Cleaner Environmental Systems 7 (2022) 100099

Contents lists available at ScienceDirect

Cleaner Environmental Systems

journal homepage: www.journals.elsevier.com/cleaner-environmental-systems

Evaluation of the smart reverse logistics development scenarios using a novel MCDM model

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ARTICLE INFO

Keywords:
Industry 4.0
Technology
Reverse logistics development scenario
MCDM
Fuzzy Delphi
Fuzzy ANP
Fuzzy COBRA

ABSTRACT

The purpose of this study was to select the most promising smart reverse logistics system development scenario which would serve as a guideline for the decision-making in the process of building sustainable systems of circular economy and closed supply chains. Four development scenarios are defined in the study and evaluated by the representatives of the main stakeholders in relation to a broad set of sub-criteria classified within the six main criteria. To solve the defined problem, a novel multi-criteria decision-making model, combining the Delphi, Analytical Network Process (ANP) and COmprehensive distance Based RAnking (COBRA) methods in the fuzzy environment, was developed. The application of the developed model resulted in selecting the scenario which most effectively balances the wide application of Industry 4.0 technologies and the necessary resources. The scenarios imply the integration of the most effective Industry 4.0 technologies, such as the Internet of Things, Automated guided vehicles, Autonomous Vehicles, Artificial Intelligence, Big Data and Data Mining, Blockchain, Cloud Computing and Electronic/Mobile marketplaces, and their most realistic applications. The widest possible application of Industry 4.0 technologies does not necessarily guarantee the most acceptable development scenario and the solution should be sought in the area of common interest of all stakeholders.

1. Introduction

Lack of raw materials, growing environmental pollution, higher level of social responsibility, environmental regulations and market change has put the reverse logistics (RL) at the focus of many sustainability studies (Agrawal et al., 2015). The development of RL systems is the main condition and prerequisite for establishing the closed-loop supply chain (CLSC), a form of the supply chain which corresponds to the concept of the Circular Economy (CE). Motives for RL and CLSC research were originally driven by public awareness, i.e. by the problems generated by the return flows to ordinary people and their environment (Dowlatshahi, 2000). With the development of the consumer society, the reduction of the product lifetime, and under the pressure of the public to solve the problems caused by the end-of-life products, these issues come into the focus of the legislative authorities, which pass various laws and directives to regulate this area (Georgiadis and Athanasiou, 2010). Finally, RL and CLSC have been perceived as the areas that can generate revenues for various participants in the supply chain (Guide and Van Wassenhove, 2009). Demands for the provision of services as well as providers of those services are emerging, i.e. a market concentrated around RL is being formed. Therefore, the aim becomes the establishment of a sustainable RL system which is in line with the goals and interests of the main stakeholders, namely the service providers, service users, administrations and citizens. They benefit from such a system through the reduction of waste disposal, an increase and the recovery of the product value and energy, the extension of the product life cycle, the extraction and recycling of materials, the creation of a competitive advantage, an acceleration of the return on investment, the improvement of customer relations, and the reduction of transport emissions (Turrisi et al., 2013; Skinner et al., 2008).

Although traditional RL systems generate all these positive effects, it is necessary to keep up with the times and development of modern technologies in order to modernize these systems, make them more efficient, affordable and acceptable. In this sense, RL systems can be significantly improved and upgraded by applying various Industry 4.0 technologies, such as the Internet of Things, Cloud Computing,

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https://doi.org/10.1016/j.cesys.2022.100099
Received 9 July 2022; Received in revised form 30 August 2022; Accepted 15 September 2022
Available online 24 September 2022

Autonomous vehicles, Artificial Intelligence, etc., thus creating smart RL systems. RL can be defined as the application of various Industry 4.0 technologies to manage complex flows of physical items, cash, data, and information in different stages of the reverse part of the supply chain with the aim of maximizing the value and material recovery from returned or waste products (Krstić et al., 2022).

Accordingly, this study deals with the creation and evaluation of smart RL system development scenarios, while taking into account the degree of the development of Industry 4.0 technologies, their possible application, as well as the social, economic, technological and sustainability trends. The goal is to select the one that has the best chance for success, wide application and most positive effects, and would thus serve as a guideline for decision-making in the process of building a sustainable smart RL system acceptable for all key stakeholders.

As a result, the scenario which provides the best balance between the wide application of Industry 4.0 technologies and the necessary resources for its development and implementation is selected. It can be concluded from the results that the widest possible application of Industry 4.0 technologies does not necessarily guarantee the most acceptable development scenarios, and the decision should be made by achieving a compromise between the interests of all stakeholders. To solve the defined problem, a novel hybrid multi-criteria decision-making (MCDM) model, which combines Delphi, ANP and COBRA methods in the fuzzy environment, has been developed in this study.

In the previous studies dealing with the topics covered by this study, no significant advancement has been made towards the development of smart RL which would employ various Industry 4.0 technologies to optimize and improve the return flows. There are also no studies dealing with the simultaneous applications of multiple technologies for performing multiple processes in multiple stages of RL. As for the developed model, the COBRA method has not been extended in the fuzzy environment so far, nor have these three methods been combined before. Therefore, the establishment of smart RL scenarios, the framework for their evaluation and ranking, and the novel MCDM model, are the main contributions of this study.

The study is organized as follows. The next section provides the background for the problem, i.e., the main aspects of the smart reverse logistics and the methods that make up the model. The third section explains the newly established MCDM model in detail. The following section provides the description of the problem structure, i.e., scenarios, criteria for their evaluation and the stakeholders interested in solving the problem, as well as the results of the model application and analysis of the results' sensitivity. The fifth section discusses the obtained results and the problem-solving framework in light of the current body of literature, as well as the empirical and practical implications. The last section provides concluding remarks and future research directions.

2. Background

Before establishing the structure of the problem and the methodology for its solution it is necessary to define smart RL and provide an overview of the methods used to build up the methodology. Accordingly, the background of the study is given in the following.

2.1. Reverse logistics

The term "Reverse logistics" appeared and began to be used more intensively in literature in the late 80's and early 90's of the last century (Prajapati et al., 2019). Over time, the meaning of this term has evolved, so the definitions have changed accordingly. One of the earliest definitions defined RL as "the field related to the skills and activities involved in the management of waste, movement and disposal of products and packages" (Kopicki et al., 1993). Thierry et al. (1995) defined RL as the "management of used or discarded products, components and materials with the aim of achieving maximum economic and environmental value while reducing the total amount of waste". One of the first modern definitions defined RL as "a set of management activities to reintroduce non-core assets in sectors with added value" (Beaulieu et al., 1999). The most widely accepted definition in literature so far, is that RL is "the process of planning, implementing and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal" (Tibben-Lembke, 1998). RL, in the broadest possible sense, can be defined as a type of supply chain management that aims at optimizing the movement of goods or materials from the end user to the seller or manufacturer while preserving their values.

Although the term RL has been in use for a long time and has been the subject of numerous research, it gained additional importance with the emergence of the concept of Circular Economy (CE). RL, which was seen as an unavoidable liability that generates additional costs and complicates supply chains in the earlier "take-make-dispose" concept of production, with the development of CE becomes one of the main tools for creating various sustainable solutions and business models (Julianelli et al., 2020). This has led to the expansion of research of various aspects of RL, the most important of which concern network design (Govindan and Gholizadeh, 2021), implementation decisions (Azadnia et al., 2021), service provider selection (Mishra et al., 2022), RL network nodes location (Egri et al., 2021), routing and scheduling (Abbasi-Tavallali et al., 2021), performance (Kazancoglu et al., 2021) and information management (Wijewickrama et al., 2021), etc. Improvements in all the mentioned fields of RL research have been made possible by the development of the concept of Industry 4.0 (Rajput and Singh, 2022), i.e. advanced technologies that represent the main "flywheel" of this concept. However, so far no significant steps have been taken towards the development of smart RL, which would involve the integration of these technologies with the aim of comprehensive optimization and efficiency improvement of return flows, which is a research gap that this study tries to cover.

2.2. Industry 4.0 technologies in reverse logistics

Technologies belonging to the Industry 4.0 concept play an important role in preserving these values. Industry 4.0 is a term that has appeared in literature and started to be widely used in the last ten years (Krstić et al., 2021). As this is an area in development, there are many different definitions, and one of the most general is that the Industry 4.0 represents "complex solutions created in the sphere of common interest of engineering, computer science and management" (Götz and Gracel, 2017). What largely defines the concept of Industry 4.0, regardless of the definition, is the development and application of modern technologies, as well as finding the new ways to connect and apply existing technologies. Industry 4.0 technologies that have recently been applied in the RL sector are: Internet of Things (IoT), Automated guided vehicles (AGV), Autonomous Vehicles (AV), Artificial Intelligence (AI), Big Data and Data Mining (BD&DM), Blockchain (BC), Cloud Computing (CC), Electronic/Mobile marketplaces (E/M marketplaces), three-dimensional printing (3D printing), and Advanced Robotics (AR).

IoT, also referred to as "embedded internet", "pervasive computing", "physical internet" or "cyber physical system", is used as a hypernym for "*various aspects of Internet and networks integration with the physical world with the aim of providing communication and connections, in space and time, between all elements of the system*" (Lu et al., 2018). Some of the most important applications of the IoT in RL identified in the literature so far are designing an RL system (Wei et al., 2021), an information system (Gu and Liu, 2013), waste collection system (Thürer et al., 2019), reverse supply chain managements system (Garrido-Hidalgo et al., 2019), end-of-life products evaluations system (Joshi and Gupta, 2019), and decision-making support system (Mboli et al., 2022), etc. The main purpose of all these systems is to improve, simplify and optimize the efficiency of RL processes, increase the degree of utilization and maintain the value of used products (Rejeb et al., 2020).

AGVs, also referred to as "self-guided vehicles", imply the "*transportation and material handling systems remotely or self-controlled by the help of magnets, radio waves, lasers, cameras, etc.*" (Jünemann and Schmidt, 2020). They are mainly used in RL to perform various intralogistics and material handling processes within RL network nodes (Fragapane et al., 2021). The aim is to simplify those processes and make them more reliable and efficient by automation and minimal involvement of people (Oyekanlu et al., 2020).

AVs are vehicles "*able to adapt, learn and operate themselves without any, or with little human intervention, using the ability to sense their surrounding environment, make independent decisions and move safely through it*" (Krstić et al., 2022). In RL, road and airborne AVs are mainly used for short-haul transport and first/last mile deliveries (Berman, 2019), while the rail and waterborne AVs are mainly used for long-haul transport between RL network nodes (Christensen, 2021). Usage of the AVs enables the increase of productivity and efficiency while reducing costs and human resource requirements in the transport operations within the RL networks (Shahandasht et al., 2019).

AI is the capacity of computers to behave in a way that requires intelligence and discernment, which are the features usually asserted to humans. AI enables some other very important intelligent technologies such as Ambient Intelligence, Virtual Reality, Augmented Reality, and consequentially Extended Reality. In the area of RL they can be used for network design, assistance with realizations of the processes such as collection, sorting, inspection, disassembly, recycling, remanufacturing, redistribution, vehicle routing, product return forecasting, etc. (Wilson et al., 2021). These technologies enable greater accuracy, efficiency, safety, timeliness, automation, etc. of RL activities and processes at the lower costs (Jacobs, 2022).

BD refers to "*the sets of data of such a volume and complexity that traditional data processing software solutions are unable to collect, manage and process them in a reasonable amount of time*" (Wu et al., 2013). DM is "*the processes of sorting through large data sets to identify patterns and relationships that can help solve business problems through data analysis*" (Clifton, 2019). As these technologies are most often used side-by-side in practice, in this study they are viewed as one integrated technology. Some of the most important applications of this technology in the area of RL are for network design (Govindan and Gholizadeh, 2021), predicting returns and estimating their quality (Nguyen et al., 2018), making decisions on their further processing (Pushpamali et al., 2019), speeding-up (Yang and Wang, 2007) and estimating performance of various RL activities (Bag et al., 2021), etc. For extensive RL flows that are carried out every day, data on locations, structure of goods and materials, delivery sizes, starting and ending points, etc. are tracked, recorded and stored, thus forming very useful BD sets which are then processed and analyzed using DM in order to provide decision makers with operational information in the form of thresholds, key performance indicators, parameters, various reports, etc. (Borgi et al., 2017).

BC implies "*the data base composed of multiple smaller bases (blocks) containing information on digital transaction and mutually connected, thus forming the chains*" (Pilkington, 2016). Some of the most important applications of BD in the RL sector are for smart contracting (Shih et al., 2021), the establishment of traceability and transparency in RL processes (Centobelli et al., 2021), the management of supplier/customer relationships (Farouk and Darwish, 2020), etc. The main aim of applying this technology is to enhance interoperability and trust in RL networks and enable companies to cope with the fierce competition in the market (Wanganoo et al., 2021).

CC is "*a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction*" (Mell and Grance, 2011). The application of cloud-based solutions for managing various processes and activities (e.g. collection, transport, storage, etc. of returns) enables the creation of a smart RL management system (Dos Santos and Marins, 2015). The most obvious motives for the application of this technology are the saving of resources and distributed collaboration between RL participants (Hamidi Moghaddam et al., 2021).

E/M marketplaces are the electronic platforms that use the Internet and various smart mobile device technologies to perform trade activities (Eng, 2004). In RL, E/M-marketplaces enable the defragmentation of the market, establishment of return aggregators, development of reasonable return policies, establishment of an efficient RL information system, diversification of RL modes, etc. (Wang et al., 2013; Kokkinaki et al., 2004). The use of widespread and easily accessible smart mobile devices and fast internet enables the reduction of uncertainty, treatment costs, complexity, and time for processing return products purchased on the E/M marketplaces (Wang et al., 2013), while improving visibility, automation, and control of the return processes (Yang and Hao-yu, 2011; Kokkinaki et al., 2004).

3D printing, also referred to as "additive manufacturing", represents the technology of production by gradually adding layers of material based on a computer-generated model (Sepasgozar et al., 2020). This technology is significant for RL because a large part of the return flows can be used as raw materials for the production of new products (Bhalla et al., 2022). Usage of returned products as raw materials enables reliable, uninterrupted and independent supply (Królikowski et al., 2020) while significantly reducing waste, transport costs, negative effects of transport (emission of gases, noise and particles, accidents, etc.), etc. (Krstić et al., 2022).

AR is a sophisticated technology that integrates advanced programming and powerful hardware and uses smart sensors to interact with real-world environments and perform tasks normally performed by humans (Sathiya et al., 2021). In combination with other Industry 4.0 technologies, they became "smarter", able to "see", "think", move freely, interact with the environment, and performing more complex operations (DHL, 2016). In RL robots can be used for the collection, transportation, classification, dismantling, storage, and retrieval of the returned products within the nodes of the RL networks (Sathiya et al., 2021; Alvarez-de-los-Mozos and Renteria, 2017). The main reasons for the application of this technology in RL are greater efficiency, flexibility, reliability and precision of the processes (DHL, 2016).

So far, the research studies have mainly analyzed the application of a single technology, or a couple of them at most, and their application in some stage of RL processes. There are no studies that attempt to comprehensively review the multiple applications of various technologies and define possible scenarios of smart reverse logistics development, which is the research gap this study is trying to fill.

2.3. Review on the MCDM methods integrated within the model

The newly proposed MCDM model integrates the Delphi, ANP and COBRA methods in the fuzzy environment. The fuzzy DANP method is used to establish the criteria weights, while the fuzzy COBRA method is used to obtain the final ranking of the alternatives. The main characteristics and the overview of the applications of these methods are presented in the following.

The ANP method, established by Saaty (1996), models a decision-making problem as a network, that is, it allows for more complex interrelationships with interdependencies and feedback relationships among the problem elements (criteria, sub-criteria and alternatives) (Mahmoudkelaye et al., 2018). The ANP forms a network by grouping the elements into clusters and establishing the relations within them (inner dependencies) and between them (outer dependencies) (Yang and Tzeng, 2011). Most methods obtain the criteria weights by accumulating the values while presuming the autonomy of criteria, which does not often properly reflect real-life situations where the criteria are mutually interrelated and dependent (Yang and Tzeng, 2011). This, in fact, is the main advantage of the ANP method, which is the capacity to consider complex direct and indirect interactions between the elements of the problem thus allowing for a comprehensive perception of the decision-making problem (Hallikainen et al., 2009). It also enables the consideration of both quantitative and qualitative criteria and ensures the consistency of evaluations. Since the problem discussed in this study implies the establishment of criteria and sub-criteria which are mutually interrelated, it was adequate and justified to use the ANP method to obtain the weights of these elements. One of the main disadvantages of ANP, as well as the other conventional MCDM methods, is its inability to deal with the ambiguity and vagueness of human thoughts. To overcome this, fuzzy logic has been integrated within the ANP method, thus making it more flexible and accurate (Tadić et al., 2014). The ANP method is very popular and has been recently applied in various fields, both in its conventional form (e.g.,Yitmen et al., 2021; Quezada et al., 2021) and in a fuzzy environment (e.g. Yang et al., 2021; Wen, 2021), either alone (e.g. Eskandari et al., 2021; Liu and Pei, 2021; Kustiyahningsih et al., 2021) or in combination with some other methods (e.g., Kumar et al., 2021; Utama et al., 2021; Pourmehdi et al., 2021).

The Delphi method, established by Dalkey and Helmer (1963), reaches a consensus on a topic, or a subject of decision-making, through the formation of groups whose members have the opportunity to evaluate, but also change their opinions based on the feedback from the other members' assessments (Mikaeil et al., 2013). It is commonly defined as "a method of systematic solicitation and collection of judgments on a particular topic through a set of carefully designed sequential questionnaires, interspersed with summarized information and feedback of opinions derived from earlier responses" (Delbecq et al., 1975). The Delphi method allows the decision-makers (DMs) to remain anonymous, it reaches the results through multiple iterations thus raising the reliability, it controls the feedback information in the decision process thus raising the stability in the DMs' responses and employs statistical measures to ensure group consensus (Zečević et al., 2017). However, it requires significant financial and time resources, as well as an effort to ensure a high rate of questionnaire return and processing of the imprecise, vague and ambiguous evaluations of the DMs (Zečević et al., 2017). In order to overcome these disadvantages, Ishikawa et al. (1993) integrated the fuzzy logic into the Delphi method which allowed for a faster convergence of the experts' opinions and more reliable consideration of their approximate and uncertain evaluations (Klir and Folger,

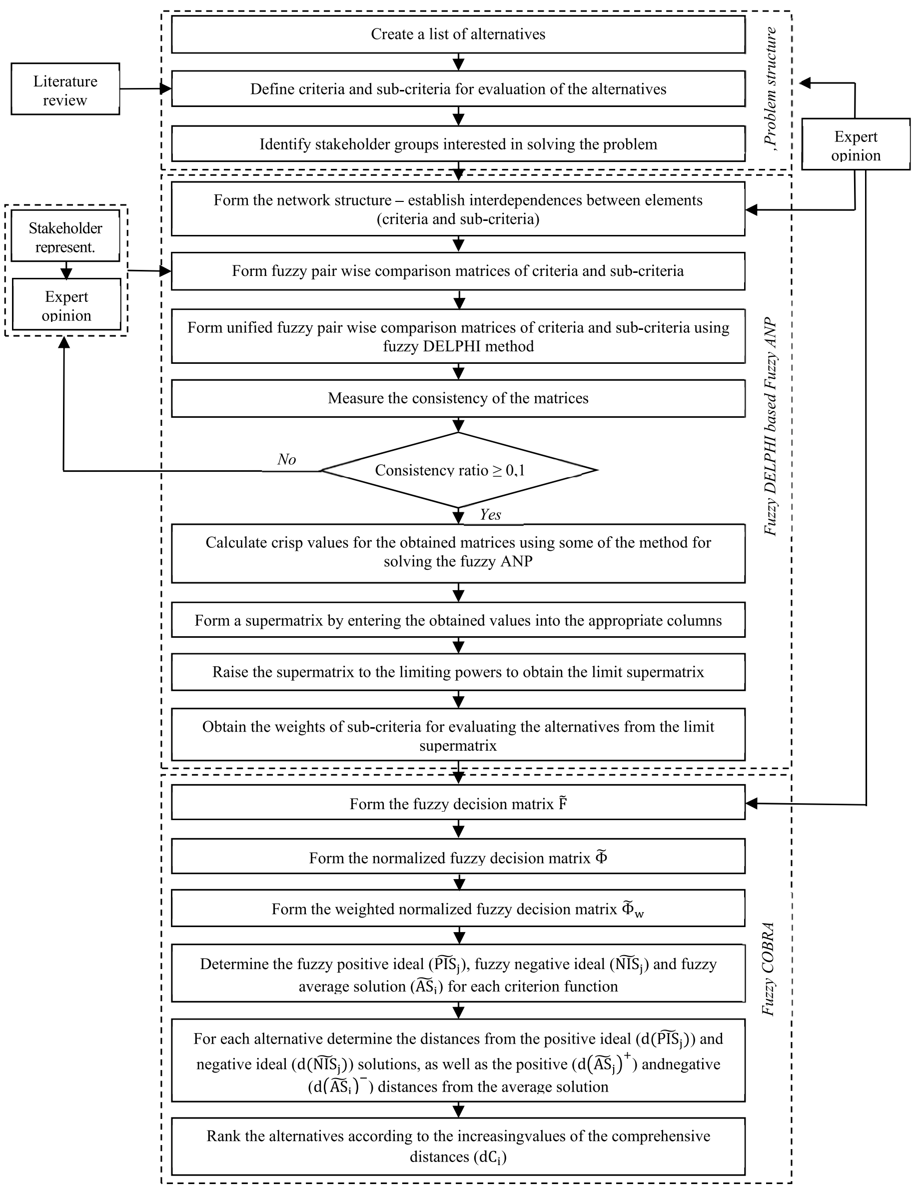

Figure 1. Concept of the proposed MCDM model

Fig. 1. Concept of the proposed MCDM model.

Table 1
Fuzzy evaluation scale.

Linguistic term	Abbreviation	Fuzzy scale
"None"	N	(1, 1, 2)
"Very Low"	VL	(1, 2, 3)
"Low"	L	(2, 3, 4)
"Fairly Low"	FL	(3, 4, 5)
"Medium"	M	(4, 5, 6)
"Fairly High"	FH	(5, 6, 7)
"High"	H	(6, 7, 8)
"Very High"	VH	(7, 8, 9)

1988). In this study fuzzy Delphi is used to unify the experts' evaluations regarding the identified criteria. Although integration of fuzzy Delphi and fuzzy ANP is not novel (e.g. Keliji et al., 2018; Zhang, 2017; Zečević et al., 2017), there are no studies in which this integrated method is applied in the reverse logistics sector, which is another research gap that this study is trying to fill.

The COBRA method was established by Krstić et al. (2022) and it is a type of a distance-based MCDM method. It ranks the alternatives by integrating two types of distances of the alternatives, namely Euclidian and taxicab, from three types of solutions, namely ideal, nadir and average. This indicates the comprehensiveness of the method, which is actually its main advantage. By using Euclidian and Taxicab distances the COBRA method enables the fine differentiation between the alternatives' distances and thus greater reliability of the obtained solution. The main disadvantage of the COBRA method is its complexity, required resources, time to obtain the results and its inability to deal with imprecise and vague evaluations by decision makers. The development of the fuzzy COBRA method, in order to overcome these disadvantages, as well as the integration of the Delphi, ANP and COBRA methods into a single MCDM model are also research gaps covered by this study.

3. Methodology

The newly developed MCDM model combines the fuzzy DANP and fuzzy COBRA methods. The conceptual representation of the model is given in Fig. 1 where the steps of the model application are described.

Step 1: Define the problem structure consisting of alternatives, sets of criteria encompassing the sub-criteria, and the stakeholders concerned with the considered problem.

Step 2: Define the fuzzy evaluation scale. To evaluate the criteria, sub-criteria and alternatives in this study, a scale presented in Table 1 was used.

Step 3: Obtain the criteria weights by applying the fuzzy DANP method (Zečević et al., 2017).

Step 3.1: Obtain the evaluations ($\widetilde{a}_{ijs} = (l_{ijs}, m_{ijs}, u_{ijs})$) indicating the importance of criteria (sub-criteria) i over criteria (sub-criteria) j, given by the stakeholder s using the scale given in Table 1. l_{ijs}, m_{ijs} and u_{ijs} represent lower, medium and upper values of the evaluation $\widetilde{a}_{ijs}$

Step 3.2: Unify the stakeholders' evaluations by applying the part of the fuzzy Delphi method adapted from Mikaeil et al. (2013):

$$\widetilde{\delta}_{ij} = (\alpha_{ij}, \beta_{ij}, \gamma_{ij}), i, j = 1, 2, \ldots, o \tag{1}$$

$$\alpha_{ij} = \min_i (l_{ijs}), s = 1, \ldots, q \tag{2}$$

$$\beta_{ij} = \left(\prod_{s=1}^{q} m_{ijs}\right)^{1/q}, s = 1, \ldots, q \tag{3}$$

$$\gamma_{ij} = \max_i (u_{ijs}), s = 1, \ldots, q \tag{4}$$

where α_{ij}, β_{ij} and γ_{ij} and are lower, medium and upper values of the unified evaluation $\widetilde{\delta}_{ij}$, respectively, $\alpha_{ij} \le \beta_{ij} \le \gamma_{ij}$, o is the total number of criteria (sub-criteria) and q is the total number of stakeholders.

Step 3.3: Form the fuzzy judgment matrix $\widetilde{\Delta}$ as follows:

$$\widetilde{\Delta} = \begin{bmatrix} / & \widetilde{\delta}_{12} & \ldots & \widetilde{\delta}_{1o} \\ \widetilde{\delta}_{21} & / & \ldots & \widetilde{\delta}_{2o} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{\delta}_{o1} & \widetilde{\delta}_{o2} & \ldots & / \end{bmatrix} \tag{5}$$

Step 3.4: Calculate the criteria weights. For each judgement matrix ($\widetilde{\Delta}$) obtain the priority vector ($W = (w_1, \ldots, w_o) > 0, \sum_{j=1}^{o} w_j = 1$) by applying the "Logarithmic Fuzzy Preference Programming" (LFPP) method (Wang and Chin, 2011). The LFPP method takes the elements of the judgment matrix ($\widetilde{\Delta}$) as their logarithmic approximations:

$$\ln \widetilde{\delta}_{ij} \approx (\ln \alpha_{ij}, \ln \beta_{ij}, \ln \gamma_{ij}), i, j = 1, \ldots, o \tag{6}$$

and solves the following nonlinear optimization model:

$$MinJ = (1 - \pi)^2 + M \sum_{i=1}^{o-1} \sum_{j=i+1}^{o} \left(\varepsilon_{ij}^2 + \eta_{ij}^2\right) \tag{7}$$

Subject to

$$x_i - x_j - \pi \ln(\beta_{ij} / \alpha_{ij}) + \varepsilon_{ij} \ge \ln \alpha_{ij}, i = 1, \ldots, o - 1, j = i + 1, \ldots, o \tag{8}$$

$$-x_i + x_j - \pi \ln(\gamma_{ij} / \beta_{ij}) + \eta_{ij} \ge -\ln \gamma_{ij}, i = 1, \ldots, o - 1, j = i + 1, \ldots, o \tag{9}$$

$$\pi, x_{i,j} \ge 0, i = 1, \ldots, o - 1, j = i + 1, \ldots, o \tag{10}$$

$$\varepsilon_{ij}, \eta_{ij} \ge 0, i = 1, \ldots, o - 1, j = i + 1, \ldots, o \tag{11}$$

where $x_{i,j} = \ln w_{i,j}$ for $i = 1, \ldots, o - 1, j = i + 1, \ldots, o$ and M is a specified sufficiently large constant such as $M = 10^3$. Variables ε_{ij} and η_{ij} for $i = 1, \ldots, o - 1$ and $j = i + 1, \ldots, o$ ensure the positive value of π. The smaller the values of these variables are, the better. Moreover, they need to comply with the following inequalities:

$$\ln w_i - \ln w_j - \pi \ln(\beta_{ij} / \alpha_{ij}) + \varepsilon_{ij} \ge \ln \alpha_{ij}, i = 1, \ldots, o - 1, j = i + 1, \ldots, o \tag{12}$$

$$-\ln w_i + \ln w_j - \pi \ln(\gamma_{ij} / \beta_{ij}) + \eta_{ij} \ge -\ln \gamma_{ij}, i = 1, \ldots, o - 1, j = i + 1, \ldots, o \tag{13}$$

If $x_j^* (j = 1, \ldots, o)$ is the optimal solution of the model (7)–(11) the crisp normalized priority vector can be obtained as:

$$w_j^* = \frac{exp(x_i^*)}{\sum_{j=1}^{o} exp(x_j^*)}, j = 1, \ldots, o \tag{14}$$

where $exp(x_{i,j}^*) = e^{x_{ij}^*}$ for $i = 1, \ldots, o - 1, j = i + 1, \ldots, o$.

The stability of results is controlled by calculating the Consistency Ratio (CR) for each matrix (Saaty, 1980):

$$CR = CI / RI \tag{15}$$

where the Consistency Index (CI) is calculated as:

$$CI = \frac{\Xi_{max} - o}{o - 1} \tag{16}$$

and the Random Index (RI) depends on the matrix size and is given in Saaty (1996). Ξ_{max} in equation (16) stands for the principal eigenvalue of the matrix $\widetilde{\Delta}$. CR values must be less than 0.10 for all comparisons.

Step 3.5: Form an initial supermatrix (W) made of multiple sub-matrices consisting of priority vectors from the previous step. Its general representation is as follows:

$$W = \begin{array}{r} \\ Goal\,(G) \\ Criteria\,(C) \\ Alternatives\,(A) \end{array} \begin{array}{c} \begin{array}{ccc} G & C & A \end{array} \\ \begin{pmatrix} 0 & 0 & 0 \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & I \end{pmatrix} \end{array} \tag{17}$$

where W_{21}, W_{22} and W_{32} are the matrices consisting of the priority vectors indicating the influences of the goal on the criteria, influences among the criteria, and influences of the criteria on the alternatives, respectively. I is the identity matrix.

Step 3.6: Obtain the limits of the supermatrix by raising the initial supermatrix to a sufficiently large power until the values in the columns converge. These converged values represent the weights of criteria and sub-criteria (w_j).

Step 4: Rank the alternatives by using the fuzzy COBRA method, that is, the fuzzy extension of the conventional COBRA method established by Krstić et al. (2022).

Step 4.1: Form the fuzzy decision matrix $\widetilde{F}$:

$$\widetilde{F} = \left[\begin{pmatrix} \widetilde{f}_{11} & \cdots & \widetilde{f}_{1o} \\ \vdots & \ddots & \vdots \\ \widetilde{f}_{p1} & \cdots & \widetilde{f}_{po} \end{pmatrix}\right] \tag{18}$$

where $\widetilde{f}_{kj} = (l_{kj}, m_{kj}, u_{kj})$ are the evaluations of the alternatives $k\ (i = 1, \ldots, p)$ in relation to criteria $j\ (j = 1, \ldots, o)$ obtained using the scale given in Table 1, o is the total number of criteria, p is the total number of the alternatives taken into consideration, and l_{kj}, m_{kj} and u_{kj} are the lower, middle and upper values of the triangular fuzzy number $\widetilde{f}_{kj}$, respectively.

Step 4.2: Form the normalized fuzzy decision matrix $\widetilde{\Phi}$ as follows:

$$\widetilde{\Phi} = [\widetilde{\varphi}_{kj}]_{p\times o} \tag{19}$$

where

$\widetilde{\varphi}_{kj} = (\lambda_{kj}, \mu_{kj}, \nu_{kj})$ is a normalized triangular fuzzy number whose lower (λ_{kj}), middle (μ_{kj}) and upper ($\widetilde{\nu}_{kj}$) values are obtained as follows:

$$\lambda_{kj} = \frac{l_{kj}}{\left(\max\limits_k u_{kj}\right)}, \forall k = 1, \ldots, p; \forall j = 1 \ldots, o \tag{20}$$

$$\mu_{kj} = \frac{m_{kj}}{\left(\max\limits_k u_{kj}\right)}, \forall k = 1, \ldots, p; \forall j = 1 \ldots, o \tag{21}$$

$$\nu_{kj} = \frac{u_{kj}}{\left(\max\limits_k u_{kj}\right)}, \forall k = 1, \ldots, p; \forall j = 1 \ldots, o \tag{22}$$

Step 4.3: Form the weighted normalized fuzzy decision matrix $\widetilde{\Phi}_w$ as follows:

$$\widetilde{\Phi}_w = \left[w_j \times \widetilde{\varphi}_{kj}\right]_{p\times o} \tag{23}$$

where w_j is the relative weight of criterion$j$.

Step 4.4: For each criterion function determine the fuzzy positive ideal ($\widetilde{PIS}_j$), fuzzy negative ideal ($\widetilde{NIS}_j$) and fuzzy average solution ($\widetilde{AS}_j$) as follows:

$$\begin{aligned} \widetilde{PIS}_j &= \left(\lambda_{kj}^{PIS}, \mu_{kj}^{PIS}, \nu_{kj}^{PIS}\right) = \left(\max_k\left(w_j \times \lambda_{kj}\right), \max_k\left(w_j \times \mu_{kj}\right), \max_k\left(w_j \times \nu_{kj}\right)\right), \forall j = 1, \ldots, o\ for\ j \in J^B \\ \widetilde{PIS}_j &= \left(\lambda_{kj}^{PIS}, \mu_{kj}^{PIS}, \nu_{kj}^{PIS}\right) = \left(\min_k\left(w_j \times \lambda_{kj}\right), \min_k\left(w_j \times \mu_{kj}\right), \min_k\left(w_j \times \nu_{kj}\right)\right), \forall j = 1, \ldots, o\ for\ j \in J^C \end{aligned} \tag{24}$$

$$\begin{aligned} \widetilde{NIS}_j &= \left(\lambda_{kj}^{NIS}, \mu_{kj}^{NIS}, \nu_{kj}^{NIS}\right) = \left(\min_k\left(w_j \times \lambda_{kj}\right), \min_k\left(w_j \times \mu_{kj}\right), \min_k\left(w_j \times \nu_{kj}\right)\right), \forall j = 1, \ldots, o\ for\ j \in J^B \\ \widetilde{NIS}_j &= \left(\lambda_{kj}^{NIS}, \mu_{kj}^{NIS}, \nu_{kj}^{NIS}\right) = \left(\max_k\left(w_j \times \lambda_{kj}\right), \max_k\left(w_j \times \mu_{kj}\right), \max_k\left(w_j \times \nu_{kj}\right)\right), \forall j = 1, \ldots, o\ for\ j \in J^C \end{aligned} \tag{25}$$

$$\widetilde{AS}_j = \left(\lambda_{kj}^{AS}, \mu_{kj}^{AS}, \nu_{kj}^{AS}\right) = \left(\operatorname*{mean}_k\left(w_j \times \lambda_{kj}\right), \operatorname*{mean}_k\left(w_j \times \mu_{kj}\right), \operatorname*{mean}_k\left(w_j \times \nu_{kj}\right)\right), \forall j = 1, \ldots, o \quad for \quad j \in J^B, J^C \tag{26}$$

where J^B and J^C are the sets of benefit and cost criteria, respectively.

Step 4.5: For each alternative determine the distances from the positive ideal ($d(\widetilde{PIS}_j)$) and negative ideal ($d(\widetilde{NIS}_j)$) solutions, as well as the positive ($d(\widetilde{AS}_j)^+$) and negative ($d(\widetilde{AS}_j)^-$) distances from the average solution as follows:

$$d\left(\widetilde{S}_j\right) = dE\left(\widetilde{S}_j\right) + \sigma \times dE\left(\widetilde{S}_j\right) \times dT\left(\widetilde{S}_j\right), \forall j = 1, \ldots, o \tag{27}$$

where $\widetilde{S}_j$ represents any solution ($\widetilde{PIS}_j$, $\widetilde{NIS}_j$ or$\widetilde{AS}_j$), σ is the correction coefficient obtained as follows:

$$\sigma = \max_k dE\left(\widetilde{S}_j\right)_k - \min_k dE\left(\widetilde{S}_j\right)_k \tag{28}$$

$dE(\widetilde{S}_j)_k$ and $dT(\widetilde{S}_j)_k$ denote the Euclidian and Taxicab distances, respectively, which are for the positive ideal solution obtained as follows:

$$dE\left(\widetilde{PIS}_j\right)_k = \sum_{j=1}^{o} \sqrt{\left(\left(\lambda_{kj}^{PIS} - w_j \times \lambda_{kj}\right)^2 + 4 \times \left(\mu_{kj}^{PIS} - w_j \times \mu_{kj}\right)^2 + \left(\nu_{kj}^{PIS} - w_j \times \nu_{kj}\right)^2\right)/6}, \forall k = 1, \ldots, p, \forall j = 1, \ldots, o \tag{29}$$

$$dT\left(\widetilde{PIS}_j\right)_k = \sum_{j=1}^{o} \left(\left|\lambda_{kj}^{PIS} - w_j \times \nu_{kj}\right| + 4 \times \left|\mu_{kj}^{PIS} - w_j \times \mu_{kj}\right| + \left|\nu_{kj}^{PIS} - w_j \times \lambda_{kj}\right|\right) / 6, \forall k = 1, \ldots, p, \forall j = 1, \ldots, o \tag{30}$$

for the negative ideal solution obtained as follows:

$$dE\left(\widetilde{NIS}_j\right)_k = \sum_{j=1}^{o} \sqrt{\left(\left(\lambda_{kj}^{NIS} - w_j \times \lambda_{kj}\right)^2 + 4 \times \left(\mu_{kj}^{NIS} - w_j \times \mu_{kj}\right)^2 + \left(\nu_{kj}^{NIS} - w_j \times \nu_{kj}\right)^2\right)/6}, \forall k = 1, \ldots, p, \forall j = 1, \ldots, o \tag{31}$$

$$dT\left(\widetilde{NIS}_j\right)_k = \sum_{j=1}^{o} \left(\left|\lambda_{kj}^{NIS} - w_j \times \nu_{kj}\right| + 4 \times \left|\mu_{kj}^{NIS} - w_j \times \mu_{kj}\right| + \left|\nu_{kj}^{NIS} - w_j \times \lambda_{kj}\right|\right) / 6, \forall k = 1, \ldots, p, \forall j = 1, \ldots, o \tag{32}$$

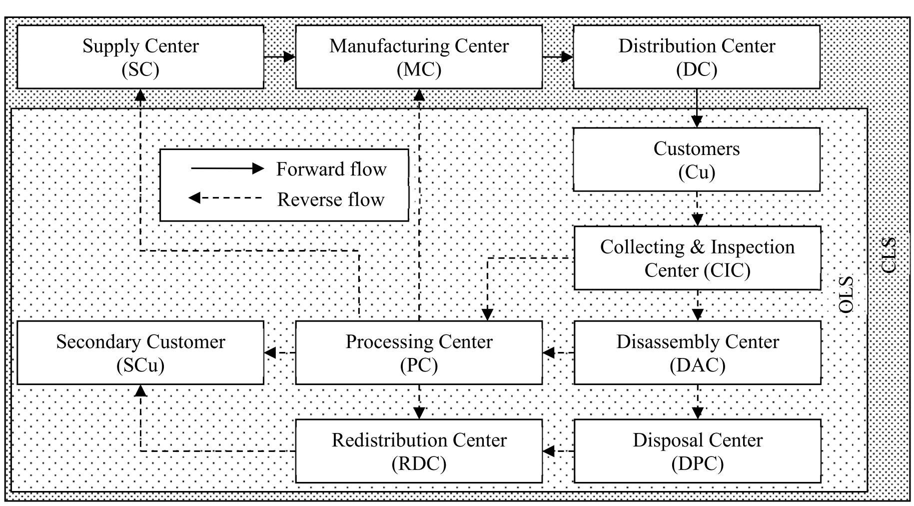

Fig. 2. Closed loop and open loop reverse logistics systems (adapted from: Sheriff et al., 2012).

$$dE\left(\widetilde{AS}_j\right)_k^+ = \sum_{j=1}^{o}\sqrt{\left(\tau^+\left(\lambda_{kj}^{AS} - w_j \times \lambda_{kj}\right)^2 + 4 \times \tau^+\left(\mu_{kj}^{AS} - w_j \times \mu_{kj}\right)^2 + \tau^+\left(\nu_{kj}^{AS} - w_j \times \nu_{kj}\right)^2\right)/6}, \forall k = 1, \ldots, p, \forall j = 1, \ldots, o \tag{33}$$

for the positive distance from the average solution obtained as follows:

$$dT\left(\widetilde{AS}_j\right)_k^+ = \sum_{j=1}^{o}\left(\tau^+\left|\lambda_{kj}^{AS} - w_j \times \nu_{kj}\right| + 4 \times \tau^+\left|\mu_{kj}^{AS} - w_j \times \mu_{kj}\right| + \tau^+\left|\nu_{kj}^{AS} - w_j \times \lambda_{kj}\right|\right) / 6, \forall k = 1, \ldots, p, \forall j = 1, \ldots, o \tag{34}$$

where

$$\tau^+ = \begin{cases} 1 & if \quad \widetilde{AS}_j < w_j \times \widetilde{\varphi}_{kj} \\ 0 & if \quad \widetilde{AS}_j > w_j \times \widetilde{\varphi}_{kj} \end{cases} \tag{35}$$

and for the negative distance from the average solution obtained as follows:

$$dE\left(\widetilde{AS}_j\right)_k^- = \sum_{j=1}^{o}\sqrt{\left(\tau^-\left(\lambda_{kj}^{AS} - w_j \times \lambda_{kj}\right)^2 + 4 \times \tau^-\left(\mu_{kj}^{AS} - w_j \times \mu_{kj}\right)^2 + \tau^-\left(\nu_{kj}^{AS} - w_j \times \nu_{kj}\right)^2\right)/6}, \forall k = 1, \ldots, p, \forall j = 1, \ldots, o \tag{36}$$

$$dT\left(\widetilde{AS}_j\right)_k^- = \sum_{j=1}^{o}\left(\tau^-\left|\lambda_{kj}^{AS} - w_j \times \nu_{kj}\right| + 4 \times \tau^-\left|\mu_{kj}^{AS} - w_j \times \mu_{kj}\right| + \tau^-\left|\nu_{kj}^{AS} - w_j \times \lambda_{kj}\right|\right) / 6, \forall k = 1, \ldots, p, \forall j = 1, \ldots, o \tag{37}$$

where

$$\tau^- = \begin{cases} 1 & if \quad \widetilde{AS}_j > w_j \times \widetilde{\varphi}_{kj} \\ 0 & if \quad \widetilde{AS}_j < w_j \times \widetilde{\varphi}_{kj} \end{cases} \tag{38}$$

The comparisons of triangular fuzzy numbers in (34) and (37) are performed according to the methods established by Dorohonceanu and Marin (2002).

Step 4.6: Rank the alternatives according to the increasing values of the comprehensive distances (dC_i) obtained as follows:

$$dC_k = \frac{d\left(\widetilde{PIS}_j\right)_k - d\left(\widetilde{NIS}_j\right)_k - d\left(\widetilde{AS}_j\right)_k^+ + d\left(\widetilde{AS}_j\right)_k^-}{4}, \forall k = 1, \ldots, p \tag{39}$$

4. Evaluation of the smart reverse logistics systems development scenarios

According to Sheriff et al. (2012), reverse logistics (RL) networks can be classified as “Closed Loop Systems” (CLSs) and “Open Loop Systems” (OLSs), as presented in Fig. 2. CLSs integrate traditional logistics forward flows, from the supply center to the customer, with the reverse flows, from the customer back to the supply center. In these systems most of the materials are being conserved and new materials are needed only to replace losses in the system. Thus, the customers are at the same time the consumers and the source of materials in the system. This system mostly corresponds to the concept of circular economy (Stahel, 2016). OLSs imply only reverse flows from the customer to the disposal center, redistribution center or secondary customer, after which they are distributed for reuse to some other places where they are needed.

Smart reverse logistics is intended in this study as reverse logistics applying various smart technologies belonging to the Industry 4.0 paradigm both in CLSs and OLSs. Since there are diverse Industry 4.0 technologies which can be applied in different stages of RL systems and have various degrees of applicability (Krstić et al., 2022), it is possible to define different scenarios of possible smart reverse logistics systems development.

4.1. Smart reverse logistics development scenarios

The most reliable way of predicting is defining an event space that contains all possible outcomes of an experiment or happening. In reality, however, it is very difficult to define all possible outcomes. Therefore, when trying to predict anything, the most likely, i.e. typical outcomes that differ significantly and represent the closest scenario of a possible realistic outcome, are defined. Of course, the greater the number of scenarios, the greater the probability of defining a possible outcome that will actually be realized. Taking into account the number of Industry 4.0 technologies and their possible applications in the field of RL, a very large number of realistic possible scenarios could be defined. The analysis of such a large number of scenarios may imply a non-meaningful differentiation. Therefore, only four basic scenarios are defined in this study, which significantly differ in the number of applied Industry 4.0 technologies, as well as in the scope of their application, i.e., the number of stages, as well as the number of processes and activities within them, in which they can be employed. The scenarios range from the basic applications of the most popular, most applicable and most developed technologies to the most complex applications of all technologies for which the possibility of application in the field of RL has been identified so far. All applications of the specified technologies for the realization of the processes mentioned in the scenarios have already been investigated in the literature, which makes the scenarios realistic possible outcomes. Each scenario represents a higher evolutionary stage than the previous one, that is, it encompasses the application of all the technologies from the previous scenario with an upgrade in terms of the application of other technologies.

Scenario 1 (Sc.1). The first scenario implies the use of the three most applicable Industry 4.0 technologies, namely IoT, CC and E/M Marketplace (Krstić et al., 2022) to perform some of the basic processes. The IoT is used in the entire network of the system for communication and information exchange between the reverse materials and nodes in the network through the use of embedded sensors and various communication standards, thus enabling cloud-based inventory monitoring and low-power and low-cost Supply Chain Management (SCM) operations. In addition, the IoT is used in the CIC to assess various designs of the End-Of-Life (EOL) products, evaluating the state of returned products and making decisions about their disassembly, remanufacturing, recycling or disposal. CC provides the platforms for the software solutions enabling the communication of the IoT objects during the collection, processing, exchange and storage of information, thus setting the ground for efficient telematics and Electronic Data Interchange (EDI) systems within the entire RL network. Platforms for the electronic trade within the RL network, called E-marketplaces, enable digital transactions, electronic trade, cooperation among the participants in the network, and defragmentation of reverse logistics markets, thus facilitating the redistribution of returns to the market.

Scenario 2 (Sc.2). In addition to the technologies and their applications in the first scenario, the second scenario includes some additional applications of the same technologies, as well as the applications of the AV, AI and BD and DM in RL networks. The IoT is used in the previous scenario to manage the supply chain with the aim of inventory optimization, as well as to make decisions regarding the materials' destination after the initial collection and inspection. In this scenario, the IoT is applied to create a comprehensive decision support system that effectively allows for the tracking, monitoring and analyzing of products in real-time with the focus on identifying the residual value of materials in all stages of the RL network and making operational decisions based on this information. Supported by the BD and DM technologies, this system can also carry out decision-making on tactical and strategic levels and estimate the remanufacturing performance. Additional assistance for making tactical decisions, such as reverse Third Logistics Providers (3 PL) and strategic decisions, including the network design and location of CIC, DAC, PC and other facilities within the network, is provided by the application of the AI technology. In addition to the services available on the cloud in the previous scenario, this one uses CC to enable the environment for the establishment of the Transport Management System (TMS), Package Management System (PMS) and Warehouse Management System (WMS) on the cloud. The electronic trade in this scenario is also upgraded by applying the platforms on which the trade is carried out using smart mobile devices and technologies such as Bluetooth, Zigbee, NFC ("Near-Field-Communication"), Wi-Fi ("Wireless Fidelity"), Li-Fi ("Light Fidelity"), WiMax ("Worldwide Interoperability for Microwave Access"), and 4G and 5G mobile networks, thus creating an M-marketplace. This scenario also includes the application of the AV to perform short-haul road transportation, primarily using small electric vehicles for waste collection between the Cu and CIC.

Scenario 3 (Sc.3). This scenario includes all the technologies applied in the previous ones, but is complemented with some additional ones. An additional application of the IoT is the establishment of the Control System which implies transformation from pushed to pulled flows (instead of collecting waste at scheduled times, it is pulled by the actual occurrence). The system provides information about the time, location and volume of waste that needs to be collected thus facilitating the management of waste collection over a large physical area covered by the RL network. The system also integrates BD and DM technology to gather and process the data necessary to plan collection points for a vast number of pick-ups and the best ways to serve them, as well as the AI technology to plan the collection, acquisition and assessment of products and transportation, including vehicle routing and determination of rules for product disposal among others. In addition to small electric road AVs, this scenario also implies the use of drones for short-haul

Table 2
Criteria and sub-criteria for the evaluation of RL development scenarios.

Criteria	Sub-criteria	Description
Economic (Ec.)	Investment costs (Ec.1)	Costs of hardware (equipment, sensors, vehicles, etc.) and software, necessary for the implementation of technologies, i.e. establishment of RL scenario.
	Maintenance costs (Ec.2)	Costs of maintaining hardware (inspection, control, repair, etc.) and software (upgrade, update, bugs fixing, etc.).
	Logistics costs (Ec.3)	Costs of performing reverse logistics activities, such as collection, transport, packing, warehousing/disposal of material etc.
	Processing costs (Ec.4)	Costs of processing the material within the nodes of the RL network, such as testing, sorting, selecting, marking, disassembling, extracting, repairing, etc.
	Preservation of material value (Ec.5)	The degree of preservation of the returned materials' main features, and thus the extent of their possible reuse, remanufacturing, repair, etc. indicating the value retained for the stakeholders in the RL network.
Technological	Development degree (Tc.1)	The level to which the technologies included within the scenarios have been developed, specifically, whether they are in the phase of an inception, developed solution or application.
	Complexity (Tc.2)	The number of technologies and their applications encompassed within the scenario, and thus the amount of effort needed to implement the scenario.
	Compatibility (Tc.3)	The level to which the technologies within the scenario are mutually compatible or able to complement each other, thus becoming more efficient and applicable.
	Security (Tc.4)	The level of vulnerability regarding the abuse of the data needed for the technology operation, influenced by the number and type of technologies and their applications within the scenario.
Environmental	Waste reduction (En.1)	The level of waste material reduction as a result of better management of the RL network enabled by the technologies applied within the scenario.
	Emissions reduction (En.2)	The level of reduction of greenhouse gasses, particles, noise and vibration emissions as a result of a more efficient road transport and shift to the other, more environmentally friendly, means of transport.
	Congestion reduction (En.3)	The level of congestion reduction deriving from the lower number of freight vehicles on the roads as a result of more efficient utilization of road vehicles and shifts to other means of transport.
	Energy resource preservation (En.4)	The level of energy preservation as a result of a better utilization of vehicles and the application of transport means with alternative drive systems (fueled by electricity, hydrogen and biofuels, for example).
Service quality	Reliability (Qu.1)	The level of reliability improvement in terms of providing the appropriate service, in the appropriate form and at the appropriate time within the RL network, as a result of the application of various technologies implied by the scenario.
	Flexibility (Qu.2)	The ability to adjust to the unannounced, unplanned or unpredicted circumstances that might occur within the RL network.
	Time efficiency (Qu.3)	The ability to move the materials timely and accurately between the various

(*continued on next page*)

Table 2 (*continued*)

Criteria	Sub-criteria	Description
		stages and nodes of the RL network, thus reducing the time wasted within the RL network.
	Visibility & traceability (Qu.4)	The level of visibility of materials, equipment, participants, etc. and their main characteristics, as well as the ability to track the changes in their status over time and space, enabled by the technologies in each scenario.
Social	Health (So.1)	The impact of the technologies applied in the scenarios, on the citizens' health issues associated with the pollution generated by freight transportation.
	Safety (So.2)	The impact of the technologies in each scenario on the wellbeing of the people involved in the processes (workers, residents), which might be endangered by the misuse of data, equipment, vehicles, etc.
	Corporate citizenship (So.3)	The attitude of the citizens based on the social, cultural, environmental, and economic impacts which define the success of the RL scenario implementation and achievement of long term sustainable success for the community at large.
	Labor market impact (So.4)	The impact of the applied technologies in the scenario on job creation/reduction as a result of automation and digitalization which reduce the need for manual labor on the one hand, but create new types of jobs on the other.
Political	Regulations (Po.1)	The existence of and the extent in which regulatory framework (laws, agreements, decrees, etc.) concerning the involved technologies induces or limits their application within the scenario.
	Subsidies (Po.2)	The level of governmental (international, national, local) support to the development of the scenario, depending on its contribution to the agenda of promoting digital transformation and sustainability.
	Tax policy (Po.3)	The level of impact of the tax policy (e.g., taxes on green vehicles' purchase and registration, equipment provision, carbon emissions, etc.) on the attractiveness of the development of the scenario.
	Plans & strategies (Po.4)	Plans and strategies on international, regional, national and local levels, which promote incentives and create the framework for the development of RL sector and circular economy.

transportation like waste collection, as well as the application of the AGVs in the main CICs to carry out operations of internal horizontal and vertical transportation. CC application is complemented with the advanced Inventory Management System (InvMS) and Information management system (InfMS). This scenario also implies the establishment of the return aggregators within E/M Marketplaces, such as the providers who handle returns from many different users, thus giving way to a closer cooperation between various stakeholders within the RL networks. E/M marketplaces are also supported by BC technology leading to the development of a system that uses smart contracts and decision-support techniques which help consumers select an appropriate pay scheme, thus preventing fraudulent behavior.

Scenario 4 (Sc.4). This is the most advanced scenario which implies the application of all applicable Industry 4.0 technologies and their known or potential applications in the RL network. The application of the IoT technology is expanded in this scenario to include the establishment of the fully integrated reverse logistics Information Management System with the aim of collecting accurate and reliable information on the products' changing attributes in real-time. The system enables the tracking, collection and management of data, as well as decision-making regarding the processing of the reverse flow materials and products and re-utilization of resources. The system is complemented with the integration of the CC based Intelligent Transport System (ITS) and Enterprise Resource Planning (ERP). The ITS supports the use of small electric road and airborne (drones) AVs for short-haul operations between Cu and CIC, as well as the larger road, rail, waterborne and airborne vehicles for long-haul transportation activities between all other nodes in the RL network. ERP integrates E/M Marketplaces which, in addition to the previously explained applications, determines the reverse flow demand in real-time, improves visibility in the reverse logistics chain, allows for the automation of the returns acquisition, creates value by maximizing the throughput and minimizing the transaction costs, effectively controls the volume of returns and minimizes the uncertainty factors in return flows. ERP also uses BC technology to integrate relationship management systems of suppliers and customers in order to improve the reliability in a commonly trustless environment, thus improving traceability and transparency in the entire RL network. The operation of the ERP system is significantly influenced and shaped by the application of the 3D printing technology. Many of the resources managed by the system can actually be used as materials for 3D printing. Eventually this leads to the reduction of the number of vehicles needed for the return collection and their traveling distances, thus decreasing transport costs as well as various adverse effects of freight transport in the entire RL network. The system also enables this production model to be independent of raw material suppliers and diversify its supply thus improving the reliability and continuity of production. In addition to their applications in the previously explained scenarios, BD and DM technologies are used in this scenario to predict product returns and other reverse activities, estimating the return quality, avoiding returns, speeding up repair and preparing for recycling; while the AI technology is also applied for product return forecasting, sorting, inspection, selection of alternatives to recycling, reassembly, and remanufacturing. This scenario also implies the application of AGVs in all network nodes to carry out processes of horizontal and vertical transport, but also AR technology in the processes of classification, dismantling, storage, and retrieval of the returned products within the facilities to process the reverse flows.

4.2. *Evaluation criteria for the smart reverse logistics development scenarios*

In order to perform an adequate evaluation of the RL development scenarios it was necessary to define a broad set of sub-criteria classified within the six main groups. The potential set of criteria and sub-criteria were identified through an extensive literature review covering this subject, including Gu et al. (2021), Senthil et al. (2018), Hasani (2015), Darbari et al. (2015), Jindal and Sangwan (2013), and Sasikumar and &Haq (2010). These criteria and sub-criteria were then discussed through the series of roundtables with the representatives of all stakeholders, resulting in a final set of unique criteria and sub-criteria appropriate for the evaluation of the defined alternatives. During the process of the final selection, care was taken to ensure that the criteria reflect the main goals of all stakeholders and consider all the main aspects of the problem. The final sets of criteria and sub-criteria are presented in Table 2. Some of the criteria could undoubtedly be viewed as quantitative (e.g. investment, maintenance, logistics and other costs, emissions reduction, etc.). However, as the value of the alternatives concerning these criteria is very vague and difficult to determine precisely, all criteria are viewed as qualitative. Apart from the fact that the quantitative values vary significantly according to these criteria, the problem is further complicated by the fact that the scenarios involve combinations of several technologies. Some of them may use common

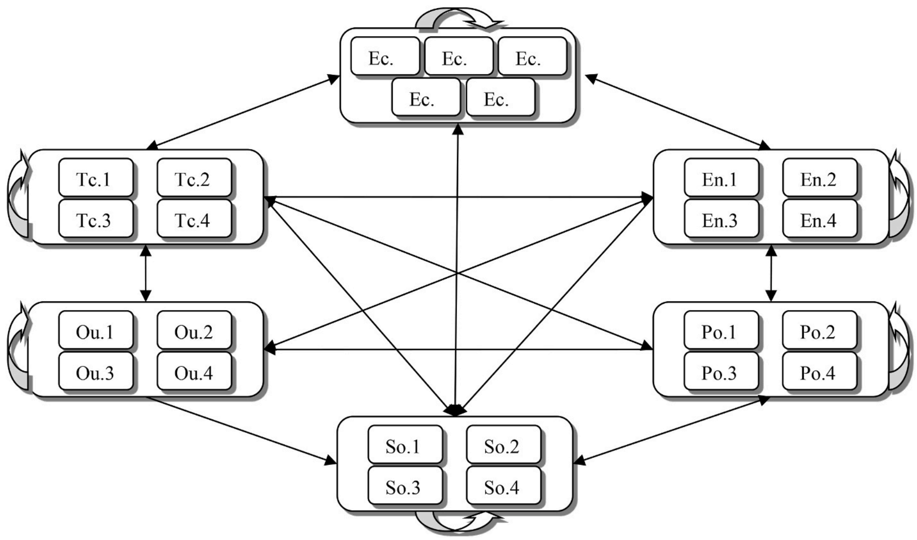

Fig. 3. Network structure of the fuzzy DANP method.

Table 3
Evaluations of inner dependencies of Economic criteria in relation to Ec.1

	Ec.2	Ec.3	Ec.4	Ec.5
Ec.2		/, /, VL	/, /, L	L, /, /
Ec.3	L, VL, /		N, /, VL	M, /, /
Ec.4	L, VL, /	/, N, /		M, /, /
Ec.5	/, L, FL	/, VL, M	/, VL, FH	

*evaluations are given in the format *Pro.*, *Use.*, *G&C*.

Table 4
Fuzzy judgment matrix and priority vector of Economic criteria in relation to Ec.1

	Ec.2	Ec.3	Ec.4	Ec.5	w_j^*
Ec.2	/	(0.44, 0.69, 1.14)	(0.55, 0.79, 1.26)	(0.46, 0.63, 0.87)	0.168
Ec.3	(0.87, 1.44, 2.29)	/	(0.79, 1.26, 1.82)	(0.61, 0.79, 1.14)	0.274
Ec.4	(0.79, 1.26, 1.82)	(0.55, 0.79, 1.26)	/	(0.58, 0.75, 1.06)	0.212
Ec.5	(1.14, 1.59, 2.15)	(0.87, 1.26, 1.65)	(0.94, 1.34, 1.74)	/	0.346

Table 5
Evaluations of the RL development scenarios.

	Sc.1	Sc.2	Sc.3	Sc.4
Ec.1	VH	FH	M	VL
Ec.2	VH	H	FH	L
Ec.3	VL	M	H	VH
Ec.4	FL	FH	VH	VH
Ec.5	L	M	H	VH
Tc.1	VH	H	FH	FL
Tc.2	VH	H	FH	FL
Tc.3	FH	H	M	L
Tc.4	VH	H	M	L
En.1	L	M	H	VH
En.2	VL	FL	H	VH
En.3	VL	FL	H	VH
En.4	L	M	H	VH
Qu.1	M	FH	H	VH
Qu.2	FL	FH	VH	H
Qu.3	M	FH	H	VH
Qu.4	FH	H	VH	VH
So.1	L	M	H	VH
So.2	L	FL	VH	H
So.3	H	VH	FH	M
So.4	FH	VH	H	M
Po.1	VH	H	M	VL
Po.2	FH	H	VH	H
Po.3	VH	H	FH	M
Po.4	M	FH	VH	H

platforms or infrastructures, which can affect the variation of quantitative values in a certain range (increase or decrease them). Accordingly, it is much simpler and less resource-consuming to use the qualitative linguistic evaluations and their quantitative fuzzy counterparts (presented in Table 1).

4.3. Stakeholders interested in solving the problem

Making an adequate decision about the currently most promising smart RL development scenario requires the engagement of all interested stakeholders. Three main groups of stakeholders are identified in this research.

The first one includes the ***providers of services*** (*Pro.*) in the domain of logistics (collection, transport, disposal, storage, redistribution) and in material processing (inspection, disassembling, recycling). They make a profit by carrying out the above-mentioned services. Therefore, their main goal is the development and implementation of smart RL scenarios that would include the maximum application of technologies enabling the greatest revenues with minimal investment and operating costs.

The second group of stakeholders refers to the ***users of services*** (*Use.*), that is, the companies from the trade, industry and utilities sector, as well as the customers intended as the product end users. They buy the service as an accompanying element necessary for the realization of their core businesses, or as a means to satisfy their own demand. Accordingly, their main goal is the development of scenarios which can offer the services of the highest possible quality at an acceptable price.

The third group includes ***governments and citizens*** (*G&C*), that is, various governing administrations at local, national, regional or international levels, and people living and working in these areas. Their main goal is the development of a scenario which will contribute the most to the development of the economy and creation of jobs, while minimizing the influence on the lives and health of the people and the environment in the areas involved.

Representatives of the main stakeholders, through the series of roundtables and interviews, provided the main inputs to solve the problem defined within this s. The pool of stakeholder representatives included a total of 54 members, out of which 17 represented providers of

Table 6
RL development scenarios ranked by fuzzy COBRA method.

	$dE(\widetilde{PIS}_j)_k$	$dT(\widetilde{PIS}_j)_k$	$dE(\widetilde{NIS}_j)_k$	$dT(\widetilde{NIS}_j)_k$	$dE(\widetilde{AS}_j)_k^+$	$dT(\widetilde{AS}_j)_k^+$	$dE(\widetilde{AS}_j)_k^-$	$dT(\widetilde{AS}_j)_k^-$	dC_k	Rank
Sc.1	0.302	0.332	0.217	0.260	0.094	0.098	0.167	0.170	0.042	4
Sc.2	0.228	0.244	0.291	0.298	0.047	0.063	0.045	0.073	−0.017	2
Sc.3	0.157	0.187	0.362	0.364	0.092	0.106	0.019	0.044	−0.073	1
Sc.4	0.233	0.272	0.286	0.318	0.120	0.126	0.123	0.124	−0.013	3

Table 7
Sensitivity analysis results.

	SAS0	SAS1	SAS2	SAS3	SAS4	SAS5	SAS6	SAS7	SAS8
dC (Sc.1)	0.042	0.057	0.003	0.064	0.067	0.064	0.023	0.026	0.035
dC (Sc.2)	−0.017	−0.018	−0.019	−0.007	−0.003	−0.010	−0.028	−0.018	0.000
dC (Sc.3)	−0.073	−0.073	−0.050	−0.075	−0.080	−0.074	−0.054	−0.059	−0.026
dC (Sc.4)	−0.013	−0.016	0.021	−0.037	−0.040	−0.036	−0.002	0.000	−0.026

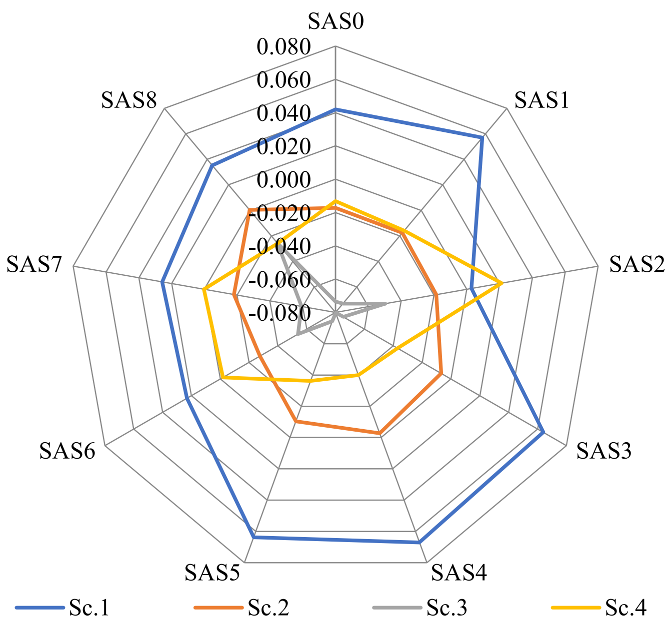

Fig. 4. Sensitivity analysis results.

services, 21 represented users of services and 16 represented governments and citizens. In addition to their prior knowledge, experience, and aspirations towards the technologies and their possible applications, the stakeholder representatives were additionally familiarized with the background of the problem, i.e. informed about the specific characteristics of each technology, with the aim of creating a sound understanding of the problem which will allow them to evaluate the criteria and the alternatives as objectively as possible.

4.4. Results of model application

Following the steps of the proposed model described in Section 3, the evaluation and ranging of the smart RL development scenarios was performed. The first steps of the model imply the establishment of the problem structure, which has been realized by defining the RL development scenarios as the alternatives (Section 4.1), identification of the criteria and sub-criteria for their evaluation (Section 4.2) and stakeholders interested in solving the problem (Section 4.3). The next steps of the model imply the establishment of the criteria weights using the fuzzy DANP method. Since the method requires the establishment of a network defined by the interrelations between the criteria and sub-criteria, the stakeholder representatives indicated the influence of each criterion and sub-criterion on all the others and evaluated the strength of that influence. Their judgments are synthesized in the way that majority of responses of certain kind (e.g. economic criteria depend on the technological) were adopted as the representative judgment of the entire stakeholder representatives' pool. The obtained network structure is presented in Fig. 3.

The stakeholder representatives used the linguistic terms presented in Table 1 to express the strength of influences between the criteria and sub-criteria. Their judgments are synthesized in the same way as the influences. The majority of responses of certain kind (e.g. the preference of the Maintenance costs over the Logistics costs are very low) were adopted as the representative judgment of that stakeholder group. An example of evaluations of inner dependencies of Economic criteria in relation to Ec.1 is presented in Table 3.

The evaluations were transformed into corresponding triangular fuzzy numbers and then unified using the equations (1)–(4), thus forming the fuzzy judgment matrix (5) (Table 4). By using the LFPP method, applying the equations (6)-(14) for the established fuzzy judgment matrix, the normalized crisp priority vector for the Economic sub-criteria in relation to Ec.1 is obtained (Table 4).

Using the equations (15) and (16) the *CR* value of 0.021 was obtained. Since the *CR* value is less than 0.1 it can be concluded that the evaluations were consistent. The same procedure used for the example of Economic criteria was repeated for all other inner and outer dependencies. The obtained priority vectors were used to form the initial supermatrix (17) presented in Table A1 in the Supporting material. The initial supermatrix was then raised to a sufficiently large power until the values by the columns converged, thus obtaining the limit supermatrix presented in Table A2 in the Supporting material. These converged values were taken as the sub-criteria weights.

After that, the RL scenarios were evaluated according to each sub-criterion by the stakeholder representatives, using the linguistic terms. Their judgments, synthesized in the same way as the influences, are presented in Table 5 Their corresponding fuzzy values as per Table 1, were used to form the fuzzy decision matrix $\widetilde{F}$ (18).

The normalized ($\widetilde{\Phi}$) and weighted normalized ($\widetilde{\Phi}_w$) fuzzy decision matrices were obtained by applying the equations (19)–(23), respectively. $\widetilde{PIS}_j$, $\widetilde{NIS}_j$ and $\widetilde{AS}_j$ for each criterion function were obtained using the equations 24–26. For each alternative $d(\widetilde{PIS}_j)$ and $d(\widetilde{NIS}_j)$, as well as $d(\widetilde{AS}_j)^+$ and $d(\widetilde{AS}_j)^-$ were obtained by applying the equations 27–38. The final ranking of the RL development scenarios was obtained by arranging the dC_i values, obtained by applying the equation (39), in increasing order. All previously mentioned distances, as well as the final ranking of the RL development scenarios are presented in Table 6.

4.5. Sensitivity analysis

In order to check whether the obtained solution was resistant to the changes in the model setup, a sensitivity analysis was performed. The results obtained in the previous section 4.4 were adopted as the basic sensitivity analysis scenario (SAS0). Eight additional scenarios were formed, each of them introducing the changes in the sub-criteria weights. In the first scenario (SAS1) all criteria were presumed to be equally important. In each of the following six scenarios the most important criteria were excluded from the model, i.e., Ec.3 in the SAS2, Tc.2 in the SAS3, Tc.4 in the SAS4, Ec.1 in the SAS5, So.2 in the SAS6 and Ec.4 in the SAS7. In the final scenario (SAS8), all of the previously mentioned criteria were excluded from the model. The results of the performed sensitivity analysis are presented in Table 7 and Fig. 4. The results show that Sc.3 is ranked as the best one in all SASs, and Sc.1 as the worst in all SASs except in SAS2. Sc.2 and Sc.4 alternated between second and third place, but in most scenarios Sc.2 was ranked as second and Sc.4 as third. Accordingly, the following order of scenarios is adopted as the final ranking: Sc3, Sc.2, Sc.4 and Sc.1.

5. Discussion

The obtained ranking of scenarios highlights the fact that a larger number of technologies and their possible applications do not necessarily mean a better solution to the problem in determining the most acceptable direction for future development and application of smart RL systems. The ranking of RL development scenarios is a compromised solution that is obtained as a result of considering and combining the goals and requirements of all stakeholders. Sc.3 implies a high level of development of a smart RL system, but not the highest. Sc.4 implies a wider range of technologies and their applications, and yet it is ranked lower, not only than Sc.3 but also than Sc.2. The reason for this is the relationship between the costs and the benefits it brings to all interest groups. Sc.4 brings a high level of reliability, efficiency, accuracy and other service quality characteristics, as well as a high level of digitization, automation and environmental protection. However, it is very complex, has high investment and operating costs and includes technologies that are not yet sufficiently developed or legally regulated and this can generate negative social and political implications. On the other hand, Sc.1 implies the development of a system that is already in use and will be overcome very quickly due to the rapid development of the Industry 4.0 framework and the impact it has on the social, economic and environmental conditions in the world. Accordingly, Sc.3 and Sc.2 represent the most acceptable scenarios for the development of RL because they represent moderate solutions that achieve the most favorable balance between costs and benefits on the one hand and a compromise between the goals of different stakeholders on the other.

The contribution of this study to the body of literature investigating RL and Industry 4.0 is that it is the first to consider defining different scenarios of RL development, taking into account different technologies of Industry 4.0 and the degree of their application. Accordingly, the theoretical implications of the study are the development of a framework to define and evaluate scenarios for future development of smart RL systems, while the practical implications are defining the course for decision making in planning, development and implementation of Industry 4.0 technologies in RL.

The previous section of the study demonstrated the applicability of the newly established MCDM model. The multidimensional nature of the defined development scenarios required the employment of multiple stakeholders in the process of decision-making, while their various and often conflicting goals imposed the definition of the vast number of clustered and mutually interdependent criteria. Hence the use of the ANP method upgraded with the Delphi method, to obtain the criteria weights, and the COBRA method to obtain the final ranking of the alternatives was justified. The methods are combined in the fuzzy environment in order to adequately capture the ambiguous nature of the stakeholder representatives' thoughts. The main limitation of the proposed model is its complexity. The ANP method requires the pairwise comparisons of all interrelated criteria, within and between the clusters, which is very resource consuming, especially for the larger number of criteria. The COBRA method also has a high degree of complexity since it requires the calculations of multiple distances from multiple reference solutions. However, this study proposes the fuzzy extension of the COBRA method, as well as the combination of the three methods in the fuzzy environment for the first time, thus significantly contributing to the MCDM body of literature. This is also the main theoretical implication of this study. The main practical implication is the establishment of a decision support framework which can help the practitioners, policy creators and decision makers at various levels of government solve other MCDM or similar problems.

A limitation of this work could be the number of defined development scenarios. The fact is that no one can predict with certainty how smart RL will develop in the future. There could be countless scenarios. However, this study defines four basic, most likely scenarios in accordance with the current level of development and application of Industry 4.0 technologies in this area. Another limitation may be the number of stakeholder representatives who performed the evaluations. A larger number of participants usually implies a better quality of inputs. However, the number included in this research was sufficient to justify the validity of the obtained results. The limitation of the MCDM model used is reflected in its complexity and robustness, which implies significant resources (time, human, financial, etc.). However, these limitations are compensated by the soundness and reliability of the obtained results.

6. Conclusion

The main goal of this study was to identify the scenario of smart RL development that will serve as a roadmap for decision-making at the strategic and tactical levels and the development of an RL system that can be accepted by all key stakeholders, thus ensuring its widest possible application and all the positive effects it will generate. Keeping this in mind, four development scenarios were developed in this study. They were evaluated in regard to the 25 criteria which took into account the aims and interests of the main stakeholders. To solve the defined problem a hybrid MCDM method, which combines the Delphi, ANP and COBRA methods in the fuzzy environment, was proposed. As the result, the scenario which implies the application of majority of the Industry 4.0 technologies-namely IoT, AGV, AV, AI, BD & DM, BC, CC and E/M marketplaces-in performing various processes and activities in all segments of the RL system was selected. This scenario was selected in spite the fact that there was a scenario which implied even more Industry 4.0 technologies and more applications of the technologies covered by the selected scenario. This leads to the conclusion that the widest possible application of Industry 4.0 technologies does not necessarily guarantee the most acceptable development scenario, and that the decision should be made as an understanding between the opposing stands of the involved stakeholders.

The main contributions of this study to the body of literature dealing with reverse logistics and Industry 4.0 is the establishment of the comprehensive smart RL development scenarios, as well as the framework for their evaluation and ranking. This study also contributes to the body of literature dealing with MCDM through the extension of the COBRA method in the fuzzy environment, as well as through the development of the novel hybrid MCDM model.

Future research could include an upgrade of the defined scenarios or the development of new scenarios, which could include some technologies which might emerge in the near future or some new applications of already existing technologies. The MCDM model could also be upgraded considering the different significance of the main stakeholders, which have been considered as equally important in this research. The newly defined MCDM model could, after minor adjustments, also be used in some future research to solve various problems in this or any other area.

In addition, the newly established fuzzy extension of the COBRA method could also be used, either solely or in a combination with other methods, to solve various MCDM problems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cesys.2022.100099.

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