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IMPROVING THE PERFORMANCE OF MANUFACTURING SYSTEMS BY MODELING WITH SPECIFIC ELEMENTS FROM SIMPY LIBRARY

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Abstract: *Modern industry requires continuous improvement of manufacturing processes to increase efficiency and reduce costs. Modeling and simulation of manufacturing systems is an essential method for performance analysis and workflow optimization. This paper explores the use of Python's SimPy library for the simulation of manufacturing processes, with applicability to the machining of casting parts. Different production scenarios are analyzed, highlighting the impact of operational parameters on processing times and resource utilization. The results obtained allow the identification of critical points in the system and the proposal of optimization solutions, demonstrating the advantages of using SimPy for the analysis and improvement of industrial processes.*

Keywords: *Discrete event simulation, SimPy, production optimization, resource management, intelligent manufacturing, Python.*

1. INTRODUCTION

Today's modern industry requires the improvement of manufacturing processes to be a decisive factor in the context of competitiveness, efficiency and cost reduction. Modeling and simulation of manufacturing systems is a very useful tool in evaluating and improving the performance of a production system, facilitating a detailed understanding of the flows, the resources required and the linkages between the various elements of the system. There are numerous tools available for modeling and simulation. One of these is the SimPy library in the Python programming language. It has become an increasingly popular choice among researchers and experts due to its efficiency and flexibility.

This paper deals with the use of SimPy tool in the modeling and simulation of a production system with the objective of improving the manufacturing system performance. Considering a case study in the field of castings machining, we will build different models of the production system, and we will simulate different versions of the manufacturing system highlighting the impact of these on the machining times. The aim of this paper is to show the efficiency of the SimPy library in simulating a production system and to provide recommendations for improving its efficiency.

This paper will also discuss the advantages and limitations of the Simpy library. Different simulation methods are analyzed in comparison

When studying the performance of manufacturing systems, it is important that the model created faithfully reflects the sequence of events. Simply is a Python library used to model and simulate discrete event-based processes by defining them as Python functions. Thus, queues and production systems can be simulated. The simplicity in use, the integration into Python language, the open-source character make this tool very attractive for specialists and researchers. [1] Systems from different domains can be modeled and simulated, ranging from production systems to healthcare systems. Its efficient event handling mechanism minimizes the resources needed to simulate complex models. Simply allows the parallel execution of multiple processes, making it a useful means of managing complex systems with multiple components.

Simulation provides a virtual environment where complex production scenarios can be replicated, tested, and optimized without interrupting the actual manufacturing processes. It enables decision-makers to identify inefficiencies, forecast outcomes under various configurations, and evaluate the impact of potential improvements. This approach is especially valuable in industries where downtime is costly and operational flexibility is limited.

2. METHODS AND TECHNIQUES USED IN THE SIMULATION OF PRODUCTION SYSTEMS

Modeling and simulation of manufacturing systems is an area of interest due to its ability to provide methods and means to improve decision making and to increase the efficiency of manufacturing system performance. Among the most widely used simulation methods are Discrete Event Simulation (DES), based on the fact that manufacturing processes are represented as a sequence of events occurring over a time interval. Using this method, manufacturing process parameters such as processing times, resource utilization and waiting times can be highlighted.

In the literature, there are several models and techniques that are used to simulate manufacturing systems. Among these, the most common are Petri net-based models, simulations with agents, and queueing network models. For example, queueing models have been used extensively to analyze the performance of production lines and industrial equipment. They allow to evaluate efficiency and identify possible bottlenecks in production processes. The simulations with agents [2] are used to model the individual behavior of each individual element, especially for scenarios with interactions between elements.

Discrete event-based simulation remains one of the most widely used techniques due to the accuracy with which complex systems can be modeled.

The paper [4] proposes a generic open-source framework for 3D visualization of Digital Twins (DT) of manufacturing systems based on discrete event simulations (DES), such as SimPy.

2.1. Using SimPy to simulate manufacturing systems

Simpy is a Python library specifically for discrete event simulation, which has been increasingly used due to its ability to model different systems and its compatibility with other Pyhton libraries. Compared to other simulation platforms such as AnyLogic or Simul8, SimPy is a more customizable solution due to its open-source nature.

For example, a study [3] demonstrated the application of SimPy for modeling a production system in a car factory, showing how it can be used to evaluate waiting time and equipment utilization. They emphasized the advantages of SimPy in creating a flexible and easily adaptable model that can be quickly extended to simulate new scenarios.

Compared to other commercial platforms, SimPy better integrates with Python programming language libraries such as NumPy and Pandas. In addition, SimPy allows the development of highly customized and scalable simulations that can be adapted for a wide range of industrial applications.

In the literature, several advantages of using SimPy over other simulation platforms have been highlighted with such as the flexibility in defining models. SimPy also provides an intuitive syntax for creating processes and events. It is ideal for researchers who want to create complex models.

Another advantage is low cost: Being open-source, SimPy does not require additional licensing costs, which makes it affordable for small organizations or academic researchers. SimPy is easy to integrate with other Python libraries, which makes it possible to process data, generate graphs, and analyze data in a more advanced way.

However, SimPy also has some limitations, such as lower performance compared to commercial platforms for very complex simulations or simulations with a large number of entities. For many industrial process simulation applications, these limitations are minimal compared to the advantages it offers.

Furthermore, this study compares different manufacturing scenarios by varying resource availability and processing conditions, offering a comprehensive analysis of how discrete-event simulation supports strategic decision-making in production environments. The inclusion of stochastic processing times, variable workflows, and shared resources aims to replicate real-world challenges and demonstrate how simulation can be used to mitigate them.

3. MODELING THE MANUFACTURING PROCESS OF CASTING PARTS

In the automotive manufacturing industry, a common process is the production of parts by die casting of an aluminium alloy. After casting, the parts are subjected to specific operations, depending on the requirements and particularities of each product. This approach is characteristic of companies specializing in this type of manufacturing. Although the manufacturing process follows a general structure, each product has its own particularities, reflected in the specific processing stages.

Next, the manufacturing structure of the products obtained by this method was presented, starting with the pressure casting process.

The manufacturing process of aluminum alloy castings includes several specific stages, each of which has the role of ensuring the final quality of the product.[5] Depending on the complexity and requirements of the part, some stages can be omitted or adapted. The first stage in the manufacturing process is casting (pressure casting). This process consists of injecting the molten aluminum alloy into a mold, under high pressure.[6] This process allows for the production of parts with complex geometries and reduced tolerances. After casting, Trimming is performed (removal of networks and cutting of burrs), where the excess material resulting from the casting process is removed by mechanical cutting. [7] This is an essential stage for eliminating unwanted edges and preparing the part for subsequent stages. For additional surface finishing, several operations can be chosen, such as: Automatic grinding and manual shotblasting. Automatic grinding helps remove imperfections, and manual sandblasting provides a uniform texture and improves the adhesion of surface treatments.

A complex operation in terms of the process itself and the resources required is machining, where parts are processed through operations such as milling, drilling or threading, to obtain precise dimensions and strict tolerances. [8] This stage is essential for parts that require fine adjustments before use. After the machining operation, deburring operations can be opted for. [9] Deburring process, an operation necessary to eliminate material residues and ensure smooth edges, thus avoiding defects or problems during assembly.

Next, the parts are subjected to a washing stage, which removes oils, dust and other impurities resulting from previous processing. [10] Cleanliness is especially essential for parts that will be subjected to rigorous tests. To verify tightness and the absence of internal defects, a Leakage test is performed. [11] This is a critical test for components that must withstand high pressures or prevent leakage of liquids and gases.

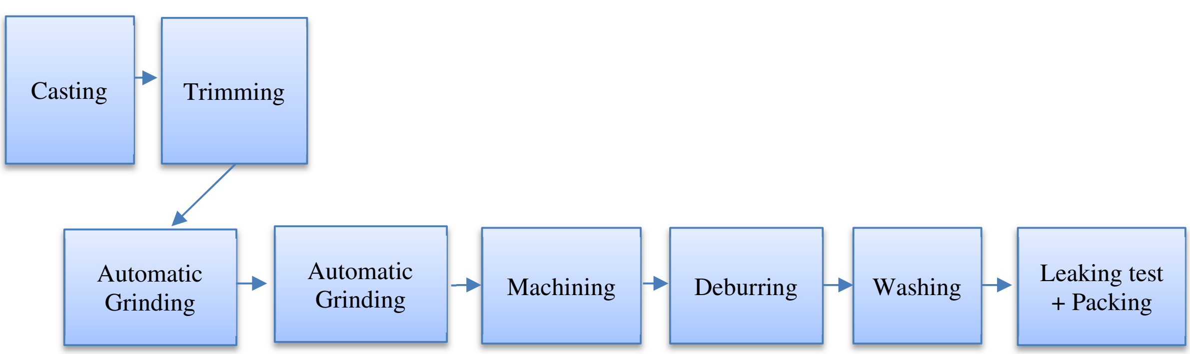

Fig. 1. Manufacturing processes for casting parts

A final step in the entire manufacturing process is packaging, which ensures the protection of the parts during transportation and storage. [12] Depending on the customer's specifications, packaging may include special methods to prevent damage or contamination.

It is important to note that after each stage of the manufacturing process, the product undergoes rigorous inspections to ensure compliance with quality standards. These checks include visual inspection, dimensional measurements, and specific tests, depending on the product requirements specific to each phase of the process. [13] The quality assurance process is integrated into the production flow so that it does not affect the pace of manufacturing but contributes to maintaining a constant level of product performance and reliability.

3.1. Implementing simulation with SimPy

To achieve the manufacturing process model, the Python programming language was used using the SimPy library. This is a tool that allows the creation of discrete event-based models. The simulation of the workflow in a manufacturing system, which includes resource analysis, is recommended to be realistic with this model time.

The model highlights the shared access to the resources of the production system for the three types of parts analyzed. Initially, model configuration parameters are defined such as the number of resources available for each workstation, for example the number of machines available for CNC machining.

The size of the manufacturing batch required to be made, the total time for which the simulation runs and the average processing time for each workstation are defined. Table 1 shows all these input variables numerically, for each operation

Not all the parts follow the same technology.

Table 1

Manufacturing process times

Manufacturing process	**Manufacturing process times [sec]**						
	Part 1	**Part 2**	**Part 3**	**Part 4**	**Part 5**	**Part 6**	**Part 7**
CASTING	50	50	75	55	50	70	65
TRIMMING	50	60	50	50	50	60	50
AUTOMATIC GRINDIND	30	25	25	25	25	120	40
MANUAL SHOTBLASTING	120	x	9	8	8	20	25
MACHINING	105	x	245	265	430	265	215
DEBURRING	x	x	30	60	60	90	25
WASHING	72	5	25	12	20	30	75
LEAKAGE TEST	50	x	21	55	55	30	55

The average manufacturing time is not constant due to various disturbing factors such as equipment wear, raw material quality, human errors. The processing time for each operation is a random time determined as a random variable in the range:

[time – amplitude factor * time , time+amplitude factor*time]

In the manufacturing system flow, there are 7 types of parts that can use common resources. The parts studied in this paper can have different technological paths.

Each machine is defined as a resource with a different working time and having a capacity defined at the beginning of the model.

```
with <process>.request() as req:
    yield req
    yield env.timeout(<process >._time())
    parts_< process >. += 1
```

One part at a given time requests a resource (machine), if it is busy, the part waits in a queue until it has priority over the requested machine.

The main simulation function in the created program defines the environment in which the simulation is performed, the resources are created for each work machine and then the processes that will produce the parts are called.

The duration of the simulation is for a period defined by a numerically established variable in the program. This variable is equal to the program for one week, 3 shifts, 8 hours per day.

The queues are managed implicitly by SimPy. Each resource (simpy.Resource) has a list of entities waiting for access to the resource (resource.queue).

Within the simulation, the queues are monitored and periodically saved in the CSV file for analysis.

The length of the queues is recorded every 500 seconds.

This information helps to identify bottlenecks. If a queue grows excessively, it means that that production step is a bottleneck and needs optimization (e.g. adding an additional workstation).

In addition to waiting queues, it is also important to monitor the utilization of each resource. This is done by calculating the actual usage time for each station. Afterwards, the occupancy rate is calculated. This is saved in the CSV file for further analysis.

A high occupancy rate (above 85%) indicates that the resource is overloaded, while a very low rate (below 50%) shows that the resource is underutilized and could be reduced to save costs.

3.2. Process execution and interaction

The simulation runs multiple processes simultaneously, each corresponding to a part going through the manufacturing stages. These processes are launched in the *run_simulation()* function, where each part is processed independently.

Each part competes for access to resources, and SimPy manages their scheduling based on the availability of workstations.

Monitoring the simulation results is done by writing them to a separate csv format file, thus allowing further analysis of the information. In the monitoring process, the following parameters are highlighted: the size of the queues for each processing operation, the occupancy rate for each resource, and the number of parts in process in each station.

The workflow in figure 2.

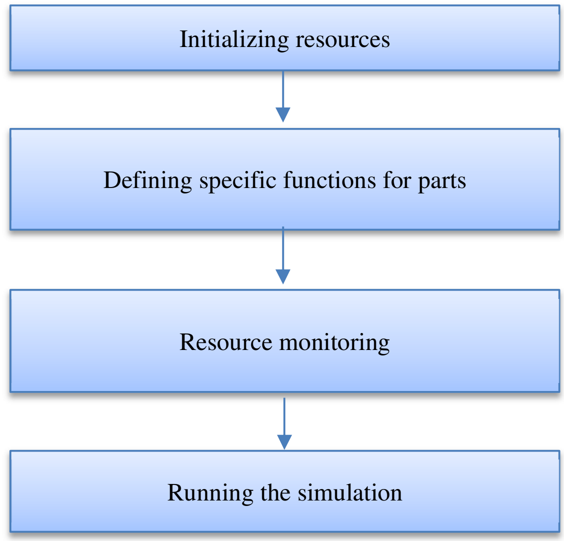

Fig. 2. Steps to create a model with the SimPy library

4. RESULTS AND ANALYSIS

By analyzing the data collected, we can draw important conclusions about the system's performance.

Large queues indicate the need to increase the capacity of a stage. A low occupancy rate suggests the possibility of reducing the number of workstations to save costs. Through simulation, we can test different configurations before implementing real changes.

The fact that we have 7 types of parts with different processing times for each part and the resources shared by the 7 production flows makes the occurrence of bottlenecks inevitable. These can occur due to long execution times, leading to high number of semi-finished products accumulated in queues or due to prioritization of some types of parts in favor of others. Another reason for bottlenecks is the inefficient use of resources if a resource is used too little, with the risk of underutilization. The performance analysis of a manufacturing system is performed by measuring the length of queues, resource occupancy rates, and total processing time.

In the performance analysis of the manufacturing system, several work scenarios are created. It starts with a scenario in which the capacity of each piece of equipment is equal to 1. The equipment capacity scenarios are presented in Table 2.

Table 2

Resource distribution in the case of the six work scenarios

	S 1	S 2	S 3	S 4	S 5	S 6
CASTING	1	1	1	1	1	1
TRIMMING	1	1	1	1	1	1
AUTOMATIC GRINDIND	1	1	1	1	1	1
MANUAL SHOTBLASTING	1	1	1	2	2	2
MACHINING	1	1	1	1	1	1
DEBURRING	1	2	3	3	4	5
WASHING	1	1	1	1	2	2
LEAKAGE TEST	1	1	1	1	1	1
CASTING	1	1	1	1	1	1

A first positive aspect is that the trimming, grinding and deburring process are not experiencing delays, which indicates a balance between demand and capacity. However, there are one problematic points: the CNC machining operation (409 units pending – figure 3). These accumulations indicate either insufficient capacity or longer processing times compared to previous stages.

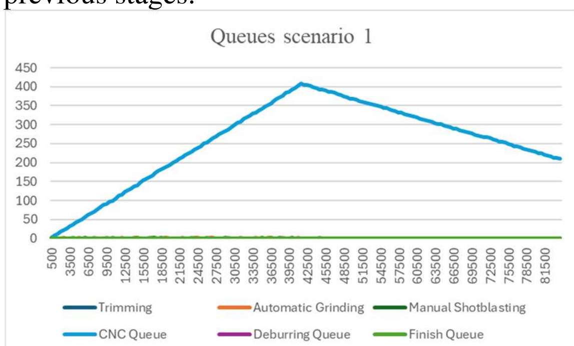

Fig. 3. Waiting time values in scenario 1

To improve process efficiency, specific measures need to be taken. In the case of polishing, one solution could be to increase capacity by using additional equipment or optimizing cycle times. Similarly, for machining, reducing bottlenecks may involve reorganizing production or increasing the resources dedicated to this operation.

Figure 4 shows the resource occupancy rates in modeling scenario 1.

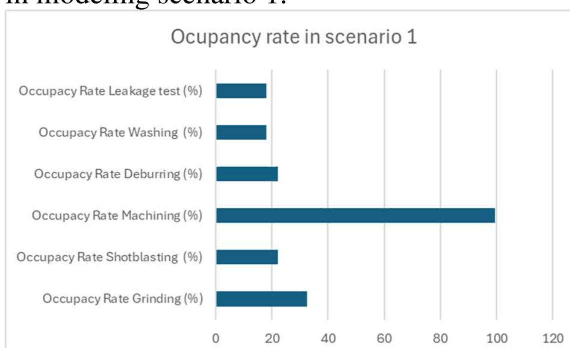

Fig. 4. Occupancy Rate in Scenario 1

The occupancy rate for the CNC machining is 100%, This is the stage with the highest occupancy rate, which indicates either a high demand for this operation or a potential capacity issue (i.e. it may be a bottleneck - a critical point that limits the process flow). Analysis may be required to see if additional equipment or optimizations are needed to avoid delays. The fact that other operations have low occupancy rates, this low utilization may be justified as resources are used occasionally or in small batches.

Table 3

Occupancy rate manufacturing process for each scenario

	Occupancy rates in different work scenarios					
	V1	V2	V3	V4	V5	V6
Automatic grinding	32.41%	43.08%	66.67%	30.68%	40.91%	48.61%
Shotblasting manual	21.99%	29.23%	48.81%	43.18%	56.06%	64.24%
Machining	99.54%	97.69%	98.81%	96.97%	95.83%	88.54%
Deburring	21.99%	31.54%	50%	55.68%	72.73%	83.33%
Washing	17.94%	40%	60.71%	52.27%	32.58%	43.4%
Leakage test+Packing	17.94%	41.54%	58.33%	60.23%	81.82%	82.01%

In this second scenario, where the number of CNC machines has doubled, we observe some interesting changes in occupancy rates. At the CNC operation even though it still has a high occupancy rate, it has decreased slightly, this suggests that the bottleneck problem has been partially alleviated, but the operation remains a critical one. The increase in occupancy for the other operations. indicates that this stage has become more utilized, probably to support the increase in CNC capacity.

Doing a full analysis of the various occupancy rates for the 6 scenarios presented in table 3, initially there was a major bottleneck, but as optimizations were made, the occupancy rate gradually decreased, it is now more balanced, which means that other operations have taken more pressure from the process. The occupancy rate for the Automatic Grinding process, has steadily increased, indicating more efficient capacity utilization. The Manual Shotblasting operation had a significant increase, especially after the third stage, suggesting that this operation is starting to become a constraint in the process. If it exceeds 70-80%, it may require expansion or automation. In the washing process the growth accelerated, which indicates a much more intense production flow, if it exceeds 85-90%, it may become a bottleneck and solutions for capacity expansion should be analyzed. Total production times reflect the impact of additional resources on the efficiency of the production process. A significant reduction in duration is observed as resources are increased. Figure 5 shows the variation in the time required to produce the entire production batch.

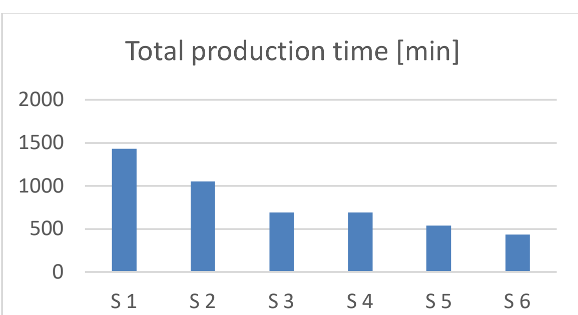

Fig. 5. Total production time

5. CONCLUSION

This research demonstrated the importance of using discrete event-based simulation for the analysis and optimization of manufacturing systems. Through the implementation of the SimPy library, different operational scenarios were evaluated, highlighting the impact of process parameters on the performance of the manufacturing system.

The results of the analysis showed that bottlenecks in production can be identified by monitoring queues and resource occupancy, Resource optimization, such as increasing the capacity of CNC equipment, significantly reducing delays and improving the production flow.

Simulations allow different configurations to be tested before actual implementation, leading to more informed production management decisions.

The use of SimPy provides a flexible and affordable alternative to other commercial platforms and is easily integrated with other Python libraries for advanced analysis.

In conclusion, modeling and simulation with SimPy is a valuable tool for improving industrial processes, facilitating data-driven decision making and optimizing resource utilization. Future studies can explore the extension of this model by integrating artificial intelligence for further optimizations and decision process automation.

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Imbunătățirea performanțelor sistemelor de fabricație prin modelare cu elemente specifice bibliotecii SimPy

Industria modernă necesită îmbunătățirea continuă a proceselor de fabricație pentru a spori eficiența și a reduce costurile. Modelarea și simularea sistemelor de producție reprezintă o metodă esențială pentru analiza performanțelor și optimizarea fluxurilor de lucru. Această lucrare explorează utilizarea bibliotecii SimPy din Python pentru simularea proceselor de fabricație, cu aplicabilitate în prelucrarea pieselor turnate. Sunt analizate diferite scenarii de producție, evidențiindu-se impactul parametrilor operaționali asupra timpilor de procesare și utilizării resurselor. Rezultatele obținute permit identificarea punctelor critice din sistem și propunerea unor soluții de optimizare, demonstrând avantajele utilizării SimPy pentru analiza și îmbunătățirea proceselor industriale.

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