Lean techniques impact evaluation methodology based on a co-simulation framework for manufacturing systems

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ABSTRACT

Lean implementation plays a major role in optimizing productivity and reducing waste. Applying the adequate integration of Lean Techniques (LT) can ensure a higher profitable benefit. Many companies face difficulties in choosing the LT that best suit their situations to reach their objectives. In this study, we propose the simulation of specific modeled industrial contexts and check the impact of implementing LT simultaneously. *Market fluctuation, demand diversification, and uncertainty of resources* contexts are studied to perceive how LT behaves accordingly. Four KPIs (Key Performance Indicators) are retained for the analysis: *Work in Progress, Lead-time, Production Throughput, and Defect Rate*. An aeronautical company is modeled and experiments are performed to demonstrate the usefulness of a developed co-simulation framework to perceive the sensitivity of LT to some industrial contexts. The results showed that Poka Yoke and 5S are context-free LT valid in any industrial context. Pull, SMED, and Cross training are contextual and deserve careful applicability regarding the simulated context. Cross training, suitable for uncertainty of resources, does not show any significant improvements when the company was exposed to market fluctuations and demand diversification contexts.

KEYWORDS

Lean manufacturing; lean tools; co-simulation; discrete event simulation; KPI

1. Introduction

The benefits of Lean implementation and its impact on industrial performance is widely studied in the literature. These benefits have been explored in various sectors, and the positive impact of Lean manufacturing on the firms' operational performances has been strongly argued (Fullerton, Kennedy, and Widener 2014; Dhiravidamani et al. 2018; Zhu, Zhang, and Jiang 2020). The main impacts are *stock reduction, unnecessary process elimination, productivity increase, quality enhancement, lead time reduction, cost reduction, and reduction of space used* (Capraro and Baglin 2002). Nevertheless, an important issue remains when managers must address lean implementation. In addition to the experiences and subjective approaches of each author, no guidelines or structured methodology exists to delineate the relevant lean techniques (LT) to adopt. A review of the literature has revealed difficulties in choosing the most appropriate LT to adopt during the implementation phase. New approaches and methodologies specific to different contexts are required as stated in (Amrani and Ducq 2020). Many authors have identified weaknesses that can hinder the performance: the wrong use of Lean practices, the incorrect implementation of LT, or the implementation of Lean tools in the wrong order. The misuse of LT induces failures and economic losses (Secchi and Camuffo 2019). Berger, Tortorella, and Rodriguez (2018) argue that dealing with contextual uncertainty and non-routine behaviors incites companies to look for solutions, and adopt LT that can help. Dora and Gellynck (2015) identify Lean implementation approaches. While defining what they called 'step3', they reinforced the importance of preparation at the organizational level, and the importance of making alignments with the sector-specific factors; managers can choose the appropriate Lean practices to implement in order to improve their companies' performances. For instance, in the food processing sector, SMEs avoid applying the pull system and JIT tools due to the uncertainty of demand variation. This finding demonstrates the necessity to observe the context prior to choosing the most suited tools. Likewise, Ohno (1988) has emphasized that Kanban can only work effectively if the demand is constant. The lack of flexible and multiple-use equipment in resource-constrained companies, like SMEs, is found to negatively affect the implementation of cellular layouts. This correlation is perhaps intuitive, but there is a shortage in studies when it comes to the relevance of Lean tools. There is a basic logical sequence in which these elements should generally be implemented. For instance, Shingo and Dillon (1989) found that SMED and Layout Improvements should be implemented before Kanban. A Kanban system implemented within an environment of fluctuating demand would be regarded as wasteful (Womack and Jones 2003).

2. Literature review

There are different lean tools and techniques that could be implemented in the company (Kumar, Mangal, and Pandy 2019). However, these tools cannot be implemented randomly. Critical success factors must be recognized and taken into consideration before Lean implementation process (Sebtaoui, Adri, and Rifai 2020). Secchi and Camuffo (2019) consider that there is a necessity to implement some Lean tools before others. For instance, stability improvements should be considered first (manpower, machines, materials and methods) during Lean implementation. Standardized work and uninterrupted process flows are the key foundations of the Toyota Production System (Ohno 1988). Easy-to-use practices such as workplace organization, visual management, and customer involvement should be given more weight in the beginning stages of the implementation than in the more advanced ones (line balancing, one-piece flow, pull, and Kanban). It has been proven, especially in SMEs, that early success and quick wins help firms sustain quality initiatives (Sony 2019; Grigg, Goodyer, and Frater 2020). We subscribe to the idea that contextualization is necessary for better understanding and clarification prior to moving forward. There is an interesting notion for prioritizing LT implementation: the techniques are chosen based on the managers' experiences and their intuitive thinking (Jadhav, Mantha, and Rane 2014; Amrani and Ducq 2020). More and more, current literature emphasizes the importance of structuring Lean techniques to one context rather than another, and to one situation prior to another. Shah and Ward (2003) studied the influence of plant size, the unionization status of the company, and plant age context-factors on 22 Lean practices that were mostly used in Lean manufacturing systems. Recently, Bortolotti, Boscari, and Danese (2015) stated that it is not only the choice of Lean practice that influences Lean manufacturing measures but also the situation and context, the complexity of products, the production typology strategy, and the demand variability. Angelis et al. (2011) and Laureani, Antony, and Setijono (2012) argued that any organization willing to implement Lean should be careful to prioritize implementing the vital tools: Cellular structures, as it is important for efficiency to group the elements required to produce products (Lee 2007); Kanban methodology needs to be fully embraced (Smalley and Harada 2009); Kaizen, which pursues the constant quest of improving quality, cost, delivery, and design; and Single-piece flow systems need to be geared towards adding value (Sharma and Gandhi 2018). Based on these findings, we would take the opportunity to build a theory on Lean tool relevance to specific industrial contexts. These first elements provided by the literature consolidate the possible existing gap caused by current methodological inconsistences. The idea is to build up a structured and constant methodology to improve the relevance of the chosen Lean techniques.

2.1 Main research interests related to Lean research topic

To study the research interests of the Lean community, seven literature reviews that deal with the implementation of Lean practices were considered, with a total of over 1300 papers being reviewed within. The most important findings of each study are summarized in Table 1. The analysis of the common factors among the references reveals some interesting common points. Different symbols are used to identify the similarities between the suggested research interests: (ω): Factors that affect Lean implementation, (λ): New approaches and developments, (φ): Development of methods to help in the Lean implementation, (Ø): Developing measures and metrics, (σ): Expanding Lean implementation beyond production to Supply chain, (β): Expanding Lean implementation beyond production to product development.

Table 1. Main research interests in Lean implementation.

Authors	Sample	Years	Main research interests
(Jasti and Kodali 2015)	n = 102	1996–2012	• Develop conceptual models related with surveys (λ) • Extend Lean approach from operation to Lean enterprise (β) • Extend the research to deal with all types of NVA (wastes) (λ) • Develop a measure of the model performance (Ø)
(Marshall 2015)	n = 546	1988–2011	• Extend research about sustainability in Lean(λ) • Lean in service, non-profit organization (β) • Supplier and supply chain research (σ) • Use empirical method other than field research (λ)
(Marodin and Saurin 2013)	n = 43	1988–2013	• Extend research about factors that affect Lean implementation including investigation factors and relationships (ω) • Involve application of methods to provide generalizability (φ) • Balance the implementation of Lean with technical emphasis and the practices that have effect on human, organizational aspects (ω) • Extend Lean in other areas, such as product development and services, not only shop floor (β) • Develop Performance measurement related to different dimensions such as human and financial (Ø) • Extend research about detailed investigation of Lean implementation that had unexpected results (λ)
(Panwar et al. 2015)	n = 104	1989–2013	• Develop Lean implementation model for process industry (φ) • Develop analytical models to quantify the leanness measure of process industries (Ø) • Extend research to supplier involvement in process industries (σ) • Develop framework to overcome constraints for continuous process industries (φ) • Conduct further empirical studies (λ) • Contribution of external factors such as social economic, political, and environmental factors (ω)
(Cherrafi et al. 2016)	n = 118	1990–2015	• Develop integrated metrics to measure Lean/Six Sigma from social, environmental, economic aspects (Ø) • Develop integrated model applicable to many sectors (φ) • Expand research about service industry (β) • Develop pre-implementation phase (φ) • Expand study to all functions of the supply chain with an analysis of supplier, customer relationship (σ) • Extend research to motivation, barriers, negative effects of integration (ω)
(Abideen, Mohamad, and Fernando 2020)	n = 93	1996–2020	• The research show that there is a considerable scope that should be widened and explored to enhance several performance metrics in manufacturing and production (Ø) • Various research proposals and gaps for future research efforts and developments (λ) • The impact of decision-making, risks, services, and strategies on lean implementation should be extensively studied (ω) • A non-conventional approach for lean implementation is needed (λ) • New manufacturing strategies are required (φ) • Expanding Lean management beyond production (β)
(Antony et al. 2020)	n = 403	2010–2020	• New avenues for future research about Lean management are required (λ) • Expanding Lean management to the service business environment as well as the supply chain network (σ) • Expanding the implementation of Lean beyond production (β) • Extend research about the obstacles and key enablers for Lean implementation (ω) • Extend Lean management to services and product development (β) • Exploring trends in the research regarding Lean in SMEs (λ) • Identifying recent developments concerning the factors that affect Lean implementation (ω) • Identifying methods and metrics to measure leanness in manufacturing organizations (Ø)

The factors that influence Lean implementation are evoked in (ω). Those factors can be human or organizational aspects (Marodin and Saurin 2013). Panwar et al. (2015) studied the external factors that influence Lean implementation, such as social, economic, political, and environmental factors. Cherrafi et al. (2016) extended the analysis to the negative factors (barriers) that should be considered in order to have a successful Lean transformation. In addition, the impact of decision-making, risks, services, and strategies on lean implementation should be extensively studied (Abideen, Mohamad, and Fernando 2020). In the samples of (λ), researchers encourage the Lean community to commit to the development of new conceptual survey-based models (Jasti and Kodali 2015) and non-conventional approach for lean implementation (Abideen, Mohamad, and Fernando 2020). As stated in Panwar et al. (2015), *'Conducting further empirical studies is welcome'*. Marshall (2015) indicates that more research in Lean sustainability is needed and that researchers should focus on the empirical method, not only on the research, which mainly leads to statistical findings with no solid research hypothesis. In the studied samples of (φ), new Lean related methods and metrics are expected to measure leanness in manufacturing organizations (Antony et al. 2020). Moreover, developing a Lean implementation framework to overcome constraints would be a promising idea (Panwar et al. 2015). The involvement of method application to provide generalizability is also highlighted (Marodin and Saurin 2013). The need to develop a framework for the pre-implementation phase and an integrated model applicable to many sectors is argued by Cherrafi et al. (2016). In addition, Lean implementation is not an isolated activity. Monitoring is necessary to assess and evaluate the level of Lean maturity implementation. This concern is an important point indicated by Marodin and Saurin (2013) to develop performance measurement related to different dimensions, including human and financial. Other authors consider the importance of developing Lean metrics and measures to calculate the model's performance (Jasti and Kodali 2015), analytical models to quantify the leanness measure of process industries (Panwar et al. 2015), and integrated metrics to measure Lean/Six Sigma in social, environmental, and economical aspects (Cherrafi et al. 2016). The degree of Lean achievement is a growing interest for the research community looking for synthetic and representative methods for Leanness degree calculation (Amrani et al. 2018). In the samples of (β), authors consider that there is a necessity to extend Lean management to services and product development and not only to the shop floor (Antony et al. 2020; Marodin and Saurin 2013). In the studied samples (σ), supply chain aspect is also of extreme importance. The Lean community asks for more studies and research into the supply chain domain (Marshall 2015). Expanding the research to all functions of the supply chain whilst analyzing the supplier–customer relationship is highlighted by Cherrafi et al. (2016). Extending research to supplier involvement in the process industries is noted by Panwar et al. (2015). The idea of extending the research beyond the scope of production is obviously stated and confirmed by many authors: extending Lean in product development and service areas is reminded by Marodin and Saurin (2013); extending to the whole enterprise is requested by Jasti and Kodali (2015) and expanding the research to the service industry is stated by Cherrafi et al. (2016) and Marshall (2015).

Based on the literature, Hu et al. (2015) conclude that there is a need for researchers to go further; the authors address the need for research that spans beyond the boundaries of a single organization, extending to supply chains and network contexts. They recommend exploring the differences between small, medium, and large organizations to assess how a company's size affects the implementation of Lean.

2.2 Distributed discrete event simulation in manufacturing industries

Simulation in manufacturing and supply chain fields is still a very commonly used approach due to its ability to reproduce a virtual system that simulates the real production system (Lu et al. 2019; Lee, Ju, and Woo 2020; Vatankhah Barenji et al. 2020). Discrete Event Simulation (DES), in particular, is one of the preferred research topics nowadays (Bara, Gautier, and Giard 2020) for its ability to simulate production system and supply chain behaviors. DES is suitable for leading the analysis of the dynamics of discrete processes such as manufacturing systems (Ingemansson and Bolmsjö 2004; Cortes et al. 2020) and other environments, such as manufacturing plants, queuing systems, distribution systems, inventory and delivery, transportation networks, and communication networks (Huynh, Akhtar, and Li 2020; Zupan and Herakovic 2015). Jeon and Kim (2016) note that DES is a frequently used tool for Production Planning and Control problems that represents more than 45% of the simulation models in the studied sample. DES becomes an essential tool in healthcare, production, agriculture, aerospace, and other domains (Devapriya et al. 2015; Zhang 2018; Oddson and Aggarwal 1985; Van, Boulanger, and Wolff 2020). However, in some cases, DES alone is not an effective solution. The simulation system must be disassembled into subsystems or nodes in order to be parallelized or distributed on a multiprocessing environment for performance enhancements (Lopez-Novoa, Mendiburu, and Miguel-Alonso 2014). In other cases, a collection of interacting simulations is needed to form a more complex system that offers other functionalities in addition to existing ones (Gorecki et al. 2020). There are also scenarios where users need to compare many different DES. These cannot be run sequentially, and also need to be parallelized or distributed on a network of processors (Possik, Amrani, and Zacharewicz 2018a). For all those scenarios, a Distributed DES should be implemented. Time management and synchronization mechanisms are necessary to avoid timing discrepancies and to ensure precise event interconnections and data communication between subsystems or simulations (Possik, Amrani, and Zacharewicz 2018b). In the research study presented here, a Distributed DES was developed to dynamically sustain the unfolding of an order book over a period of simulation, combine, and compare different parallel scenarios and possibilities.

3. Research methodology

3.1 Research approach

The research method suggests combining industrial contexts and objectives in a single conceptual model in order to define a set of cross-situations (Figure 1). The conceptual methodology is built around mathematical formulas to model the studied economic context and a simulation platform which is a necessary basis for the development of hypotheses and the testing of various scenarios. We argue that in each industrial context and depending on the objectives of the company, different LT can be tested to check their relevance.

The chosen objectives of the company are inspired by the authors referenced in Table 2.

The suggested methodology of research aims to provide guidelines to gradually implement LT suitable for different economic contexts. The context is defined as follows: '*Context is any information that can be used to characterize an entity, its condition, or its surrounding situation*' (Rosenberger and Gerhard 2018). In the scope of our research, the entity represents the whole manufacturing system, from the raw materials going through the assembly line until the final product. The manufacturing system driven by managerial decisions is undergoing different contexts. Finally, three industrial contexts are considered: *Market fluctuation, Diversification of Demand and Uncertainty of human and technical resources*. These contexts are mathematically modeled (Table 3). The context of market fluctuation and uncertainty of resources represents a situation that can be faced by any enterprise with changes in its order book. An increase in the demand causes nervousness in the production systems and a need for a company to review its production schedule. A decrease in demand causes a reorganization of the production system. In the context of demand diversification, diversity representation will be also formulated. It is necessary to define all customers that might order various products. Each customer can order different quantities of various references. The number of varieties required by the company will always remain less or equal to the total number of actual product ranges given by the company.

In the context of unreliability of resources, the enterprise faces a situation where it will not meet its production target. At the operational level, the resources considered are the workstation machines for the production/assembly line responsible for the progress of the flow, as well as the operators in charge of operating the line. The model must be able to represent the occurrence of a machine malfunction or an operator-related malfunction (absence, accident, etc.) at a given period (t). The machine malfunction represents an inability to run at a stable rate or to produce the

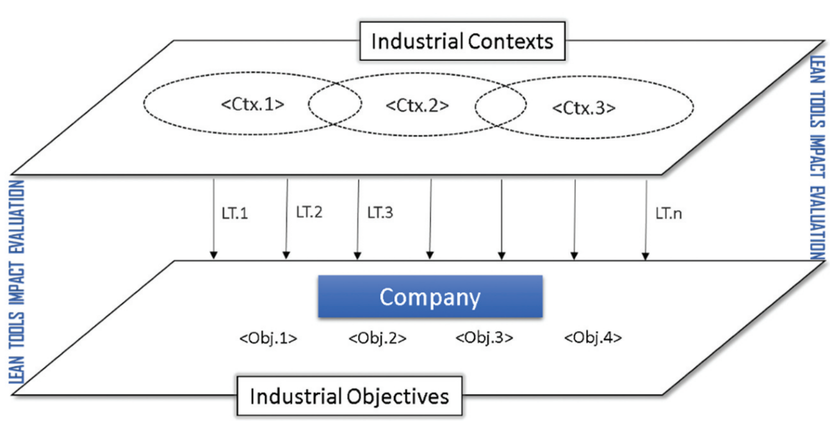


Figure 1. Combining industrial contexts and industrial objectives for Lean tool evaluation.

Table 2. Summary of industrial objectives adapted from Okoshi, De Lima, and Da Costa (2019).

Objectives	Requirements/ Target	Authors	Objectives	Requirements/ Target	Authors
Quality Obj.1	(1) To not make mistakes. (2) Products in conformity with design specifications. (3) Manufacturer offers capability to the production process.	(Wheelwright 1978)	**Flexibility** Obj.3	(1) Adapt or reconfigure the production system/production process. (2) Able to address changing demands. (3) Able to reconfigure the operations due to changes. (4) Manufacturing system is able to change at the right pace.	(Longoni, Golini, and Cagliano 2014)
Reactivity Obj.2	(1) Keep delivery promises, increase service level. (2) Correctly estimate the delivery dates. (3) Able to meet the clients' deadlines. (4) Clearly communicate dates to the client. (5) Lead time should be lower than the competitors. (6) Lead time: the total amount of time between the placing of an order and the receiving of the goods ordered.	(Okoshi, De Lima, and Da Costa 2019)	**Cost** Obj.4	(1) Manufacturing the products at low cost. (2) Being more efficient than the competitors. (3) Negotiation of low-cost resources. (4) Efficiently running the production process.	(Franco-Santos et al. 2007)

Table 3. Mathematical modeling of the chosen contexts.

Contexts	Mathematical Modeling
Ctx.1 Market Fluctuation	• Jalal Joseph Possik is considered as the set of products. • Each reference is denoted by Jalal Joseph Possik where Jalal Joseph Possik. • Jalal Joseph Possik. • Jalal Joseph Possik: Demand of the product Jalal Joseph Possik at a period of time Jalal Joseph Possik. • Jalal Joseph Possik: Demand fluctuation. • Fluctuation of the market at time t is relative to the initial value given in Jalal Joseph Possik with an increase or decrease of (Jalal Joseph Possik). $i = 1\ldots n; \exists t \in \{0\ldots m\}/\hat{D}_{XRF_{i(t)}} = D_{XRF_{i0}} \pm a_{i(t)}\%$
Ctx.2 Diversification of Demand	• (k): Maximum number of clients per company. • C_u: Client profile. • A set of clients is defined by: $S_C = \{C_u \mid u = 1\ldots k\}$. • $D^u_{XRF_i}$: Demand of product XRF_i by client (C_u). • $\overline{D_{C_u}}$: Variety of demand required by client (C_u). • f: Number of varieties required $(f \leq n)$. $u = 1\ldots k;\quad i = 1\ldots n; \exists t \in \{0,\ldots,m\}/\overline{D_{C_{u_t}}} = \sum_{i=1}^{f\leq n} D^u_{XRF_{it}}$
Ctx.3 Uncertainty of resources	• Set of Machines: $S_M = \{M_p \mid p = 1\ldots U\}$. • U: Maximum number of machines. • Set of operators: $S_H = \{H_v \mid v = 1\ldots V\}$. • V: Maximum number of operators. • $\lambda_{vt}; \lambda_{vt} \in \{0,1\}$: Operator H_v disturbance event (error or absence). • $\theta_{pt}; \theta_{pt} \in \{0,1\}$: Machine M_p disturbance event (failure, unavailability, or defect). • Q_{ti}: Quantity of products of type (i) produced at period (t). • Q_{pti}: Quantity of products of type (i) produced at period (t) by the machine (M_p). • Q_{vti}: Quantity of products of type (i) produced at period (t) by the operator (H_v). • μ_{pti}: Percentage of damage on the production system caused by machine (M_p) at the period of time (t) impacting product type (i). • ω_{vti}: Percentage of damage on the production system caused by human (H_v) at time period (t) impacting product type (i). $i = 1,\ldots,n;\quad t \in \{0,\ldots,m\}; \lambda_{vt} \in \{0,1\} \wedge \theta_{pt} \in \{0,1\};\ p = 1\ldots U{:}\ Q_{ti} = \min_t \left[\sum_p Q_{pti}(1-\theta_{pt}\ \Sigma\mu_{pti}), \sum_v Q_{vti}(1-\ \lambda_{vt}\cdot\omega_{vti})\right]$

expected quantity. An operator-related malfunction denotes a blockage at the workstation caused by the unavailability of the operator. Both cases can co-exist where machine and human dysfunctions appear in the production system.

The steps of the methodology are presented in Figure 2. After defining the objectives, the input data should be provided to the developed Graphical User Interface (GUI) simulation platform; this platform allows users to run the co-simulation framework in order to test the LT efficiency implemented in their production system. The aforementioned tools do not affect our simulation process and are considered successfully met at simulation time (t = 0). Next step would be to start the simulation run in order to test the operational Lean tools' efficiency and relevance in the considered context. At each stage, analyses are conducted to choose the most reliable LT that can be adapted for each of the studied contexts.

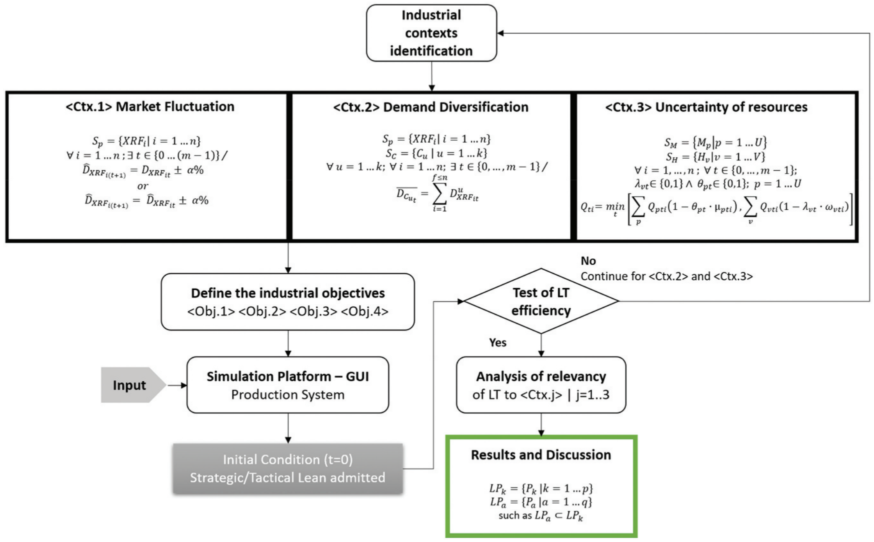


Figure 2. Methodology of Lean simulation according to context.

(1) $LP_k = \{P_k | k = 1 \ldots p\}$: *set of Lean tools tested*
(2) $LP_a = \{P_a | a = 1 \ldots q\}$: *set of adapted tools such as* $LP_a \subset LP_k$

3.2 Framework architecture

A co-simulation framework has been developed based on the HLA standard. The HLA protocol is a standard that helps in the development of distributed simulations. HLA 1.3 standard was first developed by the US DoD (Department of Defense). In the year 2000, it was adopted by IEEE and named HLA IEEE 1516–2000. Then, it was modified and updated in 2010 to encompass improvements; this last version is known as HLA Evolved (1516–2010). This framework is developed based on the HLA evolved version. HLA operates through the creation of a federation that is composed of different simulation components. These components are called 'federates'. HLA is used in this project to solve the time synchronization and interoperability issues between heterogeneous running components. Moreover, based on the time management mechanism of HLA, this framework synchronizes the simulation time of the seven DES models to make them running simultaneously in parallel. During the simulation run, each federate asks for time advancement to send new events. However, no federate can advance in time without having the time advance grant from the Run-Time Infrastructure (RTI). Furthermore, Objects/attributes and interactions/parameters exchange, between the running models and an external Java application, is required. The Java application is referred to as 'Master' federate responsible for sending/updating input data to all running models and receiving the output results from the models running in parallel to show the parallel results in a real time appealing graphical presentation. Data collaboration between the external Java application (Master) and the running models is implemented based on the publish/subscribe mechanism of HLA.

Using this platform, the user can choose the LT to load-specific inputs: the market demand for each type of product needed, the setup time and processing time of each machine, the travel time between machines, the planned/unplanned down time of each machine, and the defects rate. All data are sent or received as objects/attributes or interactions/parameters. There exists a common Federation Object Model (FOM) XML file that lists all shared objects/attributes and interactions/parameters. Input data are filled into the external Java application able to interact with all connected simulation components (Figure 3). Simulation models' federates are designed in JaamSim (King and Harrison 2013), a Java-based DES (Discrete Event Simulation) software. This simulator is used in this research instead of other simulators, because of its transparency, reliability, capability, and, most importantly, because it is an open-source software. Jaamsim runs by default as a black box

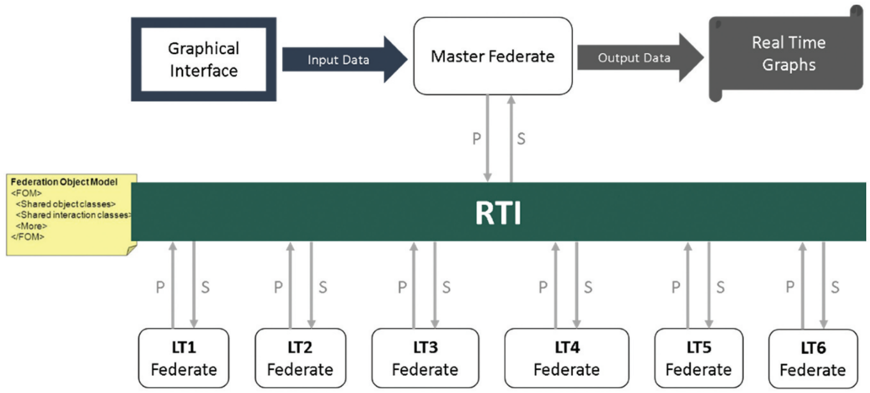


Figure 3. Framework architecture.

simulator; a substantial effort was made to convert Jaamsim to a distributed HLA-compatible simulator. With the HLA developed module, Jaamsim can now interact, collaborate, and exchange data with external simulations. In our research, these functionalities were essential to make all Lean tools running simultaneously in parallel in order to experiment the responsiveness of each Lean tool regarding an industrial context change.

3.3 Simulations can run on a network of processes, on different machines and different operating systems

Moreover, heterogeneous data are exchanged, processed, and synchronized between different simulations, without interpretation. The detailed technical implementation can be found in (Possik et al. 2019).

Aeronautic Case Study: AeroComp

The case study used is an adaptation of an aeronautic company (Amrani 2017). The product designed and manufactured by AeroComp is an aeronautic fastener composed of a metallic cylinder part, over which bearings are added on the right and left sides. Gears are then welded and screwed into the back of the metallic cylinder. The cylinder has a specific length and diameter provided by the client in a specification sheet (Figure 4, right side). Based on the order book, raw materials are sent to the cutting shop where the metallic cylinder is cut to the exact dimensions specified by the client. Goods in process are then sent to the treatment shop where a layer of zinc is added to the product. The product is then sent to the assembly shop where four workstations (noted WS) manufacture the semi-finished axis, add the bearings and then fix the gears. It is finally sent to the machining shop where two workstations place the pins and send the final aeronautic fastener to the warehouse for delivery.

As presented in Figure 4 (left side), one operator works on each workstation to efficiently complete the job and operate at capacity. Each machine has a Processing Time and a Setup/changeover Time. Processing Time is the time each machine takes to complete a prescribed job or procedure. Setup/Changeover Time is the time needed for the machine to switch from the last processed good of the previous batch to the first good of the new batch to be processed. In this study, we define $\Delta CO_{M_p XRF_i}$ as being the changeover time needed for machine 'M_p' to switch to a new product reference 'XRF_i'. AeroComp has a catalog of 12 different references of finished products. Four diameters exist (12 mm, 24 mm, 32 mm, and 41 mm). For each diameter, length can vary regarding the client's order. So, $\Delta CO_{M_p XRF_i} = \Delta COD_{M_p XRF_i} + \Delta COL$, where $\Delta COD_{M_p XRF_i}$is considered as the 'Diameter' changeover time needed for machine $M_p$to switch from one reference to another, and ΔCOL is the 'Length' changeover time needed by machine $M_p$to switch. $\Delta COD_{M_p XRF_i}$ is defined for each machine M_p and each reference XRF_i. As there is no specific or standard length, ΔCOL is calculated based on a triangular probability distribution (Gest et al. 1995). These data are sufficient to develop the production system virtualization in the framework simulation (nomenclature, processing time, operating range, product type, type of components).

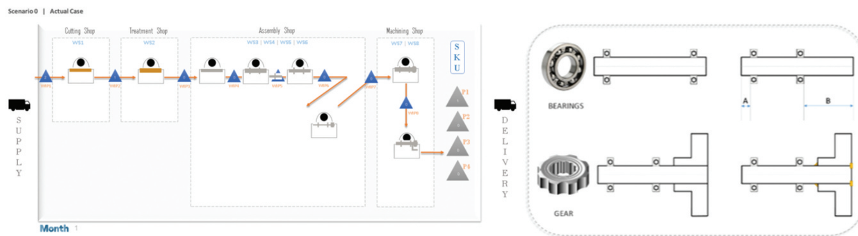


Figure 4. AeroComp production Line (left side) and product (right side).

4. Experimentation and results

4.1 Initial conditions

The retained LT for experimentation are: Pull, Cross training, SMED, 5S, Poka Yoke, and Ucell. The Pull production method strives to minimize and eliminate overproduction. In Pull scenario's configuration, each machine sends a signal to the upstream one when its WIP (Work In Progress) exceeds a predefined number of units to stop sending products in process. In cross-training model, workers are configured as multi skilled to operate on any of the existing machines. SMED model minimizes the waste resulting from lack of material, to ensure tools and machine cleanness and to organize the workshop place associated with setup/changeover processes. 5S tool aims to make a self-explaining, ordering and improving workplace. It is a set of principles that improve the workplace environment which in turn improve the quality and the production efficiency. This model reduces the production time and the defect rate of the workstations/machines. Poka Yoke means 'mistake-proofing'. This tool is a simple tool that prevents defective good in process from being delivered to the next process. The main concept of this approach is to detect, eliminate, and correct errors at their current source before reaching the customer. Ucell focuses on the flow of the product. Machines are placed close to each other in order to minimize the transport time between them.

We have identified four KPIs (Key Performance Indicators): lead-time, WIP, production throughput, and defect rate to check the efficiency of the configured situation. *Lead-time* is the time needed to provide the customer's request; from the moment the order is received until the finished product is delivered. *WIP* represents the partially finished products in the production process. *Production throughput* refers to the quantity of products that can be produced within a period of time. *Defect rate* is the percentage of items or products that failed the quality tests. Neutral scenario is defined as being context variation free. Actual model is defined as a scenario where no LT has been applied yet.

4.2 Statistical sensitivity analysis

While running the simulation, KPI values are saved to a log file and then statistically analyzed using the ANOVA test (one-way analysis of variance). This test enhances the reliability of findings and helps to determine statistically significant differences between the means of the running models' results related to the LT simulated. The KPI mean of each LT will be compared to others to perceive the variation of the results under each context run. The null hypothesis 'H_0' is defined as the case where the means of two samples obtained remain the same [$\mu_{Sample1} = \mu_{Sample2}$] with the specificity that samples are taken from equivalent populations. In H_0, no variation is observed from different samples. The alternative hypothesis is defined as the situation where the means obtained from samples are different (< or >), creating variation and sensitivity in results [$\mu_{Sample1} \neq \mu_{Sample2}$]. In statistics, we use a confidence level of 95%. The results are more accurate when the confidence level is higher. The p-value is directly related to the confidence level, it represents the probability of the null hypothesis being correct. A p-value less than or equal to 0.05 is considered statistically significant. A p-value higher than 0.05 is not statistically significant and indicates weak evidence against the null hypothesis. This results in rejection of the null hypothesis, and rejecting the alternative

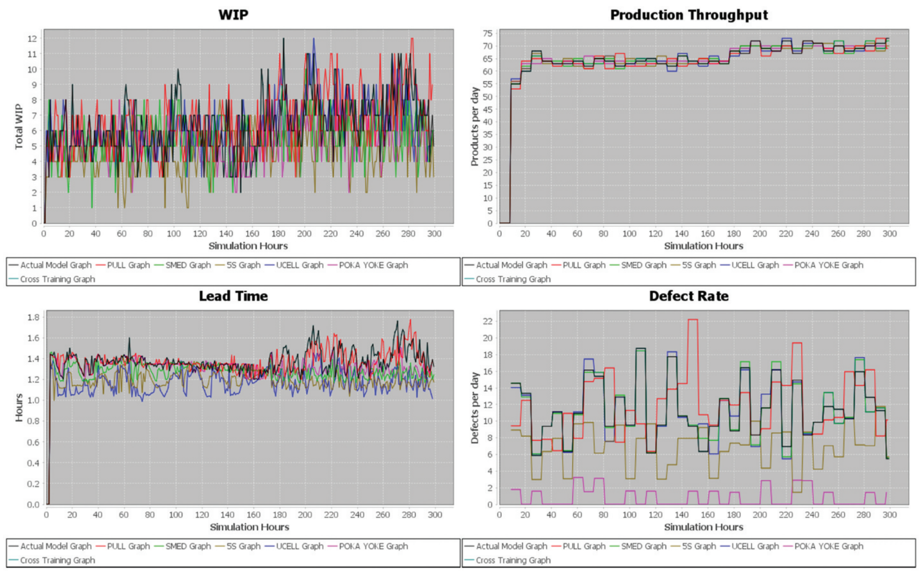


Figure 5. Simulation results of the neutral scenario.

Table 4. One-way ANOVA test of the default simulation run.

		Sum of Squares	df	Mean Square	F	p-value
WIP	Between Groups	946.144	6	157.69	57.159	<0.0001
	Within Groups	5542.410	2009	2.759		
	Total	6488.554	2015			
Lead time	Between Groups	13.409	6	2.235	305.393	<0.0001
	Within Groups	14.701	2009	0.007		
	Total	28.110	2015			
Defect rate	Between Groups	28,835.35	6	4805.8	477.226	<.0001
	Within Groups	20,231.56	2009	10.070		
	Total	49,066.91	2015			
Production throughput	Between Groups	30.603	6	5.101	0.372	0.897
	Within Groups	27,531.55	2009	13.704		
	Total	27,562.15	2015			

hypothesis. In this simulation, the different means of KPIs that underwent different contexts will be monitored.

4.3. Initial experimentation: neutral scenario

To carry out the experiments, the neutral scenario was designed to correspond to the situation where the company is free of economic context variation. Called **neutral scenario**, it is performed with no context changes to the initial order book transmitted to the company. It is considered as the 'Benchmark'. The graphs of Figure 5 display the four KPI (WIP, the lead-time, the production throughput, and the defect rate) of the neutral scenario during a simulation over a duration of one year. It can be qualified as a 'silent' scenario as there are no disruptions and no inductions performed.

In the ANOVA test (Table 4), for the *production throughput*, the difference between the results (μ. Throughput) using different LT is not statistically significant ($p > 0.05$). There is a significant difference between the WIP means, Leadtimes and Defect rate. With $p < 0.05$ for each of the three KPIs mentioned, a closer look is necessary in statistics using the Tukey–Kramer post hoc analysis (Greenhalgh 1997).

In Figure 6, multiple comparisons of all models of the neutral scenario are shown for the WIP, lead-time, and defect rate KPIs.

For the *WIP* dependent variable, the mean of the 5S model $(\mu.\text{WIP})_{5S}$ is significantly different from that of all other models, with $p \leq 0.003$. For the *lead-time* dependent variable, the mean of *5S, Poka Yoke, and SMED* models are significantly different from those of all remaining models and to each other ($p \leq 0.0001$). $(\mu.\text{Leadtime})_{\text{Actual}}$ does not have a significant p-value ≤ 0.05

p-value > 0.05

Same Model

WIP

	5S model	Actual model	Cross training	Poka Yoke	Pull	SMED	Ucell
5S model		0.000	0.000	0.003	0.000	0.000	0.000
Actual model	0.000		1.000	0.000	0.934	0.000	1.000
Cross training	0.000	1.000		0.000	0.934	0.000	1.000
Poka Yoke	0.003	0.000	0.000		0.000	0.334	0.000
Pull	0.000	0.934	0.934	0.000		0.000	0.786
SMED	0.000	0.000	0.000	0.334	0.000		0.000
Ucell	0.000	1.000	1.000	0.000	0.786	0.000	

Lead-time

	5S model	Actual model	Cross training	Poka Yoke	Pull	SMED	Ucell
5S model		0.000	0.000	0.000	0.000	0.000	0.135
Actual model	0.000		1.000	0.000	1.000	0.000	0.000
Cross training	0.000	1.000		0.000	1.000	0.000	0.000
Poka Yoke	0.000	0.000	0.000		0.000	0.000	0.000
Pull	0.000	1.000	1.000	0.000		0.000	0.000
SMED	0.000	0.000	0.000	0.000	0.000		0.000
Ucell	0.135	0.000	0.000	0.000	0.000	0.000	

Defect rate

	5S model	Actual model	Cross training	Poka Yoke	Pull	SMED	Ucell
5S model		0.000	0.000	0.000	0.000	0.000	0.000
Actual model	0.000		1.000	0.000	0.835	1.000	1.000
Cross training	0.000	1.000		0.000	0.835	1.000	1.000
Poka Yoke	0.000	0.000	0.000		0.000	0.000	0.000
Pull	0.000	0.835	0.835	0.000		0.771	0.838
SMED	0.000	1.000	1.000	0.000	0.771		1.000
Ucell	0.000	1.000	1.000	0.000	0.838	1.000	

Figure 6. Multiple comparisons (Tukey) for the neutral scenario.

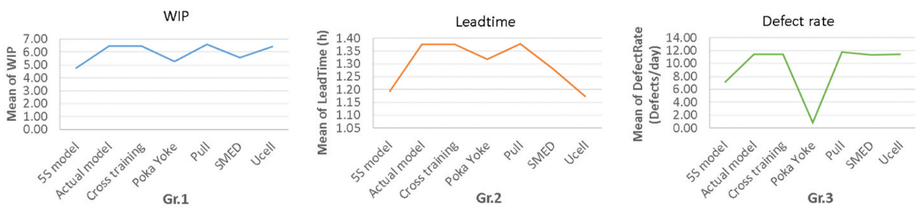


Figure 7. Group means (µ.WIP), (µ.Leadtime), and (µ.Defect) of the Neutral Simulation Scenario.

difference compared to $(\mu.\text{Leadtime})_{\text{CrossTraining}}$ and $(\mu.\text{Leadtime})_{\text{Pull},}$ with p < = 1. This means that the actual model (Lean free model) behaves the same as a model where cross training has been implemented or a pull system has been established. It is clear in the *defect rate*'s Tukey post hoc analysis that $(\mu.\text{Defect})_{\text{PokaYoke}}$ and $(\mu.\text{Defect})_{5S}$ have significant differences in comparison to other models ($p < 0.0001$). All other models do not have significant differences in mean to each other. They can be considered as similar generated results without any interesting potential improvements. The test of Tukey revealed a significant variation in results regarding three KPIs among the four KPIs chosen to lead the study.

Figure 7 highlights the variation of means to better perceive the relevance of some LT compared to others. In this scenario, cross training, pull, and Ucell models have almost the same WIP value (~6.5) as the actual model. SMED, Poka yoke, and 5S have smaller WIP values (~5.6, 5.2, and 4.8 respectively). As for the lead-time mean result, cross training, and pull had almost the same value (~1.37 h) as the actual model's lead-time mean. However, Poka Yoke, 5S and SMED decreased this value to ~1.32 h, 1.19 h and 1.17 h, respectively. The defect rate of the cross training, pull, SMED and Ucell models remained almost at the same level (~11% of daily defect rate) to the actual model's rate. 5S and Poka Yoke models decreased this rate to ~7% and 1%, respectively.

Finding.1 5S and Poka Yoke are linked to the 'quality' objective and 'WIP reduction'. They are required to improve production quality independently to the demand variation and internal equipment disturbances, so they are valid even in the Actual model. Moreover, whatever the demand is, both LT will reduce defects, thus reducing the cost associated with materials, rejects, rework and rescheduling. We highlight the necessity of considering both LT as *pre-requisites* regardless of the context.

Finding.2 As per the neutral scenario study, when no fluctuation arises, Ucell and 5S are found to be good tools to use. Both tools decrease the lead-time. The KPI targets the 'reactivity' sustaining the delivery. Indeed, Ucell helps to ensure sequence in production flow evolution by doing the operation (n + 1) as soon as (n) is ended. 5S enables a quick identification of the required tools, components in workstations ensuring accelerated processing time on workstation. Both tools are essential to accelerate production flow.

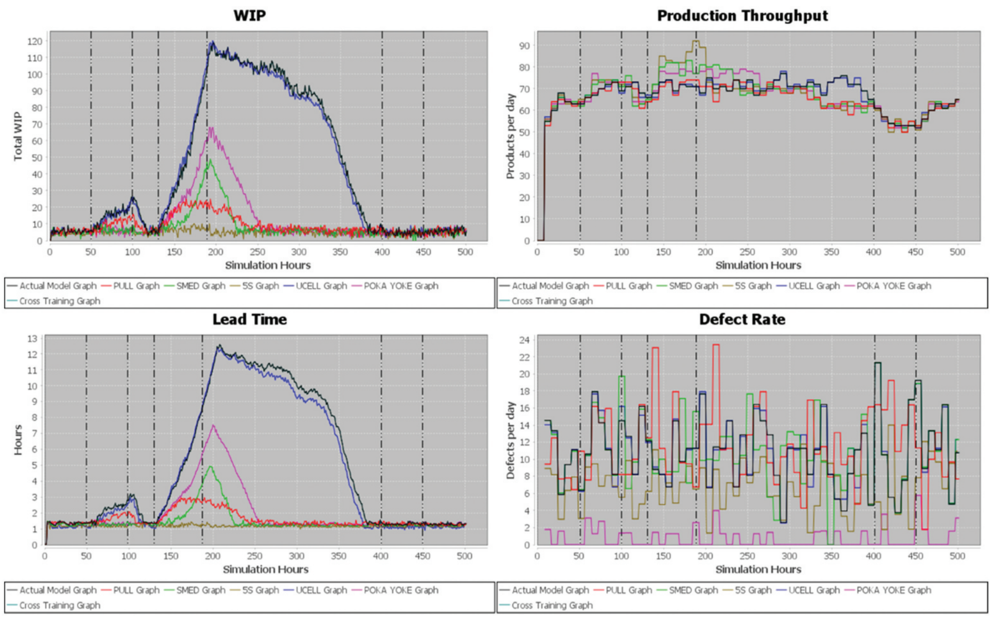


Figure 8. Simulation of the market fluctuation context.

5. Context variation scenarios

5.1. *Market demand fluctuation context Ctx.1*

In this section, the core hypothesis is checked: How may the context influence the choice of the relevant LT? In this context, industrial system behavior is tested whilst undergoing the rise or fall of the market demand ($\hat{D}_{XRF_{i(t)}}$). The demand fluctuation may be slight or huge depending on the market. The first fluctuation is a 15% increase to the market demand. At simulation time 100 h, we returned the market demand to its initial state. Second demand fluctuation is 30%. At time 190 h, we put back the market demand to its initial state. Third fluctuation is 15% demand decrease then back to its initial state at time 450 h. Figure 8 displays the KPIs' graphs of the Market fluctuation scenario undergone, with different LT possibilities.

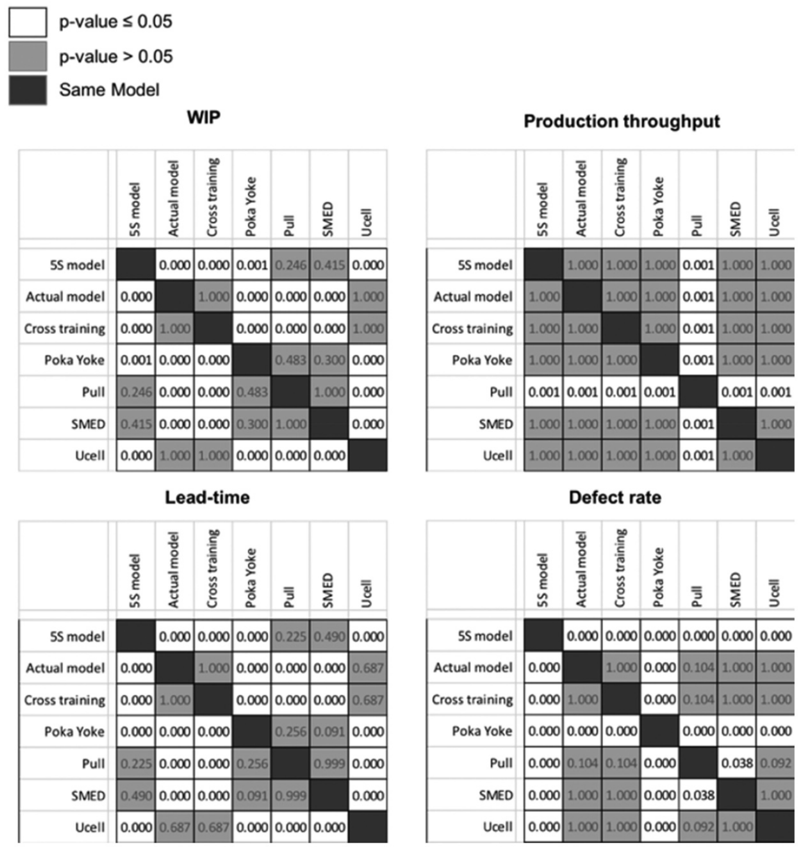
In the ANOVA test (Figure 9), all output results' means are significantly different. It means that the KPIs of the different applied LT have significant differences.

Figure 10 allows us to perceive at a glance the relevance of LT regarding the expected indicators. 5S has the smallest WIP mean (WIP = 5), SMED and pull have also interesting WIP means almost equal to 9, and Poka Yoke has a WIP mean that is almost equal to 13. Cross training and Ucell models have the same WIP mean of the actual model (~ 44). As for the lead-time mean results, cross-training and Ucell maintain almost the same value (~5 h) as the actual model's lead-time mean. However, Poka Yoke, pull, SMED, and 5S decreases this value to ~2 h, 1.6 h, 1.5 h, and 1.1 h, respectively. It is interesting to observe the same tendency for WIP and lead-times in the context of market fluctuation. The production throughput was only affected by the pull model that decreases the throughput (from ~67.5 to ~65.5). 5S and Poka Yoke models decreased the defect rate by 36% and 90%, respectively.

Finding.ctx.1.1 5S and Poka Yoke are more suitable. They can be considered as relevant LT when the decider is inducing a market increase. Regarding the previous finding about 5S and Poka Yoke, these LT seem to be context free and are suitable in any case, including as here during an increase of market fluctuation.

Finding.ctx.1.2 PULL and SMED are interesting to reduce WIP and lead-times when the industrial system is undergoing market fluctuation.

Finding.ctx.1.3 Ucell and Cross training were found to be without significant improvements on WIP nor lead-times when the company is confronted by market fluctuations.



WIP

	5S model	Actual model	Cross training	Poka Yoke	Pull	SMED	Ucell
5S model		0.000	0.000	0.001	0.246	0.415	0.000
Actual model	0.000		1.000	0.000	0.000	0.000	1.000
Cross training	0.000	1.000		0.000	0.000	0.000	1.000
Poka Yoke	0.001	0.000	0.000		0.483	0.300	0.000
Pull	0.246	0.000	0.000	0.483		1.000	0.000
SMED	0.415	0.000	0.000	0.300	1.000		0.000
Ucell	0.000	1.000	1.000	0.000	0.000	0.000	

Production throughput

	5S model	Actual model	Cross training	Poka Yoke	Pull	SMED	Ucell
5S model		1.000	1.000	1.000	0.001	1.000	1.000
Actual model	1.000		1.000	1.000	0.001	1.000	1.000
Cross training	1.000	1.000		1.000	0.001	1.000	1.000
Poka Yoke	1.000	1.000	1.000		0.001	1.000	1.000
Pull	0.001	0.001	0.001	0.001		0.001	0.001
SMED	1.000	1.000	1.000	1.000	0.001		1.000
Ucell	1.000	1.000	1.000	1.000	0.001	1.000	

Lead-time

	5S model	Actual model	Cross training	Poka Yoke	Pull	SMED	Ucell
5S model		0.000	0.000	0.000	0.225	0.490	0.000
Actual model	0.000		1.000	0.000	0.000	0.000	0.687
Cross training	0.000	1.000		0.000	0.000	0.000	0.687
Poka Yoke	0.000	0.000	0.000		0.256	0.091	0.000
Pull	0.225	0.000	0.000	0.256		0.999	0.000
SMED	0.490	0.000	0.000	0.091	0.999		0.000
Ucell	0.000	0.687	0.687	0.000	0.000	0.000	

Defect rate

	5S model	Actual model	Cross training	Poka Yoke	Pull	SMED	Ucell
5S model		0.000	0.000	0.000	0.000	0.000	0.000
Actual model	0.000		1.000	0.000	0.104	1.000	1.000
Cross training	0.000	1.000		0.000	0.104	1.000	1.000
Poka Yoke	0.000	0.000	0.000		0.000	0.000	0.000
Pull	0.000	0.104	0.104	0.000		0.038	0.092
SMED	0.000	1.000	1.000	0.000	0.038		1.000
Ucell	0.000	1.000	1.000	0.000	0.092	1.000	

Figure 9. Multiple comparisons (Tukey) for the market fluctuation scenario.

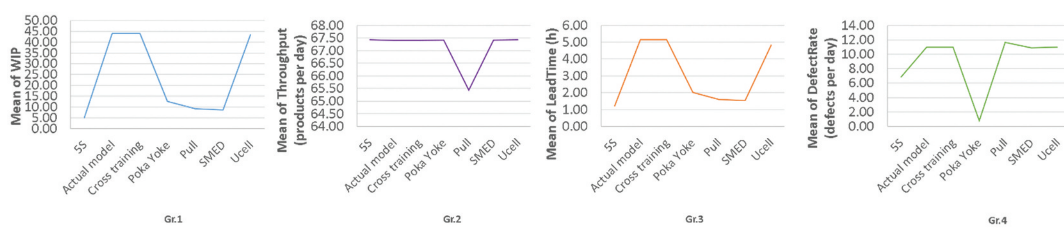


Figure 10. KPIs behavior according to the market fluctuation scenario.

Finding.ctx.1.4 Pull has been found to not influence the improvement of manufacturing throughput. Increasing the market demand and using Pull will not help the clients' demands.

5.2. Demand diversification context Ctx.2

The simulation process is fed with real-time input and updated data regarding the product portfolio that will increase or decrease over the horizon of simulation. Each black dashed line in Figure 11 represents a specific scenario of product portfolio diversification. The company with two types of products (references) was simulated first. After 50 h of production, the first change is induced where four product references are required. The overall demand quantity remained the same. At t = 150 h, we returned the number of products to its initial state (02). At 300 h, we tested the variety increase to eight references. At time 450 h, we put back the number of references to two then switched to 16 at time 650 h, and finally reset back to two at time 800 h.

The group means are represented in Figure 12. The lead-time mean results showed that Cross training and Ucell had almost the same value (~14 h) as the actual model's lead-time mean.

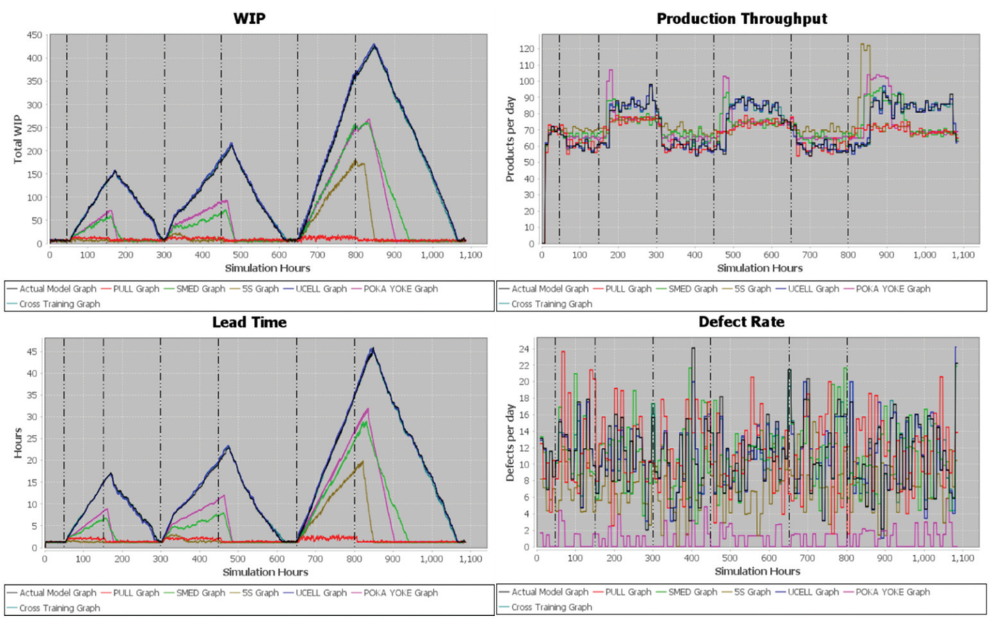


Figure 11. Simulation of the demand diversification context.

However, Poka Yoke and SMED reduced it to ~6 h. 5S decreased the lead-time to ~3 h, and pull model reduced it to 1.9 h. The production throughput was only affected by the pull model that decreased the throughput (from ~72.4 to ~67.5 products per day). The defect rate of the cross training, pull, SMED, and Ucell models remained almost at the same level (11% of daily defect rate) as the actual model's rate. 5S and Poka Yoke models decreased this rate to 7% and 1%, respectively.

Finding.ctx2.1 When there is a minor variety of products, SMED results in additional implementation costs without bringing interesting improvements to the operational process.

Finding.ctx2.2 When there is a high demand for diversification, 5S would help to decrease the WIP and lead-time KPIs. However, 5S alone would not be able to control the WIP and remove the high over-capacity from the production line. At this level, introducing a pull technique would be more efficient in terms of WIP and lead-time KPIs. Using Pull and 5S together in order to have a higher throughput and better WIP and lead-time would be better.

Finding.ctx2.3 Combining different tools would produce powerful improvements. 5S, SMED, Poka Yoke, and pull together would help the company to tackle the cost, quality, and flexibility targets by controlling its WIP, decreasing its lead-time, increasing the production throughput, and decreasing the defect rate.

5.3. Uncertainty of resources ctx.3

The third and final change to which the company may be confronted is the context of non-reliability of its resources. Uncertainty of resources can be related to operator absence or machine disruption. Three disruptions are simulated and occurred during this scenario: at *t = 25 h*, one operator from the treatment shop was absent for one day; at *t = 75 h*, the first machine of the assembly shop stopped for two hours due to a maintenance issue; and at *t = 100 h*, the first machine of the machining shop had an unexpected machine error for a - whole day of production (8 hours). Figure 13 shows the four KPIs results.

We can see below the elements that correspond to operator or machine disturbance. If a disturbance exists, the value assigned is 1. Otherwise, the value is 0.

(1) $\lambda_{vt}; \lambda_{vt} \in \{0,1\}$: *Operator* H_v *disturbance event (error or absence)*

(2) $\theta_{pt}; \theta_{pt} \in \{0,1\}$: *Machine* M_p *disturbance event (failure, unavailability, or defect)*

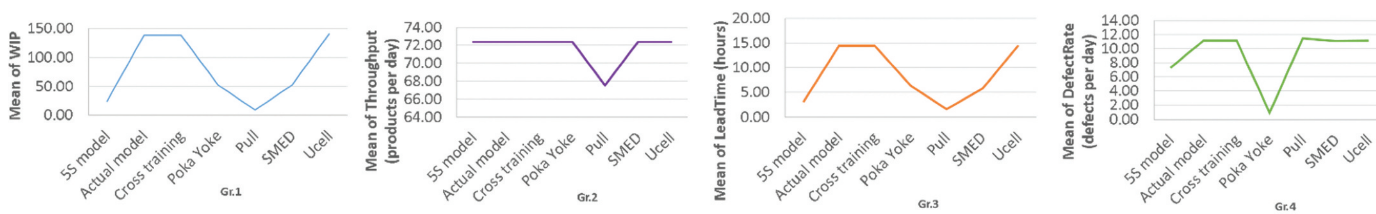


Figure 12. Group means of the demand diversification scenario.

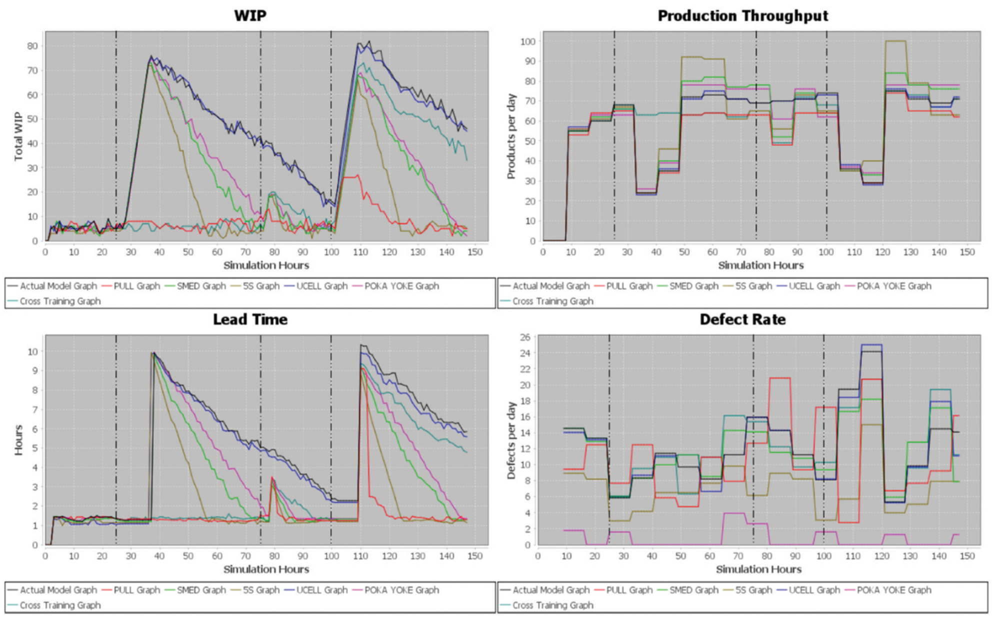


Figure 13. Simulation of the uncertainty of resources context.

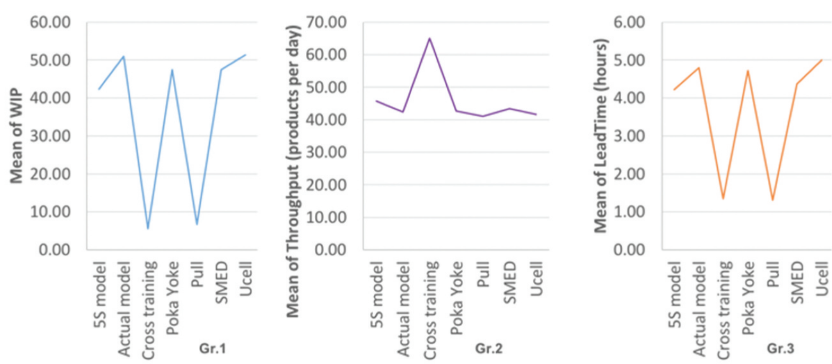


Figure 14. Group of means during employee disturbance.

The different stages of disturbance are described below.

For t = 0, $i = 1\ldots4,\lambda_{vt} = \theta_{pt} = 0$

No interesting improvements to comment. This period is very similar to the first scenario studied where no context or disruptions exist.

For t = 25 h, $i = 1\ldots4,\lambda_{vt} = 1, \theta_{pt} = 0$

In this scenario, the cross-training model significantly changed its behavior compared to the other models. In this simulation period, λ_{vt} is equal to 1, the employee of the treatment shop was absent for eight working hours. Cross training was the only tool to make its production throughput almost stable and its WIP and lead-time values stable (Figure 14). All other tools except the pull technique had a high uptrend in their WIPs and lead-times. Pull does not lead to this increase because it does not accept the overcapacity in its production process. After the 8 hours of employee disturbance, 5S appeared as the tool leading to the fastest return to a stable state.

For t = 75 h, $i = 1\ldots4,\lambda_{vt} = 0, \theta_{pt} = 1$

At t = 75 h, an unplanned machine disturbance occurred. The first machine of the assembly line stopped unexpectedly. It took 2 h to fix this disturbance and return to the production process. In this type of disturbance, production stopped for 2 hours. Pull then 5S were shown to be the most reliable tools to return to a stable production state.

For t = 100 h, $i = 1\ldots4,\lambda_{vt} = 0, \theta_{pt} = 1$

We repeat the machine disturbance at t = 100 h. This time, the disturbance lasted 8 h. During this disturbance, production stops. It is true that Pull does not allow the WIP overcapacity and that its maximum WIP allowed is ~25 products in the

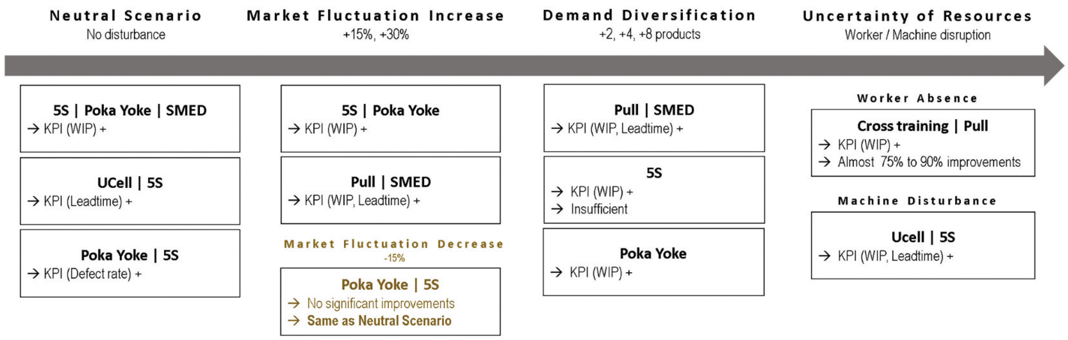


Figure 15. Lean Tools influence regarding the different contexts applied.

production process. However, 5S almost gets 65 products in its WIP and returns faster to its initial stable state of production.

Finding.ctx.3.1 When there is an employee disturbance, cross training is a crucial tool to use. When an unexpected operator unavailability occurs, other operators can cover if they are familiar with the equipment. This keeps the manufacturing process going strong and helps to cover operator shortages due to sick days, annual leaves, and so on.

Finding.ctx.3.2 When a machine disturbance occurs, the production process stops during the disturbance time. Thus, a fast and reliable tool should be applied to overcome this issue. 5S as shown to be the fastest tool to stabilize the production process after a machine disruption.

6. Discussion

A summary of simulation results by LT and KPI is given for each of the studied contexts (Figure 15).

Starting with the neutral scenario where no context or disruption occurs, all LT results are covered, and SMED and 5S show the lowest WIP values. In the neutral scenario, four product references exist, by reducing machine setup time, SMED will definitely decrease the WIP due to its ability to more quickly introduce the products into the production process. As for 5S, by reducing the defect rate and improving the processing time of machines, 5S contributed to decreasing the WIP value. When the market demand decreases by 15%, all tools' results are similar, and no interesting outcomes can be determined. The explanation for this is that decrease of the market relaxes the constraints on the system and all implemented Lean tools behave neutrally as low demand does not create a rush, and no reaction through LT seems necessary. When increasing the demand by 15%, Poka Yoke, SMED, and 5S were the most effective. However, after 30% of demand increase, Poka Yoke and SMED were not able to handle the increase. Overcapacity in their WIPs is noticed. With such an increase, 5S and Pull are more suitable. As for the demand diversification context, with 4 to 8 product references, SMED, Poke Yoke, 5S are good performers. When the variety of products becomes high (e.g. 16 references), those tools are not able to control the WIP's overcapacity, and pull production is the only solution to keep the WIP at a low level. For the context of uncertainty of resources, cross training and pull are the only tools capable of reducing the WIP if an operator disruption occurs. However, when a machine disturbance occurs, 5S was shown to be the most reliable tool.

As for the lead-time results, when the variety of products is low and no contexts are taken into consideration, Ucell and 5S are the best in terms of lead-time. For a 15% market increase, SMED, Poka Yoke, and 5S are the best. In the demand diversification context (less than 8 references), Pull and 5S, SMED are classified as more suitable. However, when increasing the number of references to 16, 5S is not able to control the WIP overcapacity which can lead to an increase in the lead-time. In the uncertainty of resources context, cross training and Pull were shown to be the most suitable techniques to use when there is an operator disruption. For machine disruption, the test considers the tool's reliability to return to the stable initial state following the disruption. 5S was shown to be the most relevant tool, it has the highest downward slope in lead-time. Poka Yoke and 5S are the most relevant tools, whatever the context, to significantly decrease the daily defect rate. Both tools behave efficiently, and are required as pre-requisites to improve the quality of production independently to the industrial context.

7. Limitations

Some limitations must be noted. To perform this study, a choice was made to test the most common and technically configurable LT. Then, LT related to human aspect (Culture, Kaizen, involvement, top management, leadership, etc.) are assumed to be acquired. They are considered as pre-requisites in this study: without human aspects, the results of the simulations are obviously not valid. The product simulated in this research is validated and no design or development of new products is considered. The results obtained through this study remain contextual to the configuration of the platform simulation. The authors don't claim to generalize the findings of relevancy of those LT of this study. Nevertheless, the simulation system of the case study allows the perception of the obvious sensitivity of some LT to some contexts and not to others. The quantitative analysis is among the first steps to confirm the hypothesis that Lean implementation cannot be deployed whilst disregarding the industrial contexts. The idea is to demonstrate that LT impact is context-sensitive (company's objectives, situations). The statistical analysis increased the reliability of the evaluation of the LT impact on KPI. Careful statistical analysis combined with the analysis led to an increase in the reliability of the research results.

8. Conclusion

This research study contributes to the comparison of different LT impacts in various contexts based on simulation. Many manufacturing companies use Lean tools inefficiently, considering that Lean brings benefits despite the nature of implemented tools. Most of these companies are experiencing failures. An increasing number of authors subscribe to the idea of considering the industrial context, the sector, and the environment in order to choose the right Lean tools or techniques that should be implemented. The aim of this study is to consolidate this notion through simulation results showing different LT behaviors according to the industrial contexts that the company confronts. HLA standard is used to develop a co-simulation framework to enable time synchronization, data exchange, and interoperability between heterogeneous components. A case study was chosen to represent the environment within which the combination among LT, contexts, and KPI is possible in a dynamic setting. Different contexts were studied to identify LT impacts regarding the context in which the company was evolving. *Market fluctuation, demand diversification, and uncertainty of resources* were modelled and implemented in the co-simulation framework. This enabled the experimentation of multiple scenarios, and the introduction of modifications and disruptions in many variables from design to commercialization. Future works will expand the built co-simulation framework to gradually integrate other LT and create a configurable decision aided tool to help practitioners to test LT relevance. So far, the framework has supported up to eight machines or workstations in the simulation models, an increase of this number can be possible to depict the impact of higher disruption simulations. A new module to experiment the company's typology of production is under development. The typology of production is an interesting context where the company has to change the organization according to whether a Make To Stock (MTS) or Make To Order (MTO) strategy is adopted.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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