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ACHIEVING SUSTAINABLE MANUFACTURING BY EMBEDDING SUSTAINABILITY KPIS IN DIGITAL TWINS

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ABSTRACT

The manufacturing industry requires highly flexible and dynamic production lines that shift from conventional mass production to cover the requirements and fulfill demands. Customized production may reduce production waste but has not been studied to a wide extent. The advancement of digital technologies, e.g., Digital Twins, enable factories to collect real-time data. Also, they can enable remote monitoring of the production processes by establishing bi-directional flows of data between the physical and virtual spaces. This study draws its sight to the potential of digital manufacturing to improve sustainability in production systems by making use of Digital Twins. This research work performs a literature review and identifies suitable KPIs for a DES model and evaluates the impact in a drone factory in four scenarios that test final assembly processes. The findings of this work can pose a first step toward the future development of a digital twin.

1 INTRODUCTION

The rapid technological development of the last years has revolutionized manufacturing, demanding smarter ways of implementing the newly available digital technologies to enable the successful digitalization of manufacturing processes. Digital technologies should support the improvement of production processes and work towards increased competitiveness by optimizing productivity and quality. At the same time, the use of digital technologies has been identified as potential support for the reduction of the overall consumption of energy and raw materials, addressing the growing need for more sustainable manufacturing (Tao et al. 2019).

The new manufacturing paradigm is shifting toward establishing sustainability as a priority in production by leveraging the use of digitalization technologies, leading researchers and practitioners to explore technologies such as the Digital Twin (Lee et al. 2014). Currently, many firms are still on their way to increasing their digital maturity, to enable not only the use of Discrete Event Simulation (DES), but eventually increasing their capabilities to achieve the transparency and visibility of models, data, and information that can better match the description of a digital twin. DES models represent a step forward in technological maturity, that can potentially lead to digital twins. Further, the integration of DES models with Key Performance Indicators (KPIs) that relate to the Triple Bottom Line (TBL) of sustainability, provides tools to achieve better decision-making support when working towards sustainable manufacturing.

This paper takes a case study approach based on the project TWINGOALS, to integrate sustainability indicators in a simulation model of a drone assembly cell at the Stena Industry Innovation Lab (SII-Lab), based at Chalmers University of Technology in Gothenburg, Sweden. This study aims to answer the two following research questions (RQ):

RQ1) Which are the most suitable KPIs to assess the sustainability of production systems through a DES /Digital Twin model?

RQ2) How can DES be used to improve the sustainability of production systems?

The posed research questions require an exploration of both literature and state-of-practice. The method followed to address the posed research questions is presented in Section 2. Further, the theoretical background for this study is presented in section 3. Section 4 describes the analyzed case along with the experimentation conducted. Last, Section 5 discusses and adds concluding remarks from the results of this study.

2 THEORETICAL BACKGROUND

2.1 Definition of Digital Twin

One of the first to coin and explain the term "digital twin" was Dr. Grieves (Grieves and Vickers 2016) who described it as a "digital informational construct of a physical system as an entity on its own". The digital construct corresponds to the digital twin and represents all the embedded information that a physical system contains by being connected to it. Digital twins do not represent the system at a precise instance, or glance, instead they showcase the system's entire life over extended periods of time. As Figure 2 depicts, a digital twin consists of two spaces; physical and virtual. The two spaces are interconnected and enable data flows from the assets and processes in the physical space to the virtual space to create a virtual representation that is updated in real-time, or at the frequency required. A digital twin has a bi-directional flow of data, where data processed in the virtual space will also retrieve feedback to the physical space. In this flow, a decision-maker can also be involved in the process and make use of the information provided by the system to take action.

Figure 1: The Digital Twin concept with a real and virtual space with bi-directional flow connecting them (Grieves and Vickers 2016).

The definitions of the physical entity and space depend on the case; it could be a product, process, or an entire system. What digital twins have in common is that they should be able to represent the physical entity with its embedded information, either of a current system or a potential of it, such as a product in a design phase, to address manufacturing challenges. A digital twin should therefore be purpose-driven, virtual, complete, or as complete as needed for the case it represents (Grieves and Vickers 2016). One common purpose is to optimize performance metrics, which requires the availability of real-world data that represents the behavior of current activities and status and can predict future scenarios of the physical setting (Shao and Helu 2020). Some important capabilities for a digital twin are connectivity, visibility, granularity, and analyzability. Connectivity implies the level of data exchange that exists between the real and virtual space. Visibility is how easily the results of a digital twin can be interpreted and understood by a human receiver. Granularity is a digital twin's level of detail. Analyzability is lastly a digital twin's ability to support decision-making in the real space (Shao et al. 2019).

Simulation models of production systems are widely used today to visualize different scenarios, make predictions, and optimize performance metrics, among other purposes. Somewhat similar to a digital twin, a simulation model also creates a virtual representation of either an already existing production system or a planned system in a design phase, but it adds the ability to perform real-time model execution and real-time two-way communication between a real and virtual space. Also, it is context-dependent, meaning that the model results and how they should be used in a real manufacturing setting can be considered unique (Gong et al. 2019), particularly in an era where sustainability is considered a priority for many industrial sectors.

2.2 Sustainability and the Triple Bottom Line (TBL)

The United Nations World Commission on environment and development introduced the concept of sustainable development in 1987 (WCED 1987). Sustainable production is often defined as ”creating goods by using processes and systems that are non-polluting, that conserve energy and natural resources in economically viable, safe and healthy ways for employees, communities, and consumers and which are socially and creatively rewarding for all stakeholders for the short- and long-term future” (Glavic and Lukman, 2007).

Sustainable manufacturing aims to consume resources effectively and efficiently by minimizing emissions and waste (Brancini and Margherita 2018). The TBL (Fig 3) supports the concept of sustainability in industries by clarifying three dimensions: economic, environmental, and social (Almström et al. 2017).

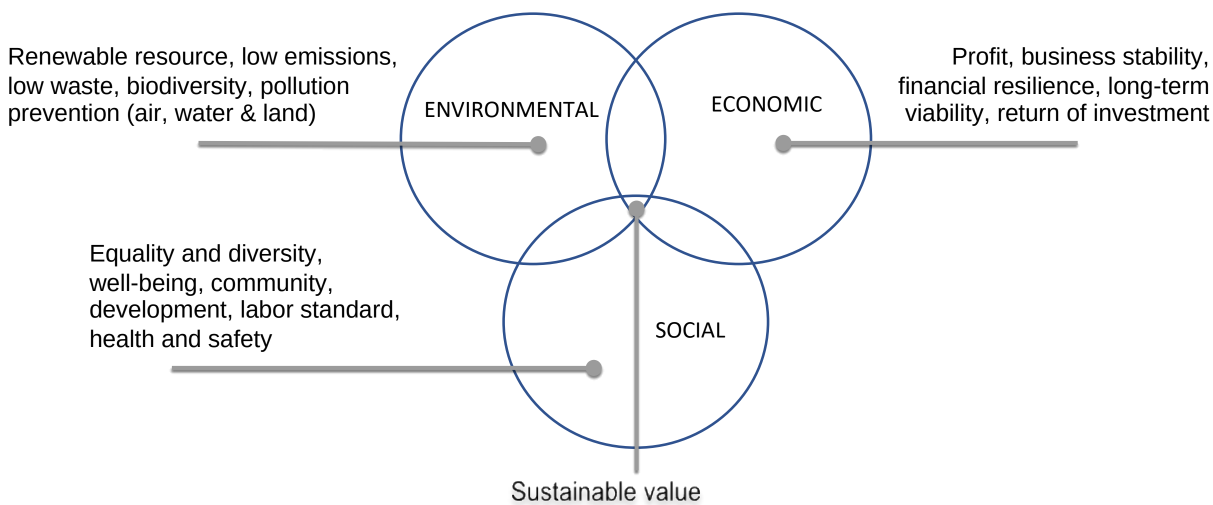

Figure 2: TBL of sustainability (Adapted from Alström et al. 2017).

2.2.1 KPIs for Assessing Sustainability

The requirements of measurement systems in production have drastically changed in the last decades, triggering a performance measurement revolution. Practitioners, consultancy firms, and academic communities have questioned and challenged how companies can improve their existing, traditionally cost-based, measurement systems with ones that reflect their current objectives and environment (Kennerley and Neely 2002).

Performance indicators play a large role in the evaluation of the efficiency and effectiveness of manufacturing systems and the way they relate to their objectives in terms of performance (e.g., cost, sustainability, energy efficiency). A selection of the most relevant indicators leads to KPIs, which help industries grow by basing their decisions on performance while prioritizing the achievement of their objectives efficiently and effectively through continuous evaluation, monitoring, and optimizing the production processes by addressing the identified improvement potentials (May et al. 2015; Ramis Ferrer et al. 2018).

Based on the ISO-standard "ISO 22400 Part 1 and 2:2014 Automation systems and integration — Key performance indicators (KPIs) for manufacturing operations management", Almström et al. (2017) were able to propose a framework where KPIs can be structured in a hierarchy, that consists of elemental KPIs at the lowest level, basic KPIs in the mid-level, and comprehensive KPIs at the higher level, where:

- *elemental KPIs*: measures obtained from specific data points
- *basic KPIs*: contain elemental KPI values or measures, useful for predicting trends
- *comprehensive KPIs*: formed by several basic KPIs.

Industrial actors tend to combine all three levels of KPIs for decision-making or benchmarking. The successful measuring of KPIs requires appropriate measuring equipment along with databases for storage of the production data, also service tools that support transforming data into information, and finally, systematic decision-making systems.

3 METHOD

The method chapter will explain the context in which the authors performed the study, the performed literature review to identify relevant sustainability KPIs to consider for the simulation and analysis, and how the model of the Drone factory was created.

3.1 The Research Project TWINGOALS

TWINGOALS was a European Institute of Innovation and Technology (EIT) funded project, that aimed to bring a new solution to the virtual representation models for manufacturing assets with the focus on commissioning manufacturing solutions easier, faster, and with higher productivity and quality (EIT Manufacturing, n.d.). The work presented in this paper was performed as a Master's Thesis project in the spring of 2022 in collaboration with the research project (Annepavar and Gopalakrishnan 2021).

3.2 Literature Review Method

This study carried out a literature review to identify previous research on sustainability KPIs in the DES and Digital Twin context, the previously proposed methods or frameworks, and their results. The goal was to use the literature results for integrating and building the DES model. Hence, the focus was to explore the most recurring or preferable sustainability KPIs that assist manufacturing industries to transform into more sustainable or eco-efficient manufacturing, by selecting the most suitable KPIS. The search process is described in Figure 1. The screening of papers was carried out in two steps; (1) reviewing the title and abstract and (2) reviewing the whole text. Those papers selected for review of the full text were used to extract the most recurrent sustainability KPIs for incorporating in the DES. The environmental and economic KPIs were selected from the literature results for integrating the KPIs with the DES model.

3.3 Simulation of a Drone Factory

This study developed a simulation model that represents the SII-Lab environment, which is a testbed for smart manufacturing utilized for both research activities, education, and industrial test purposes. The testbed includes a drone cell production system that allows experimenting on final assembly activities.

The Banks methodology was followed to create a simulation model. This methodology consists of three main phases; preparation, model building, and analysis phase. The first phase, preparation, involves identifying and defining the problem that is going to be addressed with the simulation, also to create a project plan, collecting necessary data for the representation of the real system, and developing the conceptual model (Sokolowski and Banks 2010).The second phase, model building, is when the conceptual model is translated to a model to be used for simulation, through the use of sketches that are further developed into a more robust model, also the model is verified but also validated by stakeholders of the project. The third phase, analysis, is when the results of the simulation model can be analyzed and scenarios identified of interest for the problem formulation be evaluated. In the following paragraphs, we will explain how each of the phases was executed. The results and analysis of the simulation model will be presented in the results section, 4.2.

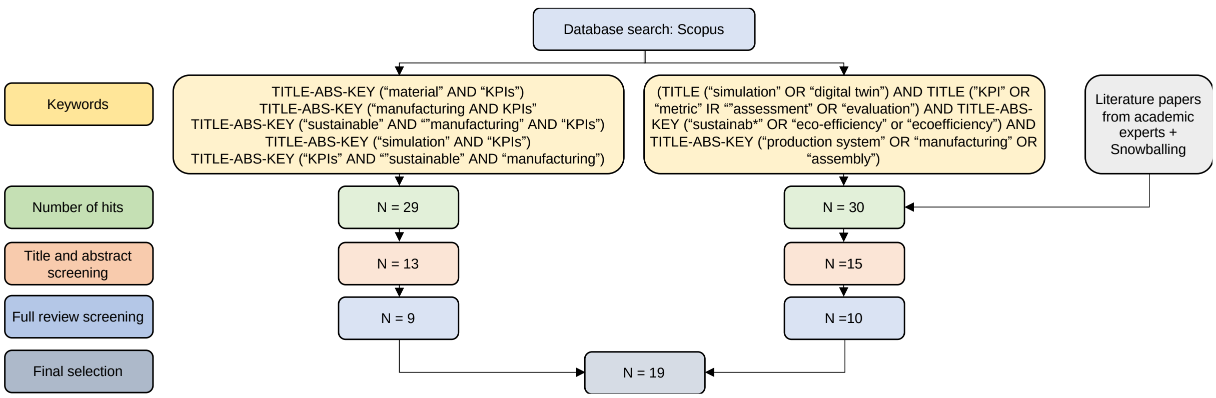

Figure 3: Literature review process (Annepavar and Gopalakrishnan 2021).

The two research questions presented in Section 1 are addressed in the preparation phase. The main focus of the problem formulation is to investigate how the most important sustainability KPIs can be integrated into a Digital Twin to demonstrate the sustainability impact a production system has. Then, to evaluate the sustainability impact of different cases and parameters, four individual scenarios were defined and conceptualized; an AS-IS scenario, a Base scenario, and Experimental 1 and 2 scenarios. A process flow accompanies each use case to conceptualize the production and material flow. We list the relevant data categories and parameters we intend to use in the case studies in Table 1.

The model building phase comes after the preparations phase. The DES model of the Drone factory was developed in software for plant simulation (hereafter referred to as Plant Simulation). The selection for this software was made because there was already a conceptual model developed in this software for the Drone factory. The digital twin representation of the Drone factory represents an assembly line that produces drones in the testbed environment SII-Lab. For further details on the model building and translation as well as how the model was verified and validated, the reader is referred to (Annepavar and Gopalakrishnan 2021).

The last phase of the simulation project is the analysis phase. The authors ran experiments on the four scenarios, modeled in the Plant Simulation, with KPIs identified in the literature review. Some of the production parameters were common for all four scenarios, but parameters that were varied included customer demand, product variants, and the number of pallets. These three parameters were varied because it was of interest to evaluate if the throughput could be increased simultaneously as the KPIs for the environmental impact could be kept at a minimum. Each scenario ran for a total time duration of six days and ten replications were performed, this process was followed to obtain stable and reliable value out of the results. The results of each simulation were exported to an excel file for further analysis. Further details of the results will be given in *4.2*.

4 RESULTS

The results are divided into the two main areas that this paper focuses on; the *Literature review* (4.1) which identifies the most important KPIs to measure the sustainability impact and the *Digital Twin* (4.2) which provides the results showing how the sustainability KPIs can be implemented and evaluated in the digital twin.

Table 1: Data categories and parameters of interest for the study.

Data category	Associated Data Parameters
Production parameters	Processing, availability, mean time to repair, setup, and scrap processing times
Work procedure	Work procedure of product variants
Material data	Material type, quantity of respective components, weight, scrap, rework, and costs
Energy data	Power consumed and similar data parameters to estimate the total energy cost
Material consumption	Material consumption

4.1 Literature Review

The literature review provides economic, environmental, and social indicators that are commonly used by industries to address the TBL of sustainability for manufacturing processes. Naderi et al. (2017) argue that it is necessary to identify the right set of manufacturing indicators to support the organizational decision-making process to achieve the company's objectives and goals. Then Kibira and Feng (2017) highlight the relevance of considering the type and scale of the industry. Also, a few appropriate and valid KPIs are preferred over numerous indicators of sustainability.

In their work, Fantini et al. (2015) suggest a holistic framework for selecting the KPIs by modeling the physical flows of a manufacturing system (i.e., products, materials, energy, and emissions, among others from the input to the output phases). Although literature proposes different methods and frameworks for KPI selection, most authors suggested that eco-efficiency indicators alone may not be sufficient for measuring sustainability performance. This is attributed to trade-offs between indicators caused by complexities and inter-dependencies among products, materials, and resource flows (Sproedt et al. 2015; Zhou et al. 2011). Similarly, in their work, Weeber et al. (2018) exemplify how energy efficiency measures that assess energy consumption levels can either increase productivity and hence emission levels, or reverse, reduce emission levels while also reducing productivity. Therefore there is a need to identify an ideal or neutral state to maintain a balance between economic, environmental, and social sustainability (Naderi et al. 2017). This literature review summarizes the KPIs found related to economic and environmental sustainability.Tthe list of social sustainability KPIs (Annepavar and Gopalakrishnan 2021), is excluded from this research work, as they were not measurable in the current process as the context of this study is in an experimental and educational environment without humans involved in the production.

Table 2 shows the results, where the complex interrelations between the identified economic and environmental indicators create an atmosphere of ambiguity for decision-makers, limiting the strategic use of the indicators with little indication of prioritization between them when aiming for improvements at production shop floor level (Sproedt et al. 2015). In Table 2, the names of the indicators are abbreviated and some are presented in groups. For instance, in the economic KPIs, quality refers to rework ratio, scrap ratio, first-pass yield, storage and transportation loss ratio, product durability, and product reliability. Cost refers to inventory, energy, material, labor, equipment, and maintenance. Delivery groups: cycle time, lead time, and TAKT time. Flexibility groups batch size, process flexibility, volume, and setup time.

To overcome difficulties with the decision-making process, current research proposes the use of DES methods in combination with integrated performance indicators to conduct virtual experimentation and analyze complex process flows to improve the sustainability of manufacturing (Lee et al. 2014; Sproedt et al. 2015).

Figure 4 shows the KPIs selected for the simulation. This selection process included selecting the most recurrent environmental and economic KPIs. Some other KPIs were discarded due to the lack of fit in the Drone factory used for the simulation model (i.e., hazardous waste).

Table 2: Resulting KPIs from Literature Review (adapted from Annepavar and Gopalakrishnan 2021).

	KPI/Ref	(Alström et al. 2017)	(Braccini and Margherita, 2018)	(Patil et al. 220)	(Naderi et al. 2017)	(Kibira et al. 2017)	(Lee et al. 2014)	(Riexinger et al. 2015)	(Fantini et al. 2015)	(Weeber et al. 2018)	(Sproedt et al. 2015)	(Assad et al. 2019)	(Amrina and Vilsi, 2015)	(Diaz-Elsayed et al. 2013)
Economic	Quality	x			x				x	x				
	Cost	x		x	x		x	x	x	x	x	x	x	
	Delivery	x			x				x			x	x	
	Flexibility	x			x				x	x				
	Productivity	x							x		x	x		
Environmental	Res. Utiliz.	x		x	x		x					x	x	x
	Emissions	x	x	x	x	x	x	x		x	x		x	x
	Renew. res.	x	x					x						
	Scrap/ waste	x	x	x	x		x				x			
	Land utiliz.						x						x	x
	Noise pollut.		x										x	
	Mat. effcy.					x			x					
	Energy effcy.					x			x					
	Quality									x				
	Share of reused/ recycled mat.	x												
	Eco-efficiency		x						x					

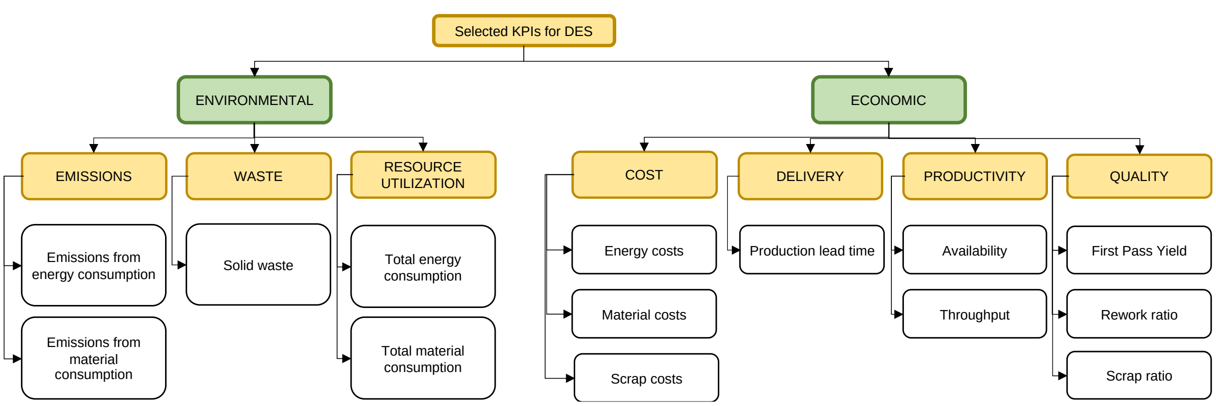

Figure 4: Selected KPIs to use in the simulation model (Annepavar and Gopalakrishnan 2021).

4.2 Digital Twin of a Drone Factory

The model used in this study was a pre-existing model of the Drone factory built in Plant Simulation. In Figure 5, the authors visualize the conceptual model and basis for the simulation model of the Drone factory. As introduced in Section 2, there are four scenarios of interest to test with simulations: the As-Is scenario, the Base scenario, and Experimental scenarios 1 and 2. Table 3 summarizes the scenarios. For more details, including process flows and data collection, we refer the reader to Annepavar and Gopalakrishnan (2021).

This section will present and explain the simulation results from the four scenarios. The parameters studied in each scenario are the number of pallets (No. Pallet), throughput, throughput per hour, and lead time. The considered KPIs include total production cost, first-pass yield, total material consumption, total energy emissions per part, and total material emissions evaluated. These were evaluated on the basis of this study, to integrate sustainability KPIs into the digital twin for enabling analysis of the sustainability analysis.

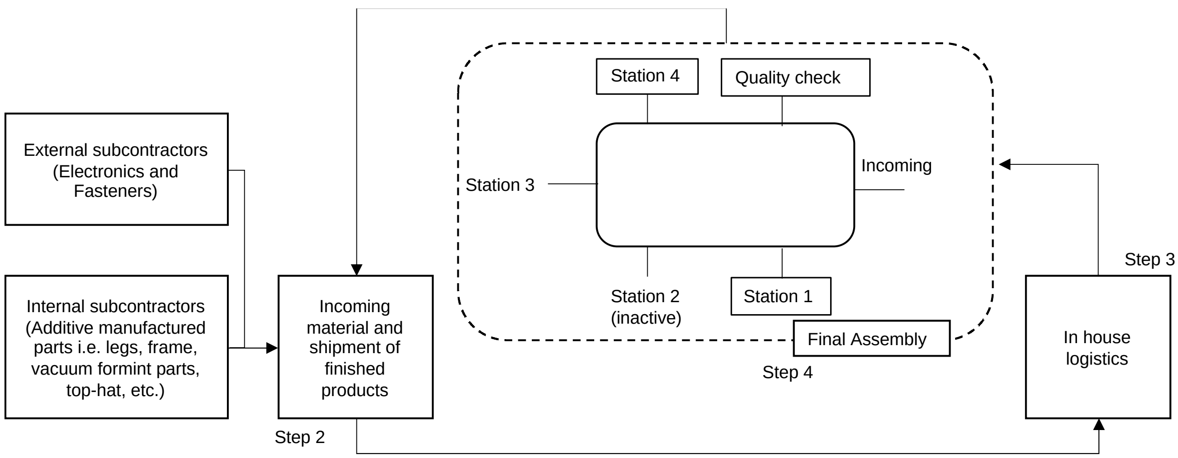

Figure 5: Overview of the Drone Factory in SII-Lab with the assembly station as well logistics (Annepavar and Gopalakrishnan 2021).

4.2.1 Scenario AS-IS

The AS-IS scenario is identical with the real setup in the Drone factory and it involves only one product variant. This scenario is therefore mainly included as a validation step of the simulation model. Part of the test in AS-IS was to vary the number of pallets as input to the system.

Based on the results in the KPI analysis in the AS-IS scenario it could be seen that total production costs increases with the increased number of pallets but throughput on the other hand is maintained approximately at the same level. The increase in total production cost is due to the fact that the overall lead-time and work in progress increases with increased number of pallets. Material and energy emissions are two other parameters that also increase with the increased number of pallets, which can be explained by the increased utilization of production resources.

4.2.2 Scenario Base

The Base scenario represents a planned future state of the Drone factory, where two product variants can be produced at the same time, in parallel. In the Base scenario, two parameters change during the testing: the number of pallets and the customer demand. The number of pallets ranged from 5-25 and it was observed from the test that an optimal number of pallets, in this case, is nine because using more pallets than that would not increase TPH, but only increase the Leadtime. Larger number of pallets impacts more on the utilization of resources resulting in more material and energy emissions. However, some trade-offs could be proposed when comparing productivity and emissions and their growth.

Table 3: Description of the fours scenarios AS-IS, Base, and Experiment 1 and 2.

Scenario	Description
AS-IS	Reflects the current work procedure used in the Drone factory and handles only one product variant, Var A, which includes three manual steps carried out at stations (stn) 1, 3, and 4 (As seen in Figure 5). It has a final quality check at the 'Quality check' station.
Base	Includes two product variants Var A and Var B where A is assembled at the manual station, Stn 1 and 3, and B at the automatic station, Stn 4. This scenario also include a 'Quality check' as the last step but it also include quality check prior to every assembly step.
1	Includes one additional station, Stn 2, which is a manual assembly station and used for the product flow of Var A. It is inserted as a parallel station to Stn 1 and 3. Similar as for base, quality checks are carried out before assembly stations and at the final stage of the flow.
2	Scenario 2 is similar to 1 with the difference that Stn 2 is inserted as a dynamically re-balanced station. It is still a manual assembly station but is able to handle both Var A and B and can therefore be used when more capacity is needed for either product variant.

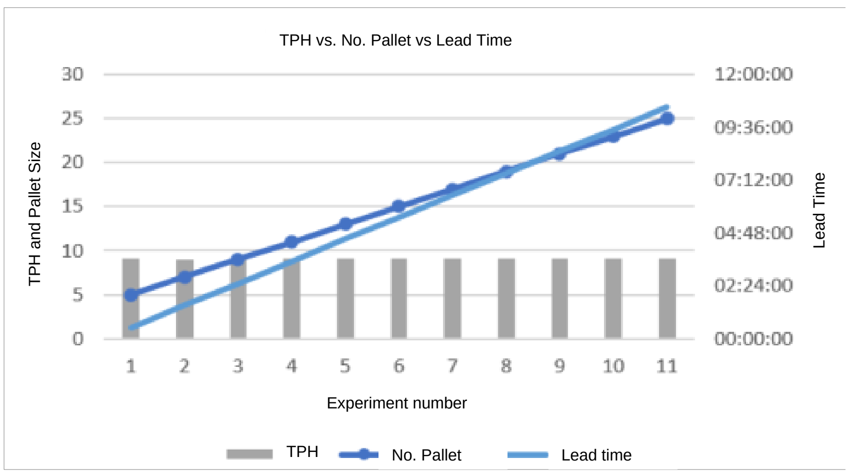

Figure 6: Throughput per hour vs No. Pallets vs Lead time (Annepavar and Gopalakrishnan 2021).

Customer demand was tested for three different cases; (1) Var A 50%, Var B 50%, (2) Var A 25%, Var B 75%, and (3) Var A 75%, Var B 25%. By varying customer demand for each product variant according to the three cases, the results show that the throughput-per-hour gained a better result for the demand ratios (1) and (2) compared to (3). This result is explained by the fact that Var A involves only manual assembly and also more components to handle in the assembly process.

The Base scenario still yields better results and performance regarding resource utilization. Stn 1 and Stn 3 have almost equal utilization when compared to the AS-IS scenario, whereas Stn 3 has the highest utilization rate and thereby created the main flow bottleneck. Even though the Base scenario provides better results compared to AS-IS, it still has an imbalance in terms of resource utilization. This affects the sustainability KPIs negatively by increasing the number of bottlenecks and the utilization rates of the resources as well as the throughput of the system. Therefore we study possible improvements in experiments 1 and 2.

Table 4: Results from the Base scenario (adapted from Annepavar and Gopalakrishnan 2021).

Data parameters					KPIs		
No. Pallet	Throughput Per Hour (TPH)	Leadtime (Hrs:Min:Sec)	Total Production Cost Per Part (SEK)	First Pass	Total Material Consumption Per Part (kg)	Total Energy Emissions Per Part ($kgCO_2eq$)	Total Material Emissions Per Part ($kgCO_2eq$)
5	15,10	0:18:32	0,80	95,92	0,41	$1{,}06*10^3$	5,06
9	17,10	0:29:57	0,79	95,96	0,41	$0{,}943*10^3$	5,06
13	17,14	0:41:53	0,79	95,96	0,41	$0{,}936*10^3$	5,06
17	17,05	0:54:05	0,79	95,98	0,41	$0{,}940*10^3$	5,05
21	17,22	1:06:22	0,79	95,94	0,41	$0{,}931*10^3$	5,06
25	17,16	1:20:02	0,79	95,99	0,41	$0{,}935*10^3$	5,05

4.2.3 Scenario Experiments 1 and 2

Scenario 1 proposes a parallel assembly station and re-balanced the production stages, whereas scenario two intents the parallel assembly station as a dynamically re-balanced station that could be activated when a station is highly utilized. We observe that both experiments 1 and 2 provide much higher throughput and throughput per hour compared to the Base scenario for all three different customer demand cases. Lead time is also lower for these two experimental scenarios compared to the Base scenario.

The improved performance results from experiment 1 are explained by the additional parallel manual assembly station, Stn 2, that can support the high load on Stn 3 in the Base scenario. Experiment 2 yields an even better result throughput per hour due to the additional station, which is used more efficiently by both product variants given that it is a dynamically re-balanced station. This scenario evens out station utilization and the capacity needs of the other stations. Compared to experiment 1, experiment 2's flexible additional supporting station avoids experiment 1's bottlenecks that shift between the resources. This allows a more seamless production that improves the overall system performance.

Regarding the environmental impact, it can be seen that experiment 2 has a lower amount of total material and energy emissions per part when compared to the base and experiment 1 scenario. The lower emissions in experiment 2, as compared to experiment 1, is due to the addition of Stn 2 which supports the system as a dynamic re-balance station and therefore not in constant work as the situation in experiment 1.

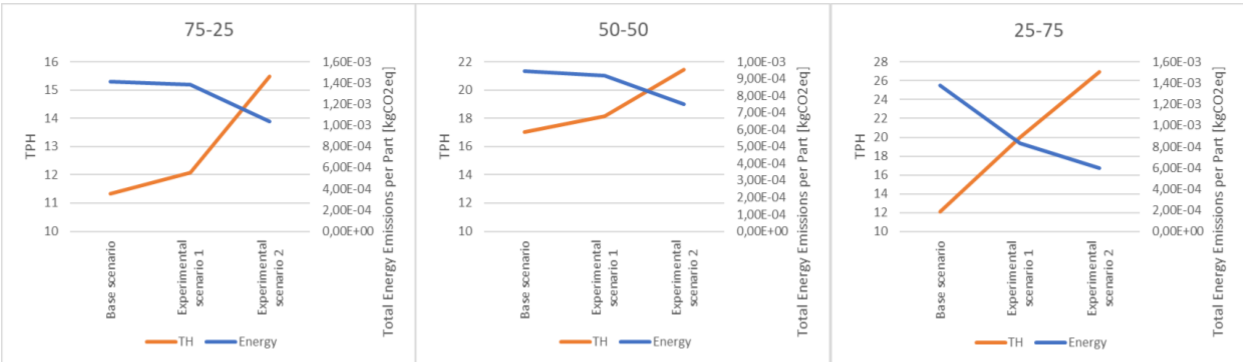

Figure 7: Comparing the TP and energy emissions for the three scenarios Base and Experiment 1 and 2.

5 DISCUSSION AND CONCLUSIONS

The case study scenarios showed the potential to autonomously utilize the production resources in an optimal manner by ensuring that the production load is evenly distributed among all the processing stations. This scenario shows that it could be possible to decrease waste and non-value-adding activities. Thereby, this scenario can contribute to higher throughput, decreased lead times, and improved material and energy efficiencies. This study contributes to theory and practice by showcasing selected suitable data points and enabling the exchange between this operative scenario and the physical assets. In future research, this simulation model could benefit from establishing bi-directional communication and eventually reaching the connectivity requirements to become a digital twin. Considering the context in which this study is performed, analyzing the potential of a digital twin could allow understanding further challenges that might appear when integrating sustainability KPIs with digital twins, allowing further advancement of this topic.

This research work was primarily focused on the identification of suitable KPIs that can be used to assess sustainability in the drone factory and their integration into a DES model, to support the future development of a Digital Twin. The study answers RQ1, by identifying the most suitable KPIs available in the literature and integrating them with the simulation model to assess sustainability in the Drone Factory. Further, RQ2 is through the KPI integrated model proposed, which can be used to increase the visibility of the impact of changes in the number of pallets. Additionally, this model can increase and provide visibility of other changes required, as the quantitative measurement of the impact that this has on a sustainability perspective allows to identify more sustainable manufacturing scenarios through changes in the production design or operations. The understanding and implementation of the mentioned chances can be further developed to comply with the definition of a digital twin.

This study is considered to be a starting point for further exploration of the possibilities of how KPIs can trigger responses in the system to enable self-adaptation and eventually reach the digital maturity required to have a functioning and useful digital twin. Future research could benefit from further integrating KPIs related to social sustainability and testing their potential in real production environments.

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DISCLAIMER

Commercial software systems are identified in this paper to facilitate understanding. Such identification does not imply that these software systems are necessarily the best available for the purpose. No approval or endorsement of any commercial product by Chalmers University of Technology is intended or implied.

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