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Table of contents

Acknowledgements	2
1. EXECUTIVE SUMMARY	6
2. INTRODUCTION: QUANTITATIVE MODELS	7
2.1 MODELS: DEFINITONS AND FEATURES	7
2.2 METHODOLOGIES APPROACHES	9
2.3 MODELLING TOOLS	11
3. MODELLING DOMAIN AND REQUIREMENTS	14
3.1. MODELLING FEATURES	14
3.1.1. Group 1: Operational features	14
3.1.2. Group 2: Circularity features	16
3.2. FUTURE SCENARIOS	19
3.3. INDICATORS	28
3.4. MODELLING REQUIREMENTS	29
4. MODELLING METHODOLOGIES	30
4.1. METHODS FOR SUPPLY CHAIN DYNAMICS	30
4.2. METHODS FOR CIRCULAR ECONOMY	32
5. SELECTION OF MODELLING METHODOLOGIES	36
5.2. SELECTION OF MODELLING TOOLS	37
6. CONCEPTUAL MODELLING FRAMEWORK	43
References	44

List of Tables

Table 1. Modelling for Circular Supply Chains.....	18
Table 2. Modelling features for Scenario 1	21
Table 3. Scenario aspect-modelling assumptions for Scenario 1.	22
Table 4. Modelling features for Scenario 2.	24
Table 5. Scenario aspect-modelling assumptions for Scenario 2.	24
Table 6. Modelling features for Scenario 3.	26
Table 7. Scenario aspect-modelling assumptions for Scenario 3.	26
Table 8. Modelling features for Scenario 4.	28
Table 9. Scenario aspect-modelling assumptions for Scenario 4.	28
Table 10. Key performance indicators	29
Table 11. Summary of tools	42

List of Figures

Figure 1. Excel form	20
Figure 2. Circular Supply Chain Node	43

1. EXECUTIVE SUMMARY

This deliverable aims to provide the methodological foundation for developing the models of the industrial partners' supply chains in order to assess the future circular scenarios envisioned in the project, so scientifically rigorous models and analysis can be developed in order to obtain sound generalisable outcomes.

First, we provide in Section 2 precise definitions for the different terms employed in the deliverable (i.e. models, modelling methodologies/approaches, and modelling tools). Then in Section 3, we elaborate the modelling features required to represent in detail the future circular supply chain scenarios described in WP1 (i.e. operational features and circularity features). Different ranges of values for each of these features are assigned for the different future circular supply chain scenarios (Section 3.2), according to the results of a survey conducted among the participants in the project. With all these elements, it is possible to characterise in detail the envisioned scenarios. Furthermore, a number of performance indicators are derived in Section 3.3. (even if these are provisional ones depending on the finalisation of the deliverable D2.2 later in the working plan of the project) in order to assess these scenarios according to the economic, environmental, and social dimensions. In Section 3.4., based on the features identified for the different scenarios, a number of modelling requirements (i.e. the characteristics that the models should possess in order to properly describe these scenarios) are developed. These modelling requirements would serve to select among the most suitable modelling methodologies commonly used in supply chain dynamics (described in Section 4.1) and circular economy (described in Section 4.2). As it turns out from the analysis carried out in Section 5, no single modelling methodology can match all modelling requirements, therefore a mix of modelling methodologies are selected. More specifically, analytical modelling is selected for developing models at the design/allocation level, while simulation is selected for developing models at the operational level. Finally, the main simulation tools available are discussed and ranked according to a number of criteria, and the AnyLogic tool is selected as the most suitable one.

This document concludes by presenting in Section 6 the modelling framework (i.e. the abstract model of the generic nodes in a circular supply chain), which would constitute the basic entity for the AnyLogic and analytical models to be developed from the industrial partners' supply chains in the deliverable D3.2.

2. INTRODUCTION: QUANTITATIVE MODELS

Quantitative models use a collection of variables that change within a specified range, explicitly defining the quantitative and causal relationships between them. This explicit definition allows the magnitude of these relationships to be meaningful and directly connected to actual variable values in real-world scenarios (Hillier and Lieberman 2021).

Since their inception, quantitative models have formed the backbone of most operations research. In Europe, this field became known as Operational Research, while in the USA, it was termed Operations Research and served as a foundation for early management consulting (Pidd 2009). Initially, quantitative modelling was heavily focused on addressing practical, real-world issues in operations management rather than on advancing scientific understanding (Ackoff 1956). However, by the 1960s, particularly in the USA, the field saw the emergence of a robust academic research trajectory. Researchers began tackling more abstract problems, using these investigations to develop scientific knowledge within operations management (Bertrand et al., 2024). During this period, much of the research drifted away from its empirical roots, with methodologies evolving primarily for these theoretical inquiries. As a result, empirically oriented research methodologies were neglected for over three decades. It was not until the 1990s that empirical research began to experience a resurgence in Operations Management. Initially, this revival had a predominantly qualitative focus (Meredith, 2001). With the advent of digital data and the incorporation of laboratory experiments into research methodologies in the 2000s, the empirical nature of quantitative, model-based research in Operations Management was significantly enhanced (Ketokivi and Choi, 2014). The research scope also expanded from focusing on single companies to encompassing entire supply chains. Consequently, the paradigms of model-based research in Operations Management have been extended to the broader field of Supply Chain Management. (Simchi-Levi, D et al. 2007).

In the subsequent subsection, we delve into an exploration of key concepts for understanding the dynamics of modelling in various domains. Specifically, we define which is a "model," elucidating its meaning as a simplified representation of a complex system or phenomenon. Also, we discuss the concept of "mathematical modelling", a powerful approach that harnesses mathematical language to describe and analyse complex systems, and how it enables us to quantify relationships between variables and simulate the behaviour of dynamic systems. Also, we present the concept of "computer simulation", a cutting-edge technique that leverages computational power to simulate real-world phenomena. Finally, we turn our attention to the critical role of "modelling assumptions" in shaping the modelling process, exploring how they define the scope and boundaries of a model.

2.1 MODELS: DEFINITIONS AND FEATURES

A **model** is a simplified representation of reality that is designed to explain, predict, or manage the behaviour of real-world systems or phenomena. Models serve as tools to understand

complex systems by highlighting their essential features while omitting non-essential details (Bertrand et al., 2024). In particular, they can be categorized as follows:

1. **Physical models:** are tangible, scaled-down versions of objects or systems. For example, an architectural model of a building helps visualize its design and structure before actual construction (Chauhan, 2023).
2. **Conceptual models:** are abstract representations that use concepts and ideas to convey understanding. They include diagrams, flowcharts, and organizational charts that illustrate relationships and processes within a system (Thalheim 2019).
3. **Mathematical models:** use mathematical language and equations to describe the behaviour and characteristics of a system. They are particularly powerful in fields like physics, economics, biology, and engineering, where they help simulate real-world phenomena and predict future outcomes (Azizi et al. 2021).

Among these three approaches, mathematical models are particularly appropriate in Operations Management and Supply Chain Management because they use equations to accurately describe, simulate, and predict complex system behaviours, facilitating better decision-making and optimization by focusing on essential features and omitting non-essential details (Bertrand et al., 2024). Specifically, a **mathematical model** is an abstract description of a concrete system using mathematical concepts and language. The process of developing a mathematical model is termed mathematical modelling. Mathematical models are used in applied mathematics and in the natural sciences, such as physics, biology, earth science, and chemistry, as well as in engineering disciplines like computer science, industrial and management engineering. Beyond these, mathematical models also find application in non-physical systems, such as the social sciences, including economics, psychology, sociology, and political science. Mathematical modelling describes a process and an object by use of the mathematical language (Giordano 2013). A process or an object is presented in a “pure form” in Mathematical Modelling when external perturbations disturbing the study are absent.

Computer simulation is a natural continuation of the mathematical modelling. Computer simulation can be considered as a computer experiment which corresponds to an experiment in the real world (Law and Kelton, 2019). Such a treatment is rather related to numerical simulations. Symbolic simulations yield more than just an experiment. They can be considered as a transformation of a mathematical model by computer, since symbolic simulations keep parameters of the model in symbolic form that corresponds to a set of actual experiments (Buchberger 1988). One can obtain numerical results as in actual experiments only after substitutions of the symbolic parameters with the numerical data (Mityushev et al., 2018). In summary, simulation model is a mathematical representation of a real-world system or process that allows for the study of its behaviour over time. Unlike mathematical models, which often rely on analytical solutions to equations, simulation models are typically implemented using computer software to mimic the dynamic behaviour of the system through numerical simulations.

A **modelling assumption** is a simplification or generalization made during the construction of a model to make it more manageable and solvable (Sterman 2000). These assumptions define

the scope and boundaries of the model, specify the behaviour of variables, and outline the relationships between different components of the system being studied (Law and Kelton, 2019). Modelling assumptions are essential because they simplify complex systems: By reducing complexity, assumptions make it feasible to develop, analyse, and understand the model (Sergent, 2013). Also, they help in concentrating on the most significant factors affecting the system, ignoring less critical details (Pidd 2004). Furthermore, they enhance manageability by simplifying the computational feasibility, especially for complex models with numerous variables (Banks, 2005). Essentially, modelling assumptions are crucial elements that shape the construction and application of models (Borshchev, 2013). They enable simplification and focus but must be carefully chosen and regularly reviewed to ensure that they do not compromise the model's validity and reliability. However, every assumption introduces a limitation (Kleijnen, 1995). Understanding these limitations is crucial for correctly interpreting model results and for identifying the scenarios in which the model can be applied. Thus, by understanding and carefully considering modelling assumptions, model developers and users can create more accurate, reliable, and useful models. This process ensures that the models are both scientifically sound and practically applicable in real-world decision-making (Robinson, 2014).

2.2 METHODOLOGIES APPROACHES FOR MODELLING

The **methodological approach** involving mathematical models and simulation in Operations Management is a sophisticated and vital aspect of modern industrial processes. Mathematical models are abstract representations of real-world systems using mathematical language and symbols to describe the relationships between variables. Simulations, on the other hand, are the techniques of imitating the operation of real-world processes or systems over time, often executed through computational algorithms. Together, these methods enable managers to analyse, predict, and optimize operational performance in a controlled and systematic manner. In the realm of operations management, mathematical modelling and simulation have become indispensable tools for tackling the complexities of modern manufacturing, supply chain, and service operations. These techniques allow organizations to capture the intricate dynamics and interdependencies within their operational processes, enabling them to make informed decisions and implement strategies that enhance efficiency, productivity, and profitability.

Mathematical models in operations management can take various forms, such as linear programming, queuing theory, inventory models, and network optimization models. These models provide a quantitative framework for representing operational constraints, resource allocation, scheduling, and logistics challenges (Hillier and Lieberman 2021). By incorporating relevant variables, parameters, and objective functions, these models can be used to optimize decision-making processes, minimize costs, and maximize operational performance.

Simulations, on the other hand, allow managers to experiment with different scenarios and evaluate the impact of various operational strategies without disrupting actual operations. Discrete event simulation (DES) and agent-based modelling (ABM) are two prominent simulation techniques widely used in operations management (Borshchev and Filippov, 2004; Banks et al., 2010). DES models the flow of entities (e.g., products, customers) through a

system, capturing the dynamics of queues, resource utilization, and process interactions. ABM simulates the behaviour and interactions of individual agents (e.g., machines, workers) within a system, enabling the study of emergent phenomena and complex adaptive systems.

Recent advancements in computational power, data analytics, and machine learning have further enhanced the capabilities of mathematical modelling and simulation in operations management. Data-driven modelling approaches, such as machine learning-based demand forecasting and predictive maintenance, have gained traction, enabling more accurate and adaptive decision-making processes (Agrawal & Srikant, 2000; Susto et al., 2015).

Moreover, the integration of mathematical models and simulations with real-time data streams and Internet of Things (IoT) technologies has opened up new avenues for dynamic optimization and real-time decision support systems. Digital twins, virtual representations of physical assets or processes, leverage mathematical models and simulations to monitor, analyse, and optimize operational performance in real-time (Tao et al., 2019).

Furthermore, the field of simulation optimization has emerged as a powerful approach, combining mathematical optimization techniques with simulation models to identify optimal solutions for complex operational problems (Fu, 2015). Techniques such as metaheuristics, evolutionary algorithms, and response surface methodologies have been employed to efficiently search for optimal solutions within the vast solution spaces generated by simulations.

One of the core challenges in applying these methodologies is the inherent complexity of operational systems. As highlighted by Hillier and Lieberman (2021), operational processes often involve numerous interconnected components and variables, making it difficult to develop models that are both accurate and computationally feasible. The complexity can lead to models that are either oversimplified, thus losing critical details, or overly detailed, making them computationally intractable. This necessitates a balance between model fidelity and computational efficiency to ensure practical applicability.

Data quality is another crucial factor influencing the effectiveness of mathematical models and simulations. Operations management relies heavily on precise data to feed into these models. Inaccurate or incomplete data can significantly skew model outputs, leading to erroneous conclusions. According to Davenport and Harris (2017), ensuring high-quality data involves rigorous data collection, pre-processing, and validation steps. Data cleaning and transformation processes are essential to maintain the integrity and reliability of the inputs used in simulations.

Computational efficiency is a critical concern in the deployment of mathematical models and simulations. High-fidelity models, while providing detailed and accurate insights, often demand substantial computational resources. This can be a limiting factor, especially for real-time decision-making scenarios. The work by Law and Kelton (2019) emphasizes the importance of developing efficient algorithms and optimization techniques to reduce computational loads, making it feasible to run complex simulations within reasonable timeframes.

The validation and verification of models are fundamental to ensuring their reliability and accuracy. Without rigorous validation, there is a risk that models may not accurately reflect real-world conditions, leading to suboptimal decisions. Robinson (2014) points out that validation involves comparing model outputs with actual system behaviour to ensure consistency and accuracy. Verification, on the other hand, ensures that the model is correctly implemented according to its specifications. Together, these processes build confidence in the model's predictive capabilities.

Incorporating uncertainty and variability into models is another significant challenge. Real-world operations are inherently uncertain and variable, influenced by numerous unpredictable factors. Models that fail to account for this stochastic nature can produce misleading results. Bertsimas and Freund (2020) discuss the importance of stochastic modelling techniques, which incorporate randomness and uncertainty into the models, thereby providing a more realistic representation of operational dynamics.

Furthermore, user-friendly interfaces are essential to ensure that these sophisticated tools can be effectively utilized by practitioners who may not have advanced technical expertise. As suggested by Powell and Baker (2017), the design of intuitive interfaces and comprehensive training programs is crucial for enabling users to interact with models and simulations effectively, thereby enhancing their utility and impact.

Interdisciplinary collaboration is also vital in the development and implementation of mathematical models and simulations. Operations managers, data scientists, and other stakeholders must work together to ensure that models are both theoretically sound and practically applicable. Cross-disciplinary collaboration fosters a holistic approach, integrating diverse perspectives and expertise to enhance model robustness and applicability. This collaborative approach is advocated by Silver, Pyke, and Thomas (2016), who emphasize the importance of leveraging collective expertise for successful model implementation.

2.3 MODELLING TOOLS

In the context of mathematical modelling and simulation in operations management, a **modelling tool** refers to a software application or programming environment designed to facilitate the development, implementation, and analysis of mathematical models and simulations. Modelling tools provide a user-friendly interface and a set of features that enable operations managers, analysts, and researchers to create, modify, and execute mathematical models and simulations without the need for extensive programming knowledge.

Modelling tools play a crucial role in addressing these challenges and ensuring that the chosen methodologies are appropriate for the goals of the study. They are software applications designed to facilitate the creation, visualization, and management of various types of models used in software development, systems engineering, and other domains. These tools provide a structured and visual approach to representing complex systems, processes, data structures, and architectures. The concept of modelling tools revolves around the idea of abstracting and simplifying complex real-world systems or concepts into visual

representations or models. These models serve as a communication medium, enabling stakeholders to understand, analyse, and collaborate on the design and development of systems or processes. Modelling tools offer a range of functionalities, including model building, data integration, simulation execution, visualization and animation, optimization and analysis, and experimentation and scenario analysis (Rossetti, 2015; Bapat & Sturrock, 2003).

Some popular modelling tools used in operations management include:

1. Simulation software: Arena (Kelton et al., 2017), AnyLogic (Borshchev, 2013), FlexSim (Nordgren, 2003), Vensim (Ventana Systems, 2018) and Simio (Sturrock & Pegden, 2010) are examples of dedicated simulation software packages that support various simulation paradigms, such as discrete event simulation, agent-based modelling, and system dynamics.
2. Optimization solvers: CPLEX (IBM, 2009), Gurobi (Gurobi Optimization, 2022), and LINGO (Schrage, 2006) are optimization solvers that can handle linear programming, mixed-integer programming, and other optimization problems commonly encountered in operations management.
3. Spreadsheet-based tools: Excel and its add-ins like Solver (Fylstra et al., 1998), Risk Solver (Frontline Solvers, 2022), and @Risk (Palisade Corporation, 2022) provide a familiar environment for building and analysing mathematical models and simulations, particularly for smaller-scale problems.
4. Programming languages and environments: Python (with libraries like PyOMO (Hart et al., 2017), SimPy (Muller & Vignaux, 2003), and AnyLogistix (Borshchev, 2013)), MATLAB (Higham & Higham, 2016), and R (Venables & Smith, 2022) offer powerful programming environments for developing custom mathematical models and simulations, as well as integrating with other data analysis and visualization tools.

Recent advancements in modelling tools have focused on integrating machine learning and artificial intelligence techniques for data-driven modelling and simulation. For instance, AnyLogic Cloud (Borshchev, 2021) incorporates machine learning capabilities for demand forecasting and predictive maintenance, while SimMine (SimMine, 2022) leverages deep learning for simulation model discovery and optimization.

Furthermore, the emergence of cloud-based modelling and simulation platforms, such as AnyLogic Cloud and Simio Cloud (Sturrock, 2021), has enabled collaborative model development, scalable simulation execution, and remote access to modelling resources.

In the field of simulation, tools such as ARENA, Simul8, Vensim, and AnyLogic offer comprehensive platforms for developing and running simulations, each with unique strengths suited to different aspects of operations management. ARENA, for instance, is well-suited for discrete-event simulation (DES), which is essential for modelling operations involving distinct events occurring at specific times. This capability makes ARENA particularly effective for

analysing manufacturing processes, production lines, and service systems where timing and sequencing of events are critical (Kelton et al., 2017).

Simul8 also excels in discrete-event simulation and is known for its user-friendly interface and rapid model development capabilities. It is often used for scenarios requiring quick prototyping and iterative testing of operational strategies. As reported by Hall (2012), Simul8's visual approach to building models facilitates easier communication of complex processes and results to stakeholders who may not be familiar with simulation modelling.

Vensim, on the other hand, specializes in system dynamics modelling, making it suitable for understanding and analysing the behaviour of complex systems over time. This tool is particularly useful for strategic planning and policy analysis, where the focus is on understanding the long-term impact of decisions and identifying leverage points within a system (Ventana Systems, 2018). Vensim's strength lies in its ability to model feedback loops, time delays, and non-linear relationships, which are common in complex organizational systems.

AnyLogic offers a unique advantage by integrating multiple simulation methodologies, including discrete-event, agent-based, and system dynamics modelling. This multi-method capability allows for a more comprehensive representation of complex systems with various interacting components (Borshchev, 2013). For example, AnyLogic can model the flow of materials through a production system (DES), the behaviour of individual agents such as customers or employees (agent-based), and the broader systemic trends and feedback loops (system dynamics). This flexibility makes AnyLogic particularly valuable for large-scale, multi-faceted studies such as optimizing supply chain efficiency, evaluating healthcare systems, or simulating urban development scenarios.

The appropriateness of these tools depends on the specific goals of the study. For instance, if the objective is to optimize production schedules in a manufacturing environment, ARENA or Simul8 would be highly appropriate due to their robust DES capabilities. If the study aims to improve supply chain efficiency, AnyLogic's multi-method approach can capture the complex interactions between different supply chain components, providing a more holistic analysis. For strategic planning and long-term policy analysis, Vensim's system dynamics modelling can reveal insights into the broader systemic impacts of various decisions.

Choosing the right tool is crucial as it ensures that the models can accurately represent the operational processes and deliver actionable insights. This choice significantly impacts the fidelity of the simulation, the relevance of the insights generated, and the overall effectiveness of the study. According to Banks et al. (2010), the choice of simulation software should align with the specific requirements of the study, including the nature of the system being modelled, the level of detail needed, and the expertise of the users. For instance, discrete-event simulation tools like ARENA and Simul8 are ideal for systems where the flow of events and processes can be distinctly identified and timed, such as in manufacturing or service operations (Kelton et al., 2017; Hall, 2012). These tools enable precise modelling of sequences and timings, which are critical for optimizing workflows and reducing bottlenecks. Thus, the choice of a modelling tool depends on factors such as the complexity of the problem,

the required level of customization, the available data sources, and the expertise of the users. Effective use of these tools can significantly enhance the decision-making capabilities of operations managers by providing insights into complex operational processes and enabling data-driven optimization strategies.

Furthermore, the level of detail required in the model also dictates the choice of tool. Detailed models that capture fine-grained interactions and specific events benefit from discrete-event simulation tools, while broader system-level analyses that explore overall trends and patterns are better served by system dynamics models. The expertise of the users is another critical factor; user-friendly interfaces and intuitive design are essential for practitioners who may not have advanced technical skills. Tools like Simul8, known for their ease of use and visual modelling capabilities, can facilitate quicker adoption and more effective use by non-experts (Hall, 2012).

In conclusion, the careful selection of modelling and simulation tools is paramount to the success of any operations management study. Aligning the tool with the study's requirements ensures that the models developed are both accurate and actionable, thereby providing reliable insights that drive better decision-making and operational improvements. This alignment not only enhances the credibility of the study's outcomes but also maximizes the practical benefits derived from simulation, leading to more informed strategies and optimized operations.

3 MODELLING DOMAIN AND REQUIREMENTS

3.1 MODELLING FEATURES

In this section the set of modelling factors and assumptions that are necessary to create a Circular Supply Chain model is provided.

Specifically, they will be divided into two different groups. The first group describes the *Operational features*, that characterize the linear production and processes. In other word, group 1 could exist in any type of SC, also in forward SCs, while group 2 defines the *Circularity features*. Thus, those features that characterize the Circular Supply Chain (CSC) archetype, the circular flows and R-imperatives.

As discussed in the previous sections, modelling is a tool that enables understanding and decision-making of complex systems and processes, such as CSC, providing a flexible and scalable approach. Thus, in addition, for each operational/circular feature, the modelling factor that enable to create a model for a CSC is exposed, as summarized in Table 1.

3.1.1 Group 1: Operational features

Supply Chain structure. It refers to the configuration of interconnected entities involved in a SC in a supplier-buyer relationship, from the extraction of raw material to the final customer.

It can be Complex or Simple depending on if it includes several actors or few actors. It can also be Global or Local, according to the geographical distribution of SC's members. In terms of modelling actors:

- Number of Nodes. The number of echelons that compose a SC need to be considered since it is the base of modelling CSCs. Moreover, since in CSC there are also interconnection between different SC, also the number of SC need to be considered. Thus, the number of nodes informs on the total number of actors that characterize the CSC model.
- Transportation lead time. It depends on the distance between the different nodes. If it is Global SC transportation led time will be higher compared if the SC is Local. In the latter case, since short distances need to be covered, thus, the model will present a short transportation lead time.

Market demand. It refers to the trend of market demand governed by the consumers. The demand of the main product that the CSC is subject to. Depending on the product, it can be seasonal or steady or influenced by the presence of secondary markets or leasing. Thus, if the market demand follows a normal distribution, in terms of modelling factors:

- Mean demand. It governs the demand volume, it can be high or low and it can vary over time when for instance mechanisms such as the “*refuse, reduce, and rethink*” are diffused. Indeed, for instance in this case the demand volume decrease.
- Demand variance. It informs on the variability of the market demand

Collaboration: It refers to the cooperation among the different actors within the SC including information and data sharing, also concerning circularity; in other works, if a collaborative approach and data sharing is enabled between different SC actors.

- Information sharing. There is information transparency concerning incoming demand values or lead times, but also circular factors, for example the number of EOL returns or the amount of waste exchanged in industrial symbiosis settings.

Efficiency of forward process: It refers to the efficiency of the linear (no circular) production processes. Since managers could decide to invest more in implementing new circular processes or, on the opposite site, to improve their existing one, this entails high efficiency for the forward production. But at the same time, if regulatory laws force circular and sustainable production, linear processes are constrained. In terms of modelling factors:

- Variability of lead time. It may be that innovative technologies are implemented in the linear production to ensure and optimized production in a timely manner. It reflects in a low variability in the production lead times. On the contrary, if circular production is prioritized, and the technologies/machines used in the linear production are less effective than those used in circular ones, the variability of lead time could be lower.
- Maximum forward production rate. If the production process is governed by regulation for raw material extraction/use (weighted to recycled material use) a limit on the linear production needs to be set.

Environmental constraints: CSCs can be subject to regulations that limits their production rates but also their environmental impacts.

- Constraints on emissions. A maximum of emissions is imposed in the production process of a SC.
- Constraints on waste/by-products generations. When waste/by-product is not upcycled, thus, there are no circular practices that generate value from them, still regulations could force the SC to limit their production.

3.1.2 Group 2: Circularity features

Degree of circularity. It refers to the percentage of end-of-life products that are reinserted in the SC after their lifecycle with consumers.

- Return rate. It refers to the percentage of market sales that are reinserted in the CSC. Indeed, after their use, only a rate of used goods is returned by the customer.
- Coefficient of variation of the return rate. It refers to the variability over time of the percentage of end-of-life products that are circulated.

End-of-life dynamics. It refers to the dynamics of reverse circular loops of used products. Specifically, since the used products can be reinserted in the original SC or in another SC, from a modelling perspective we distinguish:

- Closed-loops. When closed-loops are implemented, the end-of-life products are returned in the origin SC. Here, they are remanufactured/reused/repared to serve their original purpose, thus, to satisfy the same market demand.
- Open-loops. When open-loops are implemented, instead end-of-life products are sent to a different SC than their main one. Indeed, here, once treated, they will satisfy another final customer demand and serve a new purpose.

End-of-life cycles. It refers to the nature of the reverse process and the SC level where end-of-life products are reinserted. Indeed, depending on the R-imperative (reuse/remanufacture/recycle) different SC members can be involved in the loops.

- Returns share. Short loops when end-of-life products are subject to short loops/cycles and reverse processes such as Resell, Reuse, Repair. On the contrary, long loops when end-of-life products are subject to long loops/cycles and reverse processes such as Recycle, Remanufacture, Repurpose.

Industrial symbiosis. In industrial symbiosis the waste or by-products generated in the production process (they are not end-of-life waste) by one industry are utilized as inputs or resources by another industry instead of raw virgin material. From a modelling perspective:

- Waste rates. Between two nodes of the same or two different SCs, there can be a symbiotic exchange of waste/by-product, that is accounted by the waste rate. Here, the exchange can be bi-directional and it can involve any type of waste/by-product that is

created in the production process of a SC member that is useless for itself, but it represents a source of value for another production process.

Lifecycle of the product. It reflects the products life duration. Depending on the circular scenario, on the different strategies that are implemented in the CSC and on the product itself, the product life duration can consist of some days, e.g. agri-food sector, or several years, e.g. electronics or automotive sectors. This is an important issue when it comes to model and simulation for CSC:

- Consumption lead time. It refers to the time lag between the sale of the products and their end-of-life/collection, thus, is the time products are held by the customers.

Quality of end-of-life products. It refers to the quality of the end-of-life returned products before being treated in a reverse process. Products returned at the end of their life cycle need to be in a condition that allows for effective repair or recycling.

- Mean of reverse lead time. It expresses the quality of end-of-life products in a circular supply chain because it provides insight into the average time it takes for products to be returned, processed, and reintegrated into the supply chain after their initial use. For instance, shorter mean reverse lead time suggests that products are returned in relatively good condition, minimizing the need for extensive repairs or refurbishment.

Quality of the treated products. It refers to the quality of the end-of-life returned products after being treated in a reverse process.

- Demand from secondary market. Recovered products with the same quality of new ones, thus *as-good-as-new*, can be used to satisfy the original market demand. Thus, products generated using raw virgin material or generated using reprocessed material are identical. On the contrary, there can be recovered products with lower quality are sell at a lower price and in secondary markets. Thus, they are subject to another final customer demand.

Efficiency of reverse process. It refers to the efficiency of the technology used in the reverse process. As well as for the efficiency of forward process (above) it can be high or low depending on the technologies used.

- Coefficient of variation of the reverse lead time. This parameter indicates how efficiently a SC node reverse process is operating. An efficient reverse process has consistent and predictable lead times, meaning less variability in the time it takes to return and process used products. Thus, a low coefficient of variation indicates that the reverse lead times are consistent and there is little variability thank to reliable performance when there are fewer disruptions.

Replenishment policies. It refers to the replenishment policy that governs the reverse flows in CSCs. Since the volume of waste that is created in a productions process, or the end-of-life waste are dependent on the customer demand, they are subject to the demand sores of variability plus the variability of the circular process plus the life cycle of the product variability,

Thus, to properly manage them in their operations, SC members need a push or pull policy to govern the volume of the circular flows.

- Cycles policy. The two main policy that can govern the loops are the push and pull policies. In a push policy, end-of-life waste and/or by-products are always prioritized compared to the and once they are collected, they became available for their buyer. In a pull policy, end-of-life waste and/or by-products are managed through ordering policies as for the linear production and their buyer can chose to replenish in a linear o circular manner.

Feature	Modelling factor	Notation
Supply Chain structure	Number of Nodes/echelons	N
	Transportation lead time	L_{Ti}
Market demand	Mean demand	μ_D
	Demand variance	σ^2_D
Collaboration	Information sharing	ϵ
Efficiency of forward process	Variability of lead time	$cv L_i$
	Maximum forward production rates	S_{max}
Environmental constraints	Constraints on emissions.	S_{max}
	Constraints waste/by-product generation	
Degree of circularity rate	Mean return	α_i
	Coefficient of variation of the return rate	$cv \alpha$
End-of-life dynamics	Closed-loop or Open-loop	
End-of-life cycles	R-imperative	
Industrial symbiosis	Waste rates	ω_i
Lifecycle of the product	Consumption lead time	L_c
Quality of end-of-life products	Mean of reverse lead time	μ_{LRi}
Quality of the treated products	Demand from secondary market	
Efficiency of reverse process	Coefficient of variation of the reverse lead time	$cv L_{Ri}$
Replenishment policies	Cycles policy	

Table 1. Modelling for Circular Supply Chains

To conclude, the set of modelling factors above described are those that enable to create a model for a CSC. Indeed, combining their values it is possible to create a specific SC archetype, as well as explore possible to-be scenarios when tuned.

3.2 FUTURE SCENARIOS

Here, the four plausible future circular scenarios (to be modelled) that have been defined in D1.3 are characterized also by the above-mentioned modelling features. Thus, for each plausible future circular scenario, the operational features and the circular features are defined.

Specifically, the results have been obtained through an external validation that consisted of the following steps.

1. Modelling assumptions definition. Here, the modelling feature values has been assigned based on the scenario description in D1.3.
2. Internal workshop with the ExPliCit project consortium. During this workshop that took place on the 19th of February, the modelling factors have been detailed explained in order to give to the participant all the information to properly fill a scenario-based form that was given to them immediately after the workshop.
3. Diffusion of an excel file (see Figure 1) where for each future scenario the set of modelling factors could be defined. The scenario-based file has been filled by the participants of the workshop and also by some other members of the project.
4. Validation of the results. The results obtained has been used to validate the factors assignment proposed.

Finally, based on selections by the consortium, the values for each modelling factor in each scenario has been obtained as summarized in the following paragraph.

For the sake of simplicity, for each Scenario we present only the overview, please refer to the deliverable “D1.3 Tailored Scenario Exploration System for Circular Economy Scenarios” for further information. Moreover, based on the overview one illustrative table for each scenario is presented to provide some examples of the modelling assumptions derivation.

The image displays an Excel form with four scenarios for circular economy uptake, arranged in a 2x2 grid. Each scenario has two tables: 'Operational features' and 'Circularity features'.

- Scenario 1: Centralized circularity uptake** (Unrestricted growth + Centralised governance):
 - Operational features:** Supply chain structure (Global, Local), Market demand (High, Low), Collaboration approach (Yes, No), Efficiency of the service process (High, Low), Environmental constraints (Yes, No), Institutional capacity (High, Low).
 - Circularity features:** Degree of circularity (High, Low), Institutional demands (High, Low), Institutional systems (High, Low), Institutional products (Yes, No), Quality of material products (High, Low), Quantity of material products (High, Low), Efficiency of service processes (High, Low), Institutional policy (High, Low).
- Scenario 2: Planned circular loops** (Unrestricted growth + Centralised governance):
 - Operational features:** Supply chain structure (Global, Local), Market demand (High, Low), Collaboration approach (Yes, No), Efficiency of the service process (High, Low), Environmental constraints (Yes, No), Institutional capacity (High, Low).
 - Circularity features:** Degree of circularity (High, Low), Institutional demands (High, Low), Institutional systems (High, Low), Institutional products (Yes, No), Quality of material products (High, Low), Quantity of material products (High, Low), Efficiency of service processes (High, Low), Institutional policy (High, Low).
- Scenario 3: Decentralized circularity uptake** (Unrestricted growth + Decentralised governance):
 - Operational features:** Supply chain structure (Global, Local), Market demand (High, Low), Collaboration approach (Yes, No), Efficiency of the service process (High, Low), Environmental constraints (Yes, No), Institutional capacity (High, Low).
 - Circularity features:** Degree of circularity (High, Low), Institutional demands (High, Low), Institutional systems (High, Low), Institutional products (Yes, No), Quality of material products (High, Low), Quantity of material products (High, Low), Efficiency of service processes (High, Low), Institutional policy (High, Low).
- Scenario 4: Bottom-up circular loops** (Unrestricted growth + Decentralised governance):
 - Operational features:** Supply chain structure (Global, Local), Market demand (High, Low), Collaboration approach (Yes, No), Efficiency of the service process (High, Low), Environmental constraints (Yes, No), Institutional capacity (High, Low).
 - Circularity features:** Degree of circularity (High, Low), Institutional demands (High, Low), Institutional systems (High, Low), Institutional products (Yes, No), Quality of material products (High, Low), Quantity of material products (High, Low), Efficiency of service processes (High, Low), Institutional policy (High, Low).

At the bottom of the form, there is a section for 'Data' with a table structure.

Figure 1. Excel form

Scenario 1: Centralized circularity uptake (Unrestricted growth + Centralised governance). Characterized by concentrated economic activity in large private and public entities as well as unrestricted growth under top-down governance

Description: “In this scenario, the state and large corporations are in a coalition to promote circular innovations and technical fixes to linear production and consumption systems. Through these fixes they aim to increase economic growth, while trying at the same time to decouple economic growth from environmental impact, but only from specific elements (GHG emissions mainly). In this scenario, most decisions are made at the large-scale level since the economic activity is very concentrated in few actors: the state and large corporations. These few actors control specific strategic resources (e.g. critical raw materials for green technologies, Artificial Intelligence powered infrastructure to fuel global logistics flows) and govern and plan products and material flows. This also sparks some geopolitical conflicts among different countries that defend the interests of their national corporations. Because of the influence of large corporations, governments do not put in place hard restrictions on fossil fuels or polluting products, just some compensations for some externalities (carbon cap and trade, Extended Producer Responsibility programs and right to repair regulations). Also, governments, and not corporations, make the necessary large investments for the recycling and energy recovery infrastructure. The type of CE promoted preserves the status quo within the economic system and is mainly based on improving efficiency through massive recycling and energy recovery plants and using recycled materials instead of primary ones. Corporations use AI bots and personalised advertisements to push citizens to consume ever growing quantities of environmentally friendly and circular commodities for newly created

needs. Global supply chains deliver products very fast and are constantly optimised by very advanced technological infrastructure, which deals also with recovering them at the end of their short life to fuel “circular” but unsustainable supply chains. There is no control on planned obsolescence, which is actually used as a tool to fuel economic growth. Despite GHG emissions being partially decoupled from economic growth, this does not happen for most of the other impacts and ecological boundaries. As a consequence, there are worsening effects of the ecological crises, which put human existence at risk.”

Feature	Value
Supply Chain structure	Global
	Complex
Market demand	High volume
	High variability
Collaboration	No
Efficiency of forward process	High
	Constrained
Environmental constraints	Not on emissions
	Not on waste/by-products
Degree of circularity rate	Low
	Increase over time
End-of-life dynamics	External
End-of-life cycles	Short
Industrial symbiosis	Yes
Lifecycle of the product	Short
Quality of end-of-life products	Low
Quality of the treated products	Low
Efficiency of reverse process	Low
Replenishment policies	Pull

Table 2. Modelling features for Scenario 1

Scenario aspect	Modelling assumption
<i>promote circular innovations</i>	Several loops (open and closed)
<i>improving material efficiency</i>	High technical coefficients
<i>energy recovery plants</i>	Waste energy rates
<i>massive recycling</i>	High return rates
<i>newly created needs</i>	Different market demand
<i>no control on planned obsolescence</i>	No regulations
<i>Global supply chains</i>	Global network
<i>their short life</i>	Short consumption lead time
<i>very fast</i>	Short production lead times
<i>constantly optimized</i>	Increasing efficiency rates

Table 3. Scenario aspect-modelling assumptions for Scenario 1.

Scenario 2: Planned Circular loops (Limits to growth + Centralized governance). Characterized by concentrated economic activity in large private and public entities as well as strict limits to growth under top-down governance;

Description: “In this scenario, a collaboration between states, major corporations, and the UN leads to the establishment of limits to growth society. The system is centred around throughput rights, and aims to ensure human activities remain within safe ecological limits, and also that no one is left behind. This transformation occurs gradually and employs an authoritarian approach, placing ecological boundaries and equity at the forefront over private profits. Over time, traditional markets give way to a more technocratic and scientifically guided economic framework focused on socially desirable throughput (authoritarian environmentalism). The Circular Economy is an integral part of this paradigm shift, prompting a radical rethinking of production and consumption. Product-as-a-service models and the sharing economy proliferate. Products reach their end of life within local spheres, under the control of decentralised divisions of large corporations. This localised control contributes to resource conservation at heightened levels. Large corporations retain ownership of products while leasing them to consumers, resulting in earnings through user fees. Citizens do not own smartphones, computers, cars, and appliances and develop a new form of dependence on these large corporations that provide these essential items. Strategic materials, pivotal to these products, evolve into a novel form of capital for these corporations and nations. As a consequence of these evolving strategies, supply chains undergo a transformation, shifting towards more localised structures due to the escalating costs associated with global supply chains. A notable feature of this system is the imposition of high taxes. These taxes serve a dual purpose: firstly, to finance a universal basic income, and secondly, to guide consumers towards non-detrimental products and services. The outcome is a society that is less free, more constrained but more equitable”

Feature	Value
Supply Chain structure	Global
	Simple
Market demand	High volume
	Low variability
Collaboration	Yes
Efficiency of forward process	High
	Constrained
Environmental constraints	Yes, on emissions
	Yes, on waste/by-products
Degree of circularity rate	High
	Constant over time

End-of-life dynamics	Internal
End-of-life cycles	Long
Industrial symbiosis	Yes
Lifecycle of the product	Long
Quality of end-of-life products	High
Quality of the treated products	High
Efficiency of reverse process	High
Replenishment policies	Push

Table 4. Modelling features for Scenario 2.

Scenario aspect	Modelling assumption
<i>ecological boundaries over private profits</i>	Emission restrictions
<i>guide consumers towards non-detrimental products and services</i>	Large consumption lead times
<i>product-as-a-service</i>	Short loops
	High return rate
<i>sharing</i>	Collaboration
<i>more localized SCs</i>	Few nodes
	Short Lead Times

Table 5. Scenario aspect-modelling assumptions for Scenario 2.

Scenario 3: Decentralized circularity uptake (Limits to growth + Decentralized governance). Characterized by strict limits to growth in a highly dispersed economy, structured and governed from the bottom up. ➤

Description: *“In this scenario, although environmental limits are recognised, there are no strict constraints imposed on throughput or ecologically responsible restrictions on economic activities. The state opts for mild regulations aimed at altering demand through measures like subsidies and eco-taxes, and hopes companies develop cleaner and circular innovations and technologies. Circular Economy is interpreted as a system that retains essential materials and energy within their economic domain and is motivated by concerns regarding supply security and social efficiency, which considers the costs of waste and the direct impacts of pollution on various stakeholders. Societies are increasingly resisting the dominance of large corporations, which have benefited an exaggerated share of economic benefits and profits within the financial and economic sectors, also managing to circumvent taxes for an extended period by utilizing offshore tax havens. Social movements claim back the ownership of personal data tech companies have been using to accrue their power. After implementing targeted economic measures aimed at re-establishing local competition and countering the dominance of large corporations, economic activity becomes significantly more diffused throughout society and decentralised within various organisations. This shift away from large corporations’ hegemony not only restores more market freedom but also reinvigorates the overall economy’s capacity for innovation. Despite facing significant organisational transaction costs, small-scale actors play a pivotal role in driving change. The processes of commodification continue to explore fresh avenues for economic growth. Circular business models become increasingly prevalent, often facilitated by government incentives. However, smaller organisations often lack the economies of scale enjoyed by larger counterparts, resulting in reduced efficiency. Coordination challenges persist, especially for larger circular initiatives. In the long term, this system struggles to prevent environmental degradation, which adversely affects overall human well-being. Many negative externalities remain unaddressed, as inexpensive transportation encourages long, global supply chains involving numerous actors.”*

Feature	Value
Supply Chain structure	Local
	Complex
Market demand	Low volume
	High variability
Collaboration	No
Efficiency of forward process	High Efficiency
	Constrained
Environmental constraints	Not on emissions
	Not on waste/by-products

Degree of circularity rate	Low
	Increase over time
End-of-life dynamics	External
End-of-life cycles	Short
Industrial symbiosis	No
Lifecycle of the product	Short
Quality of end-of-life products	Low
Quality of the treated products	Low
Efficiency of reverse process	High
Replenishment policies	Pull

Table 6. Modelling features for Scenario 3.

Scenario aspect	Modelling assumption
<i>subsidies and eco-taxes to alter demand</i>	Limited emissions (e.g. shorter lead times)
<i>claim back the ownership of personal data [...] coordination challenges persist</i>	No Information Sharing
<i>long, global supply chains involving numerous actor</i>	Complex SC structure

Table 7. Scenario aspect-modelling assumptions for Scenario 3.

Scenario 4: (Unrestricted growth + Decentralized governance). Characterized by unrestricted growth under a very disperse economy structured and governed bottom-up.

Description: “In this scenario, citizens become increasingly aware that growing consumption is the source of many current and future problems and does not lead to happiness. Consequently, they demand for the establishment of a sufficiency-based system that ensures economic activity remains within the boundaries of the ecosystem while providing sufficient living conditions for all. GDP ceases to be a measure of progress, initiating a reverse commodification process aimed at fostering more convivial societies. The economic activity is

very dispersed, and the agents of change are low-scale actors and new local communities' autonomous organisations that emerge and are attentive to levels of sufficiency and ecological and social respect. These organisations autonomously decide what to produce and use circularity as a tool to lead to sufficiency, where "refuse, reduce, and rethink" strategies are prioritised over recycling strategies. Local jurisdictions self-organise and self-impose a maximum resource usage (for every limited resource) through a fair share calculation supported by scientists and youth organisations. Also, Circularity is not only understood in energy-material terms, as it includes biogeochemical cycles in connection to economic-based cycles, as well as care cycles (people caring among them and valuing care in society) or power cycles (through the distribution of power, i.e. the committee) and wealth, income and capital cycles. Supply chains are shortened and within a proximate range to the consumption locations. Production systems in the long term adapt to the available resources nearby. The loops are established from the micro and, especially, the meso level, which implies greater self-structuring needs (figuring out how to identify circularity opportunities, how to build functional agreements, how to share resources and with whom, how to reach agreements and enforce them). After some initial difficulties, during which coordination challenges cause waste and unemployment, there is a prevalent trend toward federalism and democratic practices, leading to the proliferation of models and alliances rather than hierarchical scaling-up organisations. These developments emphasise collaborative efforts over market-driven transactions, shaping a transformative landscape rooted in sufficiency and ecological harmony. Some CE committees (meso-level governance structures) assume responsibility for these functions at regional levels.

Feature	Value
Supply Chain structure	Global
	Complex
Market demand	Low volume
	Low variability
Collaboration	Yes
Efficiency of forward process	Low
	Constrained
Environmental constraints	Yes, on emissions
	Yes, on waste/by-products
Degree of circularity rate	High
	Increase over time
End-of-life dynamics	Internal & External
End-of-life cycles	Long

Industrial symbiosis	Yes
Lifecycle of the product	Long
Quality of end-of-life products	High
Quality of the treated products	High
Efficiency of reverse process	Low
Replenishment policies	Push

Table 8. Modelling features for Scenario 4.

Scenario aspect	Modelling assumption
<i>supply chains are shortened</i>	Few SC Nodes
<i>coordinating production, prices at regional levels</i>	Enabled information sharing
<i>maximum resource usage</i>	Supply constraints
<i>circularity is understood in wider terms</i>	Closed-loops, open-loops and symbiosis

Table 9. Scenario aspect-modelling assumptions for Scenario 4.

3.3 INDICATORS

In this section a set of possible Key Performance Indicators (KPI) for circular supply chains are expose. Indeed, even if it not the main objective of this deliverable (a more detailed analysis of KPIs will be carried out in D2.2 Performance evaluation framework) they serve as an example of performance evaluation when modelling CSCs. Since sustainability consists in the intersection of three different dimensions that are the economic, environmental, and social dimensions, as defined by the triple bottom line, it is important to consider all of them when evaluating the performance of a CSC.

Table 10 presents a set of possible KPIs.

Name	Dimension
Waste generation/reduction	$f(\text{environmental}, \text{economic})$
External input requirement/reduction	$f(\text{environmental}, \text{economic})$
Emissions	$f(\text{environment})$
Inventory cover/Backlog	$f(\text{economic})$
Fill rate/Service level	$f(\text{economic})$
Dynamic behaviour	$f(\text{economic})$

Table 10. Key performance indicators

3.4 MODELLING REQUIREMENTS

Based on the scenarios' definition in D1.3 and on the modelling domain exposed in the previous section, the requirements for a CSC model are set. This with the aim of properly selecting the modelling methodology.

Dynamic. It must be able to capture the dynamic aspects of the SC, as it is well-known that, in order to adequately forecast the performance of a SC, the dynamic effects should be accounted for. Therefore, the time variable is a key element in the models.

Flexibility. It must be able to model very different SC structures and policies, as the scenarios described vary substantially, not only in the number of elements and in the operation, but also in how these elements interact among them. Therefore, in order to avoid developing scenario-specific models from scratch, the modelling methodology should be able to allow a high degree of re-use of the models. This would not only reduce the required modelling workload, but also would allow fairer comparisons among the different scenarios.

Multiple granularity levels. Some of the features/indicators described in the scenarios are systemic, whereas others are at company level or SC level. Furthermore, modelling possible CSCs require the specification of a number of detailed features (such as their processing capacity or storage capacity, lead/treatment times, thus, operational and circularity features) that greatly constraint the behaviour of the system. Consequently, the modelling methodology should be able to incorporate these aspects.

Multi-range. Some of the indicators described in Section 3.3. refer to the short term, whereas others are more long-term oriented, or both.

Bottom-up and Top-down approaches. The modelling methodology must handle both approaches, as some scenarios are clearly bottom-up while others are top-down.

Complexity. Some of the future circular scenarios described may entail many heterogeneous entities with complex, non-linear relationships among them (possibly including a non-rational behaviour by some of them). Therefore, the modelling methodology must be able to capture these complexities.

Structural and functional optimization capabilities. The four scenarios foresee different forms of optimization: while the modernist SC points to a (SC-wise) optimization via coordination among partners (rather a functional optimization, i.e. an optimization of its performance), the Planned circularity scenario envisions a centralized allocation of the resources across the system, which possibly entails a sort of centralized (i.e. 'optimized') system design (rather a structural optimization, i.e. an optimization of the structure of the system). While both point out to optimization, from the modelling viewpoint it is necessary to distinguish between a centralized SC-design (which is achieved by a centralized matching of the supply and the demand), and the SC-level coordination (which is achieved via operation on an existing network). No single modelling technique can easily cope with such diverse features, so probably a combination of techniques must be sought.

4 MODELLING METHODOLOGIES

4.1 METHODS FOR SUPPLY CHAIN DYNAMICS

Modelling SC dynamics have been approached by different methodologies in the past years. Each modelling methodology is devoted to capture the dynamic behaviour of the SC, but they have different benefits and drawbacks in terms of the outcome they provide. Therefore, the adopted modelling method is mainly related to the research objective.

Different classifications of these methods have been proposed by relevant authors in the field. In the following it follows a summary of the main modelling methodologies adopted for researching the SC dynamics.

Operational Research theory: The problem is expressed as a difference equation, with some parameter variables. The solution sought is one that explicitly minimises a cost function (or a surrogate), for an assumed set of operating conditions. The dynamic performance is implied by the mathematical solution to the problem (Geary et al. 2006). OR theory comprises a disparate collection of mathematical techniques, such as linear programming, queuing theory, Markov chains and dynamic programming. Although not strictly modelling techniques, they are very commonly used in industry (Riddals et al. 2000).

Analytical models: these models describe the behaviour of the system using a number of formulae, so the variables of interest in the system may be expressed as a closed function of a series of input parameters. This modelling approach allows quantifying the effect of the input parameters in the variables of interest as well as deriving the values of these parameters to optimise the variables of interest. Their main drawback is the difficulty to obtain these closed

formulae, which sometimes require the formulation of simplifying hypotheses that may restrict their range of application (Framinan 2022).

Control theory: The problem is expressed in the frequency domain. Using an assumed control law, the solution is obtained by shaping the system frequency response to suit the needs of the user. The dynamic performance is explicit from inspecting this response, whereas the cost performance is implicit (Geary et al. 2006). Control Theory may assume either continuous or discrete time. The approach is generally based on linear systems of transfer functions. A transfer function relates the output of a system to the input of the system in frequency space. The transformation simplifies the calculations considerably, which otherwise would have been complex if executed in the time domain. In order to derive the final solution in the time domain, the solution is converted back from the frequency into the time domain (Holweg and Disney 2005).

Simulation models: These models essentially replicate in the computer the sequence of events followed by the real system that it is intended to model, either as a whole (discrete-event or continuous models) or the behaviour of each one of the individuals or agents in the system, as well as their interactions (agent-based simulation models). Simulation models can be enormously rich as they can capture very complex behaviours, but, however, they are not, in principle, well suited for optimising the variables of interest (Framinan 2022).

- **Continuous time approach:** The continuous time models are based on the notion that one observes all states of the system continuously (Holweg and Disney, 2005). The system must be considered at an aggregate level, in which individual entities in the system (products) are not considered. Rather, they are aggregated into levels and flow rates. Consequently, these methods are not suited to production processes in which each individual entity has an impact on the fundamental state of the system (Riddals et al. 2000). Key approaches include differential equations, often implemented through simulation software like VenSim or iThink.
- **Discrete time approach:** Discrete time approaches assume that time happens at discrete intervals of time. The key implication for the mathematical computation of discrete time systems is that one needs a firm sequence of events (Holweg and Disney, 2005). This approach comprises jobs and resources. Jobs, which, for the majority of applications, are physical entities, travel from resource to resource where their onward progress through the system is determined. The emergence of the discrete time simulation approach was engendered by the deficiencies of differential equation approaches to the solution of even simple problems (Riddals et al. 2006). A major drawback of this approach is the lack of a succinct descriptive language for their formulation. Consequently, the discrete time simulation approach has been primarily associated with 'black box' approaches through a variety of different software, like Arena or Anylogic.
- **Multi-agent approach:** Multi-agent simulation have the capacity to consider the interactions between large numbers of heterogeneous firms (Hearnshaw and Wilson, 2013). This approach assumes that the system is of high complexity, and thus it is very

difficult (or even impossible) to understand the system as a whole. Instead, the modeller can focus on individual elements of the system, and the global behaviour, that cannot be predicted in advance, emerges from their interactions, *i.e.* a bottom-up approach (Nilsson and Darley, 2006). The adoption of a multi-agent approach has several additional benefits, such as an increased modelling realism (e.g., individual agents can be comparable to machines, vehicles, products, or groups of such, found in a real life context), heterogeneity (e.g., there is no need to aggregate different agents' behaviours into average variables), bounded rationality (e.g., agents have local information, having their own goals and policies), scalability, and flexibility (Dominguez and Cannella, 2020).

4.2 METHODS FOR CIRCULAR ECONOMY

A recent review by Demartini et al. (2021) surveys the scientific literature with the aim of identifying and the **most used modelling approaches for circular economy and sustainability studies**. From the 43 relevant works that were in-depth analysed, the following modelling approaches were identified: Agent Based Modelling (ABM) with 15 publications, followed by Input – Output model (IOM) with 6 publications, Lifecycle Assessment (LCA), Material Flow Analysis (MFA), Network Analysis (NA), Mixed Integer Linear Programming (MILP) with 4 publications respectively, and DEMATEL, Ecological network analysis (ENA), and System Dynamics (SD) with 2 publications, respectively. The following is an overview of each modelling approach.

Agent-Based Modelling. ABM has gained significant popularity across various disciplines in recent years. ABM provides a framework to describe the behaviours of complex systems through the interactions of individual agents. These agents are autonomous, heterogeneous, and capable of communication and cooperation (Castro et al., 2020). The primary advantage of adopting ABM in an information systems (IS) network lies in its ability to elucidate learning processes and complex macrostructures by examining the interactions among individual agents. However, it is important to note that ABM is highly path-dependent, requiring extensive sets of parameters and data to accurately describe agent behaviours. Additionally, validation methods can be challenging due to the complexity involved in aligning simulations with real-world data (Pasqualino and Jones, 2020).

Input–Output Model. The IOM is a top-down approach designed to track transactions between activities, measured in monetary units, and extend them to the environmental level in terms of greenhouse gas (GHG) emissions (environmental extended input–output analysis) (Yazan et al., 2016). IOM is frequently used to analyse carbon footprints by accounting for both direct and indirect flows. It is often combined with other modelling methodologies to address dynamic problems (Pollitt et al., 2015). A common combination is IOM and LCA, which evaluates IS by considering different levels of analysis: LCA focuses on micro entities, while IOM addresses macro entities (Fang et al., 2017). IOM typically operates under three key assumptions: (i) linearity between inputs and outputs, (ii) continuity of system behaviour into the future, and (iii) instantaneous adjustment of productive factors to achieve production (Pasqualino and Jones, 2020). Consequently, its application is often limited to short-term evaluations. The primary weakness of IOM lies in the vast amounts of data required to create

the input–output table. Inaccuracies can occur if this data is not precise or if it includes varying degrees of aggregation (Mattila et al., 2010).

Life Cycle Assessment. LCA is a comprehensive tool used to quantify the amounts of resources, materials, and energy consumed, as well as the environmental impacts generated, throughout a product's life cycle—from raw material extraction to its end of life (Finnveden et al., 2009). LCA is frequently integrated with other methodologies such as DES, SD, and IOM (Löfgren and Tillman, 2011; Fang et al., 2017; Mattila et al., 2010). This integration allows for the assessment of impacts on both micro entities (via LCA) and macro entities (via DES, SD, and IOM), providing a holistic view of environmental sustainability.

Material Flow Analysis. Material Flow Analysis (MFA) is an analytical method designed to quantify the stocks and flows of materials and energy, aiming to assess environmental sustainability through various environmental indicators (Sendra et al., 2007). MFA is grounded in the concept of "mass conservation" and employs input/output flows that encompass both material and economic data. It is commonly used to evaluate the environmental impact at the macro level, such as for countries and regions, but is less frequently applied to micro entities like individual products and processes, for which LCA is generally preferred. The main limitations of MFA include its lack of a life cycle perspective and its inability to fully reflect ecosystem impacts (Sun et al., 2017). When applying MFA to industrial symbiosis (IS), specific considerations need to be addressed, as highlighted by Sendra et al. (2007): 1. The integration of MFA with energy and water flow analysis is necessary; 2. Indirect flows associated with companies should be included; 3. Evaluations should encompass both subsystems (individual companies) and the entire network.

Network Analysis. NA is a method used to evaluate the structural and functional characteristics of systems by examining the stock and flow of resources among entities, thereby revealing the underlying network patterns (Szyrmer and Ulanowicz, 1987). In the context of IS, NA employs metrics such as density, centrality, and connectivity to analyse the network structure and understand the complexity of relationships between companies (Zhang et al., 2015a,b; Chopra and Khanna, 2014). NA is also valuable for identifying the functional properties of the network, visually depicting relationships (social networks), quantifying economic and environmental interactions, and defining system boundaries (Zhang et al., 2015a,b).

Mixed Integer Linear Programming. MILP involves optimization problems where some variables are constrained to be integers while others can be non-integers. MILP is widely used in industrial applications such as production planning and scheduling. In IS networks, MILP can be employed to compare different design schemes and processes, as well as to identify potential improvements in the network structure (Wolf and Karlsson, 2008).

Decision Making Trial and Evaluation Laboratory. DEMATEL is an effective method for identifying cause-and-effect chain components in complex systems. It evaluates interdependent relationships among factors, identifying critical ones through a visual structural model. In IS, DEMATEL generates a cause-and-effect map that shows the impact of each company or factor on others (Lin, 2013). These results can be used to assess the primary causal factors that significantly affect the network.

Ecological Network Analysis. ENA tracks the flow of energy and materials from inputs to outputs within a network, analysing the system's structure and function. Applying ENA to IS helps capture indirect interactions, providing deeper insights into the functional and structural properties of the system through ecological flows (Wu et al., 2019).

System Dynamics. SD is an approach to understanding the nonlinear behaviour of complex systems over time by utilizing stocks, flows, and feedback loops. Forrester (1970) outlined key characteristics of SD: (i) system boundaries, (ii) reinforcing and balancing feedback loops, (iii) stocks, which are accumulations within the feedback loops, and (iv) flows, which are the rates of change. SD aims to understand the generation of dynamic changes and to develop strategies and policies to improve system performance (Cui et al., 2018). It traces patterns of system behaviour through feedback structures at an aggregate level over time, making it a suitable method for IS as it captures causal processes and feedback loops (Morales and Diemer, 2019).

All these methods have advantages, but also have their own limitations in order to capture different behaviours of IS and sustainable SCs. As such, some authors have advocated for a **multi-method approach**, in which several methods are combined together in order to overcome some of their limitations. Some of the most important multi-method approaches that can be found in the literature related to circular economy and IS are described next.

DES-SD. The DES-SD hybrid approach is predominantly employed for studying sustainability challenges, though it has not yet been applied to issues of IS. Both DES and SD have been extensively utilized to analyse sustainability within the healthcare sector, as demonstrated in studies by Mielczarek (2019), Mielczarek and Zabawa (2016), and Landa et al. (2018). Additionally, some research has leveraged the DES-SD hybrid model to address specific supply chain and industrial sustainability concerns, including work by Doluweera et al. (2020), Oleghe (2019), and Fakhimi et al. (2015). In this multi-method approach, DES is used to model specific entities, employing state variables that change at discrete intervals. This method effectively captures stochastic elements such as uncertainty and unexpected disruptions, monitoring the evolution of entities in a top-down manner. On the other hand, SD offers a feedback perspective, illustrating the broader system impact of DES entities. It identifies the connections and delays between DES components through feedback loops, uncovering cause-and-effect relationships and investigating the system's dynamic and evolutionary behaviours, also in a top-down approach.

ABM-SD. Several studies utilize the ABM-SD hybrid approach to focus on sustainability issues, including Sitepu et al. (2016) and Golroudbary et al. (2019). Romero and Ruiz (2014) also propose ABM-SD as a suitable method for addressing IS. In this combined approach, SD assumes homogeneity and leverages aggregation concepts. Stocks and flows are aligned with agents to store information critical for their learning processes and to understand their states. ABM captures the heterogeneity of individuals within an interconnected network by utilizing data stored in SD. This approach also employs the dynamic nature of feedback loops to manage agent behaviours over short and long-term periods.

ABM-DES. The ABM-DES hybrid approach is mainly used for analysing sustainable supply chain issues, as shown in studies by Farsi et al. (2019), Mittal and Krejci (2019), and Rondini

et al. (2017). ABM provides a high degree of flexibility and autonomy encapsulation, effectively modelling and capturing the autonomous behaviours of DES entities. The events modelled with DES enable ABM to offer significant flexibility in representing various agent behaviours, cognition, and decision-making processes. DES, known for its superior runtime performance compared to ABM, monitors agent performances and creates specific entities and events that impact agents.

ABM-DES-SD. A few studies integrate all three simulation methods—ABM, DES, and SD—to provide a comprehensive analysis, including works by Gu and Kunc (2019), Elia et al. (2016), and Wang et al. (2014). ABM models complex adaptive systems using self-organizing properties, capturing emergent and learning behaviours. DES simulates distinct agent behaviours by modelling sequences of events at specific times, considering resources, capacities, and interaction rules. SD examines the behavioural patterns and interactions within the network, utilizing aggregate variables to provide a holistic view of the system.

The review highlights the strengths and limitations of each method, advocating for hybrid approaches to address their shortcomings. For instance, the DES-SD hybrid combines Discrete Event Simulation (DES) with System Dynamics (SD) to capture both specific events and broader system feedbacks. DES is particularly effective at modelling specific entities and their stochastic behaviours, allowing for detailed examination of uncertainties and disruptions at discrete time intervals. On the other hand, SD offers a macroscopic perspective by focusing on feedback loops and the flow of resources over time. By combining these two methods, the DES-SD hybrid can provide a more holistic analysis of sustainability challenges, considering both micro-level events and macro-level system behaviours. Other hybrid approaches, such as ABM-SD and ABM-DES, also integrate multiple methodologies to leverage their respective strengths. The ABM-SD hybrid approach combines Agent-Based Modelling (ABM) with SD, effectively capturing the heterogeneity and interactions of individual agents while also considering the dynamic feedback mechanisms within the system. This approach is particularly useful for understanding how individual behaviours and decisions impact overall system dynamics over both short and long terms. Similarly, the ABM-DES hybrid approach merges the flexibility and autonomy encapsulation of ABM with the efficiency and performance of DES. ABM provides the ability to model complex adaptive behaviours of agents within a system, while DES offers superior runtime performance and detailed event-based analysis. This combination allows for a nuanced study of sustainable supply chains, where individual agent behaviours and their interactions can be examined in the context of larger system processes and constraints. By integrating these various methods, hybrid approaches provide a comprehensive toolset for studying sustainable supply chains and industrial symbiosis. They enable researchers to address the limitations of individual models, such as the extensive data requirements of ABM or the aggregation issues in IOM, and to create more robust and accurate simulations of real-world systems. This multi-method strategy enhances the ability to develop effective strategies and policies for sustainability

5 SELECTION OF MODELLING METHODOLOGIES

In the previous sections we have reviewed the main modelling methodologies for the analysis of supply chain dynamics and circular economy. We conclude that no single methodology seems to be able to fulfil all the requirements posed in section 3.4. Therefore, a combination of different methodologies (also known as a multi-method or hybrid approach) will be required. Demartini et al. (2022) also advocates for a multi-method for modelling IS. More specifically, in view of the requisites, it seems that a combination of **analytical models** (at the design/allocation level) and **simulation** (at an operation level) could fulfil the requisites posed.

Analytical models are **top-down** approaches that can be treated using optimization techniques, which are necessary to optimize the **structure and functionality** of the four scenarios that will be analysed in this project. On the other hand, simulation has been widely used in SC evaluations (Corsini et al., 2023), and it can support managers in the decision-making process because it can help them understand complexities, dynamics and interactions that characterize SCs (Oliveira et al., 2016). Simulation allows for an accurate replication of the **dynamic** aspects of the SC. In addition, simulation can easily accommodate heterogeneous entities with complex, non-linear relationships among them, making possible the development of the **complex** models that are required to capture the behaviour of ISNs. Also, current computer technology coped with the high efficiency of most simulation platforms make possible to run complex **multi-range** simulations (i.e., short-term and long-term) in a very short time. Within simulation techniques, researchers have extensively used **ABM**, due to the link between agents and SC members (Cannella et al., 2018). ABM refers to a category of computational models invoking the dynamic actions, reactions, and intercommunication protocols among the agents in a sharing environment to evaluate their performance (Abar et al., 2017). This is a **bottom-up** approach that allows to model the individual behaviour of the (physical and logical) elements in the SC and describe their interactions. This has several advantages for SC simulation, such as the possibility to develop and implement simulation models with multiple layers and achieve a resilient and flexible system (Abar et al., 2017). These features permit modelling at **multiple granularity levels**, from individual elements (such as personal or material) to higher level functionalities (such as departments or an entire company). In addition, each agent or element of the model can be combined with other agents to form a higher-level agent, allowing for nested structures and a high re-usability of each agent, model or sub-model developed. Therefore, ABM shows a high **flexibility**, and can be used to model the quite different SC structures, behaviours, and policies derived from the scenarios with less effort than other simulation techniques (such as SD, or DES) in which the elements and their behaviour are usually 'hardwired'. However, SD and DES models can be embedded within an agent (ABM-SD-DES approach, see section 4.2), enhancing the complexity of agent's behaviours and permitting a combination of bottom-up and top-down approaches. Finally, ABM is fully consistent with SC realities (Long and Zhang, 2014), and represents one of the most appropriate methodologies to analyse the complex dynamics that characterize an industrial system adopting CE practices (Romero and Ruiz, 2014; Demartini et al., 2022), as it is demonstrated by recent publications in the field of IS (Fraccascia, 2019;

Yazan & Fraccascia, 2020) as well as in the field of CLSCs (Díaz Fernández et al., 2012; Dominguez et al., 2021; Ponte et al., 2017; Naghavi et al., 2020).

5.2 SELECTION OF MODELLING TOOLS

Simulation models are developed using computer tools, which often consist in a set of libraries with pre-programmed functionalities. These tools may come with additional features such as a user interface, visualization environment (to visualize the behaviour of the model in real time) or auxiliary elements for data analysis. Following the discussion of the previous section, in this section we describe some of the most important ABM tools and provide a categorization of such tools according to a set of key features to identify the most suitable one for the development of the SC models that are required by this project. In the following we provide a brief description of each tool:

Netlogo: NetLogo is a versatile and user-friendly programming environment designed for simulating natural and social phenomena, particularly suited for agent-based modelling. Developed by Uri Wilensky in 1999 at Northwestern University, it allows users to create and manipulate models where individual agents operate based on defined rules, leading to complex, emergent behaviours. With a rich library of pre-built models, an intuitive graphical interface, and robust visualization tools, NetLogo is accessible to users at all skill levels. It is widely used in education and research for exploring complex systems in fields such as ecology, economics, social sciences, and beyond.

Repast: Repast (Recursive Porous Agent Simulation Toolkit) is a sophisticated and flexible platform for creating, running, and analysing agent-based simulations. Initially developed by the University of Chicago's Social Science Research Computing group, Repast is designed to facilitate complex modelling and simulations of agent interactions within dynamic environments. It offers a range of libraries and tools that support large-scale simulations, high-performance computing, and integration with other software. Repast is widely used in research across various disciplines, including social science, economics, biology, and environmental science, enabling researchers to model and study intricate systems and phenomena. Its modular architecture and support for multiple programming languages, including Java, Python, and C#, make it a powerful tool for developing detailed and scalable simulations.

Anylogic: AnyLogic is a powerful and versatile simulation software designed for modelling complex systems and processes. Developed by The AnyLogic Company, it supports multiple simulation methodologies, including discrete event simulation (DES), agent-based modelling (ABM), and system dynamics (SD), making it unique in its ability to model diverse types of systems within a single platform. AnyLogic is widely used across various industries, such as logistics, manufacturing, healthcare, and transportation, for tasks like optimizing operations, analysing SCs, and predicting system behaviour under different scenarios. Its user-friendly interface, extensive libraries, and integration capabilities with other tools and databases provide a comprehensive environment for developing, running, and analysing simulations, helping organizations make informed decisions and improve efficiency.

MASON: MASON (Multi-Agent Simulation Of Neighborhoods) is a high-performance, discrete-event multi-agent simulation library developed in Java by George Mason University's

Evolutionary Computation Laboratory and the Center for Social Complexity. Designed for creating and running large-scale, computationally intensive simulations, MASON provides a flexible and efficient framework for developing complex models of interacting agents. It is particularly well-suited for research applications in fields such as social science, economics, and artificial intelligence, where understanding the behaviour of decentralized systems is crucial. MASON's architecture is highly modular, allowing for the easy integration of custom visualization and analysis tools, and its ability to handle extensive simulations makes it a valuable tool for researchers and developers seeking to explore and analyse intricate system dynamics.

GAMA: GAMA (GIS Agent-based Modelling Architecture) is a robust and extensible simulation platform designed for building spatially explicit agent-based models. Developed by the GAMA development team, it is tailored for researchers and practitioners who need to model complex systems where geographic information systems (GIS) play a crucial role. GAMA supports the creation of large-scale simulations with detailed environmental data, allowing agents to interact with rich spatial environments. It features a user-friendly interface, powerful visualization tools, and a flexible scripting language that enables the development of sophisticated models. GAMA is widely used in fields such as urban planning, ecology, disaster management, and socio-economic studies, providing valuable insights into spatial dynamics and helping to inform decision-making processes. Its ability to integrate with various data sources and simulation frameworks makes it a versatile tool for analysing and understanding complex spatial phenomena.

Python (Mesa and PyABM): Python is a versatile and widely used programming language, and several libraries and frameworks support agent-based modelling. Mesa and PyABM are examples of Python-based libraries that facilitate the development of agent-based models.

- Mesa is an open-source Python library designed for building and visualizing agent-based models. Developed with a focus on simplicity and ease of use, Mesa enables researchers, educators, and developers to create complex simulations with minimal coding effort. The library provides a flexible and modular framework, supporting the rapid development and analysis of models where individual agents interact within a defined environment. Mesa includes built-in tools for visualization, data collection, and analysis, making it easy to monitor and interpret the behaviour of agents over time. Its integration with the Python ecosystem allows users to leverage a wide range of libraries and tools for further data processing and visualization. Mesa is widely used in academic research, education, and industry for modelling social systems, economic processes, ecological dynamics, and more, making it a valuable resource for understanding and exploring agent-based systems.
- PyABM (Python Agent-Based Modelling) is an open-source library designed to facilitate the development and analysis of agent-based models using the Python programming language. PyABM aims to provide a straightforward and flexible framework for researchers, educators, and developers to create simulations where individual agents operate based on specified rules and interact within a defined environment. The library supports the construction of complex models with minimal overhead, making it accessible to users with varying levels of programming expertise.

PyABM integrates seamlessly with Python's extensive ecosystem of scientific and data analysis tools, enabling users to perform in-depth analysis and visualization of their simulations. It is particularly useful for studying dynamic systems in fields such as social science, economics, ecology, and epidemiology, offering a powerful toolset for exploring and understanding the emergent behaviours of agent-based systems.

AgentScript: AgentScript is a lightweight, open-source library designed for building agent-based models in JavaScript. Tailored for web-based simulations, AgentScript allows users to create and run models directly in the browser, making it highly accessible and easy to share. The library supports the creation of individual agents that follow specified rules and interact within their environment, facilitating the exploration of complex system behaviours. With its intuitive syntax and seamless integration with web technologies, AgentScript is ideal for educators, researchers, and developers who want to visualize and analyse agent-based models online. It is particularly useful for interactive demonstrations, educational tools, and research applications that benefit from the accessibility and immediacy of web-based deployment. By leveraging JavaScript, AgentScript takes advantage of modern web development capabilities, providing a versatile platform for dynamic and interactive simulations.

JADE: JADE (Java Agent Development Framework) is a comprehensive software framework for developing multi-agent systems in Java. Designed to simplify the creation of distributed and collaborative applications, JADE provides a set of tools and libraries that facilitate the implementation of intelligent agents and the coordination of their interactions. The framework offers a rich set of features, including agent communication, message passing, and agent lifecycle management, enabling developers to build complex systems where agents can autonomously interact with each other and their environment. JADE supports various communication protocols and standards, making it suitable for building interoperable and scalable multi-agent systems. Its modular architecture and extensive documentation make it a popular choice among researchers, developers, and organizations seeking to leverage agent-based technology for solving complex real-world problems. JADE's versatility and robustness make it a valuable tool for building intelligent systems in domains such as automation, logistics, telecommunications, and more.

SCOPE: SCOPE is software tool for complex SC modelling. This tool was implemented using the Swarm libraries, specifically designed to build MAS-based models. The scalability of MAS modelling allows SCOPE to create a wide range of SC configurations with any number of companies distributed in any configuration along the SC. Agents can be customized to model a wide range of operational policies and behaviours and represent the different nodes of the SC. Thus, every node in the model can be set up with different policies and parameter values for the different business functions. The schedules (a key feature of Swarm) implement the sequence of actions that each agent perform during the simulation.

In order to select the most appropriate ABM tool, according to the requirements of the present project, we have defined a set of key features, which are summarized next:

- **User Interface:** A user interface generally makes easier the development, treatment, and analysis of simulation models
- **Programming Language:** Describes the programming language of the tool.
- **Multimethod:** The platform allows the creation of simulation models combining ABM with other suitable techniques, such as DES or SD. This is an important feature to consider, since it has several important advantages as discussed in previous sections.
- **Visualization tools:** The ABM tool integrates visualization tools or libraries that allow the visualization of the results in real time, as well as the visualization of the behaviour of the model (2D or 3D). This feature makes the interpretation of the results and the debugging of the model easier for the users, and it helps to the presentation of the results to other member of the project.
- **Support:** Refers to the current support from the developers and the community in terms of updates, forums, material, etc.
- **License:** Refers to the type of licence/s available (Open Source, PLE, Professional, etc.).
- **Team experience:** Refers to the previous experience of the team working with the tool.
- **Publications:** Number of scientific articles written in English published in journals within the topic of “supply chains”.
- **Other features:** Describes other important features of each tool that may help to make a decision.

The table below provides a categorization of each ABM tool according to these features. Based on the provided table, AnyLogic stands out as the best software for ABM for several reasons:

1. **Multimethod Simulation:** AnyLogic supports multiple modelling methods, including DES, SD, and ABM. This flexibility allows modellers to combine different methods to suit their specific needs, providing a more comprehensive modelling approach compared to other tools that may focus on only one or two methods.
2. **Visualization Tools:** AnyLogic offers advanced visualization tools, which are crucial for developing, analysing, and presenting models. High-quality visualization helps in understanding complex agent interactions and system behaviours, making it easier to communicate findings to stakeholders.
3. **Support:** The level of support for AnyLogic is rated as high, which is essential for troubleshooting, learning, and optimizing models. Good support can significantly reduce

the time needed to develop and refine models, ensuring users can effectively utilize the software's capabilities.

4. **Licensing Options:** AnyLogic offers various licensing options, including a free Personal Learning Edition (PLE), as well as university and professional licenses. This range of options makes it accessible for different user groups, from students and educators to professional modellers.
5. **Team Experience:** The team experience with AnyLogic is rated as high, indicating that the team has been substantially working with the software, including some published works in high quality journals.
6. **Publications:** With 39 publications, AnyLogic has a significant presence in academic and professional research. This high number of publications suggests that AnyLogic is a trusted and widely used tool in the field of simulation and modelling, contributing to its credibility and validation by the research community.
7. **Additional Features:** AnyLogic offers a range of additional features that enhance its utility, such as experimentation and optimization tools, as well as integration and connectivity capabilities. These features enable users to conduct thorough experiments and optimize their models efficiently, while also integrating with other systems and tools.

Comparatively, other software like NetLogo, Repast, MASON, and others have their own strengths but may lack in one or more areas where AnyLogic excels. For example, NetLogo is praised for its ease of use and integrated modelling environment, but it does not support multimethod simulation. Repast offers good multi-language support and integration with other tools but doesn't match AnyLogic's breadth of simulation methods and publication record. Finally, SCOPE is the only ABM tool rated as SC oriented, but it lacks of current support, user interface or visualization tools.

Therefore, considering the comprehensive suite of features, high support level, flexible licensing, team experience, and substantial user and publication base, AnyLogic emerges as the most suitable software for the development of this project.

	Interface	Language	Multimethod	Vis. tools	Support	License	Team experience	No. of pubs.	Other features
NetLogo	Yes	Logo (Java-based)	No	Yes	High	Open-source	None	9	Ease of use Integrated Modelling Environment Spatial dynamics
Repast	Yes	Java, Python, and C#	Yes (SD)	Yes	High	Open-source	None	6	Designed for use on workstations and small computing clusters. Multi-Language Support. Easy Integration with Other Tools
AnyLogic	Yes	Java	Yes (DES, SD)	Yes	High	Free (PLE) University Professional	High	39	Good integration of 3 simulation methods Experimentation and optimization tools Integration and connectivity
MASON	No	Java	Yes (DES)	Yes	Medium	Academic Free License	None	4	Efficiency and performance Tools and Libraries (spatial, scheduling,) Support for GIS integration
GAMA	Yes	GAML	No	Yes	Medium	Open-source	None	2	Ease of use Spatial dynamics, integrating geographic information systems (GIS) Tools for experimentation and analysis
Python (Mesa, PyABM)	No	Python	No	Yes	High	Open-source	Low	1	Ease of use Batch processing and data collection Extensibility
AgentScript	No	JavaScript	No	Yes	High	Open-source	None	0	Ease of use Web-Based Modelling Lightweight and Fast
JADE	Yes	JADE	No	Yes	High	Free (limited) Commercial	None	18	Robust infrastructure for agent communication (FIPA compliance) Scalability and extensibility Interoperability
SCOPE	No	Java	No	No	Low	Owned	High	12	Supply Chain oriented Conceived for modelling complex structures Includes traditional and circular policies

Table 11. Summary of tools

6 CONCEPTUAL MODELLING FRAMEWORK

Considering all that has been discussed the previous Sections, here a conceptual modelling framework for a generic node in a Circular Supply Chain is proposed.

Noting that the CSC definition provided by Batista et al. (2018) "*the coordinated forward and reverse supply chains via purposeful business ecosystem integration for value creation from products/services, by-products and useful waste flows*" a SC node i belonging to a CSC, in addition to the forward input and output material flows there are new flows of different nature. They can be Reverse flows, when they involve EOL products, i.e. Closed-loops or Open-loops, and they can be Symbiotic flows, when they involve waste/by-products generated in production processes. In the former case, closed-loops interest the same SC, while open-loops involve different SC. In the latter, also the flows can be inter-SC and intra-SC. Specifically, if inter-SC all SC nodes of different SCs that belong to the same CSC can provide the symbiotic flow for a specific node, if intra-SC, all the SC nodes of the same SC except for the direct downstream node, as it is its customer for the main product.

According to these definitions, it follows that in a CSC composed of K SCs where each k SC is composed of N_k nodes, the ik -th node can have $\sum_{k=1}^K N_k - 2$ possible outgoing symbiotic flows, $\sum_{k=1}^K N_k - 1$ possible incoming symbiotic flows, $K - 1$ possible incoming open-loop reverse flows, 1 possible incoming closed-loop reverse flow.

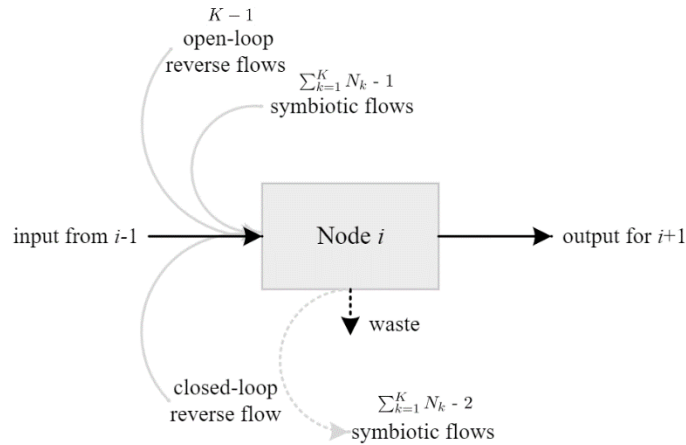


Figure 2. Circular Supply Chain Node

The generic node abstraction allows the model to be applicable across different CSC archetype since each node can be viewed as a modular component that can be easily integrated into a more complex CSS. Thus, this modularity supports the construction of complex CSC by combining multiple nodes with defined interfaces as it can be also adjusted to reflect different processes, resources, and interactions specific to each SC node. As well as the four different scenarios above mentioned.

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