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Sustainable Steel Supply Chain Network Design under Export Taxes and Import Tariffs: A Multi-objective Stochastic Programming Framework

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Highlights

- First model integrating trade policies with sustainable steel supply chain network design
- Novel multi-time-scale stochastic approach for strategic-tactical decision integration
- Custom sustainability metrics linking technology, location and material flow choices
- Innovative ε-constraint and SAA solution method for multi-objective optimization
- Data-driven policy insights from real steel industry case implementation

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Sustainable Steel Supply Chain Network Design under Export Taxes and Import Tariffs: A Multi-objective Stochastic Programming Framework

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Abstract

This paper introduces a two-stage stochastic programming model featuring multi-objective recourse functions to address the economic, environmental, and social dimensions of sustainability in steel supply chain networks. The model integrates strategic decisions (facility location, capacity acquisition, and technology selection) with tactical material flow coordination. The dynamics of steel industry-specific characteristics are captured through multi-scale time periods, technology compatibility requirements, and sustainability metrics based on location-technology-flow configurations. Furthermore, the model incorporates export taxes and import tariffs to optimise material flows between nationwide and global networks, enabling comprehensive analysis of how these policy tools influence strategic and tactical decisions whilst impacting sustainability objectives. A solution approach is developed using the ε-constraint and Sample Average Approximation methods to address demand uncertainty and the trade-offs among multiple recourse objectives. Novel algorithms are introduced to determine the upper and lower bounds of the constrained objective functions and to form the loops of the ε-constraint method. The model's application to a real-world case study demonstrates its effectiveness in achieving balanced material flows across the steel SCN after four strategic periods. Through sustainability assessment and analysis of various tax and tariff policies, we derive eight policy insights regarding their impacts on strategic and tactical decisions. The results confirm the model's capability to generate robust solutions that effectively balance network capacity against demand patterns while achieving sustainability objectives.

Keywords: Sustainable Supply Chain Network Design; Material Flow Coordination; Technology Selection; Steel Industry; Import tariffs; Export taxes; Multiple-objective Stochastic Programming

1. Introduction

The steel industry has emerged as a central point in global economic policy discussions. In March 2025, the United States imposed a 25% tariff on steel imports, creating significant ripple effects across global supply chains, particularly impacting Canada, Brazil, and Mexico, which export 6.0, 4.1, and 3.2 million tonnes of steel to the U.S. market, respectively [1]. This policy shift raises critical questions about how the US steel supply chain networks (SCNs) can manage increased costs whilst maintaining material flow balance across multiple levels. Beyond economic considerations, the steel industry faces sustainability pressures, contributing approximately 5% of CO_2 emissions in the European Union alone, whilst simultaneously supporting over 3 million European jobs [2].

Steel SCNs present unique challenges that differentiate them from other networks. They are characterised by irreversible, capital-intensive investments with extended technology lifecycles, lengthy production ramp-up periods, and prolonged returns on investment. These constraints make strategic decisions particularly consequential, as facilities cannot easily change technologies or capacities once established. Steel production's energy-intensive nature subjects these networks to additional governmental pressures regarding self-generation of electricity and compliance with evolving energy policies [3]. Furthermore, steel SCNs show sharp sensitivity to both global market dynamics and government interventions (e.g., directly through tax, tariff, and carbon policies or indirectly through infrastructure investment programmes that significantly influence demand patterns and price volatility). These challenges, coupled with increasing sustainability requirements, create a decision environment of exceptional complexity. Despite this, the operations research literature lacks integrated models that effectively address these challenges in steel SCN design. Our research makes three significant contributions to address these challenges in steel SCN design.

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First, we develop a multi-timescale two-stage stochastic programming model that integrates strategic and tactical decisions for steel SCNs. Our model optimises the configurational decisions i.e., facility location, capacity acquisition, and technology selection in the first stage for strategic periods. The second stage coordinates material flow across multiple tactical periods under demand uncertainty. This approach addresses the unique challenges of steel SCNs, particularly substantial and irreversible capital investments and technology compatibility requirements across network levels. By analysing how strategic decisions affect tactical decisions over successive time horizons, our model reduces imbalanced material flow (IMF) that would emerge from suboptimal capacity configurations. Specifically, the model evaluates how existing facilities with established technologies constrain production flow during tactical periods. It then determines optimal capacity expansion and technology selection decisions for subsequent strategic periods that ensure compatibility with installed technologies whilst minimising IMF. This integrated perspective advances beyond previous studies [4,5], providing decision-makers with a comprehensive framework for technology-compatible capacity planning.

Second, we incorporate government policy interventions through export taxes and import tariffs into our optimisation model, enabling comprehensive analysis of their impacts on steel SCN design and IMF. Our model differentiates between internal units (within the nationwide steel SCN) and external units (global units) at each level of the steel SCN, modelling bidirectional flows between them. This allows us to explicitly model both import and export flows across all network levels, creating a framework for analysing government interventions that previous models have not addressed. This contribution is particularly valuable as it captures how export taxes and import tariffs influence both IMF and, indirectly, strategic capacity and technology decisions. When network imbalances occur, units face critical decisions, either to adjust production (potentially shutting down) or to interact with global markets through imports or exports. Our model quantifies how tax and tariff policies affect these decisions across steel SCN levels, revealing their short-term impact on IMF during tactical periods and their long-term consequences for strategic network configuration during strategic periods. This approach provides policymakers with data-driven insights into the unintended consequences of interventions that are often implemented with short-term objectives but create lasting effects on nationwide steel SCN capacity and technological development.

Third, we evaluate sustainability through location-technology-flow configurations, capturing multidimensional impacts across four distinct dimensions: quantitative economic, qualitative economic, environmental, and social sustainability. Our approach incorporates sustainability into the model via a three-phase methodology, addressing existing gaps in the literature [6,7]: (1) identifying relevant sustainability measures through a literature review and expert validation, (2) estimating measure scores based on *location-technology-flow* configurations, and (3) aggregating these measures into sustainability ratios. Unlike prior works that either embed sustainability into design decisions [8] or model it solely as a function of material flow [9], our model integrates sustainability across both strategic and tactical

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decisions within our two-stage stochastic programming model. This is justified by three key considerations related to the steel industry: First, sustainability impacts are linked to actual production volumes rather than installed capacity. For example, a facility operating at half capacity generates proportionally lower environmental impacts and fewer jobs. Second, significant steel demand fluctuations over the planning horizon necessitate this dynamic, flow-dependent assessment. Third, optimising sustainability performance requires material flow variables, which are determined in the second stage, as sustainability scores are inherently based on the *location-technology-flow* configuration. The resulting multi-time scale two-stage stochastic programming model with multi-objective recourse functions represents a methodological advancement in sustainable steel SCN optimisation. We develop a solution approach combining the ε-constraint method with Sample Average Approximation (SAA), introducing dynamic floating values and lexicographic optimisation techniques for search of Pareto solutions.

2. Literature review

This section reviews the literature relevant to the design of sustainable steel SCNs. We first discuss integrated supply chain network design models and then review studies on sustainable steel SCNs.

2.1 Integrated Models for SCN Design

The design of robust and efficient SCNs necessitates the integration of strategic decisions with tactical operational planning. Early work by Verter and Dasci [10] highlighted the importance of integrating FL and technology acquisition decisions to enhance SCN adaptability. Subsequent research has stressed this perspective, emphasising that such integration is crucial for improving socio-economic outcomes and overall SCN performance [4]. The complexity of these integrated problems is increased when considering uncertainties, particularly demand fluctuations. For instance, Correia and Melo [11] and Liu et al. [12] demonstrate the necessity of integrating facility location (FL) and capacity acquisition (CA) under demand uncertainty, often in contexts requiring rapid response like pandemic preparedness. Jakubovskis [5] extended this by examining the impact of demand uncertainty on FL, CA, as well as technology selection (TS) decisions, comparing robust and non-robust optimisation approaches.

Scholars have studied the complex relationships between strategic and tactical decisions, often focusing on multi-period settings and modular capacities. Štádlerová et al. [13] and Correia and Melo [14] address multi-period FL and CA problems, with the former considering modular capacities for hydrogen infrastructure and the latter introducing temporary, modular capacity scaling for warehousing-as-a-service. These studies, along with Bakker and Nickel [15] and Alarcon-Gerbier and Buscher [16], highlight the increasing recognition of modularity, temporal flexibility, and the explicit modelling of time in capacitated location problems. Despite the importance of distinguishing between time dimensions for long-term strategic and short-term tactical decisions, explicit modelling of multi-scale decision-making has received limited attention. For example, Correia and Melo [11] address this by proposing two-stage stochastic models where facility location and initial capacity decisions are strategic (first stage), whilst capacity adjustments in the second stage can be either strategic or tactical in response to demand uncertainty. Similarly, Štádlerová et al. [17] introduce a multi-stage multi-horizon stochastic FL problem that distinguishes between strategic and operational uncertainty, utilising an innovative multi-horizon scenario tree approach to embed detailed operational problems within strategic decision nodes.

Government interventions, particularly through taxes and tariffs, influence SCN design and material flows. Lee and Tang [18] highlighted this, reviewing operations management research from 1980-2015 and posing open questions regarding the types, effectiveness, and unintended consequences of government interventions. Scholars have studied the impact of government tools on SCN design. For example, Turken et al. [19] analysed the effect of government regulations on FL and CA problems, demonstrating the high sensitivity of results to resource price changes, whilst Shang et al. [20] showed the significant impact of various tax and subsidy policies on different actors within closed-loop SCNs. The increasing global focus on sustainability and carbon emissions has brought carbon tariffs and taxes to the forefront, necessitating their explicit consideration in SCN design, particularly for global SCNs. For instance, Zhou et al. [21] explore the complex effects of carbon tariffs on global supply chains and associated coping strategies, whilst Chang et al. [22] investigate strategic responses to carbon border adjustment mechanisms, revealing critical tax intensity thresholds that alter manufacturers' decisions and impact emission reductions and exports.

Despite this growing body of research, the SCN design literature has paid limited attention to modelling import/export flows and the direct impact of such tariffs and taxes on strategic and tactical decisions across multi-level nationwide and global steel SCNs, particularly in integrated models. This gap is critical, as these interventions fundamentally change the economic viability of different technologies, locations, capacities, and material flow coordination decisions, especially when considering technology compatibility across diverse regulatory environments. Studies further confirm the importance of government interventions in shaping operational and strategic decisions. For example, Zhou et al. [23] demonstrated that carbon taxation can significantly influence firms' strategic choices and social welfare outcomes through its effects on brand-extension decisions and consumer behaviour. Similarly, Hua et al. [24] showed that tariff mechanisms affect technology adoption, market competitiveness, greenhouse-gas emissions, and social welfare under international competition. These findings reinforce the need for SCN design models that explicitly account for taxes and tariffs when evaluating technology, capacity, and material flow decisions.

2.2 Sustainable Steel SCN Design

The steel industry presents distinctive challenges for sustainable SCN design. Beyond its substantial economic contributions, steel SCNs are characterised by significant environmental impacts, including air emissions, water pollution, and the generation of chemical and solid wastes [25], alongside critical social implications such as job creation, human health and safety, and local economic development [26]. Given

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its position as a high-energy and resource-intensive industry with inherent operational hazards and risks [27], the development of robust Operations Research models for sustainable steel SCNs is essential for achieving sustainability goals. Whilst steel SCN design remains understudied in the literature, limited research such as Tsao et al. [28] offers a valuable contribution. Their eco-efficient steel SCN model integrated strategic and tactical decisions whilst also incorporating government interventions. Their study demonstrated an approximate 3% profit improvement and highlighted the sensitivity of outcomes to varying sustainability scenarios, including carbon trading and trade credit policies. Their work stressed the critical importance and inherent complexity of developing models for designing sustainable SCNs.

Traditional SCN design often relies on single-objective models, yet these approaches are inherently limited in their ability to capture the frequently misaligned objectives of economic profit, environmental impact, and social welfare [29]. This limitation has necessitated the adoption of multi-objective models as an effective approach for (conflicting) sustainability goals [30]. A growing body of literature has thus developed multi-objective models to achieve SCN sustainability objectives. For instance, Sadjady Naeeni and Sabbaghi [31] proposed a multi-objective model for SCN design incorporating economic, environmental (e.g., GHG emissions, waste, energy consumption), and social (e.g., job creation, regional social priority, worker safety, product risk) objectives. Similarly, Mogale et al. [32] developed a model considering economic (e.g., construction, transportation, inventory costs), environmental (e.g., CO_2 emissions, transportation, inventory holding), and social (e.g., job opportunities, balanced economic development, farmer welfare, public health) dimensions. Becerra et al. [33] formulated a multi-objective model aimed at minimising costs and carbon emissions whilst maximising the social impact of SCN operations. Beyond these works, the broader landscape of sustainable SCN research explores other critical aspects: Nguyen et al. [34] investigated the impact of decision-making comprehensiveness on sustainable supply chain performance, revealing curvilinear effects on economic and social outcomes. Ozyavas et al. [35] focused on designing sustainable delivery networks to reduce environmental impact and enhance efficiency. Furthermore, the role of emerging technologies is gaining prominence, with He et al. [36] analysing how blockchain technology can enhance consumer trust in sustainable products and improve demand forecasting accuracy within SCNs. Nevertheless, to the best of our knowledge, a sustainable SCN design model that integrates strategic and tactical decisions within a multi-objective framework, specifically tailored to the complexities of the steel industry, remains undeveloped.

Furthermore, a critical shortcoming in the development of models for sustainable SCNs lies in the assessment of sustainability dimensions. Barbosa-Póvoa et al. [7] identified sustainability and uncertainty as key challenges, emphasising that the value of analytical models is dependent upon accurately estimating sustainability rates. Thies et al. [6] reviewed analytical models in sustainability assessment, highlighting gaps in identifying sector-specific sustainability measures, assessing SCNs based on these measures, and aggregating them into sustainability rates. They remarked that models typically employ a limited number of sustainability measures (averaging 3.7). This deficiency in determining accurate

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sustainability rates, particularly concerning their dependence on location, technology, and material flows, can lead to misleading optimisation results. Whilst methods such as multi-criteria decision-making [37] and multivariate statistical methods [38] exist for assessing measure impact, there remains a need for more quantitative sustainability models to aggregate and determine these rates, especially when considering the dynamic interaction of location, technology, and flows.

3. Problem explanation and model development

Section 3 describes the context of the steel SCN and presents the development of the proposed two-stage stochastic programming model incorporating sustainability and tax and tariff formulation.

3.1. Problem definition

The steel SCN considered in this study consists of four levels: preprocessing (I), ironmaking (J), steelmaking (K), and the market. The units within each level $n \in N$ can be classified as either internal or external units (Figure 1), where:

$$N = (I \cup J \cup K)$$

$$N^{INT} = I^{INT} \cup J^{INT} \cup K^{INT}$$
$$N^{EXT} = I^{EXT} \cup J^{EXT} \cup K^{EXT}$$

The external units represent companies located outside the nationwide steel SCN that can engage in import and export activities. The set of internal units includes both existing units and potential facility locations for establishing new units. A technology set T (indexed by t and t') and subsets of technologies are defined for each level, including T^I for preprocessing, T^J for ironmaking, and T^K for steelmaking, where:

$$T = (T^I \cup T^J \cup T^K)$$

The parameter γ_t determines the capacity utilisation rate of a unit with technology t, whilst $\vartheta_{tt'}$ captures the compatibility between technologies t and t' across two adjacent levels of the steel network. There is a set of capacity acquisition methods $A = \{1,2,3\}$ (indexed by α) consisting of: $\alpha = 1$ (improvement) enhancing the efficiency of an existing unit; $\alpha = 2$ (expansion) adding new production facilities to an existing unit; and $\alpha = 3$ (construction) establishing a new unit in a potential location. Existing units can only select the same technology they currently use for the capacity acquisition methods of improvement and expansion, up to a maximum ratio $\mathcal{g}_\alpha$ of their installed capacity. However, units are allowed to select any technology under the capacity acquisition method of construction ($\alpha = 3$) without any capacity restrictions. We defined our problem as a multi-scale time period [11] consisting of strategic periods P (for configurational decisions) and tactical periods P' (for material flow decisions). As shown in Figure 2, decisions regarding material flow depend on the strategic decisions made at the beginning of the previous strategic period. For example, if we decide to increase the capacity of an existing unit from 1

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million tons to 1.5 million tons at the beginning of strategic period $P = 2$, it will take one strategic period for the unit to be fully operational at 1.5 million tons.

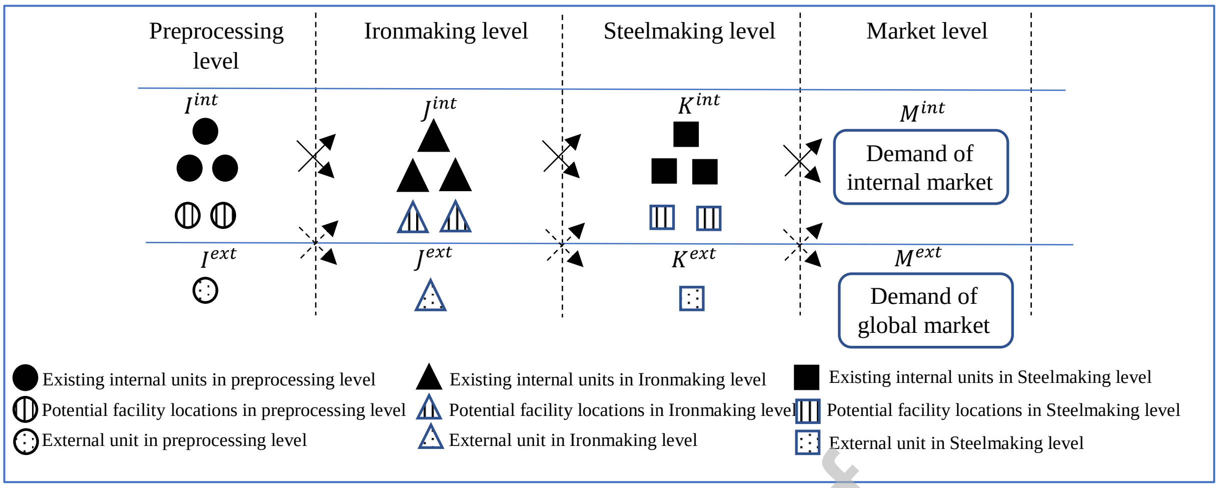

Figure 1. Steel SCN

Consequently, we can allocate a flow of 1.5 million tons during the tactical periods $p' = \{11,12,13,14,15\}$ within strategic period $P = 3$. The steel SCN operates as a pull-based network, responding to demand at each subsequent level. At the beginning of the planning horizon, internal and external demands are uncertain and represented as random variables through scenarios $s \in S$, each with probability π_s. A finite and discrete set of scenarios S is generated based on expert judgement, national development plans, and historical data from both internal and external markets. Below we describe the steel SCN structure used in our study. The notations used in this paper are listed in Appendix A.

- Our model includes three main production levels in the steel SCN: preprocessing (e.g., pelletising, sintering, high-pressure grinding rolls (HPGR)), ironmaking (e.g., blast furnace, direct reduction), and steelmaking (e.g., electric arc furnace (EAF), basic oxygen furnace (BOF), electric induction furnace (EIF)). These levels represent the primary value-added processes where our decision problems directly influence sustainability performance. Therefore, upstream activities such as mining and raw material extraction, as well as downstream processes including rolling, forming, and end-use manufacturing, are excluded from the current model scope, although the framework is sufficiently flexible to incorporate these additional levels in future extensions.
- We model material flows by treating them as a single aggregated flow between units with compatible technologies, rather than tracking multiple material types separately. This assumption enables us to focus on the critical network-balancing decisions whilst maintaining computational feasibility. Hence, differentiation of materials and resources such as scrap, nickel, and cobalt is not considered in this study, but their inclusion represents an extension that could provide deeper insights into steel SCN optimisation.
- Whilst material flows are modelled as a single aggregated stream, the model captures critical technological constraints through compatibility parameters that restrict which units can be linked

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across adjacent levels. Each production technology can only receive inputs from and send outputs to specific compatible technologies, and these constraints significantly influence optimal network configuration and capacity decisions.

- Our model represents a nationwide steel SCN with two distinct unit types: internal units (domestic production facilities) and external units (international market access points). Internal units represent domestic steel production across all levels, whilst external units represent aggregated international suppliers and buyers at each level within the steel SCN.
- Each internal unit can independently import from or export to external units, subject to taxes and tariffs. External units are modelled with unlimited capacity to represent the global market's ability to absorb or supply materials. In contrast, internal units require explicit capacity acquisition decisions.
- Dividing units into internal and external enables explicit capture of import and export flows. Whilst internal units generally prefer domestic sourcing due to transportation costs, taxes, and tariffs, the model analyses situations where international trade becomes economically viable. Specifically, it evaluates whether to import materials when domestic capacity is insufficient or to operate below optimal capacity levels. This framework enables analysis of how government interventions through tax and tariff policies influence production volumes, capacity utilisation rates, and material flows within the nationwide steel SCN.
- Our model incorporates two time dimensions: strategic periods (≥5 years) and tactical periods (annual). This multi-scale approach captures how units balance long-term capacity and medium-term flow decisions.
- Our model incorporates sustainability through a novel location-technology-flow-dependent approach that recognises how identical technologies can have different impacts based on geographical context and production volumes.

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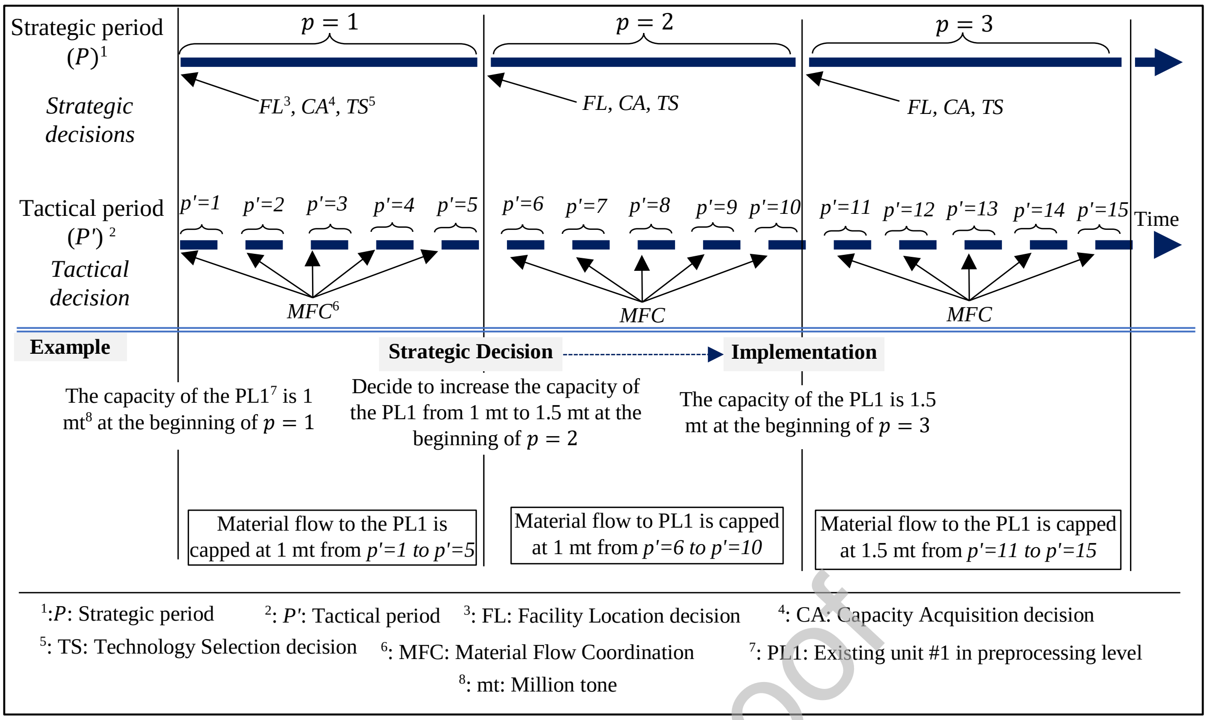

Figure 2. Multi-scale time periods models for steel SCNs

3.2 A Two-stage Stochastic formulation of the steel SCN

This section presents a two-stage stochastic programming model for sustainable steel SCN design. The first stage optimises strategic decisions across strategic periods, accounting for fixed setup and production costs. The second stage determines material flow coordination (MFC) across tactical periods, incorporating: (1) transportation and variable production costs, (2) import-export costs, and (3) sustainability objectives.

Stage I: Location, Capacity, and Technology decisions

The first-stage objective function F^I minimises the fixed setup cost and fixed production cost.

$$F^I = \min \sum_{p} \sum_{n \in N^{INT}} \sum_{t} \sum_{a} (z_{pnta} \times \varphi^{ST}_{pnta}) + \sum_{p} \sum_{n \in N^{INT}} \sum_{t} (q_{pnt} \times \varphi^{OP}_{pnt}) \qquad (1)$$

subject to:

$$\sum_{a} z_{pnta} \leq \varrho \times x_{pnt} \qquad p \in P, n \in N^{INT}, t \in T \qquad (2)$$

$$q_{pnt} \leq \varrho \times x_{pnt} \qquad p \in P, n \in N^{INT}, t \in T \qquad (3)$$

$$q_{pnt} = q_{(p-1)nt} + \sum_{a} z_{(p-1)nta} \qquad p \geq 2, n \in N^{INT}, t \in T \qquad (4)$$

$$\sum_{t \in T} x_{pnt} \leq 1 \qquad p \in P, n \in N^{INT} \qquad (5)$$

$$z_{pnta} \leq g_{\alpha} \times q_{(p-1)nt} \qquad p \geq 2, \alpha \in A \backslash \{3\}, n \in N^{INT}, t \in T \qquad (6)$$

$$z_{pnta} \in \mathbb{Z}^+, q_{pnt} \in \mathbb{Z}^+, x_{pnt} \in \mathbb{B} \qquad p \in P, t \in T, \alpha \in A, n \in N \qquad (7)$$

F^I minimises two cost components: capacity acquisition costs incurred when selecting technologies and expanding capacities, and fixed production costs proportional to installed capacity regardless of production volume. Constraints (2) ensure technology selection ($x_{pnt} = 1$) when expanding unit n's capacity in each strategic period, limiting each unit to one expansion method per period. Constraints (3) ensure selected technology (x_{pnt}) matches currently installed technology (q_{pnt}). Constraints (4) define capacity at each period, with expansions operational in the following period (see Figure 2); initial capacity at the beginning of strategic period $p = 1$ (q_{1nt}) equals current capacity for existing units and zero for potential locations. Constraints (5) limit each unit to one technology throughout the planning horizon. Constraints (6) set upper bounds on expansion as a percentage of previous capacity for all methods except method 3. Constraints (7) define first-stage variables.

Stage II: Multi-objective recourse function

We develop the recourse model in a step-by-step manner, starting with a multi-objective formulation that minimises transportation and variable production costs over tactical periods, then extending to incorporate sustainability scores (section 3.3) and import-export flows (section 3.4).

$$F_s^{II-TR} = \sum_{p'} \sum_{n \in (I \cup J)} \sum_{n' \in (J \cup K)} \left(\varphi_{p'nn'}^{TR} \times y_{p'nn's}\right) + \sum_{p'} \sum_{n \in K} \left(\varphi_{p'n}^{TR-INT} \times y_{p'ns}^{INT} + \varphi_{p'n}^{TR-EXT} \times y_{p'ns}^{EXT}\right) \tag{8}$$

$$F_s^{II-PR} = \sum_{p'} \sum_{n} \sum_{t} v_{p'nts}^{PR} \tag{9}$$

subject to:

$$\sum_{n' \in (J \cup K)} y_{p'nn's} \leq \sum_{t \in (T^I \cup T^J)} \left(\gamma_t \times q_{pnt}\right) \qquad n \in (I^{INT} \cup J^{INT}), s \in S, p \in P, \left((\zeta(p-1)+1) \leq p' \leq \zeta p\right) \tag{10-a}$$

$$\left(y_{p'ns}^{INT} + y_{p'ns}^{EXT}\right) \leq \sum_{t \in T^K} \left(\gamma_t \times q_{pnt}\right) \qquad n \in K^{INT}, s, p, \left((\zeta(p-1)+1) \leq p' \leq \zeta p\right) \tag{10-b}$$

$$\sum_{n \in K} \left(y_{p'ns}^{INT} + y_{p'ns}^{EXT}\right) \leq \xi_{p's}^{INT} + \xi_{p's}^{EXT} \qquad p' \in P', s \in S \tag{11-a}$$

$$\sum_{n \in K} \left(y_{p'ns}^{INT}\right) = \xi_{p's}^{INT} \qquad p' \in P', s \in S \tag{11-b}$$

$$\sum_{n \in K} \left(y_{p'ns}^{EXT}\right) \leq \xi_{p's}^{EXT} \qquad p' \in P', s \in S \tag{11-c}$$

$$\left(y_{p'ns}^{INT} + y_{p'ns}^{EXT}\right) = \sum_{n' \in J} \left(y_{p'n'ns}\right) \qquad n \in K^{INT}, p' \in P', s \in S \tag{11-d}$$

$$\sum_{n' \in K} \left(y_{p'nn's}\right) = \sum_{n' \in I} \left(y_{p'n'ns}\right) \qquad n \in J^{INT}, p' \in P', s \in S \tag{11-e}$$

$$\sum_{n' \in (I^{EXT} \cup J^{EXT})} y_{p'n'ns} \leq \varpi_{p'} \qquad n \in (J^{INT} \cup K^{INT}), p' \in P', s \in S \tag{11-f}$$

$$\sum_{n\in K^{EXT}} y_{p'ns}^{INT} \leq \varpi_{p'} \qquad p' \in P', s \in S \tag{11-g}$$

$$y_{p'nn's} \leq \varrho \times \sum_{t}\sum_{t'}(\vartheta_{tt'} \times r_{nn'tt'}) \qquad n \in N, n' \in N, p' \in P', s \in S \tag{12-a}$$

$$r_{nn'tt'} \leq \sum_{p} x_{pnt} \qquad n \in N, n' \in N, t' \in T, t \in T \tag{12-b}$$

$$\sum_{n'\in(J\cup K)} \left(\varphi_{p'nt}^{PR} \times y_{p'nn's}\right) \leq v_{p'nts}^{PR} + \varrho \times \left(1 - \sum_{p} x_{pnt}\right) \quad n \in (I \cup J), t \in T, s \in S, p' \in P' \tag{13-a}$$

$$\varphi_{p'nt}^{PR} \times \left(y_{p'ns}^{INT} + y_{p'ns}^{EXT}\right) \leq v_{p'nts}^{PR} + \varrho \times \left(1 - \sum_{p} x_{pnt}\right) \quad n \in K, t \in T^{K}, s \in S, p' \in P' \tag{13-b}$$

$$v_{p'nts}^{PR} \in \mathbb{Z}^{+}, y_{p'nn's} \in \mathbb{Z}^{+}, y_{p'ns}^{INT} \in \mathbb{Z}^{+}, y_{p'ns}^{EXT} \in \mathbb{Z}^{+}, r_{nn'tt'} \in \mathbb{B} \quad n \in N, n' \in N, p' \in P', s \in S, t' \in T, t \in T \tag{14}$$

Objective function (8) minimises transportation costs (F_s^{II-TR}), between units during tactical periods under scenarios s. Objective function (9) minimises variable production costs (F_s^{II-PR}) based on material flow through each unit during tactical periods under scenario s. Constraints (10) establish the relationship between the first-stage capacity variable (q_{pnt}) and material flow variables ($y_{p'nn's}$, $y_{p'ns}^{INT}$, and $y_{p'ns}^{EXT}$). Constraints (10-a) limit flow up to installed capacity between preprocessing, ironmaking, and steelmaking units, and constraints (10-b) from steelmaking units to markets (internal and external). Constraints (11) manage material flow across the network: (11-a) sets an upper bound on total flow that cannot exceed the sum of internal and external demands. (11-b) ensures that internal market demands must be exactly met in each tactical period. (11-c) ensures that flows to external markets cannot exceed their respective demands. Equations (11-d) and (11-e) balance the incoming and outgoing flows between adjacent levels of the steel network. Constraints (11-f) and (11-g) restrict import flows to internal units and markets up to a maximum allowable import ($\varpi_{p'}$). This import limit prevents the model from increasing imports instead of domestic capacity expansion due to high setup and fixed costs. Constraints (12) limit material flow between units only if they have compatible technologies. The compatibility is enforced through a binary variable ($r_{nn'tt'}$) that equals one when the selected technologies (x_{pnt}) for connected units are compatible ($\vartheta_{tt'}$). Constraints (13-a) and (13-b), which contribute to objective function (9), enforce the interdependencies of first-stage variables (x_{pnt}), second-stage variables ($y_{p'nn's}$, $y_{p'ns}^{INT}$, $y_{p'ns}^{EXT}$) and auxiliary variable production cost ($v_{p'nts}^{PR}$) at units. This represents the effect of first-stage decisions about technology selection on the total variable cost of production during tactical periods. Constraints (14) define the variables.

3.3 Incorporating Sustainability

We implemented a three-phase approach to estimate environmental and social sustainability dimensions, incorporating them into the second-stage objective function. This approach involves identifying relevant sustainability measures, estimating scores based on location-technology-flow configurations, and

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aggregating these measures into overall sustainability ratios. The details of our sustainability framework and calculations are provided in Supplementary Materials S1 and S2. The formulation of the sustainability objectives and constraints are presented below.

$$F_s^{II-EC} = \sum_{P'} \sum_{n \in N^{INT}} \sum_{t} \mathcal{v}_{p'nts}^{EC} \tag{15}$$

$$F_s^{II-EN} = \sum_{P'} \sum_{n \in N^{INT}} \sum_{t} \mathcal{v}_{p'nts}^{EN} \tag{16}$$

$$F_s^{II-SO} = \sum_{P'} \sum_{n \in N^{INT}} \sum_{t} \mathcal{v}_{p'nts}^{SO} \tag{17}$$

Subject to:

$$\sum_{n' \in (J \cup K)} \varphi_{p'nt}^{EC} \times \mathcal{y}_{p'nn's} \leq \mathcal{v}_{p'nts}^{EC} + \varrho \times \left(1 - \sum_{p} x_{pnt}\right) \quad n \in (I \cup J), t \in (T^I \cup T^J), s \in S, p' \in P' \tag{18-a}$$

$$\varphi_{p'nt}^{EC} \times (\mathcal{y}_{p'ns}^{INT} + \mathcal{y}_{p'ns}^{EXT}) \leq \mathcal{v}_{p'nts}^{EC} + \varrho \times \left(1 - \sum_{p} x_{pnt}\right) \quad n \in K, t \in T^K, s \in S, p' \in P' \tag{18-b}$$

$$\sum_{n' \in (J \cup K)} \varphi_{p'nt}^{EN} \times \mathcal{y}_{p'nn's} \leq \mathcal{v}_{p'nts}^{EN} + \varrho \times \left(1 - \sum_{p} x_{pnt}\right) \quad n \in (I \cup J), t \in (T^I \cup T^J), s \in S, p' \in P' \tag{18-c}$$

$$\varphi_{p'nt}^{EN} \times (\mathcal{y}_{p'ns}^{INT} + \mathcal{y}_{p'ns}^{EXT}) \leq \mathcal{v}_{p'nts}^{EN} + \varrho \times \left(1 - \sum_{p} x_{pnt}\right) \quad n \in K, t \in T^K, s \in S, p' \in P' \tag{18-d}$$

$$\sum_{n' \in (J \cup K)} \varphi_{p'nt}^{SO} \times \mathcal{y}_{p'nn's} \leq \mathcal{v}_{p'nts}^{SO} + \varrho \times \left(1 - \sum_{p} x_{pnt}\right) \quad n \in (I \cup J), t \in (T^I \cup T^J), s \in S, p' \in P' \tag{18-e}$$

$$\varphi_{p'nt}^{SO} \times (\mathcal{y}_{p'ns}^{INT} + \mathcal{y}_{p'ns}^{EXT}) \leq \mathcal{v}_{p'nts}^{SO} + \varrho \times \left(1 - \sum_{p} x_{pnt}\right) \quad n \in K, t \in T^K, s \in S, p' \in P' \tag{18-f}$$

$$\mathcal{v}_{p'nts}^{SO} \in \mathbb{Z}^+, \mathcal{v}_{p'nts}^{EN} \in \mathbb{Z}^+, \mathcal{v}_{p'nts}^{EC} \in \mathbb{Z}^+ \qquad n \in N, t \in T, s \in S, p' \in P' \tag{19}$$

Objective functions (15)-(17) address the three sustainability pillars: economic (qualitative), environmental, and social sustainability under scenarios $s \in S$. Constraints (18-a) to (18-f) establish the relationships between first-stage decision variables (x_{pnt}) and second-stage flow variables ($\mathcal{y}_{p'nn's}$, $\mathcal{y}_{p'ns}^{INT}$, $\mathcal{y}_{p'ns}^{EXT}$) to calculate sustainability performance across preprocessing, ironmaking, and steelmaking stages of the steel SCN. Constraints (19) define the bounds for all sustainability variables.

3.4 Import and Export Flows

Our model establishes a framework for controlling material flow between nationwide and global steel SCNs through maximum allowable imports $\varpi_{p'}$ (see constraints (11-f) and (11-g)). This enables evaluation of how government policies can enhance the sustainability of a nationwide steel SCN. Import tariff (F_s^{II-TAR}) and export tax (F_s^{II-TAX}}) are formulated in equations (20) and (21).

$$F_s^{II-TAR} = \sum_{p'} \left(\sum_{n \in (J^{INT} \cup K^{INT})} \left(\varphi_{p'n}^{TAR} \times \sum_{n' \in (I^{EXT} \cup J^{EXT})} y_{p'nn's} \right) + \sum_{n \in K^{EXT}} \left(\varphi_{p'n}^{TAR} \times y_{p'ns}^{INT} \right) \right) \quad (20)$$

$$F_s^{II-TAX} = \sum_{p'} \left(\sum_{n \in (I^{INT} \cup J^{INT})} \left(\varphi_{p'n}^{TAX} \times \sum_{n' \in (J^{EXT} \cup K^{EXT})} y_{p'nn's} \right) + \sum_{n \in K^{INT}} \left(\varphi_{p'n}^{TAX} \times y_{p'ns}^{EXT} \right) \right) \quad (21)$$

4. Solution Methodology: Multi-objective Sample Average Approximation

The compact formulation of the proposed multi-objective two-stage stochastic programming is presented in Model (22). Here, each of the seven terms in {...} corresponds to one of the recourse stage objectives (8), (9), (15), (16), (17), (20), and (21), respectively.

$$\begin{aligned} &Min{:}\, F^{I}(z) \\ &+ \left\{ \mathbb{E}_{\xi}[F_s^{II-PR}], \mathbb{E}_{\xi}[F_s^{II-TR}], \mathbb{E}_{\xi}[F_s^{II-EC}], \mathbb{E}_{\xi}[F_s^{II-EN}], \mathbb{E}_{\xi}[F_s^{II-SO}], \mathbb{E}_{\xi}[F_s^{II-TAR}], \mathbb{E}_{\xi}[F_s^{II-TAX}] \right\} \\ &\textit{Subject to:} \quad A_1 z = b_1,\ A_2 z + B_2 y = b_2,\ z \geq 0,\ y \geq 0 \end{aligned} \quad (22)$$

$\mathbb{E}_{\xi}[.]$ represents the expected values of the second-stage objective functions based on the random vector ξ of internal and external demand uncertainty $(\xi_{p's}^{INT}, \xi_{p's}^{EXT})$. A_1, A_2, B_2, b_1, and b_2 represent the coefficients and right-hand side values in the formulation. Additionally, z and y represent the decision variables for the stage I (z_{pnta} and x_{pnt}) and Stage II ($y_{p'nn's}$, $y_{p'ns}^{INT}$, and $y_{p'ns}^{EXT}$).

Osorio et al. [39] proposed a solution method for solving multi-objective two-stage stochastic programming problems under uncertainty by combining the ε-constraint method with SAA. Our work introduces a distinct solution method that differs in both the formulation of the ε-constraint method and the implementation algorithm. Specifically, in their work, the two-stage stochastic programming model includes two objective functions: one representing a two-stage stochastic objective (including first- and second-stage objective functions) and the other being a deterministic objective. In contrast, our model incorporates multiple objective functions in the recourse function of two-stage stochastic programming. In Model (22), the second-stage decisions must be optimized across multiple objectives simultaneously, where trade-offs between objectives need to be addressed. Second, while both methods use the ε-constraint concept, our approach develops an enhanced ε-constraint method. This allows decision-makers to provide preferences at each iteration of the algorithm, enabling us to generate Pareto-efficient solutions that align more closely with their priorities. Third, our implementation algorithm is designed to improve computational efficiency and solution quality. Specifically, our aggregate function within the enhanced ε-constraint method generates more efficient solutions with fewer ε-vectors. This reduces computational costs while maintaining a diverse and high-quality set of non-dominated solutions.

4.1. Sample Average Approximation

According to Shapiro [40], in SAA, we solve the problem $|\mathcal{M}|$ times using independent samples ($\mathcal{M}$ is the set of random samples, and $|\mathcal{M}|$ represents the cardinality of the set $\mathcal{M}$) each of size $\mathcal{N}$ related to uncertain parameters for single objective two-stage stochastic programming of $Min\, f(z, y, s) = C^T z + \mathbb{E}_\xi\big(f(y, s)\big)$, where $C^T z$ represents the Stage I objective function, and $\mathbb{E}_\xi\big(f(y, s)\big)$ denotes the expected value of the Stage II objective function with respect to the random vector ξ. Then the optimal solution (z^m, y^m) and optimal objective f^m $(m = 1, \dots, |\mathcal{M}|)$ would be obtained for samples in set $\mathcal{M}$ each of $\mathcal{N}$ scenarios. Now, the mean, variance, and $(1 - \alpha)\%$ Confidence Interval (CI) of the lower bound for true objective value are obtained by equations (23-a)–(23-c).

$$\mu_L^{(\mathcal{M},\mathcal{N})} = \frac{1}{|\mathcal{M}|} \sum_{m=1}^{|\mathcal{M}|} f^m \tag{23-a}$$

$$\sigma_L^{2(\mathcal{M},\mathcal{N})} = \frac{1}{(|\mathcal{M}| - 1)} \times \sum_{m=1}^{|\mathcal{M}|} \left(f^m - \mu_L^{(\mathcal{M},\mathcal{N})}\right)^2 \tag{23-b}$$

$$CI_L = (CI_L^-, CI_L^+) = \left(\mu_L^{(\mathcal{M},\mathcal{N})} - \mathrm{T}_{(\alpha/_2,|\mathcal{M}|-1)} \times \frac{\sigma_L^{(\mathcal{M},\mathcal{N})}}{\sqrt{|\mathcal{M}|}}, \mu_L^{(\mathcal{M},\mathcal{N})} + \mathrm{T}_{(\alpha/_2,|\mathcal{M}|-1)} \times \frac{\sigma_L^{(\mathcal{M},\mathcal{N})}}{\sqrt{|\mathcal{M}|}}\right) \tag{23-c}$$

$\mathrm{T}_{(\alpha/_2,|\mathcal{M}|-1)}$ represents the value from the Student's t-distribution used to account for the uncertainty in the estimation of the CI.

Then $\mathcal{N}'$ $(\mathcal{N}' \gg \mathcal{N})$ scenarios are generated randomly from set S. They are used to carry out simulation for each efficient and feasible solution (z^m) to find the optimal value of the second-stage decision variables (y_n^m) and objective function f_n^m. The average of simulation responses ($\mu^m = \frac{1}{\mathcal{N}'}\sum_{n=1}^{\mathcal{N}'} f_n^m$, where μ^m represents the average objective function value over $\mathcal{N}'$ scenarios while keeping the first-stage decisions z^m fixed) for each solution (z^m, y_n^m) is used to find the upper bound and its mean, variance, and $(1 - \alpha)\%$ CI according to equations (24-a), (24-b), and (24-c). The minimum average of simulation responses of all samples in set $\mathcal{M}$ is selected for estimating the upper bound of the true objective. Finally, the obtained solutions $(z^m, \bar{y}^m)$ are acceptable for the stochastic programming if the Gap_{SAA} (24-d) is small sufficiently (for more details of SAA implementation see [41].

$$\mu_U = min_{m=\{1,..,|\mathcal{M}|\}} \mu^m \tag{24-a}$$

$$\sigma_U^2 = \frac{1}{(\mathcal{N}' - 1)} \times \sum_{m=1}^{|\mathcal{M}|} \sum_{n=1}^{\mathcal{N}'} (f((z^m, y_n^m) - \mu_U)^2 \tag{24-b}$$

$$CI_U = (CI_U^-, CI_U^+) = \left(\mu_U - \mathrm{Z}\alpha/_2 \times \frac{\sigma_U}{\sqrt{\mathcal{N}'}}, \mu_U + \mathrm{Z}\alpha/_2 \times \frac{\sigma_U}{\sqrt{\mathcal{N}'}}\right) \tag{24-c}$$

$$Gap_{SAA} = CI_U^+ - CI_L^- = \left(\mu_U + Z\alpha/_2 \times \frac{\sigma_U}{\sqrt{\mathcal{N}'}}\right) - \left(\mu_L^{(\mathcal{M},\mathcal{N})} - \mathrm{T}_{(\alpha/_2,|\mathcal{M}|-1)} \times \frac{\sigma_L^{(\mathcal{M},\mathcal{N})}}{\sqrt{|\mathcal{M}|}}\right) \tag{24-d}$$

$\mathrm{Z}\alpha/_2$ represents the critical value from the standard normal distribution.

4.2 Enhanced ε-Constraint Method

We present the enhanced ε-constraint method proposed by [42] to transform our multi-objective problem (Model 22) into a single-objective formulation (Model 25). In this approach, we maintain F_s^{II-PR} within the aggregate objective function (25-a) while converting the remaining six objectives into constraints. Model (25) is defined as follows:

$$Min\ \left(w_1^k \times \left(F^I(z) + \mathbb{E}_\xi[f_s^{II-PR}(y,s)]\right)\right) - \mathfrak{J} \times \sum_{2\le i\le v}\left(w_i^k \times \left(\frac{\varepsilon_i^k - \bar{\varepsilon}_i^k}{\varepsilon_i^{k+1} - \varepsilon_i^k}\right)\right) + \mathfrak{T} \times \sum_{2\le i\le v}\left(R_i^k\right) \quad (25\text{-a})$$

subject to:

Constraints (2)-(7), (10)-(14), and (18)-(19)

$$\mathbb{E}_\xi\left[f_{is}^{II^k}(y,s)\right] + R_i^k = \bar{\varepsilon}_i^k \qquad 2 \le i \le v, s \in S \quad (25\text{-b})$$

$$R_i^k > 0 \qquad 2 \le i \le v \quad (25\text{-c})$$

$$\bar{\varepsilon}_i^k \ge \varepsilon_i^k \qquad 2 \le i \le v \quad (25\text{-d})$$

$$\bar{\varepsilon}_i^k < \varepsilon_i^{k+1} \qquad 2 \le i \le v \quad (25\text{-e})$$

The objective function (25-a) consists of three terms. The first term aims to directly minimise the summation of $F^I(z)$ and $\mathbb{E}_\xi[f_1^{II}(y,s)]$. The second term seeks to minimize the constrained objective functions $i, 2 \le i \le v$ by increasing the normalised distance between the upper bound ε_i^k and the floating value $\bar{\varepsilon}_i^k$ within each epsilon range $\left[\varepsilon_i^{k+1}, \varepsilon_i^k\right]$. The third term aims to minimize the slack variable R_i^k towards zero, effectively activating constraints (25-b). By minimising R_i^k, the model ensures that constraints (25-b) are satisfied as closely as possible by bringing the left-hand side of the equation closer to the floating value $\bar{\varepsilon}_i^k$. The coefficients $\mathfrak{J}$ and $\mathfrak{T}$ adjust the contributions of the trade-off terms in the objective function (25-a). Increasing $\mathfrak{J}$ shifts the Model (25) focus towards improving the constrained objective functions based on their assigned weights w_i^k, rather than prioritising the objective function $w_1^k \times \left(F^I(z) + \mathbb{E}_\xi[f_1^{II}(y,s)]\right)$. For the third term, increasing $\mathfrak{T}$ drives the model to reduce the slack variable R_i^k more aggressively towards zero, effectively binding the constraints to the floating variable $\bar{\varepsilon}_i^k$. This formulation guarantees the generation of only efficient solutions in the Pareto set, not weakly efficient ones [42,43]. Constraints (25-c) ensure that the slack variable R_i^k remains positive ($R_i^k \in \mathbb{R}^+$). Constraints (25-d) and (25-e) restrict the floating value $\bar{\varepsilon}_i^k$ within the epsilon range $\left[\varepsilon_i^{k+1}, \varepsilon_i^k\right]$. An illustrative example of the *ε-constraint* method is provided in the *Supplementary Material S3*.

4.3 Upper and lower bound for the ε-vector

The ε-constraint method requires lower and upper bounds for each constrained objective function to generate the ε-vectors used in the search for Pareto-efficient solutions. These bounds define the range

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over which the constrained objectives are systematically varied and therefore influence both the coverage of the Pareto frontier and the computational effort of the solution procedure. Furthermore, because the ε-constraint method transforms objective functions into constraints, excessively restrictive ε-values may eliminate feasible regions of the ε-constraint Model (25), whereas excessively relaxed ε-levels may lead to inefficient exploration of the Pareto frontier. In deterministic multi-objective optimisation, objective-function ranges are commonly estimated from payoff-table information. However, in the present multi-objective stochastic programming model, the objective values are scenario dependent. For the lower-bound estimation, we use SAA to obtain efficient solutions and the corresponding objective values LB_i^m for each sample $m = 1, \dots, |\mathcal{M}|$. The values $LB_i^m = \mu_{Li}^{(\mathcal{M},\mathcal{N})}$ and the corresponding solutions $(z_i^{m+}, y_i^{m+}) = (z_i^m, y_i^m)$ are obtained by solving Model (26-a).

Min $f\,(z, y, s) = C^T z + \mathbb{E}_\xi\big(f(y, s)\big)$	(26-a)
Subject to:	
Constraints (2)-(7), (10)-(14), and (18)-(19)	

The lower bound of constrained objective function $i = 2, \dots, v$ is then calculated using equation (26-b).

$LB_i = min_{m=\{1,\dots,|\mathcal{M}|\}} LB_i^m$	(26-b)

The upper bounds are estimated using the lexicographic optimisation procedure proposed by Mavrotas [43] for constructing payoff tables with efficient solutions. Algorithm 1 solves SOP model iteratively for each constrained objective function $i = 1, \dots, v$ and subsequently optimises the remaining objective functions $(f_i^{II}(y, s) = f_i^{II}(z_i^{m+}, y_i^{m+}))$ individually with $\mathcal{N}'$ scenario while maintaining the objective values obtained in previous iterations. The objective value obtained at each iteration is introduced as an additional constraint in the subsequent optimisation step, thereby implementing lexicographic optimisation and enabling the construction of the payoff table. The resulting payoff-table information is then used to estimate the upper bounds UB_i of the constrained objective functions $i = \{2, \dots, v\}$.

Algorithm 1

```
i = 2
 while i ≤ v
      For j = 2 to v and i ≠ j
      Solve
      f_j(z_j^{m+}, ŷ) = min ( C^T z_j^{m+} + E_{s={1,...,N'}} ( f_j^{II}(y, s) ) )
       Subject to: f_i^{II}(y, s) = f_i^{II}(z_v^{m+}, y_v^{m+}) and Constraints (2)-(7), (10)-(14), and (18)-(19)
   i = i + 1
   End while.
UB_j = max_{j={1,..,v}} f_j(z_j^{m+}, ŷ)
```

To use the (LB_i, UB_i) for generating the ε_i^k, we need to assure that there is no solution such that $f(z, y)$ dominates LB_i.

Proposition 1. *There is no feasible solution that its objective function dominates the proposed LB_i.*

Proofs are provided in *Supplementary Material S4*.

4.4. Proposed algorithm for multi-objective two-stage stochastic programming

Algorithm 2 solves Model (25) using SAA and an enhanced ε-constraint method. The process begins by calculating lower bounds (LB_i) through predefined equations and estimating upper bounds (UB_i) using Algorithm 1. We determine the appropriate number of grid points (∇) and calculate step sizes (Δ_i) for each constrained objective function i (where i represents F_s^{II-TR}, F_s^{II-EC}, F_s^{II-EN}, F_s^{II-SO}, F_s^{II-TAR}, and F_s^{II-TAX}). The algorithm systematically updates the ε-vectors by progressively decreasing their values from UB_i, starting with $\varepsilon_i^k = UB_i$ and $\varepsilon_i^{k+1} = (UB_i - \Delta_i)$ for each iteration k, where $\Delta_i = \frac{(UB_i^m - LB_i^m)}{\nabla}$. This creates a series of epsilon ranges $\left[\varepsilon_i^{k+1}, \varepsilon_i^k\right]$ that gradually tighten constraints. Also, within each epsilon range, decision-makers can express preferences by assigning weights w_i^k to objective functions. The algorithm employs floating ε-values ($\bar{\varepsilon}_i^k$) that dynamically adjust within each range $\left[\varepsilon_i^{k+1}, \varepsilon_i^k\right]$.

Algorithm 2

Step 1. Initialisation
Generate $\vert\mathcal{M}\vert$ independent samples each of size $\mathcal{N}$ and $\mathcal{N}'$ ($\mathcal{N}' \gg \mathcal{N}$) scenarios
Step 2. Upper and lower bound for ε-constraint method
For *i=2* to *v*
For *m=1* to $\vert\mathcal{M}\vert$
Use SAA for solving Model (26-a) and obtain $\mu_L^{(\mathcal{M},\mathcal{N})}$ by equation (23-a), $LB_i^m = \mu_L^{(\mathcal{M},\mathcal{N})}$
Calculate the LB_i using equation (26-b)
Estimate the UB_i using the Algorithm 1
Step 3. ε-constraint loops
Determine the appropriate number of epsilon vectors ∇
For *i=2* to *v*
For *k=1* to ∇
Set $\varepsilon_i^k = UB_i$, $\varepsilon_i^{k+1} = UB_i - \Delta_i$, $\left(\Delta_i = \frac{(UB_i^m - LB_i^m)}{\nabla}\right)$
Determine w_i^k
Formulate Model (25) for loop k and epsilon range $\left[\varepsilon_i^{k+1}, \varepsilon_i^k\right]$
Step 4. Generate efficient solutions in each loop
For k *=1* to ∇
For $m = 1$ to $\vert\mathcal{M}\vert$
Solve Model (25) with $\mathcal{N}$ scenarios
If a feasible solution (z^m, y^m) found for sample m
Then
Calculate the mean and variance of the lower bound for true objective value by (23-a) and (23-b)
Obtain $(1-\alpha)$% CI of the lower bound for true objective value (23-c)
Solve Model (25) with $\mathcal{N}'$ scenarios for an optimal and feasible solution (z^m)
Estimate the best upper bound using equation (24-a) and find solution $(z^m, \bar{y}^m)$
Obtain $(1-\alpha)$% CI of the upper bound estimate (24-c)
$m = m + 1$
Calculate the Gap_{SAA} using equation (24-d)
Else
$k = k + 1$
Create a set $\mathfrak{F}$ of feasible and efficient solutions (possible solutions of size $\vert\mathcal{M}\vert \times \nabla$)

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Refine set $\mathfrak{F}$ by removing solutions for which the corresponding Gap_{SAA} does not meet the decision maker's satisfaction

For each epsilon configuration, Model (25) is solved iteratively using $\mathcal{N}$ scenarios to find feasible solutions, which are then refined with $\mathcal{N}'$ scenarios to improve accuracy. The optimality gap (Gap_{SAA}) is continuously monitored to ensure solution quality. This approach guarantees feasible solutions while exploring the Pareto front through systematic epsilon parameter updates. The infeasibility may arise due to two reasons: i) infeasibility in the constrained objective function due to their upper and lower bounds $[LB_i, UB_i]$; ii) infeasibility in the second-stage subproblems when evaluated z^m against the set of $\mathcal{N}'$ scenarios. The first infeasibility is explained by the initialization mechanism of Algorithm 2. The Algorithm 2 begins with a relaxed configuration where the constraint limit ε_i^k is set to the upper bound UB_i. As defined in Algorithm 1, UB_i corresponds to the maximum value of the i objective function obtained from the payoff table (i.e., $UB_i = max_{i=\{1,..,v\}} f_i(z_i^{m+}, \hat{\mathcal{Y}})$). Because the algorithm initiates the search at this maximum relaxed constraint limit ε_i^k, at least the optimization is guaranteed to explore a non-empty feasible region at iteration $k = 1$ [42]. Proposition 2 is presented to address the potential infeasibility regarding stochastic demand satisfaction.

Proposition 2. *For any first-stage solution z^m generated by Algorithm 2, the associated second-stage subproblem remains feasible when evaluated against the set of $\mathcal{N}'$ scenarios.*

Proofs are provided in *Supplementary Material S4*.

5. Real-life Case Study

We applied our model to a real-life nationwide steel SCN case study. The data was collected by a governmental consortium that needs to remain anonymous as required by a non-disclosure agreement. Although the technologies, units, and capacities are specific to our case, the model is applicable to a wide range of problems, including emerging technologies such as hydrogen-based steel production. Our case represents an emerging economy that has transformed from a major steel importer to a producer over the past two decades. The nationwide steel SCN experienced substantial capacity expansion, with production increasing from 10 million tons in 2006 to about 30 million tons by 2022.

Despite this growth, the industry faces several critical challenges. First, *capacity expansion has created significant flow imbalances between network levels*. The imbalance reaches about 51% between preprocessing and ironmaking, and about 12% between ironmaking and steelmaking levels. Second, whereas the steel SCN has heavily invested in direct reduction ironmaking technologies using natural gas, *the natural gas infrastructure remains below the needed capacity, particularly during peak demand seasons*. Smaller units especially struggle to secure reliable gas supplies during winter months, forcing them to operate below capacity or temporarily halt production. Third, investment in small, geographically distributed units (intended to create employment across different regions) has resulted in *suboptimal facility locations and capacities,* increasing transportation costs. Fourth, economic volatility,

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development patterns, and global market pressures have created significant *demand fluctuations*, complicating capacity planning decisions. Finally, there is a *significant trade-off between economic development goals and environmental sustainability*, because steel production is water intensive. This causes conflicts between steel production units and other sectors, such as agriculture, that also depend heavily on water resources. These multifaceted challenges demonstrate the need to deploy our model and solution framework to provide data-driven insights for improving overall network efficiency while balancing economic, environmental, and social sustainability dimensions.

5.1. The Real-Life Data

We assume a 30-year planning horizon, comprising 6 strategic periods ($p = 1, \dots, 6$) of 5 years each and 30 tactical periods ($p' = 1, \dots, 30$) of 1 year each. The nationwide steel SCN consists of 9, 12, and 11 existing units for preprocessing, ironmaking, and steelmaking levels respectively. Also, five additional candidate locations are selected for new units at each level. External units are considered as global market nodes for import/export at each level, resulting in total nodes of |I|=15, |J|=18, |K|=17. Technology set (T), technology compatibility ($\vartheta_{tt'}$) and technological coefficients (γ_t) are determined by expert opinion and detailed in Table 1. The capacity and technology of the existing units are reported in Figure 3.

Fixed setup and production costs are based on three groups of projects: under-construction, under negotiation, and future projects, including decommissioning costs for technologies. Variable costs of production for existing units are obtained from annual financial reports, while potential unit costs are estimated by experts based on similar existing technologies. Transportation costs are calculated using cargo tariff, distance, and cargo weight between units. Steelmaking units face an 11% export tax and 4% import tariff; while preprocessing and ironmaking units have a 30% export tax and 13% import tariff. Maximum import allowances ($\varpi_{p'}$) vary over time: unlimited for tactical periods [1,5], then decreasing from 15mT [6,10], 10mT [11,15], 5mT [16,20], 3mT [21,25], to 2mT [26,30]. All time-dependent parameters are calculated using discounted cash flow formula (e.g. $\varphi^{ST}_{pnta} = \varphi^{ST}_{1nta} \times (1 + i)^{(p-1)}$).

The technological compatibility constraints in Table 1 illustrate a key challenge in the current network: while Blast Furnace technology can only receive inputs from Sintering units and output to BOF steelmaking, the direct reduction technologies (Midrex and PERED) have greater flexibility, accepting inputs from both HPGR and Alice Chalmers preprocessing and outputting to both EAF and EIF steelmaking. The technological coefficients indicate material transformation efficiency. For example, in our case, PERED technology in ironmaking offers a 74% yield compared to 63% for traditional Blast Furnace technology.

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Table 1. Technologies, technology compatibility and Technological coefficient for steel SCN

Technology compatibility ($\vartheta_{tt'}$)		T^J			Technological coefficient (γ_t)
		Blast furnace	Midrex	PERED	
T^I	HPGR	0	1	1	0.88
	Alice Chalmers	0	1	1	0.90
	Sintering	1	0	1	0.90
Technological coefficient (γ_t)		0.63	0.7	0.74	
Technology compatibility ($\vartheta_{tt'}$)		T^K			Technological coefficient (γ_t)
		EAF	BOF	EIF	
T^J	Blast furnace	0	1	0	0.63
	Midrex	1	0	1	0.7
	PERED	1	0	1	0.74
Technological coefficient (γ_t)		0.82	0.85	0.86	

5.2 Sustainability rates for steel SCN

A three-phase sustainability assessment framework was implemented to evaluate sustainability rates across *location-technology-flow* configurations. Table 2 illustrates the sustainability rates and corresponding sub-measures for three representative units: PP10, IM13, and SM12. In the case of PP10 (preprocessing unit), sustainability rates were evaluated for three distinct technologies: HPGR, Alice

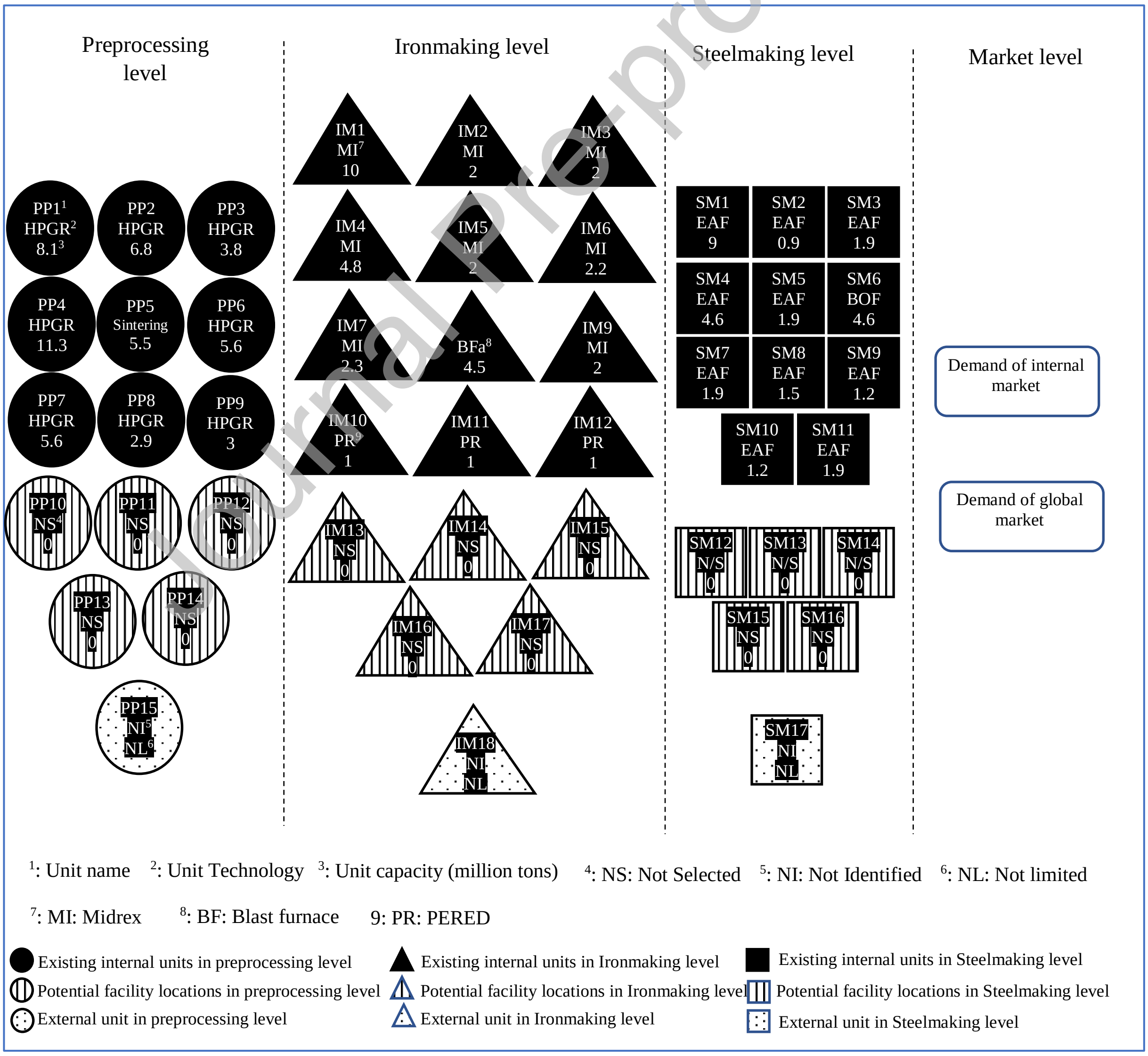

Figure 3. Current Steel SCN in our case study

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Table 2. Sustainability rates and a part of collected measures for units PP10, IM13, and SM12

Steel SC levels	Location (unit)	Technologies	Sustainability sub-measures				Sustainability rates		
			EC (kwh/t)	GC m^3/t	NMO	Flexibility	$\varphi^{ec}_{ntp'}$	$\varphi^{en}_{ntp'}$	$\varphi^{so}_{ntp'}$
PREPROCESSING	PP10	HPGR	40	27	2.85	2.1	0.681	0.442	0.611
		Alice Chalmers	25	31	1.8	2.2	0.603	0.552	0.502
		Sintering	82	9	2.1	2.8	0.658	0.599	0.391
IRON PRODUCTION	IM13	Blast furnace	400	27	2.05	2.6	0.667	0.466	0.534
		Midrex technology	134	335	2.75	1.9	0.720	0.541	0.605
		PERED	105	263	2.65	1.95	0.734	0.646	0.549
STEEL PRODUCTION	SM12	EAF	629	13.3	2.9	2.05	0.675	0.491	0.719
		BOF	130	18	1.8	2.6	0.682	0.642	0.509
		EIF	550	20	1.2	1.9	0.527	0.690	0.631

Chalmers, and Sintering. The analysis revealed that Sintering technology demonstrated superior performance in social sustainability ($\varphi^{SO}_{p'nt} = 0.391$), while HPGR exhibited the lowest environmental sustainability rate ($\varphi^{EN}_{p'nt} = 0.442$). Alice Chalmers technology achieved the highest qualitative economic sustainability rating ($\varphi^{EC}_{p'nt} = 0.603$). The sustainability assessment framework and the data collection methodology are documented in *Supplementary Materials S1 and S2*, respectively.

5.3 Scenario generation for demand

The stochastic component of demand was characterized using the Autoregressive Integrated Moving Average (ARIMA) model, a well-established approach for time series forecasting that captures both trend and random fluctuations in historical data. ARIMA was selected for its ability to model the complex temporal dependencies in steel demand patterns while accounting for non-stationarity observed in our historical data spanning from 1975 to 2022 (47 years) for internal and external demand components.

The ARIMA parameters (p, d, q) were specified using SigmaXL (version 9.1), selecting the best (or the simpler one that was close to the best) ARIMA model. Analysis of both internal and external demand components revealed nonstationary and nonseasonal time series with trend components. Through a stepwise procedure, ARIMA(1,1,0) was identified as optimal for internal demand $\xi^{int}_{p's} = C + \xi^{int}_{(p'-1)s} + \varphi_i \times (\xi^{int}_{(p'-1)s} - \xi^{int}_{(p'-2)s}) + \varepsilon_{p's}$, while ARIMA(0,1,0) with constant was selected for external demand $\xi^{ext}_{p's} = C + \xi^{ext}_{(p'-1)s} + \varepsilon'_{p's}$. The fitted ARIMA models were then used to extract the error terms $\varepsilon_{p's}$ and $\varepsilon'_{p's}$, which represent the stochastic component of demand variations. These error terms were utilized in a Latin Hypercube Sampling approach to generate an efficient fan of scenarios. This scenario generation methodology provides a robust foundation for the stochastic optimization model by incorporating realistic demand uncertainty based on historical patterns. The scenario generation methodology is presented in the *Supplementary Material S5*.

5.4 Application of the proposed multi-objective SAA algorithm

Using the internal and external equations developed in section 5.3 and the normal distribution of the error, $|\mathcal{M}| = 5$ samples with $\mathcal{N} = 20$ and $\mathcal{N}' = 120$ scenarios are generated. Our algorithm was implemented in Python 3.12 and the proposed mathematical model is solved using the Gurobi optimization solver. All experiments were conducted on a Dell C6300 system equipped with Intel E5-2690 v4 processors (2.6 GHz) and 4 GB RAM. All the results are obtained with optimality gap less than $GAP_{Opt} \leq 6\%$ and the 3 hours. Model (26) is solved for ($|\mathcal{M}| = 5$, $\mathcal{N} = 20$**)** and the LB_i is calculated with an optimality gap less than 6% within 18000s. Then, **Algorithm 1** is applied to find the UB_i. $[LB_i, UB_i]$ and the optimality gap for LB_i are reported in Table 3. Number of intervals (∇=3) is used to generate epsilon vectors and develop the equivalent formulation (25). We conducted SAA for each loop in the ε-constraint method in Model (25). Table S6 in *Supplementary Material S6* reports the 25 efficient solutions along with the corresponding computational times and the Gap_{SAA}. The minimum, maximum, and average optimality gaps are 3.25%, 4.83%, and 4.01%. Solution No.1 is summarized in Tables S7-S9 in *Supplementary Material S6*. Further analysis is carried out on this solution to examine the benefits of the proposed model.

Table 3. Upper and lower bound and optimality gap for objective functions in the second-stage

	$f_2^{II}(y,s)$	$f_3^{II}(y,s)$	$f_4^{II}(y,s)$	$f_5^{II}(y,s)$	$f_6^{II}(y,s)$	$f_7^{II}(y,s)$
LB_i	12452560	4409427	3070612	3701076	111316	79739
$GAP_{Opt_{LB}}\%$	4.67%	4.85%	5.83%	3.13%	5.28%	5.63%
UB_i	13697816	6393669	4145326	4330258	161408	115621
Time (s)	18000	18000	18000	18000	18000	18000

5.5 Analysis of results

The steel SCN need to be configured so as to reduce the IMF over planning horizon. Please see *Supplementary Material S7* for a rigorous definition of IMF. Figure 4 illustrates the IMF between preprocessing and ironmaking, and between ironmaking and steelmaking levels in Solution No.1. Initial IMF were $IMF_1^{IJ} = 51.30\%$, $IMF_1^{JK} = 12.23\%$, and $IMF_1^{K} = 29.83\%$. The maximum IMF occurs between preprocessing and ironmaking in the first strategic period. The total capacity of preprocessing units is twice as much as the total capacity of ironmaking units. Consequently, internal preprocessing units must export approximately 17.8 mT to the external unit at the ironmaking level. The model subsequently increases ironmaking capacity to 75.1 mT in strategic period 3. During this period, the IMF between the first two levels becomes positive (approximately 12%), necessitating raw material imports from external preprocessing units. While lower IMF was anticipated in strategic period 3, the results demonstrate a significant increase in ironmaking unit capacity, leading to high positive IMF percentages between preprocessing and ironmaking. The model prioritizes reducing the IMF between steelmaking and ironmaking (from 13.72% in strategic period 2 to 5.28% in strategic period 3) before addressing the IMF between the first two levels. This demonstrates the model's effectiveness in network balancing while considering SCN characteristics and available technologies. The final IMF values in the nationwide steel SCN of 1.16% and 1.07% at the end of planning horizon are acceptable given the problem's scale.

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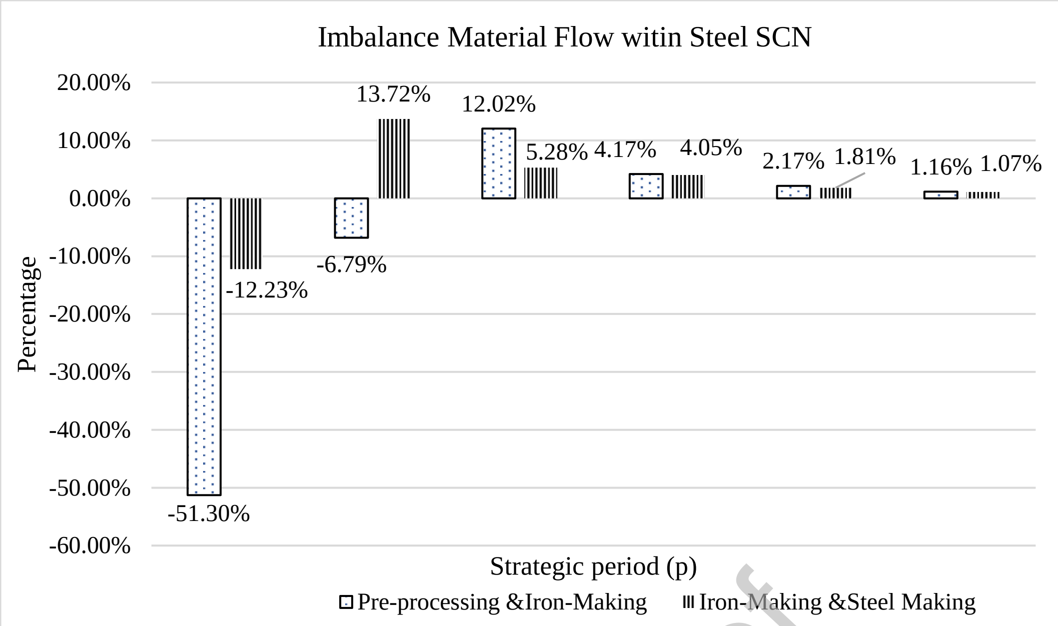

Figure 4. The IMF in Solution No.1

Supplementary Material S7 also reports on the IMF between steelmaking units and market demand.

6. Policy insights

This section develops policy insights from the proposed framework by analysing the effects of export taxes, import tariffs, sustainability rates, and fixed setup costs on strategic decisions and sustainability performance in the steel SCN.

6.1 The role of export taxes and import tariffs

Tax and tariff policies significantly influence strategic decisions in steel SCN design problems. Two policies are defined based on constant and variable rates for tax and tariff. Policy 1 maintains one rate (either tax or tariff) as constant while allowing the other to vary beyond a threshold value. Policy 2 implements variable rates for both tax and tariff, with random fluctuations throughout the planning horizon. These policies are analysed to evaluate the impact of rate variations on the IMF.

Policy 1A. Constant tariff rate: High or low rate for tax

Analysis of Policy 1A (fixed tariff rate) reveals that tax rate variations below 60% for ironmaking/preprocessing units and 30% for steelmaking units show no significant impact on network performance. However, when tax rates exceed these thresholds, capacity expansion decisions are notably delayed. For instance, preprocessing units PP10 (7.6 mT) and PP13 (6.2 mT) defer expansion from period 3 to 4, while ironmaking unit IM15 (9.2 mT) delays from period 2 to 4. Similarly, steelmaking units SM13 (7.8 mT) and SM16 (12.5 mT) postpone their expansions to later periods.

Results indicate that while higher tax rates above the threshold minimally affect IMF between ironmaking and preprocessing levels, as well as between steelmaking and ironmaking levels, they significantly impact the IMF pattern between steelmaking and market levels. As shown in Figure 5a, under lower tax rates,

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the IMF drops rapidly until strategic period 3, indicating steelmaking units' willingness to expand capacity. In contrast, with tax rates above the threshold, the IMF decreases more gradually from strategic period 1 to 3, reflecting steelmaking units' unwillingness to expand capacity. Notably, prolonged high export taxes lead to conservative capacity expansion decisions, making the network vulnerable to demand surges. This is evidenced in strategic period 3, where the IMF for low-tax policy shows -30% (excess capacity) compared to -6% for high-tax policy, indicating potential shortage risks between years 10-15 of the planning horizon (Figure 5a). Nevertheless, the network eventually achieves balanced capacity across all levels by the planning horizon's end.

Policy Insight 1: A better IMF can be achieved at each level of the SCN by optimizing the strategic decisions under constant tariff rates and high tax rates.

Policy 1B. Constant tax rate: High or low rate for tariff

In Policy 1B, we analysed the impact of varying tariff rates while maintaining fixed tax rates. The threshold values were set at 140% for preprocessing and ironmaking units, and 90% for steelmaking units. Results show no significant changes in solutions below these thresholds. However, at thresholds, notable capacity adjustments occurred: 1) at the preprocessing level, instead of establishing a capacity of 6.5 mT in the potential unit number PP14 in the strategic period 4, the capacity of 10.8 mT is established in the strategic period 2. Also, in the third strategic period, the capacity of potential unit PP10 has increased from 6 to 12.4 million tons; 2) at the ironmaking level, the capacity of potential unit IM16 is increased from 7 to 11.8 mT. Also, in the third strategic period, the capacity of potential unit IM17 is increased from 10 to 18 mT; 3) There is no change in the capacities of units at the steelmaking level. Figure 5b shows the IMF of the steel SCN over strategic periods with high or low rates of import tariff and fixed rates of export tax under policy 1B. As shown in the first and second IMF diagrams in Figure 5b, under policy 1B, in both high and low tariff rates, the model has reached an acceptable IMF at the end of the planning horizon (less than 5%). However, two significant differences can be seen in the solutions of the high and low rates of tariff. Higher import tariff rates prove more effective than lower tariff rates when managing market demand fluctuations. This strategy helps prevent IMF imbalances, particularly capacity shortages at the steelmaking level, during unstable market conditions. The increased network capacity serves as a buffer against shortages, while any surplus during low demand periods can be directed to external markets through exports.

Policy Insight 2: Under constant tax rates and high tariffs, the material flow balance can be improved by capacity increases in the upstream levels of the steel industry SCN.

Sensitivity analysis of import tariff and export tax rates demonstrates that our model responds effectively to changes in these parameters, though with distinct impacts on strategic decisions across different levels of the SCN. The analysis reveals a clear pattern of influence: export tax rates have a more pronounced effect on steelmaking units (downstream operations), while import tariffs show greater impact on

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preprocessing and ironmaking units (upstream operations). This differentiation is clearly illustrated in Figure 5a, where the IMF lines show larger gaps between steelmaking and market levels. In contrast, Figure 5b demonstrates wider gaps in IMF lines between preprocessing and ironmaking levels within the steel SCN.

Policy Insight 3: The import tariff rate is an effective tool for controlling the capacity of units in the upstream of the steel SCN, whereas the export tax rate can be utilized for regulating the downstream levels.

Policy 2. Variable rates for tax and tariff

Random variations in the rates of tax and tariff over different strategic periods led to varying outcomes that prevented drawing a consistent conclusion. It is worth noting that when the rates are variable and increase over time, the objective functions F_s^{II-TAR} and F_s^{II-TAX} experience an increase. Based on the findings of sensitivity analysis for tax and tariff rates, we distilled the following insight.

Policy Insight 4: To ensure the attainment of material flow balance in steel SCN, it is imperative to establish fixed long-term rates for tax and tariff.

Analysis of Policy 2 (variable rate) reveals several significant drawbacks. From a financial perspective, this policy not only fails to improve network balancing but also increases network costs, as evidenced by objective functions F_s^{II-TAR} and F_s^{II-TAX}. The policy faces substantial operational challenges. Internal units cannot rapidly adjust their capacity in response to fluctuating tax and tariff rates. When capacity is increased at one level, such as steelmaking, corresponding adjustments must be made across other levels of the steel SCN, specifically at ironmaking and preprocessing levels. The inability to synchronize these capacity changes results in high IMF issues, as demonstrated in Section 5.5. Network interdependencies and technology compatibility further complicate the situation. Due to vertical integration within the network, units are inherently interconnected, meaning that the impact of tax and tariff rates extends beyond individual levels. As a result, government interventions through these regulatory tools significantly influence the overall performance of steel SCNs in terms of IMF.

Policy Insight 5: Due to technological interdependencies and vertical integration across the steel SCN, changes in tax and tariff rates cannot be implemented in isolation at a single level, requiring government policies to consider their network-wide impacts on IMF.

6.2 The Role of Sustainability

We examine how technology sustainability rates influence capacity acquisition and technology selection decisions while considering the trade-offs between economic, social, and environmental sustainability in the steel SCN.

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Figure 5.a. Policy 1, IMF for high and low tax rate over strategic periods

Figure 5.b. Policy 1, IMF for high and low tariff rate over strategic periods

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6.2.1 Impact of Social and Environmental Sustainability Rates

We developed two scenarios to examine how social and environmental sustainability rates affect capacity and technology decisions. Scenario 1 (*Business-As-Usual, BAU*) uses the sustainability rates from Table 3, while Scenario 2 (*High Environmental, Social, and Governance impacts, High ESG*) features increased social and environmental sustainability rates for two technology routes: 1) sintering, blast furnace, and BOF; and 2) Alice Chalmers, Midrex and EAF technologies. Higher sustainability rates indicate poorer social and environmental performance. As shown in Figure 6, while sustainability rates influence technology selection and capacity, increasing these rates only reduces capacity expansion in existing units rather than changing their technology choices. Notably, existing units still pursue capacity increases through improvement and expansion approaches across most strategic periods (e.g., sintering, blast furnace, and BOF in Figure 6).

Policy Insight 6: Increased sustainability costs alone are insufficient to drive technology switching to a sustainable technology in existing units; only encouraging incremental technological improvements within their current technological framework.

For new capacity installations, the model selects alternative technologies with lower sustainability rates (e.g., HPGR in Figure 6). The impact of changing sustainability rates on decisions is influenced by factors including technology compatibility and economic sustainability. For instance, increasing sustainability rates solely for blast furnaces prompts the model to rebalance capacity across compatible technologies throughout the steel SCN, including sintering (preprocessing) and BOF (steelmaking)

Policy Insight 7: Sustainable transformation of the steel SCN requires developing new sustainable technologies that are compatible with existing upstream and downstream technologies.

6.2.2 Impact of Fixed Setup Cost on Social, and Environmental Sustainability

We developed two additional scenarios based on Scenario BAU; to examine how fixed setup costs affect sustainability objectives and strategic decisions. Scenario 3 (*No Fixed Costs, No FC*) eliminates fixed setup costs ($\varphi_{pnta}^{ST} = 0$), while Scenario 4 (*No Fixed Costs with High ESG*) combines zero setup costs with maximum sustainability rates (1.00) for selected technologies: sintering (locations PP5 and PP13), blast furnace (locations IM8, IM14, and IM15), and BOF (locations SM6, SM12, and SM13). With zero fixed costs, the first term of objective function (1) is removed, allowing unrestricted capacity increases. Since our model prevents capacity reduction through equation (4), we analyse total material flow rather than installed capacity. In addition, we calculated the average flow of units in each level and represent it by the red-dotted line in Figure 7.

By opening new units at the beginning of strategic period 2, the flow from external units (PP15, IM18, and SM17) drops to zero in both scenarios 3 (*No FC*) and 4 (*No FC with High ESG*). Figure 7 shows how varying social and environmental sustainability rates affect material flow (operational capacity) of each unit in the steel SCN under scenarios *BAU, No FC*, and *No FC with High ESG* at the beginning of strategic period 6. The model minimizes deviation between individual unit material flows and the average material flow at each level, while considering technology compatibility to reduce transportation costs. While reduced transportation also benefits environmental sustainability through lower shipping impacts, our analysis focuses solely on production sustainability based on *location-technology-flow* configurations, preventing detailed insights into transportation-related sustainability savings. Comparing scenarios *No FC* and *No FC with High ESG* demonstrates our model's sensitivity to social and environmental sustainability rates. Figure 7 shows reduced material flows from less sustainable technologies (those with higher sustainability rates) in scenario *No FC with High ESG* compared to scenario *No FC*. The model exhibits heightened sensitivity to sustainability rates when fixed setup costs are removed, with changes showing greater impact than tax and tariff rate adjustments.

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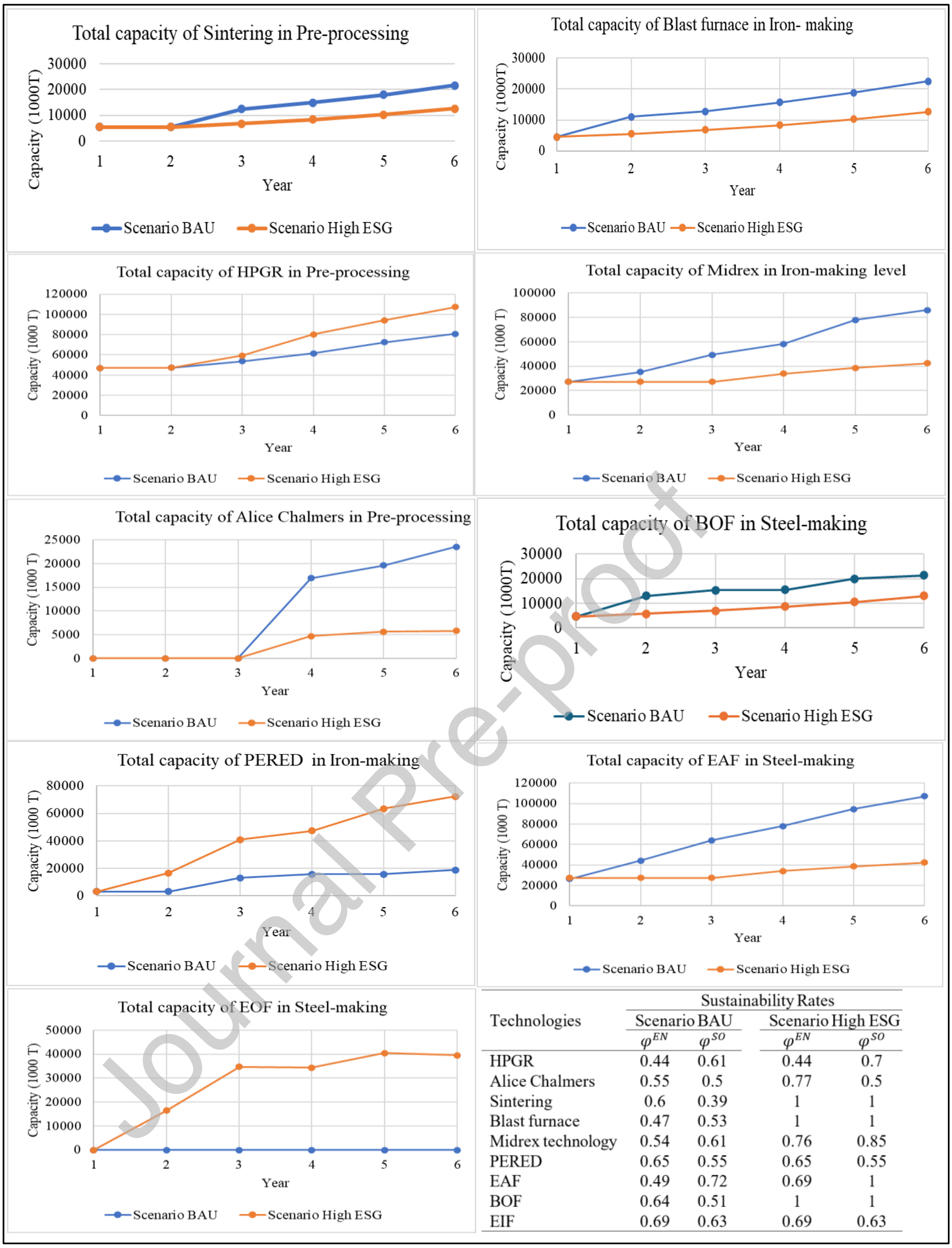

Technologies	Sustainability Rates			
	Scenario BAU		Scenario High ESG	
	φ^{EN}	φ^{SO}	φ^{EN}	φ^{SO}
HPGR	0.44	0.61	0.44	0.7
Alice Chalmers	0.55	0.5	0.77	0.5
Sintering	0.6	0.39	1	1
Blast furnace	0.47	0.53	1	1
Midrex technology	0.54	0.61	0.76	0.85
PERED	0.65	0.55	0.65	0.55
EAF	0.49	0.72	0.69	1
BOF	0.64	0.51	1	1
EIF	0.69	0.63	0.69	0.63

Figure 6. Capacity choices for each technology under sustainability rate scenarios

Addressing Lee and Tang [18] questions about intervention effectiveness and unintended consequences in government policies, we find that among various government interventions (taxation, tariff, and incentives), some can significantly impact sustainability goals in the steel SCN, matching the influence of fixed setup costs. For example, government support through long-term, low-interest loans or international investment assistance can facilitate the transition toward a sustainable steel SCN. While fixed tax and tariff rates are effective tools, their long-term escalation could increase overall steel SCN

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costs, create uncertainty about continued private sector participation, and lead to unintended consequences such as unit closures or capacity reductions and shortage.

Policy Insight 8: Government incentives are crucial for enhancing sustainability in the steel SCN. While tax and tariff rates can effectively influence sustainability performance at downstream and upstream levels respectively, more substantial incentives (such as zero-interest, long-term loans and international investment support) are needed to offset fixed setup costs and drive sustainable transformation of the steel industry.

7. Concluding Remarks

This paper makes a significant contribution by developing a comprehensive framework that integrates economic, environmental, and social dimensions of sustainability into strategic and tactical decisions for steel SCN. Our model uniquely addresses the complexities of steel SCN by optimising material flow balance across preprocessing, ironmaking, steelmaking, and market levels, whilst handling demand uncertainty through an innovative two-stage stochastic formulation with multi-objective recourse. The methodological advancement includes SAA adaptation and new bounds for constraint objective functions through ε-constraint loops, validated through a real-life nationwide steel SCN case study. This research stands out amongst the limited empirical studies that successfully bridge the gap between theoretical modelling and practical application in sustainable SCM. By developing a novel model and implementing it in a real-life steel SCN, we demonstrate both the theoretical rigour of our approach and its practical applicability, providing valuable insights for both academics and practitioners in the field of sustainable steel SCN design and operation.

Our analysis yields eight crucial policy insights that demonstrate the intricate relationships between government interventions and sustainable steel production. We find that import tariffs and export taxes are asymmetric in their impact, tariffs effectively control upstream capacity whilst taxes regulate downstream operations. However, their effectiveness is contingent upon maintaining stable, long-term rates and considering network-wide implications due to technological interdependencies. Particularly noteworthy is our finding that sustainability costs alone cannot drive technological transformation; rather, a coordinated approach combining technological compatibility and substantial government support is essential. The research reveals that achieving a sustainable steel SCN requires: 1) balanced capacity development across all network levels; 2) implementation of compatible sustainable technologies throughout the SCN; and 3) significant government intervention through both tax and tariff as well as financial incentives. Given the capital-intensive nature of the steel SCN and its crucial role in global sustainability, our findings emphasise that government support – through mechanisms such as zero-interest loans, international investment support, and carefully calibrated tax/tariff policies – is not merely beneficial but essential for driving sustainable transformation. These insights provide a robust foundation for policymakers and industry stakeholders to develop effective strategies for transitioning towards a

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more sustainable steel SCN, whilst maintaining economic viability and competitive advantage in an uncertain global market.

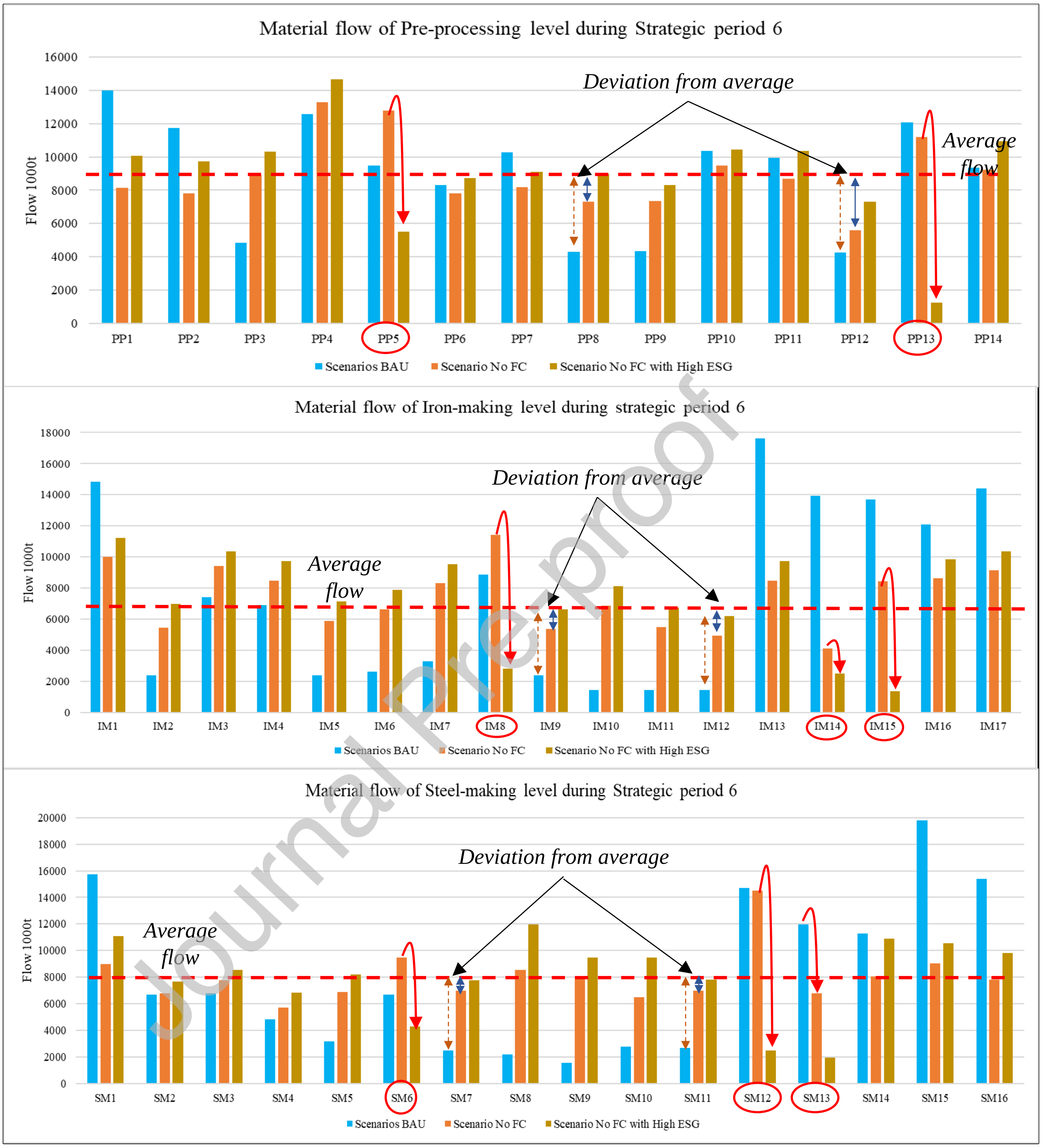

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Figure 7. Material Flow of units at different levels of steel SCN during period 6, under Scenarios BAU, *No FC*, and *No FC with High ESG*

Several promising directions emerge for future research. First, our model's flexibility allows for incorporation of additional policy interventions such as carbon taxes [44], emissions trading schemes [28], and carbon border adjustment mechanisms [45]. Analysing these mechanisms would provide valuable insights into their effectiveness in sustainable steel SCN design and operation. Second, enhancing the model by integrating technology life-cycle considerations into steel SCN design and MFC presents an important research opportunity [46,47]. This extension would address critical aspects such as decommissioning outdated processes and ensuring technology compatibility across the network – factors crucial for long-term sustainability planning in the steel industry. Third, investigating the implications of emerging hydrogen-based steel production technologies [48] represents a vital research direction. As the industry adapts to stringent carbon policies, understanding how these technologies impact network design and operational decisions becomes increasingly important for sustainable transformation of the steel SCN. Fourth, considering our model's assumptions, future research could explore the incorporation of additional levels and actors within the steel SCN. Specifically, researchers should investigate how including upstream processes, such as mining, and downstream activities, like rolling and forming, can enhance the comprehensiveness of Operations Research models. Furthermore, examining the integration of various materials and resources, such as scrap, nickel, and cobalt, could yield deeper insights into the optimisation of the steel SCN. By addressing these elements, future studies can build upon our findings and contribute to a more holistic understanding of steel SCN dynamics and the role of Operations Research in supporting strategic decision-making.

Finally, methodological challenges in applying our solution approach to large-scale problems warrant further investigation. Whilst the integrated ε-constraint and SAA loops can be computationally intensive, the strategic nature of decisions provides sufficient time for computation. Future research could explore computational efficiency improvements, such as starting with relaxed constraints and implementing early exit strategies when infeasibility occurs [43]. Additionally, developing theoretical frameworks to guarantee solution feasibility in SAA applications remains an important challenge to address.

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Appendix A

Sets	
N	All units $N = (I \cup J \cup K)$ indexed by n
I	Preprocessing units indexed by n
J	Ironmaking units indexed by n
K	Steelmaking units indexed by n
N^{INT}	Internal (domestic) units, $N^{INT} = (I^{INT} \cup J^{INT} \cup K^{INT})$
N^{EXT}	External (foreign) units, $N^{EXT} = (I^{EXT} \cup J^{EXT} \cup K^{EXT})$
I^{INT}	Internal preprocessing units
J^{INT}	Internal ironmaking units
K^{INT}	Internal steelmaking units
I^{EXT}	External preprocessing units
J^{EXT}	External ironmaking units
K^{EXT}	External steelmaking units
T	Technologies indexed by t and t', $T = (T^I \cup T^J \cup T^K)$
T^I	Technologies for preprocessing units
T^J	Technologies for ironmaking units
T^K	Technologies for steelmaking units
A	Capacity acquisition methods indexed by α
P	Strategic periods indexed by p
P'	Tactical periods indexed by p'

S	Scenarios indexed by s
Parameters	
$\xi^{INT}_{p's}$	Internal demand in tactical period p' under scenario s
$\xi^{EXT}_{p's}$	External demand in tactical period p'under scenario s
π_s	Probability of scenario s, where $\sum_{s\in S}(\pi_s)$=1 and $0 \leq \pi_s \leq 1$
$\varpi_{p'}$	Maximum allowable imports in tactical period p'
γ_t	Technical coefficient of technology t
$\vartheta_{tt'}$	1 if the technologies t and t' be compatible; 0 otherwise
$\varphi^{EC}_{p'nt}$	Qualitative economic sustainability rate for technology t in unit n during tactical period p'
$\varphi^{EN}_{p'nt}$	Environmental sustainability rate for technology t in unit n during tactical period p'
$\varphi^{SO}_{p'nt}$	Social sustainability rate for technology t in unit n during tactical period p'
$\varphi^{ST}_{pnt\alpha}$	Fixed setup cost of capacity expansion per tons for technology t under capacity acquisition method α in unit n and strategic period p
φ^{OP}_{pnt}	Fixed production cost in units n with technology t in strategic period p
$\varphi^{PR}_{p'nt}$	Production variable cost for technology t in unit n and tactical period p'
$\varphi^{TR}_{p'nn'}$	Transportation cost between units n and n' during tactical period p'
$\varphi^{TR-INT}_{p'n}$	Transportation cost to internal market from unit $n \in K$ in tactical period p'
$\varphi^{TR-EXT}_{p'n}$	Transportation cost to external market from unit $n \in K$ in tactical period p'
$\varphi^{TAX}_{p'n}$	Export tax for internal unit n in tactical period p'
$\varphi^{TAR}_{p'n}$	Import tariff for internal unit n in tactical period p'
$\mathscr{g}_\alpha$	Maximum capacity acquisition ratio for method α, $0 < \mathscr{g}_\alpha \leq 1$ $\alpha \in A\backslash\{3\}$
ϱ	Large positive number
ζ	Number of tactical periods per strategic period
Auxiliary variables	
q_{pnt}	Available capacity of unit n with technology t at the start of strategic period p
$r_{nn'tt'}$	Binary variable linking technology t, t' and unit n, n'
$v^{EC}_{p'nts}$	Qualitative economic cost for units n with technology t in tactical period p' under scenarios s
$v^{PR}_{p'nts}$	Variable production cost for units n with technology t in tactical period p' under scenarios s
$v^{EN}_{p'nts}$	Environmental impact for units n with technology t in tactical period p' under scenarios s
$v^{SO}_{p'nts}$	Social impact for units n with technology t in tactical period p' under scenarios s
Objective function – Stage I and II	
F^I	stage I
F^{II-PR}_s	stage II: Variable production cost
F^{II-TR}_s	stage II: Transportation cost
F^{II-EC}_s	stage II: Economic (qualitative) sustainability
F^{II-EN}_s	stage II: Environmental sustainability
F^{II-SO}_s	stage II: Social sustainability
F^{II-TAR}_s	stage II: Import tariff
F^{II-TAX}_s	stage II: Export tax
Decision Variable – Stage I (Strategic)	
$z_{pnt\alpha}$	Capacity expansion of unit n with technology t using method α in strategic period p
x_{pnt}	1 if technology t is selected for unit n in strategic period p; 0: otherwise
Decision Variable – Stage II (Tactical)	
$y_{p'nn's}$	Material flow between units n and n' in tactical period p' under scenarios s
$y^{INT}_{p'ns}$	Flow to internal market from unit $n \in K$ in tactical period p'under scenarios s
$y^{EXT}_{p'ns}$	Flow to external market from unit $n \in K$ in tactical period p'under scenarios s

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