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DISCRETE EVENT SIMULATION MODELLING AS AN IMPROVEMENT VALIDATION TOOL ON PRINTED CIRCUIT BOARD MECHANICAL ASSEMBLY PROCESS

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ABSTRACT

Although the application of Discrete Event Simulation (DES) as a validating tool may seem counterproductive, routinely reviewing an improvement that has been installed is crucial for industries to decide whether a process is optimal, requires further refinement, or must be discontinued and replaced with a better alternative. The objective of this paper is to demonstrate DES as a decision-making tool by validating the improvements of a mechanical assembly line for Printed Circuit Board Assembly (PCBA) manufacturing. As a case study, parameters connected to Overall Equipment Effectiveness (OEE) namely availability, performance, and quality were gathered from a PCBA mechanical assembly line in Company A that has shifted their primary assembly tools from conventional electrical torque screwdrivers into programmable torque screwdrivers. Through the data collection step, it was observed that the OEE improved upon implementing a programmable torque screwdriver. The assembly lines were then modelled in the DES system and information pertaining to OEE was gathered and analyzed to aid in validating the enhancement in the manufacturing line. Based on the simulation, the results obtained confirm that the OEE improves through the implementation of a programmable torque screwdriver, signifying that DES is a suitable tool to help validate an improvement in a process.

Keywords: deterministic model, simulation, modelling, manufacturing, overall equipment effectiveness, OEE.

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1. INTRODUCTION

As of today, a prominent phrase and subject among those engaged in areas pertaining to professionals and academicians alike is the fourth industrial revolution - commonly referred to as Industry 4.0 [1]. This transformation of how the industry functions emphasized the application of digitalized tools to enable real-time data collection and analysis, contributing beneficial knowledge to the production system [2, 3]. As per a study carried out by Rodic, some of the major advancement patterns and technologies that empower Industry 4.0 are simulation modelling, Autonomous robots/systems, horizontal and vertical system integration through new standards, green it, big data, and analytics, augmented reality, cyber security, industrial internet of things, additive manufacturing, and the Cloud [4].

The approach of discrete event simulation modelling has been applied extensively to measure how manufacturing processes perform. These models contribute to the management team of an industrial unit the capability to review diverse manufacturing procedures prior to the construction of a factory or prior to a major transformation in the plant. These procedures include, but are not limited to, experimenting on a newly proposed manufacturing process, revision of factory layout, maintenance carried out on equipment and a site's automation outline. Therefore, discrete event simulation carries on to being one of the major methods of measuring the performance of a manufacturing system [5].

Several studies relevant to the execution of discrete event simulation in the field of manufacturing schemes has already been established whereby five of them have been reviewed as follows. In 2003, Smith presented a review about implementing simulation for manufacturing design and operation. The sources of his study were categorized as manufacturing structure design, operation of a system, and the language of simulation [6]. A well-organized review encompassing a huge range of papers between 1997 and 2006 related to the topic of simulation was produced in 2010 by Jahangirian et al. which presents a larger scope of simulation methods utilized in manufacturing and business [7]. A thorough review of publications between 2002 and 2013 that is connected to discrete event simulation predominantly in the manufacturing sector was done by Negahban & Smith in 2013 that outlines the literature into three general categories of manufacturing system design, manufacturing system operation, and simulation language or package development [8]. Sarda and Dilgalwar performed an analysis of a vehicle as-assembly line in 2018 using discrete event simulation where the paper contributes to an approach to analyzing a vehicle assembly line of an automobile factory and provides an appropriate method to manage the study of complicated operations of a manufacturing procedure [9]. Renteria-Marquez et al. carried out a heijunka study for an automotive as-assembly using the aid of discrete event simulation in 2020. Their work introduces a procedure to model and simulate the production floor, warehouse, and system of material handling of an automotive assembly plant with a high level of accuracy [10].

Despite discrete event simulation being well known to be implemented in the manufacturing sector to gauge the health of an operation or its future performance, its usage as a tool to validate an improvement is very minimal. This study directs its focus on the aspect of process improvement validation via discrete event simulation.

To aid in this assessment, a case study was taken from company A to validate the improvement in the mechanical assembly line for Product X, after migrating from the usage of conventional torque screwdrivers to programmable torque screwdrivers. Programmable torque screwdrivers are a more technologically advanced version of screwdrivers in terms of usage and accuracy. The advantages of programmable screwdrivers compared to conventional tools are multiple torque outputs with one tool, incorrect part detection, missing or extra washer detection, incorrect torque output detection, the capability of automatic program selection as well as storing tightening data.

2. MATERIALS AND METHODS

A literature study was performed before proceeding with the case study associated with the hypothesis of utilizing discrete event simulation as a tool to validate the enhancement of a manufacturing system. The investigation was carried out to thoroughly understand the essential knowledge contained in this subject. The information explained throughout this chapter will function as the fundamental theme of this research and act as a groundwork for this research.

2.1 Discrete Event Simulation

Planning a system that is responsible for manufacturing is a very complex process and analyzing it to assess improvement aspects is even more challenging. Upon assessing survey literature that was established prior to this study, it was discovered that a sizeable quantity of corporation surveys regarding the utilization of operations research techniques, commonly stated discrete event simulation as one of the most well-known methods that are currently being practiced [11-13]. From the time the days when computer simulation was at its infancy stage in the 1950s, the multiplying of simulation-based software and the persistent growth in computing has supported in placing it close to the apex of the 'modelling chart' [14].

Various developments in the aspects of how simulations are improved and applied have been observed in the preceding 50 years [14]. Discrete event simulation has been known to aid in devising a manufacturing system [15] and its efficiency [16], to monitor the stability of the system [17], to overcome setbacks with regard to the scheduling of the production process [18] as well as to study the implementation of Automated Guided Vehicle inside the system [19].

Contained inside the field of operational research are numerous analytic methods. Nonetheless, simulation methods such as discrete event simulation are regarded higher when it is compared to other methods for instance, game theory, mathematical modelling [20], scenario analysis, and Petri nets [21, 22] that are suitable for the process of modelling and resolving specific parameters such as production planning and sustaining as well as recognition of bottlenecks and unnecessary time-based interruption in the system [23-25].

Discrete event simulation comprises a compilation of methods that upon application to the research of a discrete event system that is dynamic, produces a progression better known as sample paths which embodies its performance. The compilation contains modelling concepts to conceptualize the crucial information of a system into a comprehensible collection of primacy and mathematical connections between its components, custom-tailored software to aid in the transformation of these connections into a set of codes that can be fulfilled by a computer to produce the obligatory data of the sample path, techniques to translate the information obtained into an approximation of the system functionality and procedures for gauging the competency level of these approximations on a real, but unspecified, behaviors of a structure [26].

Discrete event simulation primarily carries the benefit of possessing the capability to perform investigations that would be tedious and complicated to be carried out on a manufacturing system that is real. Conventionally, before the real system is implemented, discrete event simulation is the instrument that has been utilized to carry out planning and analysis [27]. Constructing a simulation model assists in providing information that would ultimately contribute to the enhancement of the real system [28]. A few of the recognized software instruments related to discrete event simulation to execute a system modelling are FlexSim, BlockSim, Plant Simulation, ARENA, and Enterprise Dynamics [29-33].

2.2 Manufacturing System and Conceptual Modelling

A manufacturing system that retains a high level of complexity or better known as a Flexible Manufacturing System (FMS) is a unified process that uses the aid of computer-controlled involvement of equipment that handles materials in an automated manner as well as devices that are numerically controlled (NC) that can work on a medium-sized quantity of various part types in a simultaneous manner [34].

The situation of manufacturing where FMS is appropriate to be implemented has been established ever since 1973. Examples of the situations whereby the adoption of FMS would prove to be productive are a huge range of parts that require high precision are machined (commonly in job shop), a comparatively large quantity of machines utilizing direct numerical control (DNC) are involved, movement of work pieces as per the flow of input, process, and output in regards with the FMS via a selected type of automated material handling procedure and the total handling of the FMS via on-line computer control with situations of different parts production mixes and urgencies [35].

To devise a Flexible Manufacturing system, several elements need to be intertwined together to ensure the system is viewed from a wide and thorough angle and to ensure a proper design is achieved. The factors that contribute a crucial role in a successful design are

ARPN Journal of Engineering and Applied Sciences

manufacturing tactics, system design, capacity planning, performance gauging, management strategies, risk evaluation, and scenario breakdown [36].

Conceptual modelling is the process of hypothesizing a model based on a real proposed system [37]. This process is practically the element that holds the utmost significance in a simulation-based process. Throughout the development of conceptual modelling, the progression goes according to the flow of identifying and comprehending the problem, to the constraints of the model followed by what aspects must be studied within the model as well as how it is to be investigated [38].

The approach that is used to present FMS in mathematical terms is through the assistance of IDEF (Integration DEFinition), a collection of graphical modelling procedures set up to properly denote and link crucial elements of an organization's engineering project [39]. This modelling language is then applied to a function model system such as SADT (Structured Analysis and Design Technique) [40], Object Flow Diagram [41], CIMOSA (Computer Integrated Manufacturing Open System Architecture) [42], and GRAI (Graphs with Results and Actions Inter-related) [43]. There is also an option to further developed GRAI into GRAI Integrated Methodology (GIM) [44].

2.3 Key Performance Indicators

For many decades, the procedure of appraising the functionality of a system in the industry seized the focus of those in the industrial sector and researchers alike [45]. Available currently are a few structures and schemes within the said setting. For instance, Process Performance Measurement Systems (PPMS) is a performance measurement structure that can be divided into two varying stages. The first stage pays attention to gauging the performance aspect individually, relative to the flexibility, cost, and time factors. In contrast, the other level comprises an array of performance indicators that supports the efficiency and effectiveness of commerce as a single entity [46].

Extensive endeavors have been carried out to lay out a universal context related to the identification of a collection of key performance indicators (KPI) in the manufacturing sector. Based on a discovery obtained by Bennet [47], an iterative model that is a closed loop containing eight steps was constructed to aid in identifying KPIs in the manufacturing industry. This said model holds the capability to carry out constant monitoring of how the industry performs through the assistance of the preferred indicators it decides whether to reduce or increase new performance indicators upon arriving at the conclusion point of every cycle according to how crucial and relevant their aspects are [48].

Established through a study by the authors in [48], five classes of indicators were recognized via the aid of a closed-loop model namely efficiency, quality, safety and environment, production plan tracking, and issues related to employees. By selecting and focusing on the classes of efficiency and quality, based on the research carried out by Dhillon et al. [49], more key performance indicators can be placed to carry out the performance measurement at a scale of higher detail. Some of the indicators that may be utilized in the manufacturing industry performance assessment are Overall Equipment Effectiveness (OEE), Work In Progress (WIP), manufacturing lead-time (MLT), average waiting time for part preparation, production throughput, output queue length, the number of deadlock incidents and mean tardiness and rate of tardy parts.

2.4 Overall Equipment Effectiveness

The foundation for the growth of the Japan Institute of Plant Maintenance (JIPM) was set by Nakajima and others [50]. They researched the aspect of preventive maintenance (PM) measures that were carried out in the US during the times upon end of World War 2 and carried on assimilating the custom in a manner that proves to be suitable to be implemented for the manufacturing industry residing in Japan [51].

While in Japan during the 1970s, JIPM devised a concept known as Total Productive Maintenance, or TPM for short. This concept was discovered from the knowledge gained via the real-world proficiency of hundreds of Japanese corporations. Functioning as a concept that embodies corporate change, TPM incorporates methods in defining overall equipment effectiveness (OEE). OEE is defined by the elements of throughput reduction which is a result of production losses such as downtime. The three aspects that influence effectiveness are availability, performance, and quality. The relationship between OEE and the 3 parameters are [52]:

$$\text{OEE} = \text{Availability} \times \text{Performance} \times \text{Quality} \tag{1}$$

The details of each element are explained below in accordance with the study made by Zammori *et al.* [53]. Availability is the appraisal between the amount of time an equipment is actually produced and the time it was scheduled to produce. Performance indicates the judgment between the real production of equipment and the expected production at the same time. Quality signifies the segment of products produced that are within the given specifications.

The current benchmark when it pertains to the desirable value of OEE is widely known as the world-class OEE. These values can be utilized to measure the performance of the maintenance procedure by the manufacturing body, as well as to enhance the maintenance process and implement continuous improvement in the system.

As per Table-2 below, the numbers for a world-class OEE, availability, performance, and quality factors are 85 percent, greater than 90 percent, greater than 95 percent, and greater than 99 percent respectively [54]. If an evaluated OEE is equivalent to a world-class OEE, it indicates that the manufacturing process is performing in an excellent condition whereas if the OEE value is lower than the world-class OEE, immediate enhancement in

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terms of maintenance strategy is needed in order to sustain the process [54].

Table-1. World class OEE standards.

OEE Factors	World Class Rate (%)
Availability	>90
Performance	>95
Quality	>99
OEE	85

Based on a study done by Dal i., states that the adequate and realistic number for an OEE would be greater than 50 percent and more beneficial as an acceptable benchmark [55]. Ericsson states that a satisfactory OEE level may vary from 30 percent to 80 percent [56]. For this study, due to the implementation of a programmable torque screwdriver being in an infancy stage, the OEE levels are expected to not achieve the world-class standard. Hence, the OEE will be gauged purely in terms of increments.

To calculate each factor that contributes to the OEE, the formulations stated in [57] are shown below:

$$Availability = \frac{OperatingTime(h)}{LoadingTime(h)} \times 100 \tag{2}$$

$$OperatingTime = LoadingTime - DownTime \tag{3}$$

$$Performance = \frac{TheoreticalCycleTime(h) \times ActualOutput(Units)}{OperatingTime(h)} \tag{4}$$

$$Quality = \frac{TotalProduction(Units) - DefectAmount(Units)}{TotalProduction(Units)} \times 100 \tag{5}$$

2.5 Gauging Current Process and Preliminary Discrete Event Simulation Modelling

The live assembly line in Company A was assessed and data that related to availability, performance, and quality were recorded. For this case study, the information was narrowed down to PCBA with part number X (Model X) which has high complexity and frequently contributes to yield loss. Manufacturing of X comprises 64 screws and the screws are assembled in 8 different phases which are used to attach parts such as standoffs, heatsinks, and handle brackets. The data were collected across all shifts and the average number was considered during the OEE calculation stage.

Upon completing the analysis of the live manufacturing line's status, two separate DES models of the assembly lines using conventional electrical torque screwdrivers and programmable torque screwdrivers were executed as per the flowcharts shown in Figure-1 below. The parameters of the models were set to reflect the actual assembly line as closely as possible and the acceptance criteria of ± 5% for availability, performance, quality as well as OEE was set. This acceptance criterion was established to indicate whether the results from the DES models are sufficiently firm to be implemented as a validation tool to assess the improvement of a manufacturing process.

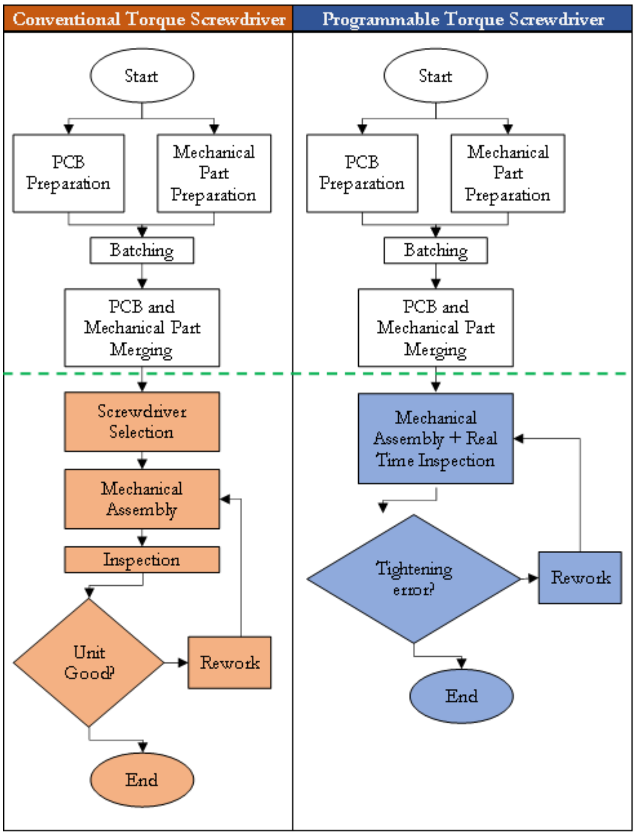

Figure-1. Comparison of process flow between the mechanical assembly of conventional torque screwdriver and programmable torque screwdriver.

3. DATA COLLECTION AND DISCUSSIONS

Upon collecting the required information for manufacturing Model X at Company A via the conventional tool and programmable tool, they were compiled in Table-2. By implementing the formulae based on Eq. (1), (2), (3),, (4) and (5), the OEE of both processes was calculated and measured.

3.1 Data of Model X's Assembly Process

Table-2. OEE Comparison of actual mechanical assembly process for Model X at Company A.

Weekly Components	Conventional Tool	Programmable Tool
Time-Related Factors (Hours)		
Total Available Time	144.00	144.00
Planned Shutdown	36.00	36.00
Scheduled Operating Time	108.00	108.00
Downtime Loss	21.00	7.00
Actual Operating Time	87.00	101.00
Ideal Cycle Time per	1.00	1.00
Output Related Factors (Units)		
Total Units	80	100
Good Units	76	99
Defective Units	4	1
OEE Factors		
Availability	0.604	0.701
Performance	0.920	0.990
Quality	0.950	0.990
OEE	52.78%	68.75%
OEE Improvement	23.23%	

According to Table-2 above, all the data collected are factored to cover the span of a weekly basis and the time elements are all in hours. The scheduled operating time for both tools is similar as these factors are pre-planned by Company A. However, the actual operating time differs due to the downtime loss which occurs without any earlier notice. Historically, conventional torque screwdrivers in Company A experience a drift in the torque output on three occasions annually. Each occurrence requires up to 7 days as the maintenance has to be carried out by a certified external calibrator. The programmable torque screwdriver only requires an annual calibration due to the requirement by the customer of Model X. The ideal cycle time was obtained from the Industrial Engineering department of Company A.

For output-related factors, the numbers were obtained by measuring and obtaining the average weekly output as well as average weekly defects for Model X. The output when a programmable torque screwdriver is utilized is 20% higher than when a conventional torque screwdriver is used. The average weekly defect rate observed from the data compiled is 5% for the conventional tool and 1% for the programmable tool. From the data obtained, it can be concluded that all components of OEE experience an improvement upon implementation of the programmable torques screwdriver. Although the numbers are not on par with the world-class OEE, there is still room for enhancement via the programmable tool.

3.2 DES Modelling

The DES software FlexSim was utilized to establish models to reflect the assembly line for Model X in Company A. The models were generated as per the flow in Figure-1. Screenshots of the models can be referred to in Figure-2 and Figure-3 below. The models were set to run for 108 hours which is the scheduled operating time per week. A downtime of 21 hours (Figure-3) and 7 hours (Figure-5) was set for the simulations of conventional and programmable torque screwdrivers respectively. A defect rate of 5% was set at the Inspection port (Figure-2) for the model of conventional torque screwdriver and a rate of 1% was set at the Mechanical Assembly_ Inspection port (Figure-4) of the programmable torque screwdriver mode.

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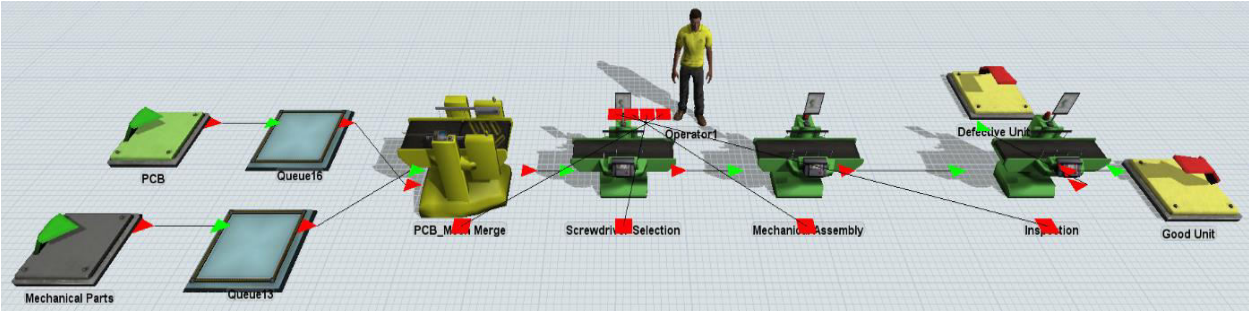

Figure-2. DES Model of assembly via conventional torque screwdriver.

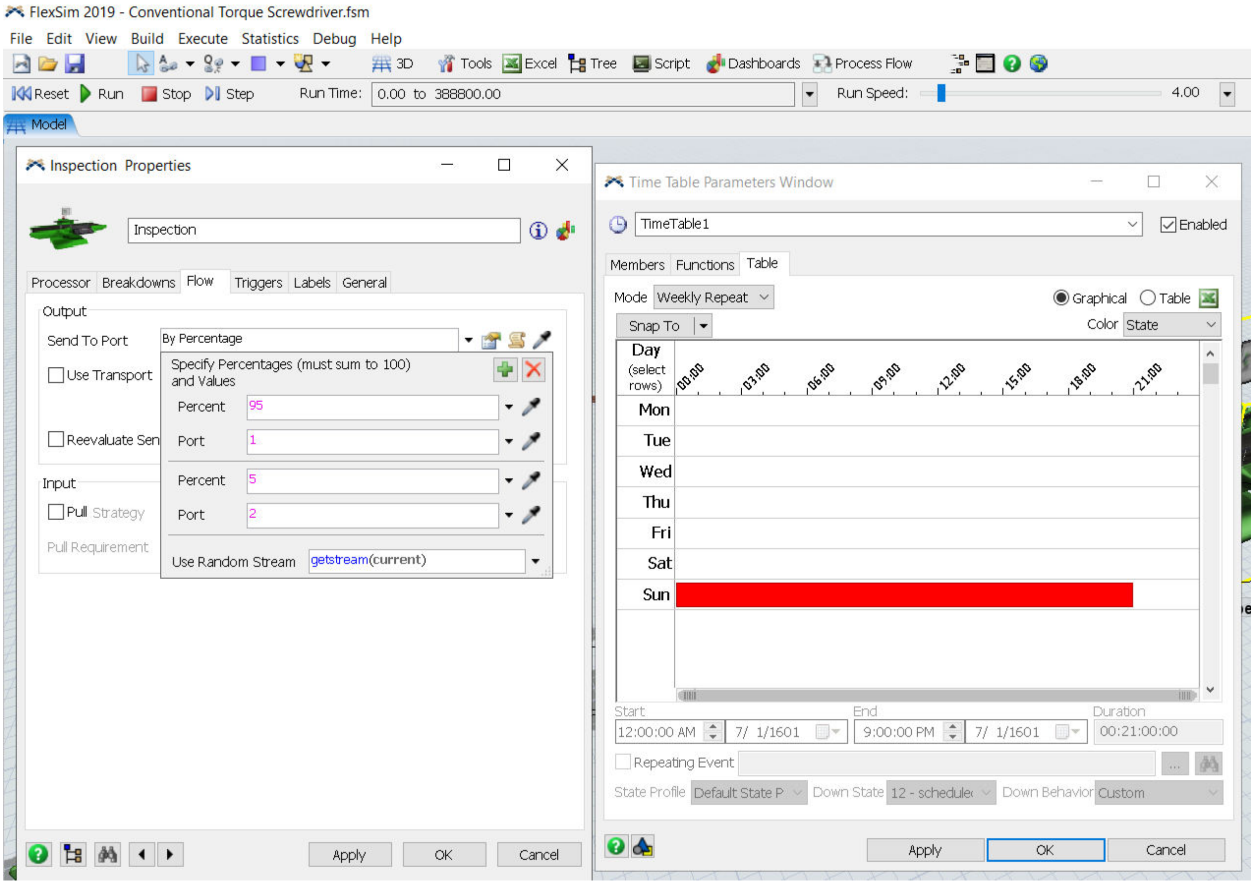

Figure-3. Parameter set up for DES model of assembly via conventional torque screwdriver.

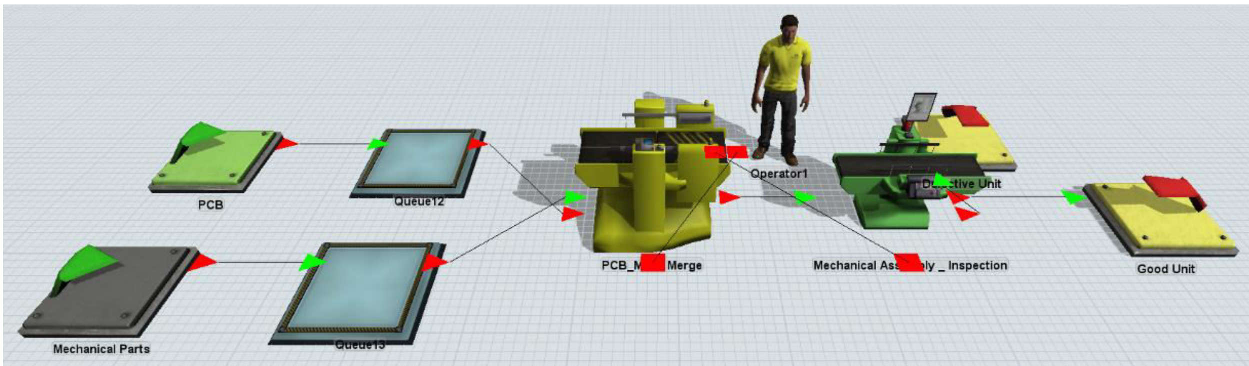

Figure-4. DES Model of Assembly via Programmable Torque Screwdriver.

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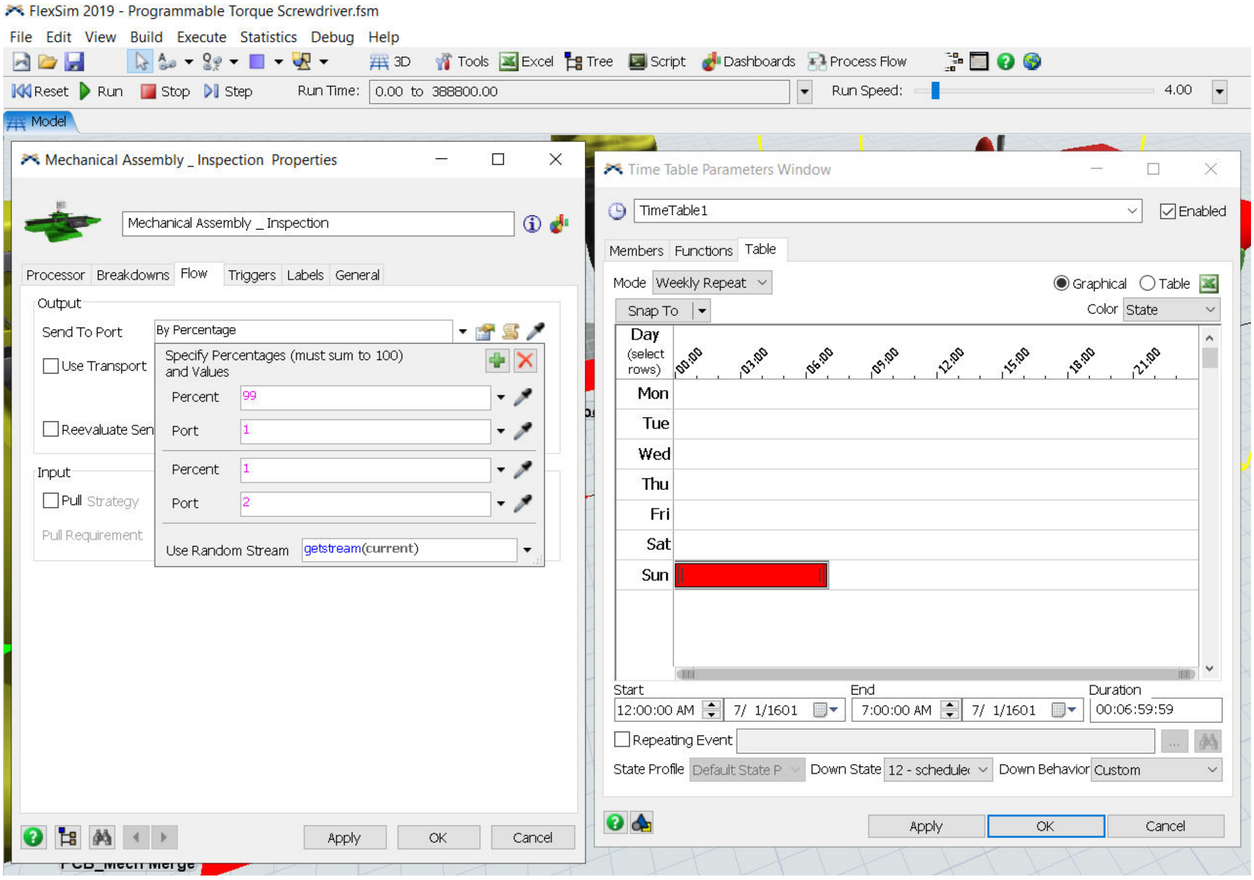

Figure-5. Parameter Set Up for DES Model of Assembly via Programmable Torque Screwdriver.

Based on the simulation that was carried out, the throughput is recorded, and Table-3 was fabricated to compile all the required information. Upon compilation, the OEE factors were also determined. To compare the variance between the actual data and simulated data, the information was compared and arranged in Table-4. As per section 2.5 of this study, the acceptance criteria for the variance between the actual and simulation manufacturing line is ± 5%.

Table-3. OEE comparison of simulated mechanical assembly process for Model X at Company A.

Weekly Components	Conventional Tool	Programmable Tool
Time-Related Factors (Hours)		
Total Available Time	144.00	144.00
Planned Shutdown	36.00	36.00
Scheduled Operating Time	108.00	108.00
Downtime Loss	21.00	7.00
Actual Operating Time	87.00	101.00
Ideal Cycle Time	1.00	1.00
Output Related Factors (Units)		
Total Units	79	99
Good Units	75	98
Defective Units	4	1
OEE Factors		
Availability	0.604	0.701
Performance	0.908	0.980
Quality	0.950	0.990
OEE	52.12%	68.06%
OEE Improvement	23.43%	

Table-4. OEE factors comparison between actual and simulated mechanical assembly process for Model X at Company A.

OEE Factors	Conventional			Programmable		
	Actual	Simulated	Percent Error (%)	Actual	Simulated	Percent Error (%)
Availability	0.604	0.604	0.00%	0.701	0.701	0.00%
Performance	0.920	0.908	1.30%	0.990	0.980	1.01%
Quality	0.950	0.950	0.00%	0.990	0.990	0.00%
OEE	52.79%	52.10%	1.31%	68.71%	68.01%	1.02%

Based on Table-4 above, the percent error of each OEE component is lesser than ± 5%. This highly indicates that the DES model reflects the actual scenario. Through this simulation, we can conclude that DES is an appropriate tool to validate the improvement in terms of OEE that were observed in the manufacturing line upon implementing the programmable torque screwdriver.

4. CONCLUSIONS

Although the application of DES as a validating tool may seem counterproductive, regularly studying an improvement that has been established is vital for industries to determine if a process is optimal, requires further progress or must be discontinued and substituted with a better method.

Through this case study, the current OEE parameters of assembling Model X in Company A via conventional torque screwdriver and programmable torque screwdriver were recorded and computed with the conventional method yielding 52.79% whereas the programmable method produced 68.71% OEE.

Upon obtaining the OEE of the actual process, the flow of the processes was modelled into a DES system, and from there; it was ensured that the results generated by the system were within ±1% of the actual manufacturing procedure. The simulation was able to produce OEE of 52.10% and 68.01% for the conventional and programmable methods respectively.

Upon calculating the variances within the actual and simulation process, the results are well within the acceptance criteria of ±5% percent error whereby the results demonstrate values of 1.31% and 1.02% of percent error between the actual and experimental data for the conventional and programmable processes respectively. This set of data indicates that the implementation of a programmable torque screwdriver does indeed further increase the OEE of the mechanical assembly process, whilst showing the gaps that can be filled to further improve its current performance.

As per the results from the study, we can conclude that DES is a suitable tool to enable cross-checking of data and validation of an improvement that was implemented thus denoting the appropriate direction that needs to be taken; to maintain the process or to further enhance it.

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