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A Decision-Making Tool to Integrate Lean 4.0 in Windows Manufacturing Using Simulation and Optimization Models

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Abstract

Lean Manufacturing (LM) is known as an effective methodology utilized by manufacturing organizations to increase productivity, improve quality, and decrease costs. On the other hand, Industry 4.0 (I4.0) transforms a traditional factory into a smart one by integrating its machines and processes using advanced information technology and robust communication systems. Simulation and production optimization have proved to be an effective tool to analyze the dynamic nature of the processes and statistically justify modifications paybacks. Currently, there is no decision-making tool that integrates LM and I4.0 using hybrid simulation and production optimization models to benefit the manufacturing processes. For that reason, a framework integrating the LM and I4.0 is developed and implemented on a local window manufacturing plant using simulation and optimization tools to improve the overall productivity of their manufacturing process. The developed framework is able to investigate process improvements and optimize the outputs to identify the bottlenecks and resources utilization, provide a useful tool to test the effectiveness of any proposed process improvements, and identify non-value adding tasks and analyze time breakdown. The framework can be applied to any manufacturing company to not only identify and eliminate the waste but also to statistically forecast the resulting benefits before changes are implemented.

Keywords: Lean manufacturing; Industry 4.0; Simulation; Production Optimization.

1. Introduction

As one of Canada's most important economic sectors, the manufacturing industry accounts for approximately $174 billion of Canada's gross domestic product (GDP), which is over 10% of Canada's total GDP (Government of Canada, 2019). Given the spread of globalization and the low trade barriers, the manufacturing industry is currently facing growing opportunities as well as tremendous competition. The unprecedented requirements for product customization have increased the volatility of the manufacturing sector (Mourtzis et al., 2014). The manufacturing sector is being challenged to cope with the rate of producing innovative products within shorter timeframes. There are new innovative technologies, theories, and idea coming out every single day, and manufacturers are striving to realize the benefits to their businesses and generate more value. In the following, an overview of literature on the application of decision-making tools in integrated LM and I4.0 systems using hybrid simulation and optimization models will be presented. After the literature review, a methodology for applying the developed decision-making tool in a manufacturing environment will be proposed, followed by the application of the methodology to a case study where a time study was conducted, then LM is employed to identify the opportunities to improve productivity. After that, simulation and optimization models were utilized to predict the after-effects of changes proposed by the lean analysis to provide managers with more confidence in adopting the changes, identify the bottlenecks and areas of under- or over-utilization of resources, optimize the resource allocation process and line balancing, and identify non-value adding tasks and quantify direct labour.

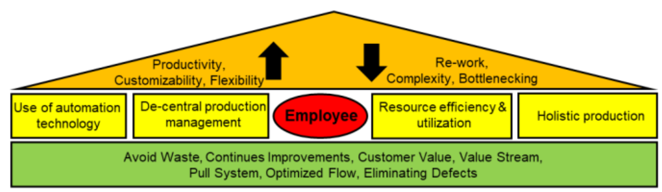
2. Literature Review

2.1. Lean Manufacturing (LM)

The concept of lean manufacturing was originated by Toyota in Japan after the Second World War, at the time when Japanese manufacturers were challenged from a shortage of resources and financial support. To overcome this, corporate leaders in Japan put their efforts into developing and refining the manufacturing process to reduce waste and non-value-added activities (Elbert, 2013). The system focuses on identifying the waste and use tools such as just-in-time (JIT), Kanbans, and setup time reduction to reduce or eliminate the wastes (Abdulmalek and Rajgopal, 2007). Through years of application, lean manufacturing has been proven to benefit the manufacturing industry. Manufacturers report improvement in productivity, net income, labour utilization rate, machine utilization rate, and return on investment, as well as decreases in the cycle time and cost (Pavnaskar, 2003). Although the core methodologies of lean are simple, a tool that can predict the gains are of a significant magnitude to justify the cost of changes would benefit the implementation of lean. In manufacturing companies, the cost of reallocating resources, purchasing new machinery, modifying manufacturing processes etc. are usually high. Lacking justification for future paybacks, the managers are usually reluctant to put lean analysis into practice. In general, one tool that can quantify and visualize the gains in the early planning stage is simulation. The statistical analysis from simulation tools can enable managers to compare the potential future performance based on the implementation of the lean analysis to the existing system (Detty and Yingling, 2000).

2.2. Industry 4.0 (I4.0)

The complexity of today's products stems from the fact that they involve a multitude of sub-systems, multiple engineering domains, and several variants and system architectures. It is also the result of the fact that these products consist of sub-systems that interact and need to be integrated. Moreover, technological convergences in various applications of engineering domains are happening at an unprecedented rate and magnitude. Such complexity of products coupled with global competitiveness among companies demands streamlined product development approaches to be implemented that can utilize the complete potential of cutting-edge technologies in design and manufacturing (Ahmad et al., 2017). The so-called Industry 4.0 or the Fourth Industrial Revolution necessitates a change of perspective in developing products that are cyber-physical systems and demand a fundamental shift in the way products are designed and manufactured, respectively. Digital manufacturing has been proposed to address the challenges faced when developing modern products. Both production paradigms, i.e. LM & I4.0, are promising to solve future challenges in manufacturing (Goienetxea Uriarte, 2018). Hence, the question arises if and how these developments can possibly support each other. According to Dombrowski et al. (2017), LM is considered as either a prerequisite for introducing I4.0 tools or I4.0 tools are regarded as promoters of LM but the combination of both yields in positive synergies. Figure 1 gives an overview of literature which supports LM and I4.0 general compatibility, perceptions, and correlations where the employee is the center of this attributed similarities and can manage both paradigms in a decentral way.



Perspective	Authors
Lean Manufacturing as enabler towards Industry 4.0	Huber (2016) , Künzel (2016), Ketteler and König (2017), Staufen (2016), Köther (2017), Wang et al. (2016), Metternich et al. (2017).
Industry 4.0 advances Lean Manufacturing	Wagner et al. (2017), Pokorni et al. (2017), Kolberg and Zühlke (2015), Spath et al. (2013)
Positive correlation between LM and I4.0	Sanders et al. (2016), Vogel-Heuser et al. (2017), Mrugalska and Wyrwicka (2017).

Figure 1. Different perspectives between LM and I4.0

2.3. Decision-Making Tools

The decision-making tools are an interactive computer-based platform that can be used to aid in complex decision-making by employing data management, communication technologies, and modelling capabilities. The decision-making process involves three interconnected components: the decision makers, central storage database, and the decision support system. The three components interact to support planning and operational control decisions for manufacturing processes as illustrated in Figure 2.

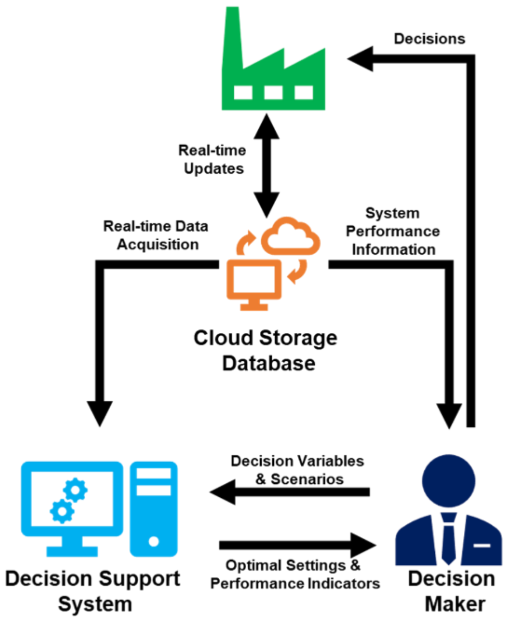


Figure 2. Decision support system process

2.4. Simulation and Optimization

Manufacturing simulation focuses on modeling the behavior of manufacturing organizations, processes and systems. Traditionally, simulation tools have been used in production system planning and design. Once the system has been implemented, the model looses its value and is set aside until other strategic decisions are made. Today, simulation models are used in all the different system levels and phases of the manufacturing system life cycle (Heilala and Voho, 2001). Naturally there is wide variety of simulation tools in the manufacturing domain. The use of discrete event simulation (DES) can be enhanced also to cover production operations planning as a decision support tool (Thompson, 1993). While some DES models are used to plan and design, other models are used in the day-to-day operational production planning of manufacturing facilities. According to Goienetxea Uriarte (2020), these "as built" models provide manufacturers with the ability to evaluate the capacity of the system for new orders, unforeseen events such as equipment downtime, and changes in operations. Having built a simulation model, experiments are then performed by changing the input parameters and predicting the response. Before taking a new order from a customer, a simulation model can show when the order will be completed and how taking the new order will affect other orders in the facility. Simulation can be used to augment the tasks of planners and schedulers to run the production more efficiently. It is important to recognize that simulation is primarily a decision support tool and does not directly seek optimal solutions. The decision is based on the data and information available at the time. There is a need for a quick response tool to evaluate alternatives and scenarios before decisions are made. Optimization and simulation modeling could be used to provide information for decision makers as illustrated in Figure 3.

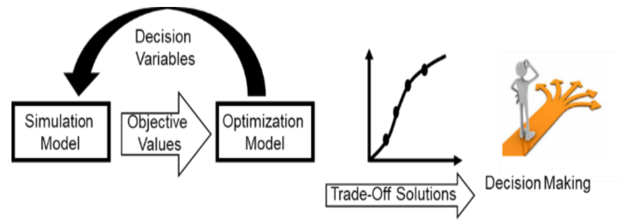


Figure 3. Simulation-based optimization to support decision-making

2.5. Comparison Matrix Between Current and Proposed Tools

As a result of an extensive review of existing literature and reasonable assessments of the authors, Table 1 depicts a matrix to illustrate which I4.0 tools can be utilized to support the analysed lean methods. The I4.0 tools are selected based on reviewing academic publications. Subsequently, the synergy potentials are briefly outlined in a condensed way showing seventeen I4.0 tools that can support twelve different lean methods in comparison with the developed decision-making tool. The findings reveal that applying the developed tool can assist in realizing the prosecution of most lean targets.

3. Methodology

To achieve the research objectives, this research will follow the methodology shown in Figure 4. A time study will be performed on a window production line. For every single operation, multiple time data are collected that are raw data in a systematic method. Also, in this stage, a process study is performed, in which operational sequence and resource layout are studied. The order information and actual productivity are also recorded. Using lean manufacturing techniques, waste in the production process is identified. This research includes the analysis of existing non-value-added procedures and corresponding solutions are proposed. Before implementing changes, future analysis in simulation is required to verify and validate the decision-maker approach. Simulation models of the window production line is built based on data from the time and process study. The models are validated using actual production numbers and current resource allocation. After implementing changes, simulation is used to identify the bottleneck in the production process and generate the best resource allocation scenario based on the developed optimization algorithm considering the non-value added activities and time breakdown results effect on productivity.

Table 1. Comparison matrix between current and proposed tools

I4.0 Tools	LM Methods												References
	JIT	Line Balancing	Continuous Flow	Heijunka	Kanban	VSM	TPM	SMED	5S	Andon	Pokayoke	Jidoka	
Additive Manufacturing	X						X	X					Mohamed et al. (2016)
Virtual Representation							X	X				X	Tokola, Niemi and Vaisto (2016)
Digital twin/Simulation	X	X		X	X	X	X	X	X				Rane et al. (2015)
Cloud Computing	X					X	X				X	X	Gurumurthy and Kidali (2011)
Internet of Things													Chu and Shih (2015)
RFID technologies	X				X	X	X	X	X		X		Wang et al. (2016)
Smart Sensors	X				X								Ketteler and König (2017)
Big Data	X	X	X	X	X	X	X				X		Köther (2017)
Machine Learning						X	X	X					Künzel (2016)
Artificial Intelligence						X	X	X					Staufen (2016)
Automation	X		X		X							X	Metternich et al. (2017)
Predictive Maintenance							X				X		Wagner et al. (2017)
Advanced Robotics	X		X		X	X			X	X			Pokorni et al. (2017)
Machine to Machine			X	X	X				X	X		X	Kolberg and Zühlke (2015)
Simulator	X	X	X			X	X	X			X		Huber (2016)
Optimizor	X	X			X	X							Spath et al. (2013)
Decision-Making Tool	X	X	X	X	X	X	X	X	X	X	X	X	Mrugalska and Wyrwicka (2017)

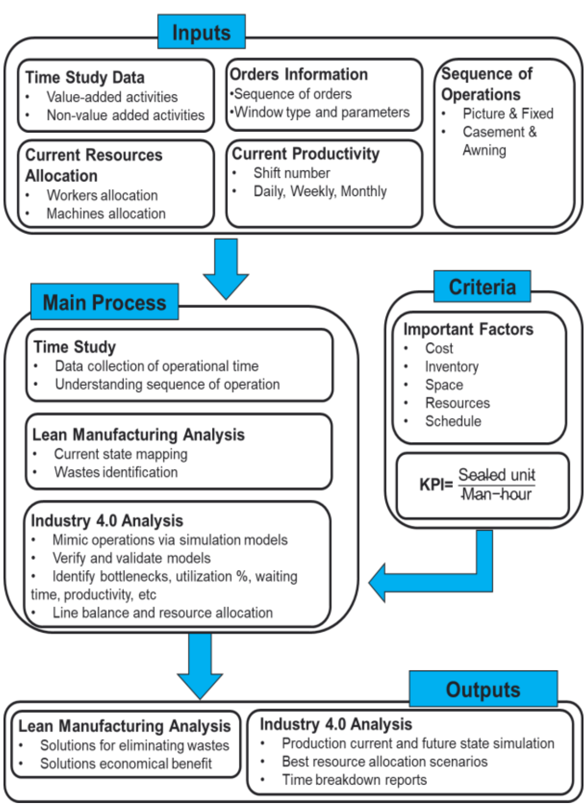


Figure 4. Based optimization to support decision-making

4. Case Study

In this case study, the DES is utilized to model the window manufacturing processes because it best reflects the actual production in which materials only transform after passing a workstation. Simphony, a simulation software, is used as modelling tool which was developed by the University of Alberta (AbouRizk et al., 2016). The first step in developing the simulation model is to abstract and identify problems of the physical system, which is designed to test out the impact of changes proposed by the lean analysis and improve the process design of window production lines to reach higher productivity. The main production line process flow diagram (PFD) is constructed as and selected to be the problem domain as represented in Figure 5.

The assumptions, inputs, and specifications are defined in the conceptual model stage. Followed by which, the draft computer simulation model is built using the information gained from the time study, the process study, and the resource allocation study as illustrated in Figure 6. According to the operational sequence listed in Figure 5, a simulation model was designed where the window production testing data was connected to a database that contains all orders information. Due to the mass personalization and customization, it was hard to find two identical windows produced in the same shift. There were many variations in each operation, which brought fluctuation to the operation time and thus multiple simulation specific attributes. In the validation stage, the validation technique used is historical data validation. The production system of the manufacturing company tracks the order information of windows, the number of workers on the line, and the number of windows produced each shift. The order information of the windows for three production days (February 04, 05, and 06, 2020) are selected to be the input of entities in the model. The simulation time is set to be 15 hours, which represents two shifts per day. At the end of the simulation time, the counter element is used to track the total number of sealed units produced. A key performance indicator (KPI), the productivity, is calculated within the model using Equation 3 after computing the production rate and production ability using Equations 1 and 2 respectively. The simulated productivity is compared to the actual productivity to check if the simulation model is close to reality and thus reflect model accuracy.

$$Production\ Rate = \frac{Production\ Time\ (h)}{Number\ of\ Workers * Number\ of\ Windows\ Produced} \quad (1)$$

$$Production\ Ability = Production\ Rate * Number\ of\ Workers * 7.5hrs \quad (2)$$

$$Productivity\ (S.U/hrs) = TP_{S.U}/TL_{Hrs} \quad (3)$$

Where,

S.U= Sealed Units

Hrs= Hours

$TP_{S.U}$= Total number of sealed units produced

$TL_{Hrs.}$= Total labor hours required

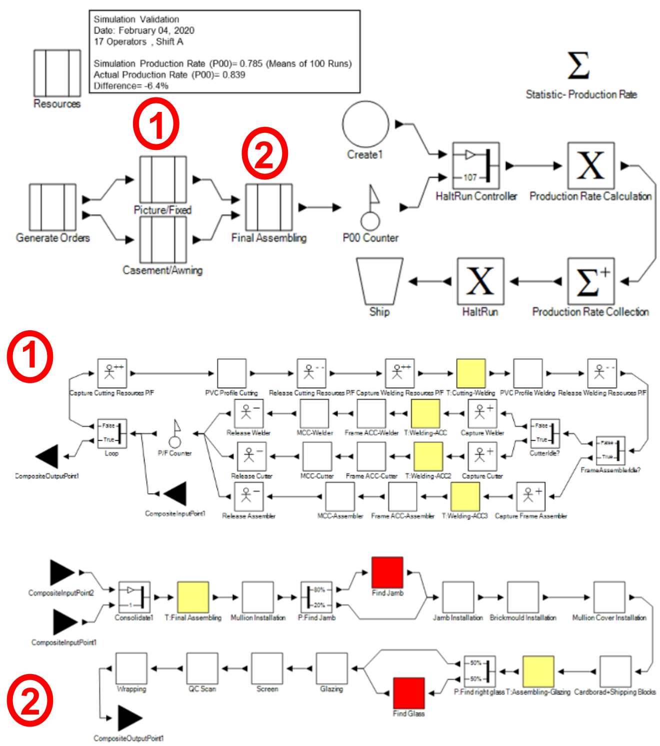


Figure 5. Window processes simulation model

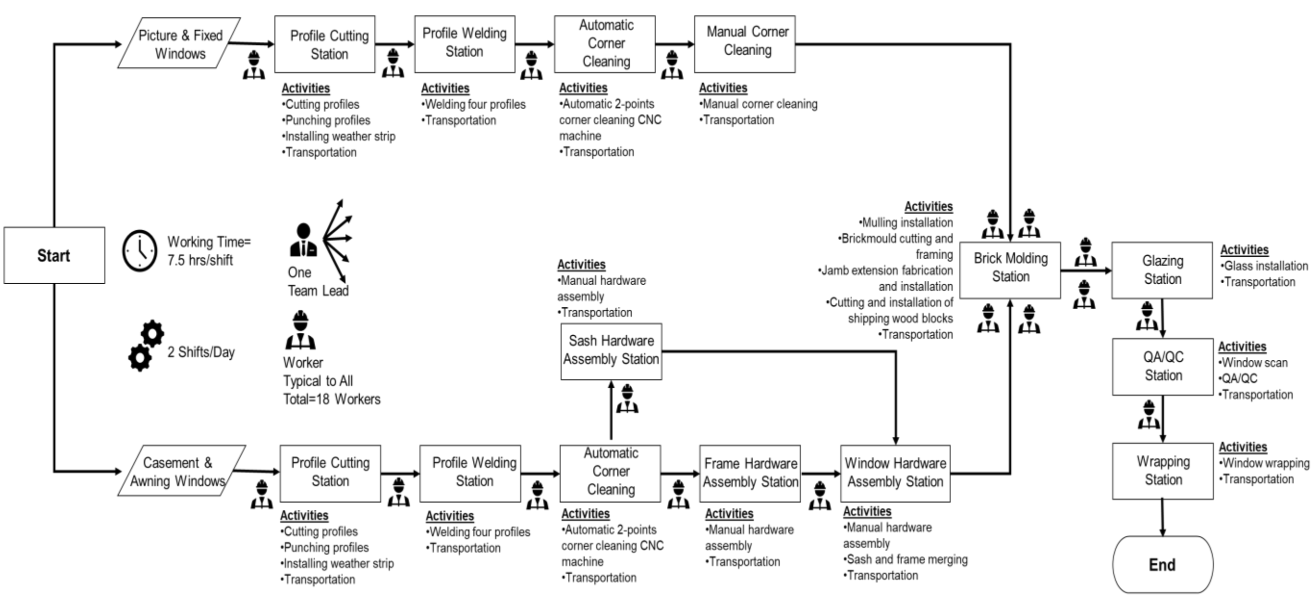


Figure 6. Window process flow diagram

In a balanced production line, the cycle time of all workstations should be close. In today's manufacturing sector, the unprecedented increase in requirements for product customization and personalization have increased the level of difficulty encountered when balancing production as product variances cause fluctuations in the cycle time of each station, which has in turn brought about difficulties in calculating line balancing using lean manufacturing exclusively. Based on the validated original model and the bottleneck deduced previously, welding, cleaning and brick modeling stations were identified as the bottlenecks on the production line. The company cannot afford the acquisition of new machines because of limited budget and available footprint. Since the company was more focused on improving productivity and was less concerned about the number of units produced per day, the best strategy to balance the line was to remove workers from the workstations where the worker utilization rates were low. An algorithm was designed to drop one worker from the workstation where the worker utilization rate was the lowest, after which, the new productivity was compared to the last scenario. If the productivity increases, the utilization rates of all resources are calculated again, and another worker would be dropped in the workstation with the lowest utilization rate. This loop is repeated until dropping a worker did not benefit productivity. Time study was carried out to determine the non-value-added time. There are many instances that workers would be performing their job without adding any value to the final product. Non-value-added times are characterized into various categories such as transportation, inventory, motion, waiting, over-production, over-processing and defect. I4.0 is utilized to develop the future simulation model to measure the effects of adopting lean manufacturing changes and to optimize the resource allocation. To achieve the above, it is important to perform the time break down analysis on various operations in the production line. In a typical production day, the productive hours are divided into internal and external hours. Internal hours are fully utilized to the production (value-added time) whereas external hours include waiting time, transportation time and non-utilized talent (non-value-added time). External time calculation is two stage process. In first stage, average percentage of external activities performed in a day are determined. In second stage, external time factors such as waiting time factor, transportation time factor and Non-utilized talent time factor are calculated. Based on operations, time calculation for window production is summarized in equations 3 to 11 as follows:

Window Operation #1

$$Internal\ time\ = x_1$$

$$Waiting\ time\ = x_1 * y_1$$

$$Total = x_1 * (1 + y_1) \tag{4}$$

Window Operation #2

$$Internal\ time\ = x_2$$

$$Waiting\ time\ = x_2 * y_2$$

$$Total = x_2 * (1 + y_2) \tag{5}$$

Window Operation #n

$$Internal\ time\ = x_n$$

$$Waiting\ time\ = x_n * y_n$$

$$Total = x_n * (1 + y_n) \tag{6}$$

$$SubTotal = x_1 * (1 + y_{1)} + x_2 * (1 + y_2) + \cdots + x_n * (1 + y_n) = \sum_{k=1}^{n} x_k * (1 + y_k) \tag{7}$$

$$Transportation\ Time = \sum_{k=1}^{n} x_k * (1 + y_k) * z_1\% \tag{8}$$

$$Non - Utilized\ Time = \sum_{k=1}^{n} x_k * (1 + y_k) * z_2\% \tag{9}$$

$$Seasonal\ Factor, etc. = \sum_{k=1}^{n} x_k * (1 + y_k) * z_3\% \tag{10}$$

$$Total = \sum_{k=1}^{n} x_k * (1 + y_k) * (1 + z_1 + z_2 + z_3) \tag{11}$$

Table 2. Worker reallocation iterations

Scenarios	WS1	WS2	WS3	WS4	WS5	WS6	WS7	WS8	WS9	WS10	# of Workers	Productivity (SU/Hour)
	Cutting	Welding	Cleaning	S. Hardware	F. Hardware	W. Hardware	Brick Molding	Glazing	QA/QC	Wrapping		
Original	2	2	2	1	1	1	4	3	1	1	17	0.96
No. 1	2	2	1	1	1	1	4	3	1	1	16	0.99
No. 2	2	2	1	1	1	1	4	2	1	1	15	1.01
No. 3	2	2	1	1	1	1	3	2	1	1	14	1.02
No. 4	2	1	1	1	1	1	3	2	1	1	13	1.03
No. 5	2	1	1	1	1	1	3	2	0	1	12	1.08
No. 6	2	1	1	1	1	1	2	2	0	1	11	1.05

5. Results and Discussions

The simulation model is developed for the window production for various processes including cutting, welding, corner cleaning, hardware assembling, brick molding, glazing, QA/QC and wrapping. Workers are allocated on these workstations as per original data collected: 2 cutting, 2 welding; 2 corner cleaning, 3 hardware assembling, 4 brick molding, 3 glazing, 1 QA/QC and 1 wrapping. This gives the total worker count to be 17 with calculated hourly productivity (SU/Hour) to be 0.96. The workstation with lowest utilization identified was cleaning and after removing one worker, its productivity increased to 0.99. After series of this iteration on other workstations having lowest utilization rate, it was found that total number of workers required dropped from 17 to 12 (29% drop) and highest productivity of 1.08 SU/hour was achieved. This process is summarized in Table 2. It was found that time consumed by most non-value-added activity was waiting time with 17.15 hours representing 8% of the total external time. Results for internal and external times are summarized in Table 3.

Table 3. Time breakdown results

Time Breakdown		Hours	Percentage
Internal Time		194.08	89.2
External Time	Waiting Time	17.15	7.9
	Transportation Time	5.835	2.7
	Non-Utilized Talent	0.435	0.2
	Total	23.42	10.8
Total Time		**217.5**	**100**

After examining and fixing all the logical errors, syntax errors, data errors, experimental errors, bugs within the model, to validate the accuracy of the model, a comparison between actual productivity and simulated productivity was performed. The The model that was built, verified, and validated using actual production data was utilized in statistically analyzing the influence of changes on productivity before actual implementation. The scanned finished order information was translated into attributes and was tabulated into a database as the input for model validation. The resources layout was set up based on the employee attendance record on the test days. The test results were given in Table 4. It was noted that the difference in each shift was less than 10%, and the difference between simulated overall productivity and actual productivity on the three days was less than 5%. The difference was minor; thus, the simulation model was considered as having passed validation. The main contribution of this research was the development of a framework that integrates the LM and I4.0 and implementing it on a local window manufacturing plant using simulation and optimization tools that results in improving the overall productivity of their manufacturing process by identifying the bottlenecks, non-value adding tasks, analyzing time breakdown, and resources utilization. Also, in this research a general template was provided to break down the window manufacturing process, collect operation time, and determine the resource layout. The template can be used in similar industries.

Table 4. Accuracy comparison between actual and simulated productivity

Date	Shift	Employee Number	Units Produced		Productivity (Sealed Unit/Labour Hour)		Difference
			Actual	Simulated	Actual	Simulated	
Feb 04, 2020	A Shift	16	165	169	1.38	1.41	3%
	B Shift	17	192	188	1.51	1.47	-3%
	Overall	33	357	357	1.44	1.44	0%
Feb 05, 2020	A Shift	15	180	170	1.60	1.51	-9%
	B Shift	16	202	202	1.68	1.68	0%
	Overall	31	382	372	1.64	1.60	-4%
Feb 06, 2020	A Shift	17	173	173	1.36	1.36	0%
	B Shift	17	199	203	1.56	1.59	3%
	Overall	34	372	376	1.46	1.47	2%

6. Conclusions

Using the developed decision-making tool not only we identify the waste and find ways to eliminate the waste, but we could also perform the detailed analysis and simulate the results before actual implementation. Simulation models were developed to mimic the dynamic changes in cycle times and by using the developed algorithm. The best resource allocation scenario can be then determined to balance and increase the productivity. As demonstrated, the developed decision tool shows its effectiveness and robustness where it can be implemented to serve as a generative decision system that proactively aids the designer in the decision-making process. The study limitations are the input data for the simulation model, which is limited to three production days, sequencing of orders can influence the productivity, and the operation time was fixed numbers. Future work will include the development of an algorithm that can dynamically perform line balancing using the simulation model by changing different factors concurrently and by implementing the linear line balancing method. Also, by developing a guideline on how to judge the accuracy of simulation models to standardize their verification & validation process.

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