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Modeling and Simulation of a Digital Twin of a Production System for Industry 4.0 with Work-in-Process Synchronization

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Abstract: One of the main problems of modern manufacturing systems is the increasing complexity related to modern Industry 4.0 technologies that are fundamentally changing manufacturing and logistics processes and operations. Industry 4.0 includes, e.g., flexible automation and robotization, which make complex manufacturing systems difficult to analyze. Some modeling and simulation methods are being used to solve industrial problems and can serve as an interface between the production level and management level. The new trend of the Digital Twin, creating simulation models as similar as possible to the real system, and a Digital Twin framework for a manufacturing line from the automotive industry, was considered. Simulation models typically start from the empty state and some warmup time is required to achieve the stable state. The Key Performance Indicators were also analyzed for the stable state. However, there are many stochastic parameters such as machinery failures, human errors, quality issues, etc., that make the real processes differ from simulated processes, and cause the instability of production throughput and changes in the Work in Process. To analyze the Work in Process in the model, initialization of the model with proper production data is required, as the Digital Twin uses data synchronization with the production database. In this paper, the digital model of a human-robot-operated manufacturing system with Work-in-Process data synchronization is analyzed, and the results of the statistical analysis of simulation experiments are presented. The obtained results show high variability of finished production, which is related to system instability due to random failures, especially when the system starts from an empty state. However, an increase in initial Work in Process results in better efficiency and stability for the whole system. The DT simulation of the manufacturing system can be very helpful, as it becomes a repository of knowledge about the real system and enables the analysis of its dynamics. However, for proper functionality, the model should include information about the current WIP state, which enables the start of the simulation with exactly the same number of queues as in the real system. The presented method can also be used in similar enterprises from other industries, especially for those with discrete processes or high WIP variability, and for further synchronization of other DT parameters.

Keywords: DES; digital twin; human factors; Industry 4.0; industrial robots; KPI; OEE; ToC; WIP

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1. Introduction

Currently, manufacturing processes in industry are becoming more and more complex because of global competition and the need for more advanced products. The answer to the growing demand of the global market is the Fourth Industrial Revolution (Industry 4.0, I4.0) [1–6].

The I4.0 concept is under development mainly in the European Union, as it was originally designed as a national initiative for the development of the German economy in 2011 [7]. Differently, in the United States, the terms Smart Manufacturing or Digital Factory are commonly used, and the National Network for Manufacturing Innovation was established [7]. In China, there is an initiative "Made in China 2025" under development, which sets to modernize China's industry, focusing heavily on Intelligent Manufacturing. Similarly, in Japan, a "Society 5.0" plan was proposed for the development of science and technology in a future society based on systems that highly integrate cyberspace and physical space [7].

Large international companies from the manufacturing sector were the ones most involved in the Industrial Revolution, including, at the forefront, the mechanical, automotive, and electrotechnical industries [8]. There is also an increasing number of publications related to Industry 4.0 and Logistic 4.0 in Small and Medium Enterprises (SME), which constitute a great part of the economy of the European Union [9].

The main goal of this work is to develop a framework for developing a simulation model as close to real production processes as possible, including the changes of the WIP and building a framework of a Digital Twin. We have analyzed some manufacturing lines for assembling and welding automotive components. Typically, the workspace consists of some robotic welding stations and some manually operated workstations, therefore, human and robot factors should both be taken into consideration. In addition, there is a significant equipment failure rate and variable quality rate, which are related to irregular changes in the WIP [10,11]. Human labor especially is very stochastic, and therefore the results of simulation experiments often deviate from the production plans, and the actual production volume may also differ. At a later stage, the model may be developed further, along with the subsequent phases of the production system life cycle, and refined to obtain a Digital Twin. Integration, including the exchange architecture, simulation creation, performance optimization, and predictive analysis of the production process conditions combine in order to obtain high flexibility of the production system [12].

This article considers the framework model of a Digital Twin for an automotive production line. The next chapters include a literature review and description of the simulation methods used to model Digital Twins and a description of the problem under consideration with an example case study. Subsequent chapters contain the results of simulation experiments for various scenarios and a discussion of the WIP results as well as final conclusions.

The Literature Review

Industry 4.0 is based on cyber-physical system technologies and includes many digital technologies such as augmented reality, virtual reality, cyber-physical infrastructure, cloud computing, Internet of Things, artificial intelligence, big data analytics, additive manufacturing, smart sensors, autonomous robots and systems, and mobile technologies.

The main areas of implementation of I4.0 technologies are production resources, transport, and storage systems [1–8]. Accordingly, an increasing use of automation and robotization can be observed, which is replacing human work. Industrial robots have a mobility similar to the human arm and, like humans, can perform a variety of complex tasks. In addition, they do not experience exhaustion or boredom and can work in harmful conditions. That is why, nowadays, more and more robots work in industry, especially performing repetitive and very precise tasks (e.g., welding) or monotonous activities requiring physical effort (e.g., machine handling, palletization, etc.) [13–16]. In addition, production and logistics processes are becoming more complex and more difficult to analyze due to many technical and organizational limitations, which determine the different performances of workstations and the formation of so-called bottlenecks during the production flow [17]. Industry 4.0 depends on the digital integration of technical and network aspects of manufacturing systems [18].

One part of Industry 4.0 is computer modeling and simulation, which are involved in managing the increasing complexity of manufacturing systems and can act as an integrator of solutions obtained in the process of improving existing or newly designed subsystems [19,20].

From the system designer's point of view, the simulation of the cyber-physical approach (digital objects, with their structure, connections, and existing meta-information and semantics) is the next step in the development and systematic approach to the design of multi-level systems. (Figure 1).

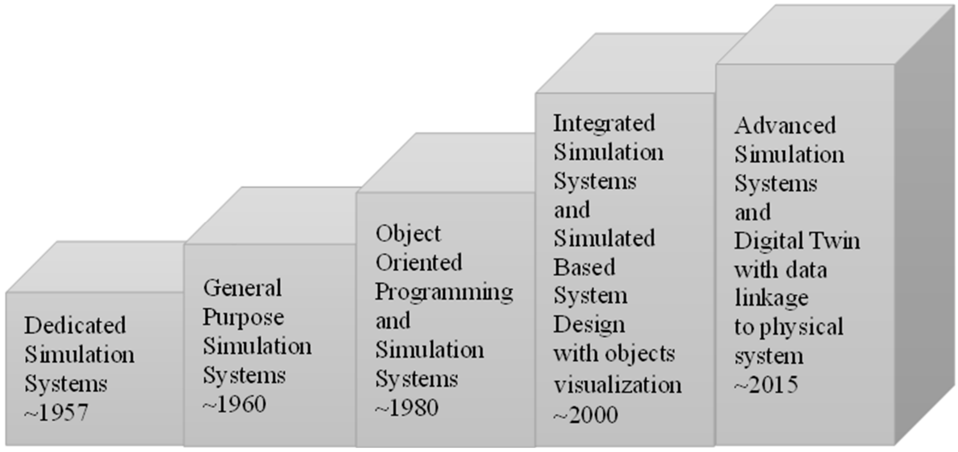

Figure 1. Development of simulation applications.

The Theory of Constraints (TOC) is a management paradigm that views any manageable system as being limited in achieving more of its goals by several constraints. The TOC gives a methodology for identifying the most important limiting factor (i.e., equipment, people, policy) that stands in the way of achieving a goal and then systematically improving the aforementioned constraint until it is no longer the limiting factor. The improvement of the manufacturing process and removal of one constraint is often referred to as shifting the bottleneck [21,22].

Tests on real production systems are usually not possible due to production being in process and the high costs associated with each delay. Mathematical analysis of complex production processes is also difficult due to the large number of interrelated parameters. Therefore, computer simulation methods are often used, i.e., the simulation of discrete events (DES—Discrete Event Simulation), which is utilized in many programs for the analysis of discrete production processes, such as Arena, Enterprise Dynamics, FlexSim, Plant Simulation, and others [23–25].

To evaluate the performance of a production system various Key Performance Indicators (KPIs) can be used [26,27]. There are financial KPIs, customer-focused KPIs, and process-focused KPIs that aim to measure and monitor operational performance across the organization. The most popular KPIs used in manufacturing include production throughput, utilization rate, number of finished and unfinished products, Work in Process (WIP), quality rate, availability, performance, etc. [28].

The term WIP is broadly used in production and supply chain management and means partially finished goods waiting for completion [29]. There is also the similar term of Work in Progress, used in a slightly broader sense and meaning the value of those unfinished goods, which is used in accounting and financial management or project management [30]. On the other hand, the Work-in-Process inventory is one of the basic components involved in the cost of production in an enterprise and it is expressed in inventory units. Articles about WIP are related to optimizing the size of the inventory [31], especially for batch production [32], or cycle time forecasting according to the fluctuation of WIP levels [33] and the allocation of buffers on the effectiveness of an assembly manufacturing system [34]. The research [31,32] shows the phenomenon of the accumulation of WIP in the process route in the manufacturing industry, which is related to a great and uneven distribution that is dependent on different factors, including batch supply transport, the maximum volume and maximum load capacity of the buffers, various types of products, complex scheduling, and a long production cycle with a bottleneck on some machines [33–35].

However, simulation models typically start from an empty state (with WIP = 0) and some warmup time is required to achieve a stable state and filled WIP, which creates an issue [36]. To reduce this gap, information about the current WIP state is required. This information can be used for model initialization, and it enables the start of the simulation with the same number of queues as in the real system.

According to the Lean Manufacturing paradigm, a large amount of inventory and WIP is a waste, because storage does not give any additional value to the product. Therefore, a small amount of stock and one-piece flow is recommended [37]. On the other hand, we can now observe heavy disturbances in global supply chains, and so producers try to increase their safety stock of scarce materials and parts. Therefore, the buffer allocation problem, which deals with finding optimal buffer sizes to be allocated into buffer areas in a production line, is becoming more important [34,38].

In addition to these simple indicators, composite metrics are also used, including OEE (Overall Equipment Effectiveness), which is a combination of Availability, Performance, and Quality [39–41]. OEE is a measure of how well a manufacturing process is utilized compared to its full potential in ideal conditions, during the periods when it is scheduled to run. Similar metrics are also utilized, including OTE—Overall Transport Effectiveness and OFE—Overall Factory Effectiveness [42–44], with slightly different designations.

The quality of the products plays an important role in a competitive market. Therefore, the TQM (Total Quality Management) paradigm is supposed to control the product quality at every stage of the production process, decrease the number of poor-quality products, and detect an insufficient quality as soon as possible in order to process the products with no faults, which would limit excessive production costs [45,46].

A common problem is determining the effectiveness of new robotic processes compared to existing manual processes. This requires taking into account many factors related to human work (human factors) and the work of a robot [47–49]. While robots work in a highly repeatable manner and it is possible to define determined work parameters for them, human work processes are subject to large fluctuations and should be defined using stochastic parameters. Another important factor is human error, which can significantly disrupt the production flow [50,51]. The main advantage of human work is flexibility in responding to changes and the ease of learning new tasks. In turn, robots require integration with the workplace and programming, which significantly extends the implementation time and increases costs. The failure rate of robots may also be a problem, because the robot requires repair, while a human can easily be replaced by another worker [52,53].

Knowledge about the current condition of the production system is necessary for the proper management of a company. Modern companies often use a Manufacturing Execution System (MES) together with an Enterprise Resources Planning (ERP) system for management support, but there is usually a gap between the business and production tiers of a company [54,55]. Consequently, there is a need to ensure that data are extracted directly from the production system, analyzed, and presented in an appropriate form. Each type of production system requires a different approach to data collection, due to the diversity of facilities and conditions. Therefore, the ability to acquire data in companies strongly depends on the specific industry, the level of automation of technological processes, the number of manual operations, the type of production, etc., [56].

A diverse market and personalized approach to customers leads to a wide variety of products. The shortened product life cycle also results in diversified products. Moreover, the global market competition forces producers to introduce new products faster and changeover their production lines more frequently.

Therefore, the Digital Twin concept emerged, which is related to creating a virtual copy of the physical system, providing a link between the real and virtual systems to collect, analyze, and simulate data in the virtual model, and thus improve the performance of the real system [57–61]. Various architectures for realizing Digital Twin cases are being developed. What is missing, however, is a clear, comprehensive architecture that includes the necessary components of the Digital Twin to realize different use cases in an intelligent automation system [62], and the other problem is a simulation of unstable human work in a non-fully automated system [36].

2. Materials and Methods

2.1. Simulation of Manufacturing System and Digital Twin

Simulations can be understood as imitations of the behavior of a dynamic system. The basic purpose of a simulation is to determine the result based on known input parameters. Their sequence and value determine the final behavior of the system [63]. The simulation model is based on the conceptual design of a real problem, for example, a newly projected manufacturing system. The creation, verification, and validation of the model are time consuming, therefore, the model is often simplified. In the case of simple models of production systems, results can be obtained relatively quickly, but they do not fully reflect the functioning of the production system, e.g., due to failures or disturbances caused by human and robotic factors which are difficult to model. The development of more sophisticated models is laborious and requires the use of advanced methods of statistical analysis of the results.

Typically, many simulating experiments are needed, usually according to an experimental scenario. The results obtained after the implementation of the simulation can be interpreted as a form of consequence for the real system. Based on those results, a decision can be made as to whether the system should be modified or whether changes to another system parameter should be investigated [31]. An illustration of the main phases of a simulation project is presented in Figure 2.

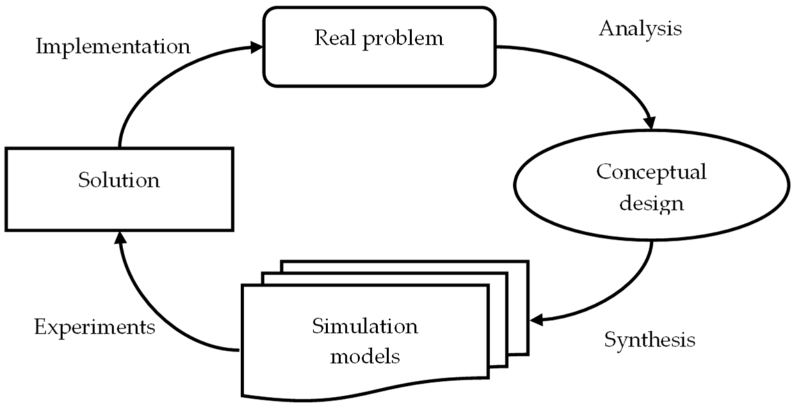

Figure 2. The main phases of the simulation methodology.

The theoretical assumptions and the principles of DES modeling and simulation have been presented in many publications, including [23–25,63]. The simulation model M of a manufacturing system can be defined as a set of components:

$$M = \{X, \Omega, R, C, T, Y\} \quad (1)$$

Including:

- X—inputs, e.g., raw materials, energy;
- Ω—objects, e.g., machines, employees, transport, stores;
- R—relations, connections between objects defining material or information transfers;
- C—constraints, parameters defining limitations of resources, e.g., buffers capacity;
- T (time)—the life cycle and timespan of modeled processes, and disturbances;
- Y—outputs, finished products with good or bad quality, waste.

The graphical representation of the model is presented in Figure 3.

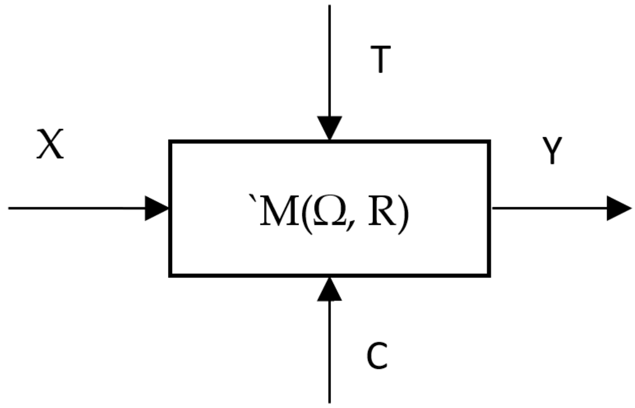

Figure 3. General scheme of the simulation model.

The state of the process at time t can be described by the transition function f(g, t), which transforms input elements X to output elements Y, based on the state of the system elements at time $t-1$:

$$Y = f(g,\ t),\ \text{and}\ g = (X,\ \Omega,\ R,\ C,\ t-1),\ \text{for}\ t\ \in T \tag{2}$$

The scheme of the modeling and simulation methodology is presented in Figure 4. The DES model should take into account all resources in the production system, i.e., machines, buffers, warehouses, means of transport, and the necessary workers or industrial robots. It is also necessary to define the relations between objects and constraints, i.e., the operating parameters of all objects (e.g., the time of execution of a given operation) and the relationships (relations) between the objects (e.g., transport routes) [44,61]. DES simulation reflects changes in the state of objects in the model that occur at certain points in time at the time of certain events (e.g., the start or end of an operation) and the flow of intermediates between the system input and output. The simulation can be used to analyze the existing production systems in the case of reorganization of production processes, as well as in the case of designing new production systems in order to analyze various concepts of the building of a production system [63,64].

Modeling requires a diverse knowledge of the system being considered. That knowledge includes understanding the historical, current, and/or anticipated characteristics of the system. The simulation then becomes a repository of that knowledge and the resulting dynamics, and it makes these available to others, for example, for management purposes [64]. However, current modeling methods and tools still rely on manual data entry and require human verification of the results. This makes the application of these methods very difficult, especially in the context of the modeling and simulation of bigger and more complex systems, which is one of the main difficulties in this field [65].

Work efficiency and the use of the means of production can be expressed by using the OEE metric that depends on three factors: availability, performance, and quality [15,41].

$$\text{OEE} = (\text{Availability}) \times (\text{Performance}) \times (\text{Quality}) \tag{3}$$

Availability is the ratio of the time spent on the realization of a planned task to the available time. Availability is reduced by disruptions at work and machine failures.

$$\text{Availability} = \frac{\text{Planned time} - \text{Failure time}}{\text{Available time}} \tag{4}$$

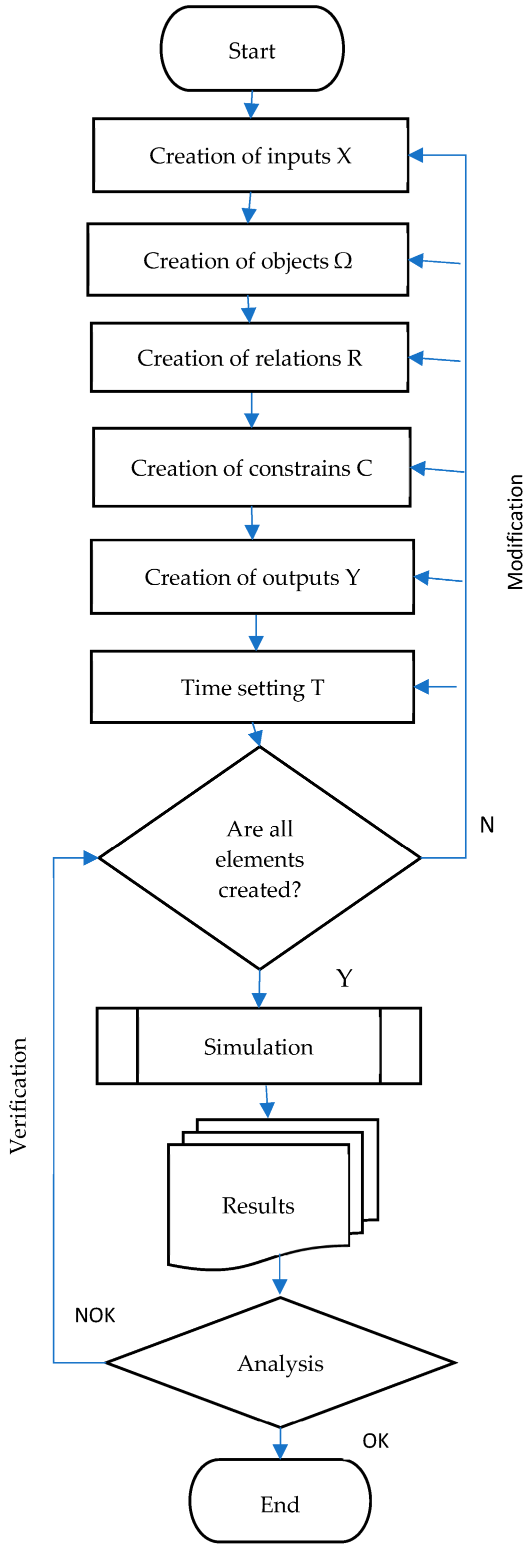

Figure 4. Scheme of the modeling and simulation methodology.

Performance is the ratio of the time to complete a task under ideal conditions compared to the realization in real conditions, or the ratio of the products obtained in reality to the number of possible products to obtain under ideal conditions. Performance is reduced (loss of working speed) by the occurrence of any disturbances, e.g., transport, machine loading/unloading, etc.

$$\text{Performance} = \frac{\text{ideal cycle time}}{\text{real cycle time}} \tag{5}$$

Quality is expressed by the ratio of the number of good products and the total number of products.

$$\text{Quality} = \frac{\text{number of good products}}{\text{total number of products}} \tag{6}$$

The number of good quality products is a random variable, which can be described by a normal distribution with standard deviation sigma. Quality levels are determined for ranges of the standard deviation sigma. In traditional production systems, the level of ± 3 sigmas is considered to be sufficient as it correspond to about 99.73% good quality products. However, in modern automated and robotic systems, the level of 4–6 sigmas is possible to achieve [15]. The quality factor can vary widely for different processes.

The structure of loss of available work time according to OEE is presented in Figure 5.

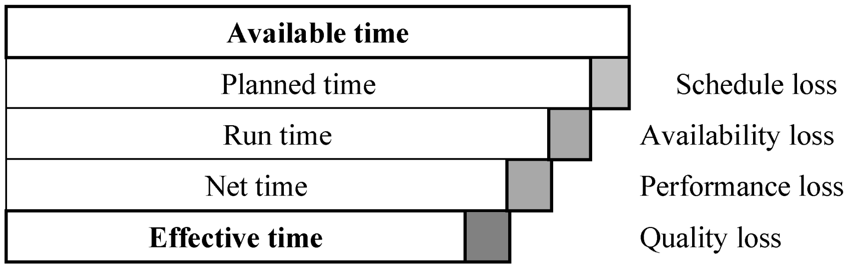

Figure 5. Loss of available work time according to OEE.

The need for making a better simulation model leads to the concept of a Digital Twin (DT). The DT is a virtual, dynamic model in the virtual world that is fully compatible with the corresponding physical existence in the real world and can simulate its physicality, characteristics, behavior, life, and performance at the appropriate time [66].

The concept of a DT of a production system is presented in Figure 6. There is a need for an information link between the real system and the digital model. Therefore, an ERP database including all data about the production system and actual processes can be used in order to achieve up-to-date and correct information for the simulation. The simulation results of a DT can be used for decision support at the management level, because it enables a better understanding of the system behavior and prediction of the future state.

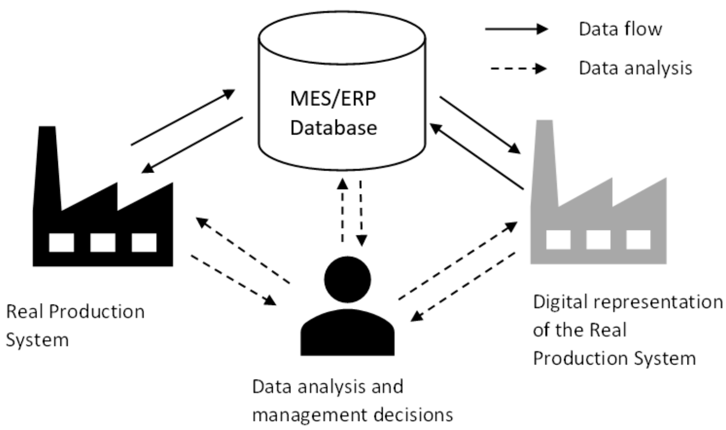

Figure 6. The concept of a Digital Twin of a production system.

There are different versions of digital models possible, including a simple digital model with manual data flow, a digital shadow with one-way automatic data flow, and a full DT with two-way automatic data flow [66,67].

In order for a DT model to be properly analyzed, information about the current WIP state is required. This information can be used for model initialization, and it enables the simulation to start without a warmup with exactly the same number of queues as in the real system. Database connectivity with SQL access and PLC (Programmable Logic Controller) emulation of simulation software combined with optimization features makes FlexSim a favorable choice for prototypes and experiments using the DT concept [67].

There is a wide variety of OPC (Open Platform Communications) or ODBC (Open Database Connectivity) software to choose from, and it is relatively easy to set up a connection with a database server including, for example, Oracle, SQL, Microsoft Access or Excel. Data obtained after simulation can be uploaded to a database similar to data from a real production system and can be used for further analysis.

2.2. Problem Description

Some manufacturing lines for assembling and welding automotive components were analyzed. Typically, there are some robotic welding stations and some manually operated workstations, therefore, both human and robot factors should be taken into consideration. In addition, there is a significant equipment failure rate and a variable quality rate, which are related to irregular changes in the WIP. Human labor especially is very stochastic and therefore the results of simulation experiments often deviate from the production plans, and the actual production volume may also be different.

Accordingly, the next chapter considers the designing of a Digital Twin frame model for an automotive production line to study the WIP phenomena. The problem is important because the formation of queues is related to the occurrence of bottlenecks and has a major impact on final production efficiency.

3. Example of a Manufacturing System

The design and simulation of a new production line for an automotive component at a plant in Poland are taken into account. The line was dedicated to the production of a dual exhaust system. Initial data included a production line consisting of one CNC bending machine, two calibrators, and three robotized welding stations, leakage testing, and geometry control. Seven operations in the manufacturing process are presented in Table 1.

Table 1. The description of the production process.

Operation	Description
OP10	Bending of the main pipe
OP20	Calibrating both end diameters of the main pipe
OP30	Manual pre-assembly of the resonator and clamping of components in the welding fixture, and robotic welding of the middle part of the exhaust
OP40	Right end manual assembly and clamping, and robotic welding
OP50	Left end manual assembly and clamping, and robotic welding
OP60	Testing the geometry of the exhaust system
OP70	Leakage testing of the exhaust system

An initial analysis of the time required for each operation showed that the stations would have to be automated to some extent, and four operators would be sufficient enough to operate the line without loss of efficiency. Operators were assigned to workstations as follows:

- Operator 1: OP10, OP20.
- Operator 2: OP30.
- Operator 3: OP40, OP50.

- Operator 3: OP60, OP70.

Figure 7 shows the designated locations of the workstations with their assigned operators. The OP30, OP40, and OP50 welding machines are equipped with two windows. Manual workpiece clamping and assembly of components is carried out in one window, while the robot welding process is carried out in the other. As a result, the welding process of the robot is not interrupted by the actions of the operator manipulating the part.

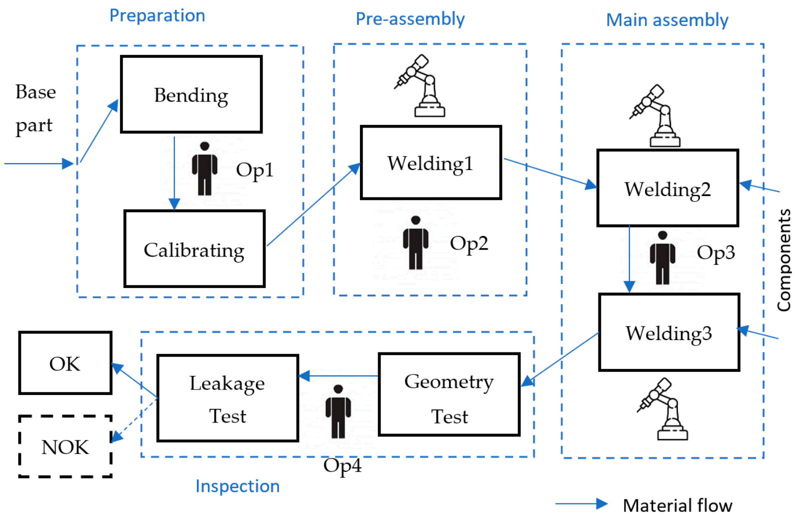

Figure 7. The initial layout of the workstations.

The production process includes the following activities:

- Operator 1 places the main pipe on OP10 and then multiple bending is performed; the pipe is then taken to OP20 for diameter calibration of both ends.
- Operator 2 sets up the pre-assembly of middle components consisting of resonator, holders, and sealings on OP30-1; then, robot1 welds the connectors on OP30-2.
- Operator 3 sets up the assembly of rear components consisting of muffler, holders, and sealings sequentially on OP40-1 and OP50-1 and then robots 2 and 3 weld the connectors on OP40-2 and OP50-2.
- Operator 4 performs a geometry check on OP60, leak test on OP70, and then segregates good and defective parts.

3.1. System Parameters and Assumptions

Recent problems with global supply chains have forced production to one shift a day, but unlimited availability of materials was assumed in order to assess the productivity of the system. The planned production capacity is 170 pieces per shift, with 7.5 h of effective working time. Constraints were assumed according to the ToC, involving availability, performance, and quality, which gives the OEE metric (Equation (3)).

Availability is related to planned and unplanned breaks (failures). The plan of a shift includes a 20 min rest break for workers, 5 min for machines at the beginning of the shift, and 5 min for turning off machines at the end of a shift.

The failures of equipment cause unplanned breaks and lower the availability index.

Robot welding workstations have stable and high welding quality compared to manual welding. However, some machinery failures may occur, including welding equipment, gun cleaner, wire feeder, and other auxiliary equipment [68–72]. Therefore, for the purposes of the simulation, the definition of failure was extended, including machine downtime affected by welding parameter adjustments and replacement of the welding machine consumables.

The Performance index is related to the loss of time needed for the manual set-up of machines, for example, loading and unloading of the workpiece. The Quality index is related to the number of good quality products compared to the total number of all products (including bad quality products). The process parameters, including the time of operations performed by employees, were obtained by time study. These data were introduced into the simulation as the set-up time per one workpiece. In turn, the machine cycle times (processing time) were established in regard to technological data.

To simulate the fluctuation of the operators' work, a normal distribution with standard deviation was used. The processing times were assumed constant due to automation, and time values for subsequent operations are presented in Table 2.

Table 2. The values of process time parameters per workpiece.

Operation	Set-up Time [s]	Stand. Dev. [s]	Processing Time [s]
10	35	2	48
20	22	2	12
30	65	3	110
40	46	2	117
50	48	2	132
60	33	2	60
70	30	2	60

Additional information on the causes and duration of machine downtime was determined based on existing, similar production processes [73], which provided a reference for the simulation. Based on this analysis, the failure rates of welding workstations were specified as follows: MTBF (Mean Time Between Failures) = 3600 s exponentially, and MTTR (Mean Time To Repair) in uniform distribution. There is a different repair time for each workstation due to the complexity of the operations: $MTTR_{30}$ = 300–600 s, $MTTR_{40}$ = 300–900 s, and $MTTR_{50}$ = 300–1200 s. The failure rate of employees was defined based on photos of the working day, MTBFp = 3 h and MTTRp = 300–600 s., which largely overlap with the time of the rest break.

The planned Quality was 95%, but the real processes sometimes show a much greater number of bad quality products, reaching about 10%. Therefore, additional visual inspection after each operation was introduced, including removing defective semi-finished products from the queues in order to reduce the costs of production. There is also a possibility of repairing some faulty products that can return into the process.

That, and equipment failures, affect the change of WIP, therefore there is a need to include the initial WIP at the start of the shift into the simulation model. Then, the final WIP state at the end of the shift can added into the database and can be used to initialize the next simulation run. The scenario includes the start of work with empty machines. Process control policies were used in order to control the flow of jobs in a manufacturing system [74], including a push policy used for the main part of the assembly and a pull policy for the subassembly components. Additionally, a closedown policy was implemented at the end of shift in order to finish all required operations and not break the work in the middle of welding and shut down empty machines [75].

Other assumptions are related to the following simplifications which were introduced to avert excessive complexity of the model and thus enhance the readability of the paper. All components and blanks in the process have been replaced with a single element that determines the sequence of material flow in the process. The robot stations were modeled as two machine-type objects. One is responsible for the simulation of the operator's loading process, and the other for the simulation of the automated welding process.

3.2. Model of the Manufacturing System

The model constructed in FlexSim 2022 according to the layout and adopted assumptions is shown in Figures 8 and 9, respectively. Figure 8 shows the model of the production system at the start of the shift with initialized WIP in queues 1–5.

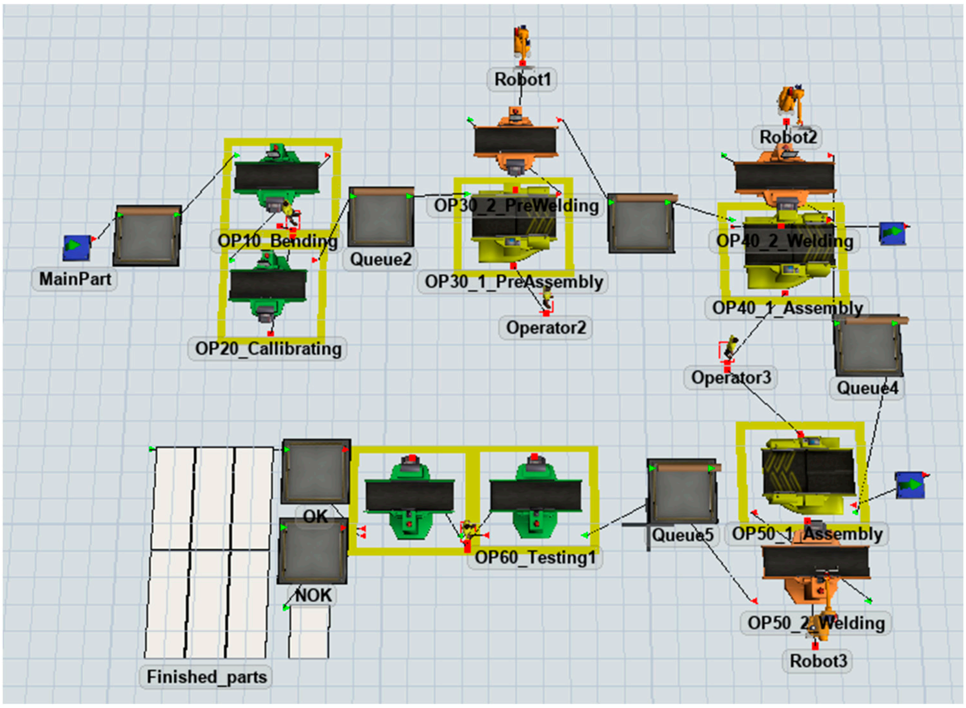

Figure 8. Model of the production system at the start of the shift with initialized WIP.

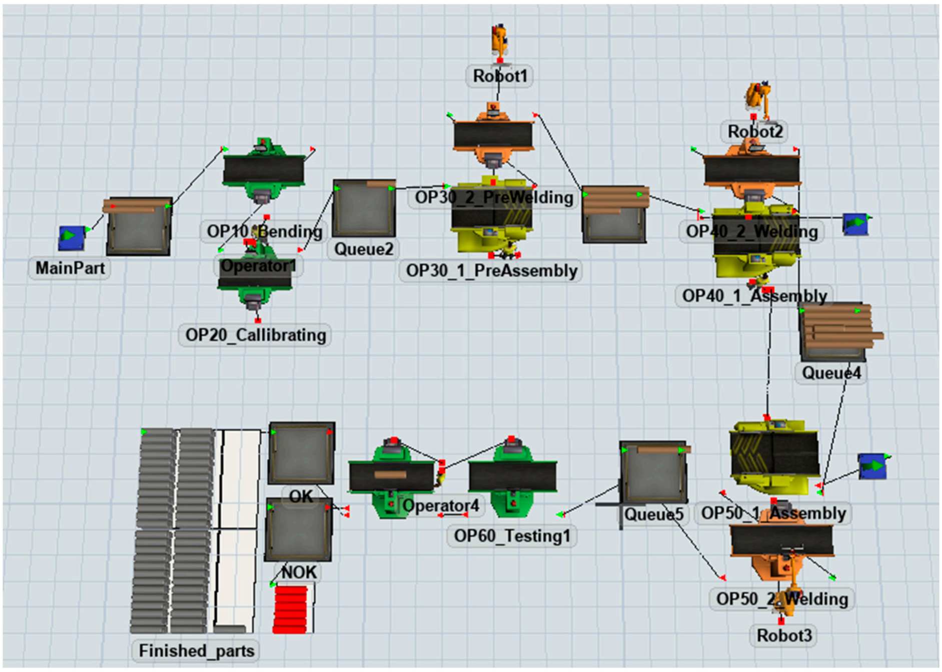

Figure 9. Model of the production system at the end of the shift with WIP change.

Figure 9 shows the state of the model at the end of the shift with different WIP states. The model includes a data import/export connection with Excel (another database can be used) in order to automatically read/write the WIP data at the start/end of the simulation of the shift. An additional procedure in Process Flow is used in order to generate the WIP items in each queue.

The meaning of the item colors in the model is as follows: brown—semifinished parts, gray—finished good quality products, red—bad quality products. The significant variation of WIP in each queue can be observed as shown in Figure 10.

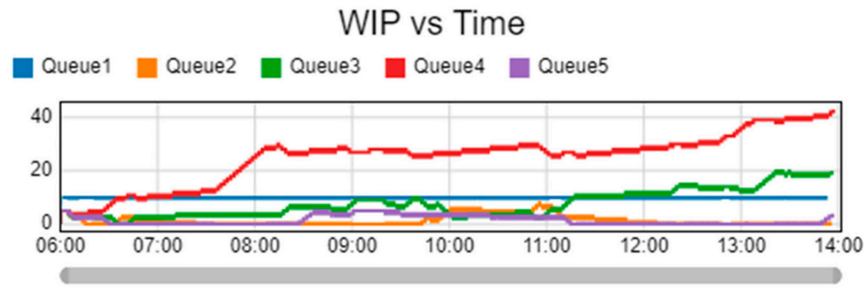

Figure 10. Chart with WIP changes in each queue during an 8 h shift.

Constructed models and obtained results are included in the Supplementary Materials. The results of the simulation experiments are presented in the next section.

4. Results

The finished production level is often lower than planned due to failures and insufficient quality, therefore a series of simulation experiments was performed in order to study the effect of WIP size on production efficiency.

4.1. Scenario 1—Series of Simulation Experiments with Different Initial WIP

The experimental scenario includes different initial parameters of WIP size from the range of 0–8 pieces for each queue. The results are presented in Table 3 and show the mean number of good quality products (OK), standard deviation of the mean, minimal and maximal production volumes, and bad quality products (NOK).

Table 3. The values of mean, minimal, and maximal productions according to different initial WIP sizes for one shift (for 20 simulation runs with a 95% Confidence Interval).

WIP Scenario	Mean Production [OK Pieces]	Std. Dev.	Min. [Pieces]	Max. [Pieces]	NOK [Pieces]
0	156.75 ± 4.20	8.97	143.00	172.00	9.00 ± 1.50
1	159.75 ± 4.14	8.84	147.00	173.00	9.25 ± 1.54
2	162.95 ± 4.29	9.16	149.00	179.00	9.35 ± 1.52
3	165.55 ± 4.13	8.83	153.00	180.00	9.60 ± 1.54
4	167.00 ± 4.01	8.56	154.00	181.00	9.65 ± 1.54
5	168.15 ± 3.93	8.40	156.00	182.00	9.65 ± 1.54
6	169.35 ± 3.71	7.94	158.00	182.00	9.75 ± 1.52
7	170.65 ± 3.65	7.80	159.00	184.00	9.75 ± 1.52
8	171.75 ± 3.54	7.57	160.00	184.00	9.00 ± 1.50

The average WIP size for each queue according to different initial WIP sizes is presented in Table 4. The capacity of Queue 1 was set to 10.

Figure 11 shows the replication box and whisker plot of the value of good quality production for each scenario.

Obtained results show that there is high variability of WIP, which is related to system instability due to random failures, especially when the system starts from an empty state (Scenario 0 with initial WIP = 0). However, the next scenarios show an increasing trend of mean production and decreasing spread between extreme values. Therefore, increasing the initial WIP gives better efficiency and stability to the whole system, and an initial value of WIP = 7 is recommended in this case in order to achieve the planned production volume.

Table 4. The values of average WIP in the queues after one shift according to different initial WIP sizes (for 20 simulation runs with a 95% Confidence Interval).

WIP Scenario	Queue 1	Queue 2	Queue 3	Queue 4	Queue 5
0	10	2.68	10.34	9.16	0.58
1	10	2.72	10.47	9.71	0.57
2	10	2.79	11.11	9.95	0.58
3	10	3.05	12.02	10.39	0.74
4	10	3.42	12.96	11.46	0.83
5	10	3.82	14.12	12.62	0.97
6	10	4.31	15.24	13.77	1.11
7	10	4.82	16.65	14.63	1.29
8	10	5.41	18.01	15.52	1.51

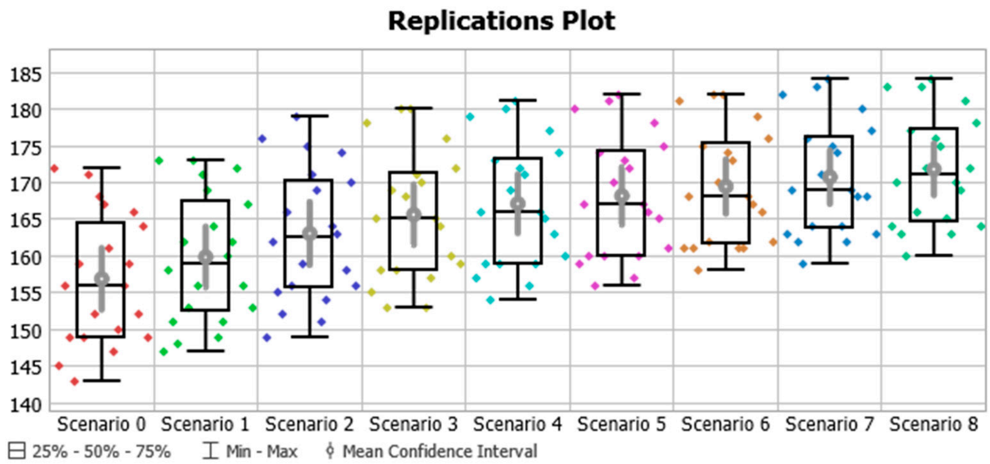

Figure 11. Replication plot of good quality products (OK) in experiments for different initial WIP scenarios.

4.2. Scenario 2—Subsequent Simulation Experiment

In the next scenario, the production of 5 days per week was assumed and 5 subsequent simulations were conducted. The first-day simulation was started from an empty state (WIP = 0) and the WIP size at the end of the shift was used for the initialization of the next simulation. The results are presented in Table 5.

Table 5. The values of WIP in the queues after one shift for five subsequent simulations.

Day	Queue 1	Queue 2	Queue 3	Queue 4	Queue 5	OK	NOK	OEE
-	0	0	0	0	0	0	0	-
1	10	1	46	29	2	161	12	0.7385
2	10	12	52	56	1	163	9	0.7477
3	10	1	68	81	2	176	8	0.8073
4	10	6	113	63	2	171	10	0.7844
5	10	3	119	77	2	179	5	0.8211

The increasing trend of WIP size in Queue 3 and Queue 4 can be observed, compared to other queues, which is a consequence of the bottleneck in the next workstations

(Operations 40 and 50). Also, significant variability in production is observed, which is consistent with the production of the real system and is the result of system instability due to random failures.

In order to assess the efficiency of the system, the OEE metric can be used. As the model includes the constraints related to Availability, Performance, and Quality, the OEE can be calculated directly from Equation (7) [43].

$$\mathrm{OEE} = \frac{OK}{TOK} = \frac{Number\ of\ good\ quality\ products}{Total\ number\ of\ products\ in\ ideal\ conditions} \quad (7)$$

The *number of good quality products* is given in column *OK* and the TOK *Total number of products in ideal conditions* value was calculated including maximal throughput of the bottleneck 27.27 pieces/hour and 8 h work per shift, which gives 218 pieces.

The average OEE was equal to 77.98% and was lower than the planned 80% (including A = 0.9375, P = 0.9, Q = 0.95) because of failures and loss of availability and loss of work speed, resulting from insufficient WIP content. The obtained result consists of average Availability = 0.9265, Performance = 0.886, and Quality = 0.95 and reflects well the course of the actual production process.

There are some possibilities for improvement of the OEE, including the enhancement of the maintenance system or change of the Quality Control System (QCS), which enables the removal of faulty semi-finished products from the process and returning of repaired products into the process, which is related to WIP change and may be taken into account during initialization of the model.

5. Conclusions

The simulation of Digital Twins of production systems is an important aspect of Industry 4.0, as it allows the support of projects related to the development and implementation of modern manufacturing systems throughout their life cycle.

The simulation of the manufacturing system is very helpful as it becomes a repository of knowledge about the real system and enables the analysis of its dynamics, but for proper functionality, the model should be closely similar to the physical system so as to constitute a Digital Twin. The main problems are related to unstable human labor and human errors, as well as machine failures, which are difficult to predict but have a major impact on production processes.

In order to properly simulate the DT model, information about current WIP state is required. This information can be used for model initialization, and it enables us to start the simulation with exactly the same number of queues as in the real system, without the need for a warmup. The main contribution of this work is the detailed methodology of building a Digital Twin for a hybrid human–robot-operated manufacturing system with unstable processes and WIP changes.

The results show that the initial WIP value has a significant effect on the productivity of the analyzed manufacturing system, as the mean value of production was increased by about 10% when the initial WIP was changed from 0 to 8 pieces. At the same time, better stability of the whole system was observed with decreased dispersion of results by −17% and the standard deviation was decreased by −26%.

The production effectiveness was measured by the OEE metric. The expected value was 0.80 according to the production plan, however, the obtained OEE values were different for each working day because of failures and quality issues, but low production during the first and second days was recovered in the following days, and the weekly production plan was realized with a total of 850 finished pieces.

The main problems were related to failures of the welding equipment, and there is still room for improvement of the availability and quality, as a World Class OEE is defined from the level of 85% or higher.

Database connectivity with SQL access and PLC (Programmable Logic Controller) emulation of simulation software combined with optimization features makes FlexSim a promising choice for experimenting with the DT concept. There is a wide variety of OPC (Open Platform Communications) or ODBC (Open Database Connectivity) software to choose from, and it is relatively easy to set up a connection with a database server including, for example, Oracle, SQL, Microsoft Access, or Excel. Data obtained after simulation can be written to a database similar to data from a real production system and can be used for further analysis.

The presented method can be also used in similar enterprises from other industries, especially for those with discrete processes, high WIP variability, and for further synchronization of other DT parameters.

Further research includes a full parameterization of the DT model with the states of all objects (including machines, employees, robots, AGVs, product types, etc.), allowing the simulation to start from the current state of the actual production system.

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References

1. Roblek, V.; Meško, M.; Krapež, A. A Complex View of Industry 4.0. *SAGE Open* **2016**, *6*, 1–11. [CrossRef]
2. Butt, J. A Strategic Roadmap for the Manufacturing Industry to Implement Industry 4.0. *Designs* **2020**, *4*, 11. [CrossRef]
3. Cotrino, A.; Sebastián, M.A.; González-Gaya, C. Industry 4.0 Roadmap: Implementation for Small and Medium-Sized Enterprises. *Appl. Sci.* **2020**, *10*, 8566. [CrossRef]
4. Papakostas, N.; Constantinescu, C.; Mourtzis, D. Novel Industry 4.0 Technologies and Applications. *Appl. Sci.* **2020**, *10*, 6498. [CrossRef]
5. Jamwal, A.; Agrawal, R.; Sharma, M.; Giallanza, A. Industry 4.0 Technologies for Manufacturing Sustainability: A Systematic Review and Future Research Directions. *Appl. Sci.* **2021**, *11*, 5725. [CrossRef]
6. López de Lacalle, L.N.; Posada, J. New Industry 4.0 Advances in Industrial IoT and Visual Computing for Manufacturing Processes: Volume II. *Appl. Sci.* **2022**, *12*, 7952. [CrossRef]
7. Pech, M.; Vrchota, J. Classification of Small- and Medium-Sized Enterprises Based on the Level of Industry 4.0 Implementation. *Appl. Sci.* **2020**, *10*, 5150. [CrossRef]
8. Richnák, P. Current Trend of Industry 4.0 in Logistics and Transformation of Logistics Processes Using Digital Technologies: An Empirical Study in the Slovak Republic. *Logistics* **2022**, *6*, 79. [CrossRef]
9. Tubis, A.A.; Grzybowska, K. In Search of Industry 4.0 and Logistics 4.0 in Small-Medium Enterprises—A State of the Art Review. *Energies* **2022**, *15*, 8595. [CrossRef]
10. Paprocka, I.; Kampa, A.; Gołda, G. The effects of a machine failure on the robustness of job shop systems-the predictive-reactive approach. *Int. J. Mod. Manuf. Technol.* **2019**, *11*, 72–79. Available online: https://ijmmt.ro/download-paper/vol11no22019/11_Iwona_Paprocka.pdf (accessed on 18 May 2023).
11. Paprocka, I.; Kempa, W.M.; Krenczyk, D. Analysis of queue-size behaviour and throughput of a system with buffer controlled by a rope and production speed controlled by a drum. *Int. J. Mod. Manuf. Technol.* **2019**, *11*, 128–136. Available online: http://www.ijmmt.ro/vol11no32019/18_Iwona_Paprocka.pdf (accessed on 16 May 2023).
12. Krenczyk, D.; Paprocka, I. Integration of Discrete Simulation, Prediction, and Optimization Methods for a Production Line Digital Twin Design. *Materials* **2023**, *16*, 2339. [CrossRef] [PubMed]
13. Kampa, A.; Gołda, G.; Paprocka, I. Discrete Event Simulation Method as a Tool for Improvement of Manufacturing Systems. *Computers* **2017**, *6*, 10. [CrossRef]
14. Gołda, G.; Kampa, A.; Krenczyk, D. The Methodology of Modeling and Simulation of Human Resources and Industrial Robots in FlexSim. In *FlexSim in Academe: Teaching and Research*; Pawlewski, P., Hoffa-Dabrowska, P., Golinska-Dawson, P., Werner-Lewandowska, K., Eds.; Springer: Cham, Switzerland, 2019; pp. 87–99. [CrossRef]
15. Barosz, P.; Gołda, G.; Kampa, A. Efficiency Analysis of Manufacturing Line with Industrial Robots and Human Operators. *Appl. Sci.* **2020**, *10*, 2862. [CrossRef]
16. Panchetti, T.; Pietrantoni, L.; Puzzo, G.; Gualtieri, L.; Fraboni, F. Assessing the Relationship between Cognitive Workload, Workstation Design, User Acceptance and Trust in Collaborative Robots. *Appl. Sci.* **2023**, *13*, 1720. [CrossRef]

17. Mahmoodi, E.; Fathi, M.; Ghobakhloo, M. The impact of Industry 4.0 on bottleneck analysis in production and manufacturing: Current trends and future perspectives. *Comput. Ind. Eng.* **2022**, *174*, 108801. [CrossRef]
18. Adamczak, M.; Kolinski, A.; Trojanowska, J.; Husár, J. Digitalization Trend and Its Influence on the Development of the Operational Process in Production Companies. *Appl. Sci.* **2023**, *13*, 1393. [CrossRef]
19. Rashid, A.; Tjahjono, B. Achieving manufacturing excellence through the integration of enterprise systems and simulation. *Prod. Plan. Control.* **2016**, *27*, 837–852. [CrossRef]
20. Rosen, R.; von Wichert, G.; Lo, G.; Bettenhausen, K.D. About The Importance of Autonomy and Digital Twins for the Future of Manufacturing. *IFAC PapersOnLine* **2015**, *48*, 567–572. [CrossRef]
21. Gundogar, E.; Sari, M.; Kokcam, A.H. Dynamic bottleneck elimination in mattress manufacturing line using theory of constraints. *SpringerPlus* **2016**, *5*, 1276. [CrossRef]
22. De Jesus Pacheco, D.A.; Antunes Junior, J.A.V.; de Matos, C.A. The constraints of theory: What is the impact of the Theory of Constraints on Operations Strategy? *Int. J. Prod. Econ.* **2021**, *235*, 107955. [CrossRef]
23. Dagkakis, G.; Heavey, C. A review of open source discrete event simulation software for operations research. *J. Simul.* **2016**, *10*, 193–206. [CrossRef]
24. Greasley, A.; Edwards, J.S. Enhancing discrete-event simulation with big data analytics: A review. *J. Oper. Res. Soc.* **2021**, *72*, 247–267. [CrossRef]
25. Shukla, O.J.; Soni, G.; Kumar, R. SimEvents-based discrete-event simulation modelling and performance analysis for dynamic job-shop manufacturing system. *Int. J. Adv. Oper. Manag.* **2021**, *13*, 167. [CrossRef]
26. Zhu, L.; Johnsson, C.; Mejvik, J.; Varisco, M.; Schiraldi, M. Key performance indicators for manufacturing operations management in the process industry. In Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management, Singapore, 10–13 December 2017. [CrossRef]
27. Contini, G.; Peruzzini, M. Sustainability and Industry 4.0: Definition of a Set of Key Performance Indicators for Manufacturing Companies. *Sustainability* **2022**, *14*, 11004. [CrossRef]
28. Ramis Ferrer, B.; Muhammad, U.; Mohammed, W.M.; Martínez Lastra, J.L. Implementing and Visualizing ISO 22400 Key Performance Indicators for Monitoring Discrete Manufacturing Systems. *Machines* **2018**, *6*, 39. [CrossRef]
29. WIP. Available online: https://dictionary.cambridge.org/pl/dictionary/english/wip (accessed on 15 June 2023).
30. Huntzinger, J.R. *Lean Cost Management: Accounting for Lean by Establishing Flow*; J. Ross Publishing: Fort Lauderdale, FL, USA, 2007.
31. Gznár, P.; Gregor, M.; Mozol, Š.; Krajčovič, M.; Dulina, L'.; Gašo, M.; Major, M. A System to Determine the Optimal Work-in-Progress Inventory Stored in Interoperation Manufacturing Buffers. *Sustainability* **2019**, *11*, 3949. [CrossRef]
32. Wang, Y. The Work in Process (WIP) Control Model and Its Application Simulation in Small-batch and Multi-varieties Production Mode. *Mod. Appl. Sci.* **2009**, *3*, 83. [CrossRef]
33. Wang, J.; Gao, P.; Li, Z.; Bai, W. Hierarchical Transfer Learning for Cycle Time Forecasting for Semiconductor Wafer Lot under Different Work in Process Levels. *Mathematics* **2021**, *9*, 2039. [CrossRef]
34. Kłos, S.; Trebuna, P. The impact of the availability of resources, the allocation of buffers and number of workers on the effectiveness of an assembly manufacturing system. *Manag. Prod. Eng. Rev.* **2017**, *8*, 40–49. [CrossRef]
35. Hemalatha, C.; Sankaranarayanasamy, K.; Durairaaj, N. Lean and agile manufacturing for work-in-process (WIP) control. *Mater. Today: Proc.* **2021**, *46*, 10334–10338. [CrossRef]
36. Burduk, A. Stability Analysis of the Production System Using Simulation Models BT. In *Process Simulation and Optimization in Sustainable Logistics and Manufacturing*; Pawlewski, P., Greenwood, A., Eds.; Springer International Publishing: Berlin/Heidelberg, Germany, 2014; pp. 69–83. [CrossRef]
37. Ben Naylor, J.; Naim, M.M.; Berry, D. Leagility: Integrating the lean and agile manufacturing paradigms in the total supply chain. *Int. J. Prod. Econ.* **1999**, *62*, 107–118. [CrossRef]
38. Jha, H.; Mohan, U. A multi-period discrete event simulation model for comparing synchronous and asynchronous facility reopening in global supply chains affected by disruption. *Supply Chain. Anal.* **2023**, *2*, 100010. [CrossRef]
39. Ng Corrales, L.D.C.; Lambán, M.P.; Hernandez Korner, M.E.; Royo, J. Overall equipment effectiveness: Systematic literature review and overview of different approaches. *Appl. Sci.* **2020**, *10*, 6469. [CrossRef]
40. Rahman, F.; Sugiono, S.; Sonief, A.A.; Novareza, O. Optimization Maintenance Performance Level Through Collaboration of Overall Equipment Effectiveness and Machine Reliability. *J. Appl. Eng. Sci.* **2022**, *20*, 917–936. [CrossRef]
41. Bengtsson, M.; Andersson, L.G.; Ekström, P. Measuring preconceived beliefs on the results of overall equipment effectiveness—A case study in the automotive manufacturing industry. *J. Qual. Maint. Eng.* **2022**, *28*, 391–410. [CrossRef]
42. Radosavljevic, D.; Manojlovic, A.; Medar, O.; Bojovic, N. Assessment of the overall effectiveness of the transport process. *Technika* **2017**, *72*, 717–724. [CrossRef]
43. Muthiah, K.M.N.; Huang, S.H. Overall throughput effectiveness (OTE) metric for factory-level performance monitoring and bottleneck detection. *Int. J. Prod. Res.* **2007**, *45*, 4753–4769. [CrossRef]
44. Foit, K.; Gołda, G.; Kampa, A. Integration and Evaluation of Intra-Logistics Processes in Flexible Production Systems Based on OEE Metrics, with the Use of Computer Modelling and Simulation of AGVs. *Processes* **2020**, *8*, 1648. [CrossRef]
45. Sundarkrishnaa, K.L. *Total Quality Management*; Springer Series in Materials Science; Springer: Berlin/Heidelberg, Germany, 2015; Volume 171. [CrossRef]

46. Van Kemenade, E.; Hardjono, T.W. Twenty-first century Total Quality Management: The Emergence Paradigm. *TQM J.* **2019**, *31*, 150–166. [CrossRef]
47. Gołda, G.; Kampa, A.; Paprocka, I. Analysis of human operators and industrial robots performance and reliability. *Manag. Prod. Eng. Rev.* **2018**, *9*, 24–33.
48. Yan, Y.; Jia, Y. A Review on Human Comfort Factors, Measurements, and Improvements in Human–Robot Collaboration. *Sensors* **2022**, *22*, 7431. [CrossRef] [PubMed]
49. Kopp, T.; Baumgartner, M.; Kinkel, S. Success factors for introducing industrial human-robot interaction in practice: An empirically driven framework. *Int. J. Adv. Manuf. Technol.* **2020**, *112*, 685–704. [CrossRef]
50. Read, G.J.M.; Shorrock, S.; Walker, G.H.; Salmon, P.M. State of science: Evolving perspectives on 'human error. *Ergonomics* **2021**, *64*, 1091–1114. [CrossRef]
51. Torres, Y.; Nadeau, S.; Landau, K. Classification and Quantification of Human Error in Manufacturing: A Case Study in Complex Manual Assembly. *Appl. Sci.* **2021**, *11*, 749. [CrossRef]
52. Kampa, A. The Review of Reliability Factors Related to Industrial Robots. *Robot. Autom. Eng. J. (RAEJ)* **2018**, *3*, 555624.
53. Bai, B.; Li, Z.; Wu, Q.; Zhou, C.; Zhang, J. Fault data screening and failure rate prediction framework-based bathtub curve on industrial robots. *Ind. Robot.* **2020**, *47*, 867–880. [CrossRef]
54. Ćwikła, G. The methodology of development of the manufacturing information acquisition system (MIAS) for production management. *Appl. Mech. Mater.* **2014**, *474*, 27–32. [CrossRef]
55. Kenge, R.; Khan, Z. A Research Study on the ERP System Implementation and Current Trends in ERP. *Shanlax Int. J. Manag.* **2020**, *8*, 34–39. [CrossRef]
56. Morawiec, P.; Sołtysik-Piorunkiewicz, A. Cloud Computing, Big Data, and Blockchain Technology Adoption in ERP Implementation Methodology. *Sustainability* **2022**, *14*, 3714. [CrossRef]
57. Jones, D.; Snider, C.; Nassehi, A.; Yon, J.; Hicks, B. Characterising the Digital Twin: A systematic literature review. *CIRP J. Manuf. Sci. Technol.* **2020**, *29*, 36–52. [CrossRef]
58. Barricelli, B.R.; Casiraghi, E.; Fogli, D. A Survey on Digital Twin: Definitions, Characteristics, Applications, and Design Implications. *IEEE Access* **2019**, *7*, 167653–167671. [CrossRef]
59. Pawlewski, P.; Kosacka-Olejnik, M.; Werner-Lewandowska, K. Digital Twin Lean Intralogistics: Research Implications. *Appl. Sci.* **2021**, *11*, 1495. [CrossRef]
60. Sobrino, D.R.D.; Rychtarik, V.; Cagáňová, D. Digital Twin design at the material flow level. *J. Phys. Conf. Ser.* **2022**, *2212*, 012012. [CrossRef]
61. Krenczyk, D. Dynamic simulation models as digital twins of logistics systems driven by data from multiple sources. *J. Phys. Conf. Ser.* **2022**, *2198*, 012059. [CrossRef]
62. Ashtari, T.B.; Jung, T.; Lindemann, B.; Sahlab, N.; Jazdi, N.; Schloegl, W.; Weyrich, M. An Architecture of an Intelligent Digital Twin in a Cyber-Physical Production System. *Automatisierungstechnik* **2019**, *67*, 762–782. [CrossRef]
63. Banks, J.; Carson, J. *Discrete-Event System Simulation*; Pearson New International Edition; Pearson Education India: Noida, India, 2013.
64. Beaverstock, M.; Greenwood, A.; Lavery, E.; Nordgren, W. Applied Simulation: Modeling and Analysis Using FlexSim. FlexSim Software Products Inc.: Orem, UT, USA, 2017.
65. Crosbie, R.E. Grand Challenges in Modeling and Simulation. *SCS MS Mag.* **2010**, *1*, 1–8.
66. Zhuang, C.; Liu, J.; Xiong, H. Digital twin-based smart production management and control framework for the complex product assembly shop-floor. *Int. J. Adv. Manuf. Technol.* **2018**, *96*, 1149–1163. [CrossRef]
67. Luściński, S. Digital Twinning for Smart Industry. In Proceedings of the 3rd EAI International Conference on Management of Manufacturing Systems, Dubrovnik, Croatia, 6–8 November 2018; EAI: Gent, Belgium, 2018; pp. 1–9. [CrossRef]
68. Chandankar, B. Productivity Improvement in Welding Robot. *Int. J. Curr. Eng. Technol.* **2016**, *6*, 251–254.
69. Consonni, M.; Chen, F.W. Repair rates in welded structures and components. *Weld. Cut.* **2012**, *11*, 61–68.
70. Chen, H.B.; Lin, T.; Chen, S.B.; Wang, J.F.; Jia, J.Q.; Zhang, H. Adaptive control on wire feeding in robot arc welding system. In Proceedings of the IEEE International Conference on Robotics, Chengdu, China, 21–24 September 2008; pp. 119–122. [CrossRef]
71. Zhang, Q.; Xiao, R.; Liu, Z.; Duan, J.; Qin, J. Process Simulation and Optimization of Arc Welding Robot Workstation Based on Digital Twin. *Machines* **2023**, *11*, 53. [CrossRef]
72. 5 Common Failures in Robotic Welding and How to Prevent Them. 2021. Available online: https://www.tregaskiss.com/5-common-failures-in-robotic-welding-and-how-to-prevent-them/ (accessed on 15 March 2023).
73. Kampa, A.; Gołda, G.; Konysz, D. Design of production systems using computer modelling of human-robot interaction. *IOP Conf. Ser.: Mater. Sci. Eng.* **2021**, *1182*, 012034. [CrossRef]
74. Urgo, M.; Terkaj, W. Formal modelling of release control policies as a plug-in for performance evaluation of manufacturing systems. *CIRP Ann.* **2020**, *69*, 377–380. [CrossRef]
75. Kampa, A.; Paprocka, I. Analysis of Energy Efficient Scheduling of the Manufacturing Line with Finite Buffer Capacity and Machine Setup and Shutdown Times. *Energies* **2021**, *14*, 7446. [CrossRef]