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A simulation model to promote digital transition in the manufacturing context

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Abstract

Digital transition is a fundamental drivers on which industries worldwide are aiming to successfully face the challenge of process optimization. Therefore, promoting a digital transformation of businesses is one of the challenges of all centuries. In this research, a production process evaluation was proposed concerning an Italian company that produces aluminum cabinets used as electric charging stations for cars. A digital model (using simulation software) was developed to perform experiments and what-if scenarios of the existing production system. The results are promising and help to focus the company's strategic decisions. The study is a pilot study scalable to different sectors not only the manufacturing sector.

Keywords: Digitalization, Sustainability, AHP, Witness

1. Introduction

The digital transition is considered one of the opportunities of the post-Coronavirus recovery, as well as a source of growth and competitiveness for all sectors (Shi et al., 2023). In this perspective, it is necessary to make companies more innovative and sustainable, taking advantage of new technologies. It has not only become a widespread thought, but a concrete need. In this context, the governments around the world have long been promoting the digital transformation as a solution capable of improving the economic competitiveness of companies, through digitization processes capable of: 1) make it possible to achieve the sustainability objectives; and 2) enabling the changes needed for a just green transition. In this scenario, new technologies can improve energy efficiency, boost the circular economy, ensure a better allocation of resources, but also reduce emissions, pollution, biodiversity loss and environmental degradation of an agency (De Felice et al., 2022).
It is clear that digital transformation are seen as the output of Industry 4.0. Particularly for manufacturing companies that have become a need. This is driven by increasing consumer demand, improved connectivity and technological advances that result in greater pressure on the industry to become more flexible and adaptable (Hein-Pensel et al., 2023). Thus, companies have to be considered in its entirety and make permanent and continuous improvements to its structure, assets, organization, management and flows. This requires the redesign of business strategies to incorporate digital technologies into all aspects of production or service activity for which companies do

not seem to be yet ready.
In this panorama, the aim of this study is to propose a rigorous scientific approach to support companies towards the digital transition. A real case concerning an Italian company that produces aluminum cabinets used as electric charging stations for cars is proposed. In particular, WITNESS software is used to build the model to produce the aluminum cabinets and to incorporating environmental data and integrating them with process optimization data. The literature analysis highlights that in the ever-evolving landscape of modern manufacturing, the quest for efficiency, productivity, and cost-effectiveness remains paramount (Dohale, V. et al. 2022). Infact, with industries becoming increasingly competitive and customer demands ever more stringent, manufacturers are relentlessly seeking innovative solutions to optimize their production processes (Duong, L. N. K et. al. 2020). In this pursuit, simulation emerges as a powerful digital replication of real-world processes becoming an indispensable asset for manufacturing companies (Rabelo, L. et. al. 2007). In this research the profound importance of simulation in optimizing the manufacturing process is analyzed. In addition, it is explored how this sophisticated tool aids manufacturers in making informed decisions, predicting potential bottlenecks, and unlocking hidden opportunities for enhancement. Additionally, we will highlight the myriad benefits simulation brings to the table, from enhancing resource utilization and mitigating risks to fostering innovation and adaptability (Ortíz, M.A. et al., 2018).
The rest of the manuscript is organized as follows: Section 2 explains the materials and methods; Section 3 provides an overview of the experimental scenario; Section 4 summarized the main results of the proposed model. Section 5 discusses future developments. Finally, Section 6 outlines the main conclusions and future developments of the study.

2. Materials and Methods

2.1. Modeling & Simulation

Simulation is used for process re-engineering. The simulation model accurately reflects the real system, allows an in-depth analysis of the process, the study of changes to be made, priorities for action and the evaluation of solutions and future scenarios (Law, A. et al 2007). In this study, reference is made to the discrete-event simulation (DES) in which the system is represented, in its evolution over time, with variables that instantaneously change their value at well-defined instants of time, i.e. the instants are those in which events occur (Wilson, J. et al. 2016).

Key components of discrete-event simulation are summarized as follows (Guizzi, G. et al., 2019):

- Events: In DES, events represent specific occurrences or activities that affect the system. These events are usually timestamped, indicating when they are scheduled to occur. Examples of events in a manufacturing process could include the arrival of a new order, the completion of a production task, or the breakdown of a machine.
- System State: The system state includes all the relevant variables, conditions, and data that define the state of the system at any given point in time. It captures the status of each entity, resources, and queues within the system. The system state is continuously updated as events occur during the simulation.
- Time Advance Mechanism: Discrete-event simulation maintains a global simulation clock that determines the sequence of events. The simulation proceeds by advancing the simulation clock to the time of the next scheduled event, and the corresponding event is then executed, updating the system state accordingly.
- Event List: To efficiently manage the sequence of events, DES typically maintains an event list or priority queue. This list contains all the scheduled events in chronological order, allowing the simulation engine to process events in the correct sequence.
- Event Handlers: Event handlers are the components responsible for processing specific types of events. Each event has an associated event handler that updates the system state, schedules new events, or performs necessary calculations based on the event's occurrence.

By simulating real-world scenarios and events, it allows decision-makers to explore different strategies and make informed choices for enhanced efficiency and performance (De Felice F. et al., 208).

This mechanism is followed by Witness, discrete-event interactive visual simulation software used in this research to reproduce the production process (Pattanaik, L. N. 2021). The construction of a model in the Witness Horizon Simulation environment is characterized by the succession of several macro-stages shown in Figure 1.

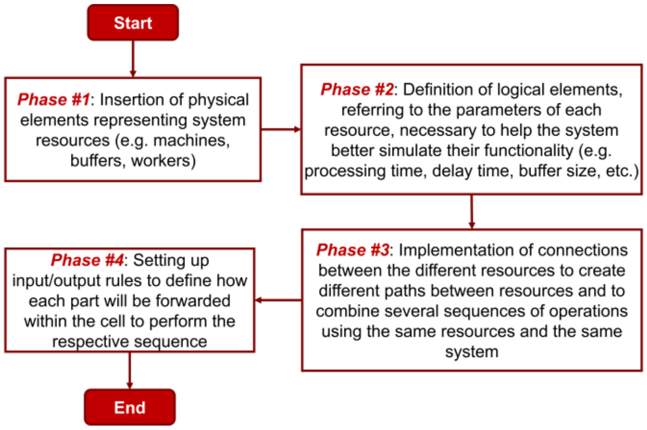

Figure 1: Phases for the construction of a digital model

In other words, DES is a powerful computational technique used to model and analyze the dynamic behavior of complex systems over time (Strachotova, D., Dyntar, J., 2021). It is particularly well-suited for scenarios where processes evolve incrementally, and events occur at distinct points in time, with each event potentially triggering subsequent events or actions Basri, A.Q., et al., 2021).
Starting from the real process, this is reconstructed in the virtual environment through various elements. Each element is carefully detailed by defining its characteristics. This is followed by the connection between resources, to define their paths, and the setting of input-output rules to delineate the sequences between operations (Schleich, B. et al. 2019).

3. Experimental Scenario

The experimental scenario of this study involves the creation of a simulated model of the production process using the Witness Horizon software. The objective is to evaluate the status of the production activity and identify strengths and weaknesses of the process. With a view to making more effective, safe and informed managerial decisions, a series of predictive analyses will be developed to assess reliable scenarios in the medium and long term. It is intended to provide indications and guidelines for strategies that are complex or have to take into account numerous factors of varying magnitude. The company, the case study of this research, is in southern Italy and produces aluminum cabinets used as charging stations for electric cars. In the past year, the market for these products has grown strongly, forcing a sharp increase in production activity, which has gone from a monthly production of 100 cabinets to a weekly production of the same amount. Therefore, an accurate and detailed study of the production system to optimize and improve it by limiting the risks associated with each change and evolution of production is necessary. Figure 2 shows some activities that make up the production process.

Figure 2: Process activities

3.1 Witness model

Using DES software Witness, a digital model of the production process was realized. This reflects the actual production activity; it is divided into two macro-flows that run in parallel and then join in a single final flow. The first activity flow returns the 'skeleton' of the cabinet (Fig.3 A) while the second gives back the three doors (right, left and front) and the cabinet cover (Fig.3 B). An assembly activity combines the skeleton and doors to create the complete cabinet (Fig.3 C). All the activities that make up each flow are summarized in the Table 1.

Table 1: Activities of the production process divided into macro-flows

Structure Flow	Doors flow	Cabinet flow
1. Laser cutting	1. Spot welding	1. Assembly of doors and cover on structure
2. Extraction	2. Tig welding	2. Screen printing
3. Brushing	3. Adjustment	3. Testing
4. Fold	4. Painting	4. Water test
5. Inserts	5. Testing	5. Testing
6. Tig welding	6. Screen printing	6. Repairs
7. Adjustment	7. Right door preparation	7. Packaging
8. On-line test	8. Left door preparation	8. Storage
9. Painting	9. Front door preparation	9. Shipping
10. Testing	10. Cover preparation	
11. Assembly of cabinet structure on base		
12. Insertion of internal details		

The cabinet is created by assembling a few macro elements: roof, base, profiles, and doors. Of these, the company produces base and roof while the other elements are purchased in their raw state and processed in-house. To build this model, a series of site visits were made to the company to acquire various information needed to digitally reconstruct the process. Specifically, the times of each activity were timed, the interconnection between activities, the distribution of workers, the type of machines used, the accumulation systems present, and the material handling systems and times were defined. The type of production was studied, an analysis was done on discarded or failed products, and the failures and setups for the automated machines in the process were quantified.

However, the model was built based on several assumptions:

- Each machine represents a process activity that, based on the number of inputs and outputs of each, is distinguished into single machine, assembly machine, production machine.
- The time of each machine is equal to a uniform distribution between the maximum and minimum values measured through different timing activities.
- Buffers, representing accumulation systems, have a maximum capacity of 50 units.
- Internal material handling times in the process were not considered.
- The screen-printing activity was not simulated in the process given the short duration (less than one minute).

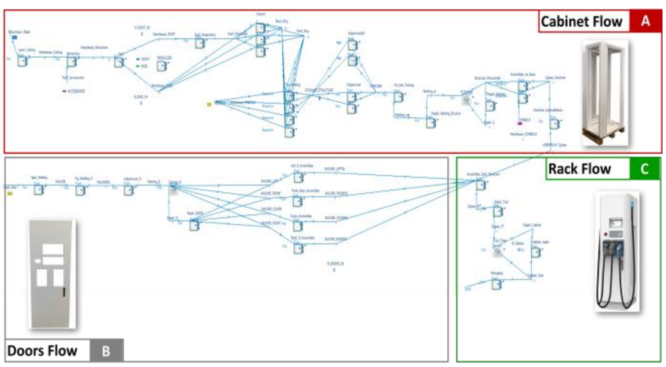

Figure 3: Digital model of production process in Witness environment

3.2 Simulation model results

The company applies a production approach that aims to minimize stocks. Therefore, it tries to produce a quantity of cabinets equal to market demand, which is around 500 units per month. On this basis, the digital model of the production process was developed and simulated for different time intervals, such as: one day one, week one, month one, and six months of work. The outputs of the model, representing the number of cabinets made in these time intervals are summarized in Table 2.

Table 2: outputs of simulation

One day	One week	One month	Six months
30	120	550	3450

To analyze and study the actual production process would require a lot of time and, more importantly, would require intervening in the activity itself causing it to slow down or even stop production. With the use of discrete event simulation, on the other hand, it is possible to generate detailed reports on event performance while also integrating external variability without intervening in any way on the real process in a very short time. Witness software has some analysis features such as *Statistics* that returns the results of various performance indicators that provide insight into the status of the activities that make up the production process. The following are statistics of the main elements of the digital machine model (Table 3), buffers (Table 4) and parts (Table 5) that enable the study of the production process.

Table 3: machine statistics

Machine	%Idle	%Busy	%Blocked	No. Of Operations
Adjustment(1)	15.067	84.933	0.000	32
Adjustment(2)	17.188	82.812	0.000	31
Assembly Door and Structure	35.766	64.234	0.000	71
Assemblay on Base	1.060	91.550	7.391	60
Cover Assemblay	0.115	99.885	0.000	60
Extraction	4.776	8.262	86.962	38
Fold	79.346	20.654	0.000	166
Front Door Assembley	27.252	72.748	0.000	73
INIZIALIZZA	100.000	0.000	0.000	0
Insertion Internal Details	49.861	10.904	39.235	102
Inserts(1)	93.797	6.203	0.000	58
Inserts(2)	93.944	6.056	0.000	57
Inserts(3)	93.815	6.185	0.000	58
Laser Cutting	0.000	43.559	56.441	113
Left D Assemblay	36.886	63.114	0.000	69
On line Testing	89.673	10.327	0.000	127
P Testing	86.781	13.219	0.000	129
Packaging	77.266	22.734	0.000	71
Repair Painting	100.000	0.000	0.000	11
Repair Painting Structur	100.000	0.000	0.000	128
Right D Assemblay	42.506	57.494	0.000	73
Ripair DOOR	100.000	0.000	0.000	11
Roof Preparation	84.094	15.906	0.000	101
Spot Welding	0.000	100.0	0.000	291
Test Final	73.271	26.729	0.000	72
Testing D	77.109	22.891	0.000	291
Tig Welding(1)	21.338	78.662	0.000	30
Tig Welding(2)	18.957	81.043	0.000	31
Tig Welding(3)	21.386	78.614	0.000	30
Tig Welding(4)	18.792	81.208	0.000	31
Tig Welding D	36.468	63.532	0.000	291
Water Test	47.370	52.630	0.000	72

Table 4: statistics of buffers

Buffer	**Total In**	**Total Out**	**Avg Time**	**Min Time**	**Max Time**
Assemblay queue	101	71	425.6	9.350	1.015.1
Base xtig	122	122	744.6	230.8	1.266.
leveling	126	126	0.235	0.00	2.727
Painting d	291	291	0.000	0.00	0.000
Painting in	128	128	0.191	0.00	2.326
Painting out	128	128	0.999	1.000	1.000
Queue insertion	122	102	99.23	0.000	488.1

Queue tf	72	72	0.000	0.000	0.000
Queue wt	71	71	0.000	0.000	0.000
racker	291	291	0.000	0.000	0.000
racker01	291	291	0.000	0.000	0.000
Racker cover	75	60	249.0	0.000	634.6
Racker cover01	71	71	36.98	0.000	334.12
racker_front	76	74	13.02	0.000	63.49
Racker front01	83	71	109.91	0.000	334.12
Racker left	70	69	6.289	0.000	28.86
Racker left01	82	71	147.88	33.47	334.12
Racker right	72	72	9.689	0.000	38.017
Racker right01	87	71	398.0	194.2	668.2
Repair d	12	11	177.28	180.0	180.0
Repair s	11	11	180.0	180.0	180.0
Roof accessories	50	0	2.114.3	0.000	2.389.
Roof x insertion	101	101	46.78	0.000	116.4
Roof x tig	118	118	630.9	222.1	1.258.
Storage structure	122	122	17.478	2.779	39.61
Structure assembly	130	122	158.80	0.000	431.75
Warehouse base	72	72	33.876	0.000	119.71
Warehouse console	0	0	0.000	0.000	0.000
Warehouse cutting	112	37	1.059.	0.000	1.928.
Warehouse extraction	165	165	92.146	40.48	135.02
Warehouse profile	0	0	0.000	0.000	0.000
Warehouse roof	100	100	31.841	0.000	82.94

Table 5: Statistics of parts

Part	No. Entered	No. Assembled	W.I.P.	Avg W.I.P.	Avg Time
Accessories	50	0.000	50.000	47.620	2.114.331
Alluminium Sheet	258	181.000	77.000	55.423	476.900
base	137	71.000	66.000	91.680	1.485.614
Console	124	123.000	1.000	1.842	32.987
Profile	504	488.000	16.000	16.000	70.476
roof	122	122.000	0.000	44.821	815.588

By carefully studying the results obtained from the process simulation for one month of work, it is possible to point out some critical issues in the process:

- Comparing the obtained output of the different time intervals, it can be said that the production process needs significant set-up time to get up to speed.
- The capacities of the current storage systems are not adequate for production as they are always saturated at the input.
- The status of some machines is found to be blocked for a significant percentage of time exceeding 50 percent. By carefully studying the results, all activities preceded to welding and adjusting show this state in an outstanding way. In fact, these activities take about an hour to execute, a significant amount of time compared to the rest of the process activities, which are around 20 minutes. Adjusting and welding can therefore be considered the bottlenecks in the process.

4. Discussion and optimization

The strength of DES is its ability to represent the dynamics of a real system with great precision, making it possible both to understand its behavior, and to evaluate different strategies for operating the system within the constraints imposed by the main Key Performance Indicators (KPIs) of interest in the different phases of production process analysis (Monek, G. D. et al 2023). An extraordinary capacity of simulation is the possibility of conducting what-if analyses and scenario analyses that allow the feasibility of an investment to be assessed, identifying not only the criteria that make it profitable (and the performance indicators), but also the innovations concerning the production process that must be made (Monek, G. D. et al. 2023). This makes it possible to investigate and define the correct sizing of the industrial automation installed or to be installed (mobile robots, AVG, stacker cranes, etc.), especially in mixed production processes, i.e. where there are phases managed by operators and phases managed by automation(Turner, C. J. et al. 2023).

It makes it possible to quantify the space and resources required for inter-operational or decoupling buffers and to assess the correct sizing of operators. Therefore, in this research, starting from the weaknesses intercepted in the production process, a series of predictive analyses are developed to evaluate possible solutions to these production difficulties. In particular, in parallel with a market survey for automated welding and adjusting tools, two scenarios were evaluated:

1. 30% increase in accumulation systems, implementation of a welding robot with an execution time of 12 minutes, and an adjustment system with an execution time of 15 minutes.
2. 40% increase in build-up systems, implementation of a welding robot with an execution time of 12 minutes and an adjustment system with an execution time of 15 minutes.

From the simulation results, the second solution seems the most successful in terms of production output and process output. There is, in fact, a reduction of the idle state of activities before welding and adjustment by 30-40% and a reduction of this idle state of the whole process by 20-30%. But also, an increase in monthly output of 250 cabinets (compared to 130 produced under the non-optimized process conditions). Implementation of this solution is currently underway. In fact, the company is in the process of expanding storage systems, and the welding robot that is shown in the Figure 4 is currently being run in.

Figure 4: Welding robot implemented in real production process

5. Future developments

From our point of view, the complexity of industrial systems should drive company managers to investigate the integration of different tools and methods in order to achieve production efficiency in terms of operational parameters and sustainability of the processes themselves.

Therefore, future research developments intend to investigare the integration of Witness software with other tools and methodologies to pursue digital and ecological transition in manufacturing processes. By leveraging the capabilities of multiple technologies and approaches, manufacturers can develop comprehensive solutions that address both efficiency and sustainability. More in detail, future research will investigate the following possible integration scenarios:

Scenario #1. IoT and Data Analytics:

Integrating Witness software with Internet of Things (IoT) devices allows manufacturers to gather real-time data from various sensors and machines on the factory floor. This data can be fed into the simulation model, enhancing its accuracy and realism. By analyzing this data using advanced data analytics techniques, manufacturers can identify opportunities for optimizing energy usage, minimizing waste, and improving overall resource efficiency, thereby fostering an ecological transition.

Scenario #2. Artificial Intelligence (AI) and Machine Learning:

Coupling Witness software with AI and machine learning algorithms can create a powerful decision-making framework. AI can be used to analyze simulation results and recommend optimal process adjustments to achieve ecological goals. Machine learning models can continuously learn from the simulation outcomes and historical data to refine process parameters and predict potential environmental impacts, aiding in sustainable decision-making.

Scenario#3. Life Cycle Assessment (LCA):

Integrating Witness software with Life Cycle Assessment tools enables manufacturers to assess the environmental impact of products throughout their entire life cycle. By simulating the production process and incorporating LCA data, manufacturers can identify eco-friendly design choices, material substitutions, and end-of-life disposal strategies, contributing to a more sustainable product ecosystem.

Scenario#4. Renewable Energy Integration:

By integrating Witness software with renewable energy forecasting and management tools, manufacturers can optimize their production schedules to align with the availability of clean energy sources. This integration ensures that energy-intensive processes are scheduled when renewable energy generation is at its peak, reducing reliance on non-renewable resources and promoting ecological sustainability.

Scenario 5. Digital Twin:

The concept of a digital twin, a virtual replica of a physical asset, can be integrated with Witness software to enable real-time monitoring and control of manufacturing processes. Manufacturers can use digital twins to simulate the impact of process changes and quickly respond to fluctuations in production parameters, achieving greater process efficiency while maintaining ecological considerations.

We strongly believe that the integration of simulation software (such as Witness software) with other cutting-edge tools and methodologies opens up a world of possibilities for manufacturers for several reasons:

R#1. Holistic Analysis: Witness software excels in simulating and optimizing complex manufacturing processes. However, integrating it with other tools and methods, such as IoT, data analytics, and AI, allows for a more comprehensive and holistic analysis of the system. By combining the strengths of multiple technologies, manufacturers can gain deeper insights into the interactions between different components, identify hidden inefficiencies, and make more informed decisions for both digital and ecological improvements.

R#2. Real-World Relevance: Integrating Witness software with real-time data from IoT devices or other sources ensures that the simulation remains relevant to the dynamic conditions of the actual system. This connection to real-world data enhances the accuracy of the simulation, enabling manufacturers to develop practical strategies that align with the current state of the manufacturing process and the environmental context.

R#3. Multi-Dimensional Optimization: The integration of Witness software with various tools and methods enables multi-dimensional optimization. Manufacturers can simultaneously target digital objectives, such as maximizing throughput and minimizing cycle times, along with ecological goals, like reducing energy consumption and carbon emissions. This approach ensures a balanced approach to process improvement that considers both efficiency and sustainability.

R#4. Predictive Capabilities: By leveraging AI and machine learning in conjunction with Witness software, manufacturers can develop predictive models that anticipate potential challenges and opportunities in the manufacturing process. Predictive capabilities empower decision-makers to proactively address environmental concerns, anticipate resource shortages, and strategize for an ecological transition even before problems arise.

R#5. Continuous Improvement: The integration of Witness software with other tools supports a culture of continuous improvement. As data is continuously fed back into the simulation, manufacturers can refine and update their strategies, responding to changing conditions and optimizing the process over time. This iterative approach allows for ongoing progress towards ecological goals while keeping up with digital advancements.

R#6. Risk Mitigation: The use of simulation, combined with data-driven analysis from other tools, helps in mitigating risks associated with process changes and ecological initiatives. By simulating scenarios before implementing them in the real world, manufacturers can identify potential pitfalls, assess the environmental impact of various alternatives, and make well-informed decisions that minimize disruptions and avoid unintended adverse consequences.

R#7. Adaptability and Innovation: Integration with various tools and methods fosters adaptability and innovation in manufacturing processes. Companies can experiment with novel approaches, sustainable technologies, and eco-friendly materials within the simulated environment, gaining insights into their viability and potential benefits. This exploration encourages a proactive attitude towards embracing new technologies and practices that contribute to ecological transition.

6. Conclusions

Digital transformation and climate transition are hot topics in contemporary society. The need for digital transformation in manufacturing is driven by several factors shaping the modern industrial landscape. Embracing digital technologies has become more than just a competitive advantage; it is critical for manufacturers to remain relevant and thrive in today's rapidly changing marketplace. Developing a smart factory is not just an option for the manufacturing sector; it has become an imperative for survival and success in today's fast-paced, digitally connected world. By adopting digital technologies, manufacturers can promote efficiency, agility, innovation and customer centricity while ensuring competitiveness and long-term sustainability. Manufacturers driving digital transformation are poised to shape the future of the industry and capitalize on the extensive opportunities presented by the evolving technology landscape. This research takes a step into that context, showing how simulation, the enabling technology of Industry 4.0 and such change, can support a manufacturing company in the transformation itself. Simulation has proven to be a very powerful tool for process analysis capable of intercepting strengths and weaknesses of manufacturing activity without compromising production activity in any way. With the development of what-if analysis, simulation has enabled the evaluation of future scenarios in a very short time and at zero cost.

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