Journal of Cleaner Production 574 (2026) 149117

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

An integrated modelling framework for feedback-driven and mass-balanced circular economy analysis

Salman Alfarisi [a,b,*], Ryu Koide [a,c,d], Jennifer L. Hawkin [e], Fanran Meng [e], Takuma Watari [a,**]

[a] Material Cycles Division, National Institute for Environmental Studies, Tsukuba, Japan
[b] Faculty of Engineering, Kyoto University of Advanced Science, Kyoto, Japan
[c] Faculty of Technology, Policy and Management, Delft University of Technology, Delft, the Netherlands
[d] Graduate School of Engineering, The University of Tokyo, Tokyo, Japan
[e] School of Chemical, Material and Biological Engineering, The University of Sheffield, Sheffield, United Kingdom

ARTICLE INFO

Keywords:
Material flow analysis
System dynamics
Circular economy
Dynamic behavior

ABSTRACT

Achieving a circular economy requires not only quantifying material stocks and flows but also understanding the dynamic processes that shape them over time. While Material Flow Analysis (MFA) is widely used to track physical stocks and flows, MFA has limited capacity to represent behavioral feedback, endogenous system responses, and temporal delays. System Dynamics (SD), by contrast, is well suited to capturing feedback structures and non-linear system behavior, but it does not inherently enforce mass conservation. Despite these fundamental differences, the two approaches are often applied without a clear conceptual distinction. Here, we compare and integrate MFA and SD to develop a modelling framework that is both mass balanced and feedback driven. Using three simplified models (MFA, SD, and integrated SD-MFA), we demonstrate that the integrated approach can simultaneously preserve mass balance and represent causal relationships, feedback loops, and time delays. The combined framework offers a more robust basis for analyzing circular economy transitions, enabling the assessment of not only how materials flow through systems, but also how socio-technical dynamics influence those flows over time.

1. Introduction

Advancing sustainable development requires innovative strategies, among which the Circular Economy (CE) has emerged as a transformative model (Saidani et al., 2019). The United Nations Industrial Development Organization (2025), for instance, has documented 99 published national CE policy frameworks and 4319 individual policy actions. The proliferation of these regulatory frameworks creates a direct need for quantitative and dynamic modelling tools capable of evaluating transition pathways towards a CE and their implications for material systems. CE goes beyond waste reduction, promoting the design of products and systems that enable recovery and reintegration of materials into the economy, provided that such processes remain viable across environmental, technical, social, and economic dimensions (Millward-Hopkins et al., 2018). It emphasizes reducing, reusing, recycling, and recovering materials throughout the product lifecycle, aiming to decouple economic growth from environmental degradation and resource depletion (Linder et al., 2017; Zhang et al., 2024). However, the impacts and challenges of the CE are multi-dimensional, systemic and inherently complex (Iacovidou et al., 2021). Fragmented interventions may therefore generate unintended consequences, including rebound effects arising from feedback loops, time delays, and interactions across multiple parts of the system (Abdoli et al., 2019). Effective implementation of CE strategies consequently requires a systems-level understanding that focuses on the relationships and interactions among system elements rather than examining them in isolation.

Material Flow Analysis (MFA) offers a basis for understanding the material stocks and flows within defined systems, grounded in mass balance principles (Baccini and Brunner, 2012; Brunner and Rechberger,

* Corresponding author. Material Cycles Division, National Institute for Environmental Studies, Tsukuba, Japan.
** Corresponding author.
E-mail addresses: salman.alfarisi@kuas.ac.jp (S. Alfarisi), watari.takuma@nies.go.jp (T. Watari).

https://doi.org/10.1016/j.jclepro.2026.149117
Received 23 April 2026; Received in revised form 14 July 2026; Accepted 29 July 2026
Available online 7 August 2026

2016). It is a widely accepted and well-used tool in the discipline of industrial ecology (Islam and Huda, 2019) and is essential to quantify and communicate the material limits to circularity (Zanon-Zotin et al., 2026). For example, it has been used to quantify the constraints on potential future steel recycling due to copper contamination (Daehn et al., 2017) and plastic recycling due to the challenges of secondary material use (Klotz et al., 2023). While this physical basis is essential, successful implementation of CE strategies and effective policies requires understanding the underlying causal relationships that determine how material flows respond to changes in demand, policy interventions and investment decisions (Müller, 2006). System Dynamics (SD) can provide such insights by modelling the structure of complex systems through material and information feedback formed around stocks, flows, and auxiliary variables (Forrester, 2017), capabilities that MFA alone cannot provide. Notwithstanding their respective strengths, both methods have fundamental limitations when applied in isolation. MFA, whilst physically rigorous, relies on externally defined flow paths and cannot capture how a material system adapts internally to policy interventions, economic signals or social decisions. SD, whilst capable of depicting complex feedback and non-linear dynamics, does not inherently guarantee mass conservation: material flows may result from behavioural rules that ignore the availability of upstream stocks, leading to physically possible but nonsensical trajectories, which Coyle (2000) described as 'ghost accumulation'. These complementary limitations motivate this work to consider their integrations.

Among the various approaches that have been combined with MFA to represent socio-economic drivers, including economically extended MFA (Kytzia et al., 2020) and broader social science modelling frameworks (Binder, 2007), SD has attracted particular attention for its ability to represent feedback dynamics, temporal delays and non-linear system responses (Forrester, 1994; Sterman, 2000), capabilities which Binder (2007) identifies as a key advantage in material flow modelling. Several studies have attempted to couple MFA and SD to describe the dynamic behavior of material systems, however, existing research has predominantly focused on application-specific implementations rather than on the fundamental structural construction of System Dynamics models themselves. Pfaff et al. (2018) attempted to combine MFA and SD by examining the dynamic interactions between mineral supply and demand. More recent applications include Zhang et al. (2024), who analyzed the impact of technological innovation on concrete systems, and Teseletso and Adachi (2022), who investigated the supply-demand balance for copper and iron using a coupled MFA-SD model. In the context of the CE, Guzzo et al. (2022) combined both methods to support transition efforts toward a CE. However, a review of these coupling efforts suggests that the conceptual relationship between MFA and SD is often not explicitly articulated, with most studies emphasizing application-specific implementations rather than clarifying how mass balance is maintained within structural boundaries (see Baars et al., 2022; Choi et al., 2016; Pfaff et al., 2018).

To address this gap, we first clarify the conceptual differences between MFA and SD and explore the main sources that distinguish the two methodologies. We then compare three different models: (i) MFA, (ii) SD, and (iii) integrated SD-MFA to represent an industrial flow case. The results of this research show that MFA and SD are structurally complementary: MFA provides the laws of mass conservation, whilst SD provides behavioural mechanisms endogenously. The integration of these two approaches resolves the fundamental tension between physical consistency and realistic systems behaviour, which neither method can resolve on its own. We demonstrate that integrating the two allows for a more cohesive representation of physical consistency, dynamic feedback, and time delays, thereby providing a stronger analytical foundation for understanding and supporting the transition to a CE.

2. Concept review

MFA and SD are two distinct methodologies, yet they possess the capacity to complement each other in the comprehension of intricate systems. We conduct a comparative analysis of these two methodologies, focusing on five aspects: roots, principles, objectives, time representation, and scope. Collectively, these dimensions capture the following: (i) the theoretical foundations (roots and principles), (ii) the analytical intention (objectives), and (iii) the modelling implementation implications (time representation and scope/boundary definition). Collectively, these aspects encapsulate not only the functionality of each method, but also the underlying rationale of its design and the mechanisms that generate insights. Fig. 1 offers a visual representation of the fundamental conceptual distinctions between MFA and SD.

Origin: MFA is rooted in industrial ecology, offering a systematic framework for the analysis of material flows and the assurance of mass balance. This method is widely used to systematically monitor the flow and stock of materials through the economy and identify areas where action is most needed. Conversely, SD, developed by Forrester (1994), is rooted in systems thinking and control theory (Richardson, 1991; Sterman, 2000). SD integrates qualitative mapping of system elements, causal relationships and flow directions (including feedback loops) alongside quantitative modeling to examine how system structures and parameters influence system behavior over time (Morecroft, 2015; Sterman, 2000).

Principle: According to Schwab and Rechberger (2018) and Laner and Rechberger (2016), MFA primarily emphasizes data quality and mass balance. MFA treats materials as entities that can be measured and tracked across predetermined system boundaries (Graedel, 2019). Accordingly, a core principle of MFA is systematic and comprehensive quantification of pertinent material flows and stocks. Another key principle is internal consistency, requiring that all flows within the system comply with the law of mass conservation. Conversely, SD focuses on elucidating how system structures influence dynamic behavior, including the effects of feedback loops, time delays and unanticipated consequences, such as rebound effects (Gonella and de Gooyert, 2024; Laner and Rechberger, 2016). As such, SD principles are the interactions between variables and the ways in which these interactions shape long-term behavior over time.

Aim: The fundamental aims of these two approaches lie in their respective focal points. The primary aim of MFA is to track the physical movement and accumulation of materials, revealing inefficiencies and dominant flows within material systems. It has been widely applied to measure material cycles at various scales and material types, including metals (e.g., copper, zinc, iron, and aluminum), plastics, construction minerals, fibers, and agricultural products, at regional, national, and global levels (Graedel, 2019). The field of SD, in contrast, focuses on the interactions between factors, feedback loops, and delays that drive system behavior. It has been applied to model such nonlinear dynamics that shape long-term trajectories across a range of complex systems, including energy and climate policy, supply chains, healthcare, and sustainability transitions (Sterman, 2018). This perspective is particularly valuable in the context of CE transitions, where interventions often produce unintended consequences (Metic et al., 2024).

Scope: As noted above, the scope of MFA includes only physical flows and stocks of materials, typically bound at a predetermined global, national or regional level (Bringezu et al., 2003). In contrast, SD encompasses broader economic, technological, and social dimensions (Chen et al., 2024; Gao et al., 2020). The primary scope of SD extends beyond physical flows to include how non-physical aspects (e.g., policy, technological innovation and socio-economic) form an interconnected structure that generates non-linear behavior.

2.1. Comparison of similar terminologies

Several terms, such as "dynamic", "stocks", and "flows", are used in both MFA and SD (Choi et al., 2016) but their meanings and applications are different in each context. This section, therefore, aims to clarify such terms to ensure conceptual accuracy in each methodology. Establishing

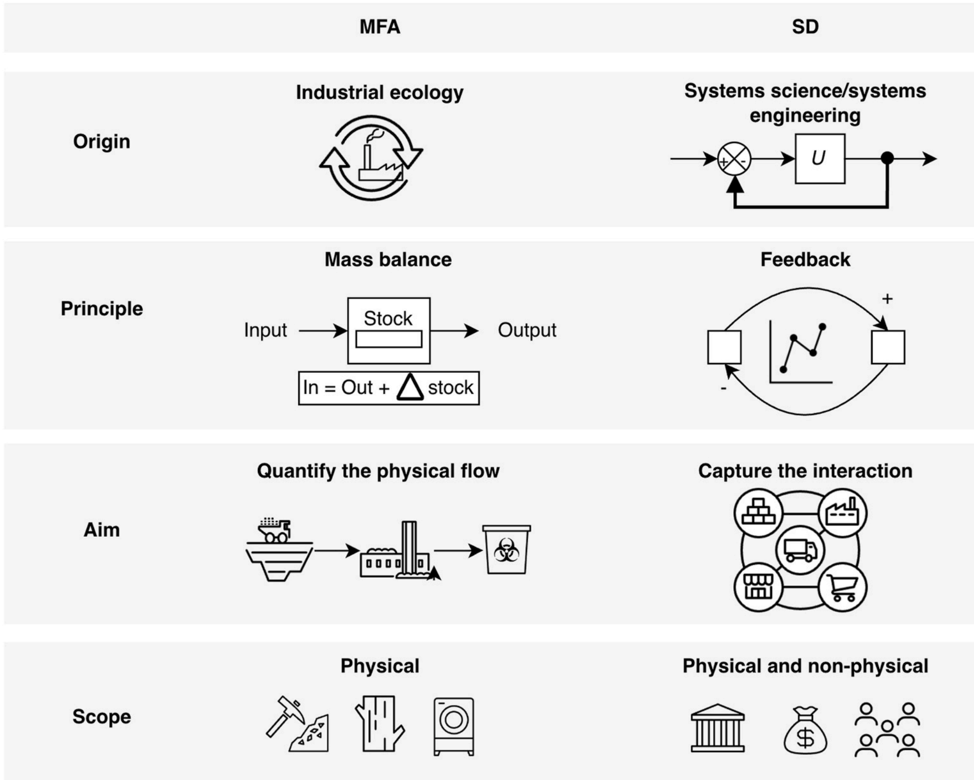

Fig. 1. Concept clarification between MFA and SD. (1) Origins - MFA: derived from industrial ecology; SD: derived from systems science and engineering, where system behavior is governed by feedback control structures; (2) Principle - MFA: the mass balance principle, which requires that all materials entering the system be accounted for as stock accumulation or outflow; SD: the feedback principle, in which stocks influence their own rate of change through causal loops; (3) Aim - MFA: quantifying physical material flows from extraction, use, to the end of life; SD: capturing the interactions behaviors among system variables; (4) Scope - MFA: physical materials tracked within defined system boundaries; SD: physical and non-physical materials (e.g. social and economic behaviors, policy).

such clarity is essential for the consistent use of terminology and, ultimately, for enabling effective model integration.

Dynamic: The term "dynamic" is used in both MFA and SD, yet it embodies different meanings. In Dynamic MFA (DMFA), the term "dynamic" is used to denote the temporal evolution of material stocks and flows. It captures how material inflows, accumulation, and outflows change over time (Deng et al., 2023). For instance, simulate stock accumulation and changes in inflows and outflows generated to maintain, expand, or replace stocks based on mineral stock accumulation (Liu et al., 2022). This enables researchers to estimate, for example, future waste availability or evaluate the impact of recycling policies (Streeck et al., 2023).

On the other hand, within SD frameworks, the term "dynamic" signifies the behavior of a system that is subject to influence by internal feedback, nonlinearity, and time delays (Wang et al., 2022; Xinfeng et al., 2023). The SD paradigm not only tracks quantities but also prioritizes understanding the interplay among system components and environments, considering aspects such as technology adoption, market reactions, regulatory changes, and user behavior. This interplay is sometimes non-intuitive (Mutingi, 2014). The modeling process uses cause-and-effect diagrams and stock-and-flow structures to simulate long-term system trajectories and evaluate the outcomes of various policy or behavioral interventions.

Systems: MFA delineates “systems” in concrete, geographical, and process-based terms. For example, the system might represent a specific facility, an industrial sector at a global scale or a defined set of materials or products within a specific region. In each case, the system is defined as a collection of physical components (or processes), the material flows that connect them, and clear spatial-temporal boundaries that often align with administrative regions to facilitate data access and policy relevance (Brunner and Rechberger, 2016). In this context, a system can be classified as open or closed depending on whether it exchanges material with its environment.

Conversely, in SD, “systems” predominantly emphasize interacting structures and behaviors, such as stocks, flows, feedback loops, and delays, which generate dynamic patterns over time (Forrester, 1994; Sterman, 2000). In this paradigm, systems are defined by the feedback loops and accumulations that drive behavior, with boundaries set by causal relevance. Accordingly, whereas MFA systems are based on measurable physical realities, SD systems capture causal structures and behaviors, enabling exploration of how system dynamics evolve over time.

Stock: In the context of MFA, “stock” is defined as the physical accumulation of materials within a defined system at a specific point in time (Müller et al., 2014). This can be expressed as stock at facilities (the accumulation of materials at production, distribution, or waste management sites), or as in-use stock (the materials embedded in products and infrastructure currently serving societal functions).

The concept of “stock” in SD extends that used in MFA, making it more abstract and system oriented. More specifically, stock is defined as the accumulated state variables that undergo temporal changes in response to inflows and outflows (Ruth and Davidsdottir, 2008). For example, variables such as desired capacity or expected demand can be represented as stocks, as they evolve gradually over time without representing physical material accumulation. Mathematically, the stock are treated as a state variable whose dynamics are commonly governed by differential equations, which may or may not be autonomous or coupled with other state variables.

Flow: The term "flow" in the context of MFA refers to the physical movement of materials into, through, and out of a system, such as production, imports, recycling, and disposal (Müller et al., 2014). This movement is typically expressed in units of mass per time (e.g., tons per year). In SD, "flows" refers more generally to the rate of change that alters existing stocks. It is driven not only by external inputs but also by the system's internal dynamics (Sterman, 1984).

2.2. Potential benefits of integrating MFA and SD

Building on the methodological distinctions outlined above, integrating MFA and SD helps address limitations that arise when physical accounting and dynamic system behavior are treated separately. Such integration enables a unified representation of CE transitions, in which material stocks and flows remain physically consistent while system behavior evolves endogenously over time.

Ensuring system behavior consistent to mass balance: every stock-flow relationship is governed by the mass balance principle, a tenet that is repeatedly emphasized in the literature (Brunner and Rechberger, 2016; Cullen and Cooper, 2022). SD offers more flexibility in representing complex dynamics and feedback loops, but it places the entire responsibility for mass conservation on the model designer. Without explicit constraints or systematic tracking of all inflows and outflows, SD models can suffer from inconsistencies or 'ghost accumulation' when flows are omitted or inaccurately represented. As Coyle (2000) posits, oversimplification in SD modelling has often led to such failures. In theory, mass balance can be enforced for each individual flow, for example, by adding constraints at each node. It is not guaranteed by the method itself, however, and this piecemeal approach can lead to inconsistencies.

In this respect, integrating MFA with SD has clear advantages. MFA systematically ensures that all material flows and stocks adhere to the principle of mass conservation, and SD provides the capability to explore dynamic behaviors, feedback and policy impacts over time. Previous integration efforts used MFA for static baseline measurements, which were subsequently used as constraints SD for scenario exploration (see Choi et al., 2016)). We propose a stronger integration in which MFA principles are directly integrated into the SD stock-flow structure, ensuring that each simulation step complies with conservation laws.

Understanding socio-economic drivers in circular economy transition: The transition to a circular economy is shaped not only by material availability but also by investment decisions, technological development, market conditions, and regulatory interventions. These factors often interact through feedback mechanisms and adjustment lags that influence system performance. SD modeling complements MFA by explicitly representing these endogenous drivers and their interactions. Consequently, integrating these two approaches enables an analysis of material systems that considers not only physical resource availability but also the behavioral and organizational processes determining how those resources are utilized over time.

Modeling time and dynamic aspects of policy intervention in circular economy: The transition to a circular economy necessitates an evaluation of policies and strategies whose impacts will only become apparent over the long term. Although MFA can technically represent flows associated with the circular economy, such as repair or reuse, MFA studies typically treat the in use phase as an aggregate black box. Consequently, the internal circulation of materials through circular economy pathways remains invisible, not due to technical limitations, but because of the most common choice of system boundaries made in practice. Further, while MFA can quantify the changes in physical stocks and flows, it cannot explore the socio-technical, or behavioral drivers that produce these changes. SD, in contrast, explicitly considers time-dependent behavior and the impact of policy interventions on the evolving use and circulation of materials over time. Integrating MFA and SD enables a simultaneous assessment of physical material circulation and dynamic system responses, thereby providing a more comprehensive basis for evaluating recycling strategies, resource recovery systems, product life extension, and various other circular economy initiatives. This integrated perspective assists decision-makers in assessing not only whether the level of circularity is increasing, but also whether such an increase remains physically achievable and sustainable in the longterm.

3. Model integration

In this section, we demonstrate the integration of MFA and SD using a simplified case. The main objective is to describe the key modeling principles necessary to achieve a coherent and mass-balanced dynamic representation of material systems. To implement an integrated model, we consider common material cycles and propose a set of guiding principles for integrating MFA and SD in a consistent and transparent manner.

3.1. Principles for integrating MFA and SD

3.1.1. System definition alignment

In this study, system definition is aligned by explicitly distinguishing between a physical accounting layer and an endogenous decision layer. Material stocks and flows are defined following MFA principles, ensuring that all life cycle stages (e.g., production, use, recycling, and disposal) are represented in consistent physical units. SD is used to model endogenous decision-making processes, including capacity expansion and investment, which exert an influence on material life cycles.

To integrate the two, we define a system boundary that includes: (i) a sub-system I (physical stocks and flows) constrained by mass balance; and (ii) sub-system II (model boundary; e.g., demand, prices, profits, investment, capacity) that evolves through feedback (Fig. 2). This modeling structure is explicitly defined: material stocks are treated as the only "state variables" maintained in the physical layer, while socio-economic variables are introduced only as auxiliary states that can influence processing rates (flows) but are not allowed to create or destroy material directly. This set of system boundaries resolves the structural incompatibility between the purely physical definition of MFA and the behavior-based definition of SD. The SD sub-system is included within the system boundary but only interacts with the MFA sub-system through flow terms that transfer material between physically defined stocks.

3.1.2. System constraints and causal relationship

In MFA, externally imposed assumptions drive change, rather than modelling the internal mechanisms that cause those changes. Constraints are physical (stock availability), and capacity is often implicit unless explicitly parameterized. In SD, causality is internal: flows are a function of endogenous variables connected through feedback loops, and constraints often enter through decision rules, adjustment delays, and saturation nonlinearities. This difference creates the first integration challenge: if SD generates high endogenous recycling throughput, it may do so without respecting the physical availability of waste materials unless the modeler explicitly constrains it.

In the integrated SD-MFA model, each material flow is governed by two simultaneous constraints: physical availability and processing capacity. Physical availability is determined by the material stock that is present in the system and becomes available for processing over time, consistent with mass balance. In this model, processing capacity evolves endogenously through SD feedback mechanisms such as demand, investment, and capacity expansion. Processing capacity is represented in the SD layer as a decision-driven variable and is not subject to mass balance constraints. Material flows are therefore realized only when both sufficient material stock and adequate processing capacity are available. The modelling choice to represent processing capacity within the SD layer reflects an assumption that economic and policy decisions constrain processing capacity, rather than material flows. Formally, processing capacity is defined as the maximum throughput of material transformation node (ton/year). In this study recycling capacity $C_{rec}(t)$ is modeled as capacity stock that evolves endogenuously through investment and depreciation processess represented as stock variables. Recy-

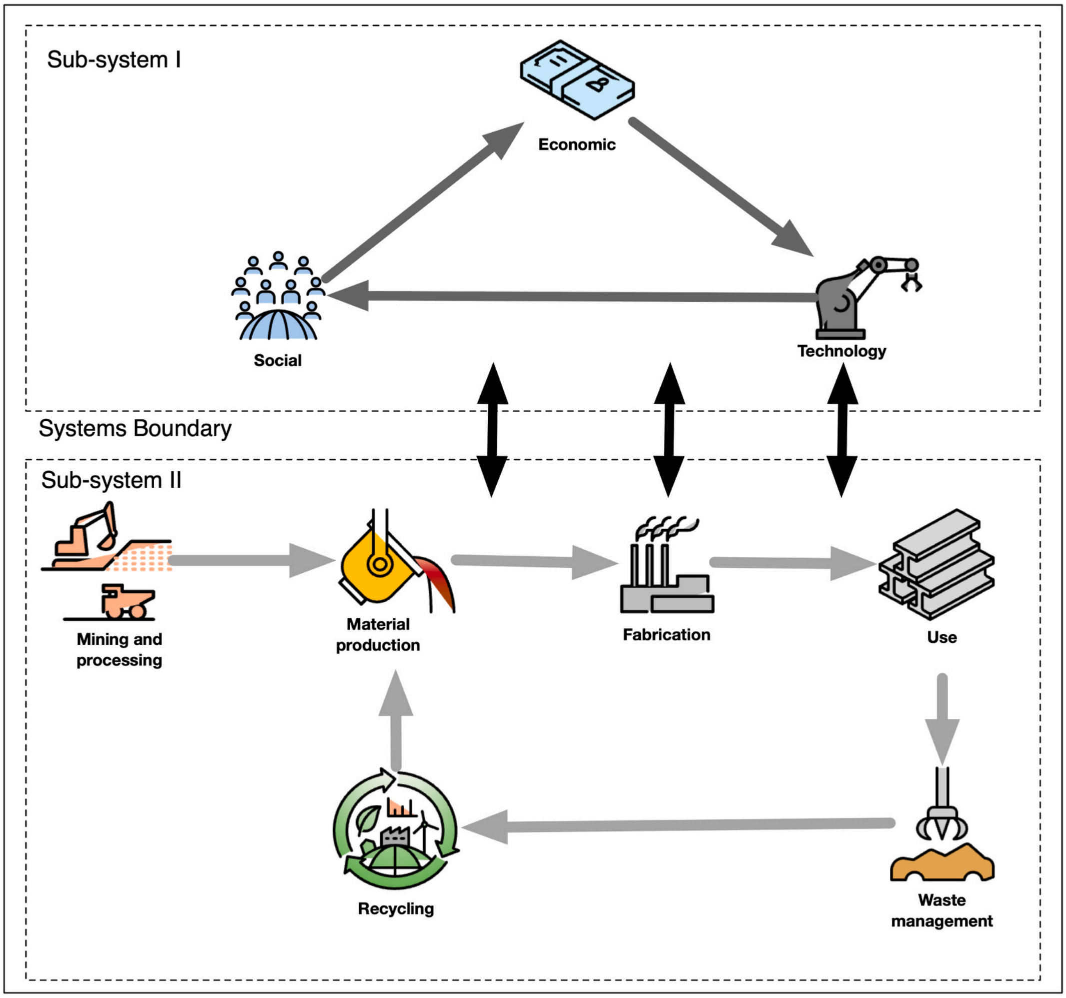

Fig. 2. SD-MFA systems boundary for this analysis. Schematic of the MFA system, SD system, and their integration in this analysis, showing system boundaries and interactions between subsystems. Grey arrows represent material flows, brown arrows represent SD causal relationships, and blue arrows represent interactions between SD and MFA. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

cling capacity is governed by Equation (1).

$$\frac{dC_{rec}}{dt} = \zeta_{rec}(t) - \delta_{rec}C_{rec}(t) \tag{Eq. 1}$$

Where ζ_{rec} represents investment in recycling, δ_{rec} is depreciation in recycling and C_{rec} represents the installed recycling capacity at time $t = 0$. The capacity-investment decision ζ_m (t) is modeled as a feedback-triggered response to perceived capacity gaps, introducing delays and nonlinear behavior that are central to SD analysis.

3.1.3. Mass balance conservation as a structural constraint

In MFA, mass balance is enforced through an explicit stock accumulation equation, in which the change in the amount of each material is strictly defined as the difference between the amount entering and leaving the system. This conservation relationship is a structural identity and must hold at all times. In contrast, SD stock-flow formulations do not automatically guarantee mass conservation when stocks represent non-material quantities, or when flow formulations are driven by behavioral rules rather than physical inventory. For this reason, the integrated framework treats MFA-based mass balance equations as hard constraints.

Therefore, we formulate the integrated model by starting from the MFA stock accumulation equation for each material stock, then incorporating the SD-generated flow formulations into the inflow and outflow terms. Each material stock is governed by the same conservation form (inflow subtracted by outflow), and no socio-economic variables are allowed to modify material stocks directly. Instead, socio-economic variables can only influence flow terms by changing (i) desired throughput, (ii) investment rates, and (iii) capacity adjustments. With this structure, endogenous feedback efforts to promote higher recycling or fabrication are automatically constrained by upstream availability and processing capacity, and the model cannot generate physically impossible trajectories. In short, SD provides behavioral causality for flows, while MFA provides conservation laws that all flows must obey.

3.1.4. Time representation

The final integration concern is time representation. Most MFA studies use discrete annual time steps, driven largely by data availability rather than by the intrinsic mathematical limitations of MFA. Recent research further confirms that continuous-flow representations can improve the interpretation of discretised dynamic MFA models (Cencic and Frühwirth, 2025). The underlying stock accumulation relationships are continuous and can be formulated as differential equations. Whereas SD treats time as continuous, thereby facilitating the modeling of continuous changes and interactions. These differences reflect common modeling practices. However, if these time representations are mixed without careful consideration, the model can become inconsistent: delays, dwell times, and capacity adjustments may be represented differently across layers, making it unclear whether the inconsistency stems from the method or the implementation.

To avoid this, we express the MFA accumulation relationship in continuous time so that the physical layer and the decision layer use the same time basis. Discrete stock change expressions are represented as stock change rates, and the lifetime mechanism is implemented as an explicit delay structure that governs the release of material from used stock to recycling and disposal. This does not change the conceptual representation of MFA but provides a continuous-time implementation that is compatible with SD integration. The advantage is that mass balance is applied at every simulation time step, while SD feedback and capacity adjustments can operate consistently on the same timeline. The conceptual drawing of the integration model proposed in this study is presented in Fig. 3.

3.2. Quantitative evidence

3.2.1. Model development

Fig. 2 represents a generic industrial system, used here as a mock-up scenario, with four physical process nodes: primary material production, in-use stock, recycling, and disposal. Three models were developed to represent this system: an MFA model, an SD model and an integrated SD-MFA model. These models share a consistent sub-system II (physical flow), encompassing the same four material process nodes, but their model boundaries differ by design. The MFA-only model excludes endogenous drivers (e.g. economic), the SD-only model excludes mass conservation constraint and the SD-MFA model operates within full integrated system boundary that enforce both. Fig. 4 presents this SD-MFA integration model that has been translated into a stock-flow diagram. The other two models are presented in detail in the supplementary information (Section S3). These models were designed to demonstrate the capabilities of each standalone model and the integrated model.

For this mock-up scenario, we do not specify the materials because it is meant to provide a generic representation. The scenario is modeled in Vensim Professional 10.4.0, using the following parameters: 100 ton/year primary input (constant, exogenous); fabrication scrap fraction of 0.25; end-of-life recycling fraction of 0.18 (capacity-constrained); product lifetime of 10 years (first-order); initial recycling capacity of 20

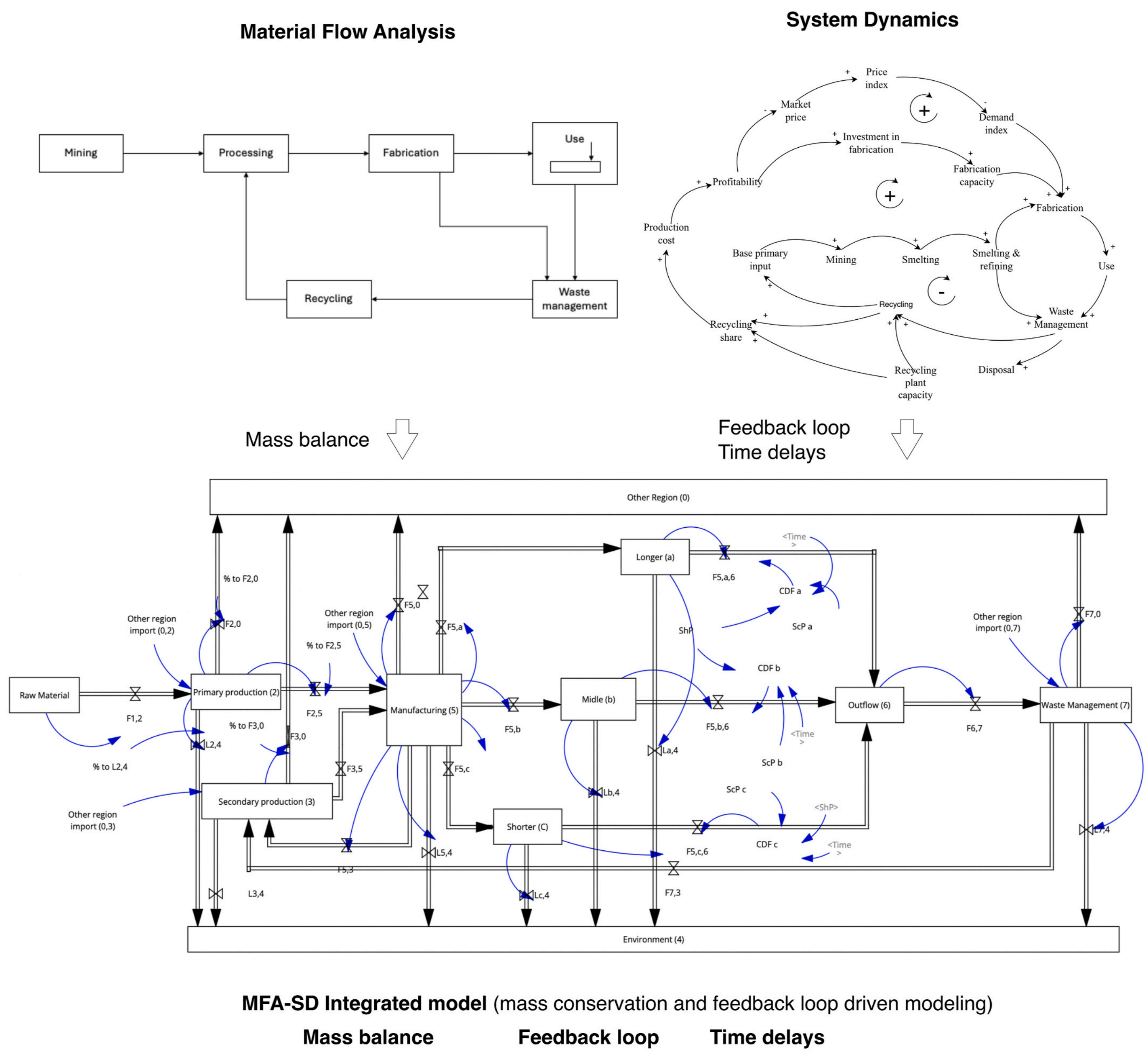

Fig. 3. The conceptual drawing of SD-MFA integrated model.

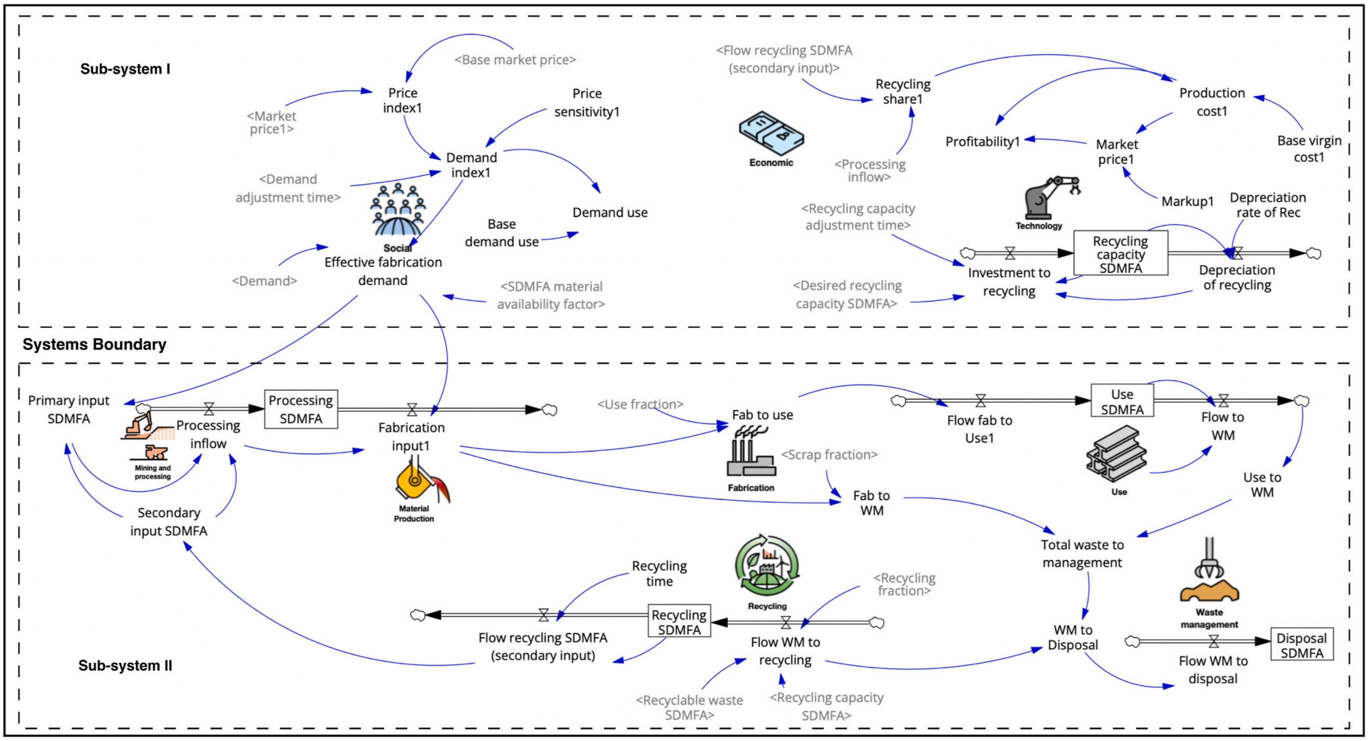

Fig. 4. Schematic of the SD-MFA model integration framework developed for this study.

ton/year; and a simulation horizon of 100 years (using 1 year time steps). A full parameter and variable table information is provided in supplementary information (SI Table 3). These models were designed to demonstrate the capabilities of each standalone model and the integrated model. Three models were developed: an MFA model, an SD model and an integrated SD-MFA model. These models shared consistent sub-system II (physical flow), encompassing the same four material process nodes, while their model boundaries differed by design where MFA model excludes endogenous drivers (e.g. economic), SD model excludes mass conservation constraint, and the SD-MFA model operates withins full integrated system boundary that enforce both. Fig. 4 presents the SD-MFA integration model that has been translated into a stock-flow diagram. The other two models are presented in detail in the supplementary information (Section S3).

In this mock-up scenario, the integrated SD-MFA model contains five state variables in two layers. The subsystem I comprises one capacity constraint; recycling capacity. The subsystem II comprises four material flows and stocks: Primary input, Processing, In-use stock, Recycling, and Disposal. The subsystem II interacts with the subsystem I exclusively through flow constraint equations: material throughput at each node is bounded by the minimum of material availability. We provide Equation (2) as an example for calculating the flow of waste to recycling:

$$F_{WM\to R} = MIN\ (W_{TM}\ x\ EOLRR, RC) \quad \text{(Eq. 2)}$$

Where $F_{WM\to R}$ represent the flow of waste to recycling, W_{TM} is total waste come to waste management, EOLRR is end-of-life recycling rate and RC is recycling capacity. Even if investment has expanded recycling capacity, recycling throughput cannot exceed physically available waste.

3.2.2. Overview and methodological implication

The three models (SD, MFA and integrated SD-MFA) were simulated over an identical 100-year horizon to ensure a consistent basis for methodological comparison. Detailed trajectories of stocks, flows, and capacities are reported in the Supplementary Information Fig. 5 presents the comparative results across three modeling approach.

The top panel of Fig. 5 considers the physical consistency of the three models. The SD model accumulates a steadily increasing mass imbalance, reaching approximately 900 tons by year 100, reflecting the absence of structural conservation constraints. In contrast, both MFA and SD-MFA maintain perfect mass conservation throughout the simulation. Therefore, the divergence observed in the top panel does not arise from differences in satisfying mass balance, as both MFA and SD-MFA adhere to the conservation principle. Instead, the difference stems from the additional behavioral constraints introduced by SD-MFA, which limit the extent to which physically feasible material flows can actually be realized through endogenous economic processes.

The bottom panel of Fig. 5, the SD model represents endogenous economic dynamics without physical material constraints. The application of mass balance constraints is realized through MFA, where all material flows adhere to the law of conservation. An integrated SD-MFA model is then obtained by applying feedback constraints, whereby the realization of endogenous feedback is further limited by physical material availability. This sequential structure allows the contribution of each modeling principle to be isolated and evaluated independently.

Both the SD and SD-MFA models represent the phenomenon of price-induced demand rebound, an instance of what Zink and Geyer (2017) term circular economy rebound, wherein a reduction in production costs drives market demand (Metic and Pigosso, 2022), investment (Ferrante et al., 2026), and processing capacity through mutually reinforcing mechanisms. As production capacity gradually increases over time, these feedback increase flows until balancing mechanism gradually limit further growth. The distinction lies in the fact that the SD model allows this feedback to translate directly into material flows, whereas the SD-MFA model constrains this realization based on physical material availability and endogenous processing capacity. Consequently, while both models exhibit similar behavioral patterns, the output trajectory of the SD-MFA model consistently remains below that of the SD model. In contrast, MFA does not represent endogenous demand responses or economic feedback. Material flows evolve solely based on stock accumulation, residence times, and predetermined recycling fractions, governed by mass balance principles. Consequently, MFA follows a

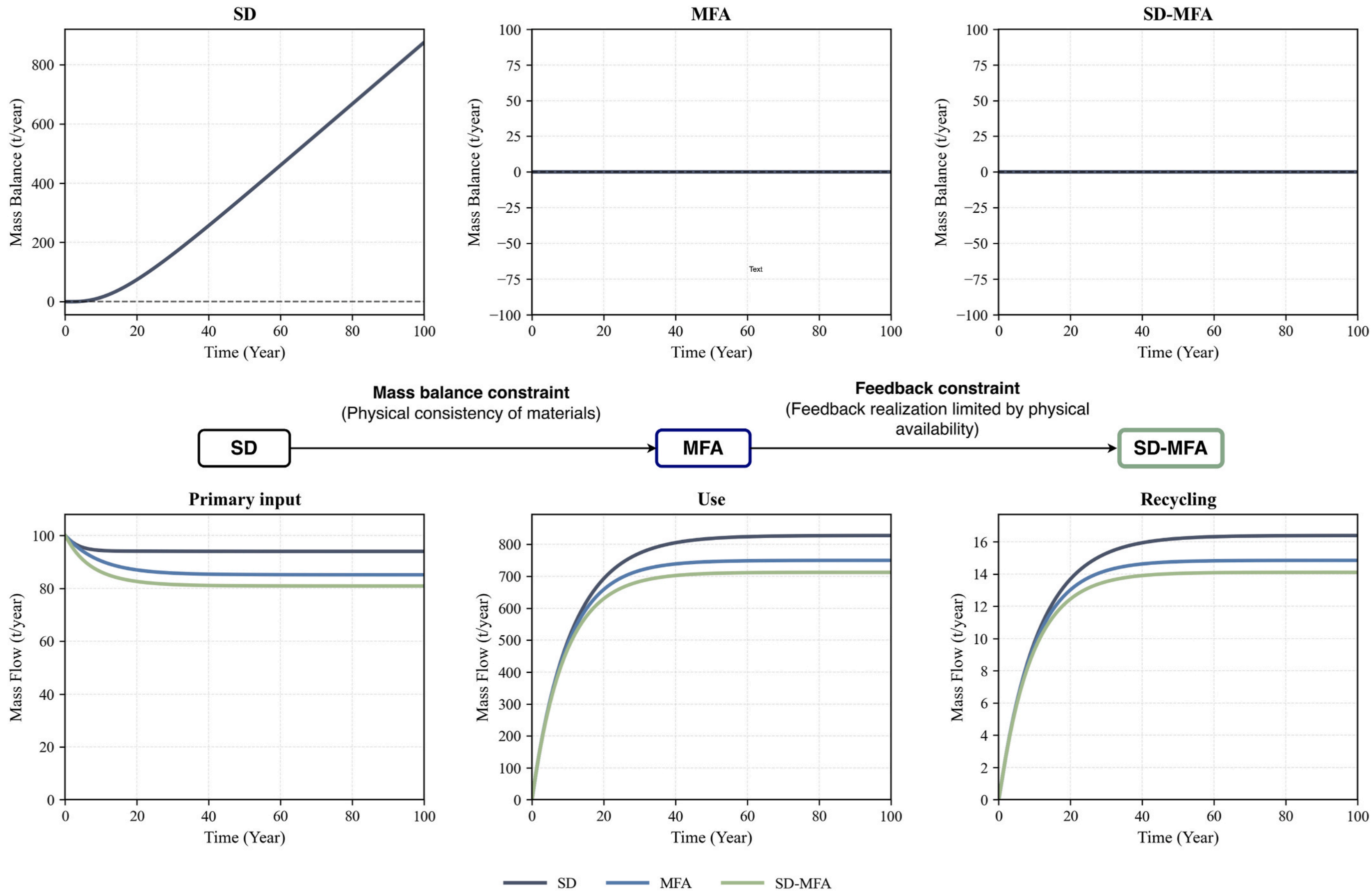

Fig. 5. Simulation results comparing the SD, MFA and SD-MFA models over a 100-year timeframe. The top panel shows mass balance verification. The middle diagram explains the structural differences underlying the simulation results by illustrating the sequential application of modelling principles: MFA incorporates mass balance constraints into SD, whilst SD–MFA further incorporates feedback constraints by limiting the realization of endogenous feedback in accordance with the availability of physical materials. The bottom panel presents the resulting trajectories of primary inputs, use and recycling, illustrating how these structural differences lead to distinct system behaviour and material flow outcomes.

physically determined trajectory rather than a feedback-driven system behavior.

These structural differences are directly reflected in the simulation results. Over a 100-year simulation period, the SD model consistently yields the highest values for primary input, usage, and recycling, as the feedback mechanisms operate without physical material constraints. By year 100, primary input reaches approximately 95 tons/year in the SD model, compared to about 87 tons/year in MFA and 80 tons/year in SD-MFA. Consumption stocks follow the same order, reaching approximately 830, 770, and 700 tons respectively, while recycling amounts to around 16.5, 15.0, and 14.5 tons/year. The difference between SD and MFA reflects the contribution of the mass balance constraint. In the SD model, demand driven by rebound effects and capacity expansion can generate material flows exceeding the supply from physically available stocks, as the law of conservation is not incorporated into the underlying equations. Applying the mass balance constraint eliminates these physically impossible flows, thereby reducing material flow rates across the system. The subsequent difference between MFA and SD-MFA reflects the contribution of feedback constraints. Unlike MFA which assumes that physically available material is processed according to predetermined allocation rules, SD-MFA retains the same endogenous feedback mechanisms found in SD but limits their realization based on physical material availability and endogenous capacity adjustments. Consequently, circular economy rebound (Zink and Geyer, 2017)are not eliminated but only partially realized, resulting in lower material flows while maintaining the same underlying behavioral patterns.

4. Discussion

4.1. Why stand-alone MFA and SD are not enough

The comparison results presented in Section 3.2 confirmed observations that already exist in the literature on industrial ecology and system dynamics. As shown in Fig. 5, the SD model presents the absence of physical stock constraints allows feedback mechanisms to drive material flows beyond physically feasible levels. With feedback operating without physical constraints, the resulting trajectories are behaviorally plausible yet physically inconsistent. This limitation has been implicitly acknowledged in previous applications, where physical consistency is assumed rather than structurally guaranteed (Coyle, 2000; Sterman, 2000). In contrast, MFA excels at ensuring physical consistency through mass balance but relies on externally determined trajectories (Pauliuk and Müller (2014) and fails to capture how the behavior dynamically responds to changes in material availability and economic feedback.

The SD-MFA model, by integrating feedback with physical stock constraints, produces the most controlled and physically credible trajectories, as demonstrated in Fig. 5. The divergence in results between MFA and SD-MFA, despite both satisfying mass balance, demonstrates that the principle of mass conservation alone is insufficient, the behavioral mechanisms governing flow evolution are equally critical. In the modeled example, the difference was small but this could be more significant, for example, in systems subject to rebound effects (Lifset and Eckelman, 2013).

4.2. Mass balance as a structural constraint in SD

Mass conservation is a structural prerequisite that allows the dynamics of integration behavior to be interpreted in physical terms. In the SD-MFA framework we developed, material conservation is applied at each time step as a governing constraint to ensure that all simulated flows remain physically feasible. Both the MFA and SD-MFA maintain $|\Delta M| = 0$ throughout the simulation, as presented in Fig. 5 (bottom panel) confirming that mass balance is successfully implemented in both. However, the SD model accumulates a mass imbalance of approximately 900 tons by year 100, confirming that endogenous feedback loops lacking physical stock constraints produce flows that violate the principle of conservation. This finding effectively addresses a gap identified in SD literature, where the law of mass conservation is not systematically integrated as a governing constraint (Sterman, 2000). Our integrated framework formalizes mass balance as the backbone of the system structure while allowing behavioral dynamics to shape the system's evolution within those constraints. This combination bridges the classic conflict between behavioral realism and physical feasibility.

4.3. Interpreting stock-capacity and delayed adjustment

One of the key insights emerging from our integrated model is the appearance of stock-capacity mismatches and delayed adjustment dynamics. In the SD-MFA model, system behavior is jointly governed by demand feedback loops and material availability constraints that limit realized demand to the level the physical system can supply. This joint constraint implies that even when economic signals call for increased production, the model appropriately limits flows, as shown in Fig. 5 (top panel). The delayed adjustment dynamics, visible in the initial decades where the three models briefly converge before diverging, reflect the adjustment times embedded in the capacity equations of the SD and SD-MFA models. This confirms that the divergence is not merely an artifact but a consequence of the interaction between feedback and physical constraints over time. This finding is conceptually related to prior work that highlights the role of stocks in shaping material system dynamics (Müller, 2006; Pauliuk et al., 2017), however, our study extends it by demonstrating how such dynamics emerge from the interaction of feedback mechanisms and physical constraints rather than from exogenous assumptions. Whereas stock-driven models emphasize how in-use stocks determine future material demand, the present results show how the timing and amount of material released from stocks, once physically available for processing, interact with capacity constraints and delayed adjustment to shape feasible system behavior over time.

4.4. Implication for CE transition strategies

The quantitative differences between SD, MFA, and SD-MFA shown in Fig. 5 have direct implications for how circular economy strategies should be assessed and designed. If recycling performance is evaluated using an SD model without physical constraints, the projected recycling flow of 16.5 tonnes/year at the 100-year mark would overestimate what is physically achievable, in this example being about 10% higher than MFA and 14% higher than SD-MFA. Policies formulated based on SD projections risk setting recycling targets that are physically unachievable because they exceed the carrying capacity of material stocks. If the MFA is used, the recycling projection of approximately 15 tons per year is indeed physically consistent, however, because this method relies on an exogenous recycling fraction, it cannot capture how investments in recycling capacity respond dynamically to price signals and profitability. Meanwhile, the SD-MFA projection provides the most credible results because it reflects the actual outcomes that can be achieved by recycling infrastructure when physical stock constraints and behavior-based investment dynamics simultaneously influence the system. For circular economy (CE) transition planning, this implies that strategies need to be designed in an integrated manner, an integrated assessment which can be structurally provided by the integrated SD-MFA framework we developed in this study.

4.5. Limitations and future research directions

This study deliberately employs a simplified illustrative case to maintain methodological clarity. While this abstraction facilitates comparison across modelling approaches, this may limit direct application in the real world. Consequently, further model development is required before applying the framework to application-specific case studies. Further research can be conducted on different industrial systems with different characteristics by incorporating user behavior, material quality degradation, changes in life cycle distribution, and the impact of technological advances. In addition, we note that further research is necessary to explore systematic validation strategies and uncertainty analysis in integrated SD-MFA models.

4.6. Managerial implication

The integrated SD-MFA framework developed in this study can be implemented using several existing software platforms; each has different capabilities and practical considerations that practitioners should take into account before adopting it. For companies with programming expertise, Python offers a completely free implementation path. Libraries such as PySD enable the execution of SD models within a Python environment, and integration with MFA stock-flow equations can be programmed directly. However, the need for programming proficiency poses the greatest barrier for practitioners without a computing background, and maintaining or modifying models requires ongoing programming effort. Another option is to use a software platform specifically designed to run dynamic system simulations, such as Vensim (Ventana Systems), which was used in this study, or Stella which provide graphical environments for developing stock-flow models and support integration with externally defined material flow equations. Various software packages offer different capabilities in terms of data connectivity and simulation features. For example, some free editions have limited support for importing external datasets, such as Excel files, whilst commercial versions generally provide more comprehensive facilities for handling empirical data and large-scale industrial models. Consequently, for applications involving large-scale industrial systems with empirical datasets, a software platform that provides advanced data management and external data integration may be more suitable.

Regardless of the platform used, data requirements remain the most significant limitation. This framework requires physical material flow data (typically available from MFA studies) as well as estimates of behavioral parameters such as investment payback time, price sensitivity to demand, and profitability thresholds. These behavioral parameters are often not systematically recorded within an organization and may require calibration based on sector-level studies or expert elicitation. For sectors that already have a well-established MFA data infrastructure, implementation can proceed more quickly.

5. Conclusion

This study examines the benefits of integrating MFA and SD to model complex industrial systems, while maintaining mass balance and feedback loops. Three models (MFA, SD, and integrated SD-MFA model) are systematically compared under identical data and boundary conditions to provide evidence-based insights into the methodological benefits of integration. The results show that the standalone MFA and SD approaches, while each robust, are insufficient to fully capture the behavior of material systems characterized by stocks, capacity constraints, and delayed adjustment. The MFA model alone ensures physical consistency but relies on exogenous flows, for example, raw materials availability or end-user demand. This limits the representation of delayed adjustments generated by endogenous feedback and internal behavioral dynamics within the system. The SD model alone captures such internal dynamic responses, but has difficulty enforcing mass balance, which limits the physical interpretability of results. By integrating MFA and SD, the proposed framework resolves this tension. Mass balance is enforced at each time step, while endogenous decision-making governs how the system evolves within these constraints. An illustrative case study demonstrates how the integrated framework can be implemented in practice. Although this case study is deliberately simplified and would need detailed sector-specific development for sectoral inference, it provides a transparent example of how mass-balanced dynamic modeling can be implemented and interpreted. The methodological insights generated from this case study can be applied to various industrial and resource systems, contributing to ongoing efforts to bridge industrial ecology and systems dynamics. Rather than positioning MFA and SD as mutually exclusive approaches, or even sometimes overlapping, the integrated SD-MFA framework demonstrates how their complementary strengths can be combined to avoid misleading system interpretations and support more robust analysis of CE transitions.

Funding information

This research was supported by JSPS KAKENHI (24K03142) and the Royal Society ISPF – International Collaboration Award (ICA/R1/23046).

CRediT authorship contribution statement

Salman Alfarisi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ryu Koide:** Conceptualization, Methodology, Validation, Writing – review & editing. **Jennifer L. Hawkin:** Conceptualization, Visualization, Writing – review & editing. **Fanran Meng:** Funding acquisition, Project administration, Visualization, Writing – review & editing. **Takuma Watari:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Validation, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:F. M. and T.W. serve as Associate Editors of the Journal of Cleaner Production. The other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2026.149117.

Data availability

Research Link Provided.

Simulation Data for SD-MFA Case Study (Original data) (Github Repository: SD-MFA).

References

Abdoli, S., Kara, S., Hauschild, M., 2019. System interaction, system of systems, and environmental impact of products. CIRP Ann. 68, 17–20. https://doi.org/10.1016/j.cirp.2019.04.051.

Baars, J., Rajaeifar, M.A., Heidrich, O., 2022. Quo vadis MFA? Integrated material flow analysis to support material efficiency. J. Ind. Ecol. 26, 1487–1503. https://doi.org/10.1111/jiec.13288.

Baccini, P., Brunner, P.H., 2012. Metabolism of the Anthroposphere: Analysis, Evaluation, Design, second ed. Massachusetts Institute of Technology.

Binder, C.R., 2007. From material flow analysis to material flow management Part I: social sciences modeling approaches coupled to MFA. J. Clean. Prod. 15, 1596–1604. https://doi.org/10.1016/j.jclepro.2006.08.006.

Bringezu, S., Schütz, H., Moll, S., 2003. Rationale for and interpretation of economy-wide materials flow analysis and derived indicators. J. Ind. Ecol. 7, 43–64. https://doi.org/10.1162/108819803322564343.

Brunner, P.H., Rechberger, H., 2016. Handbook of Material Flow Analysis.

Cencic, O., Frühwirth, R., 2025. On the advantage of assuming constant mass flow rates in discretized dynamic material flow models. J. Ind. Ecol. 29, 1977–1986. https://doi.org/10.1111/jiec.70102.

Chen, J., Chen, H., Sun, Q., 2024. Synergy or Strife? Integrated assessment of economy-resource-environment development in Yangtze River Delta region based on material flow analysis and system dynamics. Environ. Dev. Sustain. https://doi.org/10.1007/s10668-024-04759-3.

Choi, C.H., Cao, J., Zhao, F., 2016. System dynamics modeling of indium material flows under wide deployment of clean energy technologies. Resour. Conserv. Recycl. 114, 59–71. https://doi.org/10.1016/j.resconrec.2016.04.012.

Coyle, G., 2000. Qualitative and quantitative modelling in system dynamics: some research questions. Syst. Dyn. Rev. 16, 225–244. https://doi.org/10.1002/1099-1727(200023)16:3%3C225::AID-SDR195%3E3.0.CO;2-D.

Cullen, J.M., Cooper, D.R., 2022. Material flows and efficiency. Annu. Rev. Mater. Res. 52, 525–559. https://doi.org/10.1146/annurev-matsci-070218-125903.

Daehn, K.E., Cabrera Serrenho, A., Allwood, J.M., 2017. How will copper contamination constrain future global steel recycling? Environ. Sci. Technol. 51, 6599–6606. https://doi.org/10.1021/acs.est.7b00997.

Deng, T., Zhang, Y., Fu, C., 2023. Modelling dynamic interactions between material flow and stock: a review of dynamic material flow analysis. Ecol. Indic. 156, 111098. https://doi.org/10.1016/j.ecolind.2023.111098.

Ferrante, M., Sassanelli, C., Pigosso, D.C.A., 2026. Rebound effects in circular manufacturing: overview of potential rebound mechanisms activated by circular strategies across key business processes. Bus. Strat. Environ. 35, 7543–7562. https://doi.org/10.1002/bse.70562.

Forrester, J.W., 1994. System dynamics, systems thinking, and soft OR. Syst. Dyn. Rev. 10, 245–256. https://doi.org/10.1002/sdr.4260100211.

Forrester, J.W., 2017. Learning through system dynamics as preparation for the 21st century. Syst. Dyn. Rev. 32, 187–203. https://doi.org/10.1002/sdr.1571.

Gao, Chengkang, Gao, Chengbo, Song, K., Fang, K., 2020. Pathways towards regional circular economy evaluated using material flow analysis and system dynamics. Resour. Conserv. Recycl. 154, 104527. https://doi.org/10.1016/j.resconrec.2019.104527.

Gonella, S., de Gooyert, V., 2024. What are sustainable plastics? A review of interrelated problems and solutions to help avoid unintended consequences. Environ. Res. Lett. 19. https://doi.org/10.1088/1748-9326/ad536d.

Graedel, T.E., 2019. Material flow analysis from origin to evolution. Environ. Sci. Technol. 53, 12188–12196. https://doi.org/10.1021/acs.est.9b03413.

Guzzo, D., Pigosso, D.C.A., Videira, N., Mascarenhas, J., 2022. A system dynamics-based framework for examining circular economy transitions. J. Clean. Prod. 333, 129933. https://doi.org/10.1016/j.jclepro.2021.129933.

Iacovidou, E., Hahladakis, J.N., Purnell, P., 2021. A systems thinking approach to understanding the challenges of achieving the circular economy. Environ. Sci. Pollut. Res. 28, 24785–24806. https://doi.org/10.1007/s11356-020-11725-9.

Islam, M.T., Huda, N., 2019. Material flow analysis (MFA) as a strategic tool in E-waste management: applications, trends and future directions. J. Environ. Manag. 244, 344–361. https://doi.org/10.1016/j.jenvman.2019.05.062.

Klotz, M., Haupt, M., Hellweg, S., 2023. Potentials and limits of mechanical plastic recycling. J. Ind. Ecol. 27, 1043–1059. https://doi.org/10.1111/jiec.13393.

Kytzia, S., Meglin, R., Kliem, D., Scheidegger, A., Hügel, K., 2020. Co-Evolution of business strategies in material and construction industries and public policies. IOP Conf. Ser. Earth Environ. Sci. 588. https://doi.org/10.1088/1755-1315/588/4/042032.

Laner, D., Rechberger, H., 2016. Material flow analysis. https://doi.org/10.1007/978-94-017-7610-3_7.

Lifset, R., Eckelman, M., 2013. Material efficiency in a multi-material world. Philos. Trans. R. Soc. Math. Phys. Eng. Sci. 371, 20120002. https://doi.org/10.1098/rsta.2012.0002.

Linder, M., Sarasini, S., van Loon, P., 2017. A metric for quantifying product-level circularity. J. Ind. Ecol. 21, 545–558. https://doi.org/10.1111/jiec.12552.

Liu, H., Zhang, Q., Xue, Z., Zhuang, X., Li, J., 2022. System dynamics-based prediction of municipal solid waste generation in high-cold and high-altitude area: the case of Lhasa, Tibet. Waste Manag. Res. 40, 1555–1567. https://doi.org/10.1177/0734242X221084077.

Metic, J., Guzzo, D., Kopainsky, B., McAloone, T.C., Pigosso, D.C.A., 2024. A simulation-based approach for investigating the dynamics of rebound effects in the circular economy: a case of use-oriented product/service system. J. Environ. Manag. 365, 121627. https://doi.org/10.1016/j.jenvman.2024.121627.

Metic, J., Pigosso, D.C.A., 2022. Research avenues for uncovering the rebound effects of the circular economy: a systematic literature review. J. Clean. Prod. 368, 133133. https://doi.org/10.1016/j.jclepro.2022.133133.

Millward-Hopkins, J., Busch, J., Purnell, P., Zwirner, O., Velis, C.A., Brown, A., Hahladakis, J., Iacovidou, E., 2018. Fully integrated modelling for sustainability assessment of resource recovery from waste. Sci. Total Environ. 612, 613–624. https://doi.org/10.1016/j.scitotenv.2017.08.211.

Morecroft, J.D.W., 2015. Strategic and Business. John Wiley & Sons Ltd.

Müller, D.B., 2006. Stock dynamics for forecasting material flows-case study for housing in the Netherlands dynamic modelling prospects for resource demand waste management vintage effects diffusion processes. Ecol. Econ. 9, 142–156. https://doi.org/10.1016/j.eco.

Müller, E., Hilty, L.M., Widmer, R., Schluep, M., Faulstich, M., 2014. Modeling metal stocks and flows: a review of dynamic material flow analysis methods. Environ. Sci. Technol. 48, 2102–2113. https://doi.org/10.1021/es403506a.

Mutingi, M., 2014. System dynamics of information technology adoption in a complex environment. Int. J. Ind. Syst. Eng. 17, 78–97 mster.

Pauliuk, S., Arvesen, A., Stadler, K., Hertwich, E.G., 2017. Industrial ecology in integrated assessment models. Nat. Clim. Change 7, 13–20. https://doi.org/10.1038/nclimate3148.

Pauliuk, S., Müller, D.B., 2014. The role of in-use stocks in the social metabolism and in climate change mitigation. Glob. Environ. Change 24, 132–142. https://doi.org/10.1016/j.gloenvcha.2013.11.006.

Pfaff, M., Glöser-Chahoud, S., Chrubasik, L., Walz, R., 2018. Resource efficiency in the German copper cycle: analysis of stock and flow dynamics resulting from different efficiency measures. Resour. Conserv. Recycl. 139, 205–218. https://doi.org/10.1016/j.resconrec.2018.08.017.

Richardson, G.P., 1991. Feedback Thought in Social Science and Systems Theory. University of Pennsylvania.

Ruth, M., Davidsdottir, B., 2008. Changing Stock, Flows and Behaviors in Industrial Ecosystems. Edwars Elgar Publishing Limited.

Saidani, M., Yannou, B., Leroy, Y., Cluzel, F., Kendall, A., 2019. A taxonomy of circular economy indicators. J. Clean. Prod. 207, 542–559. https://doi.org/10.1016/j.jclepro.2018.10.014.

Schwab, O., Rechberger, H., 2018. Information content, complexity, and uncertainty in material flow analysis. J. Ind. Ecol. 22, 263–274. https://doi.org/10.1111/jiec.12572.

Sterman, J., 2018. System dynamics at sixty: the path forward. Syst. Dyn. Rev. 34, 5–47. https://doi.org/10.1002/sdr.1601.

Sterman, J.D., 1984. Appropriate summary statistics for evaluating the historical fit of system dynamics models. Dynamica 10, 51–66.

Sterman, J.D., 2000. Systems thinking and modeling for a complex world. McGraw-Hill.

Streeck, J., Wieland, H., Pauliuk, S., Plank, B., Nakajima, K., Wiedenhofer, D., 2023. A review of methods to trace material flows into final products in dynamic material flow analysis: comparative application of six methods to the United States and EXIOBASE3 regions, part 2. J. Ind. Ecol. 27, 457–475. https://doi.org/10.1111/jiec.13379.

Teseletso, L.S., Adachi, T., 2022. Long-term sustainability of copper and iron based on a system dynamics model. Resources 11, 37. https://doi.org/10.3390/resources11040037.

United Nations Industrial Development Organization, 2025. Global Stocktake of National Circular Economy Roadmaps and Strategies: 2025 Update. United Nations Industrial Development Organization, Vienna, Austria.

Wang, Q.-C., Chen, W.-Q., Wang, P., Dai, T., 2022. Illustrating the supply chain of dysprosium in China through material flow analysis. Resour. Conserv. Recycl. 184, 106417. https://doi.org/10.1016/j.resconrec.2022.106417.

Xinfeng, W., Tao, W., Xin, Z., Yanfeng, W., 2023. Research on strategic risk identification method of equipment system development based on system dynamics. J. Syst. Eng. Electron. 34, 1225–1234. https://doi.org/10.23919/JSEE.2023.000124.

Zanon-Zotin, M., Fortes, P., Corbier, D., Deetman, S., Edelenbosch, O., Van Engelenburg, M., Hauenstein, C., Hertwich, E., Jiang, M., Von Köckritz, L., Magalar, L., Pauliuk, S., Straub, L., Vélez-Henao, J., Van Vuuren, D., 2026. Circular economy modelling for climate change mitigation: a review of empirical evidence and modelling approaches. Resour. Conserv. Recycl. 234, 109053. https://doi.org/10.1016/j.resconrec.2026.109053.

Zhang, T., Wen, Z., Tan, Y., Shi, X., Sun, Y., Ekins, P., 2024. Advancing circular economy of pallets: a comprehensive evaluation framework. Resour. Conserv. Recycl. 211. https://doi.org/10.1016/j.resconrec.2024.107874.

Zink, T., Geyer, R., 2017. Circular economy rebound. J. Ind. Ecol. 21, 593–602. https://doi.org/10.1111/jiec.12545.