Assessment of appropriate production process: a simulation-based study

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Abstract: An appropriate production process is a critical challenge in today's competitive world. In this study, four different types of manufacturing systems in a production line: 'fixed manufacturing system (manual)', 'fixed manufacturing system (automated)', 'flexible manufacturing system', and 'programmable manufacturing system' have been analysed and evaluated using Rockwell ARENA Software. This study has implemented a discrete event simulation model and data collection techniques to help in rational decision-making to figure out what might be the best solution for the production line. The result illustrates that the four different manufacturing systems: fixed manual, fixed automated, flexible, and programmable; produce an output of 237, 303, 397, and 505 units respectively. The extended lines of programmable manufacturing systems produce nearly two times more output than the flexible manufacturing system.

Keywords: simulation; fixed manufacturing system; flexible manufacturing system; programmable manufacturing system; Industry 4.0; ARENA.

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1 Introduction

A manufacturing system or production line in an industry has to be utilised efficiently to get maximum throughput. Therefore, the system should be as flexible as possible so that 100% utilisation is ensured (Sakr et al., 2021). In this era of the fourth industrial revolution, there are several inventions such as industrial robots, automated guided vehicles (AGV) (Zacharia and Xidias, 2020), human machine interface (HMI) (Sorooshian and Panigrahi, 2020), programmable logic controllers (PLC) (Kumar et al., 2023), additive manufacturing, and the internet of things (IoT) (Moll, 2023), which make the production line fully automated, ensure product quality and achieve the highest output. Mohammad et al. (2021) have explained the significance of digital automotive transformation for original equipment manufacturers, dealers, suppliers, captive finance organisations, and others involved in the mobility ecosystem. The incorporation of IoT technologies into the industry digitised and decentralised the production sequence, resulting in a strong and highly adaptable business structure (Sony, 2020). Moreover, the only way to overcome practical challenges such as minimising idle time, energy consumption, change over time, labour cost, and maximising productivity, efficiency, and utilisation while allowing decision-making with real-time data is to adopt an advanced flexible manufacturing system (Konur et al., 2021).

Different studies illustrate the contribution of different advanced manufacturing systems in maximising the profit of the industry. In this era of industrial revolution over the past few years, manpower has been reduced by 8.73% (Szabó-Szentgróti et al., 2021), and from 2016 to 2021, the gross profit margin (GPM) of the apparel industries has increased from 45% to 50.3%, tobacco product 37.4% to 44.3%, oil and gas extraction from 12.3% to 35.8%, metal mining 13.4% to 29.9% (Díaz-Chao et al., 2021). The concept of Industry 4.0 has generated a current market share of more than USD 71.7 billion, with a forecast of more than USD 150 billion by 2024, according to the market research report (Ammar et al., 2021). Russia adopted Industry 4.0 to get a sustainable solution to optimise resources in the long run (Popkova and Sergi, 2018). In that study, a hypothesis on Industry 4.0 has been shown for digitalising the Russian economy. In a recent study, Laskurain-Iturbe et al., (2021) studied the impact of advanced manufacturing systems on the circular economy (CE). According to the study, Japan, China, and Germany have implemented modern technologies for a long time to recycle, reduce and reuse resources and maximise circularity.

Tang and Veelenturf (2019) showed that 92 out of 100 companies adopted automation along with computerised manufacturing systems. 73% of automated production line installations are for manufacturing systems and operations, with only 6% for logistics or transportation (Yao et al., 2020). Both variation and volume are limited in a fixed manufacturing system (Guo et al., 2020). Manufacturing or operations flexibility, also known as volume flexibility or product variety flexibility, can be set according to requirements in a flexible manufacturing system. Automated vehicles interact with a product or workpiece and production equipment, in today's smart production system (Mykoniatis and Harris, 2021; Cheng et al., 2022). An automated smart production system allows parts to be moved not just horizontally but also vertically, ensuring that as much space as possible is utilised (McIlhagger et al., 2020; Nagy et al., 2018). In another study, Ponis and Efthymiou (2020), identified that the implementation of IoT on the production floor reduces 50% of downtime by improving the part handling system. In this paper, four different types of manufacturing systems in a production line: 'fixed manufacturing system (manual)', 'fixed manufacturing system (automated)', 'flexible manufacturing system', and 'programmable manufacturing system' have been evaluated by simulating a real-time industrial application in ARENA and the feasibility of these systems have been compared. Furthermore, this paper has conducted a study to develop models that provides a better understanding of the feasible production line and lists some observations of four different production lines. Moreover, the result determines the total production per hour for the mentioned four production lines.

This paper is organised as: Section 2 summarises the literature review. Section 3 explains the proposed methodology whereas Section 4 delineates the simulation results. Section 5 describes the verification and validation of this research. The final section illustrates the conclusion along with recommendations for further research.

2 Literature review

Factories that use fixed manufacturing systems for production are not enough to meet demand. Because fixed manufacturing systems limit product and operation variation (Wang et al., 2022). A production line encompassing assembling, processing, and packaging was simulated with Rockwell ARENA to analyse the efficiency of stationary manufacturing systems, which revealed that some machines remain idle for extended periods (Huang, 2020; Ruppert and Abonyi, 2020). The productivity of that production line can be increased by 5% if the idle time can be removed (Chen et al., 2016). Al-Hawari et al. (2010), simulated a model of raw materials' demand, supply, and service time to analyse the performance of an automated but fixed transportation system. This simulation showed the impact of different parameters like conveyor speed, and customer demand on the service time and queue length of raw material. Romano et al. (2009), simulated a production line of washing machines to maximise product availability by minimising the processing time of each machine. A simulation model was built and run for both the existing system (fixed) and the proposed system (automated flexible). By comparing the results, 94% of machine availability has been ensured in 7.5 h of shift, where standard shift time is 8 h.

The Flexible production System (FMS) is regarded as an integral part of advanced production systems (Javaid et al., 2022; Florescu and Barabas, 2020). FMS raises production and makes production more efficient (Pei et al., 2023). Campo et al. (2022), developed an algorithm for minimising job shop processing completion time by integrating FMS with the system. The proposed algorithm simplified the complexity of the job shop scheduling problem (JSSP) and optimised 30% more time than the existing system. In the same year, Luo et al. (2022), designed a cloud simulation model for adapting flexible manufacturing systems in the production line and comprised factories, logistics, warehouses, and markets. Eventually, the number of pallets/carriers has been optimised and after analysing the simulated result, the bottleneck has been identified. Ojstersek et al. (2020), focused on adapting FMS in the production process to optimise two important parameters: energy consumption and wasted materials. The suggested FMS reduced 10.6% of energy consumption and 36.5% of scrap. Diaz and Ocampo-Martinez, (2021), proposed a non-centralised control structure for adapting FMS in the process line of compressed air and coolant supply systems as the centralised control system had made the process line quite inflexible and inefficient. The observation of the simulation of both centralised and non-centralised systems revealed that non-centralised systems showed better results and consumed less power than centralised systems. Mourtzis et al. (2020), designed a flexible manufacturing cell to minimise the printing time of a nonflexible 3D printing process. The result illustrated that it took 84 minutes to print a 3D object with a nonflexible cell whereas the flexible manufacturing cell complete the same object in 49 minutes, increasing the efficiency of the 3D printer by 41%. In another research, a simulation model of bottle production has been developed to identify the bottlenecks of the production line. Using a preventive maintenance strategy, the output rate is increased by 2.5 times of fixed manufacturing systems, and cycle time is reduced by 33.33% (Ethiopia. et al., 2020).

Industrial robots are the integral parts of a programmable manufacturing system that is used for picking, placing and assembling parts without human intervention (Arnarson et al., 2022). A recent study designed a smart manufacturing system including assembling parts, programmable logic controller (PLC), human machine interface (HMI), conveyor belts, and robotic arms for production, pick and place, and quality assurance with high accuracy. As a result, the labour cost and the production cycle time have been reduced (Maggi et al., 2021). In the same year, Enériz et al. (2021), applied Artificial Neural Networks (ANN) to track the food position, a machine learning algorithm to check food quality, and a Field Programmable Gate Array (FPGA) matrix to take the necessary steps to re-correct the food quality before packaging. This model ensured the successful delivery of an average of 92.72% of accurate products to the customer end. Further, Girma Mullisa and Abdul-Kader (2022), developed a Kanban Simulation Model to evaluate customer waiting time, product work-in-progress (WIP), and weekly throughput based on the optimal number of Kanban in an industry. Simulating the suggested model in ARENA, the result showed that the optimal Kanban number is 275 which gives a minimum customer waiting time is 0.84h, 323 Pcs of product WIP, and weekly throughput of 737 Pcs. Pereira et al. (2021), suggested a semantic web approach to adopt smart manufacturing systems. In this study, automation was fully ensured to gather information in the database and notify all the employees of the system by developing a robot using python and Selenium Web Driver. As a result, further processing of those data can be done to identify the maximum or minimum production period of the month or year or to identify the bottleneck station by observing the servicing time.

Zheng et al. (2022) proposed a programmable manufacturing system based on a program generation approach which makes the production line automated and flexible as well. The suggested system ensured 100% efficiency and a better quality product. Yang et al. (2021) proposed a software-defined cloud manufacturing system to ensure flexibility in the system and utilise all potential resources. Using different path planning and optimisation algorithms, the suggested model successfully eliminated network congestion and ensure data privacy and security. Moreover, ElMaraghy et al., (2021) developed adaptive cognitive manufacturing system and evaluated its four different factors technology, product, business strategy, and production to characterise the model. This model can collect information on customer demand, global trends, or competitor strategies and provide a suitable plan and schedule based on the collected information. The overall current themes across different manufacturing system literature are summarised in Table 1.

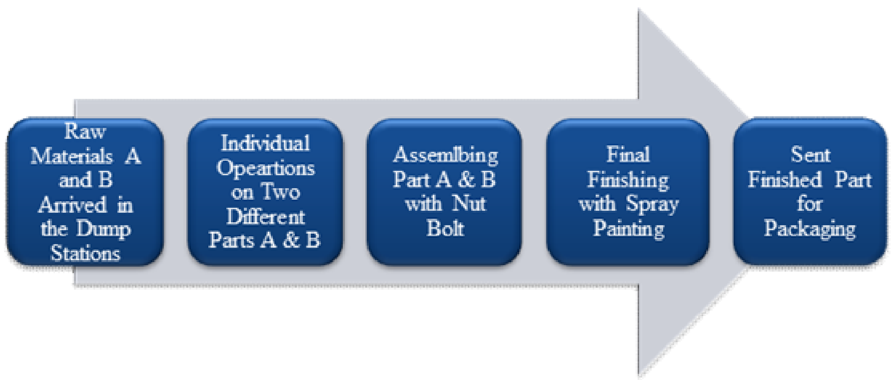
Table 1 Current research gap in the area of manufacturing systems in a production line

Author	*Fixed manufacturing system*	*Flexible manufacturing system*	*Programmable manufacturing system*	*ARENA*
Al-Hawari et al. (2010)	✓			✓
Chen et al. (2016)	✓			✓
Romano et al. (2009)	✓	✓		✓
Campo et al. (2022)		✓		
Ojstersek et al. (2020)	✓	✓		
Diaz and Ocampo-Martinez (2021)		✓		
Mourtzis et al. (2020)		✓		
Maggi et al. (2021)			✓	
Enériz et al. (2021)			✓	
Girma Mullisa and Abdul-Kader (2022)			✓	✓
Pereira et al. (2021)			✓	
Zheng et al. (2022)		✓	✓	
Yang et al. (2021)		✓	✓	
ElMaraghy et al. (2021)		✓	✓	
This study	✓	✓	✓	✓

3 Methodology

In the studied model, two different parts (Material A and Material B) have to be performed the drilling and turning operations, respectively. After that, both parts are assembled with nut bolts and painted with spray to get the final product (Figure 1). The operations, assembly, and painting are done in different workstations and multiple part handling systems have been used for moving the raw materials and parts from station to station.

Figure 1 Basic steps of the production process (see online version for colours)



In this study, four different production systems (Fixed manufacturing system (Manual), Fixed manufacturing system (Automated), Flexible manufacturing system, and Programmable manufacturing system) of the product have been simulated and the results have been compared. The methodology of this study has been illustrated in Figure 2.

3.1 Modelling and analysing system

3.1.1 Fixed manufacturing system (manual)

In the ARENA simulation model, Material A and B are individually arrived with ‘Material A’ and ‘Material B’ using Create module. The Assign module, ‘Assign Material A’ and ‘Assign Material B’, assigned the arrived materials to the Station module named ‘Dump Station 1’ and ‘Dump Station 2’ manually and sent them to the Process module, named ‘Drilling Material A’ and ‘Turning Material B’, through the roller conveyors with Convey module, named ‘Roller Conveyor of Material A’ and ‘Roller Conveyor of Material B’, to perform the operations, respectively. The Access module and Exit module must be needed to access and discharge from the conveyor module. Then they came to the Station module, ‘Station 5’ and ‘Station 6’, respectively to get assembled in the Process module ‘Manual Assemble Material A and B’. The nut bolts are also assigned at the same time to provide the joining and the joining process has been done in the Process module, named ‘Permanent Joint of Assembled Part’. Then the assembled parts wait in the Station module, named 'Waiting for Painting' to be conveyed to the Access module, named 'Semi Finished Part in Roller Conveyor'. After discharging from the conveyor, the painting process is done in the Process module named 'Painting the Assembled Part with Spray'. Thus, the final product comes out with another roller conveyor 'Finished Part sent to conveyor' (Convey module), and is sent to the Station module, named 'Finished Part Discharged' to pack the finished material. Then these materials wait in the Station module, named 'Finished Material' and are sent to the Station module, named 'Transfer FG for Packaging' with an Access module ('Multiple Discharging Conveyor'). The sequence of the whole production process is shown in Figure 3, representing the fixed manual manufacturing system. In Table 2, all assigned value for input parameters of this manufacturing system has been specified.

Figure 2 The flow of work in this study

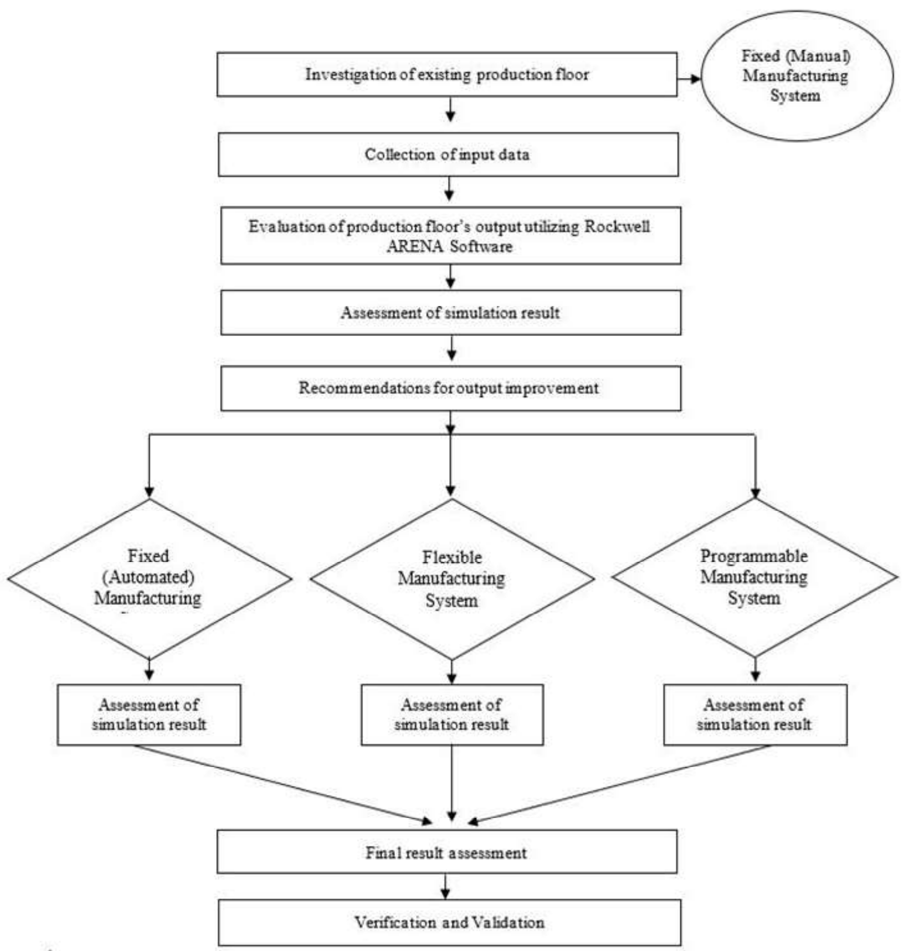


Table 2 Input values for manual fixed manufacturing system

Processes	*Time (seconds)*
Arrival of RM	210 / 275
Operations	240
Assembly	300
Painting	240

3.1.2 Fixed manufacturing system (automated)

To transform the manual process into an automated fixed manufacturing system, all the conveyors are replaced by Automated Guided Vehicles (AGV) to transport materials on the production floor from station to station, station to machine, and machine to machine. Raw materials are brought to the dump stations with AGVs. After arriving at the dump stations, AGVs are requested for transporting materials with the Transport module, shown as 'Transport Material A with AGV 1' and 'Transport Material B with AGV 2' in Figure 4. Like Convey module, the Transport module also needs to be requested and freed with the Request module 'Request for AGV 1' and Free module 'Free AGV 1' respectively. This time drilling and turning operations are done with a CNC machine in the Station modules, named 'Drilling Material A with CNC' and 'Turning Material B with CNC'. Figure 4 represents the fixed automated manufacturing system. In Table 3, all assigned value for input parameters of this manufacturing system has been specified. Table 4 illustrates the respective change for switching from Fixed Manufacturing System (Manual) to Fixed Manufacturing System (Automated).

Table 3 Input values for automated fixed manufacturing system

Processes	*Time (seconds)*
Arrival of RM	90 / 90
Operations	180
Assembly	240
Painting	240

Table 4 Identified changes for switching from fixed manufacturing system (manual) to fixed manufacturing system (automated)

Operations	*Replacement*		*Addition in Fixed manufacturing system (automated)*
	Fixed manufacturing system (manual)	*Fixed manufacturing system (automated)*	
Raw material handling	Roller conveyor	AGV	AGV reduced material handling time
Drilling and turning operations	Manual	CNC	CNC machines take less time to drill and turn

3.1.3 Flexible manufacturing system

It has been observed that due to a fixed manufacturing system, the demand can be met appropriately all the time. The productivity of the fixed manufacturing systems is not huge enough to satisfy all the demands. To overcome demand uncertainty, a flexible manufacturing system can be adopted by extending the automated fixed manufacturing production line. If the server number is increased at each workstation in a flexible manufacturing system; that extended line can be used for drilling, turning, and painting operations according to demand. Therefore, when demand exceeds the capacity of the automated fixed production process, this production line can produce additional products. The number of the extended workable server has been controlled by a Human Machine Interface that represents the working stage of each server. In Figure 5, the Arena simulation has been shown for a flexible manufacturing system. It is the extension of an automated fixed manufacturing system where Decide module is used to control the percentage of raw materials passing through the Station modules 'Drilling Material A with CNC' and 'Turning Material B with CNC' and extra two Station modules 'Drilling Material A with CNC 2' and 'Turning Material B with CNC 2' has been added for extra production. In Table 5, all assigned value for input parameters of this manufacturing system has been specified.

Table 5 Input values for flexible manufacturing system

Processes	*Time (seconds)*
Arrival of RM	60 / 60
Operations	180 with 2 servers or machines
Assembly	180
Painting	240 with 2 servers or machines

3.1.4 Programmable manufacturing system

The programmable manufacturing system is an extension of the flexible manufacturing system. Industrial robots and numerical control systems are good examples of programmable manufacturing. As CNC machines have already been used in the flexible manufacturing production line, the 'Programmable Universal Manipulation Arm' is used to assemble the parts to transform the line into a fully programmable manufacturing system. All the machine tools are controlled by a program that is coded in computer memory. In Figure 6, ARENA simulation for a programmable manufacturing system has been shown. The extended lines in programmable manufacturing systems almost give double the output than flexible manufacturing system. In Table 6, all assigned value for input parameters of this manufacturing system has been specified.

Table 6 Input values for programmable manufacturing system

Processes	*Time (seconds)*
Arrival of RM	60 / 60
Operations	180 with 2 servers or machines
Assembly	90
Painting	240 with 2 servers or machines

Figure 3 Fixed manufacturing system's (manual) simulation model in ARENA (see online version for colours)

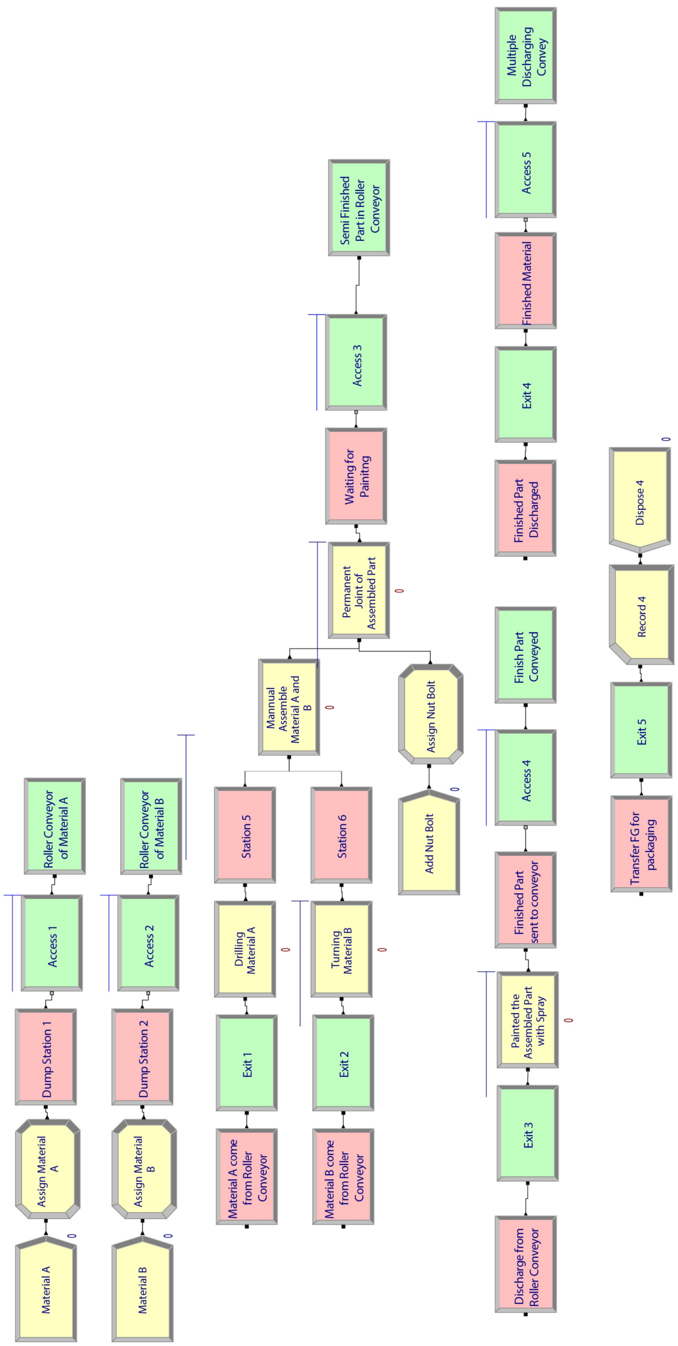


Figure 4 Fixed manufacturing system's (automated) simulation model in ARENA (see online version for colours)

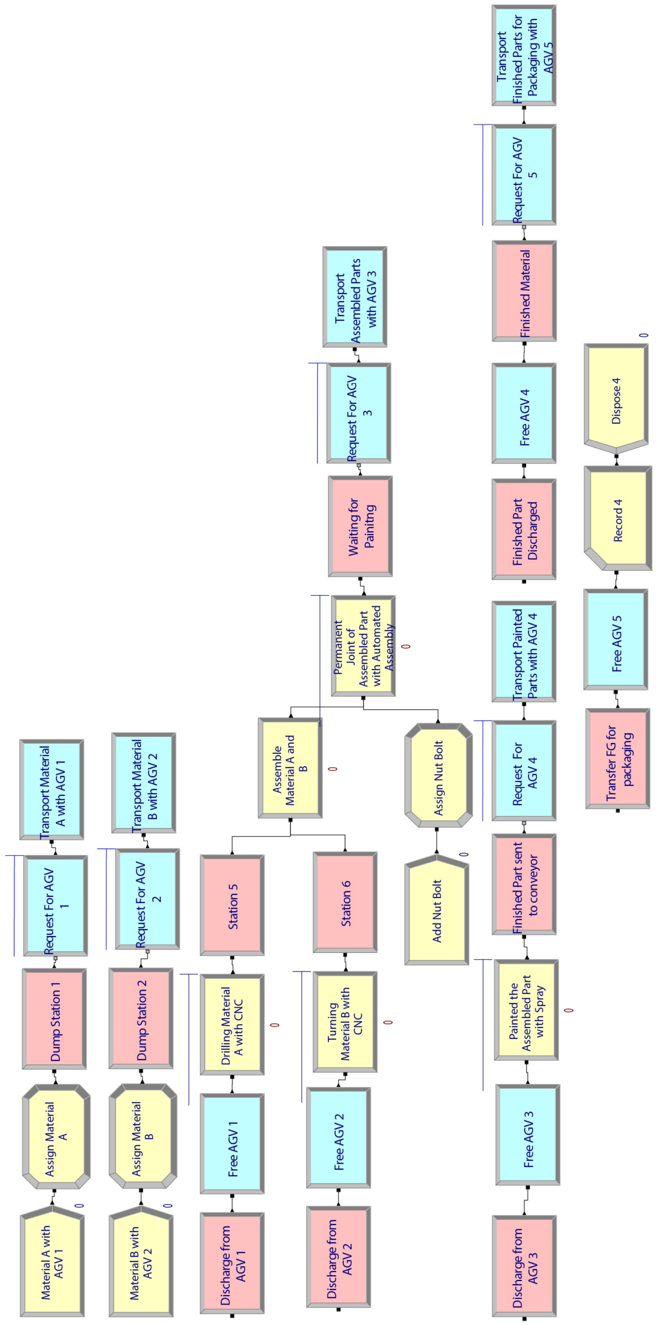


Figure 5 Flexible manufacturing system's simulation model in ARENA (see online version for colours)

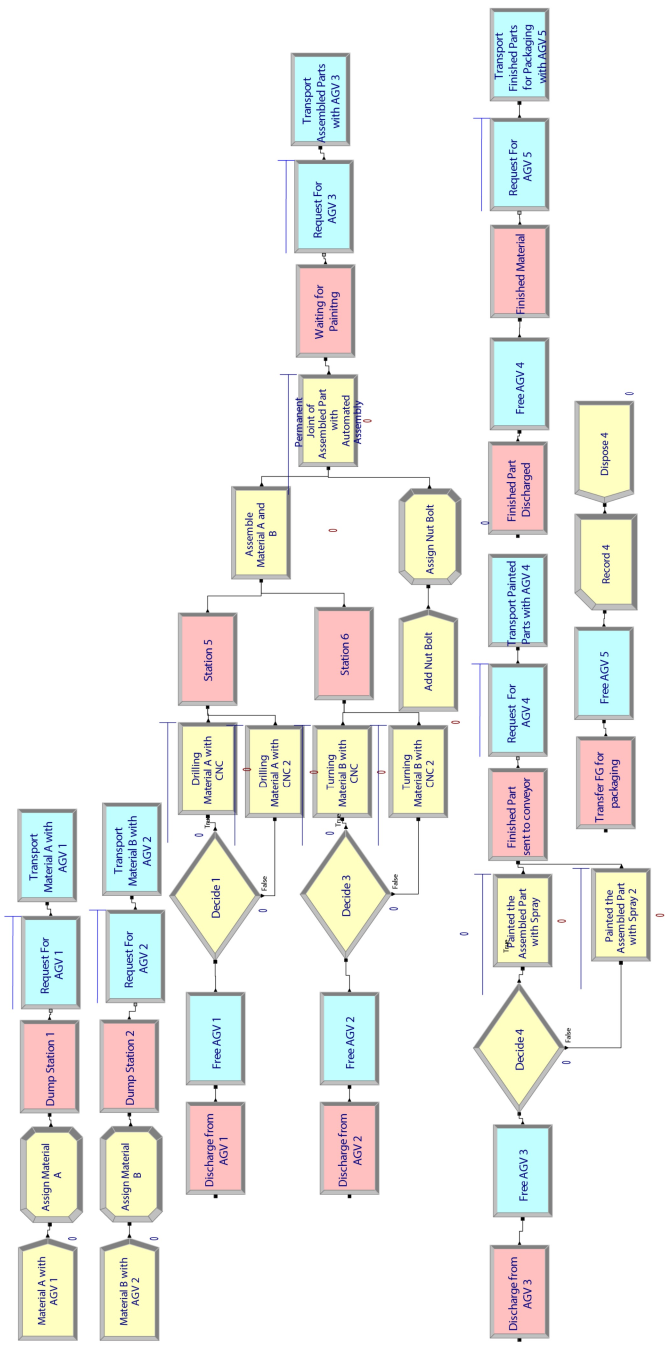
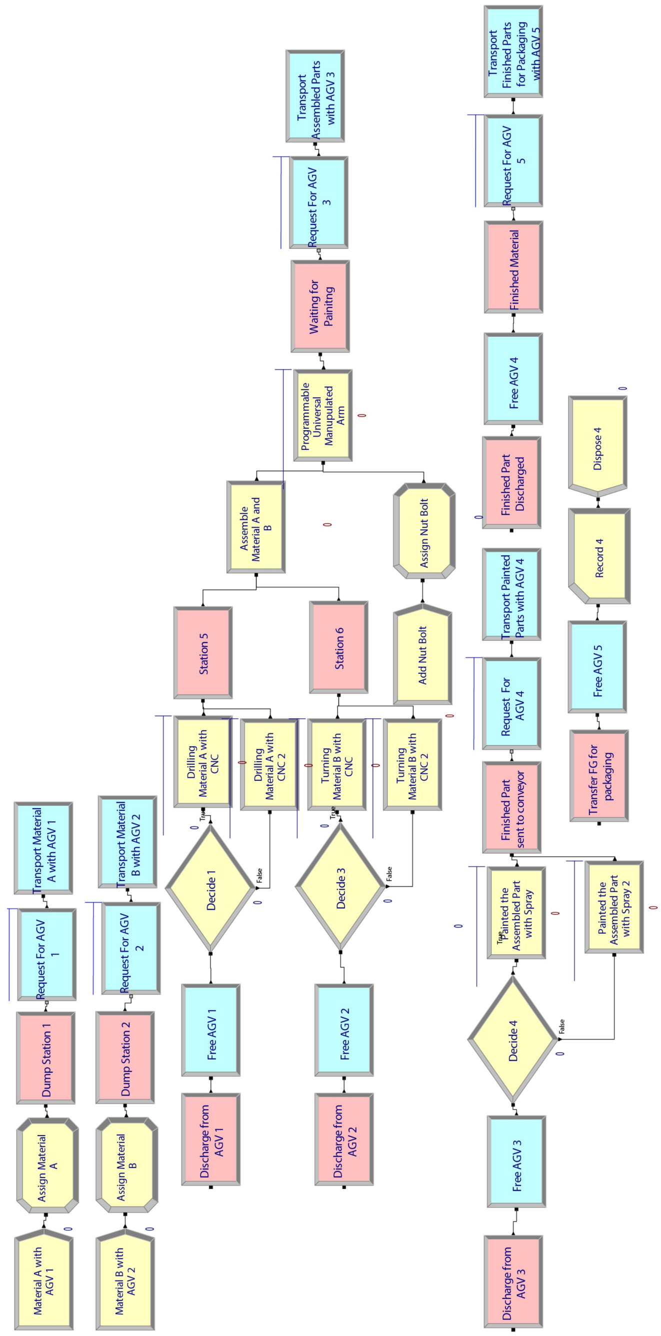


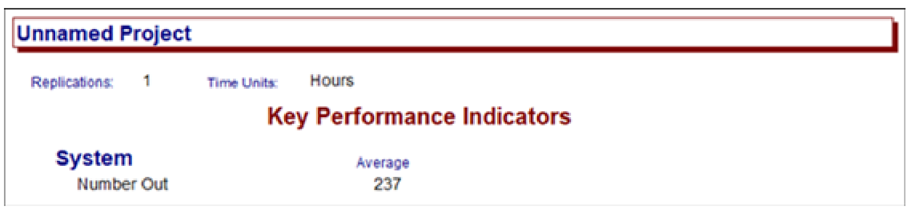
Figure 6 Programmable manufacturing system's simulation model in ARENA (see online version for colours)



4 Simulation results

The model is been developed and all the required data are implemented for the four possible manufacturing systems. In a fixed manufacturing system, Material A and Material B have been brought to the dump stations by the workers, which takes 210 s for material A and 275 s for material B and the type of arrival of Material A and B is Random (Expo). The processing time for both drilling and turning operations is 240 s which is set in triangular type. The assembling of materials starts after the arrival of nut bolts manually. The joining of two different materials through nut bolts has also been done by workers, which takes 300 s. Then the painting process is done in 240 s. With this setup, 237 units of the final product are produced per hour in the fixed manufacturing system. Figure 7 shows the simulation run result for the manual fixed manufacturing system.

Figure 7 Simulation run result for manual fixed manufacturing system (see online version for colours)



In the fixed automated manufacturing system, Material A and Material B arrived at the dump stations by AGVs which takes only 90 s. The processing time for both drilling and turning operations is 180 s, which is set in constant type. The nuts and bolts arrive every 60 seconds instead of a manual refill so that the materials don't have to wait for a long time to get assembled. The joining of two different materials through nut bolts has also been done by an automated mechanised assembly device, which takes only 180 s. Then the painting process is done in 240 s. With this setup, 303 units of the final product are produced per hour. Figure 8 shows the simulation run result for the fixed automated manufacturing system.

Figure 8 Simulation run result for fixed automated manufacturing system (see online version for colours)

As automated fixed manufacturing has a capacity of 303 units, the extended servers are allowed to give more than 303 units of output. Let, the demand for the final product is 400 units. The maximum capacity of an automated fixed manufacturing system is 303 units which is almost 75% of the total demand. In Decide module, 75% is set as Percent True to pass 300 units through ‘Drilling Material A with CNC’ and ‘Turning Material B with CNC’ and extra 100 units through the extended stations. As a result, 397 ≈ 400 units of the final product are produced per hour in flexible manufacturing which means the flexible manufacturing production line offers (397 – 303 = 94) ≈ 100 units more product than a fixed automated manufacturing system by increasing only one server in each station. This is how the output can be manipulated according to demand with extra servers which are controlled by a responsible human operator. Figure 9 shows the simulation run result for the flexible manufacturing system.

Figure 9 Simulation run result for flexible manufacturing system (see online version for colours)

The extended lines of programmable manufacturing systems almost give more output than flexible manufacturing system. According to the simulation result, the extended line gives (505-303 = 202) ≈ 200 units more product than the fixed automated manufacturing system which means the extended lines of programmable manufacturing systems almost give two times more output than the flexible manufacturing system. Figure 10 shows the simulation run result for the programmable manufacturing system.

Figure 10 Simulation run result for programmable manufacturing system (see online version for colours)

Table 7 Performance of different manufacturing systems in a production line

Manufacturing systems	*Process time (seconds)*				*Total production (per hour)*		*Observations*
	Arrival of RM	*Operations*	*Assembly*	*Painting*			
Fixed (manual)	210 / 275	240	300	240	237 units	1	Roller Conveyors are used for part handling.
						2	Manual drilling, turning, assembling and painting operations are conducted.
						3	Production volume is fixed.
Fixed (automated)	90 / 90	180	240	240	303 units	1	AGV's are used for part handling.
						2	CNC machines are used for drilling and turning operations. The assembly process is automated and printing is manual.
						3	Production volume is fixed but higher than the manual production line.
Flexible	60 / 60	180 with 2 machines	180	240 with 2 machines	397 units	1	AGV's are used for part handling.
						2	CNC machines are used for drilling and turning operations. The assembly process is automated and printing is manual.
						3	As much as the server can be extended in drilling, turning and painting workstations.
						4	Production volume is adjustable.
Programmable	60 / 60	180 with 2 machines	90	240 with 2 machines	505 units	1	AGV's are used for part handling.
						2	CNC machines are used for drilling and turning.
						3	The extended server gives double the output than the flexible production line.
						4	Production volume is adjustable.

5 Verification and validation

5.1 Verification

Verification is the process of determining whether the simulation model performed as expected. Verification entails ensuring that the model is correctly implemented in the computer program (ARENA) in terms of values, distributions, and syntax errors. The model is developed according to a logical sequence based on the real-life system that a manufacturing company follows on a regular basis. This study considers all aspects, such as the operation of different parts and the assembly of multiple parts in a production line. All data are collected manually standing in front of the production line. To ensure an accurate result, data is collected five times. The collected data in this study is divided into two categories: primary and secondary data. Secondary data is the data that has been provided by the company's official departments, whereas primary data is the data that has been collected manually from the current system.

5.2 Validation

After distributing the survey for two weeks along with company employees, 953 responses are observed. 55.36% of the responses are from top-level employees, and the survey revealed that 73.57% of employees had 15 years of experience and 95.7% of them worked in the production line having the mentioned four manufacturing systems. Moreover, 53.6% of employees work in the decision-making stage in fixed manual manufacturing systems while 68.57% work in fixed automated manufacturing systems. 72.8% of the employees work as policy-makers in flexible manufacturing systems and 56.55% of the employees are assigned as policy-makers in the programmable manufacturing system.

Whether the model does represent the actual system or not can be determined by comparing the results and the actual data. Another way is by comparing the results of the simulation run with experts' knowledge about the system. Furthermore, ground-level employees are considered the best experts since they observe the production floor directly every day. This is accomplished by comparing simulation results to survey results, as the model's implications are heavily reliant on ground-level employees. As simulation results showed the total production (per hour) for the programmable manufacturing system is 505 units while the survey showed that 500 units can be prepared from the programmable manufacturing system on the production floor with the same input. Moreover, the simulation results model showed that the total production (per hour) for the flexible manufacturing system is 397 units. When comparing this result to the survey results with the same input variables, the simulation result illustrates a very close relation.

6 Conclusions and recommendations

This paper provides a good baseline to understand different manufacturing systems such as fixed, flexible, and programmable based on the data observed from the real system. The data is used later in the simulation model. According to the data, different models are developed using ARENA simulation software that simulates the real system and gives results about the system. Then the model is validated and verified by comparing the real data and the simulation results. Results illustrate that within a certain period programmable manufacturing system gives the highest output than others. In the simulation for 1 run, the four different manufacturing systems: fixed manual, fixed automated, flexible, and programmable; produce an output of 237, 303, 397, and 505 units respectively. Furthermore, both flexible and programmable manufacturing systems have been able to produce the desired output based on demand. This paper helps the production plants department and engineers in the selection of the best manufacturing system in a production line.

The survey has been developed to maximise the production rate of a production plant. This paper gives a crystal-clear view of different manufacturing and helps to choose the suitable manufacturing systems for the manufacturing of a specific product. In the future, this study methodology can be applied to similar studies or be conducted for different manufacturing industries along with advanced equipment and sensors to make the data collection process much easier and to allow to have more data. This study has opened a new line of research in the area of manufacturing systems, aligned with technological advances based on computer vision along with artificial intelligence and industrial robots. Furthermore, for seeking to create more intelligent frameworks equipped for recognising the specific product lines, and improving the production processes, a different study needs to be conducted focusing on machine learning.

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