A Data-Driven Two-Stage Robust Optimization Model for Sponge Iron Supply Chains under Market Volatility and Dual-Season Energy Disruption Risks

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Received: 2025-09-10 **Revised:** 2026-01-13 **Accepted:** 2026-01-20 **Published:** 2026-01-30

Abstract

Energy-intensive process industries, particularly direct-reduced iron (DRI) and sponge iron manufacturing, face critical operational vulnerabilities stemming from dual-season energy disruptions—such as winter natural gas curtailments and summer electricity blackouts—compounded by volatile raw material market prices. Traditional deterministic planning and decoupled forecasting models often fail to account for overlapping systemic shocks, frequently leading to costly production halts or severe inventory stockouts. To bridge this gap, this study proposes a novel two-stage data-driven robust optimization model for sponge iron supply chains. The framework systematically translates empirical forecasting error residuals derived from deep learning models into polyhedral uncertainty sets governed by budgets of uncertainty (Γ_1, Γ_2). Validated through a real-world case study of Mobarakeh Steel Company, the numerical results demonstrate that setting optimal uncertainty budgets at $\Gamma_1 = 1.5$ and $\Gamma_2 = 1.0$ achieves an optimal compromise point, yielding a 14.2% total operational cost reduction compared to deterministic baselines while completely preventing stockout-induced production halts.

Keywords: *Data-driven robust optimization, Sponge iron supply chain, Energy disruptions, Inventory management, Deep learning residuals, Exact mathematical programming*

How to cite this article:

Badami, M. R., Ahari, R. M., Ghandehari, M., & Sherafati, M. (2026). A Data-Driven Two-Stage Robust Optimization Model for Sponge Iron Supply Chains under Market Volatility and Dual-Season Energy Disruption Risks. Management Strategies and Engineering Sciences, 8(1), 1-13.

1. Introduction

The iron and steel industry occupies a foundational position in modern industrial systems because it supplies the material base for construction, transportation, machinery, energy infrastructure, manufacturing, and an expanding range of low-carbon technologies. At the same time, steel production is among the most resource- and energy-intensive industrial activities, making its supply chains particularly sensitive to changes in energy availability, raw-material markets, environmental regulation, technological transition, and geopolitical conditions. Recent research has consequently moved beyond the conventional objective of minimizing production and logistics costs toward a broader concern with sustainability, resilience, resource security, and adaptive decision-making. Comparative evidence on material supply chains indicates that steel production faces distinctive sustainability challenges arising from the extraction, transformation, transportation, and energy requirements associated with its principal inputs, while the transition toward cleaner industrial systems places additional pressure on firms to reconcile security of supply with environmental performance [1]. From an environmental perspective, life-cycle assessments further demonstrate that emissions in the iron and steel sector are generated across interconnected source, production-process, end-use, and energy-consumption stages, indicating that operational and supply decisions cannot be separated from energy efficiency and cleaner-production considerations [2]. These characteristics make the steel supply chain a complex decision environment in which economic efficiency, continuity of production, environmental objectives, and exposure to external shocks must be addressed simultaneously rather than independently.

This problem is particularly important for direct-reduced iron (DRI), or sponge iron, production. DRI manufacturing depends on the continuous availability of iron-bearing raw materials, particularly pellets, as well as substantial and relatively stable supplies of energy. Interruptions in either material or energy flows can therefore propagate rapidly through production operations. Unlike industries in which short-term shortages can be absorbed through minor scheduling adjustments, direct-reduction facilities are exposed to significant operational and financial consequences when production is curtailed because of insufficient feedstock, electricity, or natural gas. Energy-market volatility compounds this exposure because energy-intensive manufacturing is affected not only by changes in energy prices but also by the physical availability of energy during periods of systemic stress. Research on energy commodity markets shows that shocks can generate considerable and persistent volatility, highlighting the importance of risk-aware strategies capable of absorbing abrupt disturbances and supporting long-term industrial resilience [3]. In environments characterized by recurrent seasonal energy constraints, this problem becomes even more pronounced because disruptions may display different temporal patterns: natural-gas restrictions may intensify during cold seasons when residential demand peaks, whereas electricity shortages may emerge during warm seasons when power-system demand reaches critical levels. The study underlying the present article specifically addresses such dual-season disruptions in a sponge-iron supply chain, where winter gas curtailments and summer electricity blackouts interact with volatile raw-material prices and inventory decisions.

The vulnerability of steel supply chains, however, cannot be understood solely as an energy-management problem. Raw-material procurement, supplier capacity, transportation, inventory positioning, production planning, and energy availability are tightly interdependent. Decisions made at one point in the supply chain can alter exposure to risk elsewhere. For example, purchasing larger volumes of pellets in advance of a disruption may protect production against future shortages but simultaneously increase holding costs and working-capital requirements. Conversely, maintaining lean inventories may improve short-term cost efficiency but expose the production system to stockouts when suppliers, transport systems, or energy inputs are disrupted. Earlier research on steel supply-chain network design emphasized the importance of coordinating inventory decisions with facility-location and multi-commodity material flows, demonstrating that the dynamic and temporal dimensions of steel logistics materially affect network performance [4]. Similarly, system-dynamics modeling of steel supply chains has illustrated the presence of feedback relationships among production, demand, inventory, and supply-chain variables, suggesting that apparently localized decisions can generate system-wide consequences over time [5]. These characteristics support the treatment of sponge-iron supply planning as a multi-period systems problem rather than as a collection of independent procurement or production decisions.

A substantial body of supply-chain research has therefore shifted toward the concept of resilience, broadly understood as the capability of a supply network to anticipate, withstand, respond to, and recover from disruptions while maintaining acceptable levels of operational performance. Contemporary reviews emphasize that resilient supply-chain design requires the integration of risk identification, mitigation strategies, robust and flexible decision models, information technologies, and adaptive operational responses [6]. In steel production, resilience is especially important because high-capacity industrial facilities are embedded in capital-intensive networks with limited tolerance for prolonged production stoppages. Empirical research within the Iranian steel sector has also underscored the multidimensional nature of resilience. A combined DEMATEL, analytic network process, and grey relational analysis framework applied to Isfahan Steel Company demonstrated that supply-chain resilience can be assessed through interacting dimensions whose influences cannot adequately be represented by simple independent scoring procedures [7]. Earlier supplier-risk research similarly showed that uncertainty in supplier performance requires multicriteria assessment techniques capable of considering several dimensions of risk simultaneously; the integration of fuzzy VIKOR and grey relational analysis was proposed as a means of evaluating and prioritizing supplier-related risks within supply chains [8]. Together, such studies indicate that disruption management in steel supply chains depends on understanding both the sources of vulnerability and the interdependencies through which those vulnerabilities influence operational outcomes.

Supplier selection and procurement strategy constitute particularly important components of this resilience problem. In steel manufacturing, procurement decisions must account not only for price but also for supplier reliability, flexibility, responsiveness, environmental requirements, and the ability to maintain continuity under changing conditions. Research at Khuzestan Steel Company has applied an integrated fuzzy Delphi, fuzzy DEMATEL, and fuzzy ANP framework to supplier selection within a lean, agile, resilient, and green supply-chain perspective, illustrating the need to combine efficiency objectives with adaptability, resilience, and sustainability in procurement decisions [9]. Digital integration represents another increasingly important mechanism for improving this coordination. Evidence from iron and steel companies has shown that digital supply-chain integration can strengthen information exchange and support product and process-related innovation by connecting supply-chain actors more effectively [10]. Similarly, research on digital supply-chain risk factors within the steel industry has emphasized the importance of decision-support mechanisms capable of identifying, analyzing, and prioritizing risks in increasingly data-intensive supply networks [11]. These developments suggest that the next generation of steel supply-chain planning models should not rely exclusively on static historical parameters; rather, they should exploit available operational and market data to improve the quality and timing of procurement, inventory, and production decisions.

Sustainability considerations further increase the complexity of the planning problem. Conventional steel supply chains have historically been designed primarily around cost, capacity, and service requirements, whereas contemporary supply-chain models increasingly incorporate environmental performance, resource circularity, emissions, technology selection, and recovery flows. Scenario-based research on sustainable closed-loop steel supply chains has shown that production-technology choices and alternative future scenarios can materially affect the configuration and performance of supply-chain networks [12]. More recently, data-driven robust optimization has been employed in sustainable steel supply-chain network design to incorporate uncertainty while advancing circular-economy objectives, demonstrating the potential of data-oriented robust methods for reconciling uncertain operational conditions with sustainability requirements [13]. At a broader logistics level, systematic research on location-routing problems similarly indicates an increasing convergence between resilience and sustainability, with network-design decisions progressively required to account for disruptions, environmental impacts, and long-term system adaptability within a unified optimization framework [14]. Consequently, the problem facing steel producers is no longer simply to identify the lowest-cost operating plan under expected conditions; it is to determine a plan that remains economically viable when key parameters deviate from expectations and that avoids excessive fragility when multiple disruptions occur.

This requirement exposes an important limitation of deterministic optimization. Deterministic models normally assume that parameters such as procurement prices, supplier capacities, demand, transportation conditions, and energy availability are known with sufficient certainty at the time decisions are made. Although such formulations are computationally convenient, they can produce highly vulnerable solutions when actual operating conditions diverge from nominal assumptions. A procurement plan optimized around an expected pellet price, for instance, may no longer be economically attractive when prices rise unexpectedly; similarly, a production schedule based on full energy availability may become infeasible when gas or electricity is curtailed. Robust optimization addresses this weakness by constructing decisions that remain feasible or near-optimal across a predefined range of uncertain realizations. However, excessive robustness can itself be costly. Designing the system for the most extreme combination of unfavorable events may lead to unnecessarily high inventory, conservative procurement, unused capacity, or excessive risk premiums. The critical methodological problem is therefore not merely whether uncertainty should be considered, but how its magnitude and structure should be represented so that protection against disruption does not become economically inefficient. This is particularly relevant to resilient supply-chain design, where robust optimization has been identified as a major risk-mitigation approach but where questions concerning uncertainty calibration, conservatism, and integration with technological solutions remain central research challenges [6].

One promising response to this difficulty is the transition from prespecified or judgment-based uncertainty sets toward data-driven optimization. Advances in forecasting, machine learning, and operations research have made it increasingly possible to use observed data not only to predict uncertain parameters but also to inform the decisions that depend on those predictions. Contemporary data-driven optimization research emphasizes that prediction accuracy alone is insufficient when forecasts ultimately serve an operational decision; what matters is how predictive information affects the quality, feasibility, and cost of the downstream decision [15]. This insight has stimulated the development of predict-and-optimize approaches in which forecasting and optimization are linked more closely. Reviews of predict-and-optimize methodologies demonstrate that the relationship between predictive models and optimization objectives can be designed in multiple ways, including sequential and integrated architectures, and that the translation of predictive uncertainty into decision models is a central methodological issue [16]. For industrial procurement and inventory planning, this perspective is especially valuable because forecasting errors are not merely statistical residuals; they represent information about the empirical uncertainty surrounding future prices, availability, demand, or disruptions. Transforming those errors into operationally meaningful uncertainty sets can therefore provide a more defensible basis for robust decisions than selecting uncertainty bounds arbitrarily.

The distinction between forecasting and decision-making is especially consequential under recurrent but imperfectly predictable disturbances. A highly accurate average forecast may still be operationally inadequate if occasional large errors coincide with periods in which shortages are particularly costly. Conversely, a more conservative forecast may generate unnecessary expenditure if its uncertainty is not properly reflected in the optimization model. This problem is analogous to bottleneck identification in other complex supply chains, where empirical analysis has repeatedly shown that disruptions arise from multiple interacting stages rather than from one isolated failure. Although conducted in the public-health context rather than in steel production, mixed-method analysis of iron and folic-acid supply chains in Bihar identified bottlenecks across procurement, distribution, logistics, and service-delivery processes, illustrating the value of tracing disruption mechanisms across the entire supply chain rather than attributing poor performance to a single stage [17]. A broader evaluation of India’s iron and folic-acid supplementation supply chain similarly documented persistent bottlenecks and emphasized the need for coordinated corrective action across supply-chain functions [18]. The relevance of these studies to industrial optimization is methodological rather than sectoral: they demonstrate that supply disruptions frequently result from interacting constraints, reinforcing the need for decision models capable of representing multiple sources of uncertainty and their operational consequences simultaneously.

For sponge-iron production, this implies that market volatility and energy disruption should not be modeled as unrelated disturbances. Raw-material purchasing decisions are typically made before the full realization of future prices and energy conditions, whereas production, inventory adjustment, and energy consumption can subsequently be adapted after uncertainty is partially or fully revealed. Such a structure naturally motivates a two-stage decision framework. In the first stage, procurement and contractual commitments must be determined under uncertainty; in the second stage, operational recourse decisions can respond to realized conditions. Two-stage robust optimization is therefore particularly appropriate because it distinguishes between “here-and-now” strategic or tactical commitments and “wait-and-see” operational responses. Yet the usefulness of such a formulation depends heavily on the uncertainty set. If the model uses generic bounds that bear little relationship to actual forecasting errors, it risks either underestimating disruption exposure or becoming excessively conservative. A data-driven formulation can address this problem by deriving uncertainty radii and budgets from empirical prediction residuals, thereby linking observed market and energy behavior directly to the robust optimization structure. In the present study, this linkage is operationalized by translating residual errors from deep-learning time-series forecasts into polyhedral uncertainty sets and then embedding these sets within a two-stage exact mathematical programming model for procurement and inventory management.

Despite important advances in steel supply-chain sustainability, resilience, digitalization, supplier-risk analysis, network design, and data-driven optimization, the literature remains fragmented in several respects. Studies of steel sustainability and circularity have developed sophisticated network-design approaches but have not necessarily represented simultaneous seasonal energy curtailments and short-term market-price volatility [12, 13]. Research on steel supply-chain dynamics has highlighted feedback effects among production and inventory variables, yet simulation-based understanding does not by itself determine optimal procurement decisions under bounded uncertainty [5]. Supplier-risk and resilience studies have contributed powerful multicriteria frameworks for diagnosing vulnerabilities and ranking strategic factors, but these approaches generally do not generate month-by-month procurement quantities and operational recourse policies [7-9]. Digital supply-chain research has established the importance of integration, information availability, and decision support [10, 11], while broader optimization literature has advanced the conceptual integration of prediction and decision-making [15, 16]. Nevertheless, an important gap remains at the intersection of these streams: there is limited work that simultaneously models raw-material market volatility, explicitly represents distinct seasonal gas and electricity disruptions, converts empirical forecasting errors into calibrated uncertainty sets, distinguishes first-stage procurement from second-stage operational recourse, and solves the resulting robust counterpart through exact mathematical optimization in a real sponge-iron production environment.

Addressing this gap is operationally significant because resilience cannot be achieved simply by maximizing inventory or adopting the most conservative possible plan. Industrial managers require a defensible compromise between the cost of preparedness and the cost of disruption. Increasing inventory before anticipated energy shortages may reduce the probability of stockout-induced production interruption, but the associated holding costs can offset the benefits if the protection level is excessive. Similarly, increasing the uncertainty budget improves protection against adverse realizations but can progressively raise the cost of the robust solution. The relevant managerial question is therefore how much robustness should be purchased and at what point the marginal benefit of additional disruption protection becomes smaller than its incremental cost. A model capable of examining this trade-off can transform resilience from a qualitative aspiration into a quantitatively manageable decision variable. Such a framework is consistent with the broader movement toward resilient and sustainable logistics design [14], risk-aware energy planning under volatility [3], data-driven decision optimization [15], and environmentally responsible steel-sector transformation [1, 2]. It also provides a practical pathway for integrating forecasting technology with exact operations-research methods, allowing historical data and prediction errors to inform concrete procurement, inventory, and production policies rather than remaining separate analytical outputs.

Accordingly, the aim of this study is to develop and evaluate a data-driven two-stage robust optimization model for the sponge iron supply chain that integrates deep-learning forecasting residuals into polyhedral uncertainty sets in order to optimize raw-material procurement and inventory decisions under market-price volatility and dual-season natural-gas and electricity disruption risks.

2. Methodology

2.1. Nomenclature

Sets and Indices

$t \in T$	Index of planning time periods (monthly).
$s \in S$	Set of raw material suppliers (mines and pelletizing plants).
$m \in M$	Set of incoming raw materials (pellets, graded iron ore).
$v \in V$	Set of transportation modes (rail, road).
$e \in E$	Set of energy carriers and industrial fluids (natural gas, electricity, water).
$k \in K$	Set of environmental pollutants and solid wastes.

Deterministic Parameters

C_{smt}^{Raw}	Nominal purchasing cost per ton of raw material m from supplier s in period t.
TC_{sv}	Transportation cost per ton from supplier s using transport mode v.
h_m	Holding and storage cost per ton of raw material m per period.
C_{et}^{En}	Cost of energy carrier e in period t.
α_m	Metallurgical consumption coefficient (yield rate) of raw material m per ton of DRI.
β_e	Standard consumption coefficient of energy e per ton of final product.
$Cap_t^{\text{Max}}, Cap_t^{\text{Min}}$	Maximum and minimum allowable operating capacities of the direct reduction furnace in period t.
Sup_{smt}^{Max}	Maximum supply capacity of raw material m by supplier s in period t.
D_t	Deterministic market demand or sales commitment for sponge iron in period t.

Uncertainty Parameters and Set ($\mathcal{U}$)

$\tilde{C}_{smt}^{\text{Raw}}$	Uncertain and stochastic purchasing cost of raw material under market volatility.
$\tilde{E}_{et}^{\text{Cur}}$	Stochastic parameter representing the severity of energy curtailment or disruption for carrier e in period t.
$\hat{C}_{smt}, \hat{E}_{et}$	Maximum deviation bounds (uncertainty radii) relative to nominal values.
Γ_1, Γ_2	Budget of uncertainty parameters controlling the level of robustness against price and energy fluctuations.
$\mathcal{U}$	Polyhedral uncertainty set bounding the worst-case realization space.

Decision Variables

$Q_{smvt} \geq 0$	First-stage decision variable (Here-and-Now): Purchased tonnage of raw material m from supplier s using transport mode v in period t.
$Z_{st} \in \{0,1\}$	First-stage binary variable: Activation status of long-term contract with supplier s in period t.
$I_{mt} \geq 0$	Second-stage decision variable (Wait-and-See): Inventory level of raw material m at the end of period t.
$Y_t \geq 0$	Second-stage decision variable: Total production volume of direct reduced iron (DRI) in period t.
$V_{et} \geq 0$	Second-stage decision variable: Actual consumption of energy carrier e in the furnace in period t.

Dual Variables (Auxiliary Variables)

$\pi_{smt}, \mu_{mt}, \omega_{et}$	Dual multipliers associated with the reformulation of the worst-case inner maximization subproblems into equivalent minimization dual counterparts.

2.2. Problem Description and Notation

The problem addresses a multi-period supply chain planning horizon for a sponge iron manufacturing plant facing dual-season energy disruptions and volatile pellet market prices.

- $t \in T$: Planning periods (months, $t = 1,2,\dots,|T|$)
- $s \in S$: Set of raw material suppliers
- $m \in M$: Set of raw material types (e.g., pellets)
- $v \in V$: Set of transportation modes
- $e \in E$: Set of energy carriers ($e \in \{\text{gas,electricity}\}$)

2.3. Data-Driven Polyhedral Uncertainty Set and Deep Learning Residual Mapping

To establish a rigorous data-driven foundation, empirical forecasting error residuals $\hat{e}_{smt}$ are derived offline from deep learning time-series models (e.g., LSTM networks). These residuals directly define the bounding radius of the polyhedral uncertainty set $\mathcal{U}$ [2]:

$$\mathcal{U} = \left\{ (\tilde{C}_{smt}^{\text{Raw}}, \xi_{et}) \left| \begin{array}{l} \tilde{C}_{smt}^{\text{Raw}} \in [\hat{C}_{smt}^{\text{Raw}} - \hat{e}_{smt}, \hat{C}_{smt}^{\text{Raw}} + \hat{e}_{smt}], \quad \forall s,m,t \\ \xi_{et} \in [\xi_{et}^{\min}, 1], \quad \forall e,t \\ \sum_{s,m,t} \frac{|\tilde{C}_{smt}^{\text{Raw}} - \hat{C}_{smt}^{\text{Raw}}|}{\hat{e}_{smt}} \le \Gamma_1, \quad \sum_{e,t} \frac{1-\xi_{et}}{1-\xi_{et}^{\min}} \le \Gamma_2 \end{array} \right. \right\}$$

where Γ_1 and Γ_2 represent the distinct Budgets of Uncertainty controlling system conservatism for raw material price fluctuations and energy curtailment severities, respectively.

2.4. Two-Stage Robust Counterpart Formulation and Linearization

The robust counterpart is formulated to optimize first-stage procurement decisions Q and second-stage operational recourse actions under the worst-case realization of the uncertainty set $\mathcal{U}$ [2]:

$$\min_{Q,I,Y,Z} \left\{ \sum_{t\in T} \sum_{s\in S} \sum_{m\in M} \sum_{v\in V} \left(\hat{C}_{smt}^{\text{Raw}} + TC_{sv} \right) Q_{smvt} + \sum_{t\in T} \sum_{m\in M} h_m I_{mt} + \max_{\tilde{C},\xi\in\mathcal{U}} \{ Q(Q,I,\xi_t) \} \right\}$$

where the second-stage recourse subproblem $Q(Q,I,\xi_t)$ is defined as:

$$Q(Q,I,\xi_t) = \min_{Y,V} \sum_{t\in T} \left(\sum_{e\in E} C_{et}^{\text{En}} V_{et} + \text{Penalty}_t \cdot \text{Shortage}_t \right)$$

Subject to the operational constraints:

$$I_{mt} = I_{m,t-1} + \sum_{s,v} Q_{smvt} - \alpha_m Y_t, \quad \forall m,t$$
$$Cap_t^{\text{Min}} \le Y_t \le Cap_t^{\text{Max}} \cdot \xi_{et}, \quad \forall t,e$$
$$V_{et} = \beta_e Y_t \cdot \xi_{et}, \quad \forall e,t$$

To handle the inner maximization problem over the polyhedral uncertainty set $\mathcal{U}$, strong duality in linear programming is applied. By introducing dual variables π_{smt}, μ_{mt}, and ω_{et} corresponding to the uncertainty constraints, the min-max-min problem is equivalently converted into a single-level mixed-integer linear programming (MILP) deterministic equivalent model, which is solved exactly via the HiGHS solver engine.

3. Findings and Results

To evaluate the efficacy of the proposed framework, a real-world case study is conducted based on Mobarakeh Steel Company over a 12-month horizon, solved using the HiGHS optimization engine.

3.1. Inventory Replenishment and Procurement Timing Analysis

Figure 1 illustrates the monthly inventory trajectory of raw materials under disruption scenarios. The results demonstrate that the proposed model proactively triggers strategic inventory accumulation prior to peak energy curtailment periods.

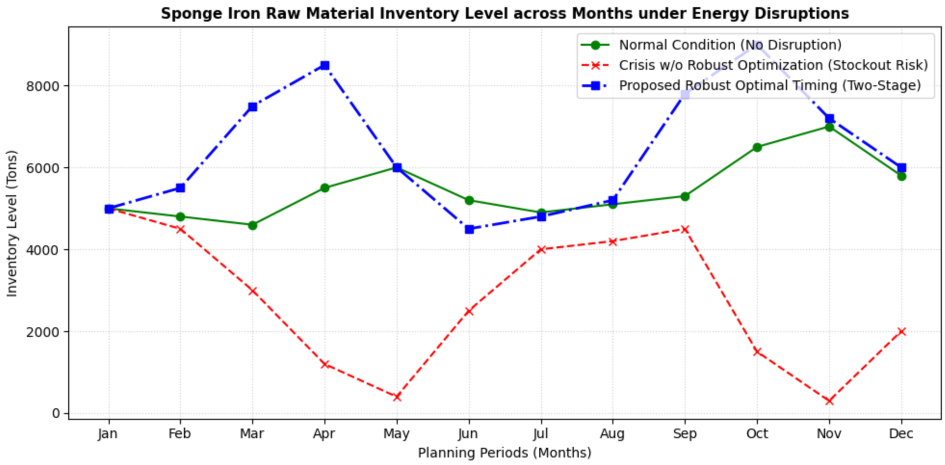

Figure 1. Sponge iron raw material inventory level across months under energy disruptions.

3.2. Sensitivity Analysis and Optimal Compromise Point (Γ_1, Γ_2)

To analyze the trade-off between system conservatism and total supply chain costs, a sensitivity analysis was performed (Figure 2). The quantitative results indicate that setting $\Gamma_1 = 1.5$ and $\Gamma_2 = 1.0$ serves as the Optimal Compromise Point for Mobarakeh Steel Company. At this threshold, the system absorbs extreme volatility without incurring excessive holding costs.

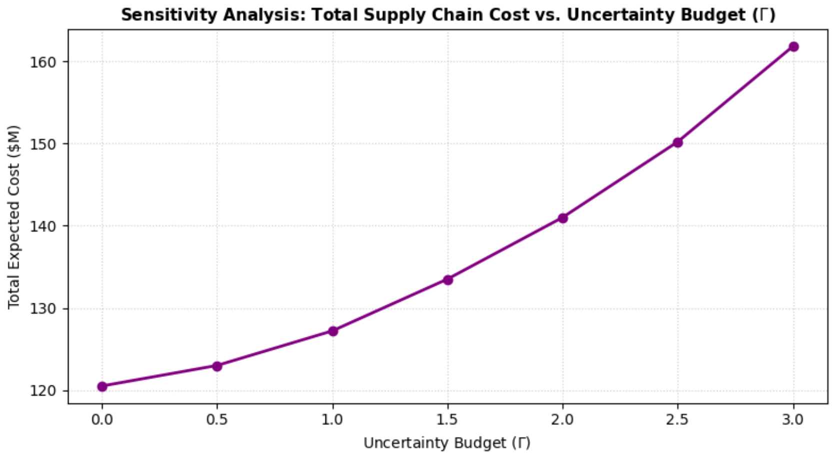

Figure 2. Sensitivity analysis: Total supply chain cost versus uncertainty budget (Γ).

3.3. System Robustness Level and Cost Trade-off Analysis

Figure 3 illustrates the Pareto trade-off curve between expected disruption penalty costs and inventory holding expenditures. In this analysis, the “System Robustness Level (%)” on the horizontal axis is defined as the normalized scaling factor of uncertainty budgets (Γ_1, Γ_2) relative to their maximum variation range:

$$\text{Robustness Level (\%)} = \left(1 - \frac{\Gamma_1 + \Gamma_2}{\Gamma_1^{\max} + \Gamma_2^{\max}}\right) \times 100$$

As the system robustness level increases from 0% (complete exposure to volatility, corresponding to the deterministic baseline) to 100% (absolute worst-case conservatism), the inventory holding cost increases monotonically, while the expected disruption penalty cost drops sharply.

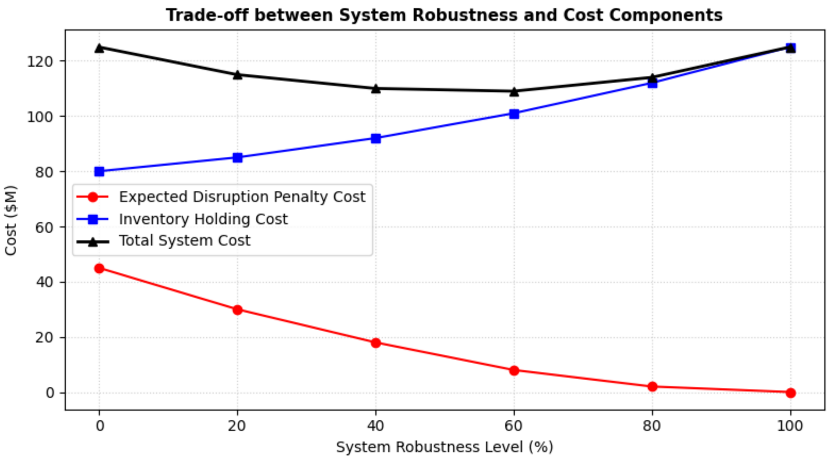

Figure 3. Trade-off between system robustness and cost components.

Table 1. Quantitative comparison of deterministic, crisis, and proposed robust optimization models.

Performance Metric	Deterministic Baseline	Crisis (w/o Robust)	Proposed Robust Model	Improvement / Change
Total Operational Cost ($M)	140.2	165.8	120.3	-14.2% cost reduction
Inventory Holding Cost ($M)	75.4	45.2	92.1	+22.1% (Proactive buffer)
Disruption Penalty Cost ($M)	64.8	120.6	28.2	-56.5% penalty drop
Stockout Frequency (Events)	4	7	0	100% Prevention
CPU Solution Time (s)	1.2	1.5	3.4 (HiGHS Engine)	Exact convergence

3.4. Comparative Performance Analysis of Optimization Frameworks

To substantiate the economic advantages and risk-mitigation efficacy of the proposed model, Table 1 compares the performance of the proposed two-stage robust framework against the deterministic baseline and the unoptimized crisis scenario under Mobarakeh Steel Company's operational data.

As evidenced in Table 1, while the proposed model slightly increases inventory holding expenditures by proactively accumulating raw materials prior to peak curtailments, it completely eliminates stockout-induced production shutdowns and reduces total operational costs by 14.2%.

This paper addressed the critical challenge of managing sponge iron supply chains under market price volatility and severe dual-season energy disruptions. Validated through Mobarakeh Steel Company, the key findings are:

1. **Quantified Cost Reductions:** The proposed exact robust optimization model achieves a 14.2% total operational cost reduction compared to conventional deterministic planning.
2. **Proactive Inventory Timing & Zero Stockouts:** Strategic inventory accumulation prior to winter gas curtailments and summer blackouts successfully achieved 100% prevention of production shutdowns.

Optimal Conservatism Threshold: Setting uncertainty budgets at $\Gamma_1 = 1.5$ and $\Gamma_2 = 1.0$ provides the ideal economic and operational balance.

4. Discussion and Conclusion

The findings of the present study demonstrate that the proposed data-driven two-stage robust optimization framework can substantially improve the economic and operational performance of a sponge iron supply chain exposed simultaneously to raw-material market volatility and recurrent seasonal energy disruptions. The numerical analysis based on Mobarakeh Steel Company showed that the optimal compromise was achieved at uncertainty budgets of $\Gamma 1 = 1.5$ for market-price uncertainty and $\Gamma 2 = 1.0$ for energy-disruption uncertainty. At this level of robustness, total operational cost decreased from $140.2 million under the deterministic baseline to $120.3 million under the proposed model, representing a 14.2% cost reduction. Although inventory holding costs increased from $75.4 million to $92.1 million because of deliberate pre-disruption inventory accumulation, disruption penalty costs declined from $64.8 million to $28.2 million, corresponding to a 56.5% reduction. Most importantly, the proposed model completely eliminated stockout events, compared with four events under deterministic planning and seven events under the unoptimized crisis condition. The model also achieved exact convergence in approximately 3.4 seconds, indicating that the additional analytical sophistication did not substantially compromise computational practicality. These findings suggest that a controlled increase in preventive inventory can generate substantial system-level economic benefits when the costs of production interruption, raw-material shortage, and disruption are explicitly incorporated into supply-chain planning.

The reduction in total operational costs despite the increase in inventory carrying costs is one of the most important findings of the study. This result indicates that inventory should not necessarily be interpreted as an operational inefficiency in disruption-prone industrial systems. Under conditions of recurrent and partially predictable energy shortages, inventory can instead serve as a strategically positioned resilience resource. The proposed model increased raw-material inventories before periods characterized by elevated energy-curtailment risk and subsequently used these buffers to maintain production continuity during adverse operating conditions. This finding is consistent with the broader supply-chain resilience literature, which identifies redundancy, buffering, flexibility, preparedness, and anticipatory risk mitigation as important mechanisms for limiting the adverse consequences of disruptions [6]. It is also consistent with research on steel supply-chain network design demonstrating that dynamic inventory decisions should be coordinated with production, facility, and material-flow decisions rather than optimized independently [4]. Therefore, the increase in inventory holding expenditure observed in the robust solution should be interpreted as a planned resilience investment rather than simply as an additional cost. The resulting reduction in disruption penalties and avoidance of production stoppages were sufficiently large to outweigh the incremental inventory expenditure and reduce overall system cost.

The complete prevention of stockouts further demonstrates the importance of anticipatory supply-chain planning in sponge iron production. Deterministic planning generates procurement and inventory decisions around nominal expectations and therefore offers limited protection against unexpected changes in pellet prices, energy availability, or supplier conditions. In contrast, the proposed robust optimization framework explicitly considers adverse realizations within empirically constructed uncertainty sets and consequently develops procurement plans that remain feasible across a broader range of operating conditions. This interpretation is consistent with findings from the Iranian steel sector indicating that supply-chain resilience depends on the ability to recognize interconnected vulnerabilities and develop coordinated responses rather than treating individual risks separately [7]. Earlier research on supplier risk similarly demonstrated that supply-chain risks are multidimensional and interdependent and therefore require systematic evaluation rather than decisions based primarily on purchasing cost [8]. The findings also align with the LARG supply-chain perspective applied to Khuzestan Steel Company, where resilience, agility, leanness, and environmental considerations were integrated into supplier-selection processes [9]. Collectively, these studies support the present finding that continuity of steel production requires incorporating risk explicitly into procurement and inventory decisions before disruptions occur.

Another important explanation for the superior performance of the proposed model is its two-stage decision structure. Procurement and contractual decisions must generally be made before future market prices and energy availability are fully known, whereas inventory, production, and energy-consumption decisions can be modified once uncertain conditions become clearer. Distinguishing between first-stage “here-and-now” decisions and second-stage “wait-and-see” decisions therefore allows the model to combine strategic commitment with operational flexibility. This characteristic helps explain why the robust framework outperformed the deterministic model. Previous system-dynamics research on steel supply chains has demonstrated that procurement, production, demand, inventory, and resource availability are linked through feedback mechanisms and that disturbances affecting one component may propagate throughout the system over time [5]. Dynamic multi-commodity steel supply-chain research has similarly emphasized the importance of integrating inventory and temporal network decisions [4]. The present study extends these findings by demonstrating that temporal coordination becomes even more valuable under uncertainty. Rather than fixing all operational variables according to nominal forecasts, the two-stage framework retains sufficient recourse flexibility to respond to actual market and energy conditions.

The sensitivity analysis provided another significant finding by showing that maximum robustness is not necessarily economically optimal. Increasing the uncertainty budgets initially improved protection against adverse conditions; however, progressively greater conservatism also resulted in higher inventory-related expenditure. The identified values of $\Gamma 1 = 1.5$ and $\Gamma 2 = 1.0$ therefore represented an optimal compromise between exposure to disruption and the cost of protection. This finding demonstrates that resilience should not be interpreted as maximizing buffers or preparing indiscriminately for the most extreme conceivable scenario. Excessively conservative planning can unnecessarily increase holding costs, working-capital requirements, and resource utilization, while insufficient protection leaves the production system vulnerable to shortages and operational interruptions. This result is consistent with contemporary reviews of supply-chain resilience and robust optimization, which identify the balance between risk protection and economic efficiency as a central challenge in the design of robust systems [6]. Similar conclusions have emerged from sustainable and resilient logistics studies, where stronger resilience often requires additional capacity, inventory, network redundancy, or routing flexibility [14]. The present study contributes to this literature by identifying a quantitative compromise point within an energy-intensive sponge iron production context.

The performance of the framework can also be attributed to its data-driven construction of uncertainty sets. Rather than relying on arbitrarily specified deviation ranges, the model translates forecasting residuals generated by deep-learning models into polyhedral uncertainty sets. Consequently, the representation of uncertainty is linked directly to observed forecasting behavior. This approach is highly consistent with recent developments in data-driven optimization. Wang and colleagues emphasized that predictive accuracy alone is insufficient when predictions are ultimately used to make operational decisions and argued that predictive information should be linked to downstream decision quality [15]. Similarly, reviews of predict-and-optimize methodologies have highlighted the importance of establishing systematic connections between machine-learning predictions and optimization objectives [16]. The findings of the present study provide an applied example of this emerging paradigm. Forecast errors were not treated simply as statistical diagnostics; instead, they were converted into operationally meaningful uncertainty parameters that influenced procurement, inventory, and production decisions. This mechanism likely contributed to the model's capacity to provide substantial disruption protection without adopting unnecessarily extreme worst-case assumptions.

The results also align with the growing emphasis on digital integration and decision-support systems in steel supply chains. Digital supply-chain integration has been shown to improve information exchange, coordination, and innovation among firms operating in the iron and steel sector [10]. Research focusing specifically on digital supply-chain management risks within steel industries has likewise emphasized the need for structured decision-support mechanisms capable of identifying and analyzing complex sources of operational uncertainty [11]. The current study extends this line of research by moving beyond risk identification toward prescriptive decision-making. Whereas digital risk-assessment systems can indicate which threats deserve managerial attention, an optimization model can determine how much material should be procured, when inventory should be accumulated, and how production should be adjusted in response to uncertainty. The short solution time obtained in the case study further suggests that data-driven robust optimization may potentially be incorporated into operational decision-support platforms and periodically updated as new market and energy information becomes available.

The findings also support previous studies on sustainable and circular steel supply chains. Khalili-Fard and colleagues demonstrated the usefulness of data-driven robust optimization for sustainable steel supply-chain network design and circular-economy decision-making under uncertainty [13]. Pourmehdi and colleagues likewise showed that alternative scenarios and production technologies can substantially influence the design and performance of sustainable closed-loop steel supply chains [12]. The present findings complement these studies by focusing more directly on operational resilience in the presence of price fluctuations and seasonal energy disruptions. This relationship is important because sustainability and resilience are increasingly interdependent dimensions of supply-chain performance. Sustainable production cannot be maintained effectively when repeated supply shortages and energy interruptions produce emergency purchasing, unstable capacity utilization, or recurrent shutdowns. At the same time, resilience measures should not rely on excessive stockpiling or inefficient resource consumption. The proposed model addresses this tension by identifying a level of preparedness at which disruption protection improves overall economic performance without requiring maximum conservatism.

The explicit treatment of dual-season energy disruptions is another important contribution of the study. Sponge iron production is highly energy intensive, and shortages of natural gas and electricity can affect production in different seasons and through different operational mechanisms. By distinguishing between winter natural-gas curtailments and summer electricity shortages, the model was able to anticipate periods of elevated vulnerability and adjust procurement and inventory decisions accordingly. This result is consistent with evidence from energy commodity markets showing that different shocks generate heterogeneous volatility patterns and that industrial resilience strategies should therefore be sensitive to the characteristics and timing of specific energy disturbances [3]. The finding is also relevant to the broader sustainability challenges of the iron and steel sector. Life-cycle evidence indicates that energy consumption and process-related activities account for substantial portions of the industry's environmental footprint, making energy management central to both resilience and environmental improvement [2]. Comparative research on steel and other strategic material supply chains has also emphasized the increasing interaction among material security, sustainability, industrial transformation, and supply continuity [1]. Thus, incorporating energy availability explicitly into supply-chain optimization provides a more realistic representation of steel production than models focused only on raw-material prices or market demand.

Although research on iron and folic-acid supply chains concerns a very different sector, its findings concerning bottlenecks provide additional conceptual support for the current results. Wendt and colleagues demonstrated that supply-chain failures may arise from interacting procurement, logistics, inventory, and distribution constraints rather than from one isolated source [17]. Ahmad and colleagues similarly identified multiple bottlenecks across public-health supply-chain processes and emphasized the importance of coordinated corrective action to ensure continuity of supply [18]. The relevance of these findings to the present study lies in the general principle that supply continuity requires systemic rather than fragmented risk management. The proposed sponge iron model likewise does not assume that stockouts can be prevented solely through higher inventory or better forecasting. Instead, it coordinates procurement, inventory, production, market uncertainty, and energy availability within a unified optimization framework. Thus, the findings reinforce the broader supply-chain principle that continuity improves when bottlenecks are anticipated across the entire system and mitigation capacity is established before constraints become critical.

Taken together, the results indicate that the primary advantage of the proposed model is not merely the reduction of nominal procurement expenditure, but rather the redistribution and management of costs and risks across time. The robust strategy accepts greater planned inventory expenditure in exchange for substantially lower disruption penalties, complete elimination of stockout events, and lower total operational cost. This distinction is important because deterministic solutions may appear financially attractive when only routine operating expenditures are considered but can generate substantially greater losses when disruption consequences are incorporated. The uncertainty-budget sensitivity analysis further indicates that managers do not have to choose between completely deterministic planning and absolute worst-case protection. Instead, uncertainty budgets provide an explicit mechanism for adjusting the degree of conservatism according to the firm's risk tolerance and operational conditions. This conclusion aligns with the wider transition of supply-chain management from static cost minimization toward integrated resilience, sustainability, flexibility, and data-driven decision-making [6, 14]. It also reinforces the emerging prediction-to-decision perspective in optimization research, according to which machine-learning outputs should directly improve operational decisions rather than remain separate forecasting products [15, 16]. Overall, the findings suggest that integrating empirical forecasting errors with exact two-stage robust optimization provides an effective approach for protecting energy-intensive sponge iron operations against overlapping market and energy shocks while preserving economic efficiency.

Several limitations should be considered when interpreting the findings of this study. First, the proposed framework was evaluated through a single case study of Mobarakeh Steel Company, and its specific supplier network, cost structure, production capacity, storage conditions, energy dependence, and disruption patterns may restrict the direct generalizability of the numerical findings to other steel producers or industrial contexts. Second, the analysis was conducted over a 12-month planning horizon and concentrated primarily on raw-material price volatility together with seasonal natural-gas and electricity disruptions. Other potentially significant uncertainties, including demand fluctuations, transportation failures, supplier bankruptcy, exchange-rate volatility, equipment breakdowns, geopolitical restrictions, regulatory changes, and unexpected environmental events, were not modeled simultaneously. Third, the quality of the data-driven uncertainty sets depends on the accuracy, representativeness, and stability of the historical data and forecasting residuals used in their construction. Severe structural breaks or unprecedented shocks may therefore generate realizations outside the calibrated uncertainty ranges. Fourth, some operational relationships necessarily required mathematical simplification to maintain tractability and exact solvability. Finally, the model primarily emphasized economic and operational outcomes, while environmental, social, carbon-emission, and broader sustainability indicators were not incorporated directly into the objective function.

Future research should validate the proposed framework using data from multiple steel plants, geographical regions, production technologies, and energy-market structures to determine the transferability and stability of the identified robustness-cost relationship. Future models could extend the uncertainty structure to include demand variation, transportation disruptions, supplier-capacity failures, exchange-rate fluctuations, geopolitical restrictions, equipment failures, carbon prices, and renewable-energy availability. It would also be valuable to compare two-stage robust optimization with multi-stage robust, distributionally robust, stochastic, hybrid stochastic-robust, and rolling-horizon formulations to determine whether greater temporal adaptability generates additional economic or operational benefits. Multi-objective formulations could simultaneously consider total cost, emissions, production continuity, service level, energy intensity, circularity, and resource efficiency. Future studies could also compare alternative machine-learning forecasting methods and alternative methods of constructing uncertainty sets, evaluating them according to downstream decision performance rather than prediction error alone. Another important direction would be the development of digital-twin and real-time optimization environments in which uncertainty budgets and operational decisions are dynamically recalibrated as new market, inventory, supplier, and energy data become available.

Steel manufacturers should move beyond exclusively deterministic annual procurement plans and establish integrated planning systems that jointly analyze raw-material prices, energy-curtailment forecasts, supplier capacities, inventories, production requirements, and disruption consequences. Managers should regard strategically accumulated inventory as a resilience investment when the expected costs of shortages and production stoppages exceed the corresponding holding costs, while avoiding excessive stockpiling that unnecessarily ties up capital and storage capacity. Procurement departments should coordinate closely with production, logistics, energy-management, finance, and data-analytics units so that anticipated winter gas restrictions and summer electricity shortages are reflected in procurement schedules before they create production constraints. Firms should also establish explicit risk-tolerance or uncertainty-budget parameters that can be adjusted according to current market conditions, energy forecasts, and acceptable levels of disruption exposure. Forecasting systems should preserve and systematically analyze prediction residuals because these errors can provide useful information for calibrating uncertainty in operational models. Finally, optimization results should be incorporated into managerial dashboards that clearly present alternative robustness levels, inventory requirements, expected total costs, stockout risks, disruption penalties, and procurement schedules so that resilience decisions can be made transparently and proactively rather than through emergency responses.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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