Original Research

Steel Supply Chain Complexity and Resilience Assessment: Interactive Network Mapping, Graph Theory, and Agent-Based Simulation

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Received: 17 Nov 2022 / Accepted: 08 July 2024/ Published online: 08 July 2024

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Abstract

Supply chain research faces significant challenges due to the intricate interactions, dependencies, and uncertainties involved. This study aims to address these complexities by developing agent-based models and simulations focused on enhancing the resilience of the Steel Industry Supply Chain (SISC). Utilizing complex adaptive system (CAS) analysis, our approach involves mapping the Iranian SISC onto a graph using the Gephi software (version 0.9.2). Through this, we analyze network indices to test the hypothesis that the SISC operates as a Complex Adaptive System (CAS). To track the behavior of intended network during disturbance, Agent-Based Modeling (ABM) is proposed, implemented using NetLogo (version 6.2.0). The experimentation is facilitated through NetLogo's integrated software tool, BehaviorSpace, which enables parameter sweeps, design, and execution of agent-based modeling experiments. Sensitivity analysis is conducted using output files exported to spreadsheets, with XLSTAT utilized for statistical analysis across six scenarios.

Keywords- Agent-Based Simulation; Complex Adaptive System; Graph Theory; Resilience; Steel Industry Supply Chain

INTRODUCTION

The cosmos abounds with systems characterized by interactive behavior, consistency, and intrinsic connections. A common trait among these systems is their confinement within limited temporal and spatial dimensions. Reductionists and mechanistic materialists view the universe as an expansive and intricate mechanical construct, in which its constituent elements form a cohesive entity governed by the iterative and discernible patterns dictated by the Law of Nature [1]. As explained by [2], the reductionist approach seeks to simplify complex structures through the creation of models. These models, generally categorized as scale, analog, and theoretical, serve to differentiate various representations. Analog models depict an object within another object with a similar structure, known as homomorphism, while theoretical models encapsulate a set of assumptions and equations that facilitate understanding the fundamental properties inherent in an object or system. Conversely, advancements in programming languages have moved away from the efficiency and versatility of simplistic models, prompting scholars to explore solutions for problems of varied complexity. Researchers studying Complex Adaptive Systems (CAS) strive to navigate the intricacies of component interactions and inherent connectivity by employing diverse hardware, software, and programming skills. Agent-based modeling (ABM) enables the representation of decision-making entities, including individual, heterogeneous, and autonomous agents. The design of an ABM can be approached through various methods, with the choice depending on several factors, such as the nature of the phenomenon under investigation, the extent of available knowledge about the phenomenon, and the software or programming language used. Within the realm of modeling, there are two principal categories, as outlined by [3]. In phenomenon-based modeling, the AB modeler seeks to replicate predefined patterns by starting with reference phenomena and then configuring a set of agents and rules to govern their behavior. In contrast, in exploratory-based modeling, the AB modeler identifies emergent patterns through the creation of agents and specification of their behaviors, aiming to elucidate the resemblance between the proposed model and the real-world phenomenon under study.

This study introduces a modeling framework aimed at the simulating resilient SISCs, prompted by the considerable expense, abundance, multiplicity, and strategic significance of the steelmaking process. The Iranian steel industry confronts a multitude of uncertainties stemming from factors such as high capital intensity, economic downturns, sanctions, fluctuating prices of steel and iron, availability of iron supplies, fluctuations in energy and transportation costs, water scarcity, environmental regulations, mining hazards, and risks associated with iron ore processing. Additionally, Iran's steel sector grapples with ongoing challenges including competition from alternative materials, escalating imports, legislative changes affecting the import and export of by-products, rising labor expenses, and the adoption of increasingly complex technologies. Against a backdrop of mounting concerns regarding resilience amid upheavals and the burgeoning adoption of Agent-Based Modeling and Simulation (ABMS) methodologies, there arises a pressing need for a Complex Adaptive Systems (CAS) resilience approach, exemplified by the SISC framework. Consequently, this study develops an agent-based simulation model utilizing Iran's SISC network to compute node-level and network-level indices pertinent to network resilience.

Due to its abstract nature, the issue of supply chain resilience analysis has always faced obstacles in terms of quantification. This issue can be extended to the robustness of the supply chain. Therefore, the main problem of this research is to find a way to quantify resilience analysis of supply chain by graph theory. The approach of this research can be described as follows: First, before the disruption, the node and network level indicators are calculated for the SISC. For this purpose, the capacity of each node is considered in CSV format for Gephi environment. The network indices are computed by Gephi (0.9.2), and by the agent based simulation space, disturbances are created in the network. Node and network level indicators are recalculated after disruption in NetLogo software. With this method, all indicators can be compared and analyzed before and after the disturbances.

The foundational concept of this study is the recognition of supply chain networks as complex adaptive systems ([4]; [5]; [6]). Additionally, a secondary premise draws an analogy between supply chains and social networks (SN) [7], recognizing that Social Network Analysis (SNA) is grounded in graph theory [8]. Investigating the resilience and robustness of intricate supply chain networks can be achieved through Agent-Based Modeling and Simulation (ABMS) techniques [9]. This research focuses on exploring the resilience of SISC networks by mapping them as complex adaptive systems onto SN's. This involves conducting graph theory and assessing network indices using graph theory fundamentals. Given the abstract nature of resilience, a quantitative methodology was necessary. Consequently, several straightforward hypotheses were considered:

(a) Utilizing a network analysis approach is appropriate for evaluating the resilience of SISCs [9];

(b) Given the primary focus on SISC resilience, the use of simple reflection agents is preferred over goal-based and utility-based agents;

(c) Recognizing the pivotal role of the steel industry, particularly its extensive domestic and international consumption, steel manufacturers are positioned as end customers within the SISC, defining the model's boundary.

This study endeavors to evaluate the resilience of Iran's entire steel chain employing a quantitative approach that aims to accurately represent the iron and steel industries as a network using available real-world data. The selection of agents in the model is guided by the availability of dependable information regarding the agents. Hence, network analysis and graph theory serve as the theoretical underpinnings for the agent-based model employed in this study. Iran's steel chain was mapped using Gephi software (0.9.2) to provide data for resilience analysis, with collected data utilized to extract variables and parameters necessary for simulation. This approach is rationalized by its focus on the structural and visual attributes of the SISC, aiming to establish a platform conducive to visualizing and exploring various types of steel networks in terms of representation and layout. The subsequent sections of this paper are structured as follows: Section 2 offers a comprehensive review of relevant literature. Section 3 delineates the research methodology, including the identification of indicators and the conceptual model. Section 4 details the model implementation, validation, and verification procedures. Section 5 delves into sensitivity analysis, while Section 6 presents the study's findings and conclusions.

LITERATURE REVIEW

Supply chains face persistent challenges due to unexpected costs. To address this uncertainty, it is essential to treat the supply chain network as a Complex Adaptive System (CAS). According to [5], extensive supply chain networks exhibit the characteristics of CAS, where interconnected entities adapt to environmental and internal changes. Various topological configurations, product varieties, entity roles, resource allocations, and process dynamics contribute to the complexity of supply chain networks ([10]; [11]). This complexity is further highlighted by aspects such as structural intricacies, system openness, emergent phenomena, and dynamic behaviors ([12]). As noted by [5], a CAS supply chain consists of numerous interrelated components, each contributing to the system's unique identity and connectivity. Due to the intricate interactions among many actors within CAS supply chain networks, Agent-Based Modeling (ABM) is the primary tool for identifying emergent behaviors. In practice, existing literature, including foundational works on the general definition and structure of ABMS ([13]; [14]; [15]; [16]; [17]; [18]; [19]; [20]), provides valuable insights into the timing and use of ABM within supply chain contexts.

Resilience can be conceptualized and observed across three distinct levels: the supply chain, the supply network, and the enterprise. At the enterprise level, resilience is defined as "the capacity to survive, adapt, and grow in the face of change and uncertainty" [21]. Conversely, [22] defines supply chain (SC) resilience as "the ability of a system to return to its original or desired state after being disturbed." Additionally, [23] describes resilience as "a network-level attribute to withstand disruptions that may be triggered at the node or arc level." Finally, [24] offers a comprehensive definition, stating that resilience is "a complex, collective, adaptive capability of organizations in the supply network to maintain a dynamic equilibrium, react to and recover from a disruptive event, and regain performance by absorbing negative impacts, responding to unexpected changes, and capitalizing on the knowledge of success or failure."

Agent-Based Modeling and Simulation (ABMS) is a robust methodology that has emerged for investigating the dynamics of resilience in communities composed of small and medium-sized enterprises (SMEs) in the aftermath of a disaster [25]. This investigation delves into two hypothetical attributes inherent in each business - customer type and resilience - alongside a community-specific hypothetical trait known as the belonging threshold. [26] outlined the development of an agent-based discrete-event simulation modeling framework integrated with a Geographic Information System (GIS) module. The goal was to formulate natural disaster evacuation plans and iteratively refine evacuation strategies. Furthermore, [27] explored the feasibility of using agent-based simulations within NetLogo to simulate a double-exit classroom environment. The objective was to enhance awareness regarding student behavior during fire evacuation scenarios. Introducing a novel approach to consider the variability in human behavior and its interaction with the environment, [28] proposed a combined agent-based discrete choice modeling framework to design evacuation plans incorporating diverse aspects and multiple routing strategies.

Similarly, [29] customized an agent-based model to simulate tourist recovery post-earthquake, considering the heterogeneous nature of tourists and systematic agent interactions. Additionally, ABM techniques were applied to model the cattle industry and transportation services as interconnected systems, evaluating the network's resilience in disaster scenarios [30]. Finally, [31] developed a spatially explicit agent-based model to assess the discrepancy between the supply and demand of humanitarian relief within disaster-affected regions over a specified timeframe. For a comprehensive understanding of the extensive applications of agent-based modeling and simulation in research within the field of supply chain management and other domains, it is highly recommended to study and review [32].

Achieving resilience in the SISC network necessitates the holistic modeling of its entirety in an integrated fashion. A fundamental aspect is the recognition of the SISC network as a complex system. Within the industry, numerous barriers to resilience exist, and one effective strategy to further streamline resilience objectives is to map SISC in Iran onto the graph and compute network indices. This endeavor revolves around assessing the resilience of our network. This study advocates for the utilization of agent-based modeling as a means to monitor the behavior of SISC during disturbance scenarios and to assess alternative scenarios. The shift towards Agent-Based Modeling and Simulation (ABMS) stems from its capacity to navigate the escalating complexity inherent in real-world social and technical systems, thereby reflecting emergent behaviors.

The modeling and simulation approach must consider the nature of decisions pertaining to the various components constituting the SISC. Given the evolving objectives of decision-makers, the transient behavior of certain sub-industries of the SISC should also be factored in based on an understanding of the environment in which other decision-makers and the SISC operate. To attain operational objectives, SISCs must align with market demand and demonstrate resilience to uncertainties and disruptions. This fosters a robust chain structure for this pivotal commodity and strategies across all its sub-industries. Scarce literature was found regarding the study of steel chain resilience utilizing the network-based ABMS approach.

RESEARCH METHOD

This article is grounded in Comte's positivist philosophy of social reality, which emphasizes interactions and relationships. It employs: (1) conceptual frameworks, (2) observation and (3) measurement techniques, and (4) mathematical analysis in line with this philosophical perspective. The research trajectory follows a path from the natural sciences to the social sciences. In detecting agents, variables, interactions, and relationships, Descartes's reductionism philosophy is employed. However, this study is intended for testing subsequent to the presentation of an agent-based model and should be regarded as a practical investigation due to its utilization of Iran's SISC for this purpose. It can be categorized as a causal study, as the phenomena under scrutiny are influenced by the interactions of different agents and the interrelationships of variables. In causal research, investigators observe the effects of changes in other variables by manipulating the variable of interest. While contemporary studies often lean towards quantitative methodologies, this study represents a mixed category by incorporating both quantitative and qualitative techniques. To some extent, such an approach facilitates the exploration of complex systems.

RESEARCH PROCESS

The primary objectives of this study encompass the development and application of agent-based modeling and simulation to assess the resilience of steel chains, leveraging complex adaptive network analysis and graph theory. Through the mapping of Iran’s SISC onto a graph, employing graph theory, network indices including degree, betweenness, centrality, network density, average path length, and network centrality, along with network layout, are scrutinized with a focus on resilience. NetLogo (version 6.2.0) served as the experimental platform for elucidating agents, environments, agent behavior, interactions, and agent and environmental rules. Gephi software (version 0.9.2) was utilized for network analysis, resilience index evaluation, and initial network design. Following the mapping of the SISC onto the network and the analysis of indicators using Gephi software, the calculated indicators were utilized as inputs for NetLogo software, as depicted in Figure 1. Subsequently, after running the simulation, the output of the agent-based simulation was employed as input for network analysis using Gephi software to assess resilience. Data collection was conducted through the review of steel industry monitoring reports generated by relevant organizations.

Within this study, data pertaining to Magnetite and Hematite mines, Iron concentration lines, agglomeration plants, DRI plants, and steelmakers has been compiled. Conceptual models are predominantly employed when existing theories are insufficient to construct robust frameworks. Figure 2 depicts the conceptual model utilized in this study, as it is imperative to elucidate the objectives, inputs and outputs, assumptions, etc., using non-software terminology when presenting the conceptual underpinnings of the simulation model.

SISC is structured into 5 tiers based on the production method employed. Iron ore serves as the primary material for steel production. The principal variables investigated in this research encompass the count of perturbation-prone, disturbed, and responding agents, along with the initial number of disturbed agents, redundancy portion, sequence for checking the status of disturbing agents, and predicted resistance. It is noteworthy that in the process of mapping SISCs as CAS’s onto SN’s, all parameters, inclusive of node and network level indices, are computed based on material flow and the capacities of mining units and plants. The theoretical underpinnings of the steel chain within the proposed framework are derived from references [33] and [34].

The SISC was elucidated as the focal point of this study, originally intended to discern a phenomenon warranting investigation. Thus, the steel chain under scrutiny in this research is depicted in Figure 3. The proposed ABM incorporates production agents, including mines, concentration lines, agglomeration units, DRI, and steel-makers. Given that iron forms the cornerstone of the steel industry, secondary materials such as coke, scrap, graphite electrode, bentonite, oxygen, lime, dolomite, etc., have been disregarded as independent agents. Due to insufficient documentation, the involvement of secondary materials in the delineation phase of the model and in determining its boundaries was dismissed. Furthermore, the casting process, along with the production of finished and semi-finished products, is excluded from the steel chain as they exhibit significant diversity, stemming from their common origin of ingot steel.

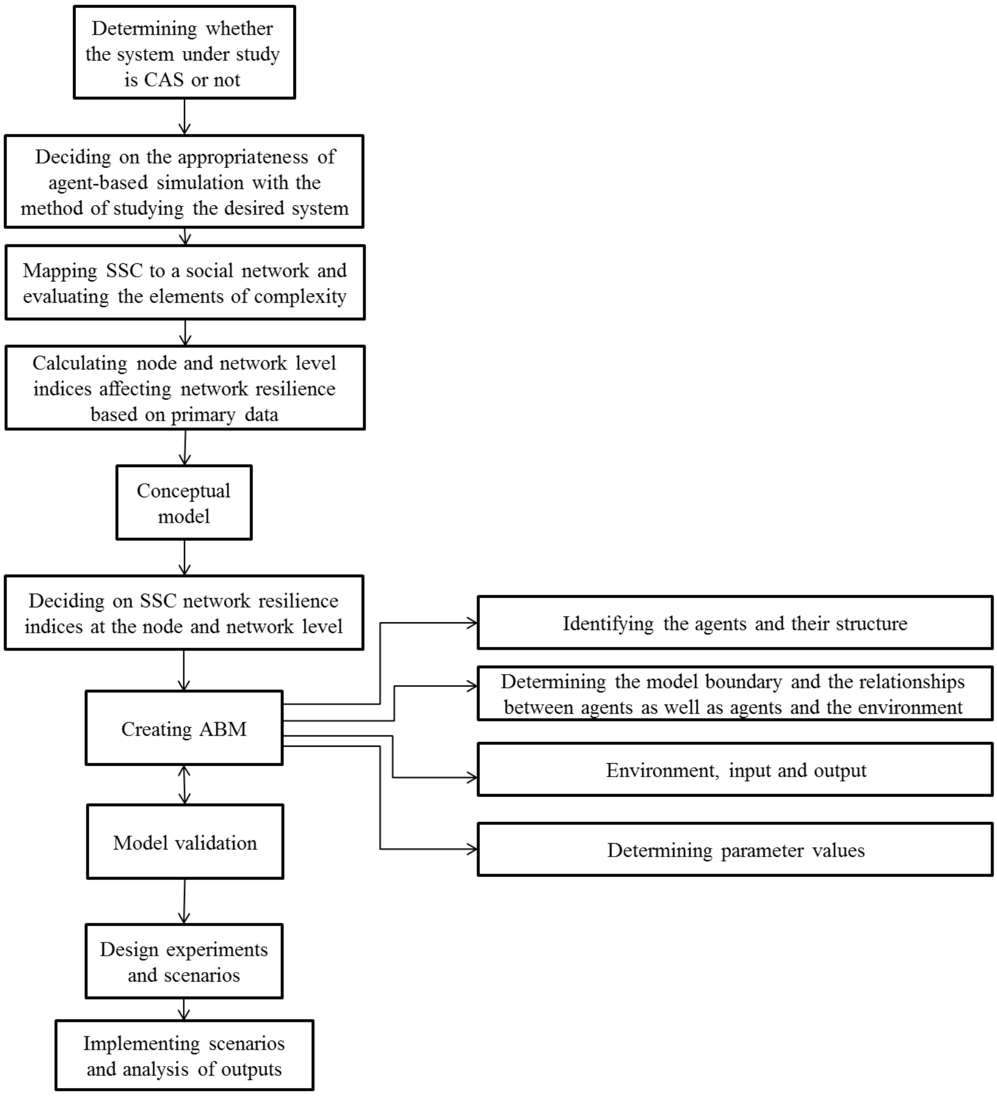

FIGURE 1
ABMS RESEARCH METHODOLOGY BASED ON NETWORK ANALYSIS

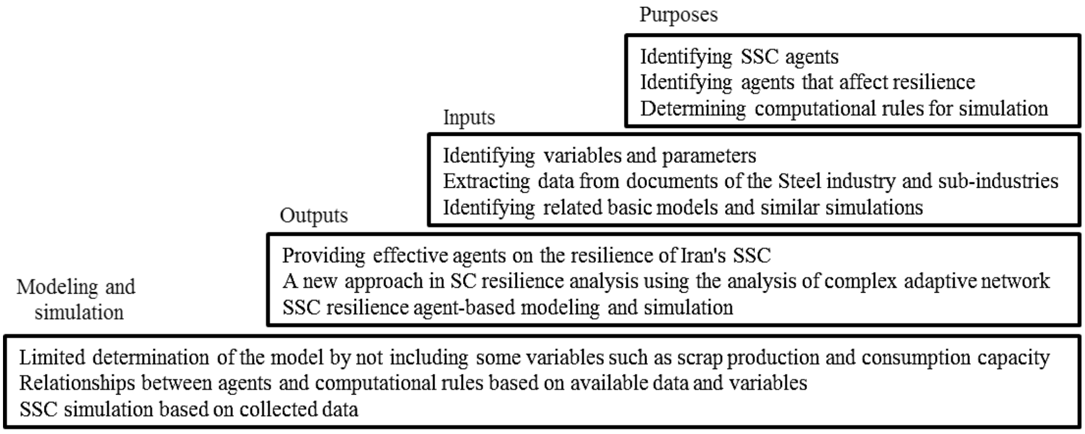

FIGURE 2
CONCEPTUAL MODEL OF RESEARCH

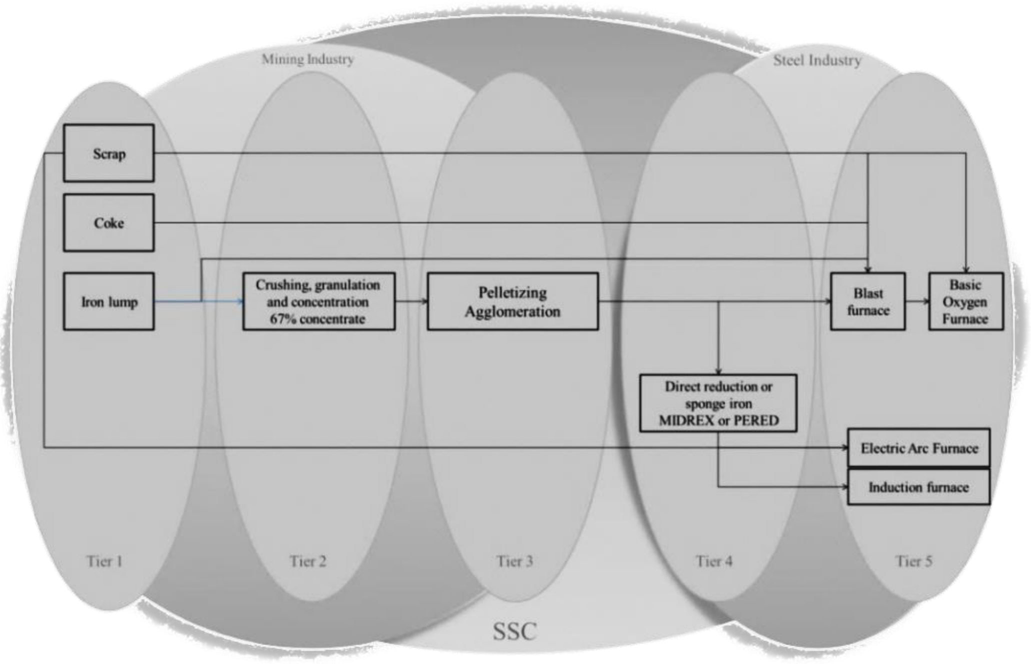

FIGURE 3.
SISC FRAMEWORK AND MODEL BOUNDARIES [35]

THE RELATIONSHIP BETWEEN RESILIENCE AND NODE AND NETWORK LEVEL INDICES IN A COMPLEX ADAPTIVE NETWORK

As depicted in Figure 4, a dense network requires greater operational effort and coordination to maintain. While a higher network density, along with an increase in membership, correlates with enhanced robustness, it also leads to reduced resilience [35]. Network density refers to the ratio of the actual number of edges in a network to the maximum possible number of edges it could have. Measuring network density provides valuable insights into the complexity and interconnectedness of supply chain networks [36].

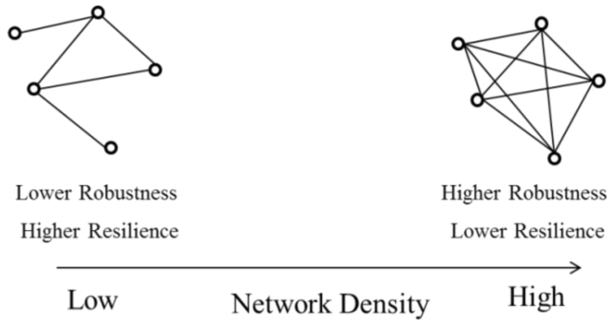

FIGURE 4
LOW DENSITY VS. HIGH DENSITY NETWORK WITH RESILIENCE APPROACH [35]

The concept of path allows exploring the structure of a given graph. A path is described as a sequence of nodes to navigate from a source node to a target node [37]. APL refers to the mean distance of the shortest paths between all possible pairs of nodes within a network. A shorter distance between two nodes signifies a faster material flow rate. Consequently, analyzing network robustness involves comparing APL before and after disruptions. Centrality analysis and SN theory have been widely applied to airport networks for analyzing the topological properties (such as connectivity, network structures, betweenness, closeness, etc.), network performances, and system robustness ([38], [39], [40]). Centrality relates to the proportion of overall network connectivity that can be attributed to a specific node. A fully centralized network has reduced robustness, as disruptions to key agents, whether directly or indirectly, can create a pervasive effect impacting other agents. The control of a highly centralized network depends on several key nodes, and activating these nodes can quickly restore the supply chain by mitigating disruptions, thus making the resilience of such networks uncertain. Betweenness centrality is one of the most prominent, as it measures the degree to which a vertex is in a position of brokerage by summing up the fraction of shortest paths between other pairs of vertices passing through it [41]. Network betweenness-centrality highlights the role of network members in material pickup and delivery. This indicates that many nodes depend on an intermediary node, making it a potentially more accurate measure of robustness than centrality. Betweenness is defined by equation (1), where σ(i,j) represents the number of shortest paths between nodes i and j, and σ(i,k,j) denotes the number of shortest paths between i and j that pass through node k. Equations (2) and (3) represent closeness centrality and centrality, respectively. These indices can be used to analyze both static stability and resilience within networks [35].

$$betweenness\ (k) = \sum_{i \neq j \neq k} \frac{\sigma(i,k,j)}{\sigma(i,j)} \quad (1)$$

$$clossness\ centrality\ (k) = \left(\sum_{t \in \mathrm{N}} \iota(k,t)\right)^{-1} \quad (2)$$

$$centrality\ (k) = \left(\max_{t \in \mathrm{N}} \iota(k,t)\right)^{-1} \quad (3)$$

Table 1 displays the agents, network parameters of the Iran’s SISC network, along with their respective initial values. Moreover, Figure 5 depicts the visual representation of Iran's steel chain network. In this visualization, the node size indicates its centrality degree, the color gradient signifies the betweenness degree, and the numerical values on the arcs indicate the material flow weight between nodes. Nodes highlighted in red represent those selected as either the source or destination node during the shortest path determination process at specific moments.

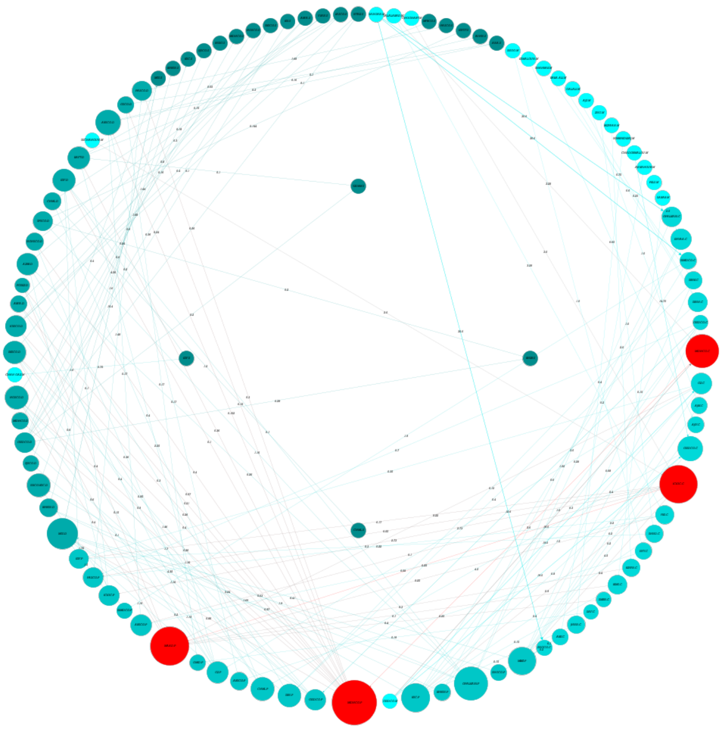

FIGURE 5
MAPPED NETWORK FOR IRAN’S SISC

TABLE 1
AGENTS AND NETWORK PARAMETERS OF IRAN'S SISC NETWORK

Label	Node Type	Weighted Degree	Closnesscentrality	Betweenesscentrality	Modularity_class	Eigencentrality
MIDHCO.P	Pellet	10.722	0.658537	65.233333	1	0.015871
MAAD.P	Pellet	2.92	0.714286	51.666667	5	0.05202
ICIOC.C	Concentrate	10.1	0.480769	50	2	0.002939
OPALKANI.P	Pellet	6.4	0.647059	41	3	0.01734
MIDHCO.C	Concentrate	27.88	0.405797	40.233333	1	0.002939
MSS.D	DRI	24.6	1	35.166667	8	0.510464
KSC.P	Pellet	10.74	0.666667	30	6	0.076561
MSC.P	Pellet	13.29	0.666667	27.833333	8	0.085231
ARSCO.D	DRI	0.702	1	22.166667	7	0.138667
GISDCO.C	Concentrate	43.25	0.451613	21.9	1	0.002939
CHML.P	Pellet	8.2	0.636364	18.4	1	0.015871
SBN.P	Pellet	1.02	0.666667	18	2	0.024541
SSICO.KSC.D	DRI	11.52	1	18	6	0.243505
HOSCO.D	DRI	4.14	1	18	5	0.228868
SKSCO.D	DRI	4.05	1	17	5	0.228868
ESF.D	DRI	1.5	1	17	6	0.232043
BAFT.D	DRI	1.21	1	15.9	1	0.070068
AZRB.D	DRI	1.46	1	15	2	0.163444
GZ.P	Pellet	5.33	0.65	14.366667	1	0.00867
IGISCO.D	DRI	1.82	1	13.9	1	0.087644
ARSCO.P	Pellet	0.35	0.6	13.333333	7	0.024541
GISDCO.P	Pellet	22.42	0.608696	13.166667	5	0.001469
GZ.C	Concentrate	24	0.458333	13.033333	1	0.001469
EHYAA.C	Concentrate	4.3	0.433333	13	4	0.001469
ICIOC.P	Pellet	4.93	0.666667	12	2	0.015871
GISDCO.D	DRI	6.33	1	11.833333	5	0.00867
OPALKANI.C	Concentrate	33	0.413793	11	3	0.001469
PASCO.P	Pellet	2.95	0.666667	11	2	0.02601
SBNH.C	Concentrate	1.25	0.454545	10	2	0.002939
ESF.P	Pellet	1.82	0.666667	10	6	0.033211
SPSCO.D	DRI	1.504	1	10	3	0.051023
PASCO.D	DRI	3.46	1	10	2	0.119622
KIMS.C	Concentrate	0.4	0.473684	9	6	0.001469
FKS.C	Concentrate	3.83	0.464286	7.833333	5	0.001469
KHRSN.D	DRI	3.92	1	7	4	0.08447
SBNK.C	Concentrate	1.55	0.5	6	8	0.001469
SHND.C	Concentrate	1.7	0.5	6	6	0.001469
RZWN.C	Concentrate	2.3	0.461538	6	5	0.001469
JHNN.C	Concentrate	0.65	0.5	6	6	0.001469
ARSCO.P	Pellet	0.42	0.6	6	7	0.00867
NGHSCO.D	DRI	0.94	1	6	1	0.070068
CHML.D	DRI	3.6	1	5.7	1	0.043822
SIMIDCO.C	Concentrate	32.5	0.571429	4	3	0.001469
NFY.C	Concentrate	1.25	0.444444	4	7	0.001469
KHRSN.P	Pellet	3.51	0.666667	4	4	0.010139
MIDHCO.D	DRI	1.76	1	4	1	0.043822
GSCO.D	DRI	0.39	1	3.833333	7	0.052492
ARFA.D	DRI	1.86	1	3.5	1	0.087644
AJIK.C	Concentrate	1.2	0.5	3	8	0.001469
AJIY.C	Concentrate	6.85	0.5	3	0	0.001469
AKK.C	Concentrate	0.4	0.5	3	8	0.001469
SNGCO.P	Pellet	3.9	0.666667	3	8	0.00867
SNGCO.C	Concentrate	32	0.5	2	3	0.001469
OMID.P	Pellet	0.35	0.666667	2	7	0.001469
SIMIDCO.P	Pellet	3.62	0.666667	2	6	0.00867
SJSCO.D	DRI	1.76	1	2	5	0.00867

As depicted in Table 2, the primary agents under investigation encompass mines, iron concentration lines, agglomeration, DRI units, steel plants, and direct connections to mines, concentrate, pellets, DRI, among others. During simulation execution, each agent endeavors to transition its state from failure to responsiveness.

Consequently, the count of disturbed agents is anticipated to diminish, leading to a corresponding augmentation in the numbers of responsive and resistant agents.

TABLE 2.
AGENTS AND LİNKS BREEDS İN SISC AGENT-BASED SİMULATİON

breed [mines mine]	Iron ore mining agents
breed [concentrates concentrate]	Cnocentrates units agents
breed [pellets pellet]	Pilletizng units agents
breed [dris dri]	DRI units agnets
breed [steels steel]	Steelmaking agents
directed-link-breed [iron-links iron-link]	Links from mine to concentrate agents
directed-link-breed [concentrate-links concentrate-link]	Links from concentrate to pelletizing agents
directed-link-breed [pellet-links pellet-link]	Links from pelletizing to DRI agents
directed-link-breed [dri-links dri-link]	Links from DRI to steelmaking agents

The agent's behavior is visually represented. Table 3 delineates the variables incorporated within the proposed agent-based modeling framework.

TABLE 3.
VARIABLES

Variables	Global variables
The amount of product disturbance status (binary) Responsiveness Disaster monitoring (disruption) Capacity Input grade Output grade Centrality Betweenness centrality Weight (product flow)	The amount of the final product Maximum quantity of products Average flow Agents identifier variables Network density

The SSCR simulation employs NW (Network) and CSV (Comma-separated values) file formats. These formats facilitate the generation of output suitable for analysis in both Excel and Gephi, and offer an efficient means for input provision. Consequently, all variables are initially prepared within the spreadsheet interface of Excel software and subsequently transformed into CSV format using NetLogo. This methodology ensures accessibility to results in Excel and Gephi throughout all stages of model implementation, validation, and sensitivity analysis.The SSCR simulation employs NW (Network) and CSV (Comma-separated values) file formats. These formats facilitate the generation of output suitable for analysis in both Excel and Gephi, and offer an efficient means for input provision. Consequently, all variables are initially prepared within the spreadsheet interface of Excel software and subsequently transformed into CSV format using NetLogo. This methodology ensures accessibility to results in Excel and Gephi throughout all stages of model implementation, validation, and sensitivity analysis.

STATISTICAL HYPOTHESIS TESTING

The complexity of the SISC network necessitates assessment by the researcher. It is commonly asserted that real-world networks exhibit scale-free properties, wherein certain nodes adhere to a power-law distribution (a model that significantly influences the structure and dynamics of complex systems through the organization of scale-free networks). Employing statistical methodologies, [42] demonstrates that across numerous networks, a lognormal distribution provides a more accurate fit for the data. Empirical evidence suggests singular variables consist of a large bell shaped concentration of values with a heavy right tail and are well suited to modelling with the log-normal distribution [43]. The application of the Kolmogorov-Smirnov test (refer to figures 6 and 7) reveals that the arrangement of nodes within the target network conforms to a lognormal distribution. Consequently, the network in question exhibits characteristics of a complex network, affirming that agent-based modeling stands as a robust approach for simulating its resilience.

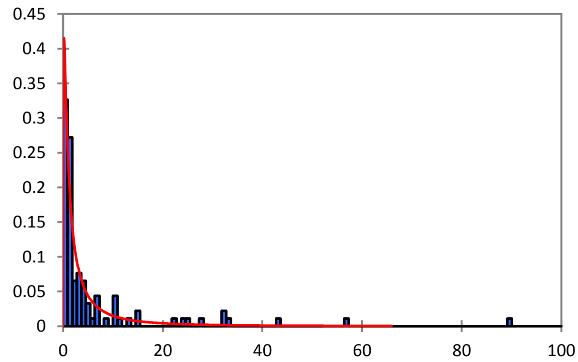

FIGURE 6
DISTRIBUTION OF DATA PERTAINING TO THE DEGREE

Kolmogorov-Smirnov test:

D	0.082
p-value	0.480
alpha	0.05

Test interpretation:

H0: The sample follows a Log-normal distribution
Ha: The sample does not follow a Log-normal distribution

As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.

The risk to reject the null hypothesis H0 while it is true is 47.97%.

FIGURE 7.
KOLMOGOROV-SMIRNOV TEST FOR NODES DEGREE DATA

MODEL IMPLEMENTATION

The model comprises two distinct phases. Initial preprocessing steps are executed by activating the "Initial Settings" button. This phase entails specifying the SCC network and its constituent agents, establishing links along with their associated variables and initial values, and defining initial parameters and indices. Illustrated in Figure 8, the initial setting and run panel feature 5 buttons, 2 choosers, and 6 sliders, facilitating model execution across various modes and enabling the extraction of diverse outputs through value adjustments. The choosers afford the selection of six distinct scenarios, each dictating the extent of interference imposed on the agents by the user. In the initial scenario, disruption affects agents at all hierarchical levels (mine, concentrate, pellets, sponge iron, and steel), while subsequent scenarios target individual tiers of agents. This range of scenarios enables exploration into the agents most susceptible to network disruptions and, consequently, those exerting greater influence on resilience. Furthermore, a dedicated panel is provided for conducting network analysis within the NetLogo environment.

Centrality metrics serve to gauge node importance within the network, with connectivity to other nodes constituting a primary determinant. This parallels real-world scenarios, wherein individuals with extensive social connections often wield greater influence. Quantitative indicators are commonly employed to ascertain node significance, necessitating robust quantification methods suitable for intricate and expansive networks. Key centrality metrics considered in the model include betweenness, closeness, and eigenvector centrality. Betweenness-centrality quantifies the number of shortest paths traversing a given node, reflecting its pivotal role in network connectivity. Closeness centrality, inversely related to the average shortest path between nodes, denotes the efficiency of node access within the network. Additionally, eigenvector centrality incorporates node influence alongside connectivity, further enriching centrality assessments. Within the proposed framework, two monitors are dedicated to outputting network density and betweenness-centrality, acknowledging the latter's pivotal role in network resilience. Output options include formats compatible with Gephi and Excel, facilitating model evaluation and sensitivity analyses. The study's output variables encompass:

Number of nodes prone to receiving the perturbation

- Number of disrupted nodes in each scenario
- Resistant nodes for each scenario
- Degree of betweenness centrality as a basic indicator for measuring the resilience of nodes
- Weight of each link in the post-catastrophic period
- Redundancy rate
- Production rate of each node

The size of each node depends on the ratio of each node to the final product. The color of each link is a red spectrum and follows the ratio of the initial weight of each link to the average flow rate of material.

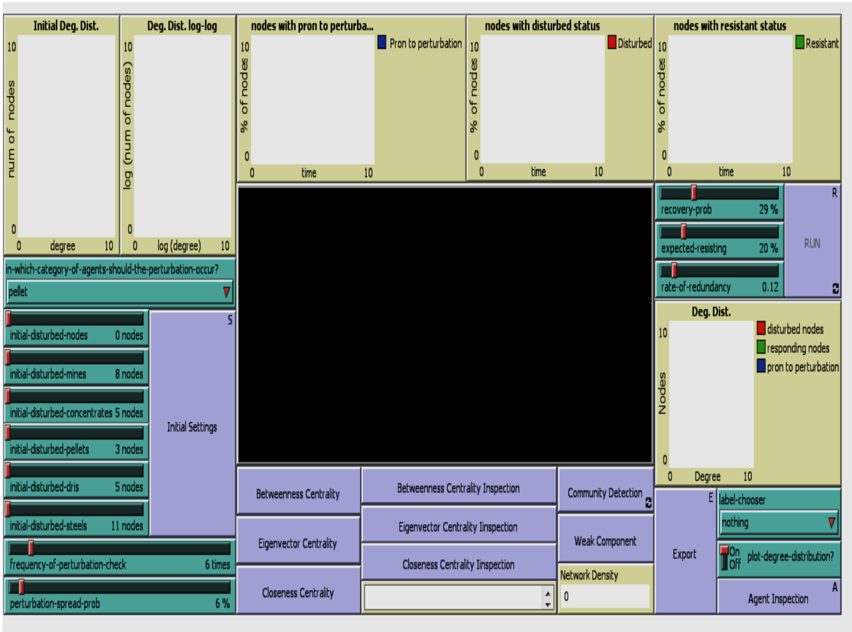

FIGURE 8
VIEW OF THE SOFTWARE ENVIRONMENT THAT IS READY TO RUN ONE OF THE SCENARIOS

This study conducted both internal (conceptual) and external validation processes to ascertain the robustness of the agent-based model. Internal validity was initially established through interviews with two subject matter experts, with necessary adjustments made accordingly to corroborate the model's fidelity. External validation involved comparing the outcomes of agent-based modeling with empirical data extracted from monitoring reports spanning the Iranian steel industry's operations from 2018 to 2020. The comparative analysis revealed a deviation of less than 20%, signifying the external validity of the proposed model.

EXPERIMENTAL DESIGN AND SENSITIVITY ANALYSIS

BehaviorSpace serves as an integrated software tool within NetLogo, facilitating the design and execution of experiments for agent-based modeling and simulation. It allows for systematic modification of model settings and the recording of results through multiple runs with varied configurations, a process commonly referred to as parameter sweeping. This tool enables exploration of the model's behavioral landscape, aiding in the identification of factors contributing to specific behaviors. The proposed model incorporates various selection and slider controls, which serve as instruments for designing diverse experiments. Based on the model's settings, an extensive array of experiments could potentially be devised, totaling 128,357,460 model implementations per iteration. However, such a vast number of tests may encounter limitations imposed by hardware capabilities. Consequently, adjustments were made to accommodate the available hardware resources, resulting in the execution of the designed experiments across 21,600 runs, as depicted in Figure 9.

This number of experiments was performed in 6 main categories according to the Table 4. Table 5 shows the output, the location of the result, and the termination conditions. The output files were obtained in two formats: Excel spreadsheets and tables used in sensitivity analysis. Commonly employed methods for sensitivity analysis encompass the Log-Odds Ratio (ΔLOR), nominal range sensitivity, Break-Even Analysis (BEA), Automatic Differentiation (AD), regression analysis, Fourier Amplitude Sensitivity Test (FAST), Mutual Information Index (MII), scatter plots, and Analysis of Variance (ANOVA). Given the stochastic simulation prerequisites and the concurrent and collective influence of multiple inputs, the nonlinear regression method was selected for sensitivity analysis due to its feasibility. Statistical summaries pertaining to the responsive node behavior model in Scenario 3 are provided in Table 6, while Table 7 offers a statistical overview concerning the validation of the behavioral model for the response node in the same scenario. Furthermore, Table 8 presents a summary of the symmetric matrix detailing the correlation coefficients between the dependent and independent variables of the response node in Scenario 3. Curve fitting statistics for the response node behavior in Scenario 3 are delineated in Table 9. Additionally, Figure 10 illustrates a distribution plot depicting the values of the dependent variable for the response node in Scenario 3, alongside the selected values of the model's independent variable, accompanied by a time series plot showcasing the residuals (observed values).

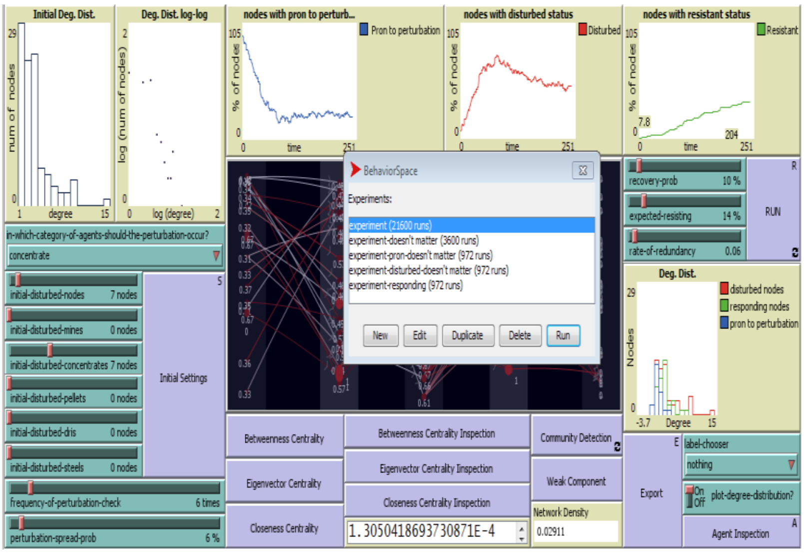

FIGURE 9

VIEW OF THE EXPERIMENTAL DESIGN SPACE.

The fitted equation (4) of the regression model for the nodes responding in Scenario 3 is as follows:

$$
\begin{aligned}
&\mathit{responding} = \\
&-6.58096021687075 \\
&-1.11376557581175*\mathit{rate\text{-}of\text{-}redundancy} \\
&+1.75834994293098*\mathit{perturbation\text{-}spread\text{-}prob} \\
&+0.248777945316252*\mathit{expected\text{-}resisting} \\
&+3.63614751471325*\mathit{frequency\text{-}of\text{-}perturbation\text{-}check} \\
&+0.989060996457068*\mathit{initial\text{-}disturbed\text{-}concentrates} \\
&-0.55204582190443*\mathit{recovery\text{-}prob} \\
&-2.03681645111337E\text{-}02*\mathit{perturbation\text{-}spread\text{-}prob}^\wedge 2 \\
&-7.2154536362563E\text{-}04*\mathit{expected\text{-}resisting}^\wedge 2 \\
&-0.107326486744447*\mathit{frequency\text{-}of\text{-}perturbation\text{-}check}^\wedge 2 \\
&-2.25936935259284E\text{-}02*\mathit{initial\text{-}disturbed\text{-}concentrates}^\wedge 2 \\
&+2.5131111567747E\text{-}03*\mathit{recovery\text{-}prob}^\wedge 2 \qquad (4)
\end{aligned}
$$

ABLE 4
EXPERİMENTAL DESİGN PROCESS SCENARİOS.

Scenario	Settings
1	["in-which-category-of-agents-should-the-perturbation-occur?" "doesn't matter"] ["rate-of-redundancy" 0 0.5 1] ["perturbation-spread-prob" 0 25 50] ["expected-resisting" 1 50 100] ["perturbation-check-frequency" 1 10 20] ["initial-disturbed" 1 10 20 30] ["recovery-prob" 10 55 100]
2	["in-which-category-of-agents-should-the-perturbation-occur?" "mine"] ["rate-of-redundancy" 0 0.25 0.5 0.75 1] ["perturbation-spread-prob" 0 10 20 50] ["expected-resisting" 1 50 100] ["perturbation-check-frequency" 1 10 20] ["initial-disturbed" 1 10 19] ["recovery-prob" 10 20 30 40]
3	["in-which-category-of-agents-should-the-perturbation-occur?" "concentrate"] ["rate-of-redundancy" 0 0.25 0.5 0.75 1] ["perturbation-spread-prob" 0 10 20 50] ["expected-resisting" 1 50 100] ["perturbation-check-frequency" 1 10 20] ["initial-disturbed" 1 11 22] ["recovery-prob" 10 20 30 40]
4	["in-which-category-of-agents-should-the-perturbation-occur?" "pellet"] ["rate-of-redundancy" 0 0.25 0.5 0.75 1] ["perturbation-spread-prob" 0 10 20 50] ["expected-resisting" 1 50 100] ["perturbation-check-frequency" 1 10 20] ["initial-disturbed" 1 9 18] ["recovery-prob" 10 20 30 40]
5	["in-which-category-of-agents-should-the-perturbation-occur?" "dri"] ["rate-of-redundancy" 0 0.25 0.5 0.75 1] ["perturbation-spread-prob" 0 10 20 50] ["expected-resisting" 1 50 100] ["perturbation-check-frequency" 1 10 20] ["initial-disturbed" 1 10 20] ["recovery-prob" 10 20 30 40]
6	["in-which-category-of-agents-should-the-perturbation-occur?" "steel"] ["rate-of-redundancy" 0 0.25 0.5 0.75 1] ["perturbation-spread-prob" 0 10 20 50] ["expected-resisting" 1 50 100] ["perturbation-check-frequency" 1 10 20] ["initial-disturbed" 1 11 22] ["recovery-prob" 10 20 30 40]

TABLE 5
EXPERİMENTAL DESİGN PROCESS İNSTRUCTİONS

(count turtles with [not disturbed? and not responding?])/ (count turtles) * 100 (count turtles with [disturbed?])/ (count turtles) * 100 (count turtles with [responding?])/ (count turtles) * 100	Commands for outputs
export-all-plots "G:/THESIS/0-negaresh/NETLOGO/0-EJRA/Sensitivity Analysis/plots"	Save results
not any? turtles	Termination condition

TABLE 6
STATISTICAL SUMMARY OF RESPONSIVE NODE BEHAVIOR MODEL IN SCENARIO 3

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
responding	669	0	669	0.000	86.994	32.458	26.121
rate-of-redundancy	669	0	669	0.500	1.000	0.831	0.237
perturbation-spread-prob	669	0	669	1.000	50.000	25.333	20.021
expected-resisting	669	0	669	1.000	100.000	49.667	40.394
frequency-of-perturbation-check	669	0	669	1.000	20.000	10.502	7.751
initial-disturbed-concentrates	669	0	669	1.000	21.000	11.105	8.180
recovery-prob	669	0	669	10.000	100.000	54.933	36.729

TABLE 7
STATISTICAL SUMMARY RELATED TO THE VERIFICATION OF THE BEHAVIOR MODEL OF THE RESPONDING NODES IN SCENARIO 3

Variable	Observations	Obs. With missing data	Obs. Without missing data	Minimum	Maximum	Mean	Std. Deviation
responding	60	0	60	0.000	88.128	31.540	25.853
rate-of-redundancy	60	0	60	0.500	1.000	0.858	0.227
perturbation-spread-prob	60	0	60	1.000	50.000	25.333	20.174
expected-resisting	60	0	60	1.000	100.000	57.767	40.609
frequency-of-perturbation-check	60	0	60	1.000	20.000	8.450	7.749
initial-disturbed-concentrates	60	0	60	1.000	21.000	9.833	8.045
recovery-prob	60	0	60	10.000	100.000	55.750	37.505

TABLE 8
SYMMETRIC MATRIX OF CORRELATION COEFFICIENTS BETWEEN THE DEPENDENT VARIABLE OF THE RESPONDING NODES AND THE INDEPENDENT VARIABLES IN SCENARIO 3.

Variables	rate-of-redundancy	perturbation-spread-prob	expected-resisting	frequency-of-perturbation-check	initial-disturbed-concentrates	recovery-prob	responding
rate-of-redundancy	**1.000**	0.000	0.019	0.012	-0.006	-0.013	0.005
perturbation-spread-prob	0.000	**1.000**	0.014	-0.018	0.000	-0.009	0.549
expected-resisting	0.019	0.014	**1.000**	-0.002	0.020	0.011	0.277
frequency-of-perturbation-check	0.012	-0.018	-0.002	**1.000**	0.008	0.016	0.387
initial-disturbed-concentrates	-0.006	0.000	0.020	0.008	**1.000**	-0.011	0.172
recovery-prob	-0.013	-0.009	0.011	0.016	-0.011	**1.000**	-0.386
responding	0.005	0.549	0.277	0.387	0.172	-0.386	**1.000**

.

TABLE 9

STATISTICS OF CURVE FITTING OF RESPONDING NODES BEHAVIOR IN SCENARIO 3.

Observations	669.000
DF	638.000
R^2	0.800
SSE	91142.057
MSE	142.856
RMSE	11.952

RESEARCH FINDINGS AND CONCLUSION

This study aimed to simulate the resilience of Iran's SISC by employing graph theory to map a complex adaptive problem onto an interactive network. The fundamental concept involves conceptualizing the supply chain network as a complex adaptive system. Examination of the data pertaining to node weights revealed a lognormal distribution, particularly in relation to the number of available connections, which encompasses the sum of input and output degrees of the node. Consequently, there is substantial evidence to suggest that the network under scrutiny adheres to the characteristics of a complex network, warranting the utilization of agent-based modeling. The findings of this study can be analyzed through various lenses:

- Providing an overview of Iran's steel chains.
- Offering a methodology for resilience analysis, focusing on disruptions and responses, by applying problem mapping to complex SN's and utilizing diverse metrics at both node and network levels.
- Identifying the determinants of Iran's SISC from a resilience standpoint.
- Describing agents, variables, and the relationships between parameters.
- Implementing simulations across six distinct scenarios, where faults may occur at any node within any category, with failures restricted to mineral nodes, concentrates, pelletization, sponge iron, and steelmaking.

Following disturbances in each scenario, betweenness-centrality is computed. This metric serves as an indicator of the resilience exhibited by individual agents within each scenario. The presence of diversity among agents demonstrating adequate resilience underscores the notion that the resilience of Iran's SISC network transcends reliance on any specific agent type. The quantitative analysis of resilience represents a pivotal advancement in this research endeavor. Network indicators offer a potent methodology for quantitatively elucidating abstract constructs such as resilience and robustness. Given that supply chain networks frequently exhibit characteristics akin to complex adaptive systems, the utilization of network indicators proves instrumental in resilience analysis. Consequently, agent-based simulation emerges as a valuable tool for simulating disruptions within the supply chain and exploring various scenarios. These scenarios encompass diverse disruptions affecting different agent types, with attention given to monitoring the recovery process until full network restoration is achieved.

The simulation utilized data sourced from Iran's National Steel Industry Monitoring Report as input for Gephi (0.9.2) to construct a network comprising fundamental agents. Node and network level indices were computed and fed into NetLogo (6.2.0) as input for network parameters. Model validity was confirmed through iterative implementation employing diverse datasets, with Figure 11 showcasing various model behaviors across different scenarios. Sensitivity analysis was conducted using NetLogo's Behavior Space tool, while the model's behaviors were elucidated through non-linear regression, representing fitted functions. Internal (conceptual) and external validation procedures were conducted to assess the proposed model's validity. Following simulation runs across each scenario, researchers can utilize the output function to extract results in Gephi format. This facilitates the computation of network indices within the data-lab module of the software.

Table 10 displays the degree of betweenness-centrality for each node, serving as an indicator of its resilience. Subsequently, the ensuing table illustrates the network-level indices of agents during SISC resilience simulation. By virtue of these indices being arranged according to the degree of betweenness-centrality, effective agents contributing to Iran's SISC resilience can be identified. As evident in Table 10, in a tested scenario, the concentrate iron and sponge iron-related agents in MIDHCO sub-network exhibit the greatest impact on network resilience. This phenomenon is attributed to the completeness of the steel production supply chain within this sub-network.

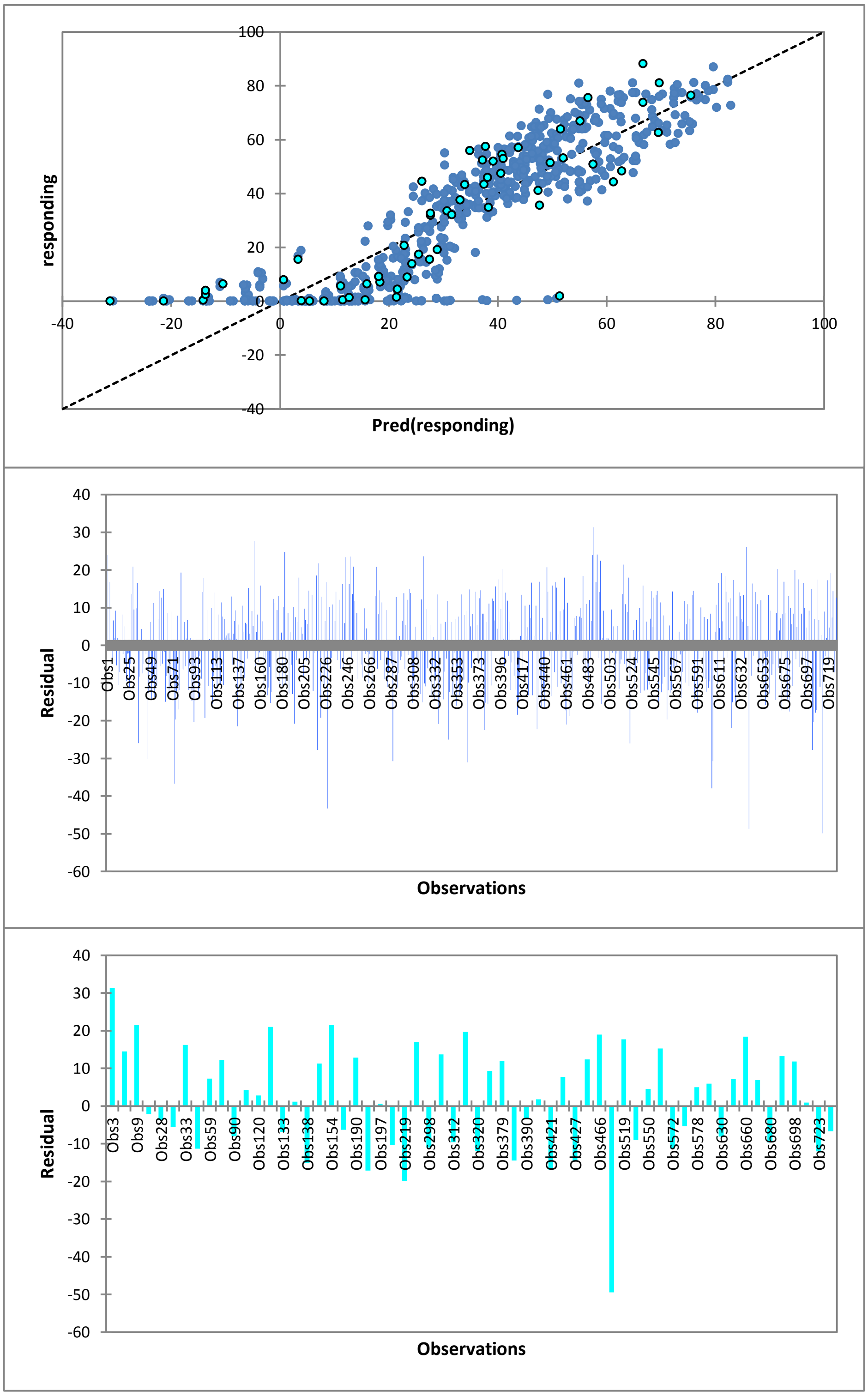

FIGURE 10
DISTRIBUTION PLOT OF THE DEPENDENT VARIABLE VALUES OF THE RESPONSE NODE IN SCENARIO 3 AGAINST THE SELECTED VALUES OF THE INDEPENDENT VARIABLES OF THE MODEL, AND A TIME SERIES PLOT OF THE RESIDUALS (OBSERVATIONS)

TABLE 10
CALCULATED INDICES FOR IRAN'S SISC AGENTS AFTER SIMULATION

Label	Node Type	Betweenesscentrality
MIDHCO.D	DRI	25.48662936
MIDHCO.C	Concentrate	25.25827325
SBNH.C	Concentrate	24.06956392
PASCO.D	DRI	23.83571432
GZ.C	Concentrate	23.51586381
SIMIDCO.C	Concentrate	23.10447464
SNGCO.C	Concentrate	22.74741227
MSC.P	Pellet	21.63025269
CHML.P	Pellet	20.82468761
ARFA.D	DRI	20.64958549
MIDHCO.P	Pellet	18.87216523
ICIOC.C	Concentrate	18.44638959
NFY.C	Concentrate	17.93474649
SHND.C	Concentrate	17.72946032
SSICO.KSC.D	DRI	17.54934721
NGHSCO.D	DRI	16.94373659
SIMIDCO.P	Pellet	15.20641751
HOSCO.D	DRI	14.6575623
OMID.P	Pellet	14.19672711
ARSCO.P	Pellet	13.58989963
AKK.C	Concentrate	13.24534732
KHRSN.D	DRI	12.57361014
PASCO.P	Pellet	12.40921554
ESF.P	Pellet	11.8239215
SKSCO.D	DRI	11.64894977
OPALKANI.C	Concentrate	11.24337814
MSS.D	DRI	10.83838555
AJIK.C	Concentrate	10.66096182
SBN.P	Pellet	10.51859582
ICIOC.P	Pellet	10.03072438
GISDCO.D	DRI	9.402743652
JHNN.C	Concentrate	9.237265943
SPSCO.D	DRI	8.728461656
OPALKANI.P	Pellet	7.538876173
AZRB.D	DRI	6.503727345
IGISCO.D	DRI	6.169915551
RZWN.C	Concentrate	5.996240493
BAFT.D	DRI	5.263032873
SJSCO.D	DRI	4.40861679
ARSCO.P	Pellet	3.845508255
GISDCO.P	Pellet	3.533222788
KIMS.C	Concentrate	3.005696798
SBNK.C	Concentrate	2.852366998
SNGCO.P	Pellet	2.281803031
EHYAA.C	Concentrate	2.127553267
GISDCO.C	Concentrate	1.196742898
KHRSN.P	Pellet	0.158440024

Scrap holds significant importance within steel chains due to its advantages over iron ore in steel production, encompassing factors such as slag reduction, up to 80% energy consumption reduction, water conservation, environmental benefits, furnace efficiency enhancement, and promotion of circular economy principles. Establishing scientific and practical frameworks for scrap metal recycling and management in Iran is imperative and can substantially contribute to supply chain resilience. Additionally, this study underscores a practical recommendation, demonstrating that a complete steel chain node exhibits the highest degree of betweenness-centrality, thereby indicating the highest level of resilience. However, a notable constraint encountered during sensitivity analysis lies in the time-intensive nature of parameter sweeping processes. In response, we advocate for the utilization and comparison of a broad spectrum of meta-heuristic algorithms.

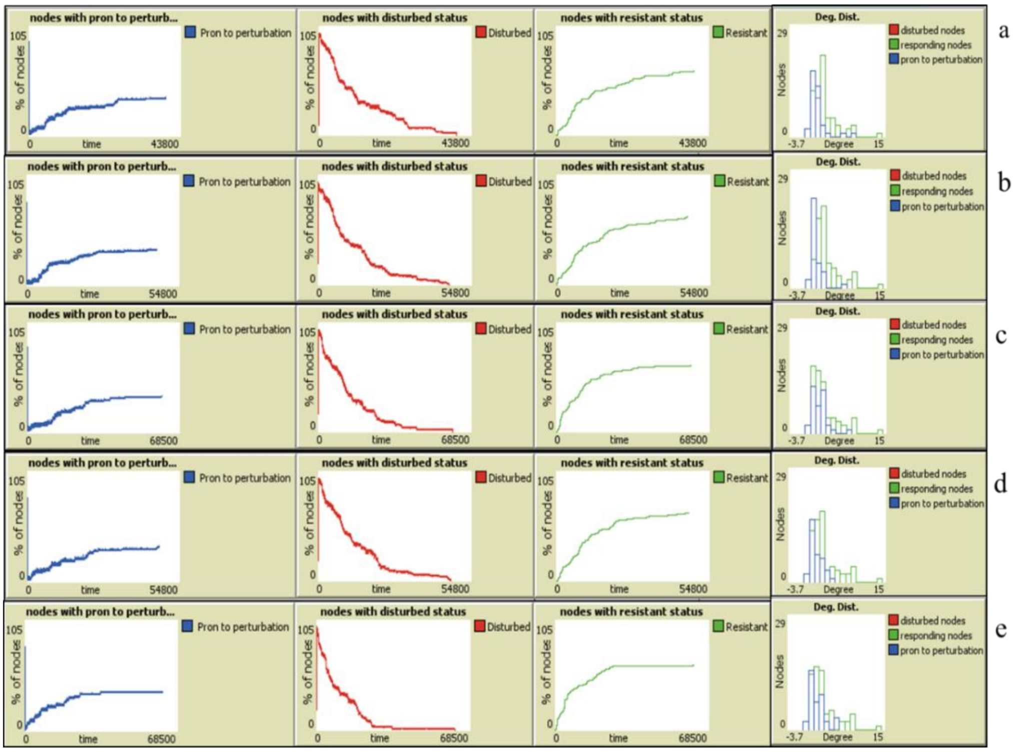

FIGURE 11

MODEL BEHAVIOR BASED ON DIFFERENT SCENARIOS DURING THE SENSITIVITY ANALYSIS PROCESS: A) DISRUPTION IN MINING FACTORS. B) DISRUPTION IN CONCENTRATE AGENTS. C) DISRUPTION IN PELLETIZING AGENTS. D) DISRUPTION OF SPONGE IRON AGENTS. E) DISRUPTION OF STEELMAKING AGENTS.

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