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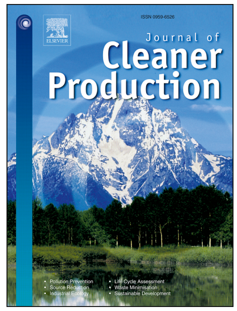

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Understanding approaches to complexity and uncertainty in closed-loop supply chain management: Past findings and future directions

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11,766 words

Abstract

This article aims to uncover knowledge gaps regarding approaches to dynamic complexity and deep uncertainty in a transition towards closed-loop supply chain (CLSC) management, and it articulates future research challenges addressing the identified gaps. Based on an abductive approach, two concepts are investigated: 'deep uncertainty' from the perspective of the decision-support literature and 'dynamic complexity' from the perspective of the complex adaptive systems literature and the transition management literature. The result is a systematic literature review of 64 CLSC management articles published in English. Conceptual gaps, process gaps and methodological gaps were found in relation to CLSC management under deep uncertainty and dynamic complexity. The analysis results in concrete research challenges for the CLSC management and sustainable supply chain management domains. The added value of this article is that the concepts of deep uncertainty and dynamic complexity for CLSC management are explored systematically for the first time. These two concepts appear to be crucial for the analysis of transitions to CLSC management.

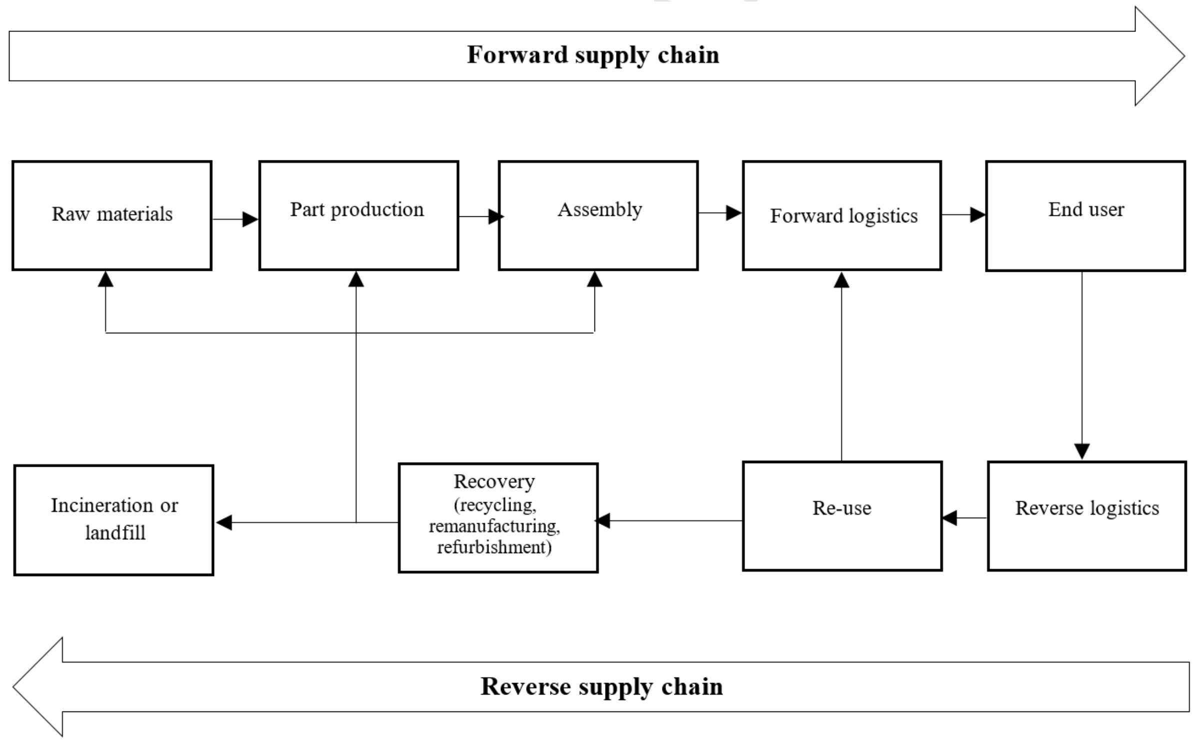
Keywords closed-loop supply chain management; dynamic complexity; deep uncertainty; systematic literature review

Paper type Literature review

1. Introduction

In the recent past, researchers', actors' and stakeholders' interests in transitioning towards closed-loop supply chain (CLSC) management have increased (De Brito et al., 2005, Fortes, 2009, Govindan et al., 2017, Guide et al., 2003, Narayana et al., 2014, Stindt et al., 2016), confirming the added value of such a transition in multiple economic, ecological and societal dimensions. A CLSC integrates a forward supply chain with a reverse supply chain, which is especially urgent for recoverable products that can be reprocessed and can re-enter a forward supply chain, with the aim of multiple value creation (Álvarez-Gil et al., 2007, Stindt et al., 2016). In Figure 1, this approach is visualized.

Figure 1 General framework of a closed-loop supply chain. Adapted from Sahyouni et al. (2007).



Such an integration requires a range of decisions made by relevant actors on issues such as when, where, and which (combinations of) business activities must be further developed, implemented and monitored to close the loop. According to Thissen et al. (2013), actors are individuals who represent a single organization or groups of individuals capable of making decisions and acting in a more or less coordinated way to directly influence the system, e.g., in the apparel industry: clothing production companies and cotton producers. In the CLSC management literature, various decision domains have been identified that support multidimensional value creation in (parts of) a CLSC, notably product design, the product-as-a-service concept, operations management, production and recovery procedures, marketing, integrated supply chain partnerships, and information technology (see Table 1) (Schenkel et al., 2015).

Table 1 Domains relevant for closed-loop supply chain management. Based on Schenkel et al. (2015).

CLSC decision domains	**Related CLSC business functions**	**Possible (uncertain) CLSC business decisions and options/activities.**
Product design	Research and development	Modularity of the design (number of components, type of connections); degree of customization; types of materials, amounts of materials; combinations of materials; quality of materials; eco-friendliness of materials
Product-as-a-service concept	Marketing	Number and type of service activities (take back, maintenance, advice on efficient use); types of result-oriented agreement (pay per service unit, pay for result)
	Finance and legal	Type of contractual agreement (leasing, renting, sharing, pooling)
Operations management	Procurement	Nature (centralized vs. decentralized) and number of facilities to purchase goods and retrieve end-of-use or end-of-life goods (multi-echelon issues); management of material requirements (quality, quantity, timing)
	Logistics	Type of forward and reverse supply chain transportation (plain, boat, truck, train); type and nature of storage and transhipment of (re)produced and returned goods (multi-echelon issues)
Production and recovery procedures	Quality management	Nature of testing and grading of end-of-use or end-of-life goods and produced or recovered goods (e.g., location, labour intensity)
	(Combination) of production and recovery	Recovery of returned goods in terms of recycling, re-use, remanufacturing, refurbishment, repair; production techniques for combined (environmentally friendly) raw materials
Marketing	Marketing and sales	Nature of marketing of recovered and raw materials, components and/or goods (market segment, price, place)
Integrated supply chain partnership	Strategy	Nature of supply chain partnership, e.g., joint ventures, mergers, acquisitions, vertical integration, horizontal integration, diagonal integration, alliances
Information technology	Information management	Type of information technology for signalling and diagnosing changes in the product and process architecture (e.g., radio frequency identification)

Recent studies have argued that transitioning towards a CLSC is hindered by the effects of dynamic complexity and deep uncertainty (Linder et al., 2017, Velte et al., 2016). Several literature reviews of closed-loop/sustainable supply chain management have suggested a need to more systematically study uncertainty and complexity and to better understand the effects of these concepts on closed-loop/sustainable supply chain management (Akçalı et al., 2009, Alexander et al., 2014, Govindan et al., 2015). For a better understanding of the effects of uncertainty and complexity in relation to CLSC management, it is important to understand the different sources of complexity and the sources and types of uncertainty and the way they are dealt with. However, several recent reviews have suggested that so far very little explicit attention has been paid to the various sources of complexity and the sources and types of uncertainty (Govindan et al., 2015), specifically regarding ‘deep uncertainty’ and the concept of ‘dynamic complexity’.

According to the complex adaptive systems and transition management literatures, *dynamic complexity* results from the existence of multidimensional nonlinear interactions between the business activities inside a system (e.g., a CLSC) and between the business activities of a system and its environment. The adjective 'multidimensional' refers to variance in the following dimensions: time horizons (short to long term); geographical scales (local to global); and organizational levels (individual actor to multi-tier system). Multidimensional nonlinear interactions cause the emergence of dynamic or even chaotic or random patterns in a system’s autonomous adaptive economic, ecological and societal behaviours (hereinafter ‘emergent patterns’). For instance, an increase in re-use and recycling in European countries can over time, lead to a decrease in employment in remote cotton producing countries, such as India (Van der Heijden et al., 2017). Furthermore, multidimensional nonlinear relationships between business activities also influence the process of anticipative and adaptive steering towards structural system change (Grin et al., 2010). In this study, anticipative steering refers to the continuous development and adjustment of possible CLSC options for future implementation in the supply chain system. Hence, anticipative steering is focused on maintaining a range of options to foster resilience in the face of an inherently uncertain future (Grin et al., 2010). In the context of a CLSC, the word 'option' may refer to new CLSC activities derived from the various decision domains such as design-for-remanufacturing, leasing or environmentally friendly material use, as well as to adjustments to existing CLSC activities. Adjustments might involve, for example, hedging or seizing activities with respect to existing CLSC business activities. Hedging activities, such as installing a safety stock to manage uncertain supply and demand of recovered materials, spread or reduce the risk of uncertain adverse effects of a business activity. Seizing activities are undertaken to seize available opportunities, such as an increase in recovery capacity because of legislation that stimulates recycling (Kwakkel et al., 2010). Adaptive steering refers to actors selecting their preferred (CLSC) options in the form of transition pathways (Grin et al., 2010). These CLSC options are implemented and adjusted, based on an evaluation of ecological, economic and societal effects on different time horizons, geographical scales and/or organizational levels.

In the decision-support literature, *deep uncertainty* is defined as the condition wherein actors do not know or, regarding a decision, cannot agree upon the future of a system (e.g., a CLSC system in clothing), the criteria for the system's success over time (Hallegatte et al., 2012), or geographical scales and/or organizational levels. In other words, deep uncertainty cannot be reduced, yet can only be dealt with (Walker et al., 2010). Alternatively, one might argue that CLSC uncertainty could possibly partly be reduced by providing actors with information via IT solutions such as radiofrequency identification (RFID). By providing a product with an RFID tag, information can be obtained about the status, quantity, timing and location of product returns. Based on the information obtained, decisions can be made that indeed contribute to a decrease in reverse logistics costs (Jayaraman et al., 2008). However, more information retrieved from IT solutions is no guarantee for eliminating deep uncertainty due to, for example, persistent disagreement among CLSC actors regarding the information obtained about the quantity, timing and quality of product returns, as well as the CLSC options based on this information. Moreover, one might also argue that closing the loop generates uncertainties that are not very easy to overcome with IT solutions and big data. For instance, CLSC actors might be able to enumerate multiple possibilities to create employment and minimize CO_2 emissions via product recovery, such as direct re-use, recycling or re-manufacturing, without being able or willing to rank order these possibilities in terms of their effectiveness over time, geographical scales or organizational levels.

In this article, a systematic literature review is conducted to explore the available approaches for understanding (dynamic) complexity and (deep) uncertainty in relation to CLSC management. The aims of this study are twofold. The first aim is to identify the specific gaps in this knowledge by exploring the answers in the literature to the following question: What are the knowledge gaps with respect to the approaches to dynamic complexity and deep uncertainty in a transition towards CLSC management? The second aim is to indicate possibilities to close the identified knowledge gaps by formulating future research challenges. Because complexity and uncertainty in CLSC management are addressed in many disciplines, this article explores the cross-disciplinary literature on closed-loop supply chain management, green supply chain management, sustainable supply chain management, and reverse supply chain management. Important to mention is the focus on studies in which the forward and reverse supply chains are explicitly integrated via one or multiple CLSC decision domains. The managerial contribution of this study lies in providing practitioners with an in-depth understanding of the different sources and types of uncertainty and the sources of complexity that hamper CLSC management, especially regarding deep uncertainty and dynamic complexity. A thorough understanding of (how to address) uncertainty and complexity is assumed to improve decision making by CLSC actors when transitioning towards a CLSC. Being better informed might influence decisions regarding, e.g., goal setting, the focus and means of a robust change strategy, and/or the partners with whom to collaborate in the transition process.

This article is structured as follows. Section 2 presents a dynamic complexity and deep uncertainty typology, with the aim of defining the criteria used to assess the selected papers. This section also elaborates on some earlier review papers related to CLSC management and (dynamic) complexity and (deep) uncertainty. Section 3 then explains the methodology applied in the systematic literature review. Descriptive and methodological research results are described in Sections 4 and 5, respectively. The results of the analysis of current gaps and research challenges to close these gaps are presented and discussed in Section 6. Section 7 presents the conclusions and limitations of this study.

2. Theoretical framework

Recent studies have argued in favour of the relevance of studying the effects of the concepts of 'dynamic complexity' and 'deep uncertainty' in relation to CLSC management. Therefore, an in-depth definition of these concepts should be provided. Before elaborating on these concepts, it is important to mention that deep uncertainty and dynamic complexity are not purely CLSC-related challenges; traditional supply chains also address them. However, the structure and parameters of a CLSC might be – at least in the beginning – unknown by the actors involved. There might also not be any historical or present information or knowledge about a specific CLSC structure and its parameters. Furthermore, because forward and reverse supply chain activities are systematically linked, the number of multidimensional nonlinear interactions might increase, e.g., because of cross-sectoral challenges, causing a CLSC to be more dynamically complex than a traditional forward supply chain or a reverse supply chain.

Finally, it might be the case that there are more actors with different and sometimes conflicting goals and interests in a CLSC than in a traditional supply chain, which makes decision making on how to 'close the loop' challenging. Based on the operational definitions of 'dynamic complexity' and 'deep uncertainty', criteria are selected, based upon which the literature review was performed.

2.1 Dynamic complexity in CLSCs and CLSC management

The components 'nonlinearity', 'anticipative steering' and 'adaptive steering' have been briefly mentioned in the introduction because they are key to understanding complex systems on the one hand, and to managing dynamic complexity in a transition process towards CLSC management on the other hand.

Nonlinearity in a supply chain refers to the fact that changes in the input of a chain may not be proportionally related to changes in its output (Surana et al., 2005). For instance, a reduction in resource availability might have little or no direct effect on the economic or ecological performance of certain business activities in a supply chain. However, it could have significant effects in the long run within a particular geographical scale of a supply chain, increasing the need to become less dependent upon these resources e.g. by transitioning towards a CLSC. To understand multidimensional nonlinearity in a CLSC, it is therefore important to study the CLSC's 'feedback mechanisms'. These mechanisms are either negative feedback (balancing) or positive feedback (reinforcing) loops. A negative feedback loop exhibits goal-seeking behaviour. Hence, after a change in the input, business activities tend to return to a state of equilibrium. In a positive feedback loop, an initial change in the input leads to further change, suggesting the presence of disequilibrium (Vlachos et al., 2007), possibly causing a relatively short period of chaos, bifurcation and instability. For instance, the introduction of a CO_2-tax might in the short term lead to higher energy and product prices, yet in the medium term it might stimulate transitions to more sustainable production and circular chains. The understanding of multidimensional nonlinear interactions is also important to fully grasp complex system behaviour in terms of emergent patterns. Identifying these patterns is important because they are often linked to weak signals indicating change, as well as surprises and counter-intuitive information (Grin et al., 2010). By understanding multidimensional nonlinear interactions and detecting emergent patterns, decision making about goal setting and CLSC options could change entirely. Feedback mechanisms in a CLSC can be introduced or strengthened by adjusting the parameters and variables of existing CLSC options. The aim of these feedback systems is to reduce the gap between actual performance and desired performance/goals of (parts of) the CLSC. Feedback mechanisms can also be used as a basis for redesigning a supply chain model, e.g., by adding new CLSC options. The underlying rationale is that better insight into the nonlinear dynamics of a complex supply chain leads to a better understanding of possibilities to influence a system's transformation into a CLSC.

In the process of *anticipative steering*, actors continuously develop and adjust potential CLSC options under deep uncertainty and dynamic complexity for future implementation. The aim of anticipative steering is to increase the responsiveness of a system to future changes (Grin et al., 2010). The development and adjustment of potential CLSC options are based on actors' changing perceptions of a CLSC, goals/objectives, ideas about CLSC options, and their potential impacts on and means for operation in the CLSC under study. *Adaptive steering* refers to the selection, implementation and evaluation of transition pathways (Grin et al., 2010, Haasnoot et al., 2013). A single pathway consists of a sequence of (CLSC) options, which the involved actors prefer to implement over time (Haasnoot et al., 2013), as well as geographical scales and organizational levels. A transition pathway also consists of adaptation tipping points, which indicate when certain (CLSC) options along this pathway are no longer economically, ecologically, and/or societally beneficial (Haasnoot et al., 2013). Adaptation tipping points consist of signposts and trigger values. Signposts refer to the "variables [related to a CLSC option] that need to be tracked", while triggers are the "values of those variables that would trigger an anticipated response" (Hermans et al., 2014, p. 375). Decisions regarding transition pathways are based on the actors’ insights resulting from underlying analyses of the multidimensional nonlinear dynamics of the specific supply chain and the sets of potential (future) CLSC options per decision domain.

The rationales underlying the concepts of ‘adaptive steering’ and ‘anticipative steering’ are: (i) the more easily actors can gain insight into the possibilities to influence a supply chain towards a CLSC under dynamic complexity, the more capable they are to formulate multidimensional goals and select a suitable set of adaptive transition pathways to steer towards a CLSC; and (ii) the more capable actors are to apply anticipated and adaptive steering in response to changes, the more mature CLSC management becomes.

2.2 Deep uncertainty in CLSCs

Above has been described what the main characteristics of decision making in business management could be in the context of a transition towards CLSC management under dynamic complexity. However, to implement these characteristics in practice is a serious challenge. A CLSC often consists of many different stakeholders and actors (Guide et al., 2009) with different, and sometimes persistently conflicting, goals and interests regarding CLSC business activities and CLSC performance. The actors might also not, or not be able to, know or agree how certain environmental challenges and CLSC options affect parts of their supply chains over time, as well as geographical scales and organizational levels. This concept is also referred to as deep uncertainty. Hence, deep uncertainty is a situation in which CLSC actors and analysts are able to enumerate a variety of possibilities, without being able or willing to rank these possibilities in terms of their perceived likelihood. Based on Walker et al. (2003, pp. 5-7), the following *sources of deep uncertainty* can be identified.

- The context: Context refers to the (CLSC) actors' ignorance and/or persistent disagreement about grand economic, ecological, political, societal, and technological challenges inside and outside a system and how, when and where these grand challenges affect the (nonlinear) dynamics of (parts of) the system.
- The structure and system behaviour: (CLSC) actors' ignorance and/or persistent disagreement regarding the structure and behaviour of the system's (qualitative and quantitative) causal models. Uncertainty about the system's behaviour involves the emergent patterns of the system and (multidimensional nonlinear) interactions between (CLSC) activities. Uncertainty about the structure of a system implies that alternative (qualitative and quantitative) model specifications might each offer plausible representations of the system.
- The parameters: Parametric uncertainty is associated with (CLSC) actors' ignorance and/or persistent disagreement regarding the specification of (future) system model parameters and the methods used to calibrate the parameters of the current system model and the future system model. Parameters are constants in the model, supposedly invariant within the chosen context and development scenarios. However, when these parameters are essentially unknown from previous investigations or actors' experiences, or they cannot be transferred from previous investigations or experiences to a new context due to the lack of similarity of circumstances, they must be calibrated on data collected for the specific case.
- Uncertainty about the system model outcome: This uncertainty refers to the (CLSC) actors' ignorance and/or persistent disagreement regarding the accumulated uncertainty associated with: (i) the current system model outcomes; and (ii) desirable future system

models' outcomes. This source of deep uncertainty is also referred to as the "prediction error", i.e., the discrepancy between the "real-world" value of an outcome and the model's predicted value.

- Finally, the uncertainty related to the (CLSC) actors' ignorance and/or persistent disagreement regarding the relative importance of a system model's outcomes.

One might argue that the definition and sources of deep uncertainty are mainly derived from quantitative modelling and analysis. However, since deep uncertainty also implies actors' persistent disagreement, one might also argue that qualitative methods are at least equally important for grasping and analysing deep uncertainty, particularly those methods that explicitly focus on the different perceptions, interests and weights related to various CLSC options and outcomes.

3. Research methodology

To support the review process, the research question formulated in Section 1 is subdivided into the following three review sub-questions.

- Which sources and types of uncertainty have been studied in relation to CLSC management?
- Which sources of (dynamic) complexity have been studied in relation to CLSC management?
- Which approaches and methods have been applied to support CLSC management under (dynamic) complexity and (deep) uncertainty?

To locate studies relevant to the research questions, an extensive set of keywords (i.e., search strings; see Table 2) was used to search the following databases (Tranfield et al., 2003) (i.e., meta-analysis): Web of Science, Business Source Complete, Science Direct, IEEE, Wiley Online Library, and Emerald Group. These databases were selected for their vast coverage of articles in the field of CLSC management under (deep) uncertainty and/or (dynamic) complexity. To collect the broadest array of relevant studies, various keywords directly related to the main research question were included. These keywords include terms related to 'closed-loop supply chain management', 'green supply chain management', 'sustainable supply chain management', and 'reverse supply chain management'. Furthermore, CLSC (management) papers were selected with an explicit focus on uncertainty and/or complexity. Hence, the search and selection phases were not limited to deep uncertainty and dynamic complexity. The meta-analysis yielded 763,222 hits. Then, the search was narrowed down by focusing only on papers in English and by searching for the keywords as topics of the papers. As a result, 320 papers were selected. These 320 papers were further studied based on titles and abstracts, with the aim of selecting CLSC-focused papers explicitly addressing (deep) uncertainty and or (dynamic) complexity. The resulting (128) papers were collected in a database. Finally, the selected articles were evaluated for duplications and an explicit focus on the integration of the reverse supply chain with the forward supply chain. As a result, 27 duplications were detected, and 37 papers appeared to focus merely on the forward supply chain without considering the reverse supply chain. The selection ultimately resulted in 64 papers, constituting a basis for the more in-depth analyses in Sections 4 and 5.

Table 2 Search strings and resulting numbers of hits

	Search strings/keywords	**Total number of search strings performed**	**No. of hits**
Direct	(deep) uncertainty AND closed loop supply chain development (operation/implementation) (monitoring) (management).	8	49,398
	(dynamic) complexity AND closed loop supply chain development (operation/implementation) (monitoring) (management)	8	108,805
Indirect	(deep) uncertainty AND sustainable supply chain development (operation/implementation) (monitoring) (management); (deep) uncertainty AND green supply chain development (operation/implementation) (monitoring) (management); (deep) uncertainty AND reverse supply chain development	24	218,149

	(operation/implementation) (monitoring) (management).		
	(dynamic) complexity AND sustainable supply chain development (operation/implementation) (monitoring) (management); (dynamic) complexity AND green supply chain development (operation/implementation) (monitoring) (management); (dynamic) complexity AND reverse supply chain development (operation/implementation) (monitoring) (management).	24	386,870
Total		**64**	**763,222**

4. Descriptive findings

In the descriptive analysis, papers were further categorized/coded and studied for the following criteria: (i) year; (ii) type of industry; (iii) product categories, i.e., single product/component/material vs. multiple product/component/material; (iv) CLSC management activities, i.e., CLSC development, CLSC operation and/or CLSC monitoring; (v) types of CLSC decision domain; (vi) sources and types of uncertainty; and, (vii) sources of (dynamic) complexity included.

4.1 Year of publication

Approximately 86 percent of the 64 selected papers were published between 2012 and 2017, 59 percent of which focused on CLSC management. The remaining 41 percent focused on reverse supply chain management, green supply chain management or sustainable supply chain management. These numbers suggest that the research in the field of CLSC management under (dynamic) complexity and/or (deep) uncertainty represents a relatively new and increasingly popular research domain.

4.2 Type of industry

The papers focused on many different industries, such as electronics (Lehr et al., 2013), energy (Stindt et al., 2016), apparel (Martí et al., 2015), automotive (Jindal et al., 2015), carpets (Biehl et al., 2007), and photocopiers (Talaei et al., 2016). Hence, one could argue that

CLSC management under (dynamic) complexity and (deep) uncertainty is a relevant (research) phenomenon for a broad range of industries.

4.3 Product categories

Approximately 40 percent of the examined papers studied CLSC management, either from a single-product perspective or from a single-material perspective. The other 60 percent focused either on multiple materials, multiple components, or multiple products or on a single product and related component(s) and/or material(s) simultaneously. The number of product categories involved in research is an indicator of the complexity of the structure and nonlinear dynamics of a CLSC model and thus of the extent to which the particular study intends to represent complex real-world situations.

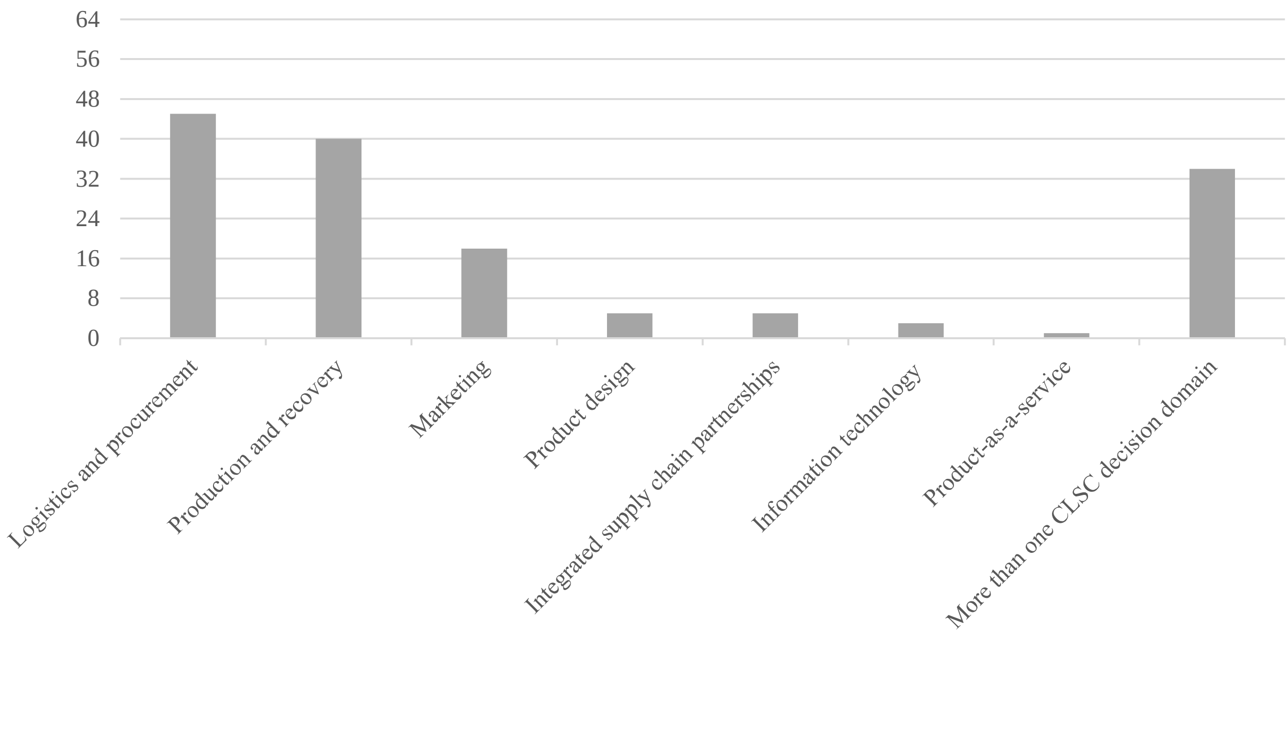
4.4 CLSC management activities

Approximately 84 percent of the 64 selected papers focused on the management activity 'CLSC development', particularly the modelling and planning of (a combination of) CLSC options. Only four paper (six percent) concentrated on the monitoring of (a combination of) (implemented) CLSC options. The remaining 10 percent concentrated on the simultaneous development, operation and/or monitoring of (a combination of) CLSC options (Golroudbary et al., 2015, Nazam et al., 2015). These findings suggest that research into the actual operation and monitoring of CLSC options under (dynamic) complexity and/or (deep) uncertainty has so far received limited attention in the literature.

4.5 Types of CLSC decision domains

The majority of the papers focused on 'logistics and procurement' (45 papers), such as location allocation, capacity, inventory, routing in a CLSC system, and 'production and recovery' (40 papers), including recovery options and sorting activities (see Figure 2). The CLSC decision domains areas were primarily addressed as a design/planning problem. Few studies focused on the domains of 'product design', 'product as a service', 'integrated supply chain partnership', and 'information technology'. Furthermore, 34 papers discussed multiple domains simultaneously (e.g., Chen et al., 2015, Dai et al., 2015, Lehr et al., 2013). For instance, Chen et al. (2015) focused on developing and optimizing (i) the number and location of distribution centres and return centres; (ii) the manufacturing and remanufacturing quantities of goods; and (iii) the flow of new and recovered goods through the CLSC. The aim was to determine the best economic solution for an individual stakeholder (OEM) to be involved in a CLSC under stochastic uncertainty.

Figure 2 CLSC decision domains to which the papers are directed



4.6 Sources and types of uncertainty

The analysis revealed that the papers showed serious attention to different sources of uncertainty, such as 'parameter uncertainty' (49 papers), 'context uncertainty' (eight papers), 'CLSC model structure uncertainty' (four papers), and 'CLSC model outcome uncertainty' (18 papers).

Parameter uncertainty. The majority of the papers focused on: (i) uncertain quality, quantity and timing of end-of-life or end-of-use goods; (ii) uncertain demand of (recovered) goods; or (iii) uncertain system costs in the design and planning of a CLSC. Parameter uncertainty was primarily addressed as stochastic (e.g., Chen et al., 2015, Martí et al., 2015) or fuzzy (Nazam et al., 2015, Zhalechian et al., 2016). 'Fuzzy' refers to the vagueness and impreciseness of qualitative and quantitative knowledge or data (Reznik et al., 2013).

Context uncertainty. The examined papers concentrated on various developments inside and outside a CLSC, affecting CLSC management. It involved developments such as customer/market demand and customer/market behaviour (Chen et al., 2015, Huang et al., 2009, Ruimin et al., 2016), legislation (Lehr et al., 2013, Vlachos et al., 2007), and changing weather conditions (Besiou et al., 2016, Shamsuddoha, 2015). Context uncertainty is treated stochastically (e.g., Chen et al., 2015, Ruimin et al., 2016).

CLSC model structure uncertainty. The focus of the examined papers was on uncertainty regarding the specification and operation of the "best fitting'" CLSC structure (i.e., the combination of CLSC options) and was addressed as either fuzzy (Rostamzadeh et al., 2015) or stochastic (Dhib et al., 2013).

CLSC outcome uncertainty. Three sub-sources of uncertainty in relation to CLSC outcomes were identified. The first source involves uncertainty regarding the effects of adding or connecting the multiple CLSC options of a single or multiple decision areas to the CLSC model outcome. Thus, the focus is on (nonlinear) trade-offs between CLSC options, for instance, the design of a hybrid manufacturing-remanufacturing system to maximize the overall profit of this system under uncertain demand for remanufactured products and return of products for remanufacturing (Shi et al., 2010). The second sub-source concerns the effects of multiple, sometimes conflicting objectives regarding the appraisal of CLSC model outcomes, hence a focus on trade-offs between objectives. Finally, the third sub-source regards the ranking and classification of multiple criteria based on the CLSC outcomes to be assessed. System outcome uncertainty is generally treated in a stochastic manner (He, 2017, Martí et al., 2015, Shi et al., 2010) or a fuzzy way (Lee et al., 2015, Zhalechian et al., 2016).

On the basis of this analysis, it can be stated that the various sources of uncertainty are primarily addressed as stochastic (33 papers) or as fuzzy (16 papers) problems. In 17 papers, the notion of uncertainty was mentioned but not further specified. Furthermore, both context uncertainty and CLSC model structure uncertainty received limited attention, compared to parameter uncertainty and CLSC model outcome uncertainty.

4.7 Sources of (dynamic) complexity

Various papers addressed CLSC management under (dynamic) complexity by considering: (i) the multidimensionality of the system dynamics and/or management task (57 papers); (ii) the nonlinearity of the CLSC to be managed (19 papers); and/or (iii) a form of anticipative and/or adaptive steering (32 papers).

Multidimensionality. A large majority of the studies simultaneously included multiple temporal, geographical, organizational dimensions, and/or multiple objectives (economic, ecological and societal) in a CLSC model. Nevertheless, 48 percent of the 57 papers did not consider multiple levels within a single dimension, for instance, by studying the nonlinear interactions between CLSC activities at both local and global levels. Additionally, very limited attention was paid to the effects of nonlinear interactions between CLSC activities across multiple dimensions. An example would be studying the plausible economic, societal and ecological effects of the recycling of clothing on the short- and long-term production of new clothing for the local and national markets. Zooming in on individual dimensions, the majority of the papers that included the temporal dimension did not explicitly specify the time horizon in which a (complex) CLSC model under uncertainty is designed and tested. Additionally, CLSCs are primarily modelled with discrete time steps. Very limited attention was paid to the concept of continuous time or used both the continuous and discrete concepts of time. In contrast, Zeigler et al. (2000) argued that addressing the time horizon explicitly and making both concepts of time clear to the actors might support the understanding of both the system dynamics and the specific system (CLSC) to be managed. The geographical dimension is primarily used one-dimensionally (13 papers out of a total of 20 papers addressing this dimension), indicating that only a specific geographical scale is focused on without considering the interactions between different geographical scales, for instance, local recycling activities on the regional scale and the economic, ecological and societal effects on the national or sub-global scale. Regarding the organizational dimension, the great majority of the papers addressing this dimension (34 papers) designed and tested a CLSC model from an individual organization's point of view. Cardoso et al. (2015) combined the geographical dimension and the organizational dimension and referred to it as the 'density ratio'. They defined density ratio as the overall connectedness of a CLSC, estimated as the ratio between the actual number of measured interactions between organizations in terms of stocks and flows and the potential number of interactions in a certain geographical area. They showed that a CLSC in which the interactions between organizations are more geographically concentrated might be more vulnerable to specific disruptions. With regard to multi-objective approaches, the majority of studies focusing on the design of a multi-objective CLSC model or the development of (robust) multi-objective strategies for complex CLSCs focused on economic and ecological objectives (e.g., Ameknassi et al., 2016, Martí et al., 2015, Nurjanni et al., 2017). In general, the inclusion of societal objectives was rather scarce.

Nonlinearity. Various studies focused on the use of nonlinear programming techniques to find a feasible solution for a given set of objectives, such as to minimize total transportation and inventory costs or to minimize CO_2 emissions, together with computational proof of its optimality (e.g., Lieckens et al., 2007, Wang et al., 2017, Zhalechian et al., 2016). Other papers concentrated on the modelling and simulation of nonlinear interactions in a current and/or future CLSC system in terms of positive and negative feedback loops and/or including system structure elements, such as 'stocks and flows' (e.g., Bhattacharjee et al., 2015, Bollinger et al., 2012, Golroudbary et al., 2015). Specific attention to the chaos and bifurcation phenomena as the results of negative feedback loops was limited. Additionally, very limited attention was paid to the exploration of emergent patterns to fully grasp complex system behaviours. A valuable example of an attempt to better grasp dynamics was described by Narayana et al. (2014). These authors explored various patterns indicating trends in the sales, prices, brands, and quality and quantity of product returns in a complex causal reverse logistics system model of the Indian pharmaceutical industry over a period of five years. As a result, actors' insights into the strong linkages between time dynamics and the complex reverse logistics system design improved.

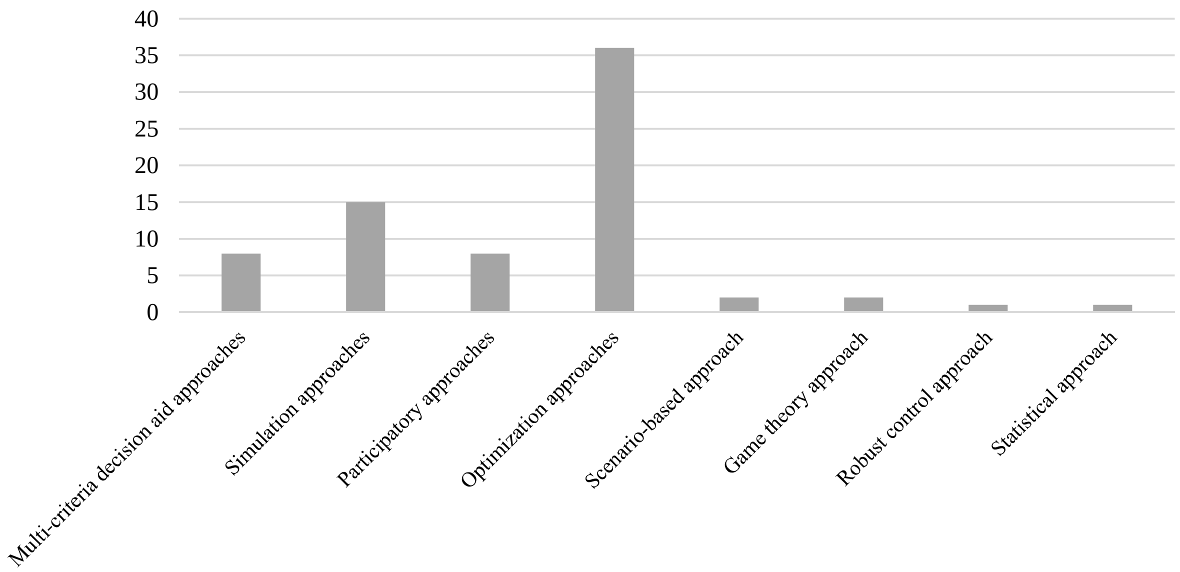
Anticipative steering and adaptive steering. Multiple papers focused on developing potential future-oriented CLSC options. This focus involved, among others, options to improve the recovery of goods, the introduction of optional collection centres, and optional collection routes (e.g., Ameknassi et al., 2016, Chen et al., 2015, Zhalechian et al., 2016). Other papers concentrated on selecting and combining robust or optimal CLSC options (e.g., Nurjanni et al., 2017, Serrano et al., 2013, Xu et al., 2017). Very limited attention was paid to the specification of adaptation tipping points for collaborative monitoring of the attractiveness and sustainability of the selected and implemented CLSC options.

From this part of the literature review it can be concluded that, in CLSC management theory, dynamic complexity is primarily addressed in terms of (multi-objective) linear or nonlinear programming or system dynamics over time. The inclusion of the geographical and organizational dimensions for the analysis of the nonlinear interactions between CLSC activities has so far received very limited attention. As a result, studies into emergent patterns have been scarce as well. Last, although various studies focused on some form of anticipative steering or adaptive steering for CLSC management, very limited attention was paid to the alignment between anticipative and adaptive steering, for instance via adaptation tipping points.

5. Analysis of methodological approaches

In the analysis of the methodological approaches, types of approaches, and instruments used for decision making regarding the design, operation/implementation and monitoring of CLSCs were considered. From the analysis it became clear that multiple approaches are applied to study CLSC management under (deep) uncertainty and/or (dynamic) complexity (see Figure 3), notably: (i) multi-criteria decision aid approaches (six papers); (ii) qualitative and quantitative simulation approaches (15 papers); (iii) participatory approaches (eight papers); and (iv) optimization approaches (36 papers).

Figure 3 Methodological approaches of the papers included



The multi-criteria decision aid approach. This type of approach addresses the process of making decisions in the context of multiple (conflicting) objectives and/or vague and imprecise (i.e., fuzzy) knowledge or data regarding the criteria of, and the weight placed on, various (implemented) CLSC options and CLSC outcomes (e.g., Chithambaranathan et al., 2015, Rostamzadeh et al., 2015). Therefore, various methods or combinations of methods have been applied, such as 'fuzzy Analytical Hierarchy Process (AHP)', 'fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)', and 'fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)'. Fuzzy AHP is applied to obtain the relative weights of (evaluation) criteria related to CLSC options derived from closed-loop decision areas, such as 'procurement and logistics', 'production and recovery procedures' and 'product design' (Nazam et al., 2015, Sari, 2017). Both fuzzy VIKOR and fuzzy TOPSIS are used to rank and assess CLSC performance in a fuzzy environment. The ranking and assessment of performance are based on the relative weights of the criteria related to the CLSC options. For instance, fuzzy VIKOR is used to generate the rankings according to the performance of CLSC stakeholders, and subsequently identifies the best performing organizations under a fuzzy environment (e.g., Sari, 2017). Fuzzy TOPSIS is, among other purposes, used to rank and assess the uncertainties associated with the implementation of

CLSC options in a fuzzy environment (Nazam et al., 2015). In addition, Monte Carlo simulation is used to conduct an in-depth analysis of the uncertainties in terms of vagueness/imprecise data regarding the weights of evaluation criteria for multiple CLSC options. The integration of Monte Carlo simulations is not limited to fuzzy AHP and fuzzy VIKOR; it can also be integrated with fuzzy TOPSIS (Sari, 2017).

(Qualitative and quantitative) simulation approaches. A different approach to modelling (complex) CLSCs and to exploring system dynamics is the use of other types of simulations. The simulation approach aims to imitate the dynamic development of complex systems. By changing the model that simulates the CLSC, one aims to understand the system dynamics over time. Therefore, the majority of simulation-based studies applied System Dynamics (e.g., Cardoso et al., 2013, Lee et al., 2015, Wang et al., 2017). With this approach, first a causal loop diagram is developed, which is a *qualitative* representation of a CLSC, to understand the positive and negative feedback loops among the different state variables of a CLSC model (e.g., Georgiadis et al., 2013, Lehr et al., 2013, Vlachos et al., 2007). In addition, qualitative stock-flow diagramming is applied to develop and understand the CLSC's model structure (Georgiadis et al., 2006, Vlachos et al., 2007). Second, the stock-flow diagram is transformed into stock and rate (i.e., differential) equations, based on which "what-if" scenario-based system dynamics simulations are performed to explore nonlinear system behaviour under uncertainty over time (Bhattacharjee et al., 2015, Vlachos et al., 2007). For instance, it is suggested to explore how the involvement of CLSC options, such as design-for-refurbishment, marketing campaigns, and refurbishment, affect the sales and profitability for various supply chain actors (Bhattacharjee et al., 2015). Although the relationships among the system variables, including the feedback loops individually might be well understood, the interplay of several of these relations can show unexpected dynamics in a simulation over time, varying geographical scales and/or organizational levels. Third and last,

as in the case of optimization-based studies, multiple papers included sensitivity analysis to, among other goals, increase understanding of the relationships between (uncertain) input and output variables in a CLSC model by varying with the parameter values (e.g., Shamsuddoha, 2015, Vlachos et al., 2007).

Participatory approaches. A small number of papers describe the involvement of relevant actors for: (i) the development of a CLSC model or causal model (Narayana et al., 2014, Shamsuddoha, 2015); (ii) the selection and evaluation of optional CLSC options, such as reverse logistics options based on various criteria (e.g., Chithambaranathan et al., 2015, Jindal et al., 2015); (iii) the identification and convergence of understandings of CLSC options; and (iv) the identification of an agreement about the complex CLSC to be managed (Stindt et al., 2016). For the development of a CLSC model, participative group model building was used by Narayana et al. (2014). For the generation of selection criteria and evaluation criteria, discussions and in-depth interviews were conducted (Jindal et al., 2015, Rostamzadeh et al., 2015). For the identification and convergence of understandings of CLSC options among the actors involved, Stindt et al. (2016) organized brainstorm sessions and applied the Delphi methodology. Brainstorm sessions were used for the identification of CLSC options, while a Delphi approach was used to converge understandings of the CLSC options and to develop a mutual basis for communication. For the identification of an agreement regarding the complex CLSC to be managed, a morphological box was developed (Stindt et al., 2016). A morphological elaborates various indicators reflecting certain dimensions (e.g., geographical dimension) and different attributes levels (e.g., regional, national, international). The result of this analysis is the specification of different scenarios for system intervention. For the development of the morphological box, both discipline-specific literature regarding the CLSC issue and expert discussions were considered.

Optimization approaches. In general, optimization approaches aim to find the exact (sub)optimal solution among a set of alternatives without violating the given constraints (Taha, 1992). An example is the optimization of dynamic facility locations and capacity adjustments in a CLSC to minimize system costs from an individual organization's perspective over multiple periods and under uncertain product demand and supply (De Rosa et al., 2013). The general drawback to using optimization is the difficulty in developing a model that is sufficiently detailed and accurate to represent the (dynamic) complexity and (deep) uncertainty of a CLSC, while keeping the model sufficiently simple to explore options or even to be solved. Various types of optimization approaches were applied to improve the handling of this matter, such as stochastic (e.g., Kaya et al., 2014, Tao et al., 2012, Zhalechian et al., 2016), robust optimization (e.g., De Rosa et al., 2013, Ruimin et al., 2016, Xu et al., 2017), and (robust) fuzzy programming (e.g., Niknejad et al., 2014, Talaei et al., 2016, Wang et al., 2010). Stochastic programming is a useful modelling approach when an accurate probabilistic description of the random variables is assumed (Keyvanshokooh et al., 2016). However, in the case of CLSC, there is often no or too little historical data available to estimate distributions. Additionally, an accurate distribution approximation requires a large number of scenarios. However, the greater the number of scenarios that are needed to represent an uncertainty, the more difficult that it is to solve the problem to optimality. To minimize these drawbacks, robust optimization has been used as an alternative approach to manage uncertainty in the input data in a CLSC design problem. Compared to stochastic programming, less precise historical data and actors' experiences can be used to derive the boundaries of uncertainty sets, without the need for precise estimates of probability distributions (Keyvanshokooh et al., 2016). The same applies to (robust) fuzzy programming. However, compared to robust programming, fuzzy programming approaches explicitly acknowledge and consider vague and imprecise data and knowledge about uncertain CLSC parameters, both in the objective functions and in the constraints of a CLSC model (Dai et al., 2015, Talaei et al., 2016). The majority of optimization-based studies developed (a relatively small ensemble) of scenarios and a (multi-objective) mixed-integer linear or nonlinear programming model for a CLSC to achieve one or multiple objectives, and they performed sensitivity analysis to address the various sources of (stochastic or fuzzy) uncertainty over time. In general, mixed-integer (linear or nonlinear) programming involves optimization problems in which some of the decision variables are restricted to having integer/binary values, while other decision variables are allowed to have non-integer values (Taha, 1992). Nonlinear programming differs from the well-known linear programming approach in that at least one nonlinear function is included in the objective functions and/or constraints. For instance, Lieckens et al. (2007) introduced the variable of nonlinear product lead time to the objective function because of the (stochastic) uncertainty in the timing of product returns.

6. Discussion and future challenges

This section discusses the knowledge gaps derived from this systematic literature review and transfers these into various challenges for future research on deep uncertainty and dynamic complexity in CLSC management. Based on the classifications in Sections 4 and 5, the knowledge gaps are categorized into three classes to be discussed in the following three sub-sections: conceptual gaps, a process gap, and methods gaps.

6.1 Conceptual gaps

Conceptual gaps refer to the following five issues.

Opportunities for considering deep uncertainty. In the CLSC management literature, uncertainty is primarily addressed as stochastic or fuzzy. This finding is directly related to the level of underlying knowledge: In cases in which actors have sufficient knowledge about the probability distribution, they tend to treat uncertainty as a stochastic issue. However, when transitioning towards CLSC management, these actors are facing uncertainties for which they have insufficient knowledge about probability distributions and the possible outcomes. In such cases, uncertainty basically cannot be addressed stochastically. The application of fuzzy logic is then proposed in the literature as an alternative to represent uncertainty about parameters and the relative importance of CLSC options and the CLSC model outcome. This finding corresponds with the findings of the literature review by Govindan et al. (2015), who stated that, instead of stochastic methods to represent uncertainty, in recent years, fuzzy logic has been regularly used to represent uncertainty. One might argue that fuzzy uncertainty relates to deep uncertainty, especially in situations in which actors cannot agree about the different sources of uncertainty. Disagreement might be a result of vague and/or incomplete information and knowledge available to actors (Reznik et al., 2013). The framework of fuzzy logic in managing the coexistence of opposing forces allows individual actor views to be retained despite the ambivalence they bring to the collective view (Reznik et al., 2013). Nevertheless, there are situations in which the actors know absolutely nothing about probability distributions and possible outcomes, which might be actor related in the sense of the sudden withdrawal of certain actors. It might also be context based in the sense of sudden economic swings, (the effects of) technological innovations, or the unknown quality of product returns. In such cases, uncertainty is neither stochastic nor fuzzy in nature, yet it can be interpreted as deep uncertainty. However, deep uncertainty in this sense is completely missing from the CLSC management literature and therefore deserves more attention in future CLSC management research. The paper by Walker et al. (2013) might help to understand deep uncertainty and decision making under deep uncertainty.

Opportunities for considering context uncertainty and CLSC model structure uncertainty. Parameter uncertainty and CLSC model outcome uncertainty are important sources of uncertainty in (transitioning towards) CLSC management. However, these are not the only sources of uncertainty, as there are also ‘context uncertainty’ and ‘CLSC model structure uncertainty’. In the latter case, there is a relationship between model structure uncertainty and calibrated parameter uncertainty. For instance, a simple supply chain model with few parameters may be calibrated with data obtained for both input and output under well-known conditions. In this case, model structure uncertainty will most likely dominate the results. However, in the case of complex supply chains, such as CLSCs, with many parameters, the level of information about the past and current input and output of unknown conditions might be low. In that case, model calibration will be difficult for the actors involved and therewith will be strongly dominated by parameter uncertainty. In other words, calibration data must contain variation in order to manage all of the parameters chosen for calibration. Otherwise, the parameter estimates become very uncertain, and the model outcome becomes uncertain accordingly (Walker et al., 2003). Regarding context uncertainty, actors in a CLSC face deep uncertainties about myriads of contextual factors, such as climate change and resource scarcity. The literature has paid very limited attention to these unpredictable factors and the way they should be dealt with, although they might have significant effects on the sustainability of the operation of supply chains.

Opportunities for considering dynamic complexity: The majority of the papers addressing dynamic complexity focused on nonlinear interactions of CLSC activities over time. However, one might argue that there exists a need to also explore the nonlinear interactions between CLSC activities over various geographical scales (local to global) and organizational levels (single actor to multi-tier system).

Opportunities for studying deep uncertainty and dynamic complexity in relation to life cycle approaches. Since CLSC management is about maximizing value creation over the entire lifecycle of a product, a life cycle approach seems obvious. Yet, at the same time it increases uncertainty and complexity, especially when the product has a long lifespan and when several recovery loops are considered. Although previous research shows that applying multiple loops over the entire life cycle of a product is both economically and environmentally beneficial (Krikke, 2010), the effects of deep uncertainty and dynamic complexity on CLSC decision making in specific life cycle assessment studies have not been systematically studied so far. *Opportunities for building a conceptual framework for a transition.* The papers studied focused mainly on the development/modelling and selection of (near-) optimal CLSC options under uncertainty and/or (dynamic) complexity. Limited attention has been paid to the development of future-based CLSC transition pathways, the implementation and operation of such pathways, and the monitoring of the sustainability of CLSC options in terms of adaptation tipping points. Hence, there seems to be a lack of a conceptual framework in which the transition towards CLSC management under dynamic complexity and deep uncertainty is proposed as a continuous process of anticipative and adaptive steering. Here, the so-called 'Capability Maturity Framework' might be useful for describing and refining this process in terms of successive maturity stages and related capabilities (Paulk et al., 1993).

6.2 Process gap: The involvement of actors in the transition process

Decision-making theories emphasize that, in addition to researchers, corporate actors can deliver valuable pieces of information and knowledge (Döll et al., 2017) for the study of transitions towards CLSC management under dynamic complexity and deep uncertainty. Furthermore, since corporate actors implement CLSC options, their decisions ultimately influence the causal (nonlinear) interactions between these business activities within a CLSC, as well as the emergent patterns. In their literature review, Alexander et al. (2014) already argued that corporate actors constitute a crucial part of the decision-making process and should not be treated as an external force beyond their spheres of influence. There have been some successful attempts to increase actor involvement, based on participatory approaches, as mentioned in Section 5. However, there remains enormous potential for applying various participatory approaches to support actors in managing deep uncertainty and dynamic complexity in transitioning towards CLSC management. The research by Hermans et al. (2017), although not focused on CLSC management, could be mentioned here because it provides an elaborate framework for linking actors to contextual factors, signposts and (transition) pathways. Also other qualitative participatory methods, such as the Delphi method and participative group model building with the aim of creating (some degree of) consensus after deliberation on contrasting viewpoints, have been successfully applied (Narayana et al., 2014, Stindt et al., 2016).

6.3 Method gaps

Various gaps become visible from the analysis of suitable instruments to support a transition process towards CLSC management under deep uncertainty and dynamic complexity.

Opportunities for implementation of (qualitative and quantitative) methods and tools to analyse deep uncertainty and dynamic complexity simultaneously. Only a few papers focused on complexity and uncertainty simultaneously, let alone on the implementation of instruments to study and address these concepts. In the majority of the papers, mixed-integer linear programming models were used to support the management of stochastic uncertainty by design. However, mixed-integer programming models (often) do not cover dynamic processes or nonlinearity. Mixed-integer nonlinear programming models do consider nonlinearity, yet they analyse primarily stochastic uncertainty and not deep uncertainty. In addition to the optimization approaches, simulation approaches have been applied to model and simulate dynamic processes and feedback loops in a CLSC. Nonetheless, causal models that are being simulated often only implicitly and partly address uncertainty, let alone deep uncertainty. For instance, parameter uncertainty is included in causal (CLSC) modelling, and sensitivity to changes is generally tested via (univariate) sensitivity analysis. However, uncertainties that exceed the boundaries of a causal CLSC model are not addressed in the simulation approaches, indicating that comprehensive sensitivity analysis to thoroughly test the (effects of variety on) different sources of (deep) uncertainty and (dynamic) complexity is lacking. To analyse deep uncertainty and dynamic complexity simultaneously, the 'exploratory system dynamic modelling and analysis' (ESDMA) approach presented by Pruyt (2010) has a place. ESDMA aims to offer decision support in the face of deep uncertainty and dynamic complexity by systematically exploring the consequences of a set of uncertainties and nonlinearity. Through many model runs and different types of clustering, subsets of uncertainty are related to groups of outputs in an attempt to determine the uncertainties that cause a particular desired or undesired outcome and emergent patterns. ESDMA combines 'system dynamics modelling' and 'exploratory modelling and analysis'. The former focuses on the use of models to explore the links between a system's causal structure and the nonlinear interactions and emergent patterns over time arising from the system structure. The latter implies the development and use of these models to support decision making under deep uncertainty. However, although ESDMA takes the temporal dimension into account, it does not explicitly focus on the geographical dimension or the organizational dimension. Regarding the geographical dimension, the approach of Xu et al. (2012) might be of added value. The authors combined system dynamics modelling, geographical information system analysis (GIS) and 3D visualization to better explain the nonlinear interactions between, and the geographical-temporal variations of sustainability indicators (society, economics, ecology) for analysing a residential development. Regarding the organizational dimension, agent-based modelling in combination with exploratory modelling and analysis might be of added value

(Kwakkel et al., 2013) to explore the effects of the deeply uncertain environment and the nonlinear interactions between heterogeneous supply chain actors on CLSC economic, ecological and societal performance.

Need to develop a large ensemble of multidimensional scenarios. Although various papers included scenarios to support the management of uncertainty, they involved a small number of primarily probabilistic scenarios: three to twenty. However, in the case of deep uncertainty, it has been argued that hundreds to thousands of (multidimensional) scenarios should be developed (Cardoso et al., 2015, Kwakkel et al., 2015). Furthermore, because of the multidimensional approach, one might argue that it is important to (loosely) connect the dimensions described in the various scenarios to fully grasp the nonlinear interactions and emergent patterns in a CLSC model. For instance, long-term global resource availability is setting the scene for long-term resource availability in the Netherlands. The concept of 'loosely connecting' allows the scenarios to frame and address the issues important to the actors involved, while having some acknowledgement of and reference to potential changes at other dimensions (levels) and how these changes might affect the CLSC under consideration (Scholes et al., 2013).

7. Conclusion, limitations and future research

7.1 Conclusion

This literature review was triggered by the question of what the knowledge gaps are with respect to (managing) dynamic complexity and deep uncertainty in transitioning towards CLSC management. Based on the analysis of the selected literature on this subject, three categories of gaps were identified: conceptual gaps, a process gap and methodological gaps. Conceptual gaps concern: (i) the insufficient representation of deep uncertainty in the study of CLSC management; (ii) the too scarce inclusion of multidimensional nonlinear interactions between CLSC activities in the models; and (iii) the lack of an elaborated conceptual framework to determine the transition pathways towards CLSC management under deep uncertainty and dynamic complexity. The process gap refers to the lack of systematic involvement of actors in the transition process towards CLSC management under dynamic complexity and deep uncertainty. The methodological gaps refer to: (i) a lack of methods and tools to study and manage deep uncertainty and dynamic complexity simultaneously; and (ii) a lack of methods and tools to systematically develop and simultaneously analyse (large numbers of) multidimensional scenarios.

7.2 Limitations

The review had several limitations. First, because of the large number of articles studied, cross-references were not included in the database. Second, the search strings used often had to be narrowed down because of the extensive number of hits that they generated. By specifically searching for terms in the abstracts and titles of the articles, some articles might have been missed. However, based on the rigour adopted in the research, one might expect the identified descriptive and methodological knowledge to be robust. Third, since this review focuses on CLSCs, papers that only focused on forward or reverse supply chain activities without any form of integration were excluded. Additionally, the review analysed studies explicitly focusing on (deep) uncertainty and/or (dynamic) complexity in relation to CLSC management. Hence, because of the strict search and selection procedures, the review ended up with a relatively small number of papers (i.e., 64 papers) for in-depth analysis.

7.3 Suggestions for future research

Based on the identified knowledge gaps, several directions for future research have been suggested. To reduce the conceptual gap, further study of the theories of deep uncertainty and dynamic complexity and their applicability in the domain of CLSC management is needed. Moreover, a way of thinking based on the ‘Capability Maturity Framework’ was suggested. The process gap could be reduced by applying participative research methods to more systematically involve stakeholders. To address the methodological gaps, the potential of the ‘exploratory system dynamic modelling and analysis’ methodology was mentioned. However, from the literature it becomes clear that developing new frames and methods and showing the added value of these approaches for CLSC management under deep uncertainty and dynamic complexity require quite some time and systematic effort. The authors of this review intend to contribute to this challenge in the near future.

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