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# Understanding the Variables for Steel Production through System Dynamics Modelling

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## Abstract

The current volatility in the marketplaces, complexity in technology, and fluctuations in customer demand motivate us to understand the dynamics involved in a complex system. This study focuses on analyzing the steel bar production system and its performance. This study uses system dynamics modelling (SDM) to model a steel plant production system and demonstrate a decision-making approach to improve steel bar production. This study uses simulation to incorporate key factors identified from existing research, including those that influence steel production. A causal loop diagram (CLD) and stock-flow diagram (SFD) are used to analyze the involved qualitative and quantitative features. In addition, sensitivity analysis was performed to analyze how the production grows with time in various scenarios of input variables. This model can be customized for specific steel plants. Industry practitioners can use this framework to make data-driven decisions regarding steel production. Additionally, practitioners can leverage this study to determine the essential variables and identify the factors that negatively or positively impact steel production.

## Keywords
System Dynamics Modelling, Vensim, Systems thinking, Simulation, Sensitivity analysis, Manufacturing.

## 1. Introduction
Manufacturing creates wealth and increases a country's prosperity by adding value to raw materials (Adane et al., 2019). Resource security is a very critical issue for natural resources; among all key mineral resources, iron and steel are the key raw materials for several industries such as vehicles, road & building construction, manufacturing tools & equipment, etc. (Hao et al., 2024).

A production system like a steel plant has multiple input and output variables. There are various feedback loops in this system, and the behaviour of the system may change in a linear or nonlinear manner. Analyzing this behavior may be complex and time-consuming. Hence, a practical framework is needed to analyze multiple scenarios, aid decision-making, identify suitable action points, and understand the interaction and evolution of various variables over time.

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This study is about how to improve the production of steel bars in a steel plant using system dynamics modeling (SDM). SDM allows us to change the parameters affecting production and observe how production is affected. This can be shown to management when making decisions that lead to increased steel production.

Human cognition has limits, and managing these complexities is difficult. Thus, a systematic approach was applied through SDM to understand the influence of each variable on steel bar production.

### 1.1 Objectives

The main objectives of this study are focused on to:

- Identifying the variables affecting the production of Steel in a steel plant.
- Understanding the system dynamics of steel production plant performance concerning all the involved variables.

## 2. Literature Review

The steel industry faces numerous complex and interconnected challenges that can be addressed through systems thinking and system dynamics modelling. One problem is to understand the production, use, and recycling dynamics of steel products. This problem was tackled by Shi et al. (2023), who developed a system dynamics-based metal resource metabolism prediction model to simulate the life cycle of steel resources. Another problem is to incorporate cleaner and greener technologies to make steel production more sustainable and environmentally friendly. Many recent studies have prioritized this issue. Gupta et al. (2018) demonstrated how to reduce CO2 emissions in steel plants, while Li et al. (2024) worked on incorporating more eco-friendly fuel options like green hydrogen in a greater number of steel plants through government subsidies.

A critical challenge in the steel industry is increasing the production of a steel plant. One approach to tackle this problem involves implementing automation and upgrading the technology in the steel plant, which leads to improvements in efficiency and effectiveness. This can be achieved by reinvesting some of the profit from the sale of steel products into implementing better technology and increasing automation. Another possible approach is reducing production delays in the steel plant by ensuring raw material availability and machine availability. Additionally, human-related inefficiencies can be reduced by providing employees with enhanced training programs, higher wages, and performance-based incentives. Based on the literature review, the identified variables are listed in Table 1.

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Table 1. Variables to analyze steel production

| Variable | Explanation of variable | References |
|---|---|---|
| Automation/Better technology (Highly dependent) | Amount of investment in the implementation of Automation/Better technology. | Vapski et al. (2023), Javaid et al. (2021) |
| Demand (Highly dependent) | The demand for Steel bars in the market. It depends on the production cost per unit. | DebRoy and Elmer (2024), Mehmanpazir et al. (2019) |
| Environmental regulations impact (Medium dependent) | The difficulty level the steel plant must face is due to environmental regulations. It increases with stricter governance. | Fan and Friedmann (2021), Wu and Lin (2022). |
| Grade (Medium dependent) | The Grade of steel required | Mohammadi et al. (2022), Sun et al. (2020), Xie et al. 2021 |
| Inventory management costs (Medium dependent) | The cost of managing the inventory. It rises with poor quality and production volume | Soori et al. (2023), Panigrahi et al. (2022) |
| Labor skills/morale (Highly dependent) | The skill/motivation level of laborers. It is boosted by management attitude and governance. | Verma and Kesari (2020), Suzuki (2019) |
| Machine Availability (Highly dependent) | The level of availability of machines. Higher with good maintenance, slightly impacted by usage | Iglesias-Escudero et al. (2019), Mehta et al. (2019) |
| Management attitude (Medium dependent) | The attitude of the management. It affects labor skills and morale. | Berhan (2020), Verma and Kesari (2020) |
| Bad Quality Rate(Scrap/rework rate) (Medium dependent) | The rate of bad quality (scrap/rework rate). It increases with higher production. | Efatmaneshnik and Shoval (2023), Al-Kindi and Al-Ghabban (2020) |
| Raw material availability (Highly dependent) | The availability of raw materials. It is affected by logistics, infrastructure, and disruptions. | Cheng et al. (2024), Florén et al. (2019) |
| Infrastructure (Highly dependent) | Level of infrastructure (for example, roadways, railways, etc. to transport finished goods with raw material. It improves logistics and reduces disruptions. | Karthik et al. (2024), Schneider. (2022) |
| Logistics and transportation (Highly dependent) | The cost of transporting materials and other stuff. Decreases with better infrastructure | Ren et al. (2021), Bhaskar et al. (2020) |
| Marketing effort (Lowly dependent) | Level of marketing. It influences demand. | Sofla et al. (2024), Komakech et al. (2021) |

Javaid et al. (2021) showed that applying automation/better technology in steel plants results in doing repetitive jobs precisely and at a lower cost. This can increase production through stricter environmental regulations forcing steel plants to adopt more eco-friendly technology. Optimizing inventory management processes decreases production and operation costs (Soori et al., 2023), increasing steel production. Management attitude and labor skill/morale are essential variables for consideration in steel plants (Verma and Kesari, 2020). Logistics and transportation are significant in a steel plant (Liu et al. 2021). Corruption exists in steel plants, and it might affect the plant's operations. Obera et al. (2020) gave an example of corruption in steel plants through a case study.

## 3. Methods

System dynamics modeling is a method used to model complex systems. This helps us analyze and understand a complex system and its behavior over time. It uses feedback loops, stocks, and flows to represent how a system's components interact. A Steel plant is a complex system with numerous components and complicated interrelations between the processes and system parameters. A change in one parameter affects both the system's output and the interconnected parameters. There have been other approaches to increase steel production. Hong et al. (2022) developed a Discrete-Event Simulation (DES) model to increase rebar production. Zhang et al. (2018) developed a superstructure-based water network optimization model to optimize the steel production process. They also used that system to perform simulations, what-if analyses, and business scenarios to identify bottlenecks and increase their production rate.

Many researchers have applied SDM in areas such as environmental improvement, life cycle analysis, and the energy consumption of steel plants. Mohammadi et al. (2022) developed an SDM for a multi-echelon steel supply chain. By applying SDM to an Iranian steel supply chain, they found that iron ore grade and tonnage played the most significant role in steel production costs. Gupta et al. (2018) developed an SDM to reduce CO2 emissions in the iron and steel industry. They analyzed the amount of CO2 emitted by various steelmaking processes, such as cooking, sintering, and rolling, and tested how various carbon reduction technologies could decrease CO2 emissions. Mehmanpazir et al. (2022) proposed a hybrid strategy using system dynamics, game theory, and fuzzy inference to predict market trends in the steel industry.

SDM has been applied in other manufacturing sectors, such as textile, automotive, and pharmaceutical manufacturing. Narassima et al. (2023) used the system dynamics approach to test the benefits of applying Lean and 5S principles in a yarn manufacturing company. Nuñez et al. (2021) tested the effects of replacing old technology, like subtractive manufacturing, and adding new technology, like additive manufacturing, using SDM in the manufacturing sector. Gupta et al. (2018) applied SDM in a radial tyre manufacturing company to identify wastes in their manufacturing process, significantly affecting their lean-green performance. Norbert et al. (2020) developed a physicochemical sub-model and a system dynamics sub-model to assess iron and steel plants' resource and energy efficiency. Li et al. (2024) developed an SDM to evaluate the effect of subsidy and regulatory policies on green hydrogen steelmaking for Chinese and European steel Industries.

Among various methods, it has been observed that SDM can help understand how different variables interact and how they can be manipulated to increase steel production in a steel plant which is very complex in other methodologies like Discrete Event Simulation. Moreover, SDM helps us model feedback loops to capture the dynamic relationships between the variables. Causal loop diagrams (CLDs) are an essential tool for representing the feedback structure of a system (Sterman, J. D, 2000). SFDs depict the system regarding stock (accumulations) and flows (rate of change). It is used to simulate and quantify how the variables change over time. CLD is a qualitative feature of SDM, whereas SFD is a quantitative feature (Mohammadi et al., 2022).

The methodology of this study is as follows. First, the variables that affect steel production in a steel plant were identified based on existing academic literature. SDM was then created using CLD and SFD to analyze the qualitative and quantitative aspects of the system. Details of the SDM, such as the polarity and equations used, are provided in the Data Collection section. Subsequently, the sensitivity analysis was performed to observe how the system behaved in different scenarios.

## 4. Data Collection

The secondary data has been collected from different research papers. Based on the existing research and researchers understanding, the assumptions about the proportionality constant have been taken up for positive and negative polarity of relations and expressed in Table 2.

Further, as human inefficiency factors are hard to quantify, the following assumptions have been considered to simplify it:

1. Human inefficiency factors consist of the factors in which production is affected due to human factors. This includes elements such as corruption and strikes.
2. It is assumed that, as the plant's profit increases, more payments are given to the employees. This decreases the human inefficiency factors.

Table 2. Proportionality constants taken

| **Dependency** | **Proportionality constants (positive polarity)** | **Proportionality constants decreasing (negative polarity)** |
|---|---:|---:|
| Highly dependent | 1.75 | 0.75 |
| Medium dependent | 1.5 | 0.5 |
| Lowly dependent | 1.25 | 0.25 |

Table 2 shows the proportionality constants we have taken for the equations for the variables in system dynamics model. For example, in the case of highly dependent (e.g., Automation/Better technology with steel bar production), we have used the proportionality constant of 1.75. In the case of low dependence (e.g., marketing effort with steel bar production), we used the proportionality constant of 1.25. Severity of the dependence is expressed in Table 3. A positive polarity means that increasing the variable results in an increase in steel production. For example, the steel production rate increases when automation/better technology is implemented in a steel plant. Conversely, a negative polarity indicates that increasing this variable decreases the steel production rate. For example, increasing the logistics and transportation costs decreases the steel production rate. The dependence column indicates how severely steel bar production depends on each variable. For instance, steel bar production is highly dependent on automation and better technology but lowly on marketing efforts.

Table 3. Formulae and explanation of the Variables used

| **Variable Name** | **Equation** | **Explanation** |
|---|---|---|
| Automation/Better technology | Reinvestment ratio * Profit | |
| Reinvestment ratio | Constant | Ratio of profit that is invested for better technology. |
| Demand | 1000 * (Production cost per unit / 100)^0.5 + 10000 | |
| Disruptions rate | -0.5 * Infrastructure | How frequently disruptions occur. It decreases production |
| Environmental regulations impact | 100 + 0.5 * Type of governance | |
| FINAL TIME | 5 | The final time for the simulation |
| Grade | 1 | |

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| | | |
|---|---|---|
| Human Inefficiency factors | -0.5 * Profit / (3.8e+07) + 1.5 * Type of governance | The level of inefficiency is due to the actions of human beings involved. For example, corruption, strikes, etc. |
| Infrastructure | 0.5 * Type of governance | |
| INITIAL TIME | 0 | The initial time for the simulation |
| Inventory management costs | 1.5 * "rate of bad Quality (Scrap/rework rate)" + 1.5 * Steel bar production | |
| Labour (Skill/morale) | -0.5 * Human Inefficiency factors + 1.5 * Management attitude + 1.5 * Type of governance | |
| Logistics and transportation costs | 100 - 0.5 * Infrastructure | |
| Machine Availability | 100 + 1 * Maintenance policy - 1e-06 * Steel bar production | |
| Maintenance policy | 1 | The level of maintenance policy |
| Management attitude | 1 - 0.5 * Human Inefficiency factors | |
| Marketing effort | 1 | |
| Production cost per unit | 10000 / Steel bar production + 10 | Decreases with increased production |
| Profit | Revenue - Production cost per unit * Steel bar production | The profit that the company generates. Some of it is reinvested for automation/tech improvements. |
| Bad Quality Rate (Scrap/rework rate) | -0.5 * "Labour (Skill/morale)" + 0.005 * Steel bar production | |
| Raw material availability | 100 - 0.5 * Logistics and transportation costs + 0.5 * Infrastructure - 0.5 * Disruptions rate | |
| Revenue | 15 * Steel bar production | Revenue from steel production |
| SAVEPER | TIME STEP | Frequency of output storage |

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| | | |
|---|---|---|
| Steel bar production | Initial steel + 1.75*"Automation/Better technology" + 1.75*Demand - 0.5*Environmental regulations impact - 0.5*Grade - 0.5*Inventory management costs + 1.75*"Labour (Skill/morale)" + 1.75*Machine Availability + 1.5*Management attitude - 0.5*"rate of bad Quality (Scrap/rework rate)" + 1.75*Raw material availability + 1.25*Marketing effort + 1.75*Infrastructure - 0.75*Logistics and transportation costs | Main production variable |
| Initial steel (Constant variable) | 1 | Initial value of steel bar production. |
| Steel bar inventory (Level variable) | Steel bar production | Shows the inventory of the steel bar produced. |
| TIME STEP | 1 | Simulation step length |
| Type of governance | 1 | The governance rating is based on ease of doing business. For example, it can be high if the plant is located in a special economic zone and the government gives tax rebates to the steel plant. |

## 5. Results and Discussion

The causal loops in the SDM are shown in Figure 1below.

**Reinforcing loops**

These are feedback loops in which actions amplify each other. The reinforcing loops present in this SDM are as follows.

R1(Steel bar production ↑ => Production cost per unit↓ => Demand ↑ => Steel bar production ↑),
R2(Steel bar production ↑ => Production cost per unit↓ => Profit ↑ => Human Inefficiency Factors↓ => Management Attitude ↑ => Steel bar production ↑,
R3(Steel bar production ↑ => Production cost per unit↓ => Profit ↑ => Automation/Better technology↑ => Steel bar production ↑,)

**Balancing loops**

These are feedback loops where actions balance each other out. The balancing loops in this SDM are as follows:
B1 (Steel bar production ↑ => Machine Availability↓ => Steel bar production ↓,
B2(Steel bar production ↑ => Inventory management costs ↑ => Steel bar production ↓),
B3(Steel bar production ↑ => rate of bad quality ↑ => Steel bar production ↓),

(↑ indicates that the variable is increasing and ↓ indicates that the variable is decreasing)

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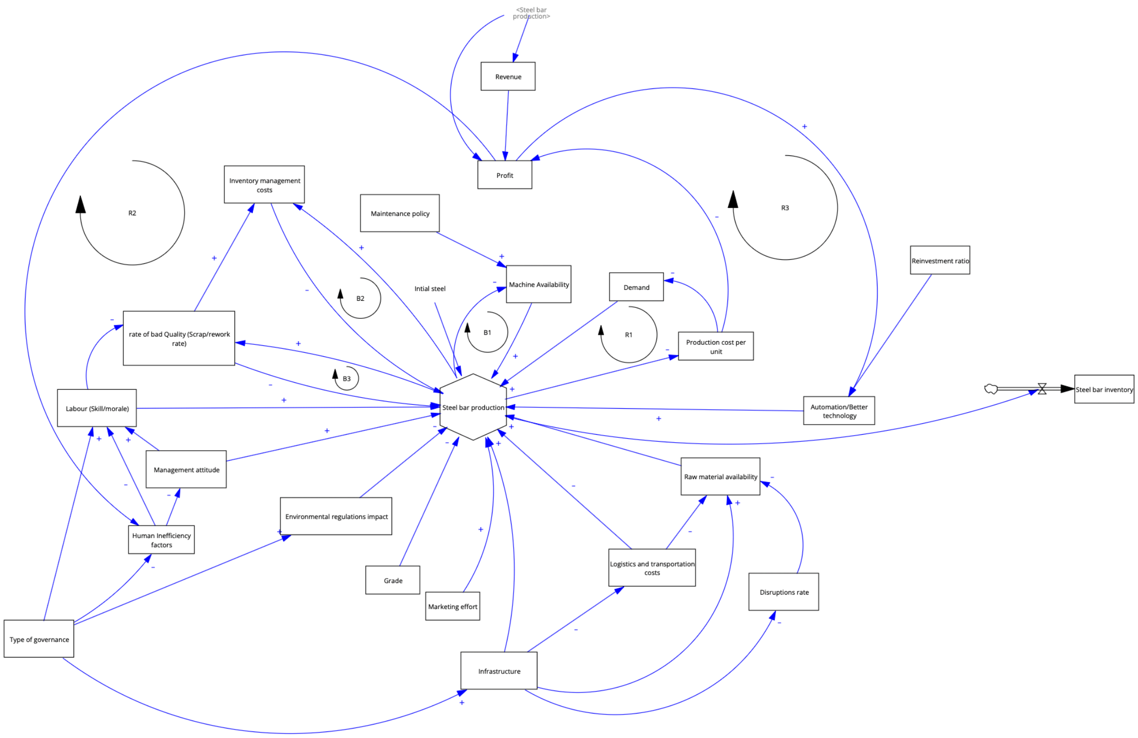


Figure 1. System Dynamics Model (Causal Loop Diagram)

Figure 1 shows the system dynamics model developed for the steel production system. This shows how different variables interact with each other and how they affect the primary variable, steel bar production. Causal loops consisting of reinforcing loops R1, R2, and R3 and balancing loops B1, B2, and B3 are shown in the model. Polarity is shown here on the arrows which indicate the variable effect on other variables and in which direction. For example, increasing automation/better technology increases steel bar production, while increasing logistics and transportation costs decreases steel bar production The mathematical equations have been defined for each relation, for example, for the variable automation/better technology, we have entered the equation as Reinvestment ratio * Profit. Here, the reinvestment ratio means how much of the profit is reinvested in automation/better technology, and profit means how much profit the steel plant makes from the steel bar production. Similarly, the equations used for other variables are shown in Table 3.

## 5.1 Graphical Results

From Figure 2. we can see near-exponential growth in the Steel bar inventory with respect to time. This is a common type of growth observed in many systems. (Sterman, J. D.,2000). It can be observed that as time increases, Steel bar inventory increases at an approximately exponential rate. Initially, it increases gradually, but as time passes, it increases quickly.

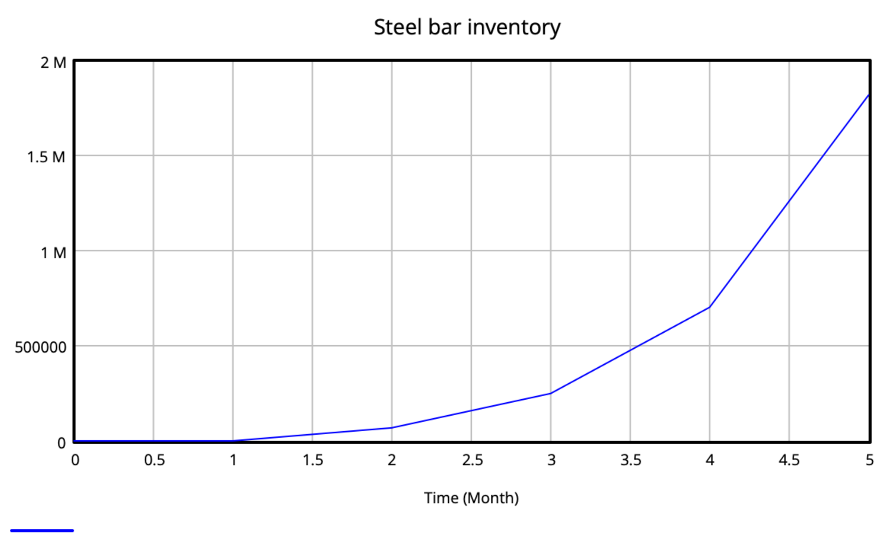


Figure 2. Steel production vs time.

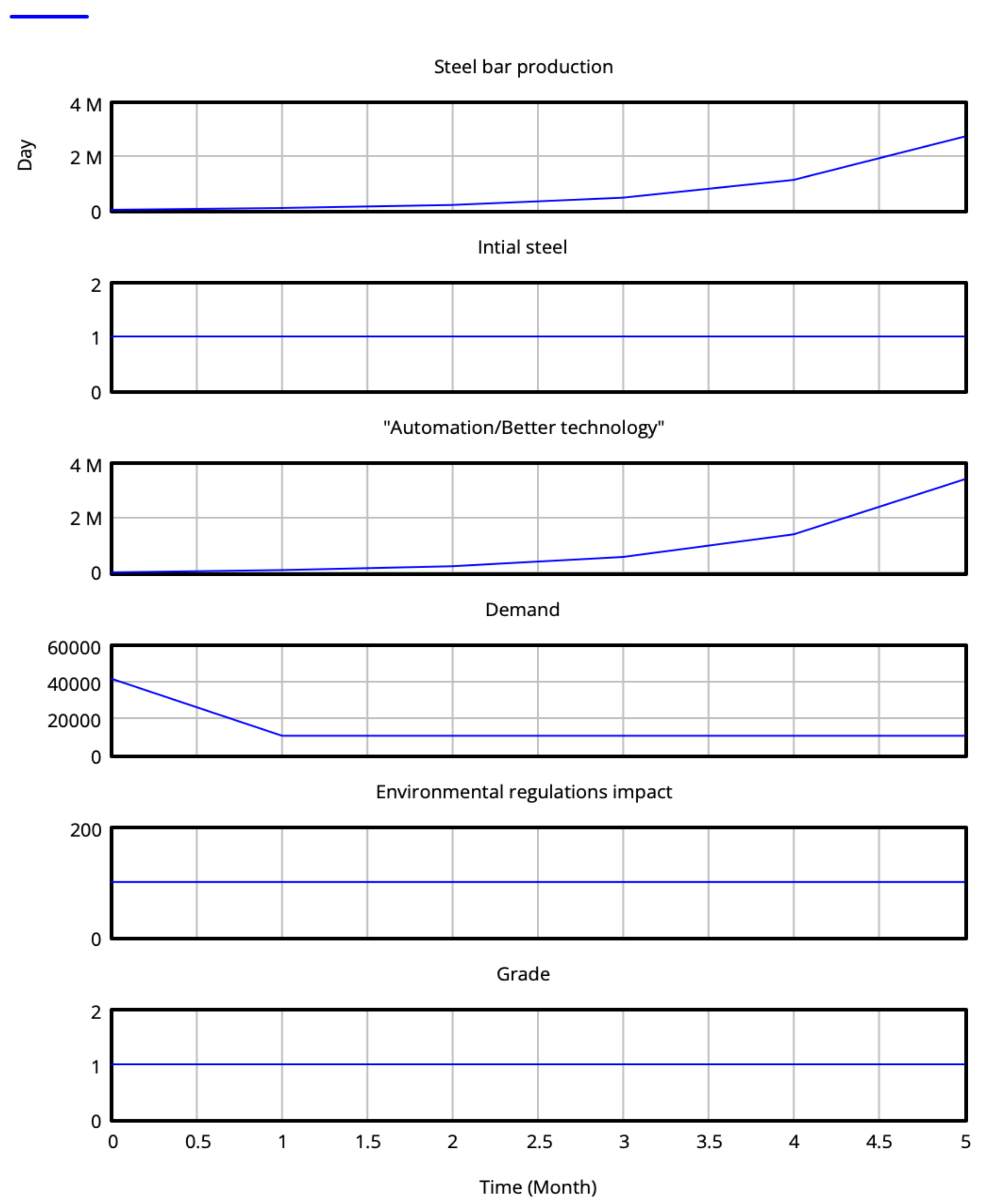


Figure 3a. How other variables behave over time

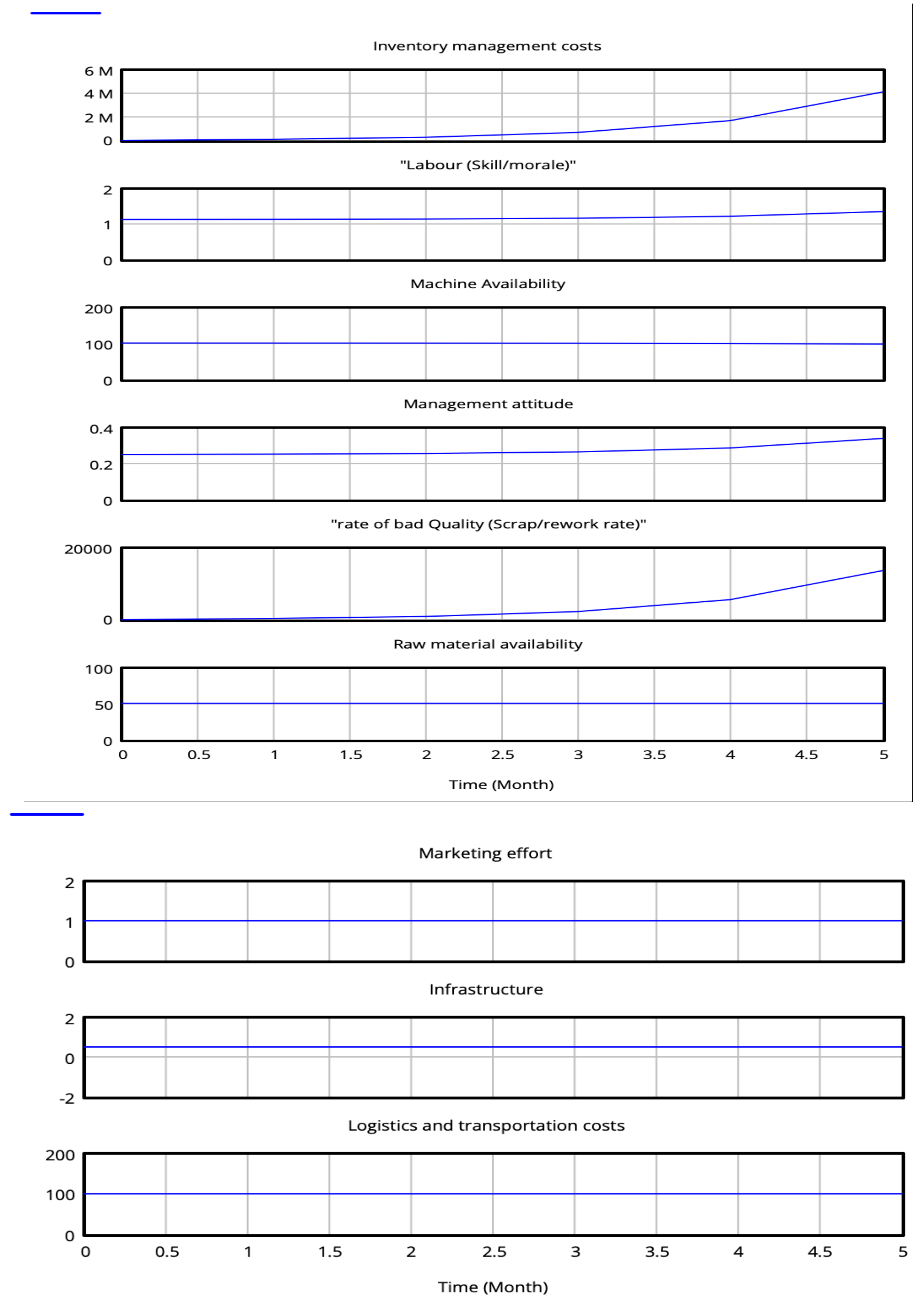


Figure 3b. How other variables behave over time

Figure 3 (#a, 3b,)describes the graph of how the other variables behave over time. For example, it can be observed that, as time passes, Inventory management costs increase. The logic can explain that the steel plant has more WIP inventory and finished goods in stock as time passes. Thus, the cost of managing them increases. Some variables, such as Grade and marketing effort, are constant with respect to time because they are not affected by the internal factors of the steel plant.

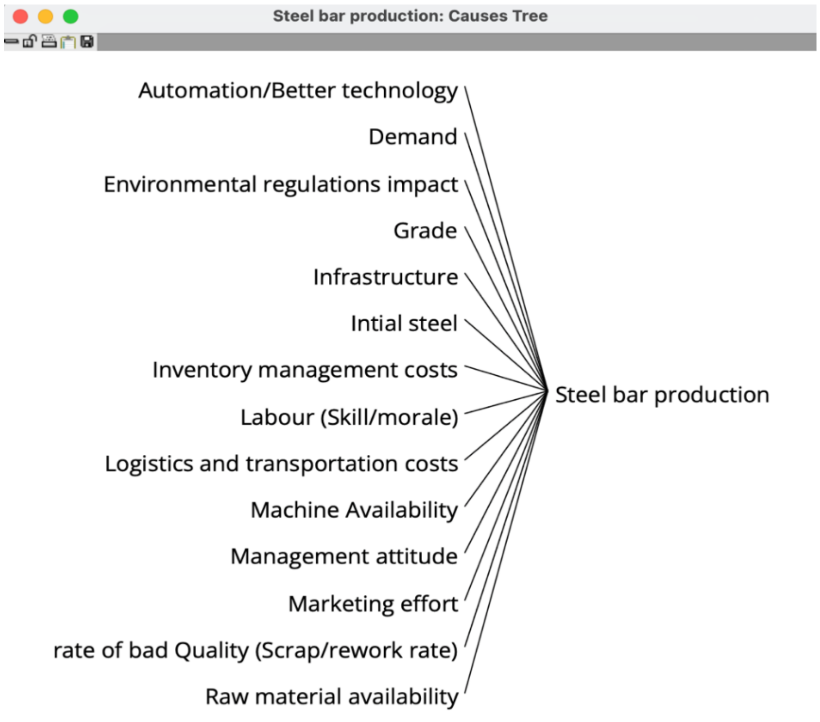


Figure 4. Causes tree for the variable Steel bar production

Figure 4 shows the causes tree for the variable Steel bar production. The causes tree represents which factors influence the variable as modeled. Each branch is a contributing factor leading to the central variable. This diagram identifies 13 variables (viz. Automation/Better technology, Demand, Environmental regulations impact, etc.) that impact steel bar production.

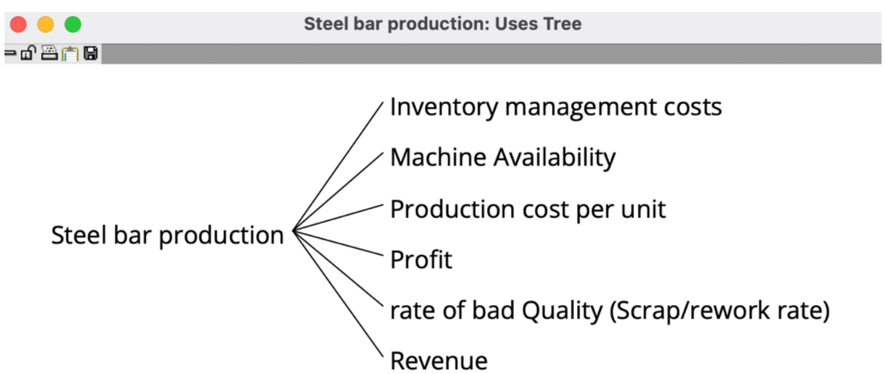


Figure 5. Uses tree for the variable Steel bar production

Figure 5 shows the Uses tree for the variable Steel bar production. Uses tree highlights which variables are influenced by the central variable. The central variable is Steel bar production, and the branches emanating from the central variable represent the consequence variables affected by the central variable. In this case, we have steel bar production as the central variable, and the six variables (Inventory management costs, machine availability, etc.) are affected by the central variable.

### 5.3 Proposed Improvements

The possible areas of improvement in the work in the future are as follows: Data can be collected from a specific steel plant and plugged into this model. Other variables of interest that may impact steel plant production (for example, the exchange rate of the country's currency, etc.) can be considered. In future work, the insights of experienced decision-makers knowledgeable in the steel industry can be gathered to identify the key variables influencing steel plant production. Based on their feedback, new variables could be added, and existing variables can be removed.

## 6. Conclusion

Decision-makers can use this model to understand how steel production varies with other variables. They can also use this model to decide where to focus resources to increase steel production. For example, as profit is reinvested into automation/better technology (Table 4), it increases steel production.

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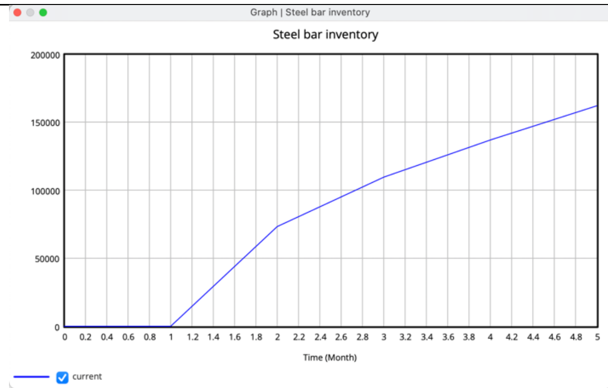
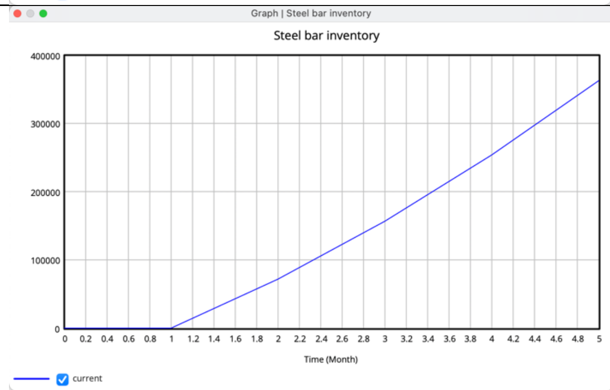
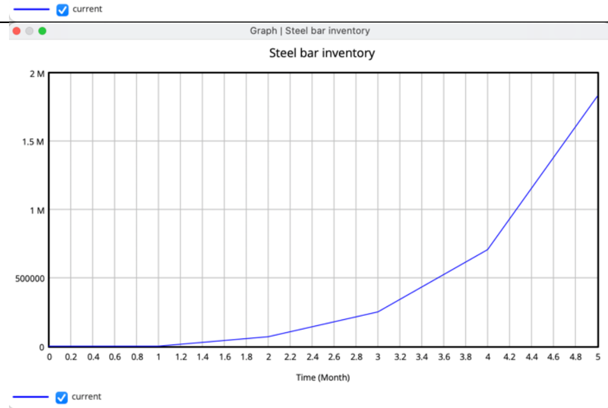
Table 4. Steel production for different reinvestment ratios

<table>
<tr><th>Reinvestment ratio</th><th>Graph of Steel bar inventory growth</th><th>Type of growth</th></tr>
<tr><td>0</td><td>
</td><td>Initial fast growth, then growth slows down.</td></tr>
<tr><td>0.08</td><td>
</td><td>The rate of growth increases with time.</td></tr>
<tr><td>0.25</td><td>
</td><td>Exponential growth.</td></tr>
</table>

As shown in Table 4, as the reinvestment ratio increases from 0 to 0.25, the total steel inventory increases from 150000 to 1.8 million. Also, the growth is not exponential for lower values of reinvestment ratios. Thus, it can be observed that the reinvestment ratio very significantly impacts steel bar production. It is the ratio of the money invested in implementing automation/better technology and the total profit. From the model, it can be observed that automation/better technology factor is a part of reinforcing loop R3. Therefore, as the reinvestment ratio increases, steel bar production increases, decreasing the production cost per unit and increasing profit, which is further implemented into automation/better technology. Consequently, if this plant wants to increase its steel production, it can focus on increasing its reinvestment ratio, i.e., invest more of the profit towards implementing automation/better technology. This kind of trend can be helpful to the top management of the steel plant in deciding how much of the profit should be reinvested for automation/better technology.

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This work contributes to the existing literature by applying CLD and SFD to analyze a steel plant's qualitative and quantitative production features. It can be challenging to understand how the variables interact with each other and how they affect production. CLD helps to visualize these relationships by incorporating arrows and polarity to indicate the complex interrelationships between these variables. Some critical reinforcing and balancing loops that influence steel production dynamics have also been identified. Decision-makers can use this model to determine where to focus resources to increase steel production. Thus, this framework can allow managers to make data-driven steel production decisions. For example, suppose a steel plant manager's objective is to increase steel production. In that case, they can apply this model in their plant to identify which factors significantly affect their production. If the most significant factor affecting production is the investment in automation/better technology, policies can be made to increase investment in implementing automation and better technology.

Additionally, practitioners can leverage this study to identify the factors that negatively or positively impact steel production. This work has certain limitations. It doesn't take into consideration specific steel plants and any unique factors that may play a key role in their production. For example, steel plants from different countries may have different factors (such as currencies) that affect their production. Decision-makers can use this model to understand how steel production varies with other variables.

Future work will be proposed to include the experts' input and real-time data to be collected from a specific steel plant and plugged into this model. Discussion with experts may bring up other variables of interest that may impact steel plant production (for example, the exchange rate of the country's currency, etc. can be considered).
Insights of experienced decision-makers knowledgeable in the steel industry can be gathered to identify the key variables influencing steel plant production. Based on their feedback, new variables could be added, and existing variables can be removed.

## References

Adane, T. F., Bianchi, M. F., Archenti, A., & Nicolescu, M. Application of system dynamics for analysis of performance of manufacturing systems. *Journal of Manufacturing Systems*, vol *53*, pp 212-233, 2019.

Al-Kindi, L. A., & Al-Ghabban, W. K. Reducing steel scrap in fabrication of steel storage tanks. In IOP Conference Series: Materials Science and Engineering Vol. 737, No. 1, p. 012200), 2020.

Berhan, E. Management commitment and its impact on occupational health and safety improvement: a case of iron, steel and metal manufacturing industries. International Journal of Workplace Health Management, vol 13, no. 4, pp. 427-444, 2020.

Bhaskar, A., Assadi, M., & Nikpey Somehsaraei, H. Decarbonization of the iron and steel industry with direct reduction of iron ore with green hydrogen. Energies, vol. 13, no 3, 758, 2020.

Cheng, C., Chu, H., Zhang, L., & Tang, L. Green supply chain for steel raw materials under price and demand uncertainty. Journal of Cleaner Production, vol. 462, 142621, 2024.

DebRoy, T., & Elmer, J. W. Metals beyond tomorrow: Balancing supply, demand, sustainability, substitution, and innovations. Materials Today, vol. 80, pp 737-757, 2024.

Efatmaneshnik, M., & Shoval, S. Stochastic modelling of process scheduling for reduced rework cost and scrap. International Journal of Production Research, vol. 61, no. 1, pp. 219-237, 2023.

Fan, Z., and Friedmann, S. J. Low-carbon production of iron and steel: Technology options, economic assessment, and policy. *Joule*, vol. 5, no. 4, pp. 829–862, 2021.

Florén, H., Frishammar, J., Löf, A., & Ericsson, M. Raw materials management in iron and steelmaking firms. Mineral Economics, vol 32, pp. 39-47, 2019.

Gupta, V., Narayanamurthy, G., & Acharya, P. Can lean lead to green? Assessment of radial tyre manufacturing processes using system dynamics modelling. *Computers & Operations Research*, vol. 89, pp. 284-306, 2018.

Hao, X., An, H., Jiang, M., & Sun, X. Supply shock propagation in the multi-layer network of global steel product chain: Additive effect of trade and production. Resources Policy, 89, 104655, 2024.

Hong, E., Yi, J. S., Son, J., Hong, M., and Jang, Y. Rebar Fabrication Plan to Enhance Production Efficiency for Simultaneous Multiple Projects. *Applied Sciences*, vol. 12, no.18, 9183, 2022.

Iglesias-Escudero, M., Villanueva-Balsera, J. Ortega-Fernandez, F., & Rodriguez-Montequín, V. Planning and scheduling with uncertainty in the steel sector: A review. Applied Sciences, vol 9, no. 13, 2692, 2019.

Javaid, M., Haleem, A., Singh, R. P., and Suman, R. (2021). Substantial capabilities of robotics in enhancing industry 4.0 implementation. *Cognitive Robotics*, vol. 1, pp. 58-75, 2021.

Karthik, M., & Dubey, O. The Impact of Port Infrastructure on International Trade–A Study on Indian Ports. Journal of International Economics, vol. 15, no. 1, pp. 18-32, 2024.

© IEOM Society International

Komakech, A. O., Liu, J., Omo, A., & Basua, E. A. A. The Impacts of Industry 4.0 on Marketing Activities and Strategies of Iron and Steel Industry in Developing Countries: Case for Uganda. Open Journal of Social Sciences, vol 9, no 5, pp. 591-626, 2021.

Li, C., Zhang, L., Wang, Q., and Zhou, D. Towards low-carbon steel: System dynamics simulation of policies impact on green hydrogen steelmaking in China and the European Union. *Energy Policy,* vol. 188*,* 114073, 2024.

Liu, T. K., Lin, S. S., and Hsueh, P. W. Optimal design for transport and logistics of steel mill by-product based on double-layer genetic algorithms. *Journal of Low Frequency Noise, Vibration and Active Control*, vol. *40*, no. 1, pp, 555-576, 2021.

Mehmanpazir, F., Khalili-Damghani, K., & Hafezalkotob, A. Modeling steel supply and demand functions using logarithmic multiple regression analysis (case study: Steel industry in Iran). Resources Policy, vol 63, 101409, 2019.

Mehmanpazir, F., Khalili-Damghani, K., and Hafezalkotob, A. Dynamic strategic planning: A hybrid approach based on logarithmic regression, system dynamics, Game Theory and Fuzzy Inference System (Case study Steel Industry). *Resources Policy,* vol. 77*,* 102769, 2022.

Mehta, M., Singh, J., & Singh, M. Reliability analysis of sheet manufacturing unit of a steel industry. In Advances in Industrial and Production Engineering: Select Proceedings of FLAME 2018 pp. 605-627, 2019.

Mohammadi, M. A., Sayadi, A. R., Khoshfarman, M., and Kashan, A. H. A systems dynamics simulation model of a steel supply chain-case study. *Resources Policy,* vol. 77*,* 102690, 2022.

Narassima, M. S., Aashrith, V., Aldo Ronald, C., Anbuudayasankar, S. P., & Thenarasu, M. Implementation of lean principles in the yarn manufacturing industry: a system dynamics approach. *Benchmarking: An International Journal*, 2023.

Norbert, R., Kim, J., and Griffay, G. A system dynamics framework for the assessment of resource and energy efficiency in iron and steel plants. *Journal of Cleaner Production,* vol. 276, 123663, 2020.

Nuñez Rodriguez, J., Andrade Sosa, H. H., Villarreal Archila, S. M., & Ortiz, A. System dynamics modeling in additive manufacturing supply chain management. *Processes*, vol. *9*, no. 6, 982, 2021.

Obera, J. J. O., Roslender, R., and Haslam, J. Corruption in Nigerian Parastatals is an Impediment to Socio-Economic Development: Case of Ajaokuta Steel Company Limited (ASCL). *Lapai Journal of Economics*, vol. *4*, no. 2, pp. 209-239, 2020.

Panigrahi, R. R., Mishra, P. C., Samantaray, A., & Jena, D. Management of inventory for firms' efficiency–a study on steel manufacturing industry. Journal of Advances in Management Research, vol 19, no. 3, pp. 443-463, 2022.

Ren, L., Zhou, S., Peng, T., & Ou, X. A review of CO2 emissions reduction technologies and low-carbon development in the iron and steel industry focusing on China. Renewable and Sustainable Energy Reviews, vol 143, 110846, 2021.

Schneider, C. Steel manufacturing clusters in a hydrogen economy–Simulation of changes in location and vertical integration of steel production in Northwestern Europe. Journal of Cleaner Production, vol. 341, 130913, 2022.

Shi, Y., Shao, S., Yang, X., Wang, D., Chen, B. and Deng, M. Metabolic Process Modeling of Metal Resources Based on System Dynamics—A Case Study for Steel in Mainland China. Sustainability, 15(13), p.10249, 2023.

Sofla, H. V. I., Sharif, M. A., & Nasrolahnia, M. Presenting an interactive marketing model based on causal, contextual and intervening variables in the steel industry. Agricultural Marketing and Commercialization, vol. 8, no. 2, 2024.

Soori, M., Arezoo, B., and Dastres, R. Internet of things for smart factories in industry 4.0, a review. *Internet of Things and Cyber-Physical Systems*, vol. 3, pp. 192-204, 2023.

Sterman, J. D. Business Dynamics: Systems thinking and modeling for a complex world. MacGraw-Hill Company, 2000.

Sun, W., Wang, Q., Zhou, Y., & Wu, J. Material and energy flows of the iron and steel industry: Status quo, challenges and perspectives. Applied Energy, vol. 268, 114946, 2020.

Suzuki, M. The formation of job-and competency-based human resource management in Japan The steel industry, 1947–1973. Japanese Research in Business History, vol. 36, pp 32-49, 2019.

Vapski, D., & Pandilov, Z. Automation of Production Line in Order to Increase the Productivity. Tehnički glasnik, vol. 17, no. 1, pp. 146-152, 2023.

Verma, B. K., and Kesari, B. Does the morale impact on employee turnover intention? An empirical investigation in the Indian steel industry. *Global Business Review*, vol. 21, no. 6, pp. 1466-1488, 2020.

Wu, R., & Lin, B. Environmental regulation and its influence on energy-environmental performance: evidence on the Porter Hypothesis from China's iron and steel industry. Resources, Conservation and Recycling, vol. 176, 105954, 2022.

Xie, Q., Suvarna, M., Li, J., Zhu, X., Cai, J., & Wang, X. Online prediction of mechanical properties of hot rolled steel plate using machine learning. Materials & Design, vol. 197, 109201, 2021.

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Zhang, K., Zhao, Y., Cao, H., & Wen, H. Multi-scale water network optimization considering simultaneous intra-and inter-plant integration in steel industry. *Journal of Cleaner Production*, vol. 176, pp. 663-675, 2018.
Zhu, W., Ouyang, P., & Kong, M. Research on the evolution mechanism of intelligent manufacturing transformation of Chinese pharmaceutical manufacturing enterprises based on system dynamics. *Heliyon*, vol. 10, no. 13, 2024.

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