System Integration for Smart Reverse Logistics Management

Xu Sun*, Hao Yu, and Wei Deng Solvang

Abstract— **To maximize the value and material recovery from waste products, smart reverse logistics aims at managing the complex flows of physical items, cash, data, and information. The effective management of these flows requires optimal decision making at strategic, tactical, and operational levels. To support the decision making, predictive, prescriptive, and descriptive analytics have been proved to be valuable at all three levels. However, because these analytical tools require different software packages, different coding languages, and different structures of data, the decision support for complex problems combining various analytical methods is usually an ad-hoc process and requires thus significant efforts. There is a lack of standardized solutions that comprise all the necessary modules for smart reverse logistics management. Thus, this paper proposes a conceptual framework with the purpose of guiding the next-generation system integration for smart reverse logistics management. It goes further with the design of six criteria for evaluating the integration maturity of a system. The initial concept is shown with existing software solutions through a case study in Norway, and several challenges are identified for future improvements.**

I. Introduction

Today, the rapid pace of technological innovation and the ever-changing consumer demands have led to higher requirements of customization with shortened product lifecycles. This further leads to largely increased waste generation. In 2019, the volume of waste electrical and electronic equipment (WEEE) generation has reached a record high level of 53.6 million metric tons which represented an increase of 21% in five years [1]. This trend is expected to continue with an estimated 30% increase by 2030 [2]. Sustainable management of this rapidly increasing waste has become a global challenge. With the focuses on function restoring and material recovery from discarded products, some regional and international reverse logistics systems have been developed [3].

Reverse logistics refers to a set of activities with the aim of the value recovery from waste products through repair, reuse, refabrication, remanufacturing, recycling, and energy recovery as well as proper disposal of non-recyclables [4, 5]. To achieve sustainable competitiveness in today's market, reverse logistics has become a strategic focus area for most companies due to, i.e., the growing environmental awareness among the general public, stricter legislation, and imposed corporate social responsibility. Effective decision support at strategic, tactical, and operational levels is therefore of essential importance for designing and operating a competitive and sustainable reverse logistics system. To do so, it is necessary to balance complex material and information flows, work with various stakeholders, and make important decisions under uncertainty. To support different decision making in reverse logistics management, predictive, prescriptive, and descriptive analytics must be combined to solve complex problems.

The use of these analytical tools requires different data sources, software packages, different coding languages, and different structures as well as aggregation of data. The combination of several analytical methods to solve a complex decision-making problem in reverse logistics management is, at present, an ad-hoc process, and often requires significant efforts to engage different tools when a new scenario turns up. How to develop an integrated system that can connect different analytic models, data, tools, and other relevant elements for providing efficient decision support is, therefore, a novel question. In this paper, considering the technological innovations in Industry 4.0, we propose a conceptual framework for the next generation of system integration methods for smart and sustainable reverse logistics management. The initial proof-of-concept is applied to a case study design for WEEE management in Norway. In this model, the prescriptive and the descriptive analytics are connected through establishing a shared database structure.

The rest of the paper is organized as follows. Section II explores reverse logistics management with an emphasis on relevant decisions and methods. Section III presents a conceptual framework for the system integration of smart and sustainable reverse logistics management. In sections IV, we demonstrate an application of this framework through a case study, and the problems of the existing software solutions are also discussed. Finally, the conclusions are given in Section V.

II. Reverse Logistics Management

A. *Reverse Logistics Management*

Reverse logistics focuses on the value recovery activities of waste products, when combining it into the forward logistics system, a closed-loop supply chain can be formed. As shown in Figure 1, the material flow in a reverse logistics system starts from the local collection of waste products from the end-users. The collected waste products will then be disassembled, inspected, and sorted at central collection centers. Based on the remaining values of the dismantled parts, they are sent for further treatment at different facilities. The ones with high remaining values will be sent either for repair and re-sell at second-hand markets or for remanufacturing and refurbishing for function restoration. The remanufactured and refurbished components can be sold

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to the manufacturers at lower prices. The other components with low remaining values can be sent to recycling plants, where they are degraded into new materials and then sold to the raw material suppliers. The non-recyclable components can be sent either for energy recovery or for proper disposal.

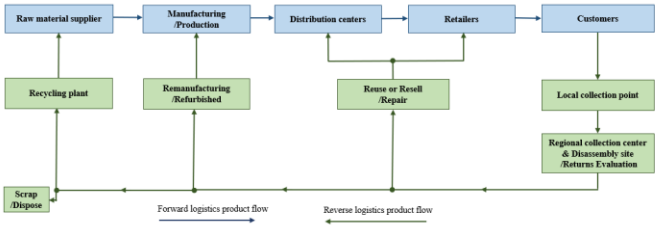

Figure 1. Reverse logistics system

TABLE I. KEY DECISIONS FOR REVERSE LOGISTICS MANAGEMENT

Level	**Key decisions**
Strategic level	• Target market situation analysis and evaluation (coordination of reverse logistic network, market size, product, etc.) • Reverse logistic network design (the number and location of facilities, capacity planning and designing of the remanufacturing/recycling systems) • Transportation strategy • New technology adoption
Tactical level	• Reverse logistics network re-optimization • Vehicle routing • Production planning • Inventory planning • Fleet management
Operational level	• Production control • Inventory control • Vehicle planning and scheduling • Risk analysis • Recovery analysis • Resilience analysis

Reverse logistics management refers to orchestrating complex flows (product, capital, and information) among multi-layered and non-homogeneous stakeholders in a highly uncertain environment. Table I shows the key decisions for reverse logistics management at the strategic, tactical, and operational levels. Strategic decisions have long-term impacts on a reverse logistics system since they are difficult or extremely expensive to change. Reverse logistics network design is the most important strategic decision [6]. Several factors and decisions are affecting the performance of a reverse logistics network, i.e., the number and locations of potential facilities, capacity planning, remanufacturing and recycling technologies, transportation strategy, and the establishment of distribution and collaboration channels for recovery products and materials [7, 8]. At the tactical level, the reverse logistics system is governed by a set of medium-term decisions, usually from one month to one year, made under the constraints set by the strategic planning [9]. The formulation of production policy, inventory policy, vehicle routing as well as fleet management are considered tactical decisions. At the lowest level, the short-term operational decisions are made for the dynamic control of product recovery operations, dynamic inventory control, real-time vehicle routing and scheduling problems, and risk analysis, etc.

B. Methods for Decision Supports

To support decision making in reverse logistics management, three advanced analytical methods: predictive, prescriptive, and descriptive analytics, are applied.

Predictive analytics is a category of applying advanced methods to predict future trends based on historical data and/or real-time data. It aims to perform an exploratory analysis using several analytical tools. Typical techniques are, e.g., artificial intelligence (AI), data mining, machine learning (ML), modeling, and statistics to estimate, predict, detect future patterns [10]. Decision trees, linear/logistic regressions, and neural networks are the most common predictive models, which can help to clean the data quality for analysis [11]. In terms of reverse logistics management, predictive analytics has been used to reduce the impact of uncertainty so that a better prediction of reverse flows can be achieved. Tuylu and Eroğlu [12] used ML to estimate the product return rate in reverse logistics. In this case, better prediction and planning were achieved by using consumer information so that unnecessary production and transportation were avoided. Lickert, et al. [13] implemented a ML method to inspect whether the quality levels and conditions of returned products were suitable for remanufacturing.

Prescriptive analytics is to select the constrained and time-dependent optimal solutions with the help of model-based analytics, e.g., mathematical programming (linear/non-linear programming, mixed integer programming, multi-objective programming, etc.), evolutionary computation (genetic algorithm, greedy algorithm, particle swarm optimization, etc.), probabilistic models (Markov decision process, etc.), logic-based models (benchmark rules, fuzzy rules, etc.) [14]. Thus, prescriptive analytics aims at suggesting the best decision options under some preconditions [15], whose results are given, in many cases, based on the outputs from model-based analytics [14]. Prescriptive analytics is the most widely used decision-support method in reverse logistic management at different levels. For example, extensive research efforts have been given to develop mathematical models for sustainable reverse logistic network design [5, 16, 17], profit maximization [18, 19], routing optimization of recycling vehicles [20].

In logistics and supply chain management, descriptive analytics is used to depict the system's behavior and to uncover the meaningful patterns from analyzing the system performance, and simulation is considered the most important descriptive tool. Simulation can be used to capture the randomness, dynamic system behaviors, and disruptions, which are more closed to real-world conditions. In reverse logistics management, simulation has become a powerful tool for decision-makers to investigate the system performance with a set of what-if scenarios. Pandian and Abdul-Kader [21] developed an agent-based simulation model for the performance evaluation of a cell phone remanufacturing system. Gianesello, et al. [22] simulated a closed-loop supply chain with disruption considerations. This simulation model provided better illustrations of the recovery decisions. Longo [23] used a simulation method to compare different inventory control policies in reverse logistics so that an optimal solution is ready to be chosen when certain pre-set conditions are met.

Despite the huge advantages the predictive, prescriptive, and descriptive analytics have, the combination of these methods/theories, which can benefit the multi-objective decision-making approach, has not been well developed. Today's rapid advancement of information and communication technology (ICT) in Industry 4.0 has provided new opportunities for reverse logistics management to become more smart, sustainable, and simplified. On the one hand, the wide adaptation of IoT embedded devices, smart sensors, and radio frequency identification (RFID) have provided effective ways for real-time data collection and processing. On the other hand, the significant development of AI and optimization algorithms has improved computational effectiveness and efficiency, which drives the increasing use of data-driven to the use of several analytical tools and the inclusion of a large amount of data from different sources and stakeholders. However, selecting the right analytical tools and right data to solve specific reverse logistics management problems requires domain expertise. Thus, this conceptual framework is proposed to explore the opportunities for the next generation of system integration for smart reverse logistics management. As shown in Figure 2, the integrated system combines various AI algorithms, optimization models, and simulations to support strategic, tactical, and operational decisions, and these elements form three layers, namely, data collection, data processing and analytics, and decision support. At the lowest data collection layer, the data can be collected from both physical sources, e.g., enterprise resource planning (ERP)/ advanced planning & scheduling (APS), smart sensors, and geographic information system (GIS), etc., and cyber sources,

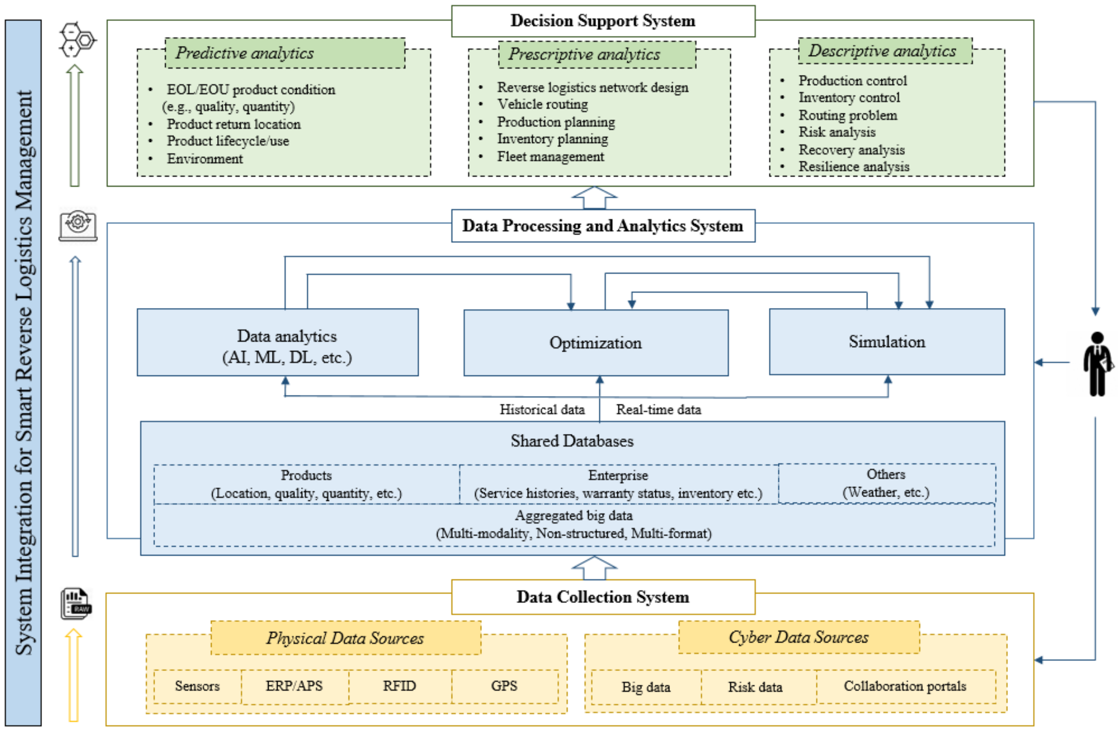

Figure 2. System Integration for Smart Reverse Logistics Management

prediction, optimization, and decision-making. However, the effective use of these new technologies in reverse logistics management requires a high level of system integration in a cyber-physical environment.

In the next session, we will propose a framework for system integration purposing smart reverse logistics management.

III. A FRAMEWORK FOR SYSTEM INTEGRATION

System integration is the process that links and integrates several physical and cyber components so that they can work together as a whole [24]. The most significant challenge of the system integration for reverse logistics management is related e.g., the information from the online collaboration portals, the online data from track and trace systems, and the product-based digital twin [25], etc. The reliability of a decision-support system depends heavily on the quality, completeness, validity, consistency, timeliness, and availability of data [26]. The raw data collected from these multiple sources can be sent and stored on a cloud-based database and be cleaned. The next step is the core of the system integration, which is the data processing, analysis, and preparation. Depending on the types of decisions to be made for reverse logistics management, the respective AI and/or optimization models and/or simulation models need to be selected and combined, and the data needs thus to be prepared accordingly in order to feed these models. For example, in the proactive planning of a waste product collection system, the historical data can be used with AI, e.g., deep learning, to provide accurate predictions of the waste generation and the maintenance periods required for the waste collection vehicles. The prediction results can be visualized and be directly converted to the inputs of the respective optimization models for routing the vehicles and scheduling the waste collection activities and vehicle maintenance. Besides, the optimization results and relevant parameters can be converted seamlessly to the simulation environment to analyze the system dynamics under different scenarios, evaluate the impacts of disruption, and test and formulate different reactive strategies. Besides, the prediction needs to be dynamically updated with the real-time data collected from various smart devices and information portals, e.g., traffic condition, vehicle utilization, etc., and the optimization and simulation models need to be re-activated accordingly to update the respective analytical results and suggestions. In making short-term operational decisions, real-time data places a more important role in the optimization of reactive decisions. Smart reverse logistics management emphasizes the importance of effective proactive planning and reactive decisions driven by both historical data and real-time data. However, in some cases, the datasets are not available or not large enough for data analytics to generate a reliable prediction. In this regard, simulation can be used at the first stage to yield the initial scenarios for a data-driven learning process [27] and the parameter estimation for optimization. For instance, a simulation method combined with a patient allocation heuristics was used to estimate the system dynamics of the medical waste generation during the early stage of the COVID-19 pandemic in Wuhan, China, whose results were then used as the inputs to a multi-objective mixed integer program to optimize the locations of temporary waste incinerators [28].

This system integration combines AI, optimization models, and computer-based simulation, which can support important decisions and test several alternatives in a risk-free environment [27]. The main features of the next generation of system integration and software development for smart reverse logistics management are discussed as follows:

- *Cyber-physical structure*: At the lowest level, the system integration needs to enable effective data collection from both physical and cyber sources.
- *Cloud-based system*: The important data and analytical models need to be stored in a cloud-based platform so that they can be easily accessed from decentralized locations.
- *Shared database and data conversion*: The parameters for different analytical models are generated from the same database and can be easily converted to feed different models with different requirements on data structure and aggregation.
- *Flexible network structure*: For different problems in reverse logistics management, the numbers of echelons and actors involved are by no means identical, so the integrated system needs to be flexible enough to adapt to different reverse logistics network structures.
- *Large model database*: The model database needs to be broad to tackle a wide range of decision-making problems at strategic, tactical, and operational levels.
- *Flexible model modification*: The model can be easily modified to adapt to the change of system requirements in the decision-making.
- *User-friendly interface*: The digital interface should be designed in a user-friendly way for practitioners and non-expert users.

IV. Maturity Evaluation of Existing Solutions

With existing software solutions, we first present the initial proof of concept with a case study of the reverse logistics network design for WEEE management. Then, three existing solutions are compared to evaluate the maturity of system integration for smart reverse logistics management. To optimize the WEEE recycling network in Norway, an analysis combining with both optimization and simulation is given, and the data flow needs to be converted between optimization models and simulation models due to their different requirements. The anyLogistix, which is a cutting-edge combined optimization-simulation software package has the functionality to convert data between the two methods in forward logistics. However, due to the difference of reverse logistics flows and the requirement to consider the carbon emission objective in decision-making, it cannot be used directly to solve this problem. Figure 3 illustrates the data flow of the decision-support process for this reverse logistics network design problem. First, the data input files need to be established in Microsoft Excel. Based on the input data, a bi-objective optimization problem considering the balance of both costs and carbon emissions is solved with a professional optimization solver, whose results are written in the output file. The input parameters need to be converted to feed the simulation model, and a set of Pareto optimal solutions suggested by the optimization model are considered several candidate network configurations. Based on this information, the performance indicators, e.g., cost, carbon emissions, periodic inventory level, etc., can be obtained under a dynamic and stochastic environment. The analytical results can then be easily visualized for better decision supports. As can be seen, to formulate the reverse logistics flows and ensure the model's flexibility, the existing software solutions cannot realize a streamlined data flow conversion between different analytical models in reverse logistics.

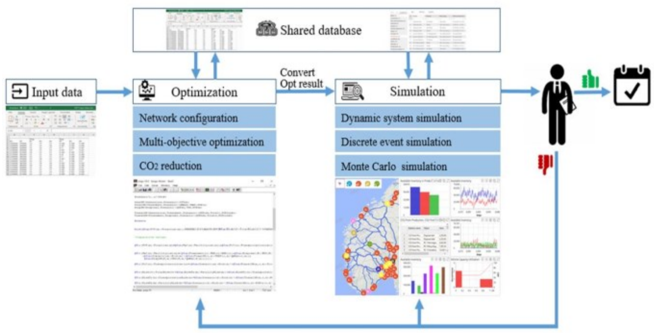

Figure 3. Data flow through the decision-support system.

To identify the gaps related to the system integration for smart reverse logistics management, three existing software solutions i.e., SAP, Optimity, and anyLogistix are compared with respect to the general features given in the previous section. In Table II, three levels of system integration maturity for smart reverse logistics are defined as follows:

- 3 is the highest maturity level, in which the process is standardized and the functionality can be well achieved for smart reverse logistics management.
- 2 means the functionality has been established at the basic level, but significant efforts need to be done to solve reverse logistics management problems.
- 1 is the lowest maturity level, which means the functionality has not been well established for reverse logistics management.

TABLE II. EVALUATION OF SYSTEM INTEGRATION MATURITY FOR THREE SOFTWARE

Main features	**Three existing software solutions**		
	SAP	***Optimity***	***anyLogistix***
Cyber-physical structure	3	2	2
Cloud-based system	3	3	3
Shared database and data conversion	3	3	3
Flexible network structure	1	1	1
Large model database	1	2	2
Flexible model modification	1	1	2
User-friendly interface	3	3	3

SAP (System Analysis Program Development) is the world's leading software provider of business process management, data processing, and information flow solutions across organizations. The SAP system has been adopted by a large number of companies in many industries. The SAP's EPR solution is a comprehensive system including various modules for finance, administration, logistics, etc., with which a high level of cross-functional integration and cross-organizational coordination can be achieved. SAP is a mature system to integrate and process data from different sources and to convert data for different purposes via a cloud-based system. In logistics planning, SAP offers a set of embedded models and algorithms to solve a wide range of problems, e.g., vehicle routing problems (VRP). However, there is a lack of standardized solution modules and models for reverse logistics management problems, e.g., network design. Besides, as a commercial system, it suffers from flexibility issues.

Both Optimity and anyLogistix focus on providing the next generation of software solutions and digital twin for managing logistics systems and supply chains. Optimity emphasizes data-driven optimization combined with both ML and a set of optimization models for better prediction and better decision support. On the other hand, anyLogistix focuses on the combination of mathematical optimization and computer-based simulation to provide solutions and analytical insights under a dynamic and realistic environment, and the data flow conversion between optimization models and simulation models is thus well developed. However, since both software packages are developed with a primary focus on forward logistics systems and supply chains, the network structure is not well adapted for modeling the material flows in the reverse logistics system, as shown in Figure 3. Besides, even though they offer model adjustment by adding and subtracting some elements, e.g., carbon cost, penalty, etc., the flexibility is extremely limited to adapt different modeling requirements, e.g., multi-objective optimization, stochastic programming, etc. Thus, there is still a long way to go in order to achieve the next generation of system integration for smart reverse logistics management.

V. CONCLUSION

The emergence and increasing use of several Industry 4.0 technologies have provided new opportunities for improved connectivity and intelligence of a system. The combination of both data-driven analytics and model-based methods is driving the paradigm change toward smart reverse logistics management. However, different tools and models need to be used to solve different decision-making problems, and these tools and models need different software packages, different inputs, and different structures and levels of aggregation of data. Thus, it is usually an ad-hoc process to combine different data sources and different models to solve complex decision-making problems in reverse logistics management, and there is a lack of standardized solution and software package that contains a comprehensive network structure and a large model collection to solve a wide range of reverse logistics management problems.

In this paper, from the user's perspective of reverse logistics management, we propose a conceptual framework for the next generation of system integration for smart reverse logistics management. Six primary parameters, i.e., cyber-physical structure, cloud-based system, shared database and data conversion, flexible network structure, large model database, flexible model modification, and user-friendly interface, are given to evaluate the maturity of system integration of smart reverse logistics management. The initial proof of concept is given by a case study in Norway. Besides, three existing software solutions, i.e., SAP, Optimity, and anyLogistix, are compared to identify the current problems and challenges of system integration. The proposed six parameters for the maturity evaluation of system integration are considered the general guidelines for the next generation of software development in order to realize smart reverse logistics management.

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