JOURNAL OF MANAGEMENT AND BUSINESS SOLUTIONS

A Scenario-Based Multi-Objective Optimization Model for Resilient Internal Transportation in Steel Supply Chains: A Case Study of Sirjan Jahan Steel Company

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ABSTRACT

Efficient internal transportation, weightbridge allocation, and stockpile management are critical yet challenging in steel manufacturing due to high material flow volumes. This study develops a scenario-based multi-objective mixed-integer programming model tailored to Sirjan Jahan Steel Company to determine optimal stockpile roles for pellets, sponge iron, and billets, alongside material flow allocation and weightbridge capacity expansion, while evaluating system resilience under five discrete disruption scenarios, including conveyor failures and supply interruptions. The first objective minimizes total operational costs, covering internal haulage, conveyor systems, stockpile setup, weighing infrastructure, holding, and shortage penalties. The second objective minimizes total truck turnaround time, encompassing queuing, service, and on-site travel, using an M/M/c queuing model to capture weighbridge and loading/unloading bottlenecks. The augmented ε-constraint method generates the Pareto frontier, with TOPSIS applied for final solution selection. The optimal plan activates stockpiles 1, 2, 3, and 12 for pellets; stockpiles 5, 6, and 7 for sponge iron; and stockpile 4 for billets, with two new weighbridges in the pellet section and two in the outbound section. The plan maintains a resilient pellet inventory of 99,611 tons to mitigate severe disruption scenarios. Compared to the current baseline—incorporating a 200,000-ton-per-month conveyor and penalty costs—the model reduces expected annual costs from \$6.16M to \$5.30M, achieving an annual saving of \$0.85M (13.87%). The optimal plan yields average turnaround times of 46.5 and 71 minutes per truck for sponge iron and billet, respectively.

Keywords: Steel supply chain, internal transportation, stockpile arrangement, disruption scenarios, Sirjan Jahan Steel Company

Introduction

The steel industry is a strategic foundation of industrial development because it supplies essential intermediate materials for construction, transportation, energy, infrastructure, machinery, and manufacturing. The scale and continuity of steel production, however, depend not only on production technologies but also on the efficient coordination of extensive material flows across procurement, storage, processing, internal transportation, and distribution activities. Steel supply chains are particularly logistics-intensive because large quantities of iron ore, pellets, sponge iron, billets, and finished products must be moved among facilities, often continuously and under strict production requirements. The relatively low value-to-weight ratio of many steel inputs further increases the economic significance of transportation and material-handling decisions, meaning that seemingly minor

Article history:
Received 26 April 2026
Revised 27 July 2026
Accepted 05 August 2026
Initial Publish 27 August 2026
Published online 01 September 2027

How to cite this article:
Nabavi, S. M., & Kazemipoor, H. (2027). A Scenario-Based Multi-Objective Optimization Model for Resilient Internal Transportation in Steel Supply Chains: A Case Study of Sirjan Jahan Steel Company. *Journal of Management and Business Solutions, 5*(5), 1-24. https://doi.org/10.61838/jmbs.4106

improvements in routing, storage utilization, fleet movement, or facility capacity can generate substantial savings when applied to millions of tons of annual material flow. Research on steel supply chain configuration has consequently emphasized the value of integrating facility-location, inventory, production, and transportation decisions rather than optimizing these functions independently (1). System-dynamics investigations of steel supply chains similarly demonstrate that production capacity, raw-material characteristics, energy conditions, and material-handling activities interact dynamically, making logistics performance an integral component of overall supply chain effectiveness (2). In the present case, these concerns are especially important because Sirjan Jahan Steel Company operates a high-volume production system in which pellets, sponge iron, and billets move through interconnected production plants, stockpiles, conveyors, weighbridges, and truck routes. The study therefore addresses a genuinely integrated operational system rather than an isolated transportation decision.

Managing such a system is complicated by the interdependence of strategic, tactical, and operational decisions. The role assigned to each stockpile influences transportation distances and material accessibility; transportation routes affect truck traffic and operating costs; weighbridge capacities determine whether vehicle flows can be processed without excessive congestion; and inventory decisions determine whether production can continue when incoming supply or transportation infrastructure is disrupted. Consequently, decisions that appear optimal when evaluated separately may become inefficient when their system-wide consequences are considered. A low-cost stockpile arrangement, for example, may produce excessive truck traffic at a shared weighbridge, whereas additional infrastructure may improve service performance but impose capital costs that are not economically justified. The broader supply chain literature has therefore increasingly emphasized the need for coordinated decision structures, including contractual and governance mechanisms capable of aligning different supply chain activities and actors (3). At the operational level, emerging data-driven and artificial-intelligence approaches likewise demonstrate how advanced analytical tools can support more consistent and responsive industrial decisions by processing interdependent operational information rather than relying exclusively on managerial intuition (4). For complex steel manufacturing environments, mathematical optimization provides an especially appropriate basis for transforming these interacting relationships into explicit decision variables, constraints, and performance objectives.

The challenge becomes more pronounced when transportation efficiency is evaluated simultaneously in economic and temporal terms. Traditional logistics models frequently emphasize total cost, yet minimizing transportation expenditure alone does not necessarily ensure acceptable operational performance. In high-throughput industrial facilities, trucks must pass through sequential service stages such as entrance control, weighing, unloading or loading, internal movement, reweighing, and departure. Limited service capacity at any of these stages can create queues that propagate through the transportation system, extending truck residence time, reducing effective fleet utilization, and ultimately threatening the continuity of material supply. Queueing theory offers a rigorous analytical foundation for evaluating such service systems through measures including arrival rates, service rates, utilization, waiting probabilities, expected queue lengths, and waiting times (5). Its relevance to logistics has been demonstrated in transportation-terminal settings, where truck appointment and flow-management decisions can significantly influence congestion and waiting times (6). Queueing considerations have also been integrated into supply chain network optimization, illustrating that service-system congestion can be incorporated directly into broader facility and flow decisions rather than analyzed only after network configuration (7). These insights are particularly pertinent to steel plants in which weighbridges, loading points, and unloading facilities effectively operate as service stations whose capacity can determine whether planned material flows are operationally feasible.

For Sirjan Jahan Steel Company, this operational perspective is critical because the existing transportation system contains multiple potential bottlenecks. Pellets enter through truck transportation as well as a conveyor system, are stored before delivery to reduction plants, and are transformed into sponge iron, which subsequently moves either toward storage or billet production. Billets are then transferred to storage and ultimately collected by outbound trucks. Each material therefore follows a distinct but interconnected route involving physical storage and transportation infrastructure. The company's existing arrangement includes three pellet weighbridges and two shared outbound weighbridges, while the pellet conveyor provides an important supplementary transportation channel. The source manuscript identifies truck delays during loading and unloading, inefficient capacity utilization, increased logistics expenditure, and service bottlenecks as important operational concerns. It further indicates that the shared outbound weighbridges are capacity-constrained under existing flows and that the current pellet weighbridge system may become insufficient when conveyor transportation is unavailable. Thus, a meaningful redesign must determine not merely the shortest or cheapest routes but also whether infrastructure can process the resulting vehicle flows while preserving acceptable truck turnaround times.

A second fundamental challenge is uncertainty. Industrial supply chains operate in environments in which demand, supply, transportation availability, equipment performance, energy access, and operating conditions cannot be assumed to remain constant. When optimization models are formulated only around average or nominal conditions, the resulting solution may perform efficiently in routine operation yet deteriorate severely during disruptions. Robust optimization has therefore developed as an important methodology for producing solutions whose feasibility and performance are less sensitive to uncertain parameters. In integrated supply chains, robust models can coordinate procurement, production, and distribution decisions while protecting the system against uncertain conditions (8). In steel supply chain network design specifically, recent data-driven robust optimization demonstrates the potential to integrate uncertainty with complex decisions involving network configuration, sustainability, resource consumption, and circular-economy considerations (9). Scenario-based approaches provide another practical mechanism by representing plausible alternative states of the system and evaluating decisions across them. Such approaches are especially appropriate when disruptions can be expressed as identifiable events, including temporary infrastructure failures or reductions in material supply. Scenario-based modeling has already been used in sustainable closed-loop steel supply chain design to account for technological and planning alternatives under uncertain conditions (10). Nevertheless, uncertainty at the level of internal steel-plant transportation—where disruptions simultaneously affect incoming material quantities, conveyor availability, stockpile requirements, and truck-processing capacity—remains less comprehensively represented.

This concern directly connects uncertainty management with supply chain resilience. Resilience describes the capacity of a supply chain to withstand disruptive events, preserve critical functions, adapt to altered operating conditions, and restore satisfactory performance after disruption. It extends conventional efficiency-oriented management by recognizing that a system optimized solely for routine conditions may contain structural vulnerabilities. Contemporary resilience research therefore emphasizes anticipation, absorption, adaptation, recovery, and the design of operational structures capable of maintaining continuity under stress (11). Reviews integrating disruption-risk and resilience management further identify flexibility, redundancy, collaboration, visibility, and adaptive capacity as central mechanisms through which supply chains can reduce disruption impacts (12).

Flexibility allows material or operational flows to shift when normal pathways are compromised, whereas redundancy provides reserve capacity or resources that can be activated during disturbances. Empirical and analytical research indicates that both mechanisms can enhance resilience, although their value depends on the nature of the disruption and the cost associated with maintaining additional capacity (13). For an internal steel transportation system, resilience may therefore depend on such tangible decisions as preserving safety inventory, maintaining alternative transportation modes, expanding weighbridge capacity, and ensuring sufficient stockpile capacity to buffer production against temporary supply failures.

Resilience is particularly important where disruptions affect a material that is essential for continuous production. In the studied steel complex, pellets constitute the principal input to direct-reduction operations, meaning that a prolonged reduction in pellet availability may propagate directly into sponge iron and subsequent billet production. The pellet conveyor reduces routine dependence on truck transportation, but it simultaneously represents an infrastructure component whose failure changes the structure of incoming transportation demand. If the conveyor becomes unavailable, truck flows and weighbridge workloads increase; if disruption simultaneously affects source supply, inventory becomes critical for sustaining production. The model examined in this study consequently considers discrete states including normal operation, short- and long-duration conveyor failures, disruption of pellet supply at the source, and a severe combined event involving supply interruption and conveyor failure. It also incorporates a resilient inventory constraint intended to protect production in severe disruption conditions (11-14). This formulation reflects the broader principle that resilience should not remain a qualitative managerial aspiration; rather, it should be operationalized through measurable decisions, capacities, and constraints that can be evaluated within optimization models.

At the same time, modern supply chain design increasingly requires consideration of sustainability in addition to cost and resilience. Sustainable supply chain management conceptualizes organizational performance as extending beyond short-term economic efficiency to encompass environmental and social consequences throughout interconnected supply chain activities (15). From a flows-and-boundaries perspective, environmental impacts arise not only within individual organizations but also through movements of materials, resources, emissions, and responsibilities across supply chain boundaries (16). Transportation is particularly important in this respect because vehicle movements contribute directly to fuel consumption, emissions, congestion, and resource use. The extensive literature on green supply chain management confirms that transportation and logistics decisions constitute major components of environmental supply chain performance and that environmental considerations are increasingly intertwined with operational competitiveness (17). Although the present model's explicit objectives focus on economic cost and truck time rather than establishing a separate emissions objective, improving transportation routes, reducing unnecessary movement, utilizing conveyor transport efficiently, controlling truck congestion, and configuring stockpiles more effectively can provide an operational foundation for more resource-efficient steel logistics. The sustainability literature therefore reinforces the need to move beyond narrowly defined cost minimization when structuring complex industrial transportation systems.

The combination of resilience and efficiency also creates unavoidable trade-offs. Redundant weighbridges, additional stockpile capacity, larger inventories, and alternative routes can improve the ability of a system to operate during disruption, but such measures require capital expenditure, inventory-holding costs, or additional operational resources. Conversely, highly lean configurations may perform economically under normal conditions but provide inadequate buffering capacity when critical infrastructure fails. The relevant decision is therefore not simply whether resilience is desirable but how much resilience should be acquired and through which combination of resources. This makes the problem inherently multi-objective. The first performance dimension concerns economic costs—including internal haulage, conveyor transportation, stockpile establishment or repurposing, new weighbridges, inventory holding, and shortage penalties—whereas the second concerns the total time trucks spend within the facility through waiting, service, and travel. Treating these objectives independently is important because converting time into an arbitrary monetary equivalent can conceal genuine operational trade-offs. Multi-objective mathematical programming instead allows decision-makers to identify a set of nondominated alternatives and explicitly examine how improvement in one criterion requires sacrifice in another.

The ε-constraint method is particularly useful for problems of this type because one objective can be optimized while alternative thresholds are imposed on another, thereby producing a set of efficient solutions along the Pareto frontier. Effective implementations of the ε-constraint method have demonstrated its ability to overcome weaknesses associated with conventional weighting procedures and to systematically generate representative efficient solutions for multi-objective mathematical programming problems (18). In the current problem, an augmented ε-constraint procedure provides a suitable mechanism for preserving the distinct meaning of economic cost and truck time while identifying different feasible trade-offs. The resulting alternatives can subsequently be assessed using a multi-criteria selection procedure rather than embedding managerial preferences prematurely into the optimization model. Such an approach is especially appropriate when infrastructure expansion provides diminishing temporal benefits: additional weighbridges may continue reducing queues, but beyond a certain point the incremental improvement in turnaround time may not justify their additional construction cost. The objective is therefore to identify a balanced configuration rather than the isolated minimum of either cost or time.

Previous research provides important components for addressing this problem but also reveals fragmentation across analytical perspectives. Steel supply chain studies have modeled inventory and facility-location decisions (1), system-level production and supply dynamics (2), scenario-based sustainable network design (10), and data-driven robust network configurations incorporating circular-economy considerations (9). Other streams of research have examined resilience capabilities (11, 12), flexibility and redundancy under disruption (13), robust decision-making under uncertainty (8), queueing and congestion (5, 6), and queuing-based supply chain network design (7). Sustainable and green supply chain scholarship has further emphasized the integration of environmental and economic concerns (15-17). Yet these strands are less frequently integrated into a plant-level internal transportation model in which stockpile assignment, multi-commodity material flows, conveyor utilization, weighbridge capacity, truck queues, disruption scenarios, resilient inventory, and cost–time trade-offs are decided jointly.

This fragmentation is particularly consequential because operational transportation factors can alter the feasibility of strategic supply chain decisions. A network configuration may satisfy aggregate capacity constraints while remaining practically infeasible if the implied truck arrival rate exceeds weighbridge service capacity. Likewise, a cost-minimizing plan may fail under a several-day conveyor disruption unless sufficient reserve inventory and alternative truck-processing capacity are available. The present case demonstrates precisely this interconnectedness: the decision problem simultaneously involves multiple material flows, alternative transportation modes, fixed stockpile capacities, queue-sensitive service facilities, equipment-disruption scenarios, source-supply interruption, and resilient inventory requirements. Accordingly, intuitive or sequential decision-making is unlikely to identify the system-wide consequences of alternative configurations. Advanced optimization is valuable precisely because it enables these relationships to be represented simultaneously and provides transparent evidence concerning the economic and operational consequences of competing infrastructure and flow-allocation decisions.

Accordingly, the contribution of the present study lies in integrating several decision layers that have commonly been investigated separately. First, it treats stockpile roles as endogenous decisions rather than fixed characteristics of the plant. Second, it allocates pellet, sponge iron, and billet flows across relevant transportation pathways while recognizing production and capacity relationships. Third, it explicitly models weighbridge, loading, and unloading bottlenecks using an M/M/c queueing structure so that truck time becomes an operational performance objective rather than an implicit consequence of flow decisions. Fourth, it incorporates probabilistic disruption scenarios representing conveyor failures and pellet-supply interruptions and introduces resilient pellet inventory to preserve system functioning under adverse conditions. Fifth, it uses a genuine multi-objective structure in which economic cost and truck time remain distinct and Pareto-efficient alternatives are generated through the augmented ε-constraint approach. Finally, the analysis is grounded in the actual operating configuration and data of a major Iranian steel producer, addressing the relative scarcity of detailed real-world studies connecting plant-level transportation design, queueing behavior, and disruption resilience. The resulting framework is consistent with the broader movement toward analytically supported operational excellence, in which mathematical models and advanced decision-support mechanisms complement managerial expertise in complex industrial environments (4), while also recognizing that coordination across supply chain decisions is fundamental to effective system performance (3).

Therefore, the aim of this study is to develop and apply a scenario-based multi-objective mixed-integer programming model for Sirjan Jahan Steel Company that jointly optimizes stockpile roles, material-flow allocation, conveyor utilization, weighbridge capacity, resilient pellet inventory, economic cost, and truck turnaround time under normal and disruption conditions.

Methods and Materials

Material Flow

The main problem addressed in this research is determining the appropriate arrangement of stockpiles, material transportation routes, weighbridge capacities, and the resilience level of the internal transportation system in the steel production supply chain. In this system, a portion of the required pellets enters the site by trucks through Gate No. 2, while the remaining amount is transferred via a conveyor belt. The amount of pellet transportation through the conveyor belt is 200 thousand tonnes per month. After being stored in pellet stockpiles, the pellets are transferred for consumption to Reduction Plant Number 1 (with an annual capacity of 960 thousand tonnes), Reduction Plant Number 2 (with an annual capacity of 1.05 million tonnes), and Reduction Plant Number 3 (with an annual capacity of 1.77 million tonnes). The output of the reduction plants is sponge iron. The sponge iron produced by Reduction Plants No. 2 and No. 3 is transferred to sponge iron stockpiles, while the sponge iron produced by Reduction Plant No. 1 is directly transported to the steelmaking plant through a conveyor belt for billet production. The billet production plant has an annual capacity of 1.0 million tonnes. Considering a consumption coefficient of 1.25, this plant requires 1.25 million tonnes of sponge iron annually. Since the production capacity of Reduction Plant No. 1 alone is insufficient to supply the total sponge iron requirement of the billet plant, the remaining sponge iron demand must be supplied from sponge iron stockpiles. The produced billets are first transferred from the billet production plant to the billet stockpile. Then, customer trucks enter the site through Gate No. 3, undergo empty weighing at one of the two weighbridges located at this gate, and proceed to the billet stockpile. After loading, the trucks undergo full weighing again and finally exit the site through the same gate.

Current Situation

According to Figure 1, in the current situation, stockpiles 1, 2, and 3 are used for pellets, stockpiles 5, 6, and 7 are used for sponge iron, and stockpile 4 is used for billets. In addition, three weighbridges are active in the pellet section, and two weighbridges are operating in the shared output section for sponge iron and billets. No new weighbridges have been constructed. The existence of a pellet conveyor belt with a transfer capacity of 200,000 tonnes per month reduces part of the daily pressure on incoming pellet trucks. However, this infrastructure itself can be exposed to failures, and in the event of a shutdown lasting several days, the incoming pellet flow becomes dependent again on trucks and incoming weighbridges. An examination of the current situation shows that the output weighbridges have reached their bottleneck capacity with the current volume of sponge iron and billet trucks and cannot provide an adequate level of service. Furthermore, in the event of a pellet conveyor failure, the capacity of the three existing pellet weighbridges will not be sufficient to fully compensate for the conveyor flow. Therefore, the problem is not merely the selection of the lowest-cost transportation route; rather, service capacity, truck waiting times, conveyor failure risks, and the risk of pellet supply disruption from the source must all be considered simultaneously in the decision-making process.

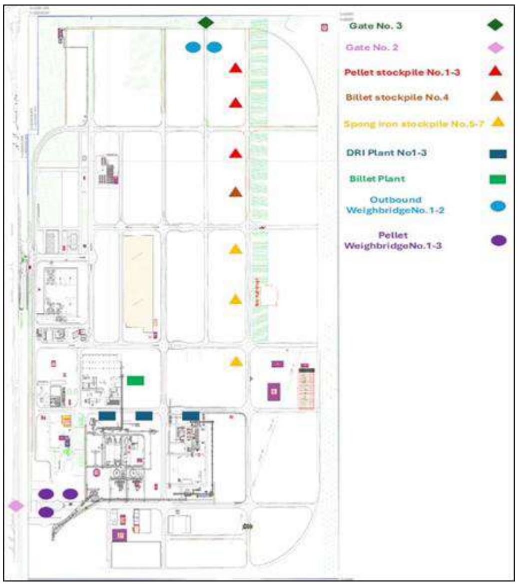

Figure 1. Current Situation

Disruption Scenarios and Resilience Logic

To avoid a subjective selection of the resilience level, several disruption scenarios are defined according to Table2 and the impact of each scenario on pellet shortages and potential production stoppages is evaluated. The disruption scenarios include short-term and long-term pellet conveyor failures, interruption of pellet supply from the source, and the simultaneous occurrence of conveyor failure and supply reduction. In the proposed model, the selected plan must be capable of avoiding pellet shortages under these scenarios. If shortages are unavoidable, their amount is reflected in the economic objective function through a significant penalty.

Necessity of Mathematical Model

The main decisions in this problem include determining the final role of each stockpile, allocating the flow of pellets, sponge iron, and billets, determining the amount of pellet conveyor utilisation, determining the amount of utilisation of the Reduction Plant No. 1 conveyor to the billet production plant, determining the resilient pellet inventory level, and determining the number of new weighbridges required in the two sections of pellets and the shared sponge iron and billet output section. In practice, the model output determines which stockpiles should be activated as pellet stockpiles, which ones should be used as sponge iron stockpiles, and which ones should serve as billet stockpiles. It also determines the amount of each material flow that should pass through each transportation route. Considering the multiple material flows, differences in transportation costs, stockpile capacity limitations, the existence of weighbridge queues, partial pellet delivery through conveyors, potential conveyor failures, and uncertainty in pellet arrivals, intuitive decision-making cannot provide a reliable solution. Therefore, this study proposes a scenario-based multi-objective mixed-integer programming model that simultaneously considers economic costs, truck time, and resilience against disruptions.

Modeling Approach

In this section, the proposed mathematical model for optimizing the internal transportation system of Sirjan Jahan Steel Company is presented. The model includes the flow of pellets from the site entrance and the pellet conveyor to pellet stockpiles and subsequently to reduction plants, the flow of sponge iron from reduction plants to sponge iron stockpiles or the billet production plant, and the flow of billets from the billet production plant to billet stockpiles. In addition, operational bottlenecks, including pellet input weighbridges, shared output weighbridges for sponge iron and billets, pellet unloading locations, and sponge iron and billet loading locations, are incorporated into the model. Based on these explanations, the model assumptions are listed as follow:

- Potential stockpiles can have one of three roles: pellet, sponge iron, or billet, and each stockpile can accept only one role at most.
- The capacity of each stockpile is considered to be 200,000 tonnes.
- In the current situation, stockpiles 1, 2, and 3 are used as pellet stockpiles, stockpiles 5, 6, and 7 are used as sponge iron stockpiles, and stockpile 4 is used as a billet stockpile.
- The cost of changing the role of a stockpile or establishing a new stockpile is considered to be 200,000 USD. Maintaining the current role of an existing stockpile does not incur any modification cost.
- The construction cost of each new weighbridge is considered to be 66,666 USD.
- The internal truck transportation cost for pellets, the transfer of sponge iron from reduction plants to stockpiles, the transfer of sponge iron from stockpiles to the billet production plant, and the transfer of billets from the billet production plant to the billet stockpile is 17 Cents per tonne-kilometre.
- The transportation cost of sponge iron from stockpiles to outside the company and the transportation cost of billets from stockpiles to outside the company are paid by customers and are considered zero in the company's economic objective function.
- The cost of conveyor-based transportation is half of the truck transportation cost, equal to 8 Cents per tonne-kilometre.

- The amount of pellet transferred through the conveyor belt under normal conditions is 200,000 tonnes per month and can become zero under failure scenarios.
- The capacity of trucks is 25 tonnes, and each pellet truck undergoes two weighing operations and one unloading operation. Sponge iron and billet trucks also undergo two weighing operations and one loading operation.
- The weighing time for each truck is 5 minutes, the pellet unloading time is 5 minutes, the loading time for sponge iron and billets is 10 minutes, and the truck movement time inside the site is considered to be 5 minutes per kilometer.

Sets and Indices

The indices used in the proposed mathematical model are defined in Table 1.

Table 1. Set and Indices

Symbol	Definition
I	Potential stockpile complex for pellets , sponge iron and billets
R= {21,22,23}	Direct reduction plant complex
T= {1,…,365}	Set of days in the planning horizon
M= {1,…,12}	Set of months
T_m	Set of days belonging to month m
Ω	Set of combined pellet arrival and disruption scenarios
K	Set of disruption scenarios

Disruption Scenarios

To account for operational uncertainty, various disruption scenarios are considered. These scenarios and their respective probabilities are presented in Table 2.

Table 2. Disruption Scenarios

Scenario	Status description	Disruption duration	Probability
0	Normal state	0 days	0.6
1	Short-term pellet conveyor belt failure	3 days	0.15
2	Long-term pellet conveyor belt failure	7 days	0.1
3	Disruption in pellet supply from the source	5 days	0.10
4	Severe combined disruption, supply interruption and conveyor belt failure	7 days	0.05

`

Parameter $a_{t\omega}^{conv}$ indicates the status of the pellet conveyor belt for each scenario:

$$a_{t\omega}^{conv} = \begin{cases} 1 & one\ day\ \omega \text{ and scenario t if the pellet conveyor belt is active on day} \\ 0 & \text{one day } \omega \text{ and scenario t if the pellet conveyor belt has failed} \end{cases}$$

Additionally, the parameter θtω represents the pellet supply ratio from the source, where θtω=1 indicates full supply, and θtω=0 represents a complete supply cutoff.

Main Parameters

Table 3 presents the definitions and descriptions of the model parameters.

Table 3. Main Parameters

parameter	Definition/value
$c^{conv} = 8$ Cents	Conveyor transport cost cent /ton-km
$F = 200{,}000$ USD	Cost of repurposing or establishing a stockpile
$F_B = 66{,}666$ USD	Cost of installing each new weighbridge

$Cap = 200{,}000$	Capacity of each stockpile (tons)
$B_m = 450{,}000$	Maximum monthly pellet inflow (tons)
$h = 3$ Cents	Daily holding cost per ton of pellet inventory
$p = 33$ USD	Shortage cost per ton of pellets
$\overline{G}^{conv} = 200{,}000$	Monthly capacity of the pellet conveyor under normal operating conditions
$Q_G^{day} = \sum_{r\in R} q_r^g = 14230.14$	The total daily pellet requirement of the three reduction plants

Decision Variables

The decision variables used in the proposed mathematical model are defined in Table 4.

Table 4. Decision Variables

Definition	Variable
1 if stockpile i is activated as a pellet stockpile, and 0 otherwise	x_i
1 if stockpile i is activated as a sponge iron stockpile, and 0 otherwise	y_i
1 if stockpile i is activated as a billet stockpile, and 0 otherwise	v_i
Number of new weighbridges installed in the pellet section	z_G
Number of new weighbridges installed in the shared sponge iron and billet outbound section	z_S
Truck-based pellet inflow to stockpile i on day t under scenario ω	$G_{it\omega}^{\mathrm{truck}}$
Conveyor-based pellet inflow to stockpile i on day t under scenario ω	$G_{it\omega}^{\mathrm{conv}}$
Amount of pellets transferred from stockpile i to reduction plant r on day t under scenario ω	$G_{irt\omega}^{\mathrm{out}}$
Pellet inventory level in stockpile i on day t under scenario ω	$I_{it\omega}^{\mathrm{G}}$
Pellet shortage at reduction plant r on day t under scenario ω	$U_{rt\omega}$
Amount of sponge iron transferred from reduction plant r to stockpile i on day t under scenario ω	$S_{rit\omega}$
Amount of sponge iron conveyed from reduction plant 1 to the billet plant on day t under scenario ω	$C_{t\omega}$
Amount of sponge iron transferred from stockpile i to the billet plant on day t under scenario ω	$D_{it\omega}$
Amount of billet transferred from the billet plant to stockpile i on day t under scenario ω	$L_{it\omega}$
Cost of changing the role of stockpile i to a pellet stockpile	A_i^{G}
Cost of changing the role of stockpile i to a sponge iron stockpile	A_i^{S}
Cost of changing the role of stockpile i to a billet stockpile	A_i^{B}
Waiting time in the pellet weighbridge queue under scenario ω	W_ω^{WG}
Waiting time in the pellet unloading queue under scenario ω	W_ω^{UG}
Travel time of a pellet truck within the site	L^{G}
Waiting time in the shared outbound weighbridge queue	W^{W25}
Waiting time in the sponge iron loading queue	W^{LS}
Travel time of a sponge iron truck within the site	L^{S}
Waiting time in the billet loading queue	W^{LB}
Travel time of a billet truck within the site	L^{B}

Mathematical model

The first objective function includes the expected economic cost of the system. This function considers internal transportation costs, conveyor transfer costs, stockpile modification costs, weighbridge construction costs, inventory holding costs, and pellet shortage costs:

$$\min Z_1 = \sum_{\omega\in\Omega} \pi_\omega \left(Z_\omega^{tr} + Z_\omega^{conv} + Z_\omega^{hold} + Z_\omega^{short}\right) + Z^{depot} + Z^{scale}$$

The costs of modifying or establishing stockpiles and constructing weighbridges are defined as follows:

$$Z^{depot} = F \sum_{i\in I} \left(A_i^G + A_i^S + A_i^B\right)$$

$$Z^{scale} = F_B(z_G + z_S)$$

Inventory holding and shortage costs are incorporated into the model in the form of scenarios:

$$Z_{\omega}^{hold} = h\sum_{t\in T}\sum_{i\in I} I_{it\omega}^{G}$$

$$Z_{\omega}^{short} = p\sum_{t\in T}\sum_{r\in R} U_{rt\omega}$$

Therefore, if, under the current conditions, queue instability or conveyor failure causes pellet shortages and production stoppage, its impact is introduced into the model as a shortage Z1 rather than being reported only in the time objective function.

The second objective function directly calculates truck time in terms of truck-minutes per year:

$$\min Z_2 = 365\sum_{\omega\in\Omega} \pi_{\omega}\,(N_{\omega}^{G}T_{\omega}^{G} + N^{S}T^{S} + N^{B}T^{B})$$

where$T_{\omega}^{G}, T^{S} and\ T^{B}$ represent the respective times for a pellet truck, a sponge iron truck, and a billet truck for example:

$$T_{\omega}^{G} = 2W_{\omega}^{WG} + W_{\omega}^{UG} + 5L^{G}$$

$$T^{S} = 2W^{W25} + W^{LS} + 5L^{S}$$

$$T^{B} = 2W^{W25} + W^{LB} + 5L^{B}$$

- **Constraints**

Each stockpile can accept at most one role:

$$x_i + y_i + v_i \leq 1 \qquad \forall i \in I$$

Capacity constraints of stockpiles for pellets, sponge iron, and billets:

$$I_{it\omega}^{G} \leq Cap\, x_i \qquad \forall i, t, \omega$$

Pellet entry through the conveyor belt depends on the conveyor status in each scenario:

$$\sum_{i\in I} G_{it\omega}^{conv} \leq a_{t\omega}^{conv}\overline{G}^{conv} \qquad \forall t, \omega$$

Source pellet supply constraint in each month and scenario:

$$\sum_{t\in T_m}\sum_{i\in I}\left(G_{it\omega}^{truck} + G_{it\omega}^{conv}\right) \leq \theta_{m\omega}B_m \qquad \forall m, \omega$$

Pellet inventory balance in each stockpile:

$$I_{it\omega}^{G} = I_{i,t-1,\omega}^{G} + G_{it\omega}^{truck} + G_{it\omega}^{conv} - \sum_{r\in R} G_{irt\omega}^{out} \qquad \forall i, t, \omega$$

Satisfying the pellet demand of each reduction plant with the possibility of shortage:

$$\sum_{i\in I} G_{irt\omega}^{out} + U_{rt\omega} = q_r^{g} \qquad \forall r, t, \omega$$

The resilient pellet inventory is calculated based on the severe 7-day disruption scenario:

$$SS_G = 7 \times Q_G^{day} = 7 \times 14230.14 = 99610.98$$

$$\sum_{i\in I} I_{it\omega}^{G} \geq SS_G \qquad \forall t, \omega$$

total number of pellet weighbridges (3 existing + new):

$$c_q^{G} = 3 + Z_G$$

total number of outbound weighbridges (2 existing + new) :

$$c_q^{out} = 2 + Z_S$$

For ensures that the daily truck-based pellet inflow does not exceed the total weighbridge service capacity. Here, $\boldsymbol{\lambda}_{tw}$ is the truck arrival rate (trucks per hour), μ is the service rate of each weighbridge

$$\sum G_{itw}^{truck} = \lambda * c_q * \mu * 24 * 25$$

The daily sponge iron requirement of the billet plant is supplied through two routes the conveyor belt and sponge iron stockpiles:

$$C_{t\omega} + \sum_{i \in I} D_{it\omega} = \beta Q_B \qquad \forall t, \omega$$

Since the conveyor belt is only located between Reduction Plant No. 1 and the billet production plant, the amount transferred through the conveyor cannot exceed the production capacity of Reduction Plant No. 1:

$$C_{t\omega} \leq q_{21}^{s} \qquad \forall t, \omega$$

Binary variables and non-negativity of flows:

$$x_i, y_i, v_i \in \{0,1\} \qquad \forall i \in I$$

$$z_G, z_S \in \mathbb{Z}_+$$

$$G_{it\omega}^{truck}, G_{it\omega}^{conv}, G_{irt\omega}^{out}, S_{rit\omega}, C_{t\omega}, D_{it\omega}, L_{it\omega}, I_{it\omega}^{G}, U_{rt\omega} \geq 0$$

Uncertainty Approache and Solution Method

- **M/M/c Queuing Model**

Since pellet arrivals are not uniform during operation, the arrival rate of pellet trucks has been modeled at three levels of 13,000, 15,000, and 17,000 tons per day, with corresponding weights of 0.25, 0.50, and 0.25. The truck arrival rate is obtained by dividing the daily flow amount by the truck capacity and the number of working hours per day.

To calculate the waiting time in the queue, the M/M/c model is used. If represents the arrival rate, represents the service rate of each server, and represents the number of servers, the system utilization coefficient is expressed as follows:

$$\rho = \frac{\lambda}{c_q \mu}$$

The queue stability condition is:

$$\rho < 1$$

The probability of an empty system and the probability of waiting are calculated using the Erlang C formula:

$$P_0 = \left[\sum_{n=0}^{c_q - 1} \frac{\left(\frac{\lambda}{\mu}\right)^n}{n!} + \frac{\left(\frac{\lambda}{\mu}\right)^{c_q}}{c_q!\,(1-\rho)} \right]^{-1}$$

$$P_{wait} = \frac{(\lambda/\mu)^{c_q}}{c_q!\,(1-\rho)} P_0$$

The waiting time in the queue and the service time are calculated as follows:

$$W_q = \frac{P_{wait}}{c_q \mu - \lambda}$$

$$W = 60\left(W_q + \frac{1}{\mu}\right)$$

The service rate of each weighbridge is equal to 12 operations per hour because the weighing time for each truck is 5 minutes. In addition, the service rate of each pellet unloading location is 12 trucks per hour, and the service rate of each sponge iron or billet loading location is 6 trucks per hour.

- **Epsilon-Constraint**

Since time is not converted into monetary cost in the final model, the problem is solved as a true bi-objective optimization problem:

$$\min Z_1, \qquad \min Z_2$$

To generate Pareto solutions, the economic cost objective is considered as the primary objective, and the time objective is introduced as a constraint:

$$\min Z_1$$

$$Z_2 \leq \varepsilon_k$$

In the augmented epsilon-constraint method, a small additional term is added to the objective function to prevent the generation of inefficient solutions:

$$\min(Z_1 - \delta s_k)$$

$$Z_2 + s_k = \varepsilon_k, \qquad s_k \geq 0$$

By changing the value$of\ \varepsilon_k$, a set of Pareto solutions is generated, none of which can be simultaneously dominated by another solution with respect to both objectives.

- **Final Solution Selection by TOPSIS**

After generating the Pareto solutions, the TOPSIS method is used to select the final solution. In this method, the decision matrix is first normalized:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

Then, the weighted normalized decision matrix is obtained:

$$v_{ij} = w_j r_{ij}$$

Since both criteria, cost and time, are considered cost-type criteria, the positive and negative ideal solutions are defined as follows:

$$A^+ = \{\min_i v_{ij}\}, \qquad A^- = \{\max_i v_{ij}\}$$

The distance of each alternative from the positive and negative ideal solutions is calculated:

$$D_i^+ = \sqrt{\sum_j \left(v_{ij} - A_j^+\right)^2}, \qquad D_i^- = \sqrt{\sum_j \left(v_{ij} - A_j^-\right)^2}$$

The closeness coefficient of each alternative to the ideal solution is equal to:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

The option with the highest value of $CC_i$is selected as the final solution.

Findings and Results

The case study of this research is related to the internal transportation system of Sirjan Jahan Steel Company. In this system, pellets enter the site through Gate No. 2. A portion of the pellets is transferred by trucks, while the remaining portion is transported through a conveyor belt with a capacity of 200,000 tons per month to pellet stockpiles. The pellets are then transferred to the reduction plants for consumption. The sponge iron produced by the reduction plants is transferred to sponge iron stockpiles, or a portion of the production from Reduction Plant No. 1 is transported to the billet production plant through a conveyor belt. The produced billets are also first transferred from the billet production plant to the billet stockpile and then loaded and transported out by trucks entering through Gate No. 3. Table 5 summarizes the annual production capacity and the daily output rate for each plant.

Table 5. Plant production data

Production Unit	Annual capacity(ton)	Daily Amount(ton)
Reduction plant1	960,000	2,630.14
Reduction plant2	1,050,000	2,876.71
Reduction plant3	1,700,000	4,657.53
Billet plant	1,000,000	2,739.73

Table7 presents the raw material requirements. Considering the consumption coefficient of 1.4 tons of pellets required for producing each ton of sponge iron, the total annual pellet requirement is 5,194,000 tons, and the total daily pellet requirement is 14,230.14 tons. In addition, considering the consumption coefficient of 1.25 tons of sponge iron required for producing each ton of billet, the billet production plant requires 3,424.66 tons of sponge iron per day. Since the total daily production of Reduction Plant No. 1 is 2,630.14 tons, even if the entire production of Reduction Plant No. 1 is transferred to the billet production plant through the conveyor belt, an amount of 794.52 tons of sponge iron per day must still be transferred from sponge iron stockpiles to the billet production plant.

Table 6. Raw material supply requirements

Description	Value(ton)
Annual sponge iron requirement for the ingot plant	1,250,000
Description	Value(ton)
Maximum annual supply from DR Plant 1 via the conveyor belt	960,000
Minimum annual supply from sponge iron stockpiles	290,000
Minimum daily supply from sponge iron stockpiles	794.52
Pellet transfer via conveyor belt under normal operating conditions	200,000
Resilient pellet inventory under the 7-day severe disruption scenario	99,610.98

Computational Results

Before presenting the results, it should be noted that the values in this section are calculated based on the final model assumptions, including the 200,000 tons per month conveyor belt, disruption scenarios, and pellet shortage penalties.

Analysis of the Current Situation

In the current situation, stockpiles 1, 2, and 3 are used as pellet stockpiles, stockpiles 5, 6, and 7 are used as sponge iron stockpiles, and stockpile 4 is used as a billet stockpile. In this condition, no new stockpile is activated, and no new weighbridge is constructed:

$$x_1 = x_2 = x_3 = 1, \qquad y_5 = y_6 = y_7 = 1, \qquad v_4 = 1$$

$$z_G = 0, \qquad z_S = 0$$

Considering the monthly entry of 200,000 tons of pellets through the conveyor belt, the base economic cost of the current situation is estimated at 5,621,000 USD. However, when disruption scenarios are incorporated into the analysis, the current system is not fully resilient against conveyor failures and pellet supply interruptions, and a portion of the required pellets does not reach the reduction plants on time.

The daily truck-based pellet entry capacity with the three existing weighbridges is calculated as follows:

$$Cap_G^{truck} = \frac{3 \times 12 \times 24}{2} \times 25 = 10800$$

While the daily pellet requirement is equal to:

$$Q_G^{day} = 14230.14$$

Therefore, during conveyor failure days, the daily pellet shortage in the current situation is equal to:

$$14230.14 - 10800 = 3430.14$$

With a shortage penalty of 33.33 USD per ton, the shortage cost for each day of conveyor belt failure is equal to:

$$3430.14 \times 33.33 = 114{,}326.56 \text{ USD}$$

The expected shortage cost across disruption scenarios is presented in Table 7 and calculated as follows:

Table 7. Expected Shortage Cost under Disruption Scenarios

Scenario	Disruption type	Total shortage	Shortage cost (USD)	Probabilistic share (USD)
1	3-day conveyor belt failure	10,290.42	343,000	51,466.66
2	7-day conveyor belt failure	24,010.98	800,333.33	80,066.66
3	5-day pellet supply interruption	71,150.70	2,371,666.66	237,200
4	7-day severe disruption	99,610.98	3,320,333.33	166,000
sum				534,733.33

Consequently, the economic objective function, adjusted for the risk of shortage, is formulated as follows:

$$Z_1^{current} = 5{,}621{,}000 + 534{,}733.33 = 6{,}155{,}733.33$$

From a time perspective, the current situation is also unstable. For output weighbridges 26 and 27, the combined flow of sponge iron and billet trucks results in 31.60 weighing operations per hour, while the capacity of the two existing weighbridges is 24 operations per hour. Therefore:

$$\rho_{25} = \frac{31.60}{24} = 1.32 > 1$$

As a result, the current system is not stable in terms of the time objective function, and the waiting time value cannot be considered reliable.

Pareto Solutions

Table 8 summarizes the Pareto options obtained by solving the scenario-based and resilience-oriented model. All these options are acceptable under the defined disruption scenarios and maintain a resilient pellet inventory of 99,611 tons.

Table 8. Pareto Solutions Obtained Using the Augmented Epsilon-Constraint Method

option	Pellet stockpiles	Spong iron stockpiles	Billet stockpiles	z_G	z_S	Z_1 (USD)	Z_2(Million truck-minutes per year)
A1	3,12 ,1,2	5,6,7	4	2	1	5,235,333.33	17.90
A2	1,2,3,12	5,6,7	4	2	2	5,302,000	12.10
A3	3,12 ,1,2	5,6,7	4	3	2	5,368,666.66	10.46
A4	3,12 ,1,2	5,6,7	4	4	2	5,435,333.33	9.80
A5	3,12 ,1,2	5,6,7	4	4	3	5,568,666.66	9.20

Final Solution

After generating the Pareto solutions, the TOPSIS method was applied to select the final solution. The ranking and selected solutions obtained from the TOPSIS analysis are presented in Table 9. The criteria weights were calculated from the decision matrix itself using a data-driven approach.

Table 9. TOPSIS Results

$$w_1 = 0.487, \qquad w_2 = 0.513$$

option	Z_1	Z_2	Closeness coefficient	Rank
A2	5,302,000	12.10	0.736	1
A3	5,368,666.66	10.46	0.697	2
A4	5,435,333.33	9.80	0.604	3
A1	5,235,333.33	17.90	0.530	4
A5	5,568,666.66	9.20	0.470	5

Therefore, the selected final solution is option A2.

$$x_1 = x_2 = x_3 = x_{12} = 1$$

$$y_5 = y_6 = y_7 = 1$$

$$v_4 = 1$$

$$z_G = 2, \qquad z_S = 2$$

Truck Time

In the final model, time is not converted into cost; therefore, time is reported based on the time spent by each truck as well as the truck-minute indicator. In the selected plan A2, the approximate residence time of each truck within the site is summarized in Table 10, as follows:

Table 10. Truck time in the selected solution

Truck type	The estimated cycle time per truck, including queuing, service, and travel times
pellet, mild scenario	Approximately 26 minutes
pellet, moderate scenario	Approximately 27 minutes
pellet, numerous scenario	Approximately 30 minutes
Sponge iron output	Approximately 46.5 minutes
Billet output	Approximately 71 minutes

These values provide a clearer picture of truck operational conditions because they are directly related to vehicle residence time within the site. The value of the second objective function is reported only for comparing Pareto solutions and is expressed in million truck-minutes per year.

Comparison

A comparison of the current state, the selected optimal solution, and the improved state is presented in Table 11, illustrating the tangible benefits of the proposed optimization model.

Table 11. Comparison Between the Current Situation and the Selected Solution

Index	Current status of the ore conveyor	The selected approach
Pellet stockpiles	3 ،2 ،1	12 ،3 ،2 ،1
Sponge iron stockpiles	7 ،6 ،5	7 ،6 ،5
Billet stockpiles	4	4
New pellet weighbridge	0	2
New outbound weighbridge	0	2
Resilient pellet inventory	-	99,611ton
Economic cost incorporating stockout risk	6,155,733.33 USD	5,302,000 USD
Objective function status over time	Unstable	Stable
Outbound weighbridge utilization rate	1.32	Less than1

The economic cost reduction resulting from optimization is calculated as follows:

$$\Delta Z_1 = 6{,}155{,}733.33 - 5{,}302{,}000 = 853{,}733.33$$

The percentage of economic improvements equal to:

$$\frac{853{,}733.33}{6{,}155{,}733.33} \times 100 = 13.87\%$$

Therefore, the proposed model not only transforms the system from an unstable condition into a stable one, as shown in Figure 2, but also generates an expected economic saving of approximately $853,733.33.

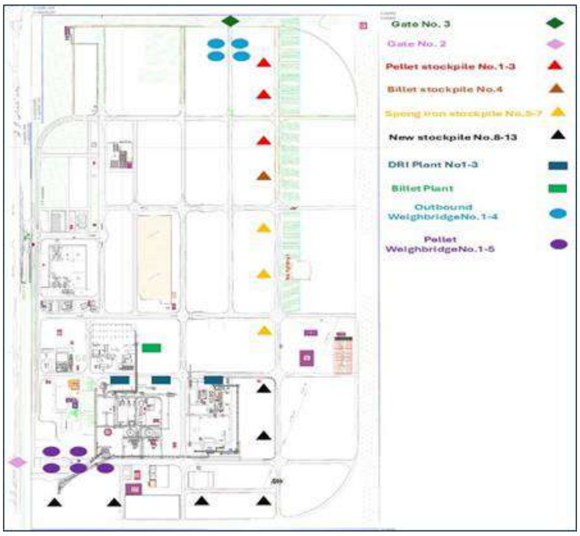

Figure 2. Proposed state

Managerial Interpretation of Results

The results show that the entry of 200,000 tons of pellets per month through the conveyor belt reduces the operational pressure on incoming trucks; however, it is not sufficient by itself to make the system resilient. In the event of a multi-day conveyor failure or interruption of pellet supply from the source, the current system faces pellet shortages and production losses. Therefore, maintaining resilient pellet inventory and increasing weighbridge capacity are necessary conditions for maintaining production under disruption conditions. Regarding stockpile selection, stockpile 12 has the greatest impact on reducing pellet transportation costs due to its favorable location relative to the reduction plants. The existing sponge iron and billet stockpiles are maintained because changing their roles is costly, and the current stockpiles adequately meet the operational requirements of the model. Furthermore, TOPSIS results indicate that constructing two new pellet weighbridges and two new output weighbridges provides the best trade-off between cost and time. This is because adding more weighbridges reduces time; however, the ratio of time reduction to cost increase is not sufficient to justify selecting more expensive alternatives as the final solution.

Discussion and Conclusion

The present study developed and applied a scenario-based multi-objective optimization framework for improving the resilience and operational efficiency of internal transportation in the steel supply chain of Sirjan Jahan Steel Company. The findings demonstrated that the existing transportation configuration was not sufficiently resilient to disruptions in pellet supply and conveyor availability and was also operationally unstable at critical service points. Under the current configuration, stockpiles 1, 2, and 3 were allocated to pellets, stockpiles 5, 6, and 7 to sponge iron, and stockpile 4 to billets, while three pellet weighbridges and two shared outbound weighbridges were in operation. Once disruption-related shortage penalties were incorporated, the expected annual economic cost of the current system reached approximately USD 6.16 million. In addition, the shared outbound weighbridge utilization exceeded stable queueing conditions, indicating that the existing service capacity was inadequate for the prevailing truck flows. The optimization model generated five Pareto-efficient alternatives and, after application of TOPSIS, selected alternative A2 as the best cost–time compromise. The selected solution retained the existing sponge-iron and billet stockpile assignments, added stockpile 12 to the pellet storage system, constructed two additional pellet weighbridges and two additional outbound weighbridges, and maintained a resilient pellet inventory of approximately 99,611 tons. This configuration reduced expected annual costs to approximately USD 5.30 million, corresponding to savings of approximately USD 0.85 million or 13.87%, while simultaneously transforming the queueing system from an unstable to a stable condition.

The substantial reduction in expected economic cost indicates that internal transportation optimization in steel production cannot be approached merely as a routing problem. Instead, transportation costs are strongly determined by the interaction among facility location, stockpile assignment, flow allocation, service capacity, inventory, and disruption exposure. This finding is consistent with Sabzevari Zadeh et al., who demonstrated that integrating facility-location, inventory, and multi-commodity transportation decisions within steel supply chain design can improve network performance and reduce overall operating costs (1). It is also consistent with Mohammadi et al., whose system-dynamics analysis showed that the performance of steel supply chains emerges from interactions among production capacity, material availability, operational constraints, and logistics processes rather than from individual decisions considered independently (2). The results of the present study extend this logic to plant-level internal logistics by showing that even when the general production configuration remains unchanged, redesigning the relationship among stockpiles, material pathways, weighbridges, and resilient inventory can produce considerable economic benefits. This integrated perspective also aligns with the broader emphasis on coordination in supply chain decision-making, where contractual, operational, and structural decisions should be understood as interconnected mechanisms affecting system-wide performance (3).

A particularly important finding was the selection of stockpile 12 as an additional pellet stockpile, while the existing sponge-iron and billet stockpile configuration was preserved. This result indicates that optimal storage configuration depends not only on nominal storage capacity but also on the spatial and operational relationship between storage locations and downstream consumption points. Activating stockpile 12 reduced pellet transportation costs because of its favorable location relative to the reduction plants, whereas changing the functions of the existing sponge-iron and billet stockpiles would have generated modification costs without sufficient compensatory advantages. The result supports previous steel supply chain research demonstrating the importance of jointly optimizing storage, inventory, and facility-location decisions (1). It also accords with the scenario-based steel supply chain model proposed by Pourmehdi et al., in which network configuration and production-technology choices substantially affected economic and operational performance under alternative conditions (10). Similarly, Khalili-Fard et al. demonstrated that robust steel supply chain network design requires coordinated facility and flow decisions under uncertain operating conditions rather than reliance on static configurations (9). The current findings therefore illustrate how the same principle applies within the boundaries of an individual steel manufacturing complex, where the functional assignment of storage infrastructure can materially affect transportation efficiency.

Another major finding concerns the inadequacy of the existing weighbridge infrastructure. In the current state, the two shared outbound weighbridges were unable to process the combined sponge-iron and billet traffic under stable queueing conditions, whereas the selected solution required two additional outbound weighbridges. Two additional pellet weighbridges were also required to ensure adequate processing capacity when conveyor-based pellet transportation was reduced or unavailable. This finding highlights the importance of explicitly incorporating congestion and service capacity into supply chain optimization. Queueing theory demonstrates that as utilization approaches service capacity, waiting times increase nonlinearly, and when arrival demand exceeds effective service capacity, a stable steady-state queue cannot be maintained (5). The present results therefore indicate that infrastructure decisions should not be determined solely from average flow volumes. A weighbridge configuration may appear adequate under routine conditions but become a serious bottleneck when transportation patterns shift because of equipment failure or supply disruption. Zhang et al. similarly showed that controlling truck arrival and service patterns can substantially reduce congestion and turnaround time in terminal transportation systems (6). In supply chain network design, Vahdani and Mohammadi likewise demonstrated the value of incorporating multi-priority queueing systems directly into optimization models, thereby connecting network decisions with actual service performance (7).

The truck-time results further reinforce the value of integrating queueing behavior with optimization. Under the selected solution, estimated residence times were approximately 26–30 minutes for pellet trucks depending on the scenario, approximately 46.5 minutes for outbound sponge-iron trucks, and approximately 71 minutes for billet trucks. These values include waiting, service, and internal travel and therefore represent an operationally meaningful measure of transportation performance rather than an abstract cost proxy. Separating truck time from the monetary objective was particularly important because the operational consequences of congestion are not necessarily captured accurately by converting every minute into an assumed financial value. The use of two independent objectives therefore allowed the model to reveal the actual trade-off between capital expenditure and service improvement. This approach is consistent with multi-objective optimization principles, according to which conflicting objectives should be represented explicitly when no defensible single conversion factor exists. The augmented ε-constraint method used in this study is especially appropriate for such situations because it generates Pareto-efficient alternatives without requiring the analyst to collapse all criteria into one weighted objective (18). The resulting Pareto frontier made it possible to distinguish alternatives that minimized cost from those that achieved stronger time performance and subsequently select a balanced solution.

The TOPSIS-based selection of alternative A2 also illustrates an important managerial implication of the Pareto analysis. The least-cost Pareto solution was not ultimately selected because its time performance was less favorable, whereas alternatives with more weighbridge capacity achieved lower truck-time values but required greater investment. A2 provided the preferred compromise between approximately USD 5.30 million in expected cost and 12.10 million truck-minutes annually. This result indicates that marginal reductions in congestion do not necessarily justify unlimited capacity expansion. After a certain point, each additional weighbridge produces progressively smaller operational gains relative to its cost. Such a finding is consistent with the resilience literature, which emphasizes that redundancy is beneficial but should be calibrated carefully. Kamalahmadi et al. showed that redundancy and flexibility can substantially enhance supply chain resilience, but the value of these capabilities depends on disruption characteristics and the costs associated with maintaining excess capacity (13). Shekarian and Mellat Parast similarly identified redundancy, flexibility, agility, collaboration, and adaptive capability as important resilience mechanisms but emphasized the need for their integration into broader disruption-risk management strategies (12). The additional weighbridges identified in the present study can therefore be interpreted as economically justified redundancy rather than excess infrastructure.

The resilient inventory result is equally significant. The model required approximately 99,611 tons of pellet inventory to protect production under the severe seven-day disruption scenario. This result demonstrates that safety inventory should be determined according to explicitly modeled disruption conditions rather than through arbitrary managerial rules or normal-demand averages. In this system, pellets are essential inputs to direct-reduction production; consequently, insufficient pellet availability can interrupt sponge-iron production and propagate disruptions downstream to billet production. The selected resilient inventory therefore operates as a buffer that absorbs temporary loss of supply and transportation capacity. This finding strongly aligns with Ivanov's resilience framework, which emphasizes the need for supply chains to maintain functionality during disturbances through structural and operational capabilities that enable absorption, adaptation, and recovery (11). It also supports the integrative resilience perspective of Shekarian and Mellat Parast, according to which effective disruption management involves both preparedness before an event and adaptive mechanisms during the disturbance (12). The contribution of the present model lies in translating this general resilience concept into a quantifiable inventory requirement directly associated with a defined severe disruption.

The disruption analysis also showed that the existing pellet conveyor, despite providing substantial operational benefits under normal conditions, does not by itself guarantee resilience. The conveyor transports approximately 200,000 tons of pellets per month and therefore reduces routine truck demand, but conveyor failure immediately transfers greater pressure to the truck-based transportation and weighbridge system. Simultaneous source-supply interruption further increases the risk of pellet shortages. Accordingly, resilience arises not from dependence on one efficient transportation technology but from the availability of complementary capabilities—including inventory buffers, alternative truck flows, and sufficient weighbridge capacity. This finding supports the conceptual distinction between efficiency and resilience emphasized by Ivanov (11). It is also compatible with robust optimization research showing that solutions optimized exclusively for expected or nominal conditions may become infeasible when key parameters deviate from their baseline values (8). Scenario-based planning provides a practical response because it exposes the decision system to several plausible operating states before infrastructure and inventory choices are finalized. Pourmehdi et al. likewise demonstrated the usefulness of scenario-based approaches in designing sustainable steel supply chain networks where production technologies and operating conditions are uncertain (10).

The superiority of the optimized solution also confirms the value of robust and scenario-oriented approaches for industrial decision-making. Conventional deterministic models tend to identify the configuration that performs best under assumed average values, but such configurations may have limited capacity to absorb failures, shortages, or abrupt changes in flow. By contrast, the current model explicitly evaluated normal operation alongside short-term conveyor failure, long-term conveyor failure, pellet-source interruption, and severe combined disruption. The resulting configuration was therefore selected not simply because it was inexpensive under routine conditions but because it remained operationally viable across adverse states. This conclusion is consistent with Ensafian and Yaghoubi, who found that robust optimization can produce more reliable integrated supply chain decisions under uncertainty (8), and with Khalili-Fard et al., who demonstrated the applicability of data-driven robust optimization to complex steel supply chain network design (9). More generally, the increasing use of advanced analytical and artificial-intelligence-supported decision systems in industrial management reflects the need to replace purely intuitive operational choices with structured, data-informed models capable of considering multiple interacting conditions (4).

Although environmental performance was not specified as an independent objective function, the results also have implications for sustainable supply chain management. Improved stockpile allocation, shorter material movements, more efficient use of conveyor transportation, reduced truck congestion, and lower unnecessary waiting can indirectly reduce fuel use and the environmental burden associated with internal logistics. Sustainable supply chain management requires economic objectives to be considered within a broader system of environmental and social flows (15). Sarkis similarly emphasized that supply chain boundaries and material flows are critical for understanding and improving environmental performance (16). The review by Fahimnia et al. further demonstrated the central role of transportation and logistics within green supply chain management research (17). Thus, although the current optimization was primarily structured around cost, truck time, and resilience, the reduction of inefficient transportation activity provides a foundation for extending the framework toward explicit sustainability criteria, including emissions, energy consumption, and environmental externalities.

Taken together, the findings indicate that resilience and efficiency in internal steel transportation are complementary when the system is designed holistically. The optimized configuration did not achieve resilience merely by increasing inventory, nor did it reduce congestion only by expanding infrastructure. Instead, performance improvement resulted from the coordinated selection of stockpile roles, material-flow routes, conveyor use, resilient inventory, and weighbridge capacity. The approximately 13.87% reduction in expected annual cost demonstrates that greater resilience need not necessarily imply higher total cost when existing inefficiencies and disruption-related losses are addressed simultaneously. This is an important result because resilience investments are sometimes regarded exclusively as additional expenses. In the present case, targeted redundancy and inventory buffering reduced expected shortage exposure while improved logistics configuration lowered transportation costs sufficiently to generate net economic benefits. Such a systems perspective is compatible with contemporary supply chain research emphasizing integrated decision structures (3), robust and adaptive supply chain design (11), economically calibrated flexibility and redundancy (13), and sustainable management of material flows (15). Overall, the results support the use of integrated multi-objective optimization as a practical decision-support framework for steel manufacturers facing simultaneous cost pressure, congestion, infrastructure limitations, and disruption risks.

Several limitations should be considered when interpreting the findings. First, the model was developed using operational data from a single steel manufacturing complex; therefore, the numerical results, infrastructure requirements, and optimal stockpile configuration are specific to the spatial layout, production capacities, material flows, and operating conditions of Sirjan Jahan Steel Company. Second, the disruption scenarios were represented by a finite number of predefined states and probabilities, whereas actual industrial disruptions may differ in duration, severity, frequency, and combinations. Third, the M/M/c queueing assumptions simplify actual truck arrival and service processes by adopting particular probabilistic assumptions that may not fully reflect time-dependent congestion, driver behavior, shift patterns, equipment downtime, or priority rules. Fourth, some operational parameters, including transportation, construction, shortage, and inventory costs, were treated as fixed during the planning horizon. The model also did not explicitly include emissions, energy consumption, labor constraints, maintenance scheduling, detailed loading-equipment availability, road congestion within the plant, or simultaneous failures of multiple facilities. Finally, the results depend on the quality and accuracy of the available operational data and estimated disruption probabilities.

Future studies could extend the proposed framework in several directions. The model could first be tested in other steel plants and heavy industrial supply chains to assess its external validity and determine how alternative layouts and production structures affect optimal decisions. Future research could use detailed hourly or shift-level data to model time-varying truck arrivals, service capacity, congestion, and equipment availability. More sophisticated queueing structures, discrete-event simulation, or simulation–optimization approaches could also be incorporated to represent non-exponential service times and complex priority rules. Additional disruption scenarios could include simultaneous weighbridge failure, loading-equipment breakdown, energy restrictions, extreme weather, road closure, labor shortages, and prolonged raw-material supply interruptions. Researchers could also formulate additional objectives relating to carbon emissions, fuel consumption, energy efficiency, service reliability, and occupational safety. Data-driven scenario generation, machine-learning-based disruption prediction, and real-time optimization could further transform the static planning framework into a dynamic decision-support system. Finally, sensitivity and value-of-information analyses could be used to determine which uncertain parameters most strongly influence infrastructure, inventory, and transportation decisions.

For practice, steel-industry managers should evaluate internal transportation as an integrated system rather than independently managing stockpiles, trucks, conveyors, weighbridges, and inventories. In the studied company, priority can be given to activating the proposed additional pellet stockpile and expanding pellet and outbound weighbridge capacity while monitoring whether actual queueing performance confirms the model estimates. Managers should establish a formally defined minimum resilient pellet inventory linked to disruption duration and production requirements instead of relying on subjective safety-stock rules. Conveyor availability, truck inflows, weighbridge utilization, stockpile levels, and loading and unloading queues should be monitored through an integrated operational dashboard so that emerging bottlenecks can be detected before production is affected. Scenario-based contingency plans should specify alternative transportation arrangements for conveyor failure and pellet-supply interruption. Infrastructure investments should also be evaluated according to both economic and service-performance indicators because the lowest-cost configuration may not provide adequate operational stability. Periodic recalibration of the optimization model using updated demand, cost, capacity, and disruption data would allow the company to maintain an efficient and resilient transportation configuration as operating conditions change.

Acknowledgments

We would like to express our appreciation and gratitude to all those who helped us carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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