test 1; if test 1 fails, modify the design, and continue the process. Following this, then go to the next stage, which is model manufacture. Following model manufacturing, test 2 will be performed until test 2 is passed. If test 2 is not passed, manufacturing will be repeated. After that, the model assembly will go to the fifth stage, and then test 3 will be performed. If test 3 inevitably fails, then alter the assembly and repeat the steps until you reach the last stage, which is control shown in figure 4.

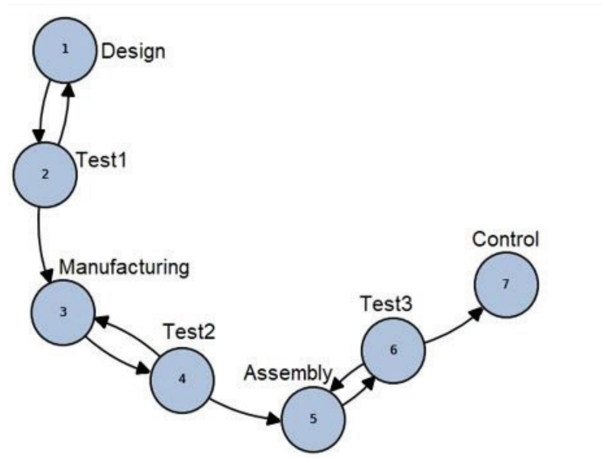

Figure 4 Workflow process from design to control with three tests in between

Result 4: As shown in figure 5 first design a model in the initial stage, then execute test 1; if test 1 fails, then modify the design and continue the process. Following this, then proceed to the next stage, which is model manufacture. Post model manufacturing, test 2 will be performed until test 2 is clear. If test 2 is not definite, then repeat manufacturing. After that, keep moving on to the fifth stage, which is model assembly, and now perform test 3. Sometimes when test 3 continues to fail, then change the assembly and repeat the step. Afterward, move on to the next stage, which is control, where we will try to find and correct errors, and finally, the model will be delivered.

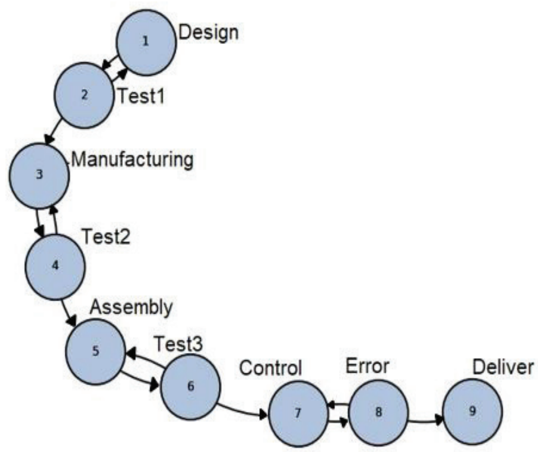

Figure 5 Workflow process from design to deliver with three Tests

Result 5: As per the proposed study the outcomes for the model which is shown with the help of figure 6 is that the first stage of the design work takes an average of 25 days. The test 1 task in the second stage takes approximately 30 days. The manufacturing task in the third stage takes an average of 55 days, while the test 2 task in the fourth stage takes an average of 70 days. The fifth stage assembly activity takes at least 90 days to complete. Test 3 work in the sixth stage requires a minimum of 110 days. The control work takes approximately 130 days in the seventh stage. The test 4 task takes exactly 140 days on the eighth stage, and the final stage delivery task took a total of 175 days.

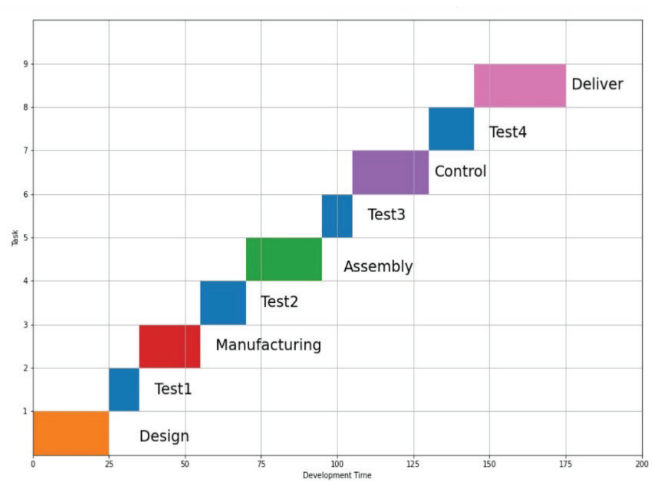

Figure 6 Development Time-Task graph

For case 2

Result 6: As shown in figure 7 design a model in the first stage, then manufacture it in the second stage, then assemble it in the third stage, and finally test it. If the test attempt fails, then go back to stage 2 of manufacturing and repeat the procedure until the test passes, and then reach the third stage, which is control, and finally, that model is delivered.

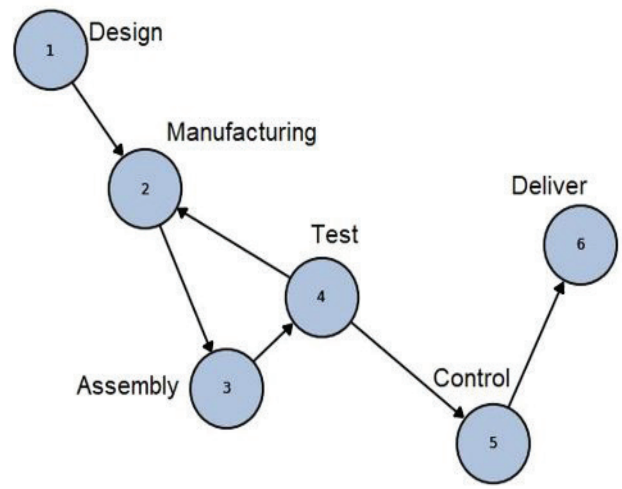

Figure 7 Workflow process in many ways from design to deliver with one test

Result 7: The development time outcomes shown in figure 8 forms by the proposed study is that the design work takes an average of 20 days to accomplish in the first step. The manufacturing task takes approximately 45 days in the second stage, and the assembly task typically takes 70 days in the third stage, followed by the test task, which takes a precise 75 days, the control task, which takes an average of 100 days, and the final deliver task, which takes an estimate of 130 days.

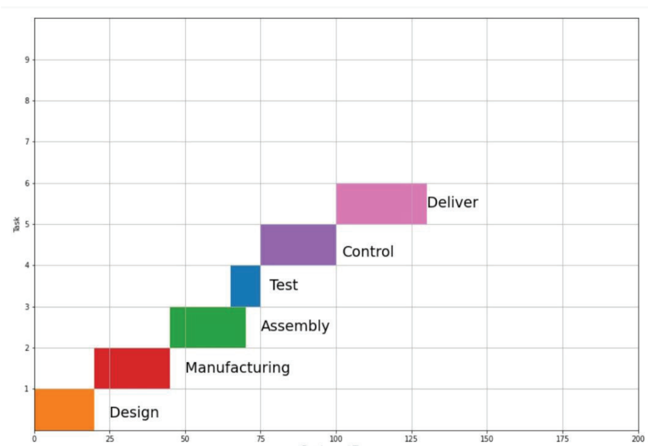

Figure 8 Development Time -Task graph for case 2

CONCLUSION

Machine learning has been widely used to solve several production line problems. Quality control and fault diagnosis are two major research directions in recent years, and machine learning approaches have been proved to be effective in these two areas. However, many problems are still not fully addressed, among which preventive maintenance is indicated as one of the important areas. In automated manufacturing systems, services are functions supplied by a system or device, such as welding activities or pick-and-place performed by inspection or robot operations offered by quality control location. Existing and future manufacturing systems can be readily reconfigured to keep up with the mass customization trend. In this proposed methodology, reconfiguration aims to enable a production system to switch rapidly from one configuration to another and cost-effectively without taking it down to develop a predictive model for the reconfiguration of automated manufacturing system with the help of the GGNN. Furthermore, the model can validate each task with a specific test before forwarding it to the next task. The prediction model generates a result prediction for each graph instance as well as activity-level relevance ratings concerning the outcome prediction.

FUTURE SCOPE

Deep learning algorithms have produced state-of-the-art outcomes in a variety of fields, but they have yet to be thoroughly examined on production lines. In a variety of domains, deep learning algorithms have achieved state-of-the-art results, but they have yet to be properly tested on production lines. Traditional machine learning techniques were used in several of the investigations. Other techniques, such as ensemble learning, transfer learning, and semi-supervised learning, can assist increase model performance or simplifying model building. Machine learning models have more processing capacity when they are processed quickly. Thus, the future scope of Machine Learning will accelerate the processing power of the automation system used in various technologies.

ACKNOWLEDGEMENT

I am extremely grateful to Prof. Sudesh Kumar Sonani, vice chancellor, IES University for providing a supportive environment of research in the university.

Declaration: *We also declare that all ethical guidelines have been followed during this work and there is no conflict of interest among authors.*

REFERENCES

Hu, Yihui, Ziyue Ma, and Zhiwu Li. "Design of supervisors for active diagnosis in discrete event systems." IEEE Transactions on Automatic Control 65, no. 12 (2020): 5159-5172.

Mehrabi, Mostafa G., A. Galip Ulsoy, and Yoram Koren. "Reconfigurable manufacturing systems: Key to future manufacturing." Journal of Intelligent manufacturing 11, no. 4 (2000): 403-419.

Patel, Ravi, Anil Gojiya, and Dipankar Deb. "Failure reconfiguration of pumps in two reservoirs connected to overhead tank." In Innovations in Infrastructure, pp. 81-92. Springer, Singapore, 2019.

Huang, Aihua, Fazleena Badurdeen, and Ibrahim S. Jawahir. "Towards developing sustainable reconfigurable manufacturing systems." Procedia Manufacturing 17 (2018): 1136-1143.

Henning, Kagermann. "Recommendations for implementing the strategic initiative INDUSTRIE 4.0." (2013).

Rodrigues, Nelson, Paulo Leitão, and Eugénio Oliveira. "Dynamic service reconfiguration with multi-agent systems." In International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing, pp. 307- 318. Springer, Cham, 2016.

Khan, Nikhat Raza, Sanjay Sharma, and P. S. Patheja. "Energy-aware multipath routing scheme based on particle swarm optimization (EMPSO)." *International Research Journal of Engineering and Technology* 5, no. 1 (2018).

Khan, Nikhat Raza, Sanjay Sharma, and P. S. Patheja. "Trust-based Multipath Routing Scheme (TMAODV)". *International Journal of Computer Science and Engineering (IJCSE) 5*, (2018).

Khan, Nikhat Raza, C. D. Kumawat, and Sanjay Sharma. "Survey Paper on Secure Multipath Routing Protocol Using Optimization". *International Research Journal of Engineering and Technology (IRJET) 5,* (2018).

Lepuschitz, Wilfried, Alois Zoitl, Mathieu Vallée, and Munir Merdan. "Toward self-reconfiguration of manufacturing systems using automation agents." IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 41, no. 1 (2010): 52-69.

Krishna, Mr. Braj, and S. C. Jayswal. "Reconfiguration of Manufacturing System." (2012).

Luo, Jian, Tao Hong, and Meng Yue. "Real-time anomaly detection for very short-term load forecasting." Journal of Modern Power Systems and Clean Energy 6, no. 2 (2018): 235-243.

Shailaja, K., B. Seetharamulu, and M. A. Jabbar. "Machine learning in healthcare: A review." In 2018 Second international conference on electronics, communication, and aerospace technology (ICECA), pp. 910-914. IEEE, 2018.

Rahman, AA Abdul, and Nor Rizan Mohamad. "Software-in-the-loop technique: an approach to support reconfiguration of the manufacturing system." *J Eng Appl Sci* 11 (2016): 9789-9795.

Zan, Xin, Zepeng Wu, Cheng Guo, and Zhenhua Yu. "A

Pareto-based genetic algorithm for multi-objective scheduling of automated manufacturing systems." Advances in Mechanical Engineering 12, no. 1 (2020): 1687814019885294.

Moghaddam, Shokraneh K., Mahmoud Houshmand, Kazuhiro Saitou, and Omid Fatahi Valilai. "Configuration design of scalable reconfigurable manufacturing systems for part family." International Journal of Production Research 58, no. 10 (2020): 2974-2996.

Kim, D-Y., J-W. Park, Sujeong Baek, K-B. Park, H-R. Kim, J-I. Park, H-S. Kim et al. "A modular factory testbed for the rapid reconfiguration of manufacturing systems." Journal of Intelligent Manufacturing 31, no. 3 (2020): 661-680.

Morariu, Cristina, Octavian Morariu, Silviu Răileanu, and Theodor Borangiu. "Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems." Computers in Industry 120 (2020): 103244.

Kaid, Husam, Abdulrahman Al-Ahmari, Zhiwu Li, and Reggie Davidrajuh. "Automatic supervisory controller for deadlock control in reconfigurable manufacturing systems with dynamic changes." Applied Sciences 10, no. 15 (2020): 5270.

Battaïa, Olga, Lyes Benyoucef, Xavier Delorme, Alexandre Dolgui, and Simon Thevenin. "Sustainable and energy- efficient reconfigurable manufacturing systems." In Reconfigurable Manufacturing Systems: From Design to Implementation, pp. 179-191. Springer, Cham, 2020.

Prasad, Durga, and S. C. Jayswal. "Reconfigurable manufacturing system–a new class of manufacturing system." Management and Production Engineering Review (2019).

Brahimi, Nadjib, Alexandre Dolgui, Evgeny Gurevsky, and Abdelkrim R. Yelles-Chaouche. "A literature review of optimization problems for reconfigurable manufacturing systems." IFAC-PapersOnLine 52, no. 13 (2019): 433-438.

Koren, Yoram, Xi Gu, and Weihong Guo. "Reconfigurable manufacturing systems: Principles, design, and future trends." Frontiers of Mechanical Engineering 13, no. 2 (2018): 121-136.

Puik, Erik, Daniel Telgen, Leo van Moergestel, and Darek Ceglarek. "Assessment of reconfiguration schemes for Reconfigurable Manufacturing Systems based on resources and lead time." Robotics and Computer-Integrated Manufacturing 43 (2017): 30-38.

Rodrigues, Nelson, Eugenio Oliveira, and Paulo Leitão. "Decentralized and on-the-fly agent-based service reconfiguration in manufacturing systems." Computers in Industry 101 (2018): 81-90.

Harl, Maximilian, Sven Weinzierl, Mathias Stierle, and Martin Matzner. "Explainable predictive business process monitoring using gated graph neural networks." Journal of Decision Systems (2020): 1-16.