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Towards a Smart Factory: An integrated approach based on Simulation and AHP

Fabio De Felice[1,*], Cristina De Luca[2], Emanuele Guadalupi[3] and Antonella Petrillo[4,*]

[1,2,4] Università degli Studi di Napoli "Parthenope", Isola C4 Centro Direzionale Napoli (NA), 80143, Italy
[3] I.M.I. Industria Monouso Italiana s.p.a. – s.s. Appia km 17,800 81043 Vitulazio (CE), Italy

[*]Corresponding author. Email address: antonella.petrillo@uniparthenope.it

Abstract

The optimization of an industrial production process is a complex problem and it implies difficult decisions in terms of technological investments, operating costs, work organization, and economic investments. This is even more true in an economic context characterized by a digital transition that involves new business strategies. In this scenario, the application of digital technologies and multi-criteria decision-making techniques helps to identify the best strategy to improve operational performance. In particular, a discrete event simulation tool to optimize production performance is proposed in this study. More in detail, the present research presents a business model based on digitalization of an Italian SME. Firstly, a digital model (using a simulation software) was developed to carry out experiments and what-if scenarios of the existing production system. Secondly, after the analysis of the results and its discussion, the definition of the most appropriate business strategy was performed using the the well-known multicriteria method, Analytical Hierarchy Process (AHP). The study shows that simulation approach integrated with a multi criteria analysis can be a very powerful tool as a decision support system towards the smart factory paradigm. The studio is an academic pilot study scalable in different sectors not just the manufacturing sector.

Keywords: Simulation, Industry 4.0, SMEs, Manufacturing, Analytical Hierarchy Process

1. Introduction

In a globalized world, the business is accelerating and increasing competition exponentially (Peillon et al., 2019). In fact, all companies are in constant competition, facing threats and risks characterizing a digital economy (Camarinha-Matos et al., 2009). In the current scenario, the use of disruptive technologies offer numerous advantages for improving production efficiencies in a smart manufacturing (Ramírez-Durán. et al., 2021; Torn, et al., 2019). The main characteristics of smart manufacturing is the process integration and transparency of information in real time (Culot, et al., 2020; Rüßmann et al 2015; Pereira, et al, 2017). The result is a competitive environment based on innovations and process improvement, where the main objective is to maximize output while minimizing resource use (Kamble et al., 2018; Anderl et al., 2015; Mittal et al., 2018). The evolution of production processes also inevitably causes effects on the market, which is completely globalized, characterized by dynamism, turbulence and internationalization of supply (Ahn, et al., 2015). Customers demand attractive products at low cost, fast delivery and adequate quality (Mittal, et al., 2018). In this context, the success of industries lies in their rapid ability to adapt to technological, social and economic conditions (Müller et al., 2018; Stentoft, et al., 2020). Thus, the development of a smart production system is identified as an effective way to increase the competitiveness of companies (Bi Z., et al., 2018; Müller et al., 2018). As pointed out by several studies in order to really implement smart manufacturing models, new digital technologies must be adopted in a joint and coordinated way (Lee et al., 2015; Hofmann, et al., 2017; Reischauer, et al, 2018; Shi, et al, 2020; Masood, et al., 2020). These technologies allow total optimization of production processes and the qualification of the company to new international business scenarios (Schumacher et al., 2016; Flores-García et al., 2021). Among the different digital technologies, simulation is an indispensable tool (Schneider et al., 2018). The simulation helps to virtually experience the operation of industrial systems in actual real operating conditions (Han Y., et al., 2018). Furthermore, the simulation helps to analyze overall performance and anticipate changes or interventions, reducing costs through the analysis of simulation scenarios (Moeuf et al., 2020; Wieland, et al., 2016). Through a simulation model it is possible to optimize the flow of materials, the use of resources and logistics with "*what-if*" analysis (Negahban et al., 2014). Among the various simulation models, the one that best fits the manufacturing context is discrete event simulation (DES). DES is dynamic (i.e., time-based), stochastic (i.e., variable based on probability functions), and rule-based from discrete events (Nam, et al., 2020; Banks, et al., 2010). DES can be used to optimize and predict performance, frequent changes in production orders, and unexpected events (Goerzig et al., 2018). Many researchers have investigated the benefits of integrating simulation models with multi-criteria decision-making methods (Ortíz-Barrios et al., 2021; Cheng Ying et al., 2016; Gao et al., 2013). However, many SMEs fail to seize the opportunities of the digital revolution. In fact, a lack of familiarity with technologies and a digital literacy gap persist, mainly in SMEs. In this context, tools would be needed that can support SMEs in developing innovative business models and defining business strategies towards the smart factory in order to increase competitiveness at national and international level (Guizzi et al., 2019). The question is what are these tools? Investing in digital technologies could certainly help (De Felice et al., 2018). But alone it is not enough. It would also be necessary to define appropriate business strategies through a rigorous and scientific approach using multi-criteria decision-making methods. Therefore, the present research presents a business model based on digitalization of an Italian SME. Firstly, a digital model (using a simulation software) was developed to carry out experiments and what-if scenarios of the existing production system. Secondly, after the analysis of the results and its discussion, the definition of the most appropriate business strategy was performed using the the well-known multicriteria method, Analytical Hierarchy Process (AHP). The rest of the paper is organized as follows: Section 2 explains the materials and methods; Section 3 provides an overview of the experimental scenario; Section 4 and Section 5 summarized the results analysis (of the digital model created with the simulation software) and discussion before optimization, respectively. Section 6 proposes and argues the optimization alternatives. Finally, Section 7 outlines the main conclusions and future developments of the study.

2. Materials and Methods

2.1 Modeling and Simulation

The simulation model developed in this research is based on discrete event simulation (DES). Discrete-event simulation is a quantitative simulation method that allows complex systems such as reality to be reproduced on the computer (Mustafee, et al., 2018; Karnon, et al., 2014). The key elements of DES are the common simulation terminology and are depicted in Figure 1.

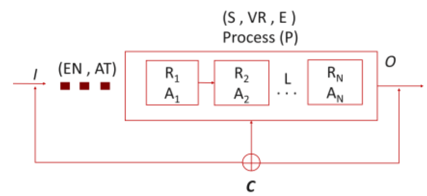

Figure 1: DES system elements

A DES includes entities (EN) that represent the inputs (I) of the system, which at the end of the process are transformed into outputs (O). Each entity and characterized by a set of attributes (AT) that uniquely identify them. During the execution phase, various system activities (A) are performed on the system entities by the system resources (R). A system resource represents the tool or medium through which model activities are performed. A task is performed using one or more model resources for a specified duration of time. The duration time of system activities depends on the nature of the activity, the durations can be:

- *Fixed duration time*: the time allocated to the activity is a fixed value;
- *Probabilistic duration time*: the time assigned to an activity incorporates randomness and variability;
- *Formula-based time duration*: the time of the activity is calculated using an expression of some system variables.

The system is described at each time instant of the simulation by the system state (S). This is quantified by a set of state variables (VR). These variables contain the information needed to describe the state of the model elements. What causes the state of the system to change are the events (E) that occur during execution. In fact, DES models are termed event-driven, in which the updating of the system state occurs as events occur. The dynamics of the model results in a time delay (D), and the operation of the system is controlled through the logic model (L) (Al-Aomar, R., et al., 2015). Figure 2 shows DES framework (Rodic, et al., 2017).

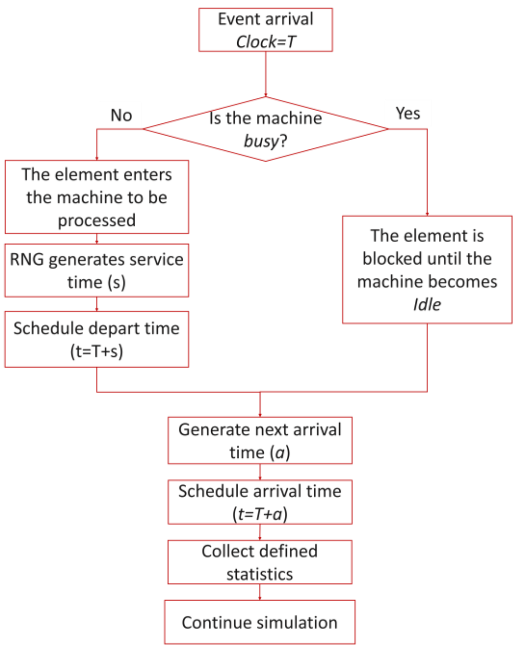

Figure 2: DES framework

The model is structured as follows:

- The first event "start" starts the simulation at clock time T=0.
- If the machine that is to execute the task is busy, the part is waiting until the machine becomes available according to the FIFO (First Input-First Output) discipline.
- If the machine that is to perform the operation is idle, the task is executed.
- The RNG generates a service time (s) and schedules the event to start at time t=T+s.
- The RNG samples an inter-arrival time (a) and schedules a new event "start" at time t=T+a.
- The simulation data are collected and the simulation continues.

In DES, events include the random arrival/departure of entities (elements) to/from service stations (machines) (Meolic, R., et al., 2022). A random numerical generation (RNG) is used to sample the inter-arrival and service times (i.e., t and s) of the elements from the selected probability distribution (dos Santos, C. H., et al., 2021). For each arrival/departure of an element, the model logic is executed based on discrete-event and time-forward mechanisms (Moetakef-Imani, B., et al., 2009). At any time in the simulation clock T, an event is scheduled chronologically in the event list (EL) according to the following formulas:

$$A = T + a \quad (1)$$

$$D = T + s \quad (2)$$

The arrival time (A) is defined as the sum of the current simulation clock time (T) and the inter-arrival time (a). While the departure time (D) is the sum of the current simulation clock time (T) and the service time (s) (Robinson, et al., 2003). The EL contains information about the types of events and the schedule of their occurrences (Mourtzis, et al.,2020). It is formalized as follows.

$$EL=\{(E1,T1),(E2,T2),(E3,T3),...(En,Tn)\} \quad [3]$$

The EL is updated with each event in terms of content and time. the concluded event is removed from the list and the next most imminent event rises to the top of the list. other events can also enter or leave the list.

2.2 Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is a multi-criteria decision support technique developed in the 1970s by the naturalized Iraqi American mathematician Thomas L. Saaty (1979). Through the AHP it is possible to compare several alternatives in relation to a plurality of criteria, quantitative or qualitative, and to obtain an overall evaluation for each of them. Therefore, you can sort the alternatives/criteria in order of preference and select the best alternative/criteria. The AHP modeling process is divided into the following phases (1982):

1. Pairwise comparison and relative weight estimation according to Saaty's scale. Saaty suggested a scale of 1-9 where a sore of 9 represents an extreme importance over another element, while a score of 8 represents an intermediate importance between "*very strong important*" and "*extreme importance*" over another element. For a general AHP application, we can consider that $A_1, A_2,..., A_m$ denote a set of elements, in A positive reciprocal matrix. While a_{ij} represents a quantified judgment on a pair of A_i, A_j. The result of the comparison is the so-called dominance coefficient aij that represents the relative importance of the component on row (i) over the component on column (j), i.e., $a_{ij}=w_i/w_j$ (Saaty, 1996). If matrix w is a non-zero vector, there is a λmax of $Aw = \lambda_{max}w$, which is the largest eigenvalue of the matrix A. If matrix A is perfectly consistent, then $\lambda_{max}w = m$.
2. After all pairwise comparison are completed, the priority weight vector (w) is computed as the unique solution of $Aw = \lambda_{max}w$, where λ_{max} is the largest eigenvalue of the matrix A.
3. Consistency index estimation. Saaty proposed the consistency index (CI) to verify the consistency of the comparison matrix. The consistency index could then be calculated by: $CI = (\lambda_{max}-n)/ n-1$. In general, if CI is less than

0.10, the satisfaction of the judgments may be derived.

2.3 Research methodology

From a methodological point of view, the development of the digital production process was developed in three phases as shown in Figure 3.

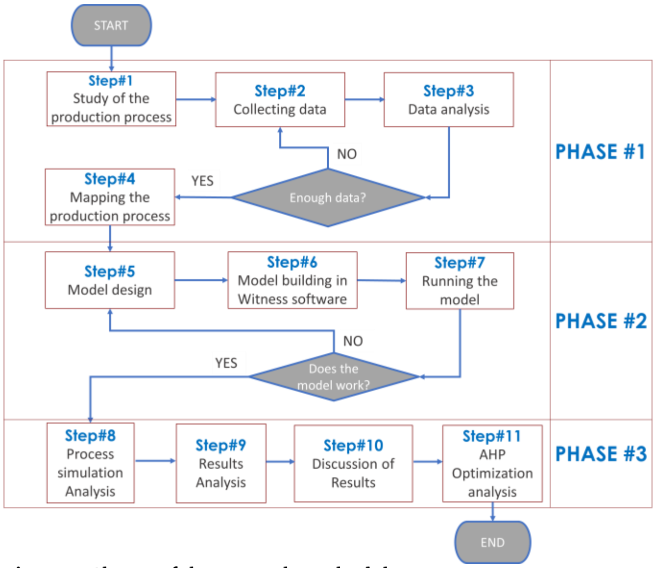

Figure 3: Phases of the research methodology

- Phase#1: The objective of the first phase was to analytically reconstruct the process. To do this, it was necessary to collect data and information through several on-site visits. Only when the information was deemed sufficient was it possible to map the existing production process through a flow chart shown in Figure 5.
- Phase#2: The objective of this phase was to simulate the process as it is. Starting from the current state of the production system, the scenario under study was designed. Once all parameters were defined, the model was built in the Witness simulation software and simulated for a defined time. However, before moving on to the next stage, the model was validated.
- Phase#3: In the last step, the process was simulated at different time intervals. The simulation results, automatically generated by the software, were studied and critically analyzed in order to identify optimization in the process. This was followed by a *what-if* analysis to validate possible solutions to intercepted bottlenecks.

3. Experimental Scenario

3.1 System description

In this research, simulation was used to reproduce the production process of an Italian company located in Naples (Southern Italy). The company entered the manufacturing sector a few years ago with the production of rack cabinets for electric vehicle charging stations. Figure 4 shows some phases of the production process.

Figure 4: Phases of the manufacturing process

The use of simulation is based on the need to develop *smart manufacturing* in accordance with the industry 4.0 paradigm. Complexity and instability characterize the market in which the company operates, which has grown exponentially in a short time. In about a year, customer demand has almost tripled. This has led the company to accelerate its production activity from a monthly production of one hundred cabinets to a weekly production of eighty. Such a change required a careful study of the process to avoid wasting resources, people or materials. The company produces several models of the same product, which differ mainly in the electrical power delivered and thus in size. In this research, the TX model is analyzed for the 50 kW DC fast charging station that can charge all electric and plug-in hybrid vehicles. Typical charging times range from 15 to 30 minutes for DC charging. The cabinet, simply put, is the result of the assembly of two macro-elements: Structure and Doors. In turn, the structure is composed of: Base; Roof and Profiles. While the doors are divided into: Doors (left, right and front side) and Roof: rear side. The production process is developed in two parallel activity streams, structure and doors, which flow into a final stream at the end of the process with an assembly activity, as illustrated in Figure 5. It is important to point out that the company does not produce all the elements that make up the cabinet but only the base and roof, while profiles and doors are purchased already finished in their raw state. To produce the bases, sheet metal with a thickness of 4 mm is used, while to produce the roofs, sheet metal with a thickness of 3 mm is used. Therefore, laser cutting, part extraction, brushing, bending, and insertion activities are performed for both the base and roofs and then joined to the profiles through the welding activity. In both process flows, there is a painting activity that is not carried out in-house but is outsourced.

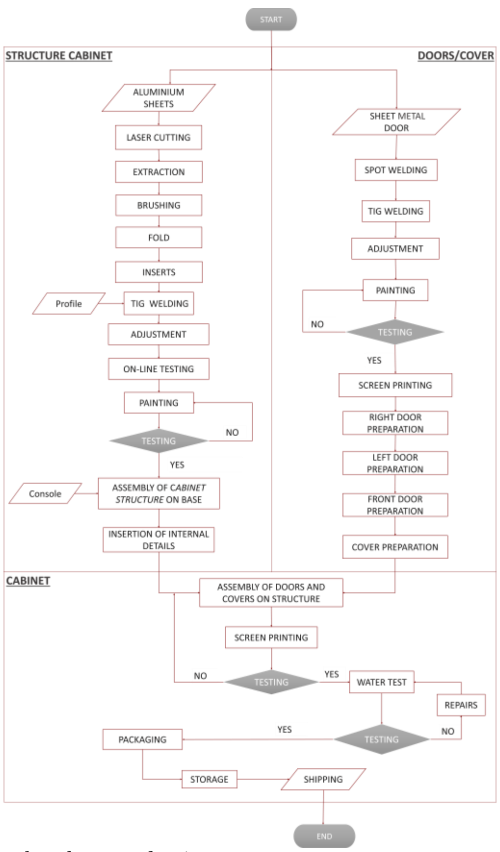

Figure 5: Flowchart Production Process

3.2 Simulation model

It is important to note that the simulation model reports all mapped activities except screen printing and brushing, which have a duration of less than one minute and therefore are not relevant to the process. Specifically, the simulation model shown in Figure 6 consists of machines, parts, buffers and labor (workers). To develop the model, the following assumptions were made:

- Process inputs are modeled in Witness through parts. Some initiate the process others are recalled at precise process steps.
- Parts recalled by activities are deposited in buffers that represent within the model places of accumulation.
- Each activity is modeled by a machine which, based on the number of input outputs of each, are distinguished: single machine, assembly machine, production machine.
- Each buffer in the system has a capacity of 50 elements.
- A daily setup of 15 minutes is associated with the laser machine.

For the activities that are part of the structure, the simulation was done considering the production of roofs; bases are included in the welding phase along with profiles as input elements of the activity. The production times of bases and roofs are equivalent to each other. Regarding the times associated with each machine, an equal number of measurements were taken in companies for each activity. In the model, it was considered appropriate to report an even distribution between the minimum and maximum value of these detections. The exception is laser cutting, which being an extremely automated machine has a predetermined cycle time that if repeated in every operation. For the paint test activities, a rejection rate of 5% was associated with the doors and 10% with the structure. While for the final testing, the associated rejection rate is 16%.

Table 1 shows the input data of the model developed using Witness.

Table 1: Simulation input data

FLOW	ACTIVITY	TYPE	CYCLE TIME [*min*]	LABOR
STRUCTURE	Roof cut	Single	5.51	1
	Removing parts Roof	Production	Uniform(4.3,5.5)	1
	Roof folding	Single	Uniform(6.17,6.2)	-
	Roof Preparation	Single	Uniform(6.4,6.55)	2
	Insertion of inserts	Single	Uniform(2.28,2.46)	2
	Structure welding	Assembly	Uniform(57.11,59.6)	-
	Structure adjustment	Single	Uniform(57.21,61.2)	-
	On-line testing	Single	Uniform (1.6,2.02)	3
	Testing	Single	Uniform (1.56,3.0)	3
	Assemblay Cabinet on Base	Assembly	Uniform(29.38,38.17)	-
	Insertion of internal details	Single	1Uniform (5.45,6.05)	-
DOORS - COVER	Spot welding	Single	Uniform (7.2,8.08)	-
	Tig welding	Single	Uniform (4.46,5.26)	-
	Door adjustment	Single	Uniform (2.41,3.37)	-
	Testing	Single	Uniform (1.5,2.02)	4
	Left door Preperation	Single	Uniform (19,21.2)	-
	Right door Preparation	Single	Uniform(16.39,19.14)	-
	Front door Perparation	Single	Uniform (21.17,23.1)	-
	Cover Preparation	Single	Uniform(35.24,38.47)	-
CABINET	Assembly Cabinet	Assembly	Uniform(18.81,21.31)	-
	Water test	Single	Uniform(15.74,16.88)	4
	Testing	Single	Uniform (7.12,9.18)	4
	Packaging	Single	Uniform (5.5,8.5)	-

Figure 6 shows the model developed in the Witness simulation environment.

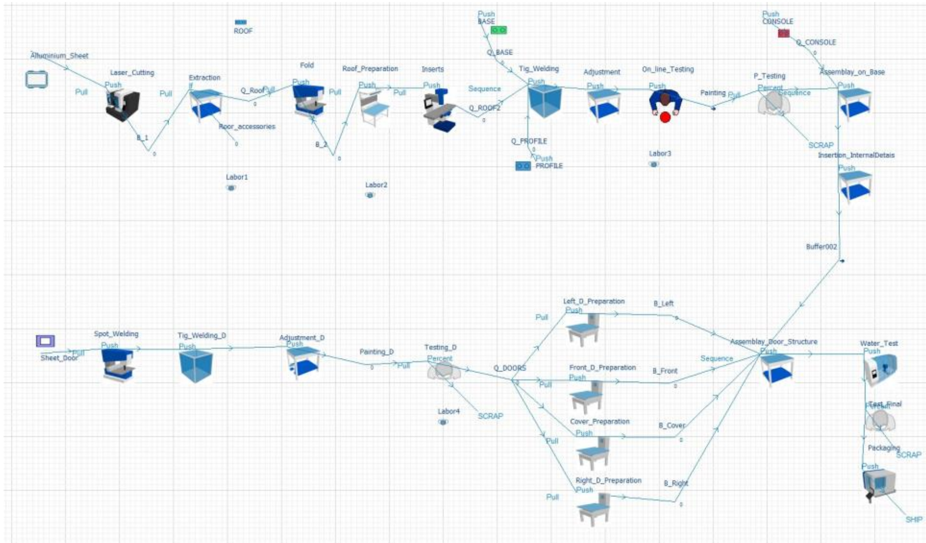

Figure 6: Simulation model in Witness environment

4. Simulation Model Results Analysis before the optimization

The model was simulated for three different time intervals representing one day, one week and one month of work, respectively. The number of cabinets produced, according to the simulated production process, is shown in Table 2.

Table 2: Process production at different simulation times.

TIME	NUMBER CABINET
One day [480 min]	4
One week [2400 min]	34
One month [9600]	156

For the analysis, simulation outputs obtained by simulating the process for one week are considered. Through the Witness Statistics function, the simulation output data can be obtained. These data are nothing but the results of performance indicators that change according to the model element. Figure 7 shows the state of the machines in percentage terms over a 40-hour shift. The machine may be busy, i.e., performing its task, or idle and thus waiting to work. It may be blocked i.e., not working because of machines ahead or behind it. The machine may be in a breakdown and/or set-up condition, which, in turn, may be affected by a worker waiting.

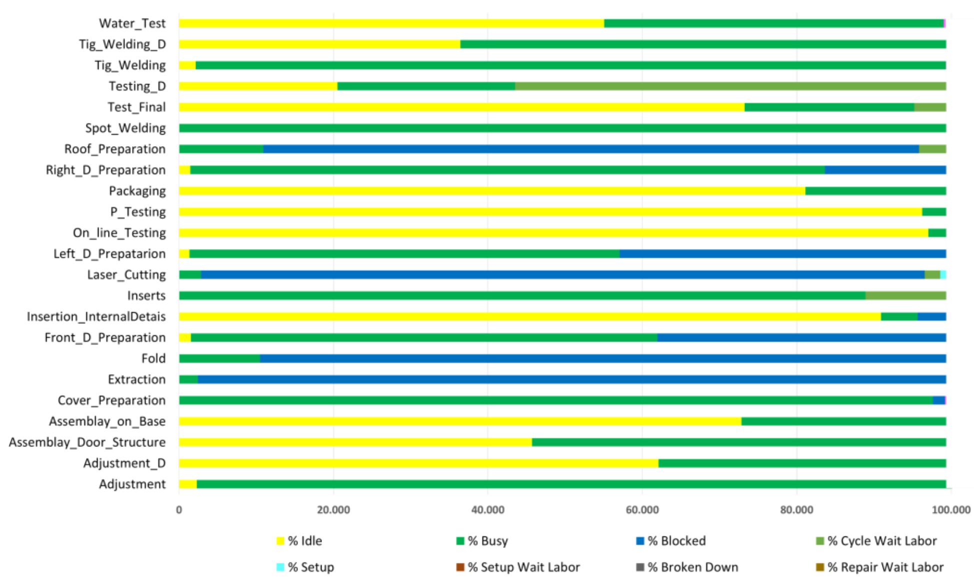

Figure 7: Machines statistics

The status of workers is shown in Table 3 in tabular form. The availability of workers (employed or inactive) and information on the number (no.) of activities performed is shown in percentage terms.

Table 3: Labor statistics

Labor	%Busy	%Idle	Qt.	N° Job Started/Ended	Avg Job Time

1	7.8	92.1	1	143.000	5.290
2	19.6	80.3	1	427.000	4.428
3	6.7	93.2	1	320.000	2.035
4	29.8	70.1	1	785.000	3.655

Finally, the last statistic shown in Table 4 shows the condition of buffers. The information provided is mainly about the number of pieces within the buffer and the time the pieces spend there, with different levels of detail.

Table 4: Buffers statistics

Name	Total In	Total Out	Avg Size	Min Time	Max Time
B_1	96	46	48.036	0.000	9.179.992
B_2	264	214	47.629	0.000	2.973.719
B_Cover	121	71	41.802	170.649	6.615.599
B_Front	121	71	45.097	177.740	6.764.137
B_Left	121	71	45.361	194.693	6.764.137
B_Right	121	71	45.600	204.948	6.764.137
Buffer002	71	71	0.000	0.000	0.000
Painting	160	160	0.000	0.000	0.000
Painting_D	693	643	30.394	0.000	1.934.924
Q_Base	212	162	49.862	25.622	2.974.536
Q_Console	50	0	49.872	0.000	9.600.000
Q_Doors	638	488	107.931	0.000	5.152.840
Q_Profile	698	648	49.729	22.622	775.521
Q_Roof	315	265	49.706	0.000	2.973.719
Q_Roof2	212	162	48.509	0.000	2.975.132
Roor_acc	0	0	0.000	0.000	0.000

5. Discussion of Simulation Model Results

Results highlighted some weaknesses as follows. Starting from the daily production, the expected weekly output would be 20 units, but there is about double the value. Therefore, it can be inferred that the production process needs set-up time. Regarding the buffers, it is observed that the number of input elements relative to the capacity of each is larger. Therefore, it can be assumed that the buffers, representing the storage systems that constitute the current process, are small compared to the production capacity. Worker statistics, on the other hand, show some availability. By examining these statistics it can be seen that some machines are locked due to the unavailability of a worker. A redistribution of these can optimize worker activity and consequently the process. The analysis of machine statistics is certainly the most complex. It emerged that many machines are locked for a significant period of time. To better investigate this condition, the two main flows, structure and doors/coverages, are studied separately. As with the whole process, we start by analyzing the outputs. In this case, the output of the flow is defined as the item returned by each machine before the assembly activity in which the structures are joined to the doors/covers. Due to the flexibility and simplicity of Witness, these outputs can be obtained quickly and are: *Output of Structure flow* (36) and *Output of Doors/coverages flow* (67). These results clearly show that the flow of structures is the slowest in the process. Paying attention to the statistics of this flow of note that all activities preceding welding and adjusting are significantly locked. It can be said to have intercepted a bottleneck in the process. However, this is confirmed by data collected from company inspections that record particularly long lead times for these two activities.

6. AHP Optimization of production process

After the analysis of the results and its discussion, the optimization of the process was performed in order to identify strategies for improving operational performance. Thus, an expert team was selected to identify the alternatives potentially affecting the inefficiencies of the production process. More in detail, te expert team was formed by 2 Production Engineer, 1 Quality Engineer, 1 Simulation Expert and 1 AHP Expert. The alternative are ranked according to global priority, as shown in Table 5.

Table 5: Ranking of Alternatives.

ALTERNATIVES	GLOBAL PRIORITIES	RANKING
A1. Low number of units produced	0,25	3
A2. Inactivity of the machines for long periods of time	0,45	1
A3. Inefficient organization of workers	0,30	2

The highest global priority is the most critical alternative. Thus, A2 is the most critical. At this point, a what-if analysis was performed to assess the potential benefits or damages of going about changing the current process. Specifically, it is intended to act on the buffer capacity and the adjustment and welding activities.

- TIG welding is performed within the production facility by a skilled worker using appropriate instrumentation. In a 4.0 perspective, an automated robot is implemented that independently performs the operation simultaneously on two structures taking about 10 minutes.
- For adjustment, on the other hand, the equipment now present is replaced with state-of-the-art systems that reduce the execution time to 15 minutes. This workstation is also doubled in that the worker who was previously dedicated exclusively to welding is completely free with the introduction of the autonomous robot.
- For the buffer the capacity is increased by 40% from 70 units each.

By making this change within the simulation model, the outputs change significantly for both the entire production process and the flow: *Production process output* (284) and *Structure output* (220). From the perspective of machine condition, the change made to the process shows improvements. Statistics show a 25-30 % reduction in machine blockage for the entire process flow. For machines ahead of critical activities this condition is reduced as follows: Laser cutting: 35 %; Extraction: 30 %.; Bending: 40%. The results obtained from an initial what-if analysis result particularly well.

7. Conclusion

This research shows how simulation integrated with a decision analysis can be a powerful tool to support the manufacturing sector. More in detail, the present research shows how the discrete-event simulation software, is used as a powerful tool and a valuable decision-making support tool. The development of the digital model allows a "top-down" view of the process without hindering or intervening in production in any way. Dynamic simulation, therefore, provides an objective assessment of alternative solutions when performance and impact on other systems is very difficult to predict. This addresses the strong business need for tools for anticipating, sizing and containing project risks. The use of simulation techniques can provide organizations with the means to evaluate Industry 4.0 principles and technologies in a virtual environment to improve decision-making on technology investments and facilitate the transition to the fourth industrial revolution. Future research aims to develop a cost-benefit analysis for the possible integration of robots, augmented reality, sensors, and cloud for a meaningful conversion to smart manufacturing.

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