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Synergies in the Application of Industry 4.0 and Lean Manufacturing at a Product Label Manufacturer – A Discrete Event Simulation Case Study

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Abstract: Industry 4.0 is a manufacturing philosophy and industry standard for the design of Cyber-Physical Production Systems. The aim of Industry 4.0 is the creation of a smart manufacturing system. A smart system which applies novel applications of developed and current technologies to simplify complex work and enable waste averse production. It is based on the concepts of data-driven decision support services, Horizontal and Vertical Information Technology-Operations Technology value-chain integration, decentralized control and flexible production. Lean Manufacturing is a value-to-customer-focused manufacturing philosophy which applies procedures designed to ingrain waste reduction and efficient, competency-building practices into workplace culture. The aim of this paper is to examine the synergistic benefits of these manufacturing philosophies on a local firm using Discrete Event Simulation. The key performance indicators of Flow Time, Waiting Time and Work in Process were used to determine the efficacy of the models investigated. The study results indicated a 52%, 57% and 58% improvement in the respective metrics of the best performing proposed model when com-pared to the existing system.

Keywords: Industry 4.0, Lean manufacturing, Discrete event simulation, Case study.

1. Introduction

The trend toward a modern, globalised market, has led firms from developed and developing nations to compete for increased market share. This is especially true of low-skilled industries [1] from regions such as the Caribbean. Such competition has motivated the development of innovative approaches and novel technological applications in a trend toward waste averse production with lower labour and resource costs [2]. One philosophy based on this trend of innovation is Lean Manufacturing (LM). LM focusses on a value-to-customer based approach that uses tools and techniques designed to ingrain efficiency and competency-building procedures into an organization's DNA [3, 4].

Amongst the novel technological applications developed were increasingly cost-effective CPS and ICT devices. These technologies, when combined with advances in artificial intelligence and high-volume data analytics, then made the concept of Industry 4.0 (I4.0) practicable [5]. I4.0 is the philosophy of integrating efficiency and value-creating technologies into all aspects of a product's value-chain. In essence, I4.0 uses novel applications of technology to simplify work and offer access to previously unfeasible solutions.

Current research supports the idea that LM practice can indeed augment compatible I4.0 technologies when enhancing productivity [6-8]. While mature LM practice is not a requirement for introducing basic I4.0 technological solutions, there is some evidence to suggest a correlation between the advanced application of I4.0 technologies and a mature understanding of LM [9]. This is particularly evident when considering the stresses that enacting the digital transformation required of I4.0 places on a firm's organizational structure and workplace culture. Organisations must adopt continuous improvement and flexible thinking in order to keep pace with the new capabilities offered by I4.0. Meanwhile workers must build upon their technical skills and core competencies if they wish to take advantage of novel technologies and opportunities [10]. LM provides excellent procedural tools and approaches in both cases.

However, there exists a scarcity of academic research into the impact of the core technologies of I4.0 on LM regarding application within developing nations [6, 11]. Factors including a firm's socioeconomic environment, supply chain positioning and access to technology and training have been proposed as influences that moderate the interaction between I4.0 and LM [7, 12]. This paper therefore aims to examine the application of I4.0 and LM as improvement measures within a Trinidad manufacturing firm using a Discrete Event Simulation (DES) case study [13].

2. Case Study

2.1. System Definition

The subject of the case study was a printed label and packaging supply firm servicing the Caribbean region. The firm had identified time and quantity shortfalls in production as areas in need of improvement. A lean approach to production was sought to improve operations. Value Stream Mapping (VSM) was used to define the current state of the existing system (see Fig. 1). Based on this understanding of the existing system's current state, a DES model was formulated using Rockwell Automation's Arena® simulation software (see Fig. 2).

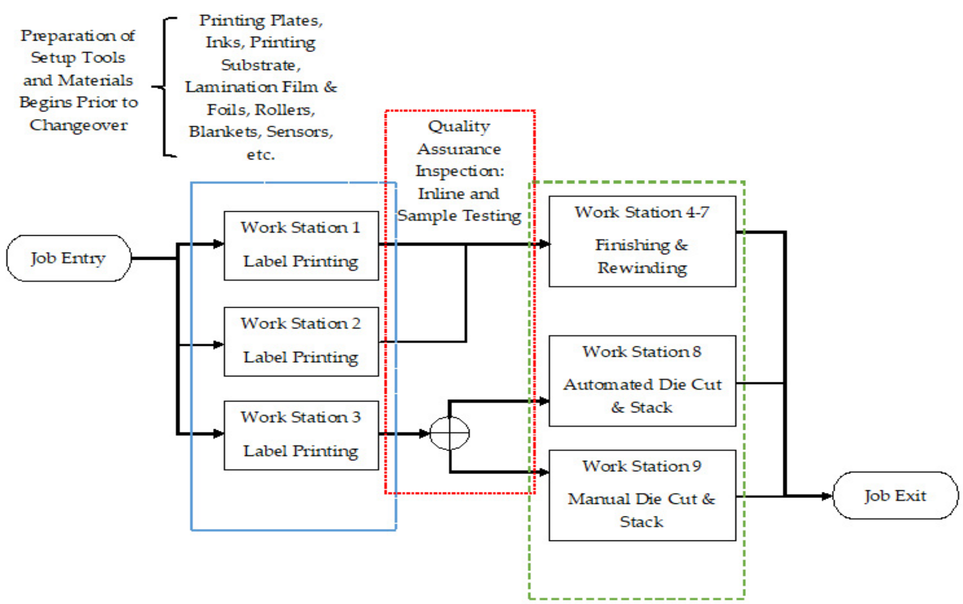

Fig. 1. Label Printing Process. A Physical Job Ticket and e-Kanban Ticket follow the Job Order from Entry to Exit.

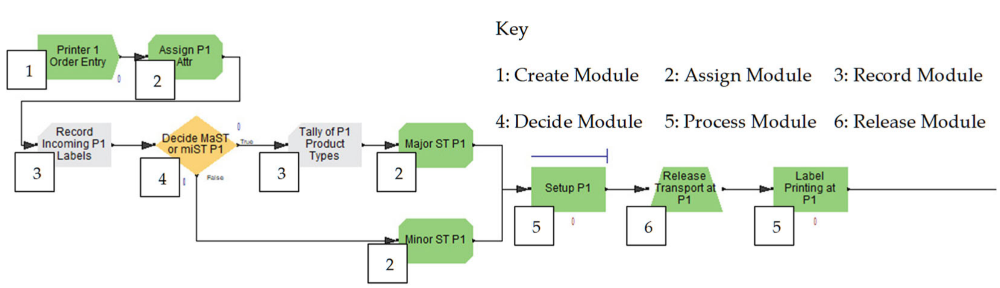

Fig. 2. Extract from Existing Model (Md0): Product Label Printing Process. Simulated Job Orders enter the system at the Create Module and are assigned user variables by the Assign Modules. Metrics are logged by the Record Modules while the job orders proceed through the system based on the logic at the Decision Module. Process Modules simulate the use of system resources while resources not used by following processes can be freed by the Release Module.

2.2. Model Formation

In addition to this model of the existing system (Md0), Arena® simulation software was also used to investigate three models (Md1, Md2, Md3) implementing proposed measures (see Table 1). The models were all configured as non-terminating simulations which reflected the current state system where, during working hours, machine tools were infrequently idle. Truncated replications were used to compensate for initiation bias. This required that a warm up period, the time needed for the operation to achieve a steady-state conditions, be determined.

Table 1. Simulation Model, Sources of Waste Addressed, LM Approach and I4.0 Approach.

Model	**Source of Waste Addressed**	**LM Approach**	**I4.0 Approach**
Md0	Existing Model	Existing Model	Existing Model
Md1	Over-Processing and Waiting	Simplified Processes, Reduced Required Setup Time	E-Kanban Ticket System, Automated Data Storage and Retrieval
Md2	Transport, Inventory	Increased Capacity of Material Transporters	
Md3	Over-Processing, Waiting, Transport and Inventory	Simplified Processes, Reduced Required Setup Time, Increased Capacity of Material Transporters	E-Kanban Ticket System, Automated Data Storage and Retrieval

A plot of Flow Time versus Simulation Time was generated using Arena Output Analyzer® data. Examination of this plot allowed for a conservative estimation of 30 hours as the duration of the warm up period [14]. Based on the available resources the simulation run length was set to 10 days, 16 hours a day for 150 replications. These parameters provided data output for the KPI with a precision of ± 1 hour for FT and WT, and ± 50,000 labels for WIP. The required number of replications to achieve this precision, n_e, was derived using Equation 1.

$$n_e = n_0 \frac{h_0^2}{h^2}, \tag{1}$$

where n_0, is the number of replications required to derive a precision of h_0 and h is the desired precision of the examined KPI [14]. Equations 2, 3 and 4 were random distributions used to determine the Interarrival Times (IAT) of the simulation entities representing incoming job orders at each printing work station.

$$\text{IAT \#1} = 1 + \text{LOGN}\ (2.72, 2.94), \tag{2}$$

$$\text{IAT \#2} = 1 + 10 * \text{BETA}\ (0.495, 0.636), \tag{3}$$

$$\text{IAT\# 3} = 1 + \text{EXPO}\ (2.31), \tag{4}$$

The Key Performance Indicators (KPI) of Flow Time (FT), Waiting Time (WT) and Work in Process (WIP) output by Md0 was compared in turn to the KPI output by the other three models, Md1, Md2, Md3, which incorporated proposed measures utilising I4.0 and LM practices. Statistical testing via SPSS was used to determine the significance of any differences observed among models at the 95 % C.I.

3. Results

The KPI for the existing and proposed models were presented in Table 2. Models Md1-3 all showed improvements to FT, WT and WIP when compared to Md0. Model Md3, when compared to Md0 improved by 52 % in FT and 57 % in WT. The models Md1 and Md3 both showed a 58 % improvement in WIP when compared to Md0.

One-way ANOVA studies were used to compare the effects of the proposed measures employed by each model (see Table 3). These studies indicated that significant differences existed at the 95% C.I. between at least two models. This result occurred with each of the examined KPI; FT, WT and WIP. The results for each KPI were, FT: (F (3, 116) = 76.899, $p < 0.001$); WT: (F (3, 116) = 67.417, $p < 0.001$); and WIP: (F (3, 116) = 22.741, $p < 0.001$).

Tukey HSD for multiple comparisons as presented in Table 4 outlined the mean differences among the model KPI which were significant at the 95 % C.I. For FT and WT; differences between Md1-3 and Md0, supported the finding that the proposed measures were an improvement over the existing system. In the case of WIP, models Md1 and Md3 also showed differences from Md0 that indicated a performance improvement. Among the proposed models depicted in Table 4, Md3 yielded the largest mean difference when compared to Md0 for FT, WT and WIP.

Table 2. Summary of Key Performance Indicators of Existing and Proposed Arena® Models: Flow Time (FT), Waiting Time (WT) and Work in Process (WIP).

KPI	Existing Model	Proposed Models			Precision
	Md0	Md1	Md2	Md3	
FT (hour)	50	27	47	24	± 1 hour
WT (hour)	42	21	39	18	± 1 hour
WIP (label)	1,200,000	500,000	1,100,000	500,000	± 50,000 labels

Table 3. One Way ANOVA studies to determine differences among the KPI of models Md0-3 ($\alpha = 0.05$). KPI: Flow Time (FT), Waiting Time (WT) and Work in Process (WIP).

KPI	Score	Sum of Squares	Degrees of Freedom	Mean Square	F-value	p-value
FT (hour)	Between Groups	6728	3	2243	76.899	< 0.001
	Within Groups	3383	116	29.17		
	Total	10112	119			
WT (hour)	Between Groups	5379	3	1793	67.417	< 0.001
	Within Groups	3085	116	26.60		
	Total	8465	119			
WIP (label)	Between Groups	1.099×10^{13}	3	3.663×10^{12}	22.741	< 0.001
	Within Groups	1.868×10^{13}	116	1.611×10^{11}		
	Total	2.967×10^{13}	119			

Table 4. Tukey Post-hoc Multiple Comparison Table. Significant Mean Differences between Models at ($\alpha = 0.05$). Key Performance Indicators (KPI): Flow Time (FT), Waiting Time (WT), Work in Process (WIP).

KPI	Model		Mean Difference	Standard Error	p-value
FT (hour)	Md0	Md1	15.92	1.39	<0.001
		Md2	3.71	1.39	0.044
		Md3	17.22	1.39	<0.001
	Md1	Md2	-12.21	1.39	<0.001
	Md2	Md3	13.51	1.39	<0.001
WT (hours)	Md0	Md1	14.25	1.33	<0.001
		Md2	3.64	1.33	0.036
		Md3	15.60	1.33	<0.001
	Md1	Md2	-10.61	1.33	<0.001
	Md2	Md3	11.96	1.33	<0.001
WIP (labels)	Md0	Md1	596,801	103,622	<0.001
		Md3	624,545	103,622	<0.001
	Md1	Md2	-585,108	103,622	<0.001
	Md2	Md3	612,852	103,622	<0.001

5. Discussion

Findings from literature have indicated that I4.0, when applied in isolation, leads to suboptimal results on productivity [7][15][16]. In contrast, a beneficial, synergistic effect has been noted when I4.0 is employed alongside other manufacturing philosophies such as LM practice [17][18][19]. In the case of LM practice this is perhaps due the technology focused, value-creation approach of I4.0 complementing the value-to-customer focused, worker competency-building approach of LM. In essence, I4.0 offers novel technological solutions that improve productivity by simplifying complex work; while LM provides simple procedures that encourage workers to internalise and put into practice new tools and techniques with efficiency [16].

Considering these findings, the proposed measures examined were a combination of LM practices and I4.0 technologies to address the wastes observed during the VSM exercise. First, in the existing system, job orders entered as both a physical work order and a matching e-Kanban ticket provided to the workstation. As part of their work setup opera-tors were then required to compare the two sets of instructions for anomalies. This procedure added unneeded complexity to the process. In notable instances, long delays were observed when the physical job order did not match the information provided by the e-Kanban ticket.

Veteran operators often opted to overlook such discrepancies instead of pausing work to request clarification. When questioned, they noted that it was common for the physical document to fail to keep pace with changes to the production plan. As a result, when instructions were in doubt, the more dynamic e-Kanban ticket was preferentially referenced. Removing the requirement of a physical job order simplified the process which decreased the time spent on setup activities.

Second, the processes for retrieving the storage location of printing plates and logging completed job orders were automated. This addressed commonly indicated sources of wasted time during setup activities [20]. These changes were represented in Md1 and Md3 by utilizing the firm's best practice standard for setup times in the relevant processes as determined by prior time and motion studies. Finally, it was noted that time was wasted when waiting for material transporters. As a result, the capacity of the transporters within the model was increased in Md2 and Md3.

The models employing proposed measures Md1-3 were each able to improve upon the KPI of Md0 through addressing a source of waste. Model Md3 showed that the greatest KPI improvements resulted from a holistic application of I4.0 tools and LM practice [21][22]. The potential synergies between I4.0 and LM practice were also inferable from Table 1. Table 1 showed that the I4.0 applications could each be reframed in terms of a suitably compatible LM practice.

6. Conclusions

The study revealed that the greatest performance improvements resulted from a beneficial synergistic application of I4.0 and LM practice. Some of the proposed changes ap-plied existing but previously underutilised capabilities of the firm's ERP system with con-sideration for the principles of LM practice. I4.0 techniques, such as automating the process of data storage and retrieval, simplified setup requirements while causing closer integration of the firm's Printing and Production Scheduling Departments. Further process improvements were noted when these I4.0 techniques were used alongside other, simpler LM approaches. For example, reducing the waiting time for material transport by ad-dressing the need for more transporters. As a result, Md3 indicated that the KPI of FT, WT and WIP could be improved by 52%, 57% and 58% respectively. This result supports the idea that the productivity-improving I4.0 technologies are compatible with the competency-building procedures of LM practice.

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