

Modeling and Construction of Circular Economy Digital Twins Based on System Dynamics

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Abstract. *This paper examines system dynamics (SD) in the context of building digital twins (DTs), particularly within circular economy systems. It begins with an overview of SD. The strengths and limitations of SD are analysed in comparison with complementary simulation methods, including Agent-Based Modeling (ABM), Petri Nets, and Discrete Event Simulation (DES), to identify potential for integration. The analysis focuses on how these methods can address specific gaps in SD, such as individual-level behaviour, discrete events, and operational workflows and enhance the accuracy, detail, and flexibility of DT development. The paper explores methodological approach for combining SD with complementary approaches and highlights the importance of selecting modeling techniques based on system characteristics and modeling goals. The feasibility of implementing such models is further examined through the analysis of relevant modeling tools, with particular attention to hybrid platforms like AnyLogic that support SD, ABM, DES, and real-time data integration in DT applications. The paper discusses future directions for simulation-based DT development in circular economy contexts, emphasizing the potential for multi-method modeling to support strategic and operational decision-making.*

Keywords. system dynamics, agent-based modeling, digital twin, petri nets, discrete-event simulation

1 Introduction

In modern organizations, value chains and business ecosystems there is a strong emphasis on increasing agility and efficiency, optimizing operations, reducing disruptions and other risks (Sabri & Sahri, 2010). This requires real-time analytical and predictive capabilities. Increasingly and in various problem areas, the solution is sought in building a DT of the system being managed (Akhtar et al., 2022). A DT is a simulation model of a physical system that reflects its function, behavior, or other properties of interest with sufficient accuracy, and is coupled to that system in such a way that it receives data about the states and

changes of its original in real time. A physical system and its corresponding DT as a cyber representation form a cyber-physical system (CPS) (Januario et al., 2019).

The choice of the method and technique of simulation modelling, which is the basis for building a DT, is critical in its construction. The focus of this paper is on the research of properties of SD in the development of a simulation model, and later a DT in the field of circular economy. SD is a method used to understand the behavior of complex systems over time. Its core strength lies in its ability to model interactions among different system components and analyze how changes in one part of the system affect others (Ding et al., 2018; Gejo-García et al., 2022). SD can be limited in predicting unexpected behaviors and external influences that can significantly affect the long-term behavior of a system. Because of these limitations, the combination of SD with other modeling methods is becoming increasingly popular (Serman, 2018). For example, ABM allows for more detailed simulations of individual behaviors within a system (Ding et al., 2018), while DTs provide real-time data and updates (Liu et al, 2021) that can improve the accuracy of the model.

The aim of the research, the results of which are presented in this paper, is to analyze the suitability of SD, independently and in combination with other methods, for simulation modeling and building DTs of physical circular economy systems.

The circular economy, which is based on the principles of waste reduction, reuse and recycling, requires models to analyze the flows of materials and energy through the system (Chenet al., 2021). Modeling circular economy processes faces challenges, like nonlinear flows of materials and energy, uncertainties in supply chains, heterogeneity of actors, and the need to integrate short-term operational with long-term strategic decisions. Precisely because of these challenges, it is important to combine multiple modeling approaches. SD is suitable for this purpose because of its ability to model complex interrelationships and feedback loops. Optimizing resource use is essential to achieving the goals of the circular economy. SD can help analyze the

effectiveness of different resource management strategies, such as reducing energy or water consumption, and assess their long-term effects on the system. This method allows testing different scenarios to identify the most effective measures to conserve resources (Akhtar et al., 2022).

The paper is structured into five chapters. Chapter 2 discusses SD and the possibility of its complementary application with other modeling methods. SD has been a subject of scientific research for decades, as well as the similarities, differences, overlaps, complements and possibilities of integration of different methods, such as ABM, Petri Nets and DES. Advantages of separate application of SD and other methods, and to use the complementarity of methods and synergistic effects on accuracy, usability, reliability and other properties of the simulation model and DT in an integrated environment (Choi et al., 2023; Ding et al., 2018; Garcia, 2020). Building a DT based on a SD and complementary methods, including the methodological framework and decision-making in the requirements definition and system design phase, is the subject of Chapter 3. After comparative analysis, followed the process of selecting methods complementary to SD in simulation modeling and possibly creating a DT of the physical system in the circular economy. Chapter 4 analyzes the possibility of applying tools for the development of DTs based on SD and complementary methods. Conclusion and future research summarize the analysis and highlight future directions for the study of DTs based on SD and complementary methods.

2 System dynamics and complementary modeling methods

As SD is a system modeling method based on stocks and flows, feedback loops (positive and negative), time delays, as well as variables and parameters that define relationships and influence system behavior over time (Bala et al., 2017; Garcia, 2020). SD is more of a set of methods and tools than a single method (Bala et al., 2017). It involves creating models that represent systems as a set of interconnected components, using simulations to predict the behavior of the system over time, and analyzing the feedback loops that govern the dynamics of the system. Data for SD models usually come from actual measurements, historical data, expert assessments, and scientific research. The process involves identifying key variables and the relationships between them and quantifying them in a way that allows for simulation and analysis (Bala et al., 2017).

SD is used in modeling and simulation of short-term and long-term dynamics. It helps to understand how changes in a system act in the short and long term, including identifying causes and effects that may not manifest immediately (Garcia, 2020). It is suitable for modelling linear and nonlinear relationships within a

system, which is crucial for understanding complex systems (Garcia, 2020). In addition to predictive analytics at the operational and tactical levels, SD is used to analyze and design policies and strategies for managing loosely coupled systems, including value chains and ecosystems in the circular economy, which is a particular subject of interest in this paper (Malbon & Parkhurst, 2023).

SD is chosen as the primary modeling approach in this article due to its unique ability to capture the structural foundations and long-term behavior of complex systems such as those found in the circular economy. Unlike other modeling paradigms that focus primarily on events or individual entities, SD emphasizes systemic structure, causal relationships, and feedback loops that drive system evolution over time. This makes it particularly suitable for identifying leverage points, simulating policy interventions, and understanding the accumulation and depletion of resources across production and recovery cycles. Moreover, its capacity to integrate both qualitative insights and quantitative data allows for flexible and transparent model construction, which is essential in domains where uncertainty, delays, and indirect effects are common (Bala et al., 2017). By using SD as the foundation, the model ensures a coherent, system-wide representation upon which more detailed methods like ABM and DES can be layered when needed.

The foundation for building a DT of a physical system is the creation of its simulation model (Biller et al., 2023). This chapter presents a comparison of SD with some other simulation modeling methods, to fill in the gaps that are missing from SD. The applicability and choice of methods for simulation modeling in general, and in the circular economy, depend on fundamental properties and expected behaviors of the physical system, such as predominantly static versus dynamic behavior; deterministic versus stochastic behavior; linearity versus nonlinearity; discrete versus continuous state changes; and the presence or absence of feedback. It should also be considered whether the objective of modeling is to understand and analyze the physical system, optimize individual aspects, predict behavior, or construct a DT.

ABM is a simulation method used to model the interactions of autonomous agents which can represent individuals, organizations, or entities, within an environment (Khazaii, 2016). It is based on bottom-up modeling, where agents follow defined rules and make decisions based on local information, often leading to complex, emergent phenomena (Khazaii, 2016). It captures the evolving state of the system over time, which is useful for studying how complex behaviors emerge from simple agent interactions, making it useful for modeling systems with non-linear dynamics. It is flexible for a wide variety of different domains, scenarios, from human behaviors social dynamics, and decision-making processes in areas like economics, sociology, and politics, through ecological modeling of interactions between species, resource usage, and

environmental changes, to simulating complex circular economy and supply chain behaviors and interactions of agents. In all these applications, ABM focuses on individual agents, which allows for granular analysis of specific behaviors, interactions and outcomes (Khazaii, 2016).

There are problems for which ABM is not a good solution for simulation modelling:

- problems that are highly deterministic or where interactions are simple and predictable
- detailed information about individual agents or their behaviors is unavailable
- optimizing processes at the system level, especially when interactions are not as important as high-level parameters
- problems requiring high-volume data processing or real-time decision-making when modeling large numbers of agents or complex environments
- change in agent behavior, which would require to calibrate the models accurately, especially when there is limited data on agent behavior.
- overfitting and to specific agents leading to reduced generalizability.

ABM is useful in many areas, and research touches on healthcare systems, smart cities, manufacturing, and the like. Research (Ding et al., 2018) presented a concrete example of SD implementation in the Vensim tool and filled in the gaps that SD cannot fill with ABM. In the area of complex systems, Cassidy et al. conducted a systematic review of the application of SD and ABM models (Cassidy et al., 2019). Their research shows that SD can help in understanding complex interaction. Agent-based models provide insight into the behavior of individual entities within the system, which can be complementary to the SD approach. SD and ABM can be successfully used complementary in simulation modeling. SD is used to study macro-level system behavior such as the movement of resources or quantities in the system over time. ABM models micro-level system behavior through the behavior of individual agents and their interactions. Examples are people, their decisions and their interactions (Cassidy et al., 2019). The combination of these methods allows for a detailed understanding of micro-dynamics and its impact on macro-dynamics. ABM is a bottom-up approach, simulating changes in the state of individual agents in the system, which can be aggregated in SD. The combination of SD and AB can reduce computational time, provide a strategic overview characteristic of SD, while at the same time capturing relevant elements of individual heterogeneity and stochasticity of agents and interactions in processes (Guerrero et al., 2016).

Petri Nets are a modeling method with a solid mathematical foundation and graphic representation used to represent and analyze discrete event systems, particularly for systems with concurrent, asynchronous, or parallel processes (Dai et al., 2020).

Digital twins driving model based on Petri net in industrial pipeline. They consist of places representing conditions or resources, transitions representing events or activities, tokens that reside in places and move between places via transitions, representing the state of the system (Dai et al., 2020). Petri nets are widely used for modeling and simulating dynamic systems, with a strong focus on the flow of information or resources and how they evolve over time. Petri nets are particularly effective at modeling systems with multiple concurrent processes and synchronization constraints. They are used for modeling various types of systems, such as time or resource-dependent processes in manufacturing, resource management and scheduling, assembly and other workflow systems with multiple interacting components. In the field of communications, they are used for modeling communication protocols, distributed systems, and network flows, where concurrency and synchronization are important, including concurrent and parallel processing (Dai et al., 2020). Areas and problems where Petri nets modeling is not a good choice are:

- modeling continuous or analog systems, such as fluid dynamics or electrical circuits, where differential equations are used,
- very complex or large systems where Petri nets are very large, computationally expensive and difficult to analyze or simulate, leading to state-space explosion problems,
- data-intensive systems that require detailed and complex data modeling, because Petri nets focus on control flow and resource allocation, but they do not directly model detailed data structures or system-level behaviors,
- systems where decision-making is complex and strategic, as they focus more on process flow and less on high-level cognitive behavior.

Petri Nets and **SD** can complement each other effectively in simulation modeling (Duggan, 2006; Viswanadham & Srinivasa Raghavan, 2000). Petri Nets are excellent for capturing the detailed, event-driven behaviors of specific processes (Viswanadham, & Srinivasa Raghavan, 2000), such as material flows, recycling processes, or product disassembly, where concurrency, resource allocation, and synchronization are important. SD, on the other hand, excels at modeling feedback loops, stock-flow relationships, and long-term behavior, such as the impact of recycling rates on resource stocks or the effects of consumer demand on product life cycles. By combining Petri Nets with SD, detailed process flows and interactions which are the result of events that occur and changes in the state at certain points in time can be captured alongside the broader, system-level dynamics. All of the above is applicable to the circular economy because it enables both operational insights and strategic, policy-driven decision-making (Duggan, 2006).

DES modeling method is used to represent systems where changes occur at discrete points in time due to specific events. In DES, the system's state is updated only when an event occurs, and events trigger changes in the system (Ragazzini et al. 2024). DES is particularly useful for modeling and simulations of the behavior of systems that are driven by discrete events, providing a detailed and realistic simulation of how systems operate over time. It can be used to model a wide range of systems, from simple queuing systems to complex manufacturing or healthcare systems and transportation networks (Ragazzini et al. 2024). DES can help in identifying bottlenecks, delays and inefficiencies in system performance and resource utilization, in a way that allows for experimentation with different system configurations, resource allocations, and process flows to test various scenarios and outcomes (Ragazzini et al. 2024). DES has limitations in modeling and simulations:

- useful only for systems where discrete events happen at distinct points in time and not for continuous or analog systems where time is a continuous variable
- can be time-consuming and resource-demanding, particularly for complex systems when accurate modeling of many events and interactions is required,
- In large or complex systems, the number of possible states and events explodes exponentially, making it difficult to manage, analyze, or interpret the results.
- may not be effective in environments requiring real-time decision-making, such as some emergency systems, where fast and dynamic adaptation to changes is crucial.

DES and SD can be complementary in simulation modeling, especially in the context of the circular economy, by combining their strengths (Morgan, 2011). While SD is excellent for modeling large-scale, long-term, and continuous feedback loops in systems like resource flows, waste recycling, and stock accumulation, DES can be used to model specific, time-dependent events like the processing of materials, product repairs, or resource transactions that occur at discrete points in time (Reed et al., 2021). When combined, SD can capture the overall dynamics and feedback mechanisms within a circular economy, while DES can model the detailed, event-driven activities (such as product disassembly or resource recovery) that drive those dynamics. Together, they provide a more comprehensive view, combining the holistic, feedback-rich system modeling of SD with the event-based, process-level detail of DES, making them effective in analyzing systems that require both high-level strategic insights and detailed operational efficiency (Jovanovski et al., 2012). Combining system dynamics and discrete event simulations- Overview of hybrid simulation models. *Journal of Applied Engineering Science*, 10(3).

Several modeling methods can complement SD in circular economy contexts. **DTs** support real-time model validation and system monitoring, though they require substantial data and resources. **ABM** enhances SD by simulating individual behaviors and interactions, offering detailed system insights, but is complex to define and implement. **Petri Nets** are effective for modeling discrete events and system synchronization, though limited to event-driven systems. **DES** excels at modeling time-specific processes like material flows and repairs, but is less suited for continuous dynamics. Each method addresses specific system characteristics, enabling a more comprehensive simulation when combined with SD.

The method selection matrix is presented in Table 1.

Table 1. Method selection matrix for combination with SD

Method	System-level understanding and analysis	Implementation complexity	Application in circular economy	Real-time analysis	Big data integration	Process management and optimization
DT	+ (Liu et al, 2021)	–	+ (Rocca, et al., 2005)	+ (Choi et al., 2023)	+ (Stojanovic et al, 2021)	+ (Liu et al, 2021)
ABM	+ (Guerrero et al., 2016)	+ (Ding et al., 2018)	+ (Lange et al., 2021)	–	–	+ (Ding et al., 2018)
Petri Nets	+ (Viswanadham, & Srinivasa Raghavan, 2000)	–	+ (Viswanadham, & Srinivasa Raghavan, 2000)	–	–	+ (Viswanadham, & Srinivasa Raghavan, 2000)
DES	+ (Ganguli & Adhikari, 2020)	+ (Ganguli & Adhikari, 2020)	+ (Charnley et al., 2019)	–	–	+ (Ganguli & Adhikari, 2020)

3 Building a DT based on a SD and complementary methods

DTs enable the creation of virtual replicas of physical systems that are continuously updated with real-world data. The combination of DTs and SD enables the modeling and simulation of physical system in near real-time. They help to identify and analyze changes in the system in real time, which can improve system prediction and management (Ganguli & Adhikari, 2020). According to Stojanovic et al. (2021) the modern approach to DTs considers them as software entities that follow the entire life cycle of their physical counterparts, including the engineering, operations, and disposal phases. A DT becomes a replica of reality by implementing the real world as closely as possible and calibrating it with data. It was originally proposed

as a concept to support decision-making in the product design and manufacturing, but is used as an analysis tool throughout the entire life cycle. (Choi et al., 2023).

Regarding the application of SD as a methodological foundation of DTs, Gejo-García et al. applied the concept of DT to manufacturing systems to assess the long-term effects of different manufacturing strategies. Their research shows how SD can simulate and optimize manufacturing processes by considering the dynamic interactions between different components of the system (Gejo-García et al., 2022). A similar approach is used by Choi et al. in simulating naval ship operations using DTs, which shows how SD can be used to optimize operational strategies and improve ship performance (Choi et al., 2023). Both studies explore the importance of SD in creating DTs for the simulation and analysis of complex systems. In the context of the importance of DTs, it is also discussed in Ganguli & Adhikari article (2020) regarding the development of the framework of the virtual model of the physical system in which the DT plays a role, but it is still necessary to create and validate the simulation model, which is from the field of SD.

SD enables the simulation of the wide world with high fidelity, and the DT is not a term referring to a specific technology, but an idea that simulates the fusion of many existing state-of-the-art technologies. Researches on combining DTs based on SD with other methods, such as Gejo-García et al., (2022) for manufacturing systems, make it possible to draw conclusions about why combining these methods has advantages. DTs based on SD simulations provide a platform for CPS in which the DT well reflects the state of the physical system in real time. By enabling simulations of states and changes in states in the near future, the DT can serve:

1. Process management and real-time optimization, and indirectly improving flexibility and resilience in unexpected conditions Goodwin et al., 2024).
2. Decision support based on data and predictions, and indirectly proactive identification of disruptions within physical systems, optimizing resource utilization, increasing efficiency, etc. (Vetrivel et al. 2024).
3. Continuous Optimization and Lifecycle Management by leveraging real-time data and simulations, and indirectly improving planning capabilities, process stability, and resource optimization (Zhou, 2024).
4. More comprehensive approach to model building that includes different levels of models, different relevant areas, flows, and decision options within the domains of single entity, value chains or ecosystems (Biller et. al., 2023).

The methodological framework for the development of DTs necessarily unites the theoretical

structure, approaches and methods of two areas: Simulation modeling methodology and Model Technology - DTs are executable models that embody the features, behaviors, and properties of physical systems. To construct such executable, efficient, reusable, and interoperable models, an appropriate modeling technology is essential (Liu et al., 2019); Systems Engineering methodology, as used for the development of SCADA (Supervisory Control and Data Acquisition) systems and software for automatic process control.

4 Practical aspects of developing DT based on SD

This chapter focuses on the practical aspects of developing DTs based on SD and complementary modeling methods. It outlines the most relevant modeling tools and discusses the structural elements and application considerations essential for creating effective SD-based DTs in circular economy contexts.

4.1 Tools for modeling and simulation

Various software tools support the implementation of SD and its complementary methods in the development of DTs. Vensim, Stella, and AnyLogic are commonly used for SD modeling, based on concepts such as stocks, flows, feedback loops, and time delays (Sapiri et al., 2017). AnyLogic, in particular, enables hybrid modeling, combining SD, ABM, and DT functionality, including real-time data validation (Farhan et al, 2020; Chakraborti et al., 2020). Tools such as NetLogo and Repast specialize in ABM, supporting simulation of heterogeneous agents with adaptive behaviors and local interactions, which is especially useful for studying micro-level dynamics and emergent phenomena (Robertson, 2005;Antelmi et al., 2022). Petri nets are implemented through tools like CPN Tools and PIPE, providing precise modeling of discrete transitions, parallel processes, and resource flows within systems characterized by concurrency and synchronization (Dworzański & Lomazova, 2013; Llado, 2022). In the context of DES, tools such as Simul8, Arena, or even AnyLogic support modeling of event-driven systems where state changes occur at specific points in time. DES is particularly effective for analyzing queueing systems, resource scheduling, and operational workflows, offering time-based precision and performance optimization capabilities (Ganguli & Adhikari, 2020).

Among the available tools, AnyLogic stands out as the most versatile and comprehensive platform for developing DTs based on SD and complementary methods. Its support for hybrid modeling, which integrates SD, ABM, and DES within a single environment, allows researchers and practitioners to simulate systems at multiple abstraction levels — from

aggregate feedback-driven dynamics to individual agent behavior and discrete event flows (Farhan et al, 2020; Chakraborti et al., 2020). Moreover, AnyLogic supports real-time data integration, enabling dynamic model calibration and validation, which is essential for implementing operational DTs.

4.2 Conceptual and system architecture for digital twin development

Fig. 1 illustrates the logical relationship between SD and other modeling methods within a DT development context.

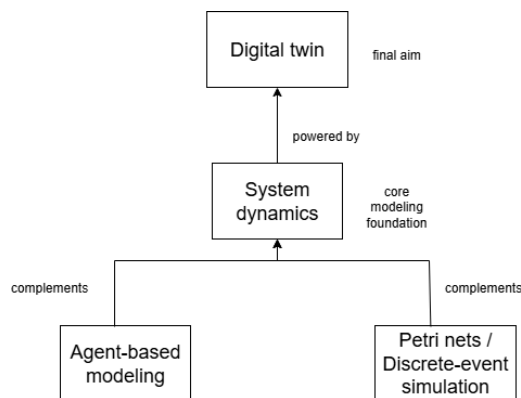


Figure 1. Conceptual modeling structure of a DT based on SD and complementary methods

SD serves as the core modeling foundation for the development of DTs, providing insight into long-term system behavior through feedback loops, stock-flow relationships, and continuous dynamics. SD has limitations when it comes to representing discrete events or individual-level behavior. To address these gaps, complementary methods are integrated: ABM enables simulation of autonomous agents and their interactions, capturing emergent and heterogeneous behaviors at the micro level; while Petri Nets and DES allow modeling of discrete, time-specific events, resource flows, and synchronization in operational processes. Petri Nets and DES are grouped together due to their shared focus on event-driven systems and process-level precision. Together, these methods complement SD by adding granularity, stochasticity, and temporal accuracy, enabling the development of DTs that are both systemic and detailed, strategic and operational, predictive and responsive.

After establishing the conceptual modeling logic in Fig. 1, which highlights the integration of SD with complementary methods such as ABM and DES, Fig. 2 presents a layered architecture that shows how such a model can be implemented within a CPS. It connects the physical environment to the modeling logic through communication infrastructure and real-time data integration, ultimately supporting applications such as monitoring, control, and decision-making.

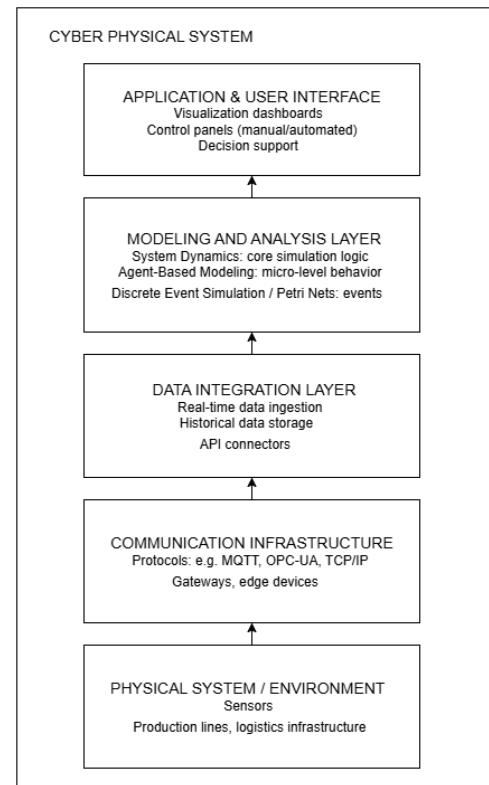


Figure 2. Layered architecture of a CPS for DT development (modified from Januario et al., 2019)

Architecture (Fig. 2) illustrates how DTs based on SD, ABM, and DES are operationalized. It spans from physical infrastructure and sensors, through communication and data integration layers, up to the simulation and application interface layers. This structure can enable real-time simulation, monitoring, and decision support in complex systems.

4 Conclusion and future research

This research analyzes SD and the need to complement it with other simulation modeling methods, such as ABM, and Petri Nets, especially in building DTs. Although SD has many advantages, such as the ability to model interactions within complex systems and analyze feedback loops, its shortcomings include limited ability to predict unexpected behaviors and external influences. By combining SD with other methods, these shortcomings can be compensated for and the accuracy and reliability of modeling can be improved, as demonstrated in this paper.

The research proposes the application of a methodological approach in building simulation models and DTs. Layered architecture is introduced to integrate various modeling methods with data infrastructure and application layers, enabling simulation models to evolve into real-time, decision-supporting DTs. This approach is particularly suited to

circular economy systems, where feedback, flow dynamics, and emergent behavior all play central roles.

Connecting different modeling paradigms like system dynamics, agent-based modeling, and discrete-event simulation enhances the representational fidelity of circular systems. This integration allows simultaneous representation of long-term trends, operational process flows, and individual behavior dynamics. In circular economy applications, such as product lifecycle extension, waste reduction, and material recovery, this multiscale perspective is essential for designing more resilient and resource-efficient systems.

Future research will focus on operationalizing the proposed conceptual framework within the textile industry. Using the architectural foundation presented in this work, a DT will be developed for a production-recycling flow with the objective of reducing generated waste. The model will incorporate real-time data streams, dynamic stock-flow structures, and event-based control, enabling scenario analysis and optimization of material reuse and resource efficiency strategies in line with circular economy goals.

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