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Automated simulation modeling: ensuring resilience and flexibility in Industry 4.0 manufacturing systems

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Abstract

Industry 4.0 brings a revolution in the way to create and think of products. Consumer needs change rapidly and production systems must adapt quickly to market changes by changing processes, resources, and configurations. In this context, as real manufacturing systems are subject to constant change, simulations can easily become obsolete. This reduces the lifetime of the simulation model, causes repeated disruption in industrial planning support, and consequently continuous maintenance by experts. Within this framework, the novelty of the following research is the development of a flexible and resilient simulation model able to adapt according to its physical counterpart. Through advanced modeling, based on the object-oriented programming paradigm, an automated simulation model has been developed. This model adapts based on input data, ensuring accuracy and real-time planning support. The research is applied to a real case study of the production system of a world leader in the energy technology sector. The results show that the applied simulation tool can analyze different configurations and enhance production planning.

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Keywords: Flexible simulation; Automated modeling; Manufacturing system; Production planning; Modular and Data-Driven based simulation; Scheduling rule

1. Introduction

The Fourth Industrial Revolution, also known as Industry 4.0, is an industrial-technological transformation based on the integration of advanced technologies such as Artificial Intelligence, the Internet of Things, Big Data, Cyber-

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physical systems, and simulation [1]. Simulation is used along the product lifecycle from production design, delivery, use, and end of life [2]. It is used to analyze the behavior of the system, reduce bottlenecks [3], reduce waste [4], energy management [5] and manage maintenance [6]. Moreover, simulation is widely used for production planning which helps companies to make the right decisions based on real-time data by identifying the strengths and weaknesses of each scenario [7]. This allows companies to optimize the use of resources, reduce downtime and improve overall planning, thus improving industrial KPI(s).

Industry 4.0 is also characterized by highly customized products. Demands for requested amounts and types of items continually change because of the constantly shifting needs of consumers and marketplaces [8]. The mass customization trend is both an opportunity and a challenge for manufacturers. On one side, thanks to the integration of Industry 4.0 technologies, high customization brings benefits to the industry sector allowing companies to improve customer satisfaction, optimize resource utilization [9], and enhance profitability by reducing production and logistics costs [10]. On the other side, manufacturers must constantly adapt the system to the changes of the market by designing new processes, new configuration lines and adopting different flexible technologies. Customized products require flexible management of resources and production processes and adaptation of new business models [11]

In this dynamic context, simulation plays a crucial role in production planning, allowing the company to find flexible planning solutions [12]. However, as real manufacturing systems are subject to constant changes, simulations can easily become out of date [13]. According to [14], manually tailored simulation models are typically rendered obsolete soon after their development. Due to this, it becomes necessary to regularly and frequently construct new simulation models regularly or manually update current ones, which is a highly challenging and costly operation [8]. Consequently, the industry must face a life cycle simulation reduction, continuous maintenance by experts and industrial planning support disruption. To address this problem, some authors have developed simulation models able to rapidly regenerate a virtual system. Some research proposed a modular approach that involves the creation of a generic module that is parameterized. The modular approach can drastically reduce the programming effort and time needed for modeling. [15] and [16] proposed simulation models based on a modular framework that allows the user to handle multiple process settings and production control strategies in different manufacturing systems. However, the papers analyzed proposed a Graphic User Interface (GUI) to parameterize each module and create step-by-step a simulation model. Therefore, the modular approach doesn’t involve the automatic creation of the system and the production. Another approach introduced in the literature involves a data-driven methodology wherein the model’s parameterization is automated through the utilization of programming code [8;17-20]. However, this approach has been used for specific case studies. Indeed, the aforementioned authors proposed tailored approaches in which is not possible to reuse the models for any manufacturing systems. Due to the emerging topic, from the literature a lack of knowledge in this field has been individuated. Although these approaches are widely used, the modular approach proposes the creation through a GUI whereas the Data-Driven approach is used just for specific case studies.

For this reason, the following research proposes an automated simulation model able to recreate any manufacturing system according to data taken as input by leveraging the combination of modular and data-driven approaches. The flexible simulation tool must support industrial planning decisions through the What If scenario and KPIs analysis. The remainder of the paper is structured as follows. Section 2 introduces the methodology used to achieve the objective. Section 3 describes the automated simulation model. In section 4, the authors introduce the case study and discuss its results and finally, section 5 reports the conclusions of the work by pointing out limitations and future research.

2. Methodology

In this section, the authors introduce the methodology employed to develop a flexible and resilient simulation model able to adapt according to real system changes. Figure 1 depicts the methodology's sequential steps, whose detailed description is reported below.

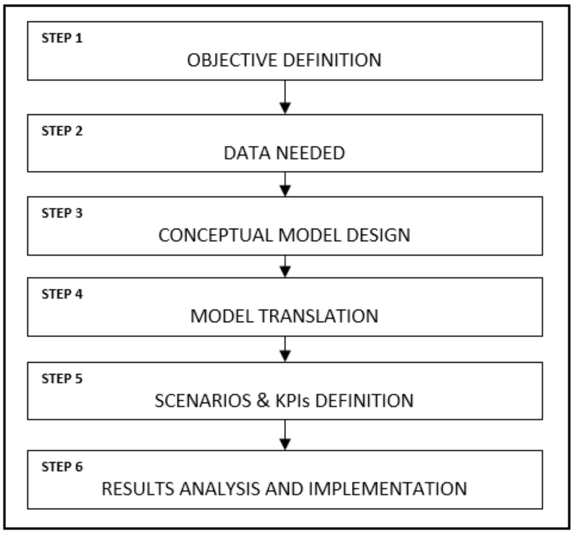

Fig 1: Methodological steps

Objective Definition

The first step of the methodology concerns the definition of the objectives that the simulation tool must achieve. As previously mentioned, the aim of this research work is twofold: to create a simulation model that supports production planning and, crucially, to develop a flexible and resilient simulation model that can autonomously adjust itself to dynamic input datasets. Hence, the simulation model replicates a standard manufacturing system and assists in making decisions using What If analysis, which is determined by the user during the initial setup.

Data definition

Once the initial step is accomplished, the second step regards the definition of the simulation model input dataset. This phase holds significant importance within the methodology, as the model's adaptability heavily relies on the data it receives as input. In this context, the authors have delineated three primary categories of data that the simulation model can utilize as input and whose short description is reported below:

Workstation list: this dataset contains all the manufacturing system resources. In this case, a resource is production equipment used to carry out a process (milling machine, welding station, cutter, dryer, etc.). Human and transportation resources are excluded from this list. Each resource has the following information: workstation ID, energy consumption and maintenance information.

Orders list: this dataset includes all the information concerning the manufacturing system production orders such as order ID, product type, order quantity, scheduled start date and promising end date.

Bill Of Processes (BOP): this data set includes for each product type the list of processes needed to realize it. Each process is associated with a set of information, including a unique process ID, its sequence within the production flow, the required processing time, and the corresponding resource.

Conceptual Model

The purpose of this step is to create a conceptual model, the translation of which leads to the development of the simulation model. The conceptualization took place by considering a simple definition of a production system: a production system is a set of resources that work together to fulfill production orders by manufacturing products. In a generalized way, each production resource has a local behavior and manages individual processes, queues, and priorities. So, the generic nature of a production system is given by the generalization of the resources that constitute it.

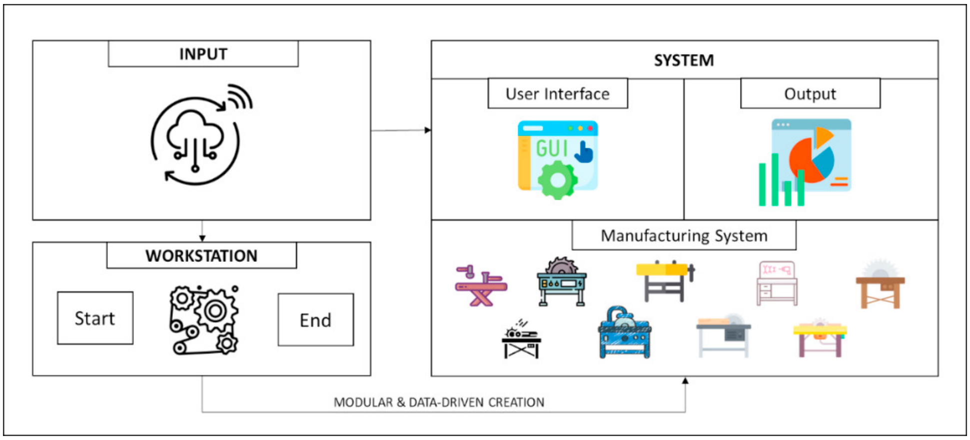

Fig 2: Flexible conceptual model

Starting from this simple definition, by following the literature seen in the previous section, in this step it has been used a combination of the modular and the data-driven approaches. The conceptual model was developed through the creation of 3 modules: Input, Workstation and System (Fig. 2) and its logic can be summarized below.

- The Input module creates a link to the dataset and extracts the list of workstations, the list of production orders, and the BOP of each product. Based on the list of workstations extracted, the combination of data-driven & and modular approaches allows the automatic creation of the simulation model. Indeed, by leveraging the generic "Workstation" module, for each workstation taken from the input list, will be created a resource within the "System" module.
- The Workstation module includes the main logic, on which the conceptual model was developed. Inside there are all the logics that manage the production of a process such as the management of queued processes, start and end of production, and the modeling of the transport of the semi-finished product in the buffer of another resource.
- The System module, in addition to containing all the resources created, manages the initial phase of production. According to the order list, it triggers the production process and contains all the production information. In addition, it manages the configuration of the initial scenario and all the KPIs useful in the planning and decision-making process.

Model translation

The objective of this step is the translation of the conceptual model into the simulation model. In this phase, downstream of the choice of the development environment, the modeling of all the logic conceived in the conceptual model takes place. The model translation is combined with the development of an automated simulation model whose description will be detailed in paragraph 3.

Configuration and KPIs definition

The objective of this step is to define the production scenarios that impact the performance of the manufacturing system under study. Based on the case study, it is also necessary to define the KPIs to be analyzed during the simulation runs. These outputs will be used to analyze the best configurations and therefore the best strategies that allow to improve the performance of the real physical system under observation.

Results Analysis and Implementation

Downstream of the different simulation runs, based on different production scenarios, the last methodological step concerns the analysis of the results. Based on the KPIs chosen in the previous step, different scenarios are evaluated supporting the user in planning decisions.

3. Automated Simulation Model

This section introduces the automated simulation model. As previously mentioned, the research aims to develop an adaptable simulation model capable of representing a generic production system and assessing its performance. To attain this objective, an advanced modeling approach has been employed, drawing upon both object-oriented programming and a fusion of the two methodologies found in the existing literature: the modular and data-driven approaches. The subsequent subsection will elaborate on the model's simulation development in detail (see section 3.1). Following that, in section 3.2, the operational mechanics of the model will be outlined, encompassing data input that the simulation model feeds and a user interface that facilitates the configuration of production scenarios (see section 3.3). Lastly, in section 3.4, the simulation's outputs, integral for evaluating and analyzing production system performance, will be elucidated.

3.1. Model development

The development of the simulation model starts with the choice of the simulation software. For this purpose, based on the conceptual model complexity it has been chosen Tecnomatix Plant Simulation [21], a Discrete Event Simulation (DES) software developed by Siemens (further information on Plant Simulation can be found at www.sw.siemens.com).

The flexibility that the authors aim to achieve, requires an advanced modeling approach based on object-oriented programming and the combination of modular and data-driven approaches. Indeed, the simulation model was not constructed using the usual method of dragging and dropping objects from a default library. Instead, it was crafted by generating classes of objects that mirror the logic from the conceptual model. The use of Simtalk 2.0, a specific programming language integrated into Plant Simulation, not only facilitated more complex modeling but also guaranteed an automatic model generation when the simulation began. Furthermore, this modeling approach ensures the utilization of a rapid simulation tool capable of swiftly assessing numerous scenarios. Following the conceptual model, this phase involved the modeling of three classes of objects: Input, Workstation, and System.

The Input class connects the external environment to the simulation model. At each start, it extracts data from the dataset (Orders list, Workstation list, and BOP). Based on the list of resources, through a modular approach, it creates instances of objects of the Workstation class generating the overall production system. For each instance of this class is assigned the name of the workstation taken as input. The Workstation class models the logic of a resource. It simulates processes, manages priorities, and communicates with other objects in the same family. The communication and exchange of processes and information with other "workstation objects" permits modular modeling of the production system. The set of objects created allows to model the behavior of the entire production system by adding the local behaviors of each resource that is part of it. The system class has several functions. In addition to containing the system generated in the initial phase (workstation objects), it manages the user interface, calculates output and KPIs, and initializes production orders based on the production start date of the order. Figure 3 depicts an extract of the System class.

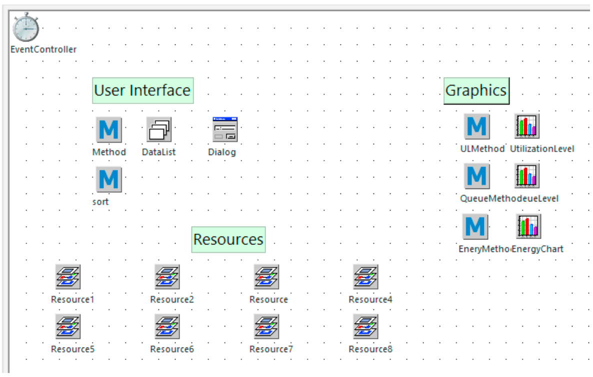

Fig 3: System class extract

3.2. Data input

The simulation model takes all required data from the external environment. The novelty of this work is that by changing external data the simulation model will automatically change. For this purpose, an Excel file (configuration.xlsx) containing the following sheets has been used:

- Workstation sheet: it represents the list of resources that make up the production system. For each resource, the following information is reported:
  - ID name: it is used to identify the resources. The same ID is also present in the BOP information (described below).
  - Mean Time To Repair (MTTR): it denotes the time needed to repair the resource.
  - Mean Time Between Failure (MTBF): it indicates the time between two failures.
  - Date: it represents the latest maintenance date. Along with MTTR and MTBF information, it identifies the next maintenance operation.
  - Energy Working: it is the electric power of a resource when it works.
  - Energy Waiting: it is the electric power when the resource does not work.
- Orders sheet: It contains the list of the orders ongoing and planned in the production system. For each order, there are the following information:
  - Order ID: it identifies the specific production order during the simulation.
  - Product Type: it is used to identify the list of processes (BOP described below) needed to realize the order.
  - Start Date: it represents the scheduled start production date.
  - Due Date: it denotes the end date scheduled by the planner. It is used to calculate the order tardiness and to assign the priority rule when the scheduling rule chosen at the beginning of the simulation is "Duedate".
- Bill of Process: it contains the list of processes needed to realize a specific product type. For each product type, there is the following information:
  - ID task: it identifies a unique process of the product type. Along with the Next Task (see below) it denotes the successor processes.
  - Next task: it is used to identify the next process through an ID task.
  - Processing time: it represents the time that the resource will take to realize the process. Although for each process there is a single time, during the simulation the process is distributed according to a uniform distribution.
  - Machine: it indicates the resource that performs the process. It has the same ID name present in the Workstation sheet (see above).

3.3. User Interface: Initial configuration setting

The simulation model has a user interface through which the production configuration is set. As the scenario changes, the results also change, and the user can simulate different configurations to understand the best strategy to adopt based on the input data. As shown in Fig. 4, the user interface has a window consisting of several sections.

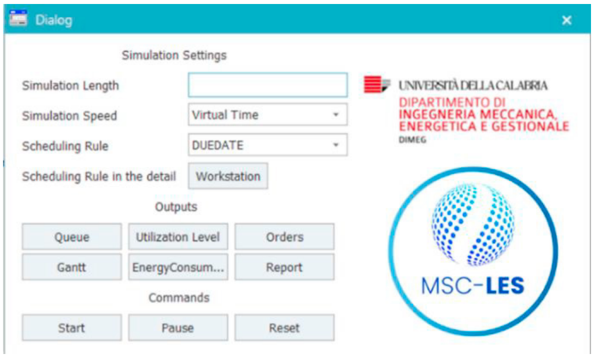

Fig 4: User Interface

On the top left, there are the simulation settings in which the user can enter the following:

- Simulation Length: it expresses the simulation days on which to perform the analysis.
- Simulation Speed: it is possible to set the simulation speed (Real, Fast, and Virtual). By using “Real” the simulation time is equal to the real-time (time in the simulation progresses as in reality). This configuration is useful when a specific aspect of the simulation needs to be understood in detail. With "Fast" the tool simulates 1 hour of production in one second. This setting allows you to focus on a precise moment of the simulation and focus on the trend of production over time. Through “Virtual” the simulator quickly launches the simulation and returns the results in a few seconds.
- Scheduling Rule: through this function, it is possible to assign a priority rule to all the resources that the tool takes as input. These rules are used in production planning to improve the efficiency of production plans and optimize resource allocation. The tool has several load rules: First In First Out (FIFO), Last In First Out (LIFO), Earliest Due Date (EDD), Shortest Processing Time (SPT), Longest Processing Time (LPT), Number In the Next Queue (NINQ), Workload In the Next Queue (WINQ) and Last WorkLoad Remaining (LWKR) [22].
- Scheduling rule in detail: by using this setting, it is possible to set a different scheduling rule for a specific resource (by using the “Scheduling Rule” will set the same scheduling rules for each resource whereas by using this setting it is possible to enter a different scheduling rule for each resource taken as input).

The central side of the user interface all the output of the simulation. These are described in detail in section 3.4. Finally, on the bottom left side, there are the general commands of the simulation: Start, Pause, and Reset.

3.4. Output

In this subsection, the authors present the outputs of the simulation tool used to analyze the production scenario configured at an early stage (see 3.3). During the simulation, it is possible to view graphs, tables, and indices that show the progress of production supporting the user in decisions. Here below all the outputs are introduced in detail.

Utilization Level

The following graph (Fig. 5) shows the utilization percentage of each resource taken as input, during the simulation run. It permits the user to understand the saturation levels of the plant allowing the identification of possible inefficiency of the production system. In Fig. 5, the green part is the percentage of resource usage, in red the percentage of set-up and in blue the percentage in which the resource is waiting. For instance, it is possible to observe that “Resource 6” and “Resource 7” have a higher saturation level for the simulated scenario. That could suggest a better allocation of resources to optimize production.

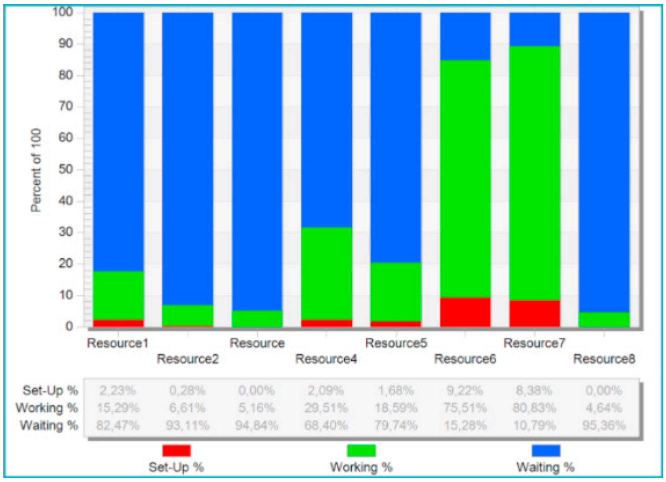

Fig 5: Utilization Level graph

Queue Level

Figure 6 illustrates the queue levels, representing the number of processes awaiting execution on each resource. This number helps the user to understand the bottlenecks of the production line. The red rectangle shows the "Real Time" queues that occur while the simulation is running. It is useful for understanding the queues in the system from time to time as it provides graphical information throughout the simulation. The rectangle in green shows the peaks of queued processes. It can be useful to size the resource buffer. The one in blue gives information on the average of the jobs in the queue allowing to understand the mean occupancy level of the buffer during the time. Comparing the following graph with the previous one (Fig. 5), although “Resource 7” is heavily used, by observing the levels of the queues it is possible to establish that it does not represent a bottleneck unlike “Resource 6” which is also the bottleneck of the system.

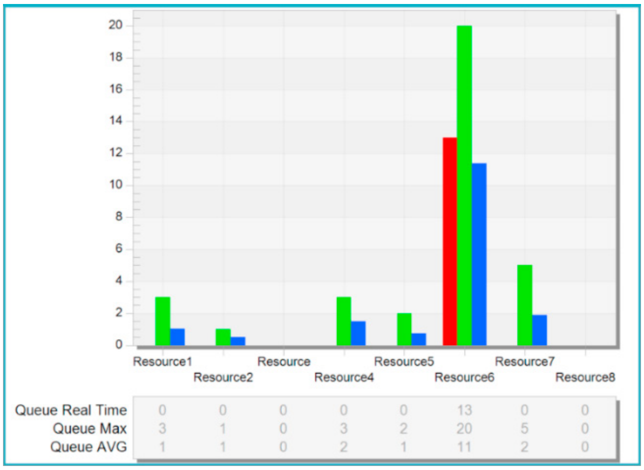

Fig 6: Queue level graph

Gantt diagram

The Gantt diagram (Fig. 7) shows the timeline of production over time. This diagram allows the user to have an overview of the entire production timing. As shown in Figure 7, on each line, there is an input resource in which the processes carried out are displayed. Each color expresses a process and approaching with the mouse it is possible to see the process ID, the start and end date. Also in this case, for the simulated scenario, it is possible to note that "Resource 6" and "Resource 7" elaborate many processes.

Fig 7: Gantt diagram

Energy consumption graph

This output (Fig. 8) represents the electrical energy consumed (expressed in kWh) during the simulation span used to realize the production taken as input. It can be useful to understand the impact of the energy wait consumption (when the resources don't work) on production. Indeed, by optimizing production planning, it is possible to allocate resources more efficiently, resulting in reduced energy consumption during waiting periods. In Figure 8 the green rectangle represents the consumption of the machine when it works whereas, the one in red displays the consumption of the machine when it is waiting. By watching this graph, it is possible to note that some resource has an energy wait consumption higher than the energy working consumption. This might suggest shutting down the machines during certain shifts.

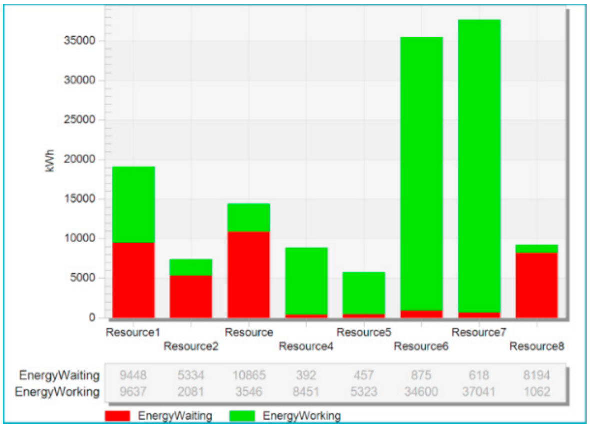

Fig 8: Energy consumption graph

Production simulation

The following output is a dynamic and nested table in which the data of production orders are continuously updated during the simulation run. Each row, which represents an order, contains in the columns the following information:

- Order ID: it identifies the order.
- Product type: it represents the type of product.
- Start date: it is the date when the production starts.
- End date: it represents the date when the last process order ends.
- State: it can be "Ongoing" or "Completed" and represents the status of the order.

- Due date: it is the date assigned by the planner taken from the Excel file (Configuration.xlsx)
- Flow time: it is the difference between the end date and the start date.
- Tardiness: if the end date is greater than the due date, it is due by the end date minus the due date else is equal to zero.
- Bill Of Process: it is a nested table in which there is the production order in detail. This table includes information on all processes needed to realize the order. Each row represents a single process. Each process has the following information: Start date, end date, state, duration, resource, and time in the queue.

This output helps the user to analyze the production in detail for each single process allowing him to understand the production as a whole.

ProductionList

The production list is a table that includes the record of the processes carried out (or to carry out) on each resource. Each row in the table corresponds to an individual process, providing information such as the start date, end date, duration, and time spent in the queue.

This output can be useful for the planner to assign the task order. Indeed, by simulating different scenarios the tool can find a good production list able to optimize the resource allocation.

Final report

This output, generated at the end of the simulation, corresponds to a report showing the following KPIs:

- Average (AVG) Flowtime: it represents the mean flowtime.
- Average (AVG) Tardiness: it is the average tardiness.
- Orders late: it denotes the number of orders that end after its scheduled due date.

4. Case Study

The purpose of this section is to showcase how the proposed automated simulation model can be employed in a real-world case study. The case study regards a manufacturing system producing turbine components. The entire simulation model can be generated simply by modifying data in the Excel file, greatly reducing the modeling effort. Furthermore, the subsequent section will emphasize the utility of this tool in analyzing various production scenarios. The manufacturing system operates with 15 production resources working continuously across three shifts from Monday to Friday and two shifts on Saturdays. The production plant produces three distinct turbine components destined for the energy technology market. Currently, there is a production plan in place for 12 orders. The company's primary goal is to assess various scenarios aimed at enhancing overall performance. To achieve this objective, different scenarios have been simulated, taking into consideration KPIs such as Flowtime and Tardiness (see section 4.1). Downstream the experimentation, customized graphs will be presented in section 4.2 to highlight the high flexibility of the simulation model based on data input.

4.1. Experimentation and discussion

In this section, five scenarios (5 different scheduling rules) are simulated and analyzed to find an optimized production strategy. For each scenario, the authors conducted 10 simulation runs to mitigate the impact of errors. These multiple runs were necessary due to the stochastic nature of the simulation, which inherently introduces variability. Specifically, this variability is a result of process times being subject to a uniform distribution with a range of +/- 10%.

For each production scenario, minimum, maximum, and average values have been found. Moreover, a value range through the t-student (95% confidence level) has been identified. Downstream this step, each scenario has been evaluated by comparing it with the FIFO strategy which is the current approach used by the company. The first scenario under evaluation is the FIFO strategy, which is presently employed by the company. The second scenario is EDD, according to which the process that has the most imminent expiration date is processed. The third scenario analyzed is SPT, according to which priority is given to the job that has the least processing time. The fourth scenario is LPT, according to which the job with a longer processing time has more priority. Finally, the LWKR scenario according to which among multiple processes in the queue, the process with the shortest remaining processing time (the time left to complete the entire product) is given the highest priority.

Table 1: Flowtime results

Scenario	MIN [day]	MAX [day]	AVG [day]	Confidence Interval 95 % [day]
FIFO	149,45	156,03	152,57	151,39 / 153,75
EDD	147,95	153,61	151,17	149,74 / 152,62
SPT	145,35	147,73	146,36	145,74 / 146,97
LPT	162,53	173,51	169,04	166,41 / 171,67
LWKR	136,94	142,80	138,23	136,96 / 139,49

Table 2: Tardiness results

Scenario	MIN [day]	MAX [day]	AVG [day]	Confidence Interval 95 % [day]
FIFO	48,90	55,20	51,66	50,54 / 52,79
EDD	41,78	45,79	43,90	42,86 / 44,95
SPT	48,46	49,87	49,16	48,78 / 49,55
LPT	55,04	65,21	61,07	58,60 / 63,54
LWKR	38,41	46,11	40,07	38,47 / 41,66

Beginning with the findings presented in Table 1 and Table 2, which respectively showcase the FlowTime and Tardiness values for various scenarios, this discussion delves into an analysis of the least favorable configuration (LPT) and the most favorable one (LWKR) compared to the current load rule employed in the productive system (FIFO).

The LPT scenario, which prioritizes the job with the longest processing time, proves to be the least effective configuration in this specific case study. In fact, all KPIs exhibit poorer results compared to the alternative scenarios. On the other hand, the LWKR scenario, where the job with the shortest remaining processing time is processed, emerges as the optimal configuration among the five simulated scenarios.

It’s important to observe that some confidence intervals (reported in the last column of the tables) do not overlap. This illustrates how different loading rules can optimize industrial production within the analyzed production system. It's worth mentioning that the current configuration utilized on the production line is the simplest to implement. This simplicity arises from the ease of managing a buffer using a FIFO approach. However, it becomes significantly more complex when employing a rule that necessitates calculating the processing time for each operation based on the complement of the entire product (LWKR). All of this underscores the relevance of adopting the simulation tool developed in this research within real production scenarios. The simulation's ability to project the entire production process into the future enables more informed decision-making.

4.2. Current configuration outputs

In this section, the authors aim to demonstrate the simulation model's capacity as a decision-support tool by presenting simulation outputs pertaining to the FIFO scenario, which represent the current strategy employed within the manufacturing system.

Fig. 9 shows the utilization levels of each plant resource.

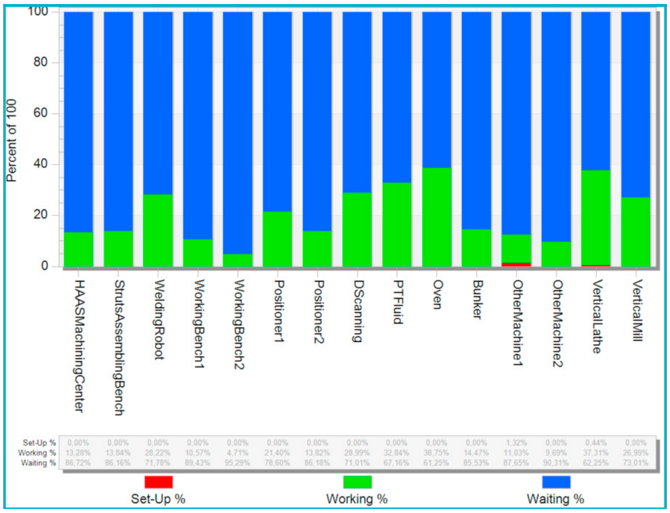

Fig 9: Case study utilization level

Similarly, Fig. 10 shows the levels of processes that occur during the production process.

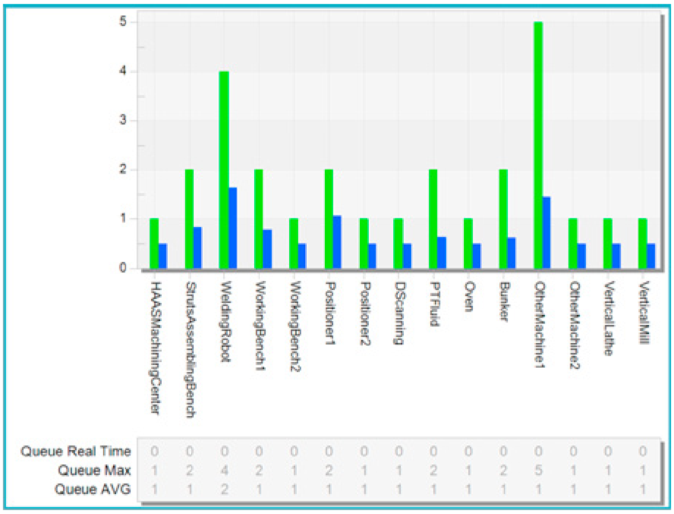

Fig 10: Case study queue level

In Fig. 11 the energy consumption of resources is shown. Consumption depends on both the level of usage and the hourly consumption of the resource.

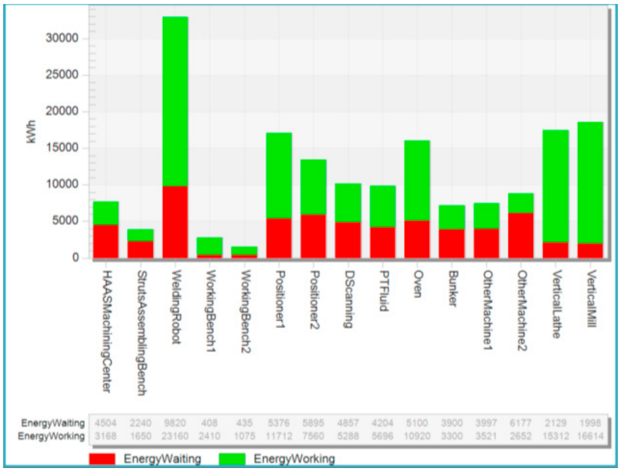

Fig 11: Case study energy consumption

The Gantt chart shown in Fig. 12 shows how each resource works during the simulation.

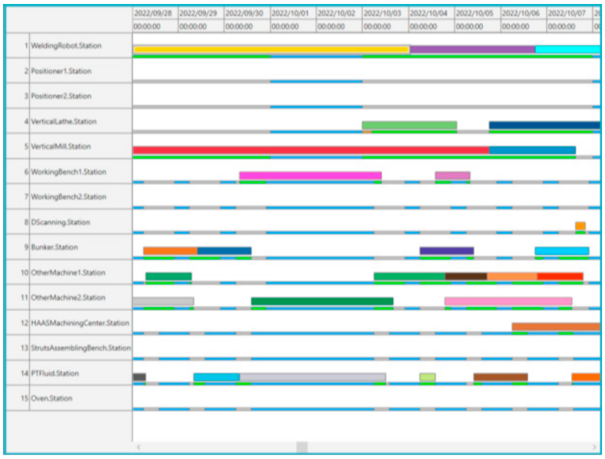

Fig 12: Case study Gantt diagram

5. Conclusion

In the era of Industry 4.0, production systems become increasingly changeable as the market changes. Production systems are forced to adapt quickly by changing products, production resources, line configurations, and strategy. In this context, simulation models that support industrial production face major challenges. The continuous change of the real system causes interruptions and malfunctions and consequently repeated maintenance by experts. The objective of this study was to develop a simulation model that is flexible and resilient to the changes in the real counterpart. To this end, an automated simulation model has been developed that regenerates the production system at each start based on the updated data it takes as input. The results show that the simulation model can change the configuration of the production system at each run and analyze different production scenarios supporting industrial planning decisions.

Although the results are considerable and show an important contribution to the sector, there are some limitations to consider. The first limitation concerns the non-real-time data to which the model is powered. Although modeling is automatic, it involves manual data entry on the Excel file that must respect a specific data structure. Another limitation is that the model does not start from an AS-IS situation of the plant. In fact, at each run the production starts "from scratch" without considering possible processing on the line.

The limitations identified open the way for future research. The idea is to create a Digital Twin, constantly connected to a real system and able to change automatically according to the changes that occur in the system. In addition, a second research idea is to generalize the concept of the product by increasing the flexibility and scope of the Digital Twin. Another possible research line is adding a Genetics Algorithm (GA) flexible logic to rapidly find a good scheduling rule for each resource able to enhance industrial performance while maintaining the tool flexibility. The flexibility achieved also opens the possibility of creating an online simulation as a service for SMEs.

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