TECHNICAL UNIVERSITY OF CLUJ-NAPOCA

ACTA TECHNICA NAPOCENSIS

Series: Applied Mathematics, Mechanics, and Engineering
Vol. 66, Issue Special II, October, 2023

DIGITAL TWIN IN BLENDING TECHNOLOGIES: INTEGRATION OF TECHNOLOGY AND LOGISTICS USING INTERNET OF THINGS SOLUTIONS

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Abstract: *Industry 4.0 has brought new technologies and approaches that can make a major contribution to improving the performance of production and service processes. For companies using blending technologies, the integration of technology and logistics is becoming increasingly important, in addition to the optimization of process parameters, as a well-designed logistics system can greatly enhance the efficiency of technological processes. The author proposes a digital twin-based solution to enhance the efficiency of technological processes in companies using blending technology through real-time optimization of technological and logistic processes supported by a digital twin solution. The presented models and methods demonstrate that significant improvements in technological and logistic processes can be achieved through the application of the presented model using digital twin solutions.*

Key words: *digital twin, blending technology, real-time optimization, logistics, cost efficiency.*

1. INTRODUCTION

Blending technologies represent a specific area of industry where continuous material supply is of particular importance. One of the main reasons for this is that, as blending technologies are essentially used in continuous technologies (chemistry, pharmaceuticals, food industry), continuous material supply is highlighted. Although blending technologies are nowadays highly automated, further cost savings can be achieved by integrating the whole value chain related to the technology, which can further enhance competitiveness. Industry 4.0 technologies offer new advanced solutions for transforming conventional manufacturing technologies into cyber-physical systems, with the digital twin as the main integration tool.

Continuous material supply can be a particular challenge in a multi-tier, multi-supplier supply chain where raw materials are sourced from a long geographical distance, as disruptions in the supply chain can cause severe problems in production, resulting in severe cost reductions and revenue losses.

Digital twin solutions can greatly improve the efficiency of industrial processes by offering new opportunities for real-time decision making that are not possible with traditional enterprise resource planning and manufacturing execution systems due to the lack of real-time data from business processes, which can be processed and analyzed to make real-time forecasts, scenario analysis and process optimization.

Based on these fact, this paper is organized as follows. Section 2 presents a short literature review. Section 3 describes the potential Industry 4,0 technologies, which are suitable to extend the conventional blending technology into an IoT solution, where digital twin technology supports the real decision making process to improve efficiency. Section 4 demonstrates the functional model of digital twin supported blending technologies focusing and describes a mathematical model, which makes it possible to analyze the impact of digital twin on the cost efficiency of blending problems in the case of supply chain or inventory disruptions. Conclusions are discussed in Section 5.

2. LITERATURE REVIEW

This article presents the results of a research focusing on the potential integration aspects of digital twin technologies in blending technologies. Within the frame of this chapter, the scientific background is discussed based on a short literature review focusing on the integration aspects of digital twin solutions.

The integration plays an important role in the efficiency improvement of production systems. This efficiency improvement can be based on unified platforms, which make it possible to integrate the whole value chain of a product, from design through manufacturing to maintenance. Fu et al. proposes in a research on integration potentials in production, an information-physical framework to support the smooth, defect free design-production-maintenance [1]. As from the research work of Shen et al. can be concluded [2], there is a lack of integration framework supporting the standardization of data available in a complex system. This research demonstrates an integration approach focusing on the communication between building information modelling (BIM) and digital twin. This integration platform makes it possible to support the real-time monitoring of real-world resources, in this approach buildings, but this integration can be also applied in production systems between enterprise resource planning (ERP), manufacturing execution systems (MES) and digital twin.

Chiachío et al. emphasizes in a research on structural engineering [3] that a suitable digital twin can support simulation, learning and management of real-world systems, and autonomous interactions, automated decision makings can also be performed. The same aspects are demonstrated by Zhang et al. [4] from the integration of design, production and services point of view. These approaches validate that in the case of blending technologies, where real-time interaction in blending and dosing processes is important, digital twin solutions can significantly increase the efficiency and productivity of technological processes. As Tancredi et al. concluded in a research on anomaly detection in food plant using digital twin technology [5], integration of digital twin, machine learning and Industry 4.0 technologies plays an important role in the control of key performance indicators. In this approach smart sensors plays an important role, because they make it possible to monitor specific plant parameters. This approach can also be used for blending technologies, where complex sensor-actuator sets are responsible for the process control. The integration of this sensor-actuator set and machine learning can lead to autonomous, automatized decision making. The same aspects are discussed in [6], where the integration of artificial intelligence is analyzed in the lifecycle of digital twin applications. As Overbeck et al. concluded [7], the long-term application of digital twin solutions can significantly increase the efficiency of production systems through the systematic integration of value making processes. In their study, they validate the suitability of discrete event simulation tools and methodologies in the analysis of the impact of digital twin solutions.

Mhenni et al., proposes a novel meta-model for system models integration within a digital twin framework [8]. In this model, the authors are focusing on the integration of systems engineering, safety analyses and multiphysics. These aspects can be taken into consideration also in the case of blending technologies. Based on the proposed approach it is possible to analyze potential scenarios and make forecasting.

Based on this short literature review, the main contribution of this article is the description of the IoT supported model framework of vendor managed inventory problems with consignment contract and the just-in-sequence supply based on crossdocking. The digital twin solutions are used in a wide range of industry. As Rogachev et al. shown in a research on digital twin application in agriculture [9], the introduction of digital twin solutions has strengths, weaknesses, opportunities, and threats and these aspects must be analyzed before application.

All these research results and research directions suggests that it is important to perform a research work on analysis of integration aspects of digital twin technologies in blending technologies.

3. MATERIALS AND METHODS

Within the frame of this chapter, the blending technologies are characterized, and the available IoT solutions that are relevant for the integration of physical and digital layers of blending technologies are discussed. There are two important types of blenders, continuous and batch blenders. Continuous blenders are typically used for extrusion, while batch blenders are for injection molding. In the case of continuous blenders, the control is generally based on the loss-in-weight methodology, where the quantity to be added to the blending process depends on the weight loss of materials in the supply storage. The control of the operation of continuous and the batch blenders are based on dosing units, which are suitable to feed the blender depending on the real-time material demand. In the case of batch blenders timed flapper or plunger-style valves, rotating augers are used to control the material flow in the blender [10]. The operation of blending technologies can include a wide range of technological solutions, these solutions can be discussed and summarizes as follows.

Enterprise Resource Planning (ERP): ERP is a significant part of blending processes, because the design and operation of blending technologies needs to perform a wide range of design and operation tasks. In addition to the conventional ERP functions, special modules appear in the ERP, such as Recipe Development, Weight/Volume Communication, Hazardous Materials Management and Laboratory Management Information System. ERP is responsible for the following main tasks: gives access to required business data, schedules technology and logistics from purchasing through production to distribution and sales, integrates business and technology, inventory control.

Manufacturing Execution Systems (MES): MES is responsible for the following tasks: data collection from the physical processes (technology and logistics), analysis production process, enforce process requirements [11].

Digital Twin (DT): DT is a digital copy of the physical processes. In the case of DT, the information flow is bidirectional and automatized, in the case of digital model there is no direct information flow between the digital layer and the physical layer, while in the case of digital shadow, there is an automatized information flow from the physical layer to the digital layer. DT makes it possible to collect real time data from the physical layer (from the manufacturing system) and support the real time decision making [12].

Smart Sensors (SS): SS collect data at the physical layer, but these data are preprocessed, analyzed and compressed before sending to the next level of the control system. For example, the smart humidity sensor measures the humidity every 10 ms, but the numerical value of the humidity of the material is transmitted only in every 10 seconds as an average value. Using this solution, we can avoid the occupation of bandwidth and avoid delays in communication. Smart sensors are generally based on edge computing solutions.

Identification technologies, barcode or radiofrequency identification (RFID): Identification technologies can significantly increase the efficiency and availability of resources. RFID can be used for both identification and tracking in in-plant processes.

Edge computing: In the case of edge computing, raw data is processed near the end device (e.g. smart sensor) and the preprocessed data is uploaded to the cloud [13].

Cloud computing: As Cheng et al. defines [14], “cloud computing offers an unrivaled level of agility, security, and scalability and significantly increases data handling capacity”. Cloud computing represent core solutions for big data problems, where huge amount of data is generated and collected by IoT.

Augmented reality (AR): Augmented reality integrates digital information and physical information, while in the case of virtual reality we are talking about a digital environment. AR can support the work of human operators, because digital information regarding the operation of the physical system can be added real time to the operators working environment.

Machine learning (ML): ML means applications that can learn without any explicit instruction. Machine learning is generally based on neural networks and artificial intelligence solutions. These technologies are fundamental solutions for a suitable digitalized blending process.

4. RESULTS

Industry 4.0 technologies make it possible to improve the processes of blending technologies. Within the frame of this chapter, the functional model of digital twin technology supported blending technologies are discussed. Based on this model, the optimization potentials are also discussed to demonstrate the impact of digitalization on the efficiency improvement of blending technologies caused by real-time decision making.

4.1 Functional model of digital twin supported blended technology

The functional model of the digital twin supported blending technology is shown in Figure 1. The physical layer includes the technological, logistics and human resources of blending and dosing. The connection between the physical and digital layer is initialized by the smart sensors, which collect status information and failure data from the blending and dosing process. Typical sensors are temperature, weight, volume, humidity and pressure sensors. Sensor data are preprocessed as an edge computing solution and preprocessed information is sent to programmable logical controllers. Sensor data is uploaded to a database. The digital twin can collect data to their operation both from this database and directly from the sensors. The digital twin uses the direct data from sensors to perform real time analysis to make real time decisions, while data from data base is suitable to make long term decisions. The digital twin integrates three important tasks. The first task is the forecasting of blending both on micro- and on macro-level. Micro-level forecasting focuses on the dosing of blenders and specify the required amount of raw materials depending on the real-time parameters of the raw materials, while macro-level forecasting analysis the customers' demands and generates predictions for the future demands of blending.

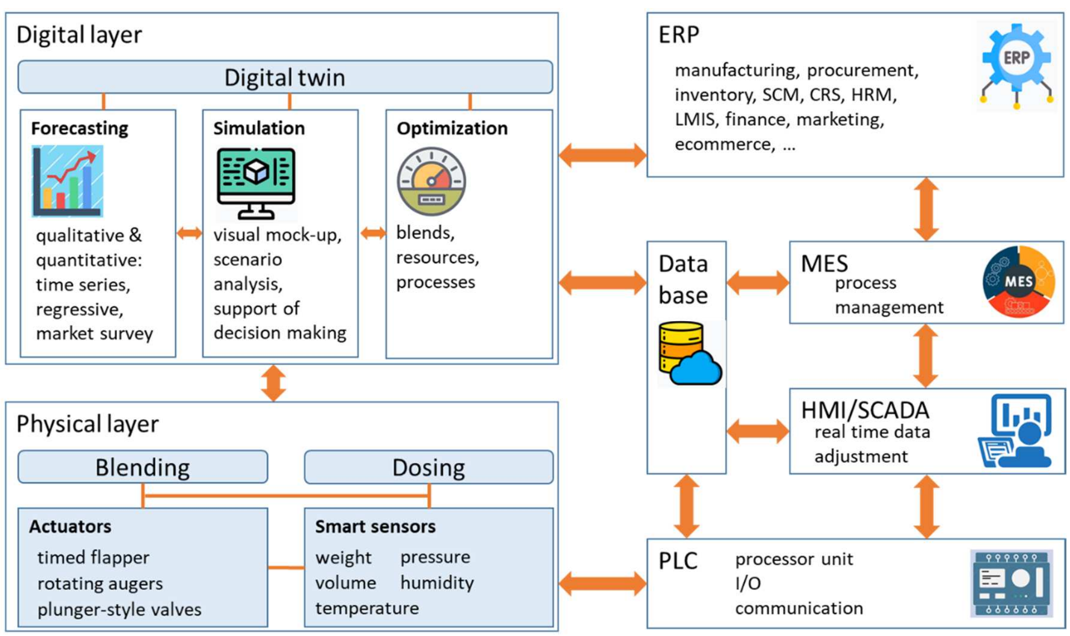

Fig.1. Cyber-physical supply chain management model in the case of vendor-managed inventory with consignment contract and in the case of cross-docking facility-based just-in-sequence supply

The second task of the digital twin is the visualization (visual mock-up), the analysis of different scenarios and based on the results of the analysis the real time and long term decision making. The digital twin is connected to a discrete event simulation tool, and the simulation tool uses a dynamic model, which is permanently upgraded by the digital twin, depending on the status of the resources of the blending technology. The third task is the optimization, which can be also divided into two main parts. The first part is the real time optimization focusing on the blending and dosing process optimization, while the second part is the long term optimization of technology and logistics related processes. Long term optimization is for example the supplier selection depending on the specific quality parameters of the customers. The digital twin uploads all information to the database. This lead to big data problems, therefore cloud computing solutions are required to solve big data problems. The human machine interface is responsible for real time data management. MES focuses on process management, while ERP integrates the conventional modules and the special modules for blending and dosing technologies and solutions. These special modules are the Blending Recipe module and the Laboratory Management Information System. It is important to integrate the whole process, and in this approach the main integrator is the digital twin connecting and supporting the operations of the vertically integrated value chain including sensors, PLCs, HMI/SCADA, MES and ERP. As the main integrator, digital twin makes it possible to connect sensor data of blending and dosing processes, laboratory processes, in-plant materials handling processes, purchasing and distribution processes. This integration is based on the processing of real time data, simulation supported forecasting and optimization and real time decision making. Within the frame of the next chapter, the potential advantages of optimization based on real time data are discussed.

4.2 Optimization of blending processes based on digital twin integration

In this model, the impact of digital twin supported procurement management on the profit of the blending technologies is discussed. The objective function of the optimization is the maximization of the total profit:

$$P = I - O \rightarrow max., \qquad (1)$$

where

$$I = \sum_{j=1}^{j^{max}} p_j \cdot \left(\sum_{i=1}^{i^{max}} \sum_{t=1}^{t^{max}} d_{ijt} \right), \qquad (2)$$

and

$$O = \sum_{k=1}^{k^{max}} \sum_{j=1}^{j^{max}} \sum_{i=1}^{i^{max}} \sum_{t=1}^{t^{max}} x_{ijt} \cdot s_{x_{ijt}} \cdot q_{ijtx_{ijt}}. \qquad (3)$$

There are different quality and quantity related constraints to be taken into consideration. The quality related constraint defines, that it is not allowed to exceed the predefined quality parameters of the final product:

$$\forall i, j, t, q: \alpha_{ijtq}^{min} \leq \alpha_{ijtq} \leq \alpha_{ijtq}^{max}, \qquad (4)$$

where

$$\alpha_{ijtq} = \frac{\sum_{k=1}^{k^{max}} (x_{ijtk} \cdot q_{ijt} \cdot \beta_{kq})}{\sum_{k=1}^{k^{max}} x_{ijt}}. \qquad (5)$$

The quantity related constraint defines, that it is no allowed to exceed the available raw material stock. In the conventional model the availability is a fix parameter, while in the case digital twin application, the real time decision makes it possible to find additional suppliers:

$$\forall k: \sum_{j=1}^{j^{max}} \sum_{i=1}^{i^{max}} \sum_{t=1}^{t^{max}} x_{ijtk} \cdot q_{ijtk} \leq a_k^1, \qquad (6)$$

The description of the used variables is shown in Table 1.

Table 1

Description of variables.

Variable	Description	Unit
P	profit of the blending process	[USD]
I	income of the blending process	[USD]
O	outcome of the blending process	[USD]
p_j	specific price of final product j	[USD/pcs]
d_{ijt}	demand of customer i for product j in time window t	[pcs]
x_{ijt}	assignment matrix, if $x_{ijtk} = k$ then raw material k is assigned to demand j of customer i in time window t	[-]
$s_{x_{ijt}}$	specific price of raw material k	[USD/pcs]
$q_{ijtx_{ijt}}$	volume or weight of used raw materials in time window t in final product j for customer i	[pcs]
α_{ijtq}^{min}	the lower limit of quality parameter q in time window t in final product j for customer i	[%]
α_{ijtq}^{max}	the upper limit of quality parameter q in time window t in final product j for customer i	[%]
α_{ijtq}	quality parameter q in time window t in final product j for customer i	[%]
β_{kq}	quality parameter q of raw material k	[%]
a_k^1	availability of raw material k	[pcs]

Within the frame of the scenario analysis a blending process is analyzed, comparing the conventional and digital twin supported decision making process regarding availability of raw materials to be blended. The are 5 blendings as final products in this scenario, the customer's demands and the related incomes are shown in Table 2.

Table 2

Forecasted demand of blendings.

ID	B1	B2	B3	B4	B5
Demand [pcs]	100	120	95	138	72
Spec. income [USD/pcs]	5.50	6.25	7.18	3.25	6.62

There are 9 different types of raw materials, their five different quality parameters and their specific purchasing costs are shown in Table 3.

Table 3

Component parameters of the Scenario analysis.

CID	Par1 [%]	Par2 [%]	Par3 [%]	Par4 [%]	Par5 [%]	Price [USD/pcs]
C1	2	6.8	5.3	4.4	7.9	2
C2	3.9	7.9	8	6.9	2.1	3.9
C3	2.3	5.6	4.3	5.7	3.3	2.3
C4	4.7	6.9	5.6	4	2.6	4.7
C5	2.8	5	4.3	5.6	2	2.8
C6	4.4	7.7	1.58	2.3	4.6	4.4
C7	7.3	2.2	6.9	4.9	6.2	7.3
C8	7.7	5.4	5.8	3.9	2.1	7.7
C9	7.6	7.7	7.4	7.7	6.9	7.6

Table 4 shows the predefined quality parameters for all final products. In this scenario, the quality parameters of the final products are defined as a minimal % of ingredient.

Table 4

Specific parameters of blended products.

PID	Par1 [%]	Par2 [%]	Par3 [%]	Par4 [%]	Par5 [%]
P1	4.15	2.35	3.00	4.12	5.20
P2	3.14	5.12	4.00	3.25	4.20
P3	3.95	3.40	4.00	4.52	3.35
P4	5.10	3.22	3.50	2.35	2.12
P5	4.23	3.88	4.20	2.60	2.05

The model takes logistics parameters into consideration, such as the availability of raw materials. In this scenario, the planned availability of raw materials is defined in the following availability array:

$$a^P = [66,120,70,90,120,55,120,55,120], \quad (7)$$

but supply chain disruptions lead to lack of raw materials, therefore in the case of conventional blending control the following modified availability array must be taken into consideration:

$$a^1 = [66,75,70,90,120,55,70,55,60]. \quad (8)$$

Regarding the above mentioned mathematical model, the solution of this blending problem can be defined as a linear integer programming problems, and it can be solved using any commercial solver. The optimal blending to produce the customer's demands are shown it Table 5.

Table 5

Solution matrix for the first scenario.

CID/PID	P1	P2	P3	P4	P5
C1	3	63	0	0	0
C2	0	0	10	1	64
C3	36	33	0	0	0
C4	0	0	0	89	1
C5	0	0	0	0	0
C6	0	1	39	0	0
C7	61	9	0	0	0
C8	0	0	0	48	7
C9	0	14	46	0	0

The optimal blending parameters resulted a maximum profit of 527.84 tEUR in the conventional solution. The quality parameters of the final products are shown in Figure 2. The optimization leads to final products without exceeding the predefined quality parameters.

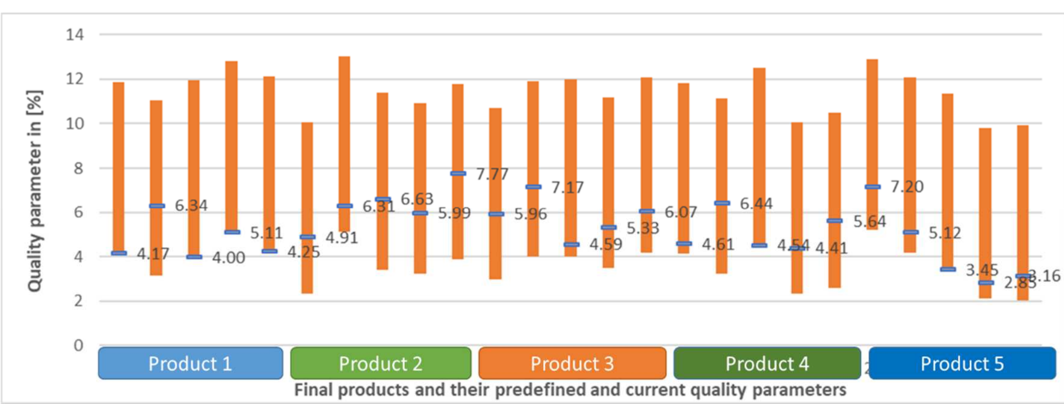

Fig.2. Quality parameters of the final products in the case of optimal blending and conventional optimization

In the case of digital twin supported blending technologies, the available raw material is permanently monitored from quality and quantity aspects, and in the case of lack of raw materials it is possible to make real time decision regarding the optimization of the blending process from technological and logistics point of view. In the case of technology, LMIS can analyze the recipe and make upgrades if necessary, while in the case of logistics it is possible to find new supplier to order the missing amount of raw materials in order to produce the original final products according to the original recipe. In the case of this solution, the profit is 1010.24 tEUR, which means a cost savings of about 48%. As Figure 3 shows, the quality parameters do not exceed the predefined lower and upper limits in this digital twin supported solution, which means that the digital twin supported technology can lead to cost savings while the quality parameters of the final products are expected.

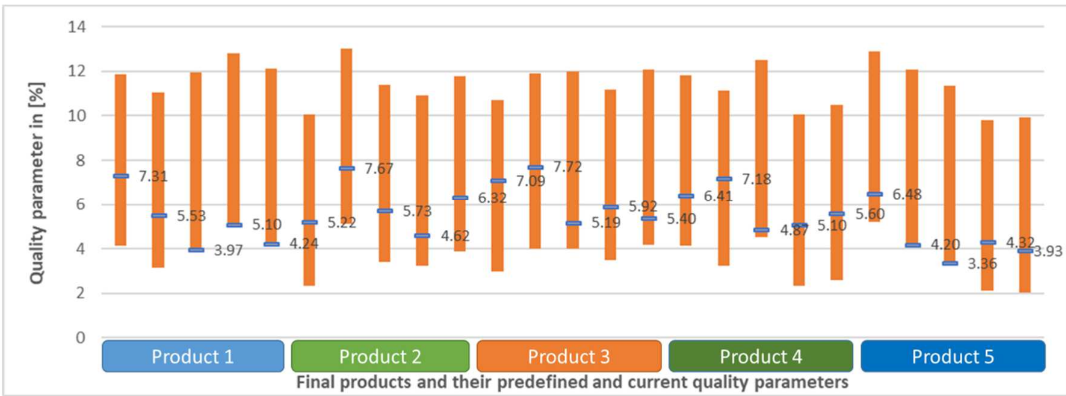

Fig.3. Quality parameters of the final products in the case of optimal blending and conventional optimization.

5. CONCLUSION

Optimization of technology and logistics is an increasingly important goal of production companies. In the case of blending, the technology has significant impact on the processes, because the quality parameters of raw materials define and influences the quality parameters of final products. Therefore, it is important to improve the process control in blending technologies. Industry 4.0 technologies offer new potential to increase the efficiency of blending technologies. In this paper, the author presents a digital twin technology-based approach that is suitable for the real-time control of blending processes from technological and logistics point of view. The application of the presented functional model makes it possible to save costs through a real-time decision making supporting purchasing processes depending on the availability of raw materials. The essence of this approach is that depending on the availability of raw materials, demands of customers and current blending processes, the digital twin can make forecasts and simulations to support the decision making process of the purchasing department. The discussed methodology is validated using a mathematical model and a scenario analysis, showing the resulted cost savings. The model can be used in many types of industry. The limitation of the model is that the parameters are deterministic, but in the future stochastic parameters can also be taken into consideration.

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Tehnologii digitale: integrarea tehnologiei și logisticii prin utilizarea soluțiilor oferite de internetul lucrurilor

Industria 4.0 a introdus noi tehnologii și abordări care pot aduce o contribuție majoră la îmbunătățirea performanței proceselor de producție și servicii. Pentru companiile care folosesc tehnologii de amestecare, integrarea tehnologiei și a logisticii devine din ce în ce mai importantă, pe lângă optimizarea parametrilor procesului, întrucât un sistem logistic bine conceput poate spori mult eficiența proceselor tehnologice. Autorul propune o soluție bazată pe soluții digitale twin pentru a spori eficiența proceselor tehnologice în companiile care utilizează tehnologia blending prin optimizarea în timp real a proceselor tehnologice și logistice susținute de o soluție digitală tip twin. Modelele și metodele prezentate demonstrează că se pot obține îmbunătățiri semnificative în procesele tehnologice și logistice prin aplicarea modelului prezentat folosind soluții digitale de tip twin.

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