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Assembly Cell Automation Selection: A Simulation-Based Exploratory Evaluation

Ananthan Indukaladharan [a,1], Carolina Ames Zegarra[a], Gary Linnéusson[a] and Sagar Rao[a]
[a] *School of Engineering, Jönköping University, Sweden*

Abstract. The manufacturing industry faces the challenge of providing copious product variety at a competitive price. This development has escalated into the point where SMEs are becoming in need to consider product mix as a relevant aspect for automation selection despite low volumes. Apparently such a manually operated production cell has productivity limitations in addressing these increasing demands of mass customization and competitive prices. Therefore, this paper proposes using discrete-event simulation (DES) to assist the decision-making process (DMP) for implementing a new automation technology within a production cell and showcase key performance indicator (KPI) identification using simulation. Two modeling scenarios were designed and contrasted to showcase implementing automation. One consists of a manually operated assembly line, and the other represents a semi-automated assembly line of the same process but with robots in specific areas of the production line. The results indicate that the comparative study between the two scenarios of a manually operated assembly cell and a semi-automated one can provide valuable insights into the DMP. The proposed approach has shown several influencing factors to consider in the DMP. The choice of prioritizing which element should have precedence depends on the requirement specifics. The insights from the study also indicate the requirement of further research in this context, considering different parameters apart from the current research and understanding their influence on the DMP. Moreover, acknowledging the secondary aspects concerning this study context, such as ergonomics, space utilization, workplace safety, and sustainability, require further investigation.

Keywords. Assembly cell, Automation, Discrete event simulation, Decision making, Robots

1. Introduction

Rapid adaptiveness and responsiveness to changes are key factors that companies, especially small and medium-sized enterprises (SME), are currently considering for staying in markets[1]. In addition, there is now a growing need for companies to implement modern technologies at a lower cost to improve different aspects of manufacturing, for instance, mass production at low cost, flexibility to provide customized products, and sustainability regarding performance[2]. So, to pursue and fulfill those parameters, process automation is an alternative that is more within reach of organizations to become more modern and improve their indicators through a large variety of tools, perspectives, and state-of-the-art methods related to automation[3]. Modernization also presents its requirements, such as improved worker skills, further development of better human skills, and progress related to the workplace layout[4].

[1] Corresponding Author,ananthan_i@outlook.com.

Industrial automation proposals enable companies to reach and change their flexibility, functionality, productivity, and quality degree[5]. Also, recent developments in robotics have been highly considered into automation to facilitate better production performance, efficiency improvement for processes, and easiness for employees in task execution[6]. Therefore, different European enterprises within the production industry, including the pharmaceutical industry, precast concrete production, and the Swedish agriculture sector, are gradually becoming automated[2,7,8].

For companies to implement an automated system, it is necessary to know which kind of automation solution is required based on different and relevant aspects, such as the company's current conditions, which performance indicator to consider, and economic factors. Furthermore, the manufacturing system is considered unique within each company because of the difference in characteristics such as specific situations, information systems, bottlenecks, and problems within the system. Therefore, it is a topic that strongly relates to the system and its components[9]. Also, each evaluation is data-driven in a particular system. Therefore, it requires a tool that allows studying different complex scenarios and situations without compromising the existing system, such as interrupting its regular and daily operations or avoiding any relevant failure or damage to the existing system[5].

Additionally, assembly operations represent a significant field of study for researchers and academia since they present several types, depending on the various level of a final product[10]. Also, it involves many operations related to the material handling to perform an appropriate specific task such as loading, moving material, or equipment shifting[11]. Previously, performing assembly operations was mainly confined to humans, and theories and frameworks have been formulated to generate positive data for the decision-making process concerning human aspects. Nevertheless, thanks to the breakthrough of technology and research, a significant share of assembly can be performed by robots nowadays. The introduction of robotics led to automation, transforming the assembly line and other areas of the production system mechanized and achieving better time measurements and quality standards[12]. According to Dorf & Kusiak[13], automation technology supports operations by providing a set of instructions and feedback so that they can be performed as similarly as humans.

However, knowing which operations or areas need to be automated is a primary challenge that manufacturing companies deal with presently. A simulation study is one tool that can lessen this type of decision-making perplexities relating to automation. Of them, discrete-event simulation (DES) can benefit conditions analysis as it is data-driven and related to how a specific manufacturing system works with its components[9]. This paper presents some key aspects of using a simulation-based software platform based on DES to subdue the setbacks by understanding its workability in automation selection and how DES can evaluate and benchmark the different work setups.

2. Simulation, performance evaluation, and indicators

Researchers have been using simulation as a vital tool in their studies for more than half a century [14]. The application field has varied on different areas of the manufacturing system like layout optimization, production planning, life cycle analysis, automation in the production cell and their imperfections, and broadening up to virtual commissioning of plant activities and performance comparison modularization[15–21]. All these studies have indicated the tremendous usage of simulation tools in evaluating production systems without emulating them into a real production system, thereby saving time and cost yet producing valuable knowledge. The emphasis in these works has been on using discrete event simulation (DES). DES, in simple terms, is a collection of techniques that, when applied to a discrete event-driven dynamic system, generates sequences that characterize its behavior, including the mathematical relationships between various elements, modeling the concepts highlighting the system features [22,23]. DES may also include computer software that converts these relations to computer-executable codes and has procedures to convert these system data into system performance estimates and methods to assess how well these estimates are true [22]. DES enables the user to explore the progression of operation through a system at an operational level where the individual interactions and the variations experienced by the system over time are visible [24]. The applicability of DES in a wide array of industrial applications has been extensively growing in the analysis of production systems due to the flexibility, realism, and predictive accuracy offered by the simulation technique, which no other quantitative methods can provide [25]. This simulation method aspect is exploited in this paper to understand the different interactions, relationships, and tradeoffs between performance indicators used to benchmark a system.

In addition, to make a proper analysis of performance, it is strictly necessary to consider several performance indicators. Thus, these present tradeoffs between the different indicators, how connected they are, and investigate how they will improve or get worse. Furthermore, these indicators highlight improvement opportunities for numerical data to be measured and compared. Therefore, it is relevant to establish and select which indicators will be considered for the performance analysis of the process so that the study might be performed appropriately [20].

Performance measurement (PM) is a fundamental requirement for any industry to strive in the competitive world and Key performance indicators (KPI) are parameters that permit the evaluation [26]. It is the fundamental principle of management because it presents the gap between the past and present and directs the management in decision-making to achieve the desired performance [27]. It is a phenomenon not restricted to the shop floor level but extended to a multitude of the organizational level and their needs. For SMEs, the focus on PM is of much greater importance and sometimes precise due to its high level of competitiveness. The main reason for this specificity is the unavailability of knowledge and resources that support them [26].

The enterprise defines the sets of KPI's considered relevant for organizational growth and performance improvement. These KPIs vary longitudinally within the organization from process level to organization level. Moreover, it is multiple criteria regarding the decision-making problem since the evaluation base is on multiple variables [28]. Companies use several process level KPI's such as setup time, takt time, availability, utilization efficiency, work in progress, production volume, inventory levels, and time to failure depending upon their manufacturing setup and organizational goals. Nowadays, consideration is also given to time-related indicators (delivery time/ total lead time) and quality-related indicators (rework and scrap) apart from the performance indicators mentioned above [29,30].

3. Design Science methodology

Design science is fundamentally a problem-solving phenomenon, concerned with deriving information from the designer's perspective from applied knowledge of natural sciences. It addresses the problem of determining and classifying all circumstances of the system that is to be designed along with the design process [31]. The primary purpose of this kind of research method is utility since artifacts are designed, built, and evaluated to understand the current problem easily and to meet an actual requirement [32].

The challenge that was in focus for the model building was to mix model products in the same production line. It was necessary to focus on having a high variety product yet followed a simple assembly process. Due to the COVID-19 restrictions, an active study based on visual observation of an actual production system was unworkable, resulting in a virtual production system. Therefore, a methodical framework is required to drive the study unidirectional while building such a system. The aim of using the design science approach was because this method can be used for multiple purposes, from designing a new system, producing a new system that never existed, or modifying an existing system to achieve a better result [33]. Also, it supported the study's intention, which was to explore and understand how the system responds to a condition, based on different solutions and determine and evaluate the performance factor along with the process [31]. In this paper, the base system was developed on a hypothetical production system scenario with a virtual assembly line and arbitrary production schedules and operating data. Consequently, seeing to the fact that this kind of research method emphasizes utility rather than accuracy of the developed artifact in understanding the current problem and understanding the feasibility to meet the actual requirement [32].

3.1. Modeling process

The modeling of the simulation setup was based on Factory Analyses in Conceptual phase (FACTS) Analyzer, a simulation software platform that uses a discrete event system for material flow analysis. The software enables rapid modeling, multi-object optimization, and analysis of production systems.

The modeling process began with the motivation of a need for an automation solution for mid-sized product segments in the manufacturing industry. However, the problem discovered was the lack of an evaluation tool that enables the SMEs to evaluate different possibilities between manual operations and automated operations solutions.

The second step was defining the objectives for the solution inferring from the problem statement and knowledge basis, in this case, the literature review was conducted to understand what was possible and feasible to address the problem [34].

The third step was the development of an artifact; in this case, the conception of a simulation model of an assembly cell with the aid of simulation software to represent the different scenarios and analyze them.

The final step was the evaluation, in which the evaluation phase measured to what extent the artifact supported the solution to the problem. It involved comparing the objectives of a solution to actual observations deduced from the use of the artifacts. The refinement of the evaluation process was iterative towards the attained results where each iteration included the decision to improve the effectiveness of the developed artifact or to stop and leave for further research [34]. In the proposed model, the evaluation was carried out by running different case scenarios of the developed simulation model and generating empirical results to compare different performance factors, and by comparing and justifying the results from the findings with a literature review to validate the deductions and proposals. Hence, evaluating the developed artifacts was vital as it provided feedback for further development and forms the foundation for further research [35].

3.2. Simulation experiments

The production system considered for this study consisted of a pump assembly. The motive for selecting a pump assembly was the straightforward assembly steps compared to other manufacturing processes such as automobile components. Two assembly scenarios were developed: one with a fully manual operator model (FMOM) and the second with a robot and semi-automated model (RSAM) for analysis and comparison.

The two scenarios have six working days per week with three shifts consisting of eight hours per day in each shift. The processes' disturbances or system failure scenarios are mainly confined to human resources, including fatigue, idle time, absence, and biological breaks. For machine components, corrective maintenance, also known as firefighting, is considered in the simulation model as shortstops [36] since these do not take a long rectification time, and when they occur, they address immediately to continue with the production process. On the other hand, preventive maintenance is not a part of the simulation setup as it requires planification and a longer time for implementation. So, the setup is assumed to have scheduled preventive maintenance during weekend sessions without affecting the production processes to address equipment failures in the assembly line and robots in the second scenario.

All the technical parameters considered for equipment are standard in both cases; this ensures an equitable term for both cases. Table 1 shows a comprehensive view of the two scenarios. The table presents the parameters considered for the simulation experiments for both cases. It shows which attributes are considered identical and which one have different for the setup.

Table 1. Parameters considerations between Manual and Automated setup.

Parameter	Manual setup (FMOM)	Automated setup (RSAM)
Process time	Different	Different
Setup time	Identical	Identical
Disturbance	Different	Different
Availability	Identical	Identical
MTTR	Identical	Identical

For the fact that a simulation is fundamentally an approach to study models that are predefined for a definite purpose [37], it helps in understanding the dynamic changes in variable relations within the model and how the system reacts to changes. In this paper, the simulation is carried out for two scenarios. Changes in the parameters are compared, analyzed, and reflected.

An one-year time horizon is considered for simulation. But the warm-up phase, required to achieve a steady-state production condition in equilibrium, is deducted from analyzing the specific warm-up periods. The quality indicator is assumed to have a fixed value that is 99% due to the constrain that the simulation software used does not provide support to consider rejects and reworks while simulating. For calculating the quality rate, one requires the defect rate; since these details are not available, it is assumed that the production line follows a zero-defect goal.

3.2.1. Fully Manual Operator Model (FMOM)

In this setup, all the operations are handled by manual operators. The operations vary from simple pick and place to precision insertion and alignment. Multiple disturbances such as fatigue and shortstops were considered commensurate with a real production system. The processing time was defined in terms of triangular distribution to accommodate the variations in the processing speed of resources. Human operators handle the material movements with forklifts and manual labor.

3.2.2. Robot and Semiautomated Model (RSAM)

In this setup, simple operations such as placing, pick and drop, point to point material movements are replaced by robots and automated guided vehicles. The process time was constant for such operations. The remaining operation was the same as in the FMOM case.

Therefore, a comparative result of the two cases FMOM and RSAM on performance output was carried out. This contemplates four measures which three of them represent Overall Equipment Effectiveness (OEE) factors which are: availability, which consists of the production of time that an equipment is capable of operative relative to the schedule hours of production; rate is the actual speed the production system is working and, quality refers to the number of good products obtained from the total of processed products. The last measure is the OEE obtained from the multiplication of the three previous factors. The comparison of these four measures is shown in Figure 1.

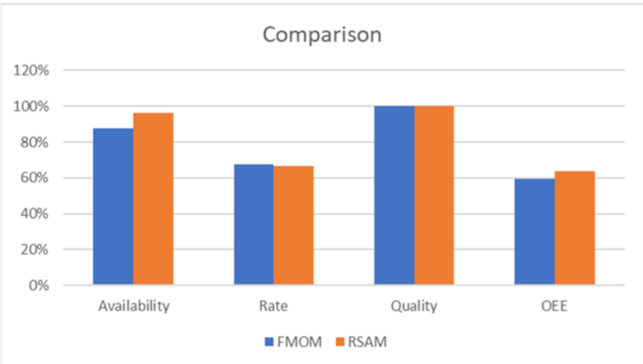

Figure 1. Performance Indicator comparison

Both the cases are simulated for one year, and the steady-state analysis gave a warm-up time of 52 days for getting a steady state. So, the practical result was considered for 313 days, excluding the warm-up time. Nevertheless, as Figure 1 depicts the results showing that RSAM has a better performance. Even though there is a marginal increase in the availability factor, the rate factor shows a dip in the RSAM case meaning that in terms of the production system speed there is not a relevant improvement. This is because the waiting time of equipment in the latter case is higher when compared to the former case, a comparison of the different categories of times is described in the next section. The increase in the OEE parameter reflects the increased availability of the machines and resources.

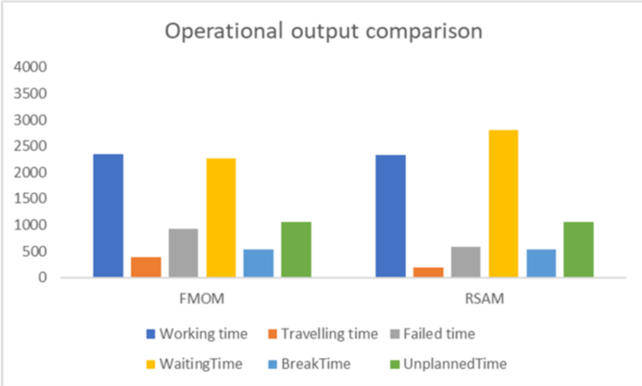

Figure 2. Comparison -Operational perspective

Figure 2 illustrates a comparison between the results from the two scenarios (FMOM and RSAM) from an operational perspective. In most of the sections, both cases are identical. The working time remains the same in both cases. There is a reduction in traveling time since, in the semi-automated case, the robots are fixed for each process and not shared, so no traveling is required, whereas, in the manual scenario, the traveling time between operations can vary from time to time, even if there is standardized processing time due to workload and fatigue. The failed time is also reduced since it accounts for both resource and operation disturbance in the manual operation, whereas in the case of a semi-automated system, it is only the process failure. All these improvements are due to task automation and because robots are suitable for this type of task since the high maneuverability of the robot enables speed management and repeatability[38]. The waiting time increases due to machine idle caused by a blockage in the line and waiting for part entry. Finally, the break and unplanned periods remain equal because the entire system follows the same schedule.

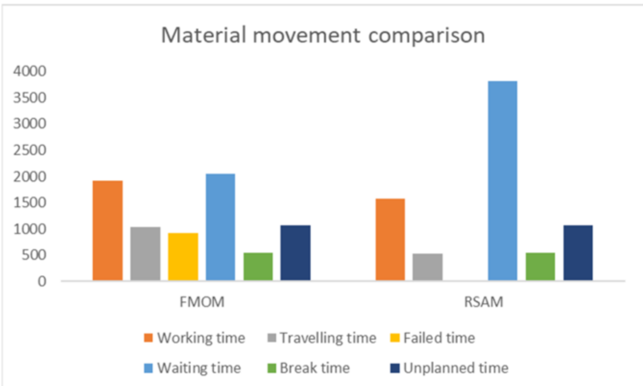

Figure 3. Comparison -Material movement perspective

Figure 3 compares the material movement (handling) perspective between the two scenarios. The working time is reduced because the process times are fixed for the robot operation and do not have any variability, and the difference is accounted in the waiting time which is almost double when compared to the manual scenario, which is a drawback and stipulates to further optimization requirement in the latter case. Furthermore, the traveling time is reduced by 50 percent since robots work under pre-programmed instructions, and there are very few disturbances and follow a fixed path in their operations. On the other hand, when it comes to the failed time, in the semi-automated scenario it is not presented since robots handle all the material movements and this eliminates the failure aspect considering the assumption of planned maintenance. On the contrary, in the case of manual setup, failure is due to human interventions.

4. Discussion and conclusions

Facing the reality check of current competition and staying alive in the market poses a great sense of pressure on SMEs to shift towards automation, which sometimes ends up on adversities on the current performance. Within the SME's perspective, there are several variables and constraints to be considered when deciding and prioritizing the process hierarchy for automation. This paper has figured out the possibilities to consider discrete event simulation as an effective tool to support the decision-making process when considering automating the production line and solve the dilemmas about automating a process from a completely manual setup. It also demonstrates practical usage of simulation as a platform to investigate novel concepts and hypotheses that face difficulty in experimenting with an existing production line, which in this case applied a virtual production line to showcase the two scenarios.

The first setup of the case considered a manual assembly line, and the second scenario is an alternative with automated production. The comparative cases highlight how the system reacts and performance factors change when shifting to an automated setup. As mentioned earlier, adapting the production process to improve the performance parameters and responsiveness to demand is key to sustaining the current market setup. The adaptability factor of the production process directly impacts the production parameters. This paper has tried to explain the effects by illustrating a comparative study taking examples of utilization and overall equipment effectiveness indices of the two scenarios and showing the improvements with automation. Responsiveness can be correlated to performance improvements and dramatically influences external and internal environmental factors such as market demand, resource management, and material availability. However, this study has not thoroughly addressed this and requires further research.

Another vital area that companies still have challenges with is - what to automate and where to automate. Even if automation is introduced, how it affects the current monitored key performance indicators is ambiguous. The second contribution of this paper is to showcase the use of discrete-event simulation (DES) platforms in addressing this challenge. In this study, the staged cases indicate how simulation can be a practical tool for the decision-making process in automation selection. The two cases experimented on in this study are only exemplifications of the usage of the simulation tool. The two cases depicted in this study showed an elementary transition of a manual system to a semi-automated model and explained how the different performance parameters were derived and compared. The study's outcome coincides as expected with the results of similar simulation studies by other researchers [15–21] who presented the advantage of automation over manual systems regardless of the minor setbacks.

Considerable improvements were visible in the automated setup, but it necessarily be not the same in all cases. In this study the factor of waiting time increase is a regression and can be considered as an indicator for further improvement. So, simulation can assist in identifying these regressing indicators. DES specifically can aid in refining these setbacks due to its dynamic nature and algorithmic relationship between the elements. It can expose the induced losses that may occur in a future state when simulating since DES is time bound setup. Ultimately, these regression indicators and losses can be considered as feedback for further work on improving the production system to eliminate the bottlenecks and reap the full benefit.

Finally, this study is only a rudimentary effort to showcase the potential of simulation platforms as a prospective tool for selecting automation solutions and how they can aid in the decision-making process. The future work in this path perseveres with possibilities of comparing different scenarios-with a Cobot environment against a fully automated system or with a customized product which is a high-variant low-volume product, versus a modular product which is a low-variant high-volume product category. Additionally, considering ergonomics, space utilization, and economic aspects will also be beneficial.

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