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A dynamic material flow analysis–system dynamics model of Japan's special steel supply chain: toward decision support for critical mineral supply resilience

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Abstract

Critical minerals are essential for clean-energy technologies and established industrial materials. Japan's special steel industry uses alloying elements such as nickel, chromium, and molybdenum, and disruptions in their supply may affect downstream industries. An auditable representation of special steel product flows is therefore needed to support future supply-risk and resilience assessments.

Using publicly available fiscal year (FY) statistics, we develop a dynamic material flow analysis–system dynamics (DMFA–SD) model of Japan's special steel product flows. The model separates order backlog, work-in-process, and makers' finished-goods inventory, represents yield losses and production and shipping decisions, and is evaluated using historical fit, naive benchmarks, and observed annual balance residuals. The analysis explicitly distinguishes model consistency from agreement with observed statistics.

In-sample correlations for production (FY1994–2023), shipping and makers' inventory (FY2009–2023) are 0.960, 0.935 and 0.602, respectively, with corresponding mean absolute percentage errors of 5.25%, 3.66% and 5.50%. Production for FY1994–2008 is estimated from hot-rolled production using a later-period mean yield. Production and shipping perform similarly to orders-based benchmarks, limiting evidence for additional feedback contributions. An audit of published flows gives a mean balance residual of 1.18% of production for the makers' inventory boundary, compared with 4.90% when imports are routed through total inventory. In an illustrative one-year constraint limiting production starts to 80% of orders, doubling inventory coverage reduces accumulated excess backlog by 64%. The resulting model is an auditable baseline for exploring aggregate supply constraints, rather than a validated forecast or element-specific resilience assessment.

Keywords System dynamics · Dynamic material flow analysis · Critical minerals · Special steel supply chain · Decision support · Supply resilience

1 Introduction

1.1 Critical minerals and strategic importance

Since the adoption of the Paris Agreement in 2015, decarbonization has become a global megatrend, and Japan has also declared the goal of achieving carbon neutrality (CN) by 2050. Achieving CN requires not only an energy transition but also the redesign of industrial and societal systems accompanied by a shift toward a circular economy (CE) (METI 2024; Ellen MacArthur Foundation 2021). Keeping resource inputs in circulation rather than discarding them is essential for reconciling economic security with

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environmental sustainability, and internationally the importance of resource efficiency and securing critical minerals (CMs) has been emphasized (IEA 2025).

At the same time, the expansion of advanced industries—such as batteries, high-performance motors, and semiconductors—has strengthened structural dependence on CMs. Demand is already increasing rapidly, and the IEA (2025) highlights both the demand surge driven by the clean-energy transition and associated supply risks. Compared with 2023, lithium demand increased by about 30% in 2024, while demand for nickel, cobalt, graphite, and rare earths grew by 6–8% (IEA 2025). Moreover, projected demand multipliers for clean-energy applications toward 2040 are approximately 12.8-fold for lithium, 6.4-fold for cobalt, and 6.5-fold for nickel (METI 2024; JOGMEC 2022). The challenge is not only quantitative scarcity. Mining and refining are geographically concentrated, and geopolitical shifts can directly disrupt supply chains, creating a systemic-risk structure that readily triggers cascading effects such as price spikes, delayed investment, and slowed technological development.

In response, the United States has developed definitions and strategies for securing "CMs" from the perspective of domestic industry and national security (USGS 2022), and Japan has likewise set out policies including strategic stockpiling and strengthened recycling (METI 2025). Therefore, auditable baseline models of special steel product-flow dynamics are needed as a basis for future supply-risk and resilience assessments, not only for policymaking but also for corporate strategic decision-making.

In Japan in particular, a large share of demand for these CMs is embodied in the production of special steel (Sect. 3). Special steel contains substantial amounts of CMs such as Ni, Cr, and Mo and is widely used in mobility, equipment, and infrastructure that support decarbonization; thus, CMs supply constraints can affect supply resilience through the special steel supply chain. Since fiscal year (FY) 2021, Japan has produced hot-rolled special steel at a scale of approximately 15.4–18.3 Mt/year (SSAJ n.d.), and many studies have reported material use and applications of special steel (Nagasaka and Hino 1996; Nakajima et al. 2007; Daigo et al. 2009, 2010). However, research remains limited that integratively addresses supply chain dynamics in which international market conditions, domestic recycling, and economic security policies (e.g., national stockpiling) interact—such as inventory adjustments, scrap collection, and policy time lags—and evaluates them using comparable indicators useful for practice and policy. In this paper, "CMs" refers to mineral resources positioned as strategic resources by countries and institutions because of their high risk of supply disruption and high economic and industrial importance. Our focus is on CMs as alloying elements that support decarbonization technologies and foundational materials industries.

1.2 Potential of material flow analysis and system dynamics

A systematic review of 91 simulation studies in the CMs domain reports that system dynamics (SD) and dynamic material flow analysis (DMFA) are the most frequently used approaches and that hybridization is advancing, while also highlighting challenges such as mineral-type bias (a strong focus on Li, Co, Ni, and Cu) and the underrepresentation of social and ecological impacts (Güz and Murakami 2025). Our integration of material flow analysis (MFA) and SD aims to contribute to this hybridization by simultaneously satisfying structural causality and quantitative consistency.

MFA, a core method in industrial ecology, maps "industrial metabolism" and quantifies material circulation across stages such as input, processing, use, collection, and losses (Graedel 2019). By explicitly defining system boundaries and applying conservation laws (mass balance), MFA makes supply chain structures visible. However, as comprehensive reviews indicate, approximately 92% of prior MFA studies are static (static MFA; SMFA), whereas DMFA accounts for only about 8% (Chen and Graedel 2012). SMFA provides snapshot representations of flows in a given year—often using Sankey diagrams—and is effective for describing current structures and identifying issues. For example, studies that depict detailed flows of end-of-life vehicles (ELVs) and special steel (Ohno et al. 2014, 2017) have clarified branching, dissipation, and uncollected portions, thereby indicating entry points for intervention.

Nevertheless, MFA faces data challenges regardless of the specific approach (Graedel 2019). First, recycling and remanufacturing statistics are often incomplete due to informal transactions and undercoverage of small and medium-sized actors. Second, estimating material contents in composite products is difficult because of design diversity and changing product mixes. Third, product lifetimes are uncertain: usage conditions, maintenance, and reuse broaden lifetime distributions. These limitations become more consequential for future projections and policy assessment, and reliance on SMFA alone makes it difficult to address time-dependent effects such as delays, accumulation, and spillovers. In addition, practical efforts have been reported to integrate MFA with supply chain resilience analysis and complement data gaps through industry interviews (Böcher et al. 2024).

DMFA has emerged to help address these limitations. DMFA describes stocks (S) and inflows/outflows (I/O) as functions of time and estimates temporal profiles of accumulation and release through lifetime distributions and

demand scenarios. DMFA can be implemented in diverse ways depending on purpose, including combinations of top-down (e.g., national statistics) and bottom-up (e.g., product cohorts) approaches and uncertainty propagation (e.g., sensitivity analysis and Monte Carlo simulation), although standardization remains limited (Chen and Graedel 2012).

However, when flows change endogenously through interactions among prices, policies, technologies, and behaviors—as in CMs supply chains—tracking physical flows alone is insufficient. SD is particularly useful in such settings. Whereas DMFA describes the temporal evolution of "flows" (quantities), SD represents the underlying "structure" that generates those flows—ordering and inventory policies, capacity adjustment, price expectations, and policy responses—using causal loop diagrams (CLDs) and stock and flow diagrams (SFDs), making endogenous dynamics explicit, including delays, nonlinearities, and threshold effects (Sterman 2000). Supported by extensive knowledge on manufacturing, inventories, and supply networks (Jahangirian et al. 2010; Angerhofer and Angelides 2000) and methodological flexibility (Chowdhury 2023), SD has been used as a learning tool for price fluctuations (Morandi et al. 2014) and for participatory decision support (Machado et al. 2019; Lo et al. 2024). For policy comparisons in CMs, system-structure-based analysis is particularly valuable because the effectiveness of leverage points (intervention points) can differ substantially in time constants and side effects (Sterman 2000).

This study adopts an integrative stance by linking MFA, which provides mass conservation and data discipline, with SD, which represents endogenous feedbacks, decision rules, and delays. In the present implementation, this integration is used primarily to reproduce the historical behavior of aggregate special steel product flows and to clarify the model boundary, observational definitions, and data-consistency checks. By linking structural hypotheses accumulated in prior SD research in the steel sector (Shigeno 2009; Pinto et al. 2019; Norbert et al. 2020) with the quantitative constraints of MFA/DMFA, the proposed framework provides an auditable baseline for future scenario analysis. Decision levers such as collection and sorting, strategic stockpiling, import diversification, and inventory and work-in-process operations are therefore positioned as model elements for future extensions, rather than as interventions whose effects are directly compared in this paper.

1.3 Application of SD to MFA

SD has been widely applied in the mineral-resources domain. For rare-earth elements (REEs), studies have analyzed supply-chain resilience, price volatility, and the role of recycling (Sprecher et al. 2015; Mancheri et al. 2019; Hamed et al. 2024). For other CMs, applications have accumulated by resource type, including assessments of greenhouse-gas impacts of lithium-ion batteries (Golroudbary et al. 2019) and analyses of nickel demand and the contributions of recycling and mining (Nell et al. 2024). In the steel sector, SD has been used mainly for manufacturing efficiency and environmental impact assessment, including integration with lifetime-based MFA (Shigeno 2009), integration with life cycle assessment (LCA) (Pinto et al. 2019), and evaluation of CO_2-reduction processes (Kim et al. 2014; Norbert et al. 2020). Decision-support applications closer to practice have also advanced, such as CE design and business models (Franco 2019), optimization of collection and recycling (Golroudbary and Zahraee 2015), comparisons of emissions and energy policies (Anand et al. 2006; Longbin 2007), and supply-chain flexibility (Singh et al. 2019). In addition, studies have reported efforts to endogenize the social acceptability of mining through participatory approaches combined with SD—linking feedbacks such as delays in trust building to policy design (Dall-Orsoletta et al. 2025)—as well as resilience-oriented discussions that integrate energy systems and risk management (Mille et al. 2025). A synthesis review (Güz and Murakami 2025) suggests the usefulness of modeling and policy comparison in the CMs domain.

However, much of the prior literature focuses on: (1) the life cycle of specific resources and applications such as electric–vehicle batteries, (2) global supply networks for REEs, or (3) process level assessment in steel manufacturing. Studies remain limited that focus on special steel which contains diverse critical metals as alloying elements, and that comprehensively address supply chain dynamics in which international market conditions, domestic recycling, and economic security policies (e.g., national stockpiling) interact. There is thus a research gap in treating the entire loop—resource procurement, manufacturing, use, and collection—as a single system and in explicitly representing structural factors such as inventories, capacity, information delays, and side effects.

This study aims to develop an annual DMFA–SD model of Japan's special steel supply chain using publicly available statistics and to assess whether the model can reproduce the historical behavior of aggregate special steel product flows, namely production, shipments, and inventories. The primary contribution of this paper is therefore not an element-by-element quantification of CMs such as Ni, Cr, Mo, and Co, nor a direct quantitative assessment of supply resilience outcomes. Rather, the study demonstrates that, in auditable MFA–SD modeling, consistency between the model boundary and the observational boundary is a central condition for interpreting model fit and model credibility. By applying this perspective to Japan's special steel supply chain, the study

presents an auditable product-flow baseline that clarifies system boundaries, observational definitions, data consistency, and feedback structures. This baseline is intended to support future extensions toward element-specific DMFA, supply-constraint scenarios, and comparative decision-support analyses involving inventory management, collection and sorting, stockpiling, and import diversification.

Accordingly, this study addresses the following research questions

> RQ1: What feedback structure can represent the annual-scale behavior of key aggregate flows—production, shipments, and inventories—and organize scrap-related feedback loops in Japan's special steel supply chain?
> RQ2: To what extent can a DMFA–SD model parameterized with publicly available statistics reproduce the historical behavior of aggregate special steel product flows at an annual resolution, and how do observational definitions, particularly inventory definitions, and adjustment time constants affect model fit and interpretation?
> RQ3: How can decision levers such as inventory and work-in-process (WIP) management, collection and sorting, stockpiling, and import diversification be organized within the proposed model structure as elements for future element-specific flow analysis and CM supply-resilience scenario analysis?

Importantly, the purpose of this paper is not to determine which intervention scenario is superior. Nor does this paper directly quantify element-specific CM flows or evaluate supply resilience using formal resilience indicators. Instead, it assesses whether an annual DMFA–SD model grounded in public statistics can reproduce the principal historical behavior of special steel product flows, audits its boundary against observed balances, and illustrates with one limited supply-constraint scenario how the structure can be used for future scenario analyses. Comparative evaluation based on intervention magnitude, duration, baseline assumptions, and resilience-related key performance indicators (KPIs) requires additional data and evaluation design and is therefore left for future research.

2 Literature & theoretical framing

2.1 Scope and limitations of MFA/DMFA

MFA is a core method for visualizing the overall structure of industrial metabolism based on conservation laws (mass balance). However, the literature remains biased toward static descriptions (Graedel 2019; Chen and Graedel 2012), which makes it difficult to address time-dependent effects—such as lifetime distributions, delays, and accumulation—when conducting future projections or policy assessment. Meanwhile, the CE provides a normative framework for resource circulation, but prior work points to definitional ambiguity, an overemphasis on the 3Rs, and insufficient linkage to social and institutional dimensions (Kirchherr et al. 2017). Critiques have also been organized regarding an unclear theoretical basis, structural barriers to implementation, and uncertainty about contributions to sustainability (Corvellec et al. 2021). In steel recycling, scrap quality and composition are important constraints: ELV-derived scrap can unintentionally introduce alloying elements such as Cr, Ni, and Mo into steelmaking, causing contamination and losses and thereby highlighting the importance of sorting and grade control (Matsubae et al. 2014; Ohno et al. 2014). Recently, cases have also emerged that integrate resilience analysis into materials MFA and complement data gaps through industry interviews (Böcher et al. 2024), broadening perspectives that connect CMs supply risk with circular design.

To address these limitations, DMFA treats stocks and flows as functions of time and can depict temporal profiles of secondary-resource potential and supply risk under different lifetime and demand scenarios (e.g., lithium and stainless steel) (Ziemann et al. 2018; Daigo et al. 2009, 2010). Simultaneous MFA of Ni, Cr, and Mo provides policy implications for design for recycling and sorting technologies (Nakajima et al. 2013; Kitamura 2007; Ohno et al. 2014). Regarding endogenizing structure via SD, CMs supply chains involve interactions among prices, policies, technologies, and behaviors that change flows endogenously. SD formalizes decision rules and delays—such as ordering and inventory policies, capacity adjustment, price expectations, and policy responses—using CLDs and SFDs, enabling comparisons that consider time constants and side effects of leverage points (Sterman 2000; Jahangirian et al. 2010; Angerhofer and Angelides 2000; Chowdhury 2023). In the steel sector, SD frameworks for process and resource efficiency (Norbert et al. 2020) and integrations of LCA and SD (Pinto et al. 2019) have been proposed; more broadly, SD has been extended toward practice-oriented decision support, including CE design, collection optimization, and emissions policy comparison (Franco 2019; Golroudbary and Zahraee 2015; Anand et al. 2006; Longbin 2007; Singh et al. 2019). Taken together, the MFA/DMFA–SD integration adopted in this study is positioned as a methodological foundation for simultaneously addressing quantitative consistency based on mass conservation and structural causality based on decision rules and delays. In this paper, this integration is used to reproduce the annual historical behavior of special steel product flows, to clarify model boundaries, observational definitions, and data consistency, and to organize decision levers that can be linked to future supply-resilience-oriented

scenario analysis. Accordingly, policy and management levers are not compared comprehensively in this paper; one inventory policy is examined only in a limited illustrative scenario, and the other levers are positioned as model elements for future analyses in which resilience-related KPIs are explicitly defined.

2.2 Decision-support positioning and theoretical framing

As discussed above, to jointly address quantitative consistency based on conservation laws and structural causality based on decision rules and delays, it is important to position the model as decision support grounded in the theoretical framework of SD. SD structures decision rules and time delays—such as inventory control, ordering, capacity adjustment, and price expectations—using CLDs and SFDs, thereby making endogenous dynamics explicit (Sterman 2000; Jahangirian et al. 2010; Angerhofer and Angelides 2000). Building on this theoretical foundation, this study aims not to directly compare the effects of decision levers in the present paper, but to clarify the model elements and boundary conditions required for future comparative scenario analysis, including the treatment of ramp-up time constants and potential side effects (see, e.g., applications to price learning: Morandi et al. 2014).

To enhance usefulness for future decision support, we explicitly document the model boundary, observational definitions, key assumptions, data sources, data-consistency checks, and candidate evaluation indicators for future scenario analysis. Such explicit treatment of system boundaries and assumptions has long been recognized as essential for robust assessment of technology-driven material transitions (Andrae 2010). These transparency requirements are consistent with discussions in systemic practice that emphasize methodological flexibility and boundary critique (Chowdhury 2023), as well as with the tradition of systemic intervention (Midgley 2000, 2018). Accordingly, we present the model as a foundation for future decision support and clarify the conditions under which results should be interpreted.

At present, we have not conducted action research (AR) as an iterative intervention cycle. However, future work could extend the approach through participatory modeling to examine and refine assumptions, observational definitions, and candidate indicators and to develop toward AR that includes consensus building and implementation evaluation (Machado et al. 2019; Lo et al. 2024). Theoretically, we emphasize: (i) boundary transparency and examination of alternative boundaries (Pinto et al. 2019; Norbert et al. 2020); (ii) auditability achieved by linking MFA's conservation laws with SD's structural causality (Sterman 2000); and (iii) the organization of candidate indicators required for future policy comparison, such as emissions, costs, inventory stability, supply continuity, and resource diversification, while making trade-offs and time constants explicit (Angerhofer and Angelides 2000). In addition, decision rules related to collection rates, sorting accuracy, and design changes, as well as policy functions such as social acceptance, regulation, stockpiling, and taxation, are positioned as elements for future extensions that should be evaluated together with explicitly defined resilience-related indicators (Franco 2019; Golroudbary and Zahraee 2015; Dall-Orsoletta et al. 2025).

3 Context & scope

This study analyzes Japan's special steel supply chain, which underpins key domestic industries. In this study, "special steel" is operationally defined according to the steel-grade classification used in Japanese public statistics. Following the classification reported by the Special Steel Association of Japan (SSAJ n.d.), special steel is broadly divided into tool steels, structural steels, and special-purpose steels. These categories comprise carbon tool steels, alloy tool steels, high speed tool steels, other tool steels, structural carbon steels, structural alloy steels, spring steels, bearing steels, stainless steels, heat-resisting steels, free-cutting steels, piano wire rods, high tensile strength steels, high-manganese steels, and other special-purpose steels. The present model aggregates these steel grades into a single special steel product-flow category. Special steel is widely used in infrastructure, digital devices, energy systems, medical applications, aerospace, and automobiles. Japan's hot-rolled special steel production reached approximately 15.4 Mt in FY2024, of which structural steels account for 44% and special-purpose steels for 55% (SSAJ n.d.). Moreover, for representative alloying elements among CMs (e.g., Ni, Co, Mo, and Cr), more than 50% of domestic demand is reported to be consumed in special steel applications, positioning special steel as a hub of domestic CMs flows (Table 1).

Table 1 is used to demonstrate the relevance of special steel as a major domestic use sector for selected CMs. It does not imply that this paper constructs complete element-specific material balances for alloying elements such as Ni, Cr, Mo, or Co. The quantitative implementation in this study focuses on the annual behavior of aggregate special steel product flows, namely production, shipments, and inventories. Element-specific flow tracking, composition- and grade-level management, cascade use, and dissipation pathways are positioned as extensions for future work.

According to JOGMEC (2007), the estimated consumption of seven alloying elements (Mo, Cr, Ni, Co, W, V, and

Table 1 Alloying elements for special steel: functional contributions and special steel's share of domestic demand in Japan. (Source: JOGMEC 2021; METI 2021)

Elements	Symbol	Enhancement of functional properties	Special steel's share of demand (FY2019)	Reference
Nickel	Ni	Toughness, Heat resistance	84.4%	METI (2021)
Nickel scrap and Nickel alloy scraps	Ni (scrap)	Same as Nickel	99.2%	METI (2021)
Chromium	Cr	Wear resistance, Corrosion resistance	≈95%	JOGMEC (2021)
Molybdenum	Mo	High-temperature strength, Hardness	89.3%	METI (2021)
Vanadium	V	High-temperature strength, Wear resistance	84.8%	JOGMEC (2021)
Manganese	Mn	Strength, Hardness	≈97%*	JOGMEC (2021)
Tungsten	W	High-temperature strength, Hardness	6.8%	METI (2021)
Cobalt	Co	High-temperature strength	51.0%	METI (2021)
Antimony	Sb	Wear resistance, Hardness	38.9%	METI (2021)

Shares indicate the proportion of each element (or scrap) consumed by special steel relative to total domestic demand. "Ni (scrap)" denotes nickel and nickel-alloy scrap used as inputs to special steel. Data sources are shown in the reference column

*For manganese, the shares include not only special steel but also other steelmaking applications

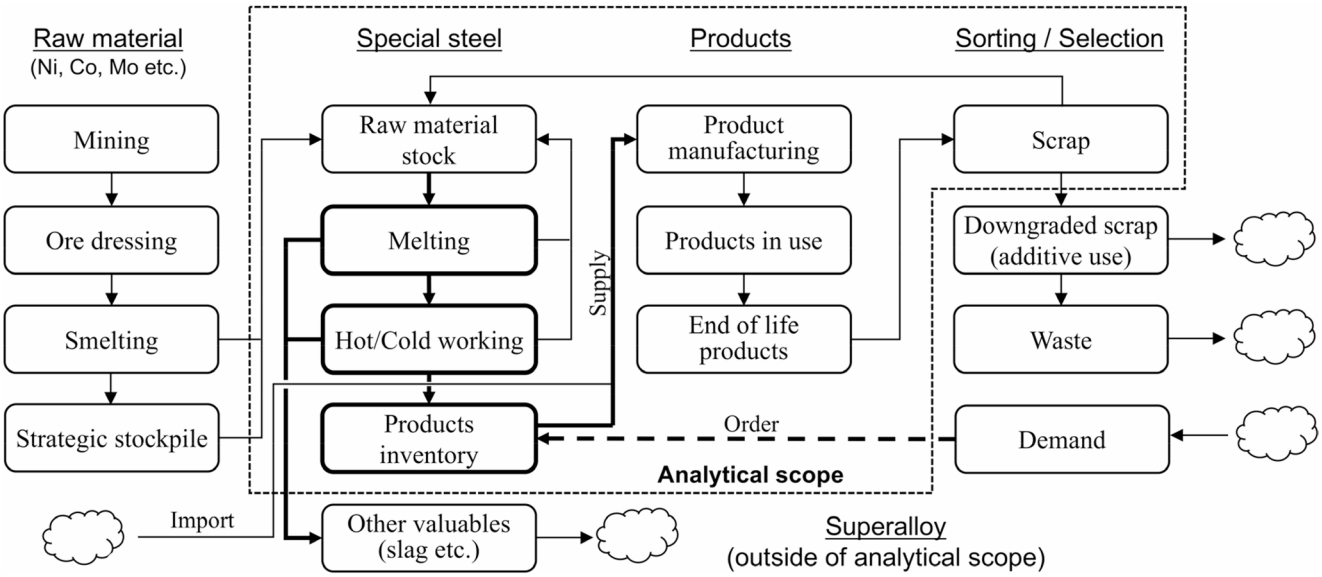

Fig. 1 Conceptual diagram of the special steel supply chain within the analytical scope of this study. The dashed box indicates the analytical scope, which is represented in the CLD (Fig. 3); in-scope processes include raw materials (alloying elements (CMs)), production, in-use stocks, end-of-life (EoL) discharge, collection, sorting (high-alloy/low-alloy/mixed), and scrap remelting. Bold elements indicate the part quantified in the SFD (Fig. 4); the other elements are conceptual and are positioned as future extensions (Table 2). Orders are modeled as the exogenous driver; imports are outside makers' inventory and are used only for the mass-balance audit. Losses and downgrading are treated as side flows. Superalloys are out of scope. The scope refers to process coverage, with a primary spatial focus on Japan

Mn) in Japan's special steel manufacturing in 2005 was 1.31 Mt, corresponding to 6.4% of hot-rolled special steel production (20.4 Mt). As a more recent estimate with comparable scope and definitions could not be obtained, the 2005 ratio was applied to FY2024 hot-rolled special steel production (15.4 Mt), yielding an estimated consumption of approximately 1.0 Mt of these seven alloying elements.

In this paper, we focus on those CMs that are added to special steel as alloying elements. The main objective is to reproduce annual-scale behavior of special steel product flows and to establish a model structure in which decision levers can be organized for future scenario analysis, rather than to make element-by-element material balances the central task. Detailed analyses—such as element-specific flow tracking and the representation of dissipation and quality grades (cascading)—are left as extensions for subsequent work.

To establish a DMFA for special steel, we treat special steel in aggregate rather than disaggregating by steel grade. The system boundary covers raw materials → special steel manufacturing → use (product manufacturing) → end-of-life (EoL) → collection → sorting → scrap recovery (Fig. 1). Although superalloys are strategically important, publicly available Japanese statistics do not provide

time-series data that clearly distinguish superalloys from special steel, nor do they offer product-group composition data and scrap-routing information in a form suitable for quantitative, reproducible analysis. Ensuring auditability is therefore difficult at present. Accordingly, this paper prioritizes a baseline model for special steel that can be evaluated using public statistics and excludes superalloys from the system boundary. The spatial scope is primarily Japan, and—because establishing the DMFA is the priority—we exclude price-related factors (e.g., exchange rates and international market prices) that would substantially complicate causal structure.

We identify special steel manufacturers, raw material and alloy suppliers, scrap processors and traders, and user industries such as automotive, machinery, and construction as the main stakeholders. Decisions related to inventory policies, capacity adjustment, investments in collection and sorting, stockpiling operations, and imports are important decision domains relevant to supply resilience. However, the quantitative implementation in this paper does not compare these levers comprehensively; it prioritizes the historical reproduction of annual aggregate special steel product flows and examines one inventory policy only in a limited supply-constraint scenario. These decision domains are therefore positioned as model elements for future implementation and evaluation in element-specific flow analysis and supply-resilience-oriented scenario analysis.

4 Methodology

In this study, we model the annual behavior of aggregate product flows in Japan's special steel industry using SD, positioning the model as a baseline that can be linked to future element-specific DMFA and supply-resilience-oriented scenario analysis. The purpose of this paper is not to construct a complete element-specific flow model of CMs themselves, but to reproduce aggregate product flows—production, WIP, inventories, and shipments—using publicly available statistics, while explicitly documenting model boundaries, observational definitions, and data consistency. We used Vensim PLE Plus (ver. 10.4.0) for CLD development and SD implementation, and a Python implementation of the same equations for calibration and sensitivity analysis.

The study is based on a three-layer design that integrates MFA with SD (Fig. 2). Layer 1 explicates hypothesized structure via a CLD; Layer 2 ensures quantitative consistency via an SFD; and Layer 3 organizes model elements and candidate indicators that can be used in future scenario analyses.

4.1 Research approach

The methodology of this study connects the quantitative consistency of MFA based on mass conservation with the structural causality of SD based on feedback structures and time delays, and aims to reproduce the annual behavior of special steel product flows using publicly available statistics. The model developed in this paper is not a completed model that directly quantifies element-specific CM flows or supply resilience. Rather, it is positioned as an auditable product-flow baseline model that can be linked to future element-specific flow analysis and supply-constraint scenario analysis.

Specifically, we first organize the major material flows and decision structures in Japan's special steel supply chain based on the literature, publicly available statistics, and industry materials, and visualize them as a CLD (Fig. 3). Next, among the structures represented in the CLD, the

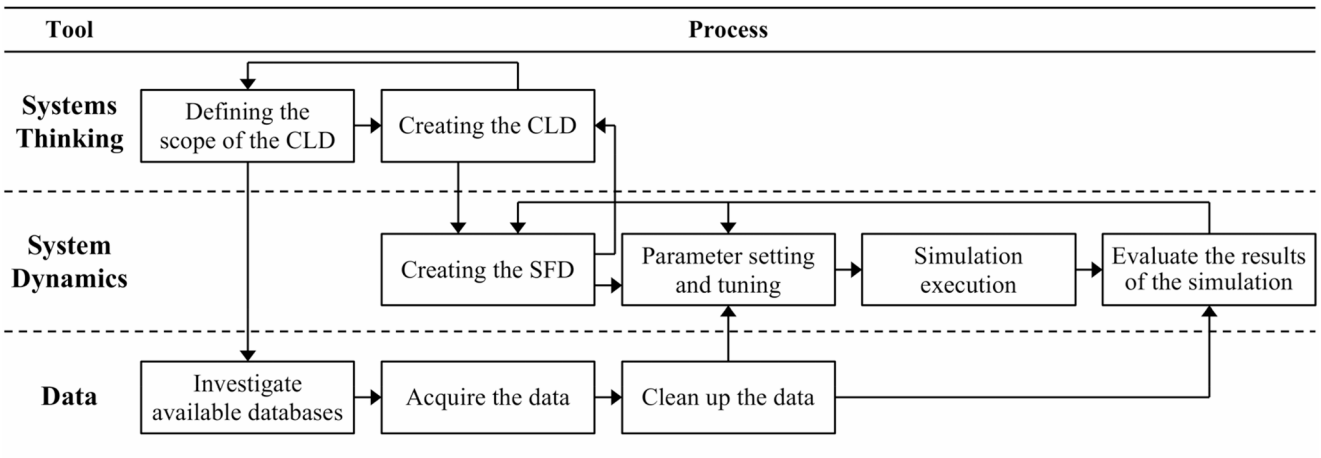

Fig. 2 Integrated workflow connecting systems thinking, SD and data exploration. Systems thinking defines the scope and articulates feedback via the CLD; SD translates this into a stock and flow model with parameterization, simulation, and evaluation; data exploration underpins the model through database investigation, data acquisition, and data cleaning

demand–supply and manufacturing loops (*B1* and *B2*) are implemented as an SFD (Fig. 4), while the other loops remain conceptual (Table 2). In the SFD, *Orders* are treated as the exogenous variable, *Order backlog*, *WIP* and *Products inventory* are defined as stocks, and *Production starts*, *Production output* and *Shipping* are defined as the main flows, allowing us to examine how order fluctuations and internal production–inventory adjustments shape annual behavior.

The model is evaluated in terms of in-sample historical fit against publicly available statistics compared with naive benchmarks, consistency between the model boundary and observational definitions, and the auditability of data processing, rather than by comparing the superiority of intervention scenarios. In particular, the model boundary is audited with annual balance residuals computed from observed production, imports, shipments and inventory changes, and the observed inventory series is selected accordingly. Therefore, what is conducted in this paper is not formal uncertainty propagation or global sensitivity analysis, but checks related to boundary conditions, observational definitions, adjustment time constants (one-at-a-time sensitivity and identifiability analyses; Sect. 4.4), and data consistency. In addition, one limited supply-constraint scenario illustrates how the structure responds to a constraint (Sect. 4.5).

Furthermore, decision levers such as collection and sorting, stockpiling, import diversification, and inventory and WIP management are not compared comprehensively in this paper. Instead, they are organized as model elements for future element-specific flow analysis and supply-resilience-oriented scenario analysis. In this way, the study reproduces the annual macro-level behavior of the special steel supply chain using publicly available statistics and presents a methodological foundation that can be extended to future comparative analyses of recycling-oriented circularity, supply constraints, stockpiling, and import diversification.

4.2 System description and model structure

In this section, we first structure the analytical boundary shown in Fig. 1 as a CLD and then formalize the adjustment mechanisms for production and inventories as an SFD. The CLD captures "what circulates and which loops matter," whereas the SFD specifies "which stocks and flows implement the mechanisms." The CLD of raw materials, manufacturing, and use for special steel is shown in Fig. 3. The elements are connected by causal relationships, represented by arrows. Each causal link is assigned a polarity—positive (+) or negative (–)—indicating the direction of change in the outcome when the causal variable changes. For major feedback loops, identifiers indicate whether the loop is reinforcing (R) or balancing (B). A positive (+) relationship means that, all else equal, an increase in the cause leads to an increase in the effect, and a decrease in the cause leads to a decrease in the effect (Sterman 2000).

The CLD (Fig. 3) refines the scope in Fig. 1 and incorporates balancing loops *B1–B4* and reinforcing loops *R1* and *R2*. *B1* is a demand–supply balancing loop, in which decisions responding to market conditions influence *B2*

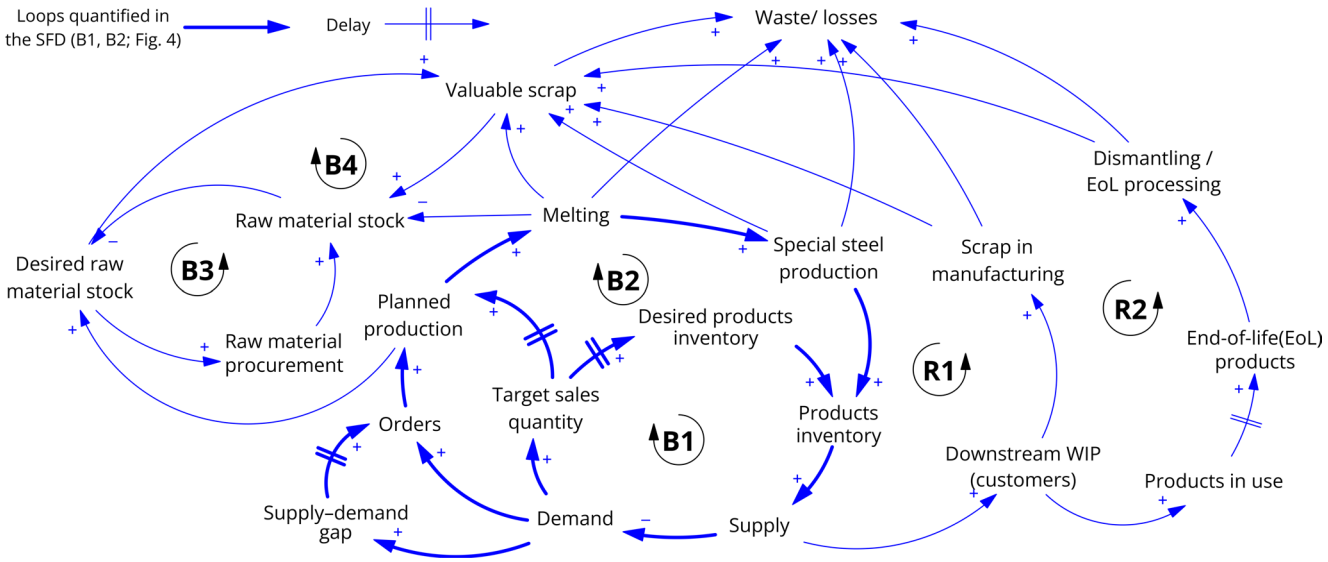

Fig. 3 CLD of special steel material flow. Balancing loops (*B1–B4*) regulate market supply–demand balance, production scheduling, and the procurement of primary raw materials and scrap, while reinforcing loops (*R1* and *R2*) capture feedback from scrap generated during production and at EoL. Bold arrows indicate the loops quantified in the SFD (*B1* and *B2*; Fig. 4). Link signs (+/−) denote polarity (same- or opposite-direction change of the affected variable). The structure supports a systemic understanding of resource circulation and identifies key model elements that can be linked to future scenario analysis

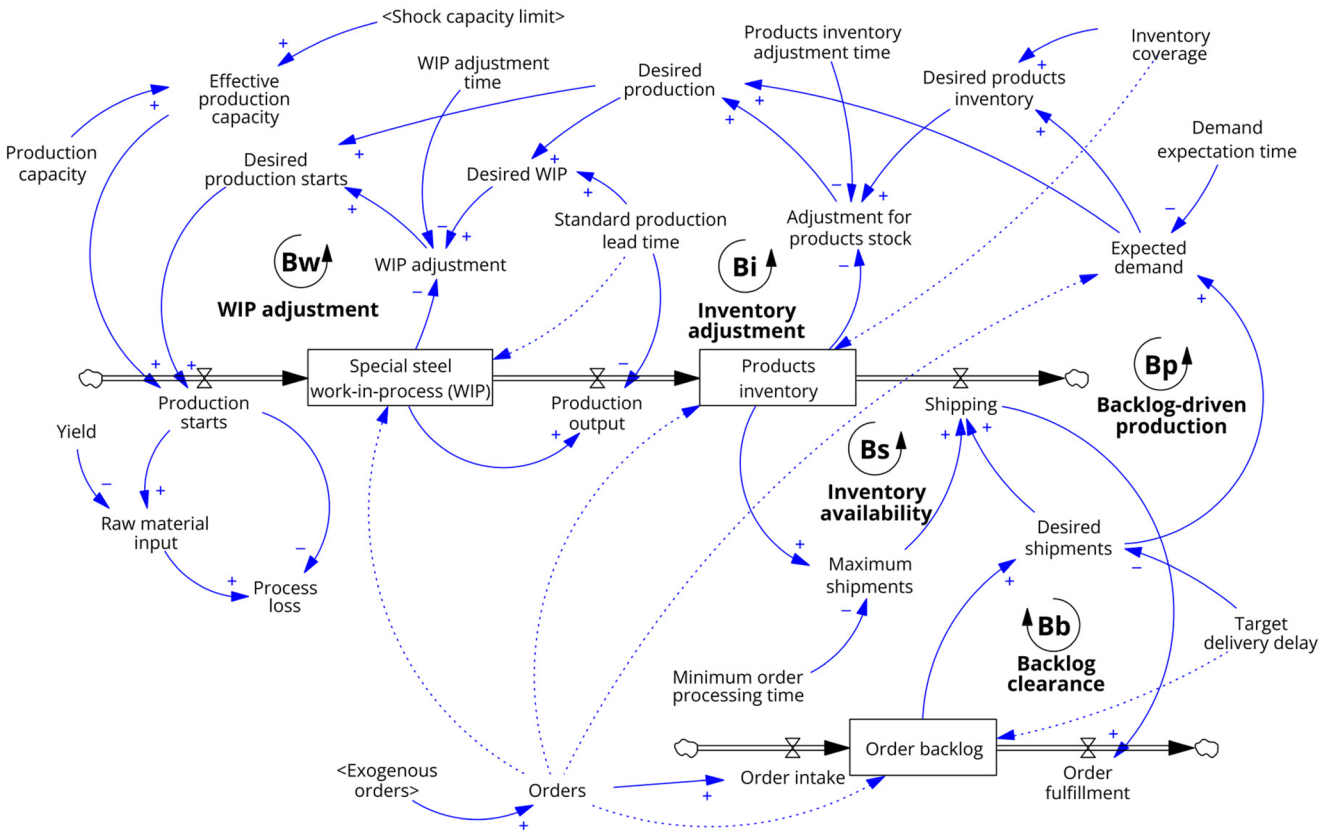

Fig. 4 SFD integrating CLD loops *B1* and *B2*. This SFD comprises three stocks—*Order backlog*, *Special steel work-in-process (WIP)* and *Products inventory*—connected by five balancing feedback loops: *Bp* (*Backlog-driven production*), *Bb* (*Backlog clearance*), *Bs* (*Inventory availability*), *Bi* (*Inventory adjustment*) and *Bw* (*WIP adjustment*). *Orders* are treated as the exogenous input, and the system adjusts toward *Desired production*, *Desired WIP*, and *Desired products inventory*. < *Exogenous orders*> supplies either the historical orders or the constant scenario level, and < *Shock capacity limit* > is used only in the scenario of Sect. 4.5

Table 2 Feedback loops in the CLD (Fig. 3) and their implementation in the SFD (Fig. 4)

Loop	Name	Description	Implementation in the SFD (Fig. 4)
B1	*Demand–supply balancing loop*	Demand, sales targets and desired inventory adjust to supply, with delays in inventory decisions.	Quantified: *Bi* (*Inventory adjustment*; expected demand and desired inventory); *Bb* (*Backlog clearance*); *Bs* (*Inventory availability*)
B2	*Manufacturing balancing loop*	Orders determine production; material passes through processing and accumulates as finished products, which are shipped to reduce outstanding demand.	Quantified: *Bp* (*Backlog-driven production*); *Bw* (*WIP adjustment*)
B3	*Raw material procurement balancing loop*	Procurement keeps raw material inventory at its target.	Not quantified; future extension (raw material input and process loss are accounted for, without procurement decisions)
B4	*Scrap procurement balancing loop*	Procurement keeps scrap inventory at its target.	Not quantified; future extension
R1	*Manufacturing-origin scrap reinforcing loop*	Scrap generated in downstream fabrication returns as input.	Not quantified; future extension
R2	*Post-use scrap reinforcing loop*	EoL products generate scrap that returns as input.	Not quantified; future extension

"Quantified" loops are implemented in the SFD (Fig. 4) and evaluated in this study; "Not quantified; future extension" loops are represented only in the CLD and indicate the scope for the element-specific and recycling-oriented extensions discussed in Sect. 5.3. In Fig. 3, the quantified loops are shown with bold arrows. "*Downstream WIP (customers)*" in Fig. 3 is work in process at customers after delivery and is distinct from *Special steel work-in-process (WIP)* in Fig. 4

(manufacturing process balance). The production plan determined in *B2* then propagates to the balancing loops for *B3* (raw material procurement) and *B4* (scrap procurement). After delivery to customers, the supplied materials are processed into a variety of final products. Scrap is generated both from manufacturing processes and at EoL, while unavoidable waste/loss also occurs. Generated valuable scrap is reinjected as an input to *B2* as long as it meets quality requirements, thereby forming a closed loop. An overview of the loops is summarized in Table 2, and repetition in the main text is kept to a minimum. The CLD design was based on industry reports, government statistics, and publicly available materials, supplemented by generally established practical knowledge of production and inventory management. On this basis, we organized the main structural hypotheses common to Japan's special steel supply chain.

The overall SFD of special steel material flows, which constitutes the core of our analysis, is shown in Fig. 4; it draws on the make-to-stock manufacturing structure described by Sterman (2000), adapted to annual aggregate statistics. Following standard SD notation, the model represents dynamic system behavior through "stocks," which accumulate physical materials and information, and "flows," which change those quantities over time. The model describes the operational and decision-making processes from production planning in response to customer orders through manufacturing and shipment.

At the center of the model are three primary stocks that characterize production and inventory management. The first is the *Order backlog*, an information stock representing orders received but not yet shipped. The second is the *Special steel work-in-process (WIP)* stock, representing material that has entered production but is not yet completed (in output-equivalent tonnes). The third is the *Products inventory*, representing makers' finished goods awaiting shipment to customers; imports do not pass through this stock (Sect. 4.4). These stocks are controlled by multiple feedback loops embedded in the model.

Whereas the CLD provides an overview of causal relationships, the SFD implements the stock and flow structure with CLD loops *B1* and *B2* at its core. The overall structure is as follows. First, *Orders* accumulate in the *Order backlog* and are depleted by *Shipping*; a larger backlog raises desired shipments and thus *Shipping* (*Bb)*, while *Shipping* is limited by the available *Products inventory* (*Bs*). *Production starts* are determined based on expected demand and decision rules for inventory and WIP. *Production starts* accumulate in *WIP* and are depleted by *Production output*. In parallel, *Bw (WIP adjustment)* is an internal operational control loop—excluding raw-material and scrap elements—that adjusts *Production starts* according to the gap between *Desired WIP* and actual *WIP*, thereby maintaining *WIP* near its intended level. Coupled to these loops, *Bi (Inventory adjustment)* adjusts *Desired production* so that *Products inventory* converges toward *Desired products inventory*, allowing inventories to function as a buffer against demand fluctuations. In *Bp* (*Backlog-driven production*), a growing backlog raises expected demand and thus production, which replenishes inventory and clears the backlog.

These loops incorporate real physical and decision-making time delays. For example, there is a time lag from a customer "order" to actual "shipment" due to *Standard production lead time* (*LT*) and the *Target delivery delay*. Such delay structures are a fundamental source of supply-chain dynamics, including over- and under-stocking behavior.

For each adjustment loop, we explicitly implement physical and decision delays such as *Standard production lead time*, *WIP adjustment time*, *Products inventory adjustment time* and *Demand expectation time*. If delays are mis-specified, *WIP* and inventories may overshoot or oscillate. Therefore, the adjustment times were calibrated against observed production, shipping, and inventory series (Sect. 4.3).

The SFD targets annual macro behavior. At this stage, prices and exchange rates are not endogenized; instead, their effects on demand are contained in the exogenous *Orders*. On the supply side, the replenishment mechanisms corresponding to *B3* (raw material procurement) and *B4* (scrap procurement) in Fig. 3 are positioned only at the CLD level. The SFD implementation in this paper focuses on reproducing the annual behavior of *Production output*, *Order backlog*, *WIP*, *Products inventory* and *Shipping*. Detailed endogenization of raw material procurement, scrap procurement, collection, and sorting is left as a future extension toward element-specific flow analysis and supply-resilience-oriented scenario analysis.

4.3 Specifications of the SFD model and data mapping

This paper focuses on annual behavior of steel mass (product flows). The model describes annual-scale behavior of Japan's special steel supply chain using an SFD parameterized from public data. The modeling environment is Vensim PLE Plus (ver. 10.4.0). To ensure numerical stability, we set the simulation time step to $\Delta t = 1/128$ year (Euler method) and aggregate outputs to annual values. Units are t/year for flows and t for stocks, and all series are harmonized to the FY basis. The exogenous variable is *Orders* (the sum of *Domestic orders* and *Export orders*); Imports (imports of special steel products) are used only in the balance audit (Sect. 4.4). The key stocks are *Order backlog*, *WIP* and *Products inventory*, and the main flows are *Production starts*, *Production output* and *Shipping*. Because transient

oscillations can occur at the beginning of simulation, the model starts in equilibrium in FY1980, and FY1980–1993 serves as a 14-year warm-up period (Online Resource 1, Table S1).

Data sources for orders, production, shipments, inventories and imports are constructed by harmonizing long-term statistics from the Special Steel Association of Japan and annual time series from Tekko Shimbun Corp.'s Tekkō Nenkan (Iron and Steel Yearbook) (SSAJ n.d.; Tekko Shimbun Corp. 1995–2024), with FY harmonization applied as needed (Table 3). For imports, to avoid double counting by end-use categories, we extract the items corresponding to special steel products and aggregate them on a weight basis. Two observed inventory series are available: makers' finished-goods inventory and total inventory (makers' plus dealers' inventory). Because imports do not pass through makers' inventory (Sect. 4.4), the model is evaluated against makers' finished-goods inventory (Fig. 5).

4.3.1 Model equations

Let B, W and I denote *Order backlog*, *WIP* and *Products inventory* [t], and O *Orders* [t/year]. The stocks evolve as

$$\frac{dB}{dt} = O - S,\ \ \frac{dW}{dt} = PS - P,\ \ \frac{dI}{dt} = P - S \tag{1}$$

where S is *Shipping*, PS *Production starts* and P *Production output* [t/year]. *Shipping* is the smaller of *Desired shipments*S^* and the rate that inventory allows:

$$S^* = \frac{B}{DD},\ S = \min\left(S^*,\ \frac{I}{\tau_{\min}}\right) \tag{2}$$

where DD is the *Target delivery delay* and $\tau_{\min}$ the *Minimum order processing time*. *Expected demand*D^e smooths *Desired shipments*, so that it reflects both new orders and backlog pressure:

$$\frac{dD^e}{dt} = \frac{S^* - D^e}{\tau_E} \tag{3}$$

$$I^* = c\,D^e,\ \ P^* = \max\left(0,\ D^e + \frac{I^* - I}{\tau_{Inv}}\right) \tag{4}$$

$$W^* = P^*\,LT,\ \ PS^* = \max\left(0,\ P^* + \frac{W^* - W}{\tau_{WIP}}\right) \tag{5}$$

$$PS = \min\left(PS^*,\ K_{\text{eff}}\right) \tag{6}$$

$$P = \frac{W}{LT} \tag{7}$$

where τ_E is the *Demand expectation time*, c the *Inventory coverage*, τ_{Inv} the *Products inventory adjustment time*, LT the *Standard production lead time* and τ_{WIP} the *WIP adjustment time*; I^*, P^*, W^* and PS^* are *Desired products inventory*, *Desired production*, *Desired WIP* and *Desired production starts*. *Effective production capacity* is

$$\begin{aligned} K_{\text{eff}}(t) &= \min\left(K,\ K_{\text{shock}}(t)\right), \\ K_{\text{shock}}(t) &= \begin{cases} (1-s)\,O(t), & t_s \le t < t_s + d \\ K, & \text{otherwise,} \end{cases} \end{aligned} \tag{8}$$

where K is *Production capacity*, K_{shock} the capacity limit during a supply shock, and s, t_s and d the shock depth, start time and duration (Sect. 4.5). *Raw material input RM* and *Process loss L* follow from the *Yield Y*:

Table 3 Model variables and data sources

Model variable	Role	Definition	Unit	Source	Period (FY)
Domestic orders, *Export orders*	Exogenous input	Orders received by makers	[t/year]	Tekko Shimbun Corp. (1995–2024)	1994–2023
Production output	Evaluation target	Completed special steel products	[t/year]	Tekko Shimbun Corp. (1995–2024); FY1994–2008 estimated from SSAJ (n.d.)	1994–2023
Shipping	Evaluation target	Makers' domestic + export shipments	[t/year]	Tekko Shimbun Corp. (1995–2024)	2009–2023
Products inventory	Evaluation target	Makers' finished-goods inventory at FY-end	[t]	Tekko Shimbun Corp. (1995–2024)	2009–2023
Imports, dealers' inventory, apparent consumption	Mass-balance audit only	Not model variables	[t/year], [t]	Tekko Shimbun Corp. (1995–2024)	2009–2023
Hot-rolled production	Yield; FY1994–2008 production estimate	Hot-rolled special steel products	[t/year]	SSAJ (n.d.)	1994–2023

Units are tonnes (t) for stocks and t/year for flows. *Production output* for FY1994–2008 is estimated by multiplying hot-rolled production by the average yield between FY2009 and 2023

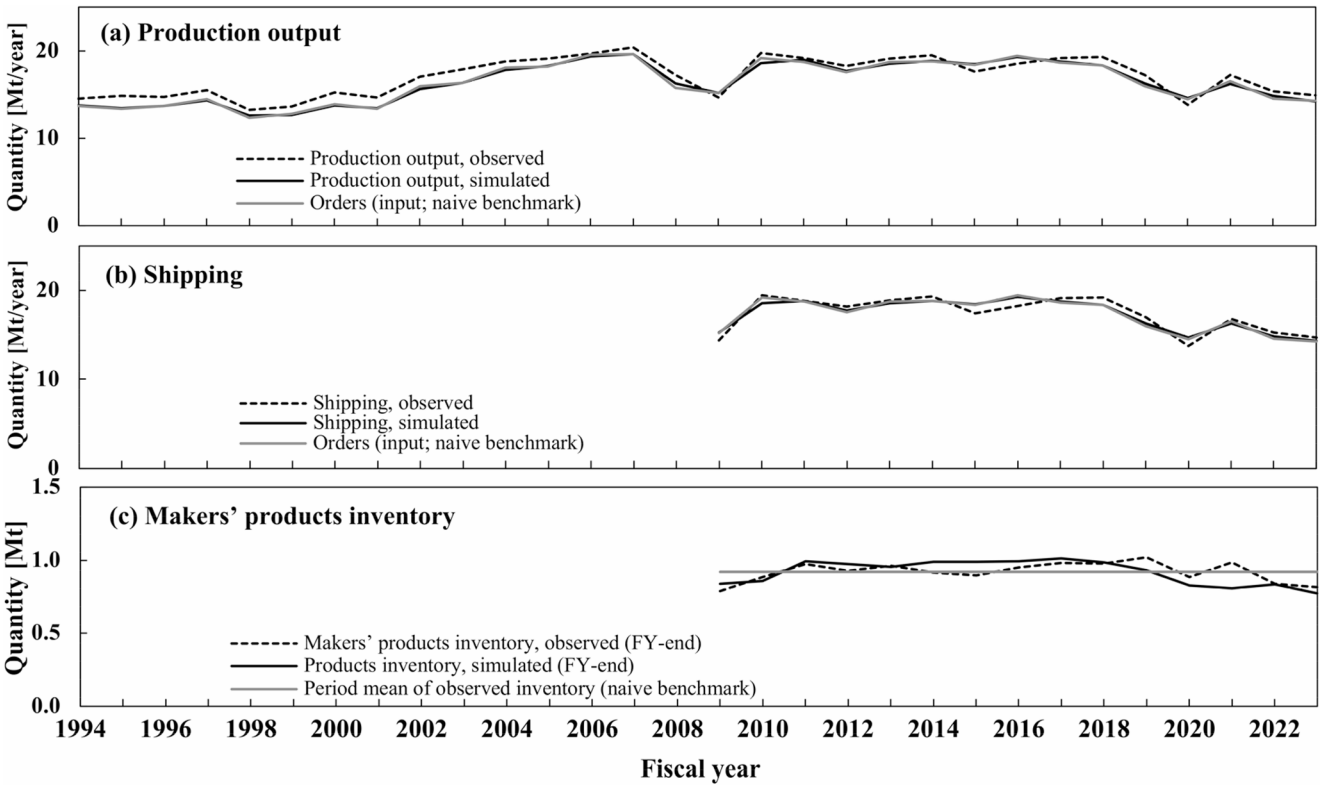

Fig. 5 Reproduction of historical behavior (observed vs. simulated). Panels show annual (**a**) Production output, (**b**) Shipping, and (**c**) Products inventory. In (**c**), Observed (makers' finished goods) is compared with Simulated. Grey lines show the naive benchmarks (Orders in (**a**) and (**b**); period mean in (**c**)). Observed = dashed; Simulated = solid. Period: (**a**) FY1994–2023 (FY1994–2008 estimated from hot-rolled production); (**b**, **c**) FY2009–2023

Table 4 Key model parameters

Parameter	Symbol	Value	Basis	Source / note
Standard production lead time	*LT*	1/3 year	Assumption	Representative value (4 months); 0.1–0.5 year in sensitivity
WIP adjustment time	τ_{WIP}	0.0625 year	Calibrated	Grid 0.05–0.5 year
Products inventory adjustment time	τ_{Inv}	0.5 year	Calibrated	Grid 0.25–4 years
Demand expectation time	τ_{E}	0.0625 year	Calibrated	Grid 0.03125–0.25 year
Target delivery delay	*DD*	0.15 year	Calibrated	Grid 0.05–0.25 year
Inventory coverage	*c*	0.0531 year (19.4 days)	Data	Mean makers' inventory / mean shipping, FY2009–2023
Yield	*Y*	0.938	Data	Mean production / hot-rolled production, FY2009–2023; affects input and loss only
Production capacity	*K*	21.4 Mt/year	Assumption	1.05 × maximum production in the compiled series (20.4 Mt, FY2007; estimated from hot-rolled production and yield)
Minimum order processing time	τ_{min}	0.02 year	Assumption	Sensitivity 0.01–0.05 year

Initial conditions and numerical settings are listed in Online Resource 1, Table S1. Capacity binds only briefly (about 4 months) in FY2010; without it, the inventory MAPE would be 5.37% instead of 5.50%. Basis: Assumption = set by the authors and examined in the sensitivity analysis; Calibrated = selected on the 1,500-combination grid (Online Resource 1, Table S2); Data = computed from the FY2009–2023 statistics

$$RM = \frac{PS}{Y},\ L = RM - PS \tag{9}$$

4.3.2 Parameterization and initial conditions

We specify the *WIP adjustment time*, τ_{WIP}, the *Products inventory adjustment time*, τ_{Inv}, the *Demand expectation time*, τ_E, and the *Target delivery delay*, *DD*, as adjustment time constants (Table 4). These values were calibrated on a grid of 1,500 combinations by minimizing the mean of the mean absolute percentage errors (MAPE) of production, shipping and makers' inventory; combinations with any parameter on a bound of its search range were excluded (Online Resource 1, Table S2). This procedure was not

intended as global sensitivity analysis, but as in-sample historical calibration to support model interpretation at an annual resolution. Accordingly, the fit statistics reported in this study represent calibration-period historical fit and should not be interpreted as out-of-sample predictive validation. The *Standard production lead time* was set to an assumed representative value (4 months), because annual data cannot identify it separately from the *WIP adjustment time* (Sect. 4.4). For the initial conditions, all stocks start in equilibrium with the FY1980 *Orders* (Online Resource 1, Table S1). Because order statistics are available only from FY1994, the FY1980–1993 warm-up is driven by the mean orders of FY1994–2003.

4.3.3 Evaluation windows and fit metrics

Production output is evaluated over FY1994–2023, while *Shipping* and *Products inventory* are evaluated primarily over FY2009–2023, reflecting data availability. Model agreement is reported using the correlation coefficient *R*, the MAPE, the root mean squared percentage error (RMSPE) and the mean bias (Eq. 10; Table 5). As naive benchmarks, *Production output* and *Shipping* are set equal to *Orders*, and *Products inventory* equal to its period mean.

$$\begin{aligned} \mathrm{MAPE} &= \frac{100}{n}\sum_{i=1}^{n}\left|\frac{a_i - f_i}{a_i}\right|, \\ \mathrm{RMSPE} &= 100\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{a_i - f_i}{a_i}\right)^2}, \\ \mathrm{Bias} &= \frac{100}{n}\sum_{i=1}^{n}\frac{f_i - a_i}{a_i} \end{aligned} \tag{10}$$

ai:*observed value*, *fi*:*predicted value*, *n*:*number of observations*

4.3.4 Consistency checks

We confirm that the mass balance (raw material input = change in WIP + output + loss) holds at all times, with a numerical error of below 10^{-5} t; that totals after unit conversion and FY conversion match the original series; and that the observed annual balance residuals are interpretable (Sect. 4.4). These checks support the internal consistency and auditability of the annual-resolution SFD structural hypotheses, with orders treated as the exogenous input; they do not by themselves validate agreement with observations, which is examined in Sect. 4.4. The curated time-series dataset, the Vensim model file (.mdl) and a Python implementation are available in a public repository (Araki and Nagamatsu 2026).

4.4 In-sample historical fit and goodness of fit

In this section, we evaluate the in-sample historical fit of the constructed SD model by comparing Observed values from public statistics with Simulated model outputs within the calibration period. The evaluation covers *Production output*, *Shipping*, and *Products inventory*. *Orders* are treated as the exogenous input, whereas *Production output*, *Shipping*, *Order backlog*, *WIP*, and *Products inventory* are determined by the endogenous feedback loops in the model, namely *Bp*, *Bb*, *Bs*, *Bi* and *Bw*.

For *Production output* and *Shipping*, the MAPE values were 5.25% and 3.66%, and the correlation coefficients were 0.960 and 0.935, both statistically significant at the 1% level (Table 5; Fig. 5). These results indicate reasonable in-sample historical fit within the calibration period for production and shipping. However, these fits are almost identical to those of the naive benchmark equal to *Orders* (MAPE 5.28% and 3.59%), and simulated production is on average 4.1% below observed production. This suggests that the system is strongly driven by exogenous order fluctuations at an annual resolution, and that the historical fit of production and shipping does not by itself demonstrate the contribution of the endogenous feedback structure.

For *Products inventory*, model fit depended strongly on the observational definition. The observed balance residuals (Table 6) show that makers' finished-goods inventory corresponds to the model boundary: the makers' balance leaves a residual of +206 kt/year (1.18% of production), positive in 13 of 14 years, which cannot be decomposed further with published statistics, whereas routing imports through

Table 5 Fit between observed and simulated annual values, with naive benchmarks (in-sample)

Target (period, FY)	Model	*R*	MAPE [%]	RMSPE [%]	Bias [%]
Production output (1994–2023)	This model	0.960	5.25	5.69	−4.08
	Naive: = *Orders*	0.961	5.28	5.74	−4.12
Shipping (2009–2023)	This model	0.935	3.66	4.10	−0.37
	Naive: = *Orders*	0.935	3.59	4.10	−0.52
Makers' products inventory (2009–2023)	This model	0.602	5.50	7.05	−0.15
	Naive: period mean	–	6.16	7.53	0.54

Production output for FY1994–2008 is estimated from hot-rolled production (Table 3). Naive benchmarks: production and shipping equal to *Orders* in the same year; inventory equal to its FY2009–2023 mean. Bias = mean of (simulated − observed)/observed; negative values indicate underestimation. Metrics are defined in Eq. (10)

Table 6 Observed annual balance residuals, FY2010–2023 (mean)

Balance	Definition	Mean residual [kt/year]	Share of production [%]
Makers' balance (adopted boundary)	Production − shipping − Δ makers' inventory	+206 (positive in 13 of 14 years)	1.18
Imports routed through inventory (alternative boundary)	Production + imports − shipping − Δ total inventory	+866	4.90

Residuals are computed from published statistics only (Tekko Shimbun Corp. 1995–2024), without the model

Δ denotes the change in FY-end inventory. The difference between the two residuals equals imports minus the change in dealers' inventory; annual values and the decomposition are given in Online Resource 1 (Fig. S1, Table S6)

Table 7 Illustrative scenario: production starts limited to 80% of orders for one year (FY2023 orders)

Inventory coverage	Peak backlog increase [Mt]	Max. delivery delay [year]	Recovery time [year]	Excess backlog × time [Mt·year]
×1 (observed, 19.4 days)	1.62	0.31	1.98	1.13
×2 (38.7 days)	0.86	0.24	1.79	0.41

Orders are held constant at the FY2023 level (14.2 Mt/year). Coverage ×1 is the data-derived inventory coverage; ×2 doubles it, adding 0.76 Mt of inventory before the shock. Pre-shock delivery delay 0.15 year. Recovery time: until the backlog stays within ± 1% of its pre-shock level. Excess backlog × time: integral of the backlog above its pre-shock level. Robustness to parameters and structure: Online Resource 1, Table S5

inventory raises the residual to +866 kt/year (4.90%); the difference equals imports minus the change in dealers' inventory (Online Resource 1, Fig. S1 and Table S6). Imports are therefore kept outside makers' inventory in the model. Against makers' finished-goods inventory, the correlation coefficient was 0.602 and the MAPE 5.50%, slightly smaller than that of the period-mean benchmark (6.16%) within the calibration period. Accordingly, the inventory results are interpreted primarily as evidence of the importance of alignment between the model boundary and the observational boundary, rather than as evidence of accurate inventory reproduction.

Production depends on LT and τ_{WIP} only through the combination $LT\,\tau_{WIP}/(LT+\tau_{WIP})$, so the two parameters are not separately identifiable from annual data (Online Resource 1, Table S4); for LT = 0.1–0.5 year, with the *WIP adjustment time* adjusted accordingly, the production fit is unchanged and the inventory MAPE ranges from 5.37% to 6.86% (Online Resource 1, Table S5). In one-at-a-time sensitivity analyses, the inventory fit is most sensitive to the data-derived *Inventory coverage c*, whereas the time step, the warm-up length (0, 14 or 30 years) and the initial stocks have negligible effects (Online Resource 1, Table S3).

This section evaluated the in-sample historical fit of the annual-resolution DMFA–SD model using publicly available statistics in an auditable manner by explicitly documenting data-consistency checks, including unit conversion, FY conversion, and identity checks. *Production output* and *Shipping* showed reasonable fit within the calibration period, comparable with the naive benchmark. *Products inventory* was sensitive to observational definitions and was reproduced with a slightly smaller error than the benchmark once the observed series was matched to the model boundary. Future work should therefore address the unexplained residual of the makers' balance, and connect the model to future scenario analysis based on agreed KPIs and intervention designs.

4.5 Illustrative supply-constraint scenario

One scenario illustrates the response to a supply constraint, such as a shortage of alloying elements; the constraint is reduced-form and does not represent a specific element. *Orders* are held constant at the FY2023 level, and production starts are limited to 80% of orders for one year (s = 0.2 and d = 1 year in Eq. 8), comparable to the largest observed single-year declines (− 19.9% in production in FY2020 and − 19.7% in orders in FY2008). Two inventory policies are compared: the observed inventory coverage (×1) and doubled coverage (×2). The indicators are the peak backlog increase, the maximum delivery delay, the recovery time and the excess backlog × time (Table 7). Inventory holding costs are not evaluated.

by 1.62 Mt and recovery takes 1.98 years (Table 7; Fig. 6). Doubling coverage reduces the peak increase to 0.86 Mt and the excess backlog × time by 64%. The reduction is 62–66% across the 160 parameter sets within 0.25% points of the best objective over all 1,500 combinations and 53–73% for LT = 0.1–0.5 year, but the backlog does not recover within eight years if production is planned on orders only with the observed coverage (Online Resource 1, Table S5). These results are exploratory and hold only under the stated assumptions.

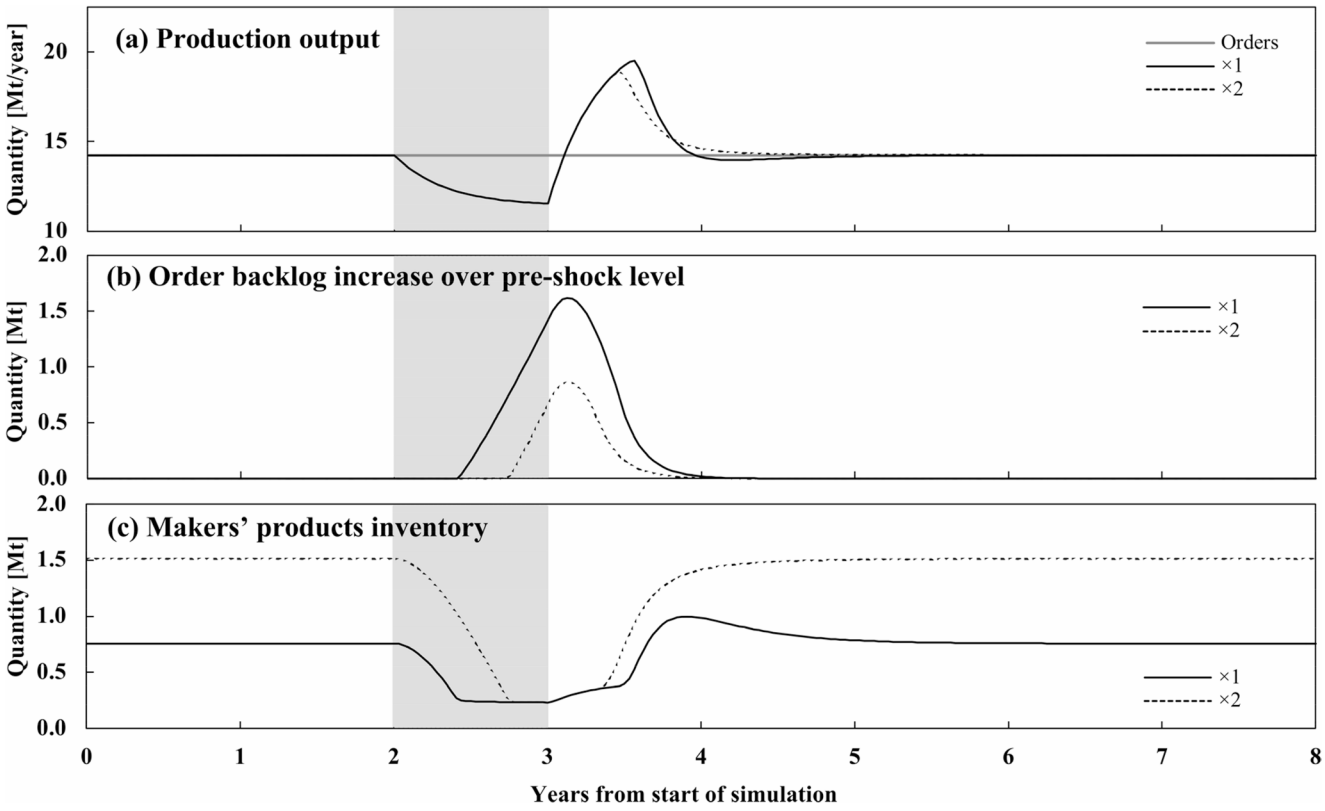

Fig. 6 Illustrative supply-constraint scenario. Illustrative scenario: (**a**) production output, (**b**) increase in the order backlog over its pre-shock level and (**c**) makers' products inventory, with inventory coverage ×1 (solid) and ×2 (dashed). Orders are constant at the FY2023 level; the shaded period is the one-year constraint limiting production starts to 80% of orders

5 Discussion

5.1 Interpretation of findings

Our simulations show reasonable in-sample historical fit for *Production output* and *Shipping* within the calibration period, with exogenous *Orders* as a major driver (Fig. 5); because this fit is comparable with a naive benchmark, it cannot be used to claim that the feedback structure explains past behavior. For *Products inventory*, results are sensitive to the observational definition; makers' finished-goods inventory is reproduced with a slightly smaller error than a naive benchmark within the calibration period, but this has not been confirmed outside it (Sect. 5.3). These results are consistent with a system structure in which the annual-scale behavior of the special steel supply chain reflects interactions among (i) the amplitude of orders, (ii) internal WIP and inventory adjustments, and (iii) production capacity utilization. With annual aggregation, short-term (quarterly/monthly) fluctuations are smoothed and offset by within-firm adjustment actions, and the basic flow—order-following production → WIP adjustment → finished-goods inventory as a buffer—provides a useful representation of the observed annual-scale patterns.

This behavior is consistent with the feedback structure defined by the CLD and SFD. In Fig. 4, *Bp* and *Bb* represent the mechanisms by which production and shipping clear the *Order backlog* following an order shock. *Bw* adjusts *Production starts* in response to the gap between actual *WIP* and *Desired WIP*. The sensitivity analysis shows that changes in the *WIP adjustment time* affect the fit of makers' inventory, while the production and shipping fits remain relatively stable (Online Resource 1, Table S3). *Bi* represents the inventory-buffer response to demand shocks. The explicit structure matters most when supply is constrained: in the illustrative scenario, the backlog, delivery delay and recovery depend on the inventory buffer and on how production planning responds to the backlog (Sect. 4.5). A critical point is to distinguish makers' finished-goods inventory from total inventory (makers' plus dealers' inventory).

This difference can be interpreted as reflecting the degree of alignment between the model boundary and the observational boundary. Total inventory includes dealers' inventories in addition to makers' finished goods; therefore, exogenous variations that cannot be explained by the makers' decision loops—such as inventory adjustments on the distribution side and imports—are superimposed. The observed balance residuals confirm this: if imports are

Table 8 Comparison with selected dynamic models of steel and critical-material supply chains

Study	Scope	State variables	Feedback structure	Data mapping and validation
Shigeno (2009)	Japan, steel; annual, 1950–2050	In-use steel stocks in five end-use sectors (Weibull lifetimes); scrap	Scrap recycling to EAF steel	Crude steel supply by end use; visual comparison of simulated and statistical EAF steel production; no fit statistics
Pinto et al. (2019)	Europe, steel; LCA integrated in SD; annual, 200 years	In-use stocks in six sectors; scrap; EAF and BF–BOF processes	Recycling, refurbishment and repair loops; declining ore quality	worldsteel and Eurostat data; reproduction of results of earlier SD and LCA studies
Sverdrup and Olafsdottir (2019)	World, stainless steel (Fe, Cr, Mn, Ni); annual, 1850–2350	Metal mined; stocks in use; recycled and lost metal	Price-driven supply and recycling; resource depletion	Simulated world production compared with observed data ($r^2 = 0.97$ for the production rate; $r^2 = 0.998$ for cumulative supply, 1850–2017); long-term scenarios
Shi et al. (2023)	Mainland China, steel; annual, 1990–2020 with projections; national and provincial	Steel production; in-use stock by end-use sector; EoL scrap	Production–use–EoL recycling (scrap returned to production)	Transfer rates fitted to statistics (R^2 for production, in-use stock and scrap); comparison with previous estimates
Nell et al. (2024)	World, nickel; annual, 1994–2100	Nickel mined; nickel in use by application; recycled nickel	Recycling of end-of-life products supplies part of demand	Historical mining as input; demand scenarios and sensitivity to recycling rate; no historical fit statistics reported
This study	Japan, special steel products; annual, FY1980–2023	Order backlog; WIP; makers' finished-goods inventory; mass-balance accounts	Five balancing loops (*Bp*, *Bb*, *Bs*, *Bi*, *Bw*)	Exogenous orders; fit of production, shipping and makers' inventory with naive benchmarks; observed balance audit; sensitivity and identifiability

Summarized by the authors from the cited publications. "No fit statistics reported" means that no goodness-of-fit statistics against historical series were found in the publication

EAF electric arc furnace, *BF–BOF* blast furnace–basic oxygen furnace

routed through inventory, the residual (4.9% of production) is four times that of the makers' balance (1.2%) (Table 6). This result also shows that data availability alone is insufficient for auditable MFA–SD modeling. Publicly available data must correspond to the modeled stock or flow in terms of coverage, classification, and observational boundary; otherwise, numerical comparison may be misleading even when a statistical series is available.

This structural interpretation becomes possible by linking MFA's quantitative consistency based on mass balance with SD's structural representation of decision rules and delays. For future element-specific extensions, previous studies on alloying-element dissipation and scrap-quality management provide important considerations for linking the present product-flow baseline to recycling-oriented analysis (Ohno et al. 2014).

In relation to previous studies (Table 8), the contribution of this study can be summarized in three points. Previous SD-based models of steel and its alloying metals focus on in-use stocks, scrap recycling and long-term resource supply and are evaluated by reproducing earlier results, by visual comparison or by goodness-of-fit statistics (R^2) for a limited set of series, while studies of critical-material resilience quantify recovery after disruptions without simulating the producing industry. First, the study shows that consistency between the model boundary and the observational boundary is a central condition for auditable MFA–SD modeling. This point is most clearly illustrated by the inventory results: auditing the model boundary against observed annual balances showed which inventory series is meaningfully comparable with the simulated stock. This finding further indicates that data availability must be evaluated together with the coverage and classification of the available statistics. Second, the study developed an annual-resolution DMFA–SD model for special steel and assessed its in-sample historical fit against naive benchmarks together with an identifiability analysis, using exogenously given orders. Third, it organized decision levers such as improved collection rates, investment in sorting accuracy, stockpiling operations, and import diversification as model elements and evaluation axes for future element-specific flow analysis and resilience-oriented scenario analysis, and illustrated one of them (inventory coverage) in a supply-constraint scenario whose indicators (peak backlog, delivery delay and recovery time) are of the same kind as the resilience indicators proposed by Sprecher et al. (2017). Thus, this study presents an auditable product-flow baseline model and a transferable modeling lesson for boundary-explicit MFA–SD analysis using public statistics, rather than drawing conclusions about the superiority of specific interventions.

5.2 Implications for decision-makers and policy

Based on the model structure and the in-sample historical fit examined in this study, this section identifies key decision-making issues for future supply-resilience-oriented scenario analysis. The implications discussed here are not intended to determine the superiority of specific interventions. Rather,

they concern how measures such as collection and sorting, stockpiling, import diversification, and inventory and WIP management should be represented as model elements and evaluation criteria in future analyses. Specifically, clarifying the observational definition of finished-goods inventory, the definition of WIP, adjustment time constants, and the relationship between collection rates and sorting accuracy is important for improving the auditability of scenario analysis. In this paper, the evaluation focuses on the in-sample historical fit of production, shipments, and inventories and on one illustrative scenario. Under the stated assumptions, holding about 20 days of additional inventory reduced integrated excess backlog by about two-thirds under a one-year constraint limiting production starts to 80% of orders; this benefit must be weighed against holding costs, which are not evaluated here, and depends on how quickly production planning responds to the accumulated backlog. For CM supply disruptions that constrain special steel production, the makers' inventory policy is therefore one lever that affects how far such disruptions propagate to downstream industries. Resilience-related KPIs such as inventory stability, supply continuity and supply shortages should be explicitly defined in future scenario analyses.

From a decision-support perspective, it is important to make model boundaries, observational definitions, and assumptions transparent and to ensure the auditability of the results (Chowdhury 2023). In this study, the system boundary was limited to Japan's special steel supply chain, and superalloys were excluded at this stage. Price dynamics were not endogenized, and orders were treated as exogenous variables. Under these explicitly stated assumptions, the model was parameterized through triangulation of publicly available statistics and literature information, and model fit was evaluated against makers' finished-goods inventory, whose boundary was checked with observed annual balances. Such transparency enables critical examination of model boundaries and observational definitions and enhances the potential for hypothesis refinement and future connections to participatory modeling and workshop-based decision support (Machado et al. 2019; Lo et al. 2024).

For future extensions of the model, an important design consideration is that the management of "quantity" and "quality" in the special steel supply chain should be addressed simultaneously while considering time delays and side effects. Specifically, inventory and WIP adjustment are represented as mechanisms associated with quantitative fluctuations in production and shipments, whereas the design of scrap collection, sorting, and remelting will be important for evaluating quality degradation and cascade use in future element-specific flow analysis. Therefore, for future supply-resilience-oriented scenario analysis, important issues include: (a) selecting inventory series that are consistent with the model boundary; (b) obtaining the production lead time from operational data, because it cannot be identified from annual statistics; (c) representing collection rates and sorting accuracy as a "quantity × quality" issue for future element-specific recycling analysis; and (d) linking stockpiling and import-diversification rules with resilience-related KPIs. By making these issues explicit, the model can be connected to future analyses that compare collection and sorting strategies, stockpiling, and import diversification in terms of their expected effects, time delays, and side effects.

5.3 Limitations and future research

Several limitations should be clarified when interpreting the results of this study. First, the quantitative model developed in this paper does not fully reproduce element-specific material balances for Ni, Cr, Mo, Co, or other alloying elements. Instead, it focuses on the annual behavior of aggregate special steel product flows, namely production, shipments, and inventories. Accordingly, Table 1 and the system boundary demonstrate the relevance of special steel as a major use sector for CMs, but they do not constitute a complete element-specific CM flow model, and the alloying-element ratio in Sect. 3 is based on 2005 estimates and is used only as an indicative reference. Second, this paper does not directly quantify supply resilience using formal indicators such as supply shortage, service-level loss, or vulnerability; the illustrative scenario uses a reduced-form constraint, constant orders and delivery-related indicators only, and costs, prices and substitution are not represented. The term resilience is used to motivate future scenario analysis rather than to claim that resilience has already been assessed in the present model. Third, the historical fit of production and shipping is comparable with a naive benchmark, and the inventory fit has not been confirmed outside the calibration period; the model is therefore not suitable for forecasting. The production lead time is not identifiable from annual data and is an assumed value, and scenario magnitudes vary with it. Although this study conducts one-at-a-time sensitivity analyses, it does not conduct formal uncertainty propagation such as Monte Carlo simulation or global sensitivity analysis. Therefore, claims related to robustness are limited to transparency, auditability, and data consistency under the specified model boundaries and observational definitions. In addition, the makers' balance leaves an unexplained residual of about 1.2% of production, and production before FY2009 is estimated with a constant yield. Fourth, recycling-related processes are represented primarily at the conceptual level in the present model, while detailed treatment of scrap generation, collection, sorting, remelting, and broader CE strategies such as reuse, repair, refurbishment, remanufacturing, and repurposing remains outside the present quantitative

implementation and should be addressed in future extensions when product-level data become available.

This study modeled the macro-level behavior of Japan's special steel supply chain at an annual resolution and evaluated its in-sample historical fit using publicly available statistics. Because the model is based on annual aggregate data, monthly or weekly operational optimization would require a different and more detailed model structure. In contrast, the annual resolution provides a temporal basis for future comparison of medium- to long-term measures whose effects emerge over several years to decades, such as collection and sorting, stockpiling, and import diversification. Superalloys, which contain higher concentrations of certain CMs than general special steel grades, are currently outside the model boundary. In addition, prices, exchange rates, and policy shocks are treated as exogenous conditions. As demonstrated by previous work integrating MFA and resilience analysis for silicon carbide (Böcher et al. 2024), incorporating market and institutional factors could enable more comprehensive policy-oriented assessment in future work.

The recycling characteristics of superalloys differ from those of general special steel grades. High-grade superalloy scrap with well-defined alloy composition and low impurity levels is mainly recycled through closed-loop remelting as feedstock for superalloy production (Satya Prasad et al. 1996; Kollová and Pauerová 2022). Such specialized material flows are not represented in the present macro-level model. Future work should therefore incorporate alloy-grade classification, impurity limits, remelting yields, cascade use, dissipation pathways, and their associated time constants. This would enable more detailed assessment of resource strategies for strategically important sectors such as aerospace. For stainless steels in particular, disaggregation into austenitic and ferritic categories would provide a more informative basis for future recycling- and resilience-oriented analyses. The present model does not implement this classification because it relies on aggregate special steel statistics.

International prices and overseas supply–demand conditions are also treated as exogenous boundary conditions in the present model. In the long term, however, these factors may interact with domestic collection and sorting investments, policy interventions, inventory targets, and stockpiling rules through feedback loops. Future research should extend the model boundary to global supply chains and develop a multi-region framework that endogenizes price expectations, inventory targets, and stockpiling rules. Such an extension would enable future evaluation of shock propagation and resilience-related indicators, rather than implying that these outcomes have already been assessed in the present study.

Finally, the classification standards of the underlying data require further improvement. Superalloys are not always strictly distinguished in publicly available statistics, and the boundary between special steel grades and superalloys may be ambiguous depending on the reporting body. Future work should improve the standardization of alloy-grade and composition management and harmonize observational definitions, especially the distinction between makers' and dealers' inventories. Such improvements would help establish a more auditable data infrastructure that better aligns statistical classifications and observational definitions with the mass-balance requirements of MFA (Graedel 2019).

Element-specific extensions should distinguish the material stock in use, the EoL generation and the secondary supply that is practically recoverable for special steel production. Xu et al. (2026) proposed a classification of urban minerals that separates availability (resources) from accessibility (reserves) under technological, economic and policy conditions, and Xiong et al. (2026) resolved secondary resupply by technology for electric-vehicle batteries and motors, finding that the nickel and manganese loops remain difficult to close through domestic recycling alone. For special steel, an analogous extension would add in-use and EoL stocks by end-use sector and steel grade, and define recoverable supply by collection rate, sorting accuracy and the impurity limits of each grade. In the present structure, recoverable scrap would enter as an additional source of *Raw material input*, and the capacity constraint of Eq. (8) could be replaced by element-specific supply constraints.

Through these extensions, the auditable product-flow baseline model developed in this study could be expanded into comparative analyses incorporating element-specific flow tracking, supply-constraint scenarios, and resilience-related indicators such as inventory shortages and recovery time. In this sense, the present model should not be interpreted as a direct quantitative assessment of CM supply resilience, but rather as a foundation for future evaluation design.

6 Conclusions

This study developed an annual-resolution DMFA–SD model of Japan's special steel supply chain by integrating the quantitative consistency of MFA based on mass conservation with the endogenous feedback structures and time delays represented in SD. The primary purpose of this paper was to evaluate the in-sample historical fit of aggregate special steel product flows—production, shipments, and inventories—using publicly available statistics and to present an auditable product-flow baseline that can support future element-specific flow and supply-constraint analyses.

With respect to RQ1, the proposed CLD and SFD organize the annual-scale behavior of the special steel supply chain through feedback structures linking *Orders*, *Order backlog*, *Production output*, *WIP*, *Products inventory* and *Shipping*. The quantitative SFD represents the backlog–production–WIP–inventory–shipment structure through five balancing loops (*Bp*, *Bb*, *Bs*, *Bi* and *Bw*), while scrap-related processes are retained primarily at the conceptual level for future element-specific extensions. This structure provides an interpretable representation of how orders, production, WIP, products inventory, and shipments are linked through adjustment processes at an annual resolution.

With respect to RQ2, the model showed reasonable in-sample historical fit for production and shipping within the calibration period. The correlation coefficients were 0.960 and 0.935, and the corresponding MAPE values were 5.25% and 3.66%, respectively. These results indicate consistency between the simulated outputs and the main annual-scale patterns in the observed production and shipping series, rather than out-of-sample predictive performance, and they are comparable with a naive benchmark equal to orders. Inventory reproduction depended strongly on the observational definition; makers' finished-goods inventory, which corresponds to the model boundary, was reproduced with $R = 0.602$ and MAPE = 5.50%. The adjustment time constants were treated as calibration parameters affecting tracking speed and phase alignment and were selected on a parameter grid; the production lead time cannot be identified separately from the WIP adjustment time with annual data.

The observed balance residuals further show that data availability alone is insufficient for auditable MFA–SD modeling. A statistical series must correspond to the modeled stock or flow in terms of coverage, classification, and observational boundary. Thus, consistency between the model boundary and the observational boundary is not a secondary technical issue but a central condition for interpreting historical fit and model credibility.

With respect to RQ3, the proposed framework organizes inventory and WIP management, collection and sorting, stockpiling, and import diversification as model elements for future element-specific flow and supply-resilience-oriented scenario analyses. The present study does not compare the effectiveness of these interventions; one inventory policy was examined in an illustrative scenario, in which doubling inventory coverage reduced the integrated excess backlog by about two-thirds under a one-year constraint limiting production starts to 80% of orders, with a magnitude that depends on the lead time and the planning rule. Future extensions should incorporate element-specific flows, compositions, alloy grades, dissipation pathways, and cascade use in special steel grades and superalloys, together with explicit resilience-related KPIs such as inventory shortages, recovery time, supply continuity, and reduced import dependence. Further development toward a multi-region framework incorporating prices, exchange rates, international supply–demand conditions, stockpiling rules, and import diversification would enable analysis of their interactions with domestic collection, sorting, and inventory management.

Overall, the main contribution of this study is methodological: it highlights the importance of boundary-explicit and auditable data mapping when integrating MFA and SD using public statistics, including judging historical fit against naive benchmarks and auditing model boundaries against observed balances. The resulting model should therefore be interpreted as an auditable product-flow baseline, rather than as a direct quantitative assessment of CM supply resilience. Future extensions can build on this baseline by incorporating element-specific flows, alloy-grade classifications, supply-constraint scenarios, and resilience-related indicators for policy and industrial decision support.

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Authors' contributions W.A. led the conceptualization and study design, curated the time-series data, developed the model, performed the analyses, and drafted the manuscript. A.N. supervised the research, contributed to interpretation of the results, and provided critical comments and revisions to improve the manuscript. All authors read and approved the final manuscript.

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Data availability The data used in this study were compiled from published Japanese steel-industry statistics, as documented in Table 3 and the original sources cited therein. The curated time-series dataset, Vensim model (.mdl), Python implementation, and supporting files for model calibration, historical-fit evaluation, sensitivity analyses, and scenario simulations are available on Zenodo, a public research repository (https://doi.org/10.5281/zenodo.23901718). Model equations are given in Sect. 4.3, and calibrated parameters and initial conditions in Table 4 and Online Resource 1.

Declarations

Use of generative AI ChatGPT (OpenAI) and Claude (Anthropic) were used to assist with translation, language editing, manuscript organization, responses to reviewer comments, model-equation consistency checks, Python code development, and verification of numerical results. AI-assisted outputs were critically reviewed by the authors, including assessments of model assumptions, consistency of reported results, and scientific interpretation. The authors retained responsibility for the research design, model specifications, data analysis, scientific

interpretation, and conclusions. All authors reviewed and approved the final manuscript and take full responsibility for its content.

Ethics approval / consent Not applicable; this study did not involve human participants, personal data, or animals.

Competing interests The authors declare no competing interests.

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