A Digital Reverse Logistics Twin for Improving Sustainability in Industry 5.0

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Abstract. The rapid development of information and communication technology (ICT) and digitalization in the Industry 5.0 era have opened up new opportunities for reverse logistics management to become digitalized, smarter, more sustainable, and simplified by incorporating disruptive technologies, e.g., Internet-of-things (IoT), artificial intelligence (AI), big data analysis, simulation, blockchain, etc. Digital twin is one of the most promising concepts in Industry 5.0, which can re-create a physical object or system in the digital world. In this paper, different from the widely practiced product-based definitions, we extend this concept to a system-oriented digital reverse logistics twin. Based on a conceptual framework allowing for a high level of system integration, we present the key enabling elements for a digital reverse logistics twin that can support decisions in a complex and uncertain environment. Through an illustrative example of a remanufacturing network design problem in Norway, the initial proof-of-concept illustrates how different systems and models can be combined in a digital reverse logistics twin in order to support different decisions.

Keywords: Reverse Logistics, Digital Twin, Industry 5.0, Decision Support System, Simulation, Optimization.

1 Introduction

Nowadays, the accelerated pace of technological innovation and development has resulted in an ever-faster pace of product renewal and shortened product life cycles, which, in consequence, leads to an exponential increase in the generation of end-of-life (EOL) and end-of-use (EOU) products [1]. Meanwhile, sustainable logistics and supply chains have been a major research subject in recent decades due to increased global awareness and concerns associated with economic, environmental, and social sustainability in socio-economic activities [2, 3]. To properly manage the increased waste streams, while simultaneously promoting resource recovery from both EOL and EOU products, reverse logistics is considered to be one of the most crucial steps for moving toward sustainable development and circular economy [4, 5]. Due to this reason, as a profitable and sustainable business strategy, reverse logistics has gained increasing attention from worldwide companies and organizations.

The emerging concept of Industry 5.0 has shown a blueprint of the human-centric transition that predominantly focuses on the social and environmental dimensions of sustainable development. Several cutting-edge technologies of Industry 5.0 are driving firms to shift business strategies to be more sustainable [6, 7]. This process requires more information involved and the integration of interconnected smart components, real-time monitoring and control devices across the entire manufacturing network and logistics systems, which potentially enables virtual product and virtual process planning in order to provide better and more comprehensive decision support and system control [8]. As one of the most important enablers of Industry 5.0, digital twin is increasingly focused on by both industrial practitioners and academia.

Even though the concept of digital twin has been widely discussed in the context of different industries and businesses, most of them, especially in reverse logistics, are mainly defined from the product perspective, e.g., a data-intensive digital model that can track the product conditions and information throughout its entire life cycle [9]. However, reverse logistics is a complex system, and there is a lack of definition and conceptualization of digital reverse logistics twin from the system-oriented perspective. Thus, considering smart reverse logistic features and, in particular, cyber-physical integration for effective system visualization and data-driven decision-making, we provide a systematic conceptual framework of the digital reverse logistics twin to fill the literature gaps. The initial proof-of-concept is provided by an illustrative example of a compressor remanufacturing network design from EOL refrigerators in Norway. The proposed framework aims at showing a clear roadmap for future system integration that allows a high level of interaction between the digital and physical worlds of a smart reverse logistic system, with which various decision-making problems can be better supported.

The rest of the paper is organized as follows. Section 2 gives the theoretical background of reverse logistics management, Industry 5.0, and digital twin. Section 3 presents the methodology. Section 4 conceptualizes and shows a generic framework of digital reverse logistics twin. An initial proof-of-concept is presented in Section 5. Finally, Section 6 concludes the paper.

2 Theoretical Backgrounds

2.1 Reverse Logistics Management

Reverse logistics refers to a set of value recovery operations regarding the process of shipping EOL and EOU products or parts from the consumer point for possible reuse, remanufacturing, recycling, or proper disposal of materials, components, and products [10, 11]. The effective management of these operations is not an easy endeavor due to the complexity of reverse logistics systems that need the participation and collaboration of various stakeholders [12]. Due to the unpredictability and large variations of the EOL and EOU products in the reverse flow, the uncertainty related to reverse logistics operations is substantially larger than that in forward logistics [13], which results in greater impacts on decision-making [14].

Furthermore, reverse logistics operations may be affected by many unpredictive events and disruptions. For example, the COVID-19 pandemic has posed considerable challenges to global logistics systems and supply chains. The border closure, city lockdown, and reduced and limited transportation capacity have severely interrupted goods movements, increased logistics costs, and increased uncertainty of total transit time. In reverse logistics, the transborder movement of EOL and EOU products has been largely affected. Thus, the resilience and flexibility of logistics systems become increasingly important [15]. Furthermore, in an effort to overcome and minimize the negative impacts of logistics operations, the pandemic has also spurred many businesses and companies to adopt new technologies and methods from the latest industrial revolution to increase automation and reduce the need for human resources [16]. Therefore, there is a need to develop new solutions for reverse logistics management considering the emerging sustainable development challenges in the post-pandemic era under a highly uncertain and fluctuating global environment.

2.2 Industry 5.0

The fifth Industrial Revolution, namely, Industry 5.0, has the most potential to substantially optimize logistics in a strategic way [16], which offers new opportunities for smart and sustainable reverse logistics management by building up competitive and innovative business models and better managing the operations. While Industry 4.0 primarily emphasizes the role of automation and digitization through connecting physical objects with the real world to enhance manufacturing productivity, intelligence, and flexibility, Industry 5.0 focuses, however, on the human-centric transformation in the age of augmentation [17, 18]. Enabled and empowered by disruptive technologies, the importance of personalization, environmental sustainability, and human-centric societal transition are simultaneously emphasized [19]. Compared with Industry 4.0, despite smartness, connectivity, digitalization, and autonomy are still the core elements of Industry 5.0, the role of the human becomes most crucial in the transformation, where the potential of both human and technology can be largely exploited in a human-machine collaborative environment [16, 20].

Industry 5.0 empowers human intelligence to work with cognitive computing and intelligent automation [21], which paves the way for enabling smart logistics systems through achieving proactive planning with big data, real-time decision-making, responsive communications, better resource allocation, and smoother material flows [22, 23]. However, on the other hand, there are still numerous obstacles related to the implementation of new technologies in reverse logistics [24], e.g., the technological maturity and compatibility, the life-cycle environmental footprint of new technologies [25], etc. Thus, further research is needed to provide comprehensive decision support to better plan the smart reverse logistics transformation in the Industry 5.0 era.

2.3 Digital Twin

Digital twin is one of the most essential technologies in Industry 5.0 [19]. The terminology was first put forward as a concept practiced in the aerospace and aviation industry in the 1960s [26]. A “ twin” concept was developed by NASA to assess and simulate conditions onboard Apollo 13 so that the astronauts and the controlling center can monitor the spaceship's condition remotely and make decisions in an emergency event [27]. Digital twin was depicted as the “digital equivalent to a physical product” by Michael Grieves at the University of Michigan in 2003 [28]. Digital twin has become one of the top strategic technology trends since 2017 with a worldwide focus on digitalization. Research activities on digital twin have been dramatically increased by the explosion and rapid development of machine learning, wireless communication, and cloud computing [29]. The digital twin market is predicted to increase with an annual growth rate of 58 percent from USD 3.1 billion in 2020 to USD 48.2 billion by 2026 [30].

The origins of digital twins describe replicating products [8]. One of the key features of digital twin is the capability of transmitting and providing diverse types of data and information in an interoperable and consistent format [31]. Digital twin has various industrial applications at different lifecycle stages including product design, manufacturing, service, and EOL products [28, 32]. Among others, the application of digital twin in manufacturing has gained predominant focus, which can effectively help with production planning and control, maintenance, and layout planning [8]. It is a fundamental enabler of a highly integrated and collaborative smart manufacturing environment, which can effectively respond to real-time customer needs and conditions in the factory [33]. For example, a simulation-based digital twin is used to support heat monitoring and predictive maintenance of an automotive braking system in order to make prompt decisions and reduce accidental risks [34]. Digital twin, enabled by intelligent analytical tools, e.g., AI, simulation, optimization, etc., provides new opportunities for processing large volumes of data, achieving data-driven operation, realizing the real-time interaction, communication, and integration between cyber and physical worlds, and diversifying value creation.

3 Methodology

The methodology of system integration for reverse logistics management involves the utilization of various analytical tools and the integration of a wide range of data from different sources and stakeholders. As shown in Fig.1, the integrated system combines different data analytics tools like AI algorithms, machine learning, deep learning, optimization models, and simulations to facilitate strategic, tactical, and operational decision-making. This methodology is structured into three layers, namely, data collection, data processing and analytics, and decision support. The methodology of this paper builds upon the framework for system integration for smart reverse logistics management proposed by Sun, et al. [35]. This paper aims to extend the framework by introducing the concept of digital reverse logistics twins, with an emphasis on representing a more comprehensive, human-centric, and inclusive approach to provide decision-makers with more effective and robust decision support at different levels to improve sustainability in Industry 5.0 era.

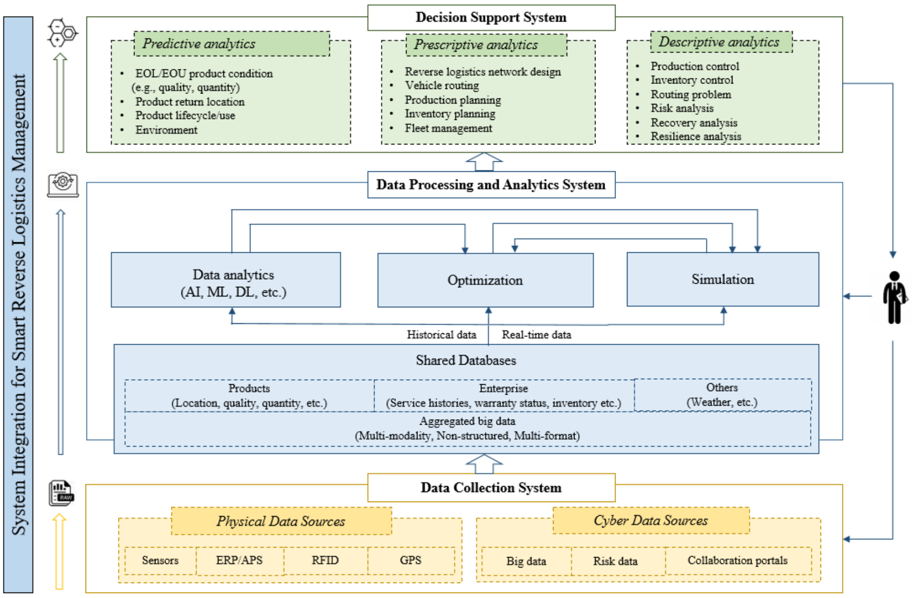

Fig. 1. System Integration for Smart Reverse Logistics Management [35]

4 Digital Reverse Logistics Twin

4.1 Human-centric Smart Reverse Logistics Transformation

The increasing adoption of cutting-edge technologies in Industry 5.0 will eventually lead to a smart reverse logistics transformation in various aspects including the smart collection of EOU and EOL products, smart transportation, smart remanufacturing and recycling, and smart disposal [36, 37]. As illustrated in Fig.2, reverse logistics has experienced paradigm shifts from unstructured isolated activities to today's highly structured, automated, and connected operations that aim at sustainable value recovery of EOL and EOU products and materials. Enabled by new technologies, e.g., IoT, AI, CPS, etc., the human-centric smart reverse logistics transformation has become the emerging hotspot in the Industry 5.0 era. For example, as an innovative business model, the collection activities of EOL and EOU products can be scheduled based on individual customer demands [38], where real-time truck utilization data and traffic data can be used to optimize routing and resource allocation. Besides, AI-enabled smart robots can be used in the sorting center to relieve human workers from harsh working conditions, where, in a collaborative environment, human workers can help the robots to categorize different types of waste streams. This human-centric smart reverse logistics transformation requires a high level of system integration to connect the physical world with the digital world. In this regard, digital twin plays an essential role.

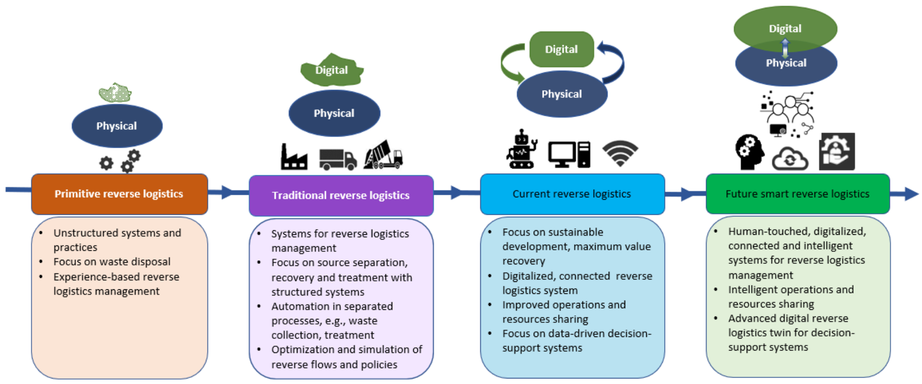

Fig. 2. Smart reverse logistics transformation.

4.2 Digital Twins for Reverse Logistics Operations

Currently, the application of digital twin is still in the way of exploratory development [39]. Among other reverse logistics activities, remanufacturing has become the most focused area of the adoption of digital twin [39], since it is becoming today's mainstream practice for recovering the EOL components at high value [40]. In remanufacturing, the concept of digital twin is defined from the product- or process-oriented perspective. A product-oriented digital twin tracks the product conditions through its entire lifecycle and provides valuable information for remanufacturing that usually suffers from high uncertainties related to the quantity, quality, and demand of EOL products [41]. In this regard, the primary enablers are to establish a cloud-based automatic data collection and sharing system with IoT, smart sensors, cloud technology, etc., as shown in Table 1.

Table 1. Table Comparison between the product-oriented digital twin and the system-oriented digital twin in reverse logistics.

	Product-oriented digital twin	System-oriented digital twin
Scope	Management of the entire product lifecycle	Management of the entire reverse logistics system
Data	Product condition throughout the entire lifecycle	System or process information at different locations and routes
Applications	Data and Information supports, e.g., EOL product quality, prediction of equipment failure, etc.	Decision support at strategic, tactical, and operational levels, e.g., real-time routing, proactive maintenance, operational planning, etc.
Key enablers	Connectivity enablers	Both connectivity and intelligence enablers

A process-oriented digital twin is similar to a system-oriented digital but with a smaller scope that focuses on a specific reverse logistics operation or activity, e.g., equipment maintenance, demand forecasting, etc. For example, a big data-driven hierarchical digital twin can be used for predictive remanufacturing planning [42]. Market demand can be predicted using big data analytics so that rapid reconfiguration of sustainable products and remanufacturing processes can be achieved. Ghorbani and Khameneifar [43] developed a digital twin to predict the repair volume in the remanufacturing of damaged aero-engine blades. Simulation is a core element in a process- or system-oriented digital twin [44]. For instance, a simulation-based digital twin can be used to predict maintenance needs and potential equipment failures in remanufacturing operations [45]. Combining real-time data simulation with decision evaluation, a data-driven disassembly process can be achieved [46].

4.3 Digital Reverse Logistics Twin

Even though product- and process-oriented digital twins have been investigated in reverse logistics, there is still a lack of conceptualization of a system-oriented digital reverse logistics twin. Thus, this paper investigates the concept of digital reverse logistics twin from the system perspective. A digital reverse logistics twin is a data-based digital avatar of the entire logistics system, which combines both physical smart devices, i.e., IoT-sensors and intelligent robots, and cyber intelligence, i.e., AI, big data analytics, advanced optimization algorithms, and simulation tools, so it can be considered a high-level of CPS that enables effective system visualization and data-driven decision making with better proactive planning and real-time reactive adjustments. To support decision-making at different levels, data-driven analytics and decision-support models need to be effectively combined [47], which requires a high level of system integration to provide comprehensive decision support in a complex and uncertain environment [35].

A digital reverse logistics twin can be used to simulate dynamic processes or behaviors of reverse logistics operations and comprehensively assess the impact of dynamic situations. AI and big data analytics can be used to build data-driven forecasting systems in the proactive phase before EOL/EOU products enter the value recovery phase, which helps reduce uncertainties and generate adequate and more accurate data as the input for optimization and simulation models for further decision supports, e.g., remanufacturing planning, transportation scheduling, etc. Then, based on the needs of different decisions, a single method or a combination of both optimization and simulation methods will be selected to conduct various data-driven analyses with historical data and real-time data adjustment.

For example, in the proactive planning phase of an EOL product collection system, AI-based data analytics can be used at the initial step for reducing uncertainties based on historical data to accurately predict the generation of EOL products and the required maintenance in each period. The predicted results can be directly converted to the input of the corresponding optimization models for resource assignment, routing, collection schedule, and vehicle maintenance. Furthermore, the optimized setups and decisions can also be automatically converted to the simulation environment for analyzing system dynamics under various scenarios, e.g., traffic congestion, accidents, etc., based on which reactive strategies can be formulated and tested. With the help of the real-time data collected from various smart devices and information portals, the prediction results can be updated and the short-term operational decisions, e.g., routing and collection schedules, can be dynamically optimized to improve the overall system performance in terms of operating costs, fuel consumption, emissions, working hours, and service levels. Thus, based on the discussions above, we define a digital reverse logistics twin from the system perspective as follows:

Digital Reverse Logistics Twin is a data-based digital representation of a real-world reverse logistics system, which forms a multi-architecture and high-level integrated information platform by integrating different stakeholders, data, and analytical tools to support various proactive and/or reactive decisions.

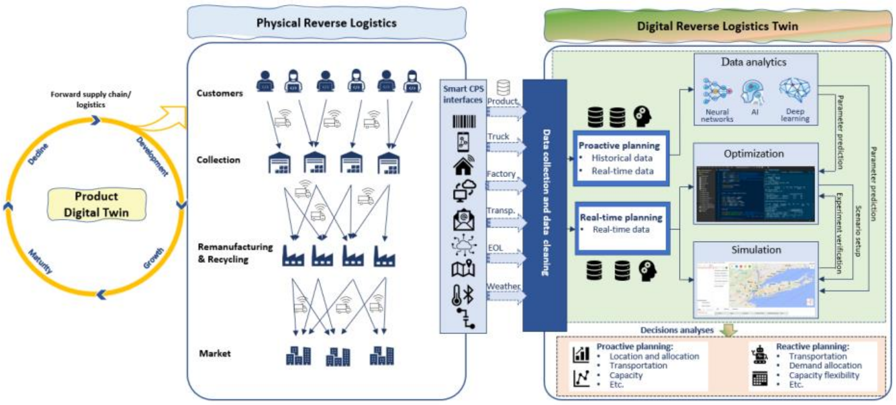

Fig. 3. Digital reverse logistics twin.

Fig. 3 shows a generic framework of digital reverse logistics twin, which aims to digitize the physical entities and activities of a reverse logistics system into a cloud-based virtual environment, where smart devices, data, and analytical models can be used for proper needs. It requires three layers including the physical system layer, the cyber-physical layer, and the smart analytical layer. The first two layers link the physical world to the cyber world, which allows data collection, treatment, and processing from the physical devices, sensors, and processes, and the third layer supports critical decisions with AI, optimization, and simulation models in an interactive way. In addition, the product-orient digital twin is also considered a key enabler for this generic framework. For example, these digital twin models established for individual products throughout their entire lifecycle, e.g., electronic products, vehicles, etc., provide key data for various reverse logistics activities. Besides, the end-users can easily provide updated information related to these products via digital platforms, which will be used for a better organization of respective value recovery activities in a sustainable reverse logistics system.

As can be seen, data is the most essential element in the digital reverse logistics twin, which is the bridge connecting the physical world and the cyber world. The accuracy of data represents the fidelity of the digital model. Furthermore, data connects different analytical tools in the smart analytical layer, with which different analytical models can be seamlessly connected and implemented in the decision-making of specific reverse logistics planning problems. However, this is one of the major challenges of system integration since AI, optimization, and simulation are usually performed as ad-hoc processes and implemented in different environments, so further development is needed to promote a high level of system integration in a digital reverse logistics twin [35].

5 Initial Proof-of-Concept

In this section, we use an illustrative example of a remanufacturing network design problem in Norway to show the initial proof-of-concept and potential applications of digital reverse logistics twin. In this example, a compressor remanufacturing network from EOL refrigerators is planned. The compressors are mainly collected from 16 cities in the southern part of Norway, and 3 candidate locations are selected for opening the remanufacturing plant. The un-remanufactured parts and components can be treated by three waste management companies, and Fig.4 shows the locations of the respective actors. The experimental data is estimated based on Statistics Norway and the European Commission's database.

A digital reverse logistics twin model is built to optimize network decisions under various scenarios. Conventionally, formulating such a decision-making problem starts with the establishment of a mathematical model, based on which relevant data is collected and tested. Afterward, these network decisions may further be evaluated with a dynamic simulation model with more realistic operating rules. However, this is usually an ad-hoc process, and the re-use of the analytical models in other scenarios may require large efforts to modify the model's structures, elements, and setups. Furthermore, implementing these models may require different software, programming languages, and data structures [39]. Thus, this is an inefficient process that suffers from a lack of universal applicability.

Establishing a digital reverse logistics twin takes an opposite perspective, where a highly integrated information platform is required to connect the GIS system, AI algorithms, analytical optimization models, dynamic simulation elements, as well as other physical and cyber components to support different decisions. Feeding real-world data, the physical system can be digitized into the virtual world by combining with different analytical tools, where the level of data accuracy shows the fidelity of the digital reverse logistics twin. As shown in Fig.5, based on the physical remanufacturing network structure, we converted the relevant facility operating data, transportation data, collection data, and market data into a comprehensive data model in anyLogistix, through which the remanufacturing network is digitized by automatically selecting different modeling elements. The analytical optimization and dynamic simulation can then be seamlessly connected and interacted with via the automatic data conversion to different levels of required aggregation. For example, the optimized remanufacturing network can be easily evaluated under various operational policies with a realistic planning horizon and lower data aggregation in the simulation environment.

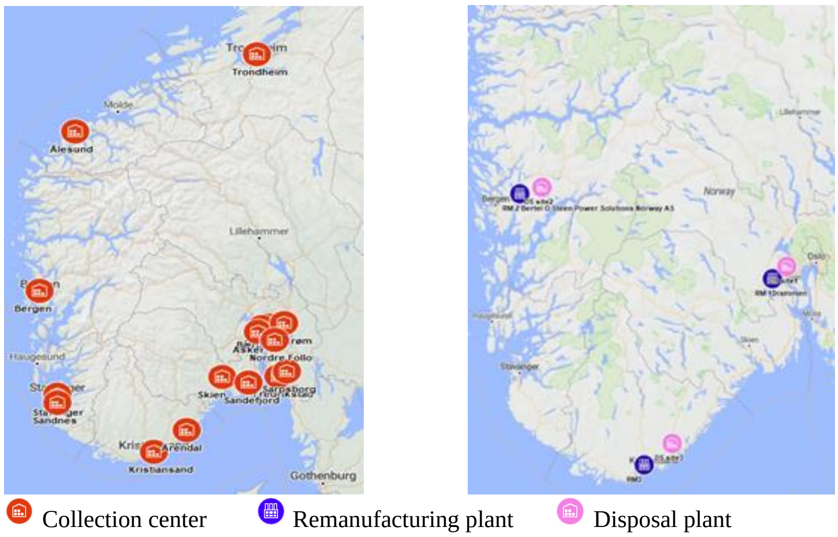

Fig.4. The locations of respective reverse logistics actors.

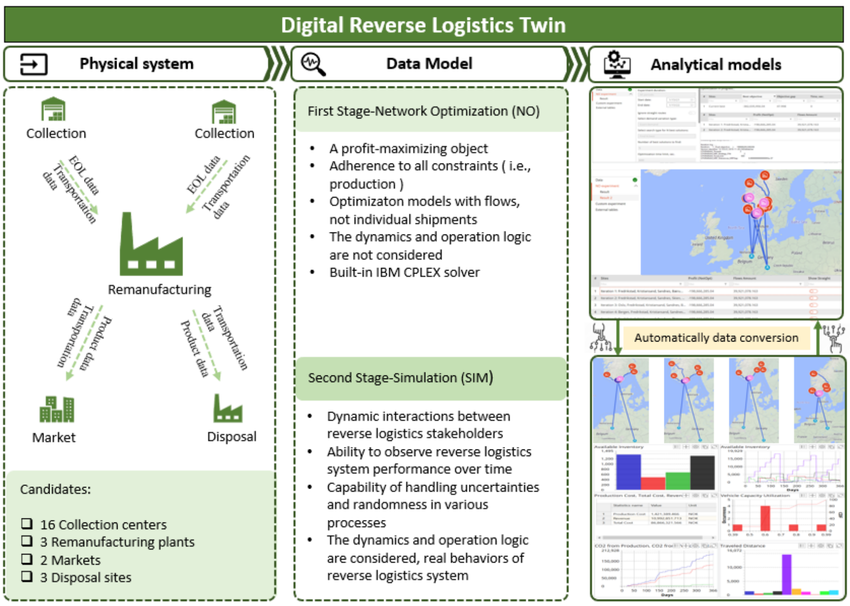

Fig. 5. Digital reverse logistics twin for remanufacturing network design.

The successful implementation of a digital reverse logistics twin requires a high level of system integration of both physical and cyber components, whose maturity is evaluated by seven key indicators, namely, cyber-physical structure, cloud-based system, shared database, large model database, user-friendly interface, and flexible models and networks [35]. In this example, the use of digital reverse logistics twin is shown through supporting strategic network decisions, where key implications can be obtained through combining optimization and simulation with historical data. With the help of automated data conversion, strategic remanufacturing network decisions can be further analyzed and evaluated considering and incorporating, e.g., different inventory policies, sourcing policies, transportation policies, triggered events, the dynamics and operation logic, etc. At tactical and operational levels, the data model can be further developed by, for instance, connecting with the company's business intelligence (BI) and smart devices to support real-time operational decisions, e.g., vehicle routing.

6 Conclusion

With the focus on human-centricity and sustainable development in Industry 5.0, technological enablers are increasingly emphasized for promoting a smart digital transition, which will shift the paradigms of many industries and businesses. Digital twin is one of the most promising Industry 5.0 enablers, which has been extensively focused on during the last decade. In reverse logistics management, the concepts of digital twin are mainly studied from the product- and process-oriented perspectives. Thus, in this paper, we extend the scope of this concept and define the digital reverse logistics twin from the system perspective. The generic definition and framework summarize the most essential features of the digital reverse logistics twin, which can be adapted for a wider range of applications. For example, the product- and process-oriented digital twin applications can be considered important elements and enablers within this concept.

In a digital reverse logistics twin, data plays the most crucial role to link different physical and cyber elements, with which the system performance can be monitored, and the respective decisions can be dynamically optimized. An initial proof-of-concept is given based on a remanufacturing network design problem in Norway. Through a common and shared data model, the network optimization and dynamic simulation can be seamlessly connected to optimize the reverse logistics network configuration and evaluate the performance under different scenarios. The result shows the effectiveness of integrating different analytical tools via data model in a smart and sustainable digital reverse logistics twin.

The results of this research provide a decision-making framework that contributes to both increased knowledge and its valuable implication in practice in the field. More specifically, this research expands the existing understanding of system integration for smart reverse logistics management. It builds upon the framework proposed by Sun, et al. [35] and extends it by introducing the concept of a digital reverse logistics twin. This new concept adds value to the field by leveraging digital technologies to enhance reverse logistics processes and operations.

From the managerial perspective, the research has yielded a practical decision-making framework that facilitates the effective management of reverse logistics operations. This framework presents a systematic methodology that can be readily applied in practical situations. Its implementation empowers decision-makers to improve their choices and optimize different facets of reverse logistics management, i.e., product returns, recycling, reprocessing, and remanufacturing.

This research serves as a bridge connecting theoretical concepts with practical applications. It also aims to provide practitioners with a tangible decision-making tool that enhances the efficiency and effectiveness of reverse logistics processes within organizations. However, it is important to note that the current framework has a limitation due to restricted access to data, as it does not consider the need to process large datasets that are prevalent in real-life scenarios. Consequently, future efforts will be directed towards integrating additional data analytics, e.g., AI algorithms, into the framework to address this limitation.

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