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# A country-level multi-objective optimization model for a sustainable steel supply chain

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## Nota dos Autores

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## Abstract

Steel supply chains have been pushed to consider environmental and social aspects, other than financial, however, in the context of Operational Research, the few papers proposing mathematical formulations and algorithms tackle only few dimensions of the problem. This study proposes a solution for sustainable steel production by formulating a multi-objective, multi-level, multi-modal, multi-product, and multi-period model and also devising an evolutionary algorithm for the problem. The results provide a Pareto front mapping the conflicting nature of economic, environmental and social objectives; show how changes in the production technology and transportation mode impact the objectives, and how locations with social vulnerability influence the decision of where and when to locate facilities. This paper provides a broad-ranging formulation and the results show its potential to help decision makers of the steel supply chain to make decisions considering not only economic factors.

*Keywords*: sustainable supply chain design; multi-objective optimization; steel industry; genetic algorithms

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## 1 Introduction

Despite the critical role played in several sectors of the economy, steel supply chains (SSC) are the largest energy consumers of the industrial sector and massive greenhouse gas (GHG) generators. Steel production and distribution deploy lots of renewable and non-renewable natural resources causing environmental issues (Conejo et al., 2020). According to United Nations (2015), the steel industry should consider its social and ecosystem impact, going beyond the financial aspects and devising a green supply chain management (GSCM) with focus on a careful process for supplier selection, process integration, and reverse logistics activities (Tseng et al., 2019; Mc Loughlin et al., 2021).

Beyond environmental preservation, industries have been encouraged for decades to review the need for considering social development (Mota et al., 2018; Tseng et al., 2019). Despite some progress, the incorporation of social and sustainability factors while building a steel supply chain is slow (Elkington, 2013; Eskandarpour et al., 2015; Arampantzi & Minis, 2017) and this is partially explained by the lack of studies proposing practical formulations that can indeed help the organizations to include such factors in their process decision making (Nielsen, 2017; Zhang et al., 2019).

There are optimization models tackling these issues, but they mostly consider few dimensions of the supply chain in terms of layers, periods, products, technological routes and the number of objectives to be optimized, limiting their practical application (Barbosa-Póvoa et al., 2018; Moreno-Camacho et al., 2019). In this context, the focus of this study is to provide a country-level sustainable steel production solution by formulating a multi-level, multi-modal, multi-product, multi-period and multi-objective model that is able to suggest where and when to build new plants and distributions centers or modify the capacity of the existent ones; also devising an evolutionary algorithm to solve the proposed model. The provided data enabled the investigation of the Brazilian steel industry, and the proposed solution can be generalized to other countries to extend the supply chain simultaneously improving the economic, environmental, and social indicators.

## 2 Literature Review

In SSCM, traditional indicators are **economical, environmental and social,** coining the term Triple Bottom Line (TBL) as a foundation of the SSCM (Elkington, 2013). Common examples of economic indicators refer to minimizing total costs, maximizing total profit or minimizing the net present value (Barbosa-Póvoa et al., 2018). The **environmental** indicators include the Life Cycle Assessment (LCA) or CO2 measures (Macowski et al., 2020). The **social** dimension of TBL is still the least discussed in the literature (Brandenburg et al., 2014), most assessments use the number of jobs generated (Arampantzi & Minis, 2017; Zhang et al., 2019). Other metrics tend to prioritize less



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developed areas to locate facilities (Arampantzi & Minis, 2017), increase community services, and even donations to non-governmental organizations.

In this context involving different goals, multi-criteria decision-making methods are adequate. SCND models can encompass environmental issues by quantifying the impacts generated in monetary terms on the objective function, assigning weights to the sustainable performance, or by using multi-objective models (Tosarkani & Amin, 2018; Castro Vivas et al., 2019; Moreno-Camacho et al., 2019). Both, exact methods, such as the epsilon-constraint, and metaheuristics can solve these models (Kadziński et al., 2017; Zarbakhshnia et al., 2019; Macowski et al., 2020). The use of metaheuristics has grown, but it represents only 5% to 13% of 134 reviews studies made by Brandenburg (2014) with similar findings among the 87 papers reviewed by Eskandarpour et al (2015), approaching techniques such as Simulated Annealing (Chalmardi & Camacho-Vallejo, 2019; Khan et al., 2021), Genetic Algorithms (GA) (Sahebjamnia et al., 2018; Noh & Kim, 2019) and other Evolutionary Algorithms (EA) (Kadziński et al., 2017).

Studies on SCND approaching TBL are scarce, especially in South America, which has received little attention so far (Moreno-Camacho et al., 2019; Tseng et al., 2019). The published literature has little explored the problem of planning sustainable steel chains from a broader and strategic point of view, that is, on the country level. The few studies on country-level steel planning concentrate on a single objective, such as energy efficiency (Ates ,2015) or production efficiency (Nielsen, 2017) focusing on state planning versus market-based comparisons, which is different in scope from this study.

Table 1 and Table 2 summarize a literature review of relevant papers published in the last 10 years formulating optimization models for the SSCM, also including information of the present work to better situate it in the literature. The columns of Table 1 refer to different features presented by the formulations, as follows:

1) Multi-objective optimization (MO): methods able to create a Pareto front of nondominated solutions. In a priori methods, preference information is first asked from the decision makers and then a solution is found. In a posteriori method, a set of nondominated solutions is first found and then the decision makers must choose one of them. All models of the table have multiple objectives but some formulations use weighted sum of objectives to crate a single objective function, not being considered multi-objective in the present context.

2) Multi-level (ML): multi-level, multi-layers or multi-echelon models refers to a logistic network having multiple entities such as: suppliers, plants, distribution centers, retailers, customer zones, collection/inspection centers, among others.

3) Multi-product (MP): multi-product models.

4) Multi-period (MPR): multi-period models.



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5) Multi-modal (MM): formulations with multiple modes of transportation.
6) Objective function: economical (Ec.), environmental (En.), and social (S).
7) Product (Prod): product or industry for which the model was designed or tested.

Table 1 shows that most of the formulations that are able to create nondominated solutions have implemented "a priori" methods. The majority of the models are multi-layers and multi-products but a minority are multi-period and multi-modal. All models have economical objectives with most having also an environmental objective, but few of them also have a social objective.

**Table 1**

*Literature classification based on problem features for the SSCM*

| Paper | MO | ML | MP | MPR | MM | Ec. | En | S | Prod. |
|---|---|---|---|---|---|---|---|---|---|
| Devika, 2014 | post. | yes | no | no | yes | yes | yes | yes | goods |
| Zhang, 2016 | post. | yes | no | no | no | yes | yes | no | goods |
| Rezapour, 2017 | no | yes | no | no | no | yes | no | no | goods |
| Kadziński, 2017 | post. | yes | no | no | yes | yes | yes | no | furniture |
| Tosarkani, 2018 | prior | yes | yes | yes | no | yes | no | no | battery |
| Sahebjamnia, | prior | yes | yes | no | no | yes | yes | yes | tires |
| Sarkar, 2018 | prior | yes | no | no | no | yes | yes | no | automob |
| Khorasani, 2018 | prior | yes | yes | no | no | yes | yes | no | steel |
| Castro Vivas, | no | yes | yes | no | no | yes | yes | yes | oil & gas |
| Zarbakhshnia, | prior | yes | yes | no | no | yes | yes | no | goods |
| Noh & Kim, 2019 | no | no | yes | no | yes | yes | yes | no | goods |
| Yadav et al., 2019 | no | yes | no | no | no | yes | yes | no | goods |
| Resat & Unsal, | prior | yes | yes | yes | no | yes | yes | no | packing |
| Vafaeenezhad, | prior | yes | yes | yes | no | yes | yes | yes | paper |
| Macowski, 2020 | prior | yes | yes | yes | no | yes | yes | no | sugarcan |
| Khan et al., 2021 | no | yes | no | no | yes | yes | yes | no | goods |
| Seydanlou et al., | post. | yes | yes | yes | yes | yes | yes | yes | olive |
| Khoshfarman, | prior | yes | yes | yes | no | yes | yes | yes | steel |
| **Current work** | **post** | **yes** | **yes** | **yes** | **yes** | **ye** | **ye** | **ye** | **steel** |

The environmental objectives in Table 1 mostly refer to the impacts of the network caused by opening facilities; such as minimizing the total GHG emissions of the supply chain; impacts of manufacturing, transportation, handling and disposal of products. The economical costs include the minimization of production costs, purchase of raw materials, cost of establishment of production facilities, transportation of goods, operating and inventory costs. The most common social objectives aim to maximize the creation of job

opportunities and workers' safety such as the number of accidents. Sahebjamnia et al. (2018) also consider the lost days for work during the establishment of facilities and the loss of days caused work's damages during the manufacturing and distributing, collecting and recycling. Vafaeenezhad et al. (2019) consider the total travel distance of employees with the aim of improving local development. Among the six papers comprising multi-period models, usually the time period refers to 12 months; and the five papers approaching different transportations models commonly refer to road, sea and rail transportation.

Tables 2 summarizes the mathematical programming techniques used by the papers to solve their respective formulation of the optimization problem. There are many building a mixed-integer linear programming (MILP) and then applying ε-constraint multi-objective method to generate a Pareto Front. Because this method creates linear combinations of the objective functions it is considered a "a priori" method; and these combinations have the limitation of building a set of nondominated solution only in a convex objective function space. It seen that the most used methods include GA (Genetic Algorithms) based on NSGA-II. Some papers (Castro Vivas 2019; Resat & Unsal, 2019) use multi-criteria decision-making techniques such as AHP and PROMETHEE to give weights for the objective functions.

Comparing with the current work, only two papers are applied to steel supply chain, where Khorasani & Almasifard (2018) provides a formulation able to manage some uncertainty regarding demand by using Fuzzy, but do not consider multiples time periods and without a social objective function. The model has three sets (suppliers, customers and products) while this works has eight: factories, distribution centers, local retailers, products, raw materials, transportation modes, technological routes and time-periods. Khoshfarman et al. (2023) have very recently proposed a model with the three BTL objectives, but without multiple transportations modes. The objective of the model is to optimize the flow of products in an existent network while this work decides locations to set industrial plants and DCs. Both works (Khorasani & Almasifard, 2018 and Khoshfarman et al., 2023) apply "a priori" multi-objective methods while the proposed work has applied "a posteriori" method.

Table 1 and 2 shows this work provides a formulation with a broader set of relevant features when compared with others from the related literature. A Genetic Algorithm (GA) is devised to solve the proposed multi-objective SCND model using "a posteriori" method that is more efficient to explore the objective space solution when compared with "a priori" methods. The proposed model is also multi-level, multi-modal, multi-product, multi-period and multi-objective. The model provides several managerial insights for the government's top management team responsible for industry policy-making and regulation helping to build a sustainable supply chain.



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**Table 2**

*Literature - Mathematical programming formulation*

| Citation | Mathematical programming |
|---|---|
| Devika, 2014 | AICA; VNS |
| Zhang, 2016 | MOABC; MILP |
| Rezapour, 2017 | MILP |
| Kadziński, 2017 | SPEA2; NSGA-II (GA) |
| Tosarkani, 2018 | Fuzzy; ε-constraint |
| Sahebjamnia, 2018 | GA, SA, Tabu Search; ε- constraint |
| Sarkar, 2018 | WGP; GP |
| Khorasani, 2018 | Fuzzy |
| Castro Vivas, 2019 | AHP; PROMETHEE; GP |
| Zarbakhshnia, 2019; | MILP; ε--constraint |
| Noh & Kim, 2019 | GA; Fuzzy |
| Yadav et al., 2019 | MILP; CPLEX solver |
| Resat & Unsal, 2019 | AHP; ϵ-constraint |
| Vafaeenezhad, 2019 | MILP; ε-constraint |
| Macowski, 2020 | MILP; ε-constraint |
| Khan et al., 2021 | MINLP; Tabu search; SA |
| Seydanlou et al., 2022 | GA; SA |
| Khoshfarman, 2023 | MILP; ε-constraint |
| **Current work** | GA |

The following section describes the proposed mathematical formulation and metaheuristic. Section 4 presents results for experiments analyzing trade-off scenarios considering real data from the Brazilian steel sector and managerial implications to the global steel industry. Finally, Section 5 concludes and presents future directions for this study.

## 3 Method

This is an applied, quantitative and explanatory research. In the context of Operational Research, the literature review showed there is a lack of papers proposing optimization models to design sustainable supply chains, particularly about the steel industry. The existents models tackle few dimensions of the supply chain; therefore, this research developed a broader formulation (Section 3.1) comprising factories, distribution centers, local retailers, products, raw materials, transportation modes, technological routes and time-periods. The designed formulation allows the decision maker to decide where and when to open new plants and DCs, and also to change the capacity of the existent facilities;



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considering simultaneously the three TBL objectives. Following the creation of this formulation, it was necessary to devise a mean to solve the mathematical model; and the authors have chosen a genetic algorithm, more specifically, an algorithm based on NSGA-II, for several reasons: a metaheuristic is more suitable to solve NP-Hard problems (which is the case of the proposed formulation); it is a "posteriori" multi-objective method; it is suitable to explore non-convex search space and multi-modal equations. The next step consisted in modifying the well know NSGA-II algorithm (Sections 3.2-3.4) to incorporate the features of the studied problem, devising a representation, data structure, decoding, crossover and mutation. Finally, the mathematical model and algorithm were tested (Section 4) in instances using data from several Brazilian institutional reports; firstly, with preliminary tests to adjust the parameters of the algorithm; and then, performing specific experiments to test the algorithm and learn from the results how the solutions found by the optimization managed simultaneously three objectives that have completely different nature.

### *3.1 Mathematical formulation*

This section describes the proposed mathematical formulation for sustainable steel network design problem. The multi-objective optimization model aims at minimizing the network operations costs, the CO2 emissions, and maximizing social well-being. Social well-being is established by setting facilities in locations with a high social vulnerability index (SVI), supporting the local community, and promoting its development.

The steel production equations incorporate a cradle-to-cradle approach by considering steel production by Electric Arc Furnace (EAF) using steel scrap. The network consists of industrial plants, distribution centers (DCs), and local retailers. The steel logistics supply chain includes available transport links between the network elements, and the industrial plants acquire raw materials, like coal and charcoal, and process the products to satisfy the local retailers' demand. The finished products are sent to DCs, and then from DCs to local retailers.

The entrant steel networks must consider the pre-existing competing chain and candidates' facilities locations. The candidate municipalities are set in advance considering a wide range of characteristics, such as (i) the availability of minimal infrastructure of transport; (ii) the transport modes; (iii) the distance to local retailers; (iv) the access to ports for exportation; and (v) additional qualitative characteristics which are out of scope of this work, as the presence of universities for technical support and training, and the availability of raw materials nearby.

The model shows whether a facility along with its steel production route (technological process) should be established or not in the candidate location. Possible steel production routes for industrial plants comprise integrated production with coke, native



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charcoal, planted charcoal, and semi-integrated EAF. Unmet local retailers' demands are back-ordered and subject to a penalty.

The notation and definitions of the model are given next. The steel network elements are set by $j = 1, \dots, J$factories, $k = 1, \dots, K$ distribution centres, $l = 1, \dots, L$ local retailers, $p = 1, \dots, P$ finished products, $m = 1, \dots, M$ raw materials, $s = 1, \dots, S$ transportation modes, $r = 1, \dots, R$ production routes, and $t = 1, \dots, T$ time periods. Each long term trade-off scenario presents strategic planning decisions comprising the location to set industrial plants and DCs; the total capacity of each facility in each period, considering the possibility of expansion or retraction; the activation of DCs in each period; the steel production route in established industrial plants; the production volume per period for each type of finished product to be processed in each plant; the amount of finished product transported between industrial plants, DCs, and local retailers, for each mode of transport and each period; and the amount of back-ordered demand for each finished product and each local retailer, in each period. Tables 3 to 6 describe the model parameters, and Table 7 presents its variables.

**Table 3**

*Market, production, and logistics parameters*

| Parameter | Description | Unit |
|---|---|---|
| $D_{pl}^{t}$ | Demand for finished product p by local retailers l in period t | t |
| $BM_{mpr}$ | Raw material m needed to manufacture one ton of product p by route r | t |
| $MP_r$ | Maximum production capacity in a factory that uses route r | t |
| $IP_r$ | Initial and minimum production capacity of a factory that operates with route r | t |
| $QUD_k$ | Maximum product storage capacity on DC k | t |
| $QID_k$ | Initial and minimum storage capacity on DC k | t |
| $DF_{jks}$ | Distance between industrial plant j and DC k by transport mode s | km |
| $DC_{kls}$ | Distance between DC k and local retailer l by transport mode s | km |

**Table 4**

*Environmental parameters*

| Parameter | Description | Unit |
|---|---|---|
| $ET_s$ | $CO_2$ emissions generated during transport by mode s | g $CO_2$/ tku |
| $EP_r$ | $CO_2$ emissions generated during production by route r | g $CO_2$/ t |

**Table 5**

*Social parameters*

| Parameter | Description | Unit |
|---|---|---|
| $JF_j$ | Social Vulnerability Index of the city where industrial plant j is located | - |
| $JD_k$ | Social Vulnerability Index of the city where DC k is located | - |



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**Table 6**

*Economic parameters*

| Parameter | Description | Unit |
|---|---|---|
| $P_p$ | Penalty applied for not meeting the demand for product p | $/ t |
| $CFA_{jr}$ | Fixed costs of setting factory j with production route r | $/t |
| $CDA_k$ | Fixed costs of establishing DC k, per ton of capacity | $/ t |
| $CPP_{pjr}$ | Variable cost of product p at industrial plant j by route r | $/ t |
| $CA_{rj}$ | Fixed costs for maintaining factory f with route r | $ |
| $CC_k$ | Fixed costs for maintaining DC k | $ |
| $CS_m^t$ | Raw material m cost in period t | $/ t |
| $CT_s$ | Transport cost per tku using mode s | $/ tku |

**Table 7**

*Model variables*

| Variable | Description | Unit |
|---|---|---|
| $sf_{jr}$ | Decision whether a plant j is established with route r or not | - |
| $sd_k$ | Decision indicating whether DC k is established or not | - |
| $of_{jr}^t$ | Decides if industrial plant j is opened at period t or not | - |
| $od_k^t$ | Decide whether DC k is opened at period t or not | - |
| $vp_{jr}^t$ | Positive change in capacity at industrial plant j in period t | t |
| $vn_{jr}^t$ | Negative change in capacity at industrial plant j in period t | t |
| $vc_k^t$ | Positive change in capacity at DC k in period t | t |
| $vcn_k^t$ | Negative capacity change at DC k in period t | t |
| $qaf_{jr}^t$ | Capacity of industrial plant j in period t | t |
| $qad_k^t$ | Distribution Centre capacity k in period t | t |
| $dn_{pl}^t$ | Backordered demand for product p and local retailer l in period t | t |
| $qfd_{pkjs}^t$ | Production p shipped from plant j to DC k, by mode s in period t | t |
| $qdc_{pkls}^t$ | Production p sent from DC k to retailer l, by mode s in period t | t |
| $qpp_{pjr}^t$ | Production p produced at industrial plant j in period t by route r | t |

The sustainable steel SCND model comprises economic, environmental, and social objectives. In doing so, the model is aligned with the Triple Bottom Line of sustainable supply chain management. The economic indicator concerns the minimization of total network production and logistics costs. The models' environmental bottom line minimizes carbon dioxide emissions during transport and production. The social indicator maximizes social well-being by establishing facilities in areas with higher SVI.

The model economic objective function (Equation 1) consists of: (a) penalty for back-ordered demand; (b) the purchase costs of raw materials; (c) the variable costs of processing the products; (d) the fixed costs of facilities operations; (e) the transport costs from DCs to local retailers and from industrial plants to DCs; (f) the fixed costs of establishing industrial plants and DCs and (g) the facilities capacity variation costs.

$$Obj1 = Minimize: (a)\sum_{t\in T}\sum_{l\in L}\sum_{p\in P} P_p \cdot dn_{pl}^t \quad +(b)\sum_{t\in T}\sum_{m\in M} CS_m^t \cdot \sum_{p\in P}\sum_{j\in J}\sum_{r\in R} BM_{mpr}\cdot qpp_{pjr}^t +(c)\sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\sum_{r\in R} CPP_{pjr}\cdot qpp_{pjr}^t \ +(d)\sum_{t\in T}\sum_{j\in J}\sum_{r\in R} CA_{rj}\cdot of_{jr}^t + \sum_{t\in T}\sum_{k\in K} CC_k \cdot od_k^t +(e)\sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\sum_{k\in K}\sum_{s\in S} CT_s \cdot DF_{jks}\cdot qfd_{pjks}^t \sum_{t\in T}\sum_{p\in P}\sum_{k\in K}\sum_{l\in L}\sum_{s\in S} CT_s\cdot DC_{kls}\cdot qdc_{pkls}^t +(f)\sum_{j\in J}\sum_{r\in R} CFA_{jr}\cdot IP_r\cdot sf_{jr} + \sum_{k\in K} CDA_k\cdot QID_k\cdot sd_k \quad +(g)\sum_{t\in T}\sum_{j\in J}\sum_{r\in R} CFA_{jr}\cdot\left(vp_{jr}^t - vn_{jr}^t\right) + \sum_{t\in T}\sum_{k\in K} CDA_k\cdot (vc_k^t - vcn_k^t) \qquad (Eq.1)$$

The environment-related objective function (Equation 2) consists of (a) minimizing carbon dioxide emissions during transportation and (b) minimizing carbon dioxide emissions in production.

$$Obj2 = Minimize:$$

$$(a)\sum_{t\in T}\sum_{p\in P}\sum_{k\in K}\sum_{l\in L}\sum_{s\in S} ET_s\cdot DC_{kls}\cdot qdc_{pkls}^t + \sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\sum_{k\in K}\sum_{s\in S} ET_s\cdot DF_{jks}\cdot qfd_{pjks}^t + (b)\sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\sum_{r\in R} EP_r\cdot qpp_{pjr}^t \qquad (Eq.2)$$

The social-related objective function (Equation 3) comprises (a) the SVI of the city in which the industrial plant can be located, multiplied by the production in the period; (b) the SVI of the city of the DC location multiplied by the number of products it received in the period. The multiplication of SVI by production discourages industrial plants that are not producing, as these would not be positive for the city's development.

$$Obj3 = Maximize: (a)\sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\sum_{r\in R} JF_j\cdot qpp_{pjr}^t + (b)\sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\sum_{k\in K}\sum_{s\in S} JD_k\cdot qfd_{pjks}^t \qquad (Eq.3)$$

The multiple objective functions are subject to several constraints. Equation 4 ensures that local retailer demand in period t must be met or back-ordered.

$$\left(\sum_{s\in S}\sum_{k\in K} qdc_{pkls}^t\right) + dn_{pl}^t = D_{pl}^t + dn_{pl}^{t-1} \forall t\in T, l\in L, p\in P \qquad (Eq.4)$$

Equations 5 and 6 are constraints concerning industrial capacities.

$$qaf_{jr}^t = qaf_{jr}^{t-1} + \left(vp_{jr}^t - vn_{jr}^t\right)\forall j\in J, r\in R, t\in T \qquad (Eq.5)$$

$$qaf_{jr}^0 = IP_r \forall j\in J, r\in R \qquad (Eq.6)$$



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Equation 7 limit the industrial plants' capacities are within pre-established minimum and maximum limits at any given period.

$$IP_r \leq qaf_{jr}^t \leq MP_r \forall j \in J, r \in R, t \in T \quad (Eq.7)$$

Equation 8 ensures that an industrial plant production level does not extrapolate its current capacity.

$$\sum_{p \in P} qpp_{pjr}^t \leq qaf_{jr}^t \forall t \in T, j \in J, r \in R \quad (Eq.8)$$

Equation 9 states that a plant is set with only one production route.

$$\sum_{r \in R} sf_{jr} \leq 1 \forall j \in J \quad (Eq.9)$$

An industrial plant can only operate in any period if it is established with a specific production route and location (Equations 10 and 11).

$$of_{jr}^t \leq sf_{jr} \forall j \in J, r \in R, t \in T \quad (Eq.10)$$
$$qpp_{pjr}^t \leq of_{rj}^t \times M \forall r \in R, j \in J, p \in P, t \in T \quad (Eq.11)$$

Equations 12 and 13 establish product flow conservation in the facilities.

$$\sum_{s \in S} \sum_{k \in K} qfd_{pjks}^t = \sum_{r \in R} qpp_{pjr}^t \forall j \in J, p \in P, t \in T \quad (Eq.12)$$
$$\sum_{p \in P} \sum_{j \in J} \sum_{s \in S} qfd_{pjks}^t \leq qad_k^t \forall k \in K, t \in T \quad (Eq.13)$$

Equations 14 to 19 are constraints to model the flow of products over the distribution elements of the steel supply chain.

$$qad_k^t = qad_k^{t-1} + (vc_k^t - vcn_k^t) \forall k \in K, t \in T \quad (Eq.14)$$
$$qad_k^0 = QID_k \forall k \in K \quad (Eq.15)$$
$$QID_k \leq qad_k^t \leq QUD_k \forall k \in K \quad (Eq.16)$$
$$\left(\sum_{s \in S} \sum_{j \in J} qfd_{pjks}^t\right) = \left(\sum_{s \in S} \sum_{l \in L} qdc_{pkls}^t\right) \forall k \in K, p \in P, t \in T \quad (Eq.17)$$

Equation 18 states that a DC can only open in a period t if it is set, and Equation 19 makes sure that a not-opened DC cannot receive any products in that period.

$$od_k^t \leq of_k \forall k \in K, \forall t \in T \quad (Eq.18)$$
$$M \times od_k^t - \sum_{s \in S} \sum_{j \in J} qfd_{pjks}^t \geq 0 \forall k \in K, t \in T, p \in P \quad (Eq.19)$$



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Equation 20 states that the back-ordered demand in period zero is null, i.e., at the beginning of the planning horizon, there is no back-ordered demand.

$$dn_{pl}^{0} = 0 \forall p \in P, l \in L \qquad (Eq. 20)$$

Finally, the variables $sf_{jr}$, $of_{jr}^{t}$, $sd_{k}$, $od_{k}^{t}$ are binary for all $j \in J, r \in R, t \in T$, while the variables $vp_{jr}^{t}$, $vn_{jr}^{t}$, $vc_{k}^{t}$, $vcn_{k}^{t}$, $qaf_{jr}^{t}$, $qad_{k}^{t}$, $dn_{pl}^{t}$, $qfd_{pkjs}^{t}$, $qdc_{pkls}^{t}$, and $qpp_{pjr}^{t}$ are non-negative continuous variables for all $j \in J, k \in K, p \in P, t \in T, s \in S$.

The problem is NP-Hard; therefore, we adopted a metaheuristic to solve it in non-prohibitive time, modifying the popular NSGA-II support decision-making in the search for a more sustainable steel industry.

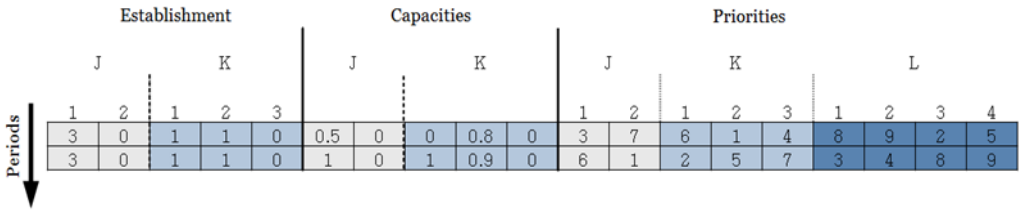
### *3.2 Representation and decoding*

In this study, the individuals are represented by a modification of priority-based encoding (Gen et al., 2006) in which a solution consists of a chromosome of length $|I + J|$, where I is the set of sources and J is the set of destinations. The position of a gene represents a facility, while its value corresponds to the priority of that facility. A chromosome represented only by destinations has been used to solve supply chain problems (Kadziński et al., 2017).

This work adopted a chromosome comprised of a $T * (3J + 3K + L)$ matrix, where J is the number of plants, K is the number of DCs, L is the number of local retailers, and T is the number of periods. The J + K first genes indicate whether a facility is set, or not. DCs are set to zero if they are not established, and to one otherwise. Industrial plants also receive zero, in case they are not established, otherwise, they receive an integer between 1 and R, where R is the set of possible production routes. The J + K following chromosomes define the facilities' capacities, where the capacity in any given period is equal to the minimum capacity if the gene value is zero and equal to the maximum if its value is one. For intermediate values, the capacity is obtained by multiplying the gene's value by the difference between the maximum and minimum capacities and adding the result to the minimum capacity. The remainder part of the chromosome is a priority-based representation to determine product flow, and each row represents one period. Figure 1 shows an example of the representation for an instance of two plants, three production routes, three DCs, 4 local retailers, and 2 periods.

**Figure 1**

*The chromosome representation for the steel planning case study*




Algorithm 1 is used to make the first stage of decoding, deciding the production in each industrial plant, considering the plant capacities, local retailers' demands, and the total capacities of the open DCs.

**Algorithm 1**

*Decoding production in each factory*

**Input:** $D_{pl}$, $IP_r$, $MP_r$ , qad(k), qaf(j), CPP(pj), V(j) // chromosome priority
**Output:** qpp(pj)

1. qpp(pj), ← 0, $\forall j \in Jp \in P$
2. **While** { $\sum_{k\in K} qad\ (k)$, $\sum_{l\in L,p\in P} D\ (lp)$,$\sum_{j\in J} qaf\ (j)$, V(j)}> 0:
3. j* = **argmax**{V(j)} //choose highest priority plant
4. **While** {qaf(j*), $\sum_{k\in K} qad\ (k)$}> 0 **and min** {CPP(p,j*)} < ∞:
5. p* = **argmin**{CPP(p,j*)} // choose lowest cost product
6. qpp(p*,j*) = **min**{$\sum_{l\in L} D\ (lp\ \ )$, $\sum_{k\in K} qad\ (k)$, qaf(j*)}
7. $\sum_{l\in L} D\ (lp\ \ )$= $\sum_{l\in L} D\ (lp\ \ )$- qpp(p*,j*) //update quantities
8. $\sum_{k\in K} qad\ (k)$= $\sum_{k\in K} qad\ (k)$- qpp(p*,j*)
9. MP(j*) = MP(j*) - qpp(p*,j*)
10. CPP(p*,j*) = ∞
11. V(j*) = 0 //go to next plant

Algorithm 2 is used to set the next two stages of product flow between plants and DCs and between DCs, and local retailers. Finally, Algorithm 3 describes the overall chromosome decoding procedure.



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**Algorithm 2**

*Decoding product flow from plants to DCs*

**Input:** qpp(pj), qad(k) CPP(pj), CTS(s), DF(jks), V(k) // chromosome priority
**Output:** qfd(pjks)

1. qfd(pjks) ← 0, $\forall p \in P, j \in J, k \in K, s \in S$
2. **While max{**V(k)} > 0 **and min**{CTS(s) * DF(jk*s)} < ∞
3. k* = **argmax**{V(k)}// choose highest priority DC
4. s*, j* = **argmin{**CTS(s) * DF(jk*s)}// choose lowest cost plant and transport type
5. p* = 0
6 **While** qad(k*)> 0 and **max**(qpp(pj*))> 0 and p < |P|:
7. qfd(p*j*k*s*) = **min**{qad(k*), qpp(p*,j*))}
8. qad(k*) = qad(k*) - qfd(p*j*k*s*) // update quantities
9. qpp(p*j*) = qpp(p*j*) - qfd(p*j*k*s*)
10. p* = p* +1
11. **If** qad(k*)= 0, **then** CTS(s) * DF(jk*s) = ∞ **and** V(k) = 0 $\forall s \in S, j \in J$
12. **If** $\sum_{p \in P} qpp$= 0, **then** CTS(s) * DF(j*ks) = ∞, $\forall s \in S, k \in K$

**Algorithm 3**

*Overall Decoding Procedure*

//V← priorities, //A ← facility establishment, //C← capacities

1. t*= 1;
2. dn(0, lp), = 0 $\forall p \in P, l \in L$
3. **While** t* < (T + 1)**:**
4. // Update demands
5. D(t*lp) = D(t*lp) + dn(t*- 1, lp), $\forall p \in P, l \in L$
6. **For** j ∈ C: // decode plant capacities
7. r = A(j) //plant production route
8. qaf(j) = IP(r) + C(j) * (MP(r) - IP(r))
9. **For** k ∈ C: // decode DCs capacities
10.. qad(k) = QID(k) + C(k) * (QUD(k) - QID(k))
11. **For** k ∈ K**:**
12. **If** V(k) = 0 **or if** A(k) = 0**:**
13. qad(k) = 0 // DC closed
14. **For** j ∈ J**:**
15. **If** A(j) = 0:
16. V(j) = 0 //plant closed
17. // Use Algorithm 1 to obtain production quantities:
18. qpp(t*pjr) $j \in J, s \in S, p \in P, r \in R$
19. // Use Algorithm 2 to obtain product flow from plants to DCs:
20. qfd(t*pjks), $\forall p \in P, j \in J, k \in K, s \in S$
21. // Use Algorithm 2 to obtain product flow from DCs to local retailers
22. qdc(t*pkls) $\forall p \in P, k \in K, l \in L, s \in S$
23. // Update backordered demand
24. dn(t*pl) = $D(t \quad lp) - \sum_{k \in K} \sum_{s \in S} qdc\,(t \quad pkls) \forall p \in P, l \in L$
25. t* = t*+1

### *3.3 Crossover and Mutation*

The crossover operator used to generate new solutions from parent solutions is a linear ordered crossover where every two parents generate two children. Initially, a cutting point is selected at random on the chromosome. The first child's genes are filled with the



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values of the first parent up to the cut-off point. After that point, the order of the second parent is followed, skipping those inserted values. The same procedure is repeated for the second child, with the exception that the values are copied from the second parent first.

Mutation operators are used to introducing diversity into the population through the utilization of an insertion operator where a sequence of random size is removed and inserted into another position, also selected at random. Four sequences are selected: two from the facilities establishment section and two from the capacities and priorities sections.

Although mutation is important to introduce diversity into the population, it can also result in low-quality random solutions if poorly designed. In this study, the mutation probability parameter is defined dynamically, starting with a value of 0.4 and updated along the generations as the number of generations without improvement divided by the number of generations of the stopping criteria. Therefore, as the number of generations without improvement gets closer to the stopping criteria, the mutation probability increases, hopefully helping the algorithm to escape from a local optimum.

### *3.4 The multi-objective GA framework*

The GA is carried out as follows: firstly, an initial population ($nb$) is generated at random, where each individual in the population must be decoded and their objective function values are calculated. Secondly, the fitness of each individual is measured in terms of dominance and crowding distance. Then, a binary tournament operator is used to select parents where two individuals are randomly selected from the population and the one with the best fitness value is chosen as a parent. Every two parents generate two children by crossover and, with a given probability, the offspring is submitted to mutation. Once another $nb$ individuals have been generated, they are inserted into the parent population forming a new population of size $2 * nb$. This new population is then classified by non-dominance, as only the $nb$ fittest individuals survive to the next generation. Initially, individuals from the first non-dominated front are added to the next population, as long as the number of individuals on the front is smaller than $nb$. The last front to be added in the new generation is classified by crowding distance, and the best individuals are selected until the remaining spots are filled, completing the new population. As long as the maximum number of generations without improvement is not reached, this procedure is repeated, and the new population becomes the parent population.

After preliminary experiments, $nb$ was set to 100 and the algorithm is stopped when reaching 20 generations without improvement in any of the three objectives.



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## 4 Results and Discussion

The experiments have focused its attention on scenarios from Brazil but the proposed solution can be extended to other cases.

### *4.1 Brazilian Case Study*

Brazil is the sixth-largest greenhouse gas generator (IABr, 2018, Climate Watch, 2020), where pig iron and steel production are responsible for about 44% of the CO2 emissions of Brazilian industries (Climate Observatory, 2020). Brazil has the largest steel industrial park in South America, represented by 15 companies that operate 31 industrial plants distributed over ten states. It has 51 million tons of annual capacity and is the world's sixth-largest net steel exporter (IABr, 2021).

The Brazilian steel industry has the particularity of using charcoal as a reducer in some blast furnaces. About 20% of Brazilian pig iron production uses charcoal (SINDIFER, 2019), which is an eco-efficient renewable fuel, therefore a more advantageous environmental alternative, since part of the carbon emitted in production would be captured during the growth stage of forests. Furthermore, there may be socio-environmental barriers because in some countries, like Brazil, part of the charcoal used by independent pig iron producers comes from native forests and is produced in precarious working conditions. These facts motivated this work to perform experimentations based on Brazilian data.

### *4.2 Experiments*

For the experiments, this paper devises instances using data gathered from several Brazilian institutional reports (IABr, 2018; IABr, 2019; Climate Observatory, 2020; CNT, 2019; ANTT, 2012; Ministry of Environment, 2013; EPL, 2018; SICETEL, 2019; Usiminas, 2020) and previous studies approaching steel production and transportation (Hasanbeigi et al., 2016; Conejo et al., 2020).

The experiments adopted the SVI, a social index ranging between zero and one, with zero corresponding to the ideal situation and one corresponding to the worst-case situation (IPEA, 2020) with a region having a higher level of social vulnerability in terms of urban infrastructure, human capital, income, and labor. The SVI is a comprehensive indicator and readily available for all Brazilian municipalities. To better understand the properties of the solutions returned by the algorithm, test instances with different complexity levels (small-size, a medium-size, large-size) were created and solved (Table 8). These test instances (I1, I2, I3) have different size for each one of its eight sets, comprising typical cases of the Brazilian steel industry. A link with more details of the instances is provided after Section 6.

**Table 8**

*Set size for each instance*

| Set | I1 | I2 | I3 |
|---|---|---|---|
| Plants | 8 | 18 | 28 |
| DCs | 8 | 18 | 28 |
| Local retailers | 9 | 19 | 29 |
| Products | 5 | 10 | 14 |
| Raw material | 3 | 5 | 10 |
| Modes of Transport | 1 | 2 | 2 |
| Routes | 2 | 3 | 4 |
| Periods | 2 | 4 | 6 |

The GA was implemented in Python 3.7 and solved on an Intel Core i7-3537U processor, CPU @ 2.0 GHz, and 8GB RAM. Due to the random nature of a GA, the experiments executed the algorithm 10 times with different random seeds. Preliminary experiments trained the model to select the best parameters for population size, selections and crossover rates.

### *4.3 Trade-off analysis of the objective functions*

Considering the conflicts among the three objectives, it is a challenge to improve one objective without deteriorating the others, therefore it is important to discuss the trade-offs. Figure 2 presents the GA results of an experiment solving the instance I3. Because there are three objectives, and two-dimension projections are more intuitive than three-dimensions, the figure shows the three combinations of 2 by 2 objectives. In Figure 2(a), the Pareto front shows that the SVI values increase with the raised CO2 emissions. The social indicator increases when more facilities are open; however, the emission level also grows. In Figure 2(b), one may note that the costs tend to be higher for lower emission scenarios. An investigation showed that the algorithm tried to improve the environmental objective (influenced by greenhouse gas emissions) by reducing the production of the plants, but the side effect was to increase the costs due to penalty payments for back-ordered demand.



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**Figure 2**

*Two-dimension projections for the GA results. (a) Environmental vs. Social; (b) Environmental vs. Economic and (c) Economic vs. Social decisions dimensions*

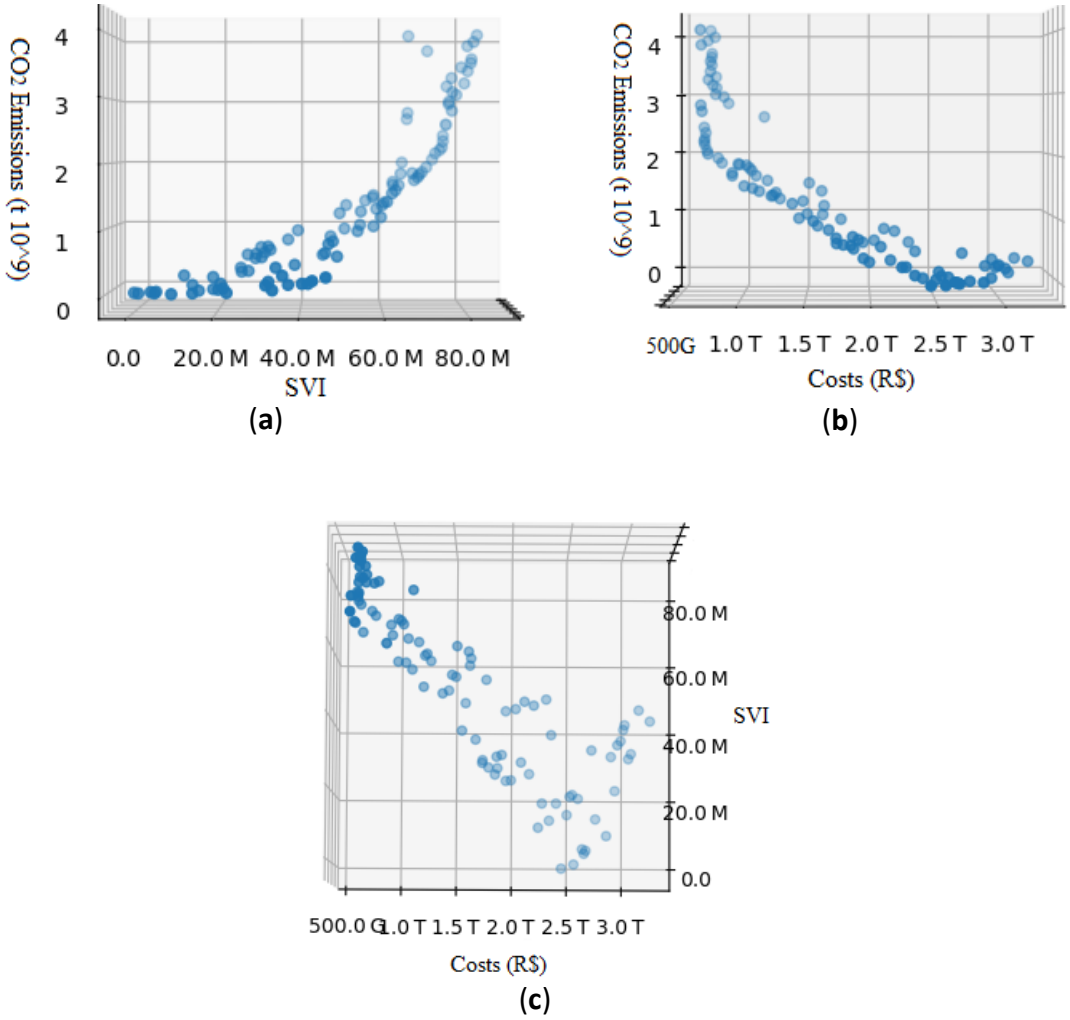


Figure 2(c) shows that a lower social index is related to higher associated costs since few opened industrial plants reduce the social index while increasing production and logistics costs due to penalty payments for back-ordered demand. Figures 2(a), 2(b) and 2(c) make clear that indeed there is trade-off among he three proposed objective and the result of the algorithm is able to identify and quantify the relationship of the objectives. The other instances returned similar results.

### *4.4 Effect of changing the production route (technology)*

In the perspective of the decision maker in a steel industry, one important decision regards the type of technology to be implemented in the operations plants. To study the effect of selecting different technologies, we performed a set of experiments to analyze different

production route decisions, assuming that only one of the four types of technological routes is adopted: production route with coke, native charcoal, planted charcoal, and EAF. For the sake of comparison, the production route using coke is the baseline scenario, and the metric is the mean value of each objective function (OF). Figure 3 shows the overall mean change for each OF when the production route (technology) changes from coke to another process route (native charcoal, planted charcoal, or Electric Arc Furnace -EAF), solving the instance I3 (the biggest).

**Figure 3**

*Effects in each OF when production route switches from the coke route to each of the other three production route*

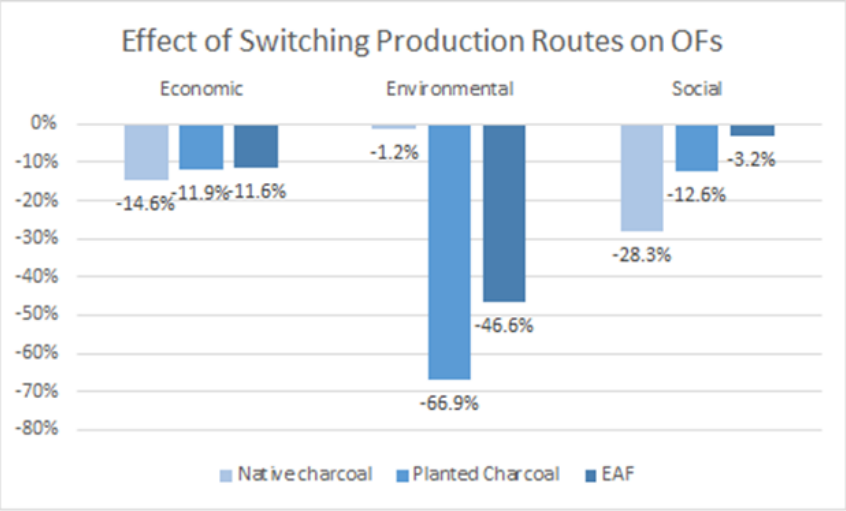


Figure 3 shows that the environmental OF is mostly impacted by the change from coke to planted charcoal, where the average emissions are reduced by 66.9%. The EAF route also helps to improve environmental performance, reducing average emissions by 46.6%. The results also show that the economical dimension is not severely impacted by the alternative production routes, obtaining reductions from 11.6% to 14.6%, evidencing that integrated industrial plants that adopt coke have higher production yields, contributing to higher production scenarios. Therefore, a higher production index based on coke also contributes to a higher social index, as described in the problem definition. The three alternative routes reduced the social impact when compared to the coke production route' scenario. Adopting the native charcoal production route reduces the social index by 28.3%, the highest negative variation for the social dimension. It is useful to notice form the results that a change from coke to any of the other technologies has approximately the same economic impact, opening possibilities to find a solution benefiting the environmental and social objectives.



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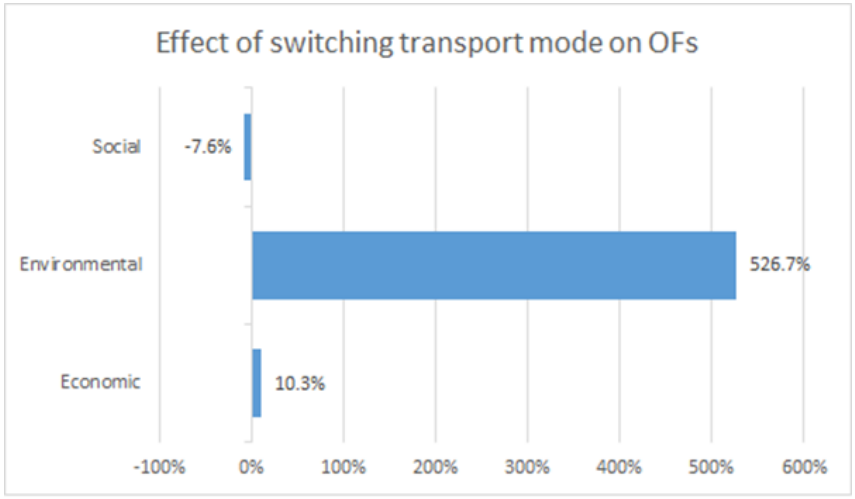
### *4.5 Effect of changing the transportation mode*

In the Brazilian steel industry, the typical transportation modes are: highways and railroads. To compare the effects in the objective functions when using one mode or the other, an experiment has been performed. The results show that when switching from railroads to roads, the economic and social values of the OFs remain virtually the same, however, it severely impacts the environment index. The resulting environmental costs increase by 526.7% (see Figure 4). This result makes clear that the environmental objective is much more sensitive to the change of the transportation mode than the other two objectives.

**Figure 4**

*Effects in each OF when transport mode switches from railroad to roads*




### *4.6 Effect of changing candidate locations to open facilities*

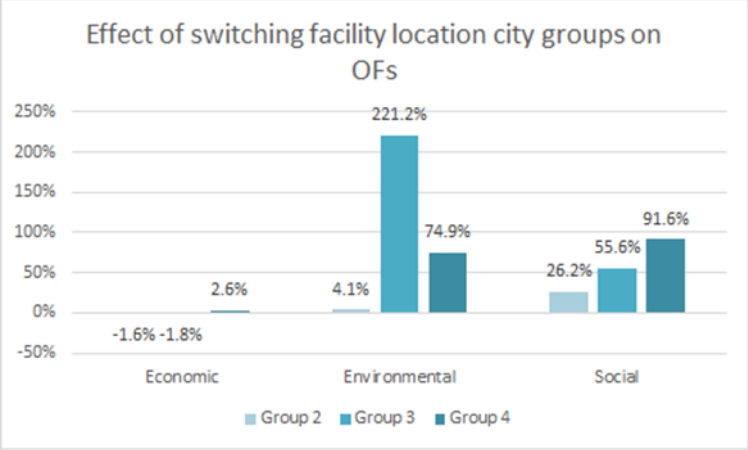
In real problems, it is common to select a set of candidate locations before running the optimization that will select the best ones. Here, an experiment is proposed to learn about how different sets of candidate locations influence the result of the optimization. In this experiment, a data base of 28 locations (municipalities) is sorted by their social vulnerability index (SVI) and then separated into four groups comprised of seven locations each. Ranging from the lowest to the highest SVI, the first group refers to locations with the lowest SVI, while the fourth group refers to locations with the highest SVI. For each group, the problem was optimized using only the locations of the respective group. Figure 5 shows the changes in the mean of the objective functions values (OF) when changing from the first group (with lowest SVI), to the other three groups, with higher SVI. The first group is used as a baseline and Figure 5 reports relative percentages.

The solution returned from the algorithm when using Group 4 as a set of candidate locations increases the social objective by 91.6% when compared to the baseline group (Group 1), as presented in Figure 5. Therefore, the result shows that the social index

improves with the SVI increase. It is also seen that the values for the economic index do not vary significantly, ranging from -1.6 to 2.6%.

**Figure 5**

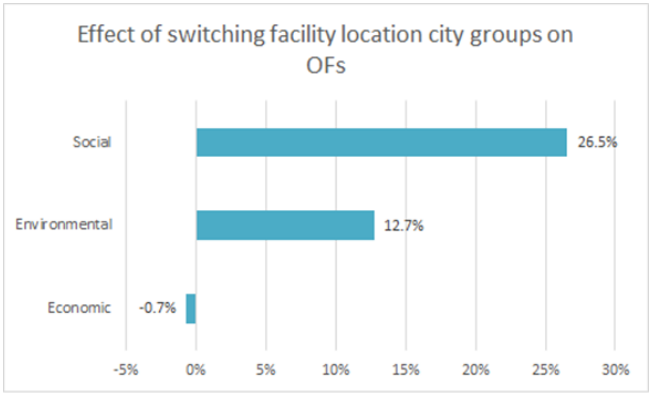
*Effects in each OF when candidate municipalities are changed*




Still, in Figure 5, it is seen that Groups 3 and 4 show an increase in the environmental dimension. Group 3 contains a city that is not accessible by rail, resulting in an increase in CO2 emissions due to the use of roads. Additionally, the separation of groups by SVI rank creates a concentration of municipalities in a single region, for instance, the most vulnerable cities are in the North and Northeast regions of Brazil. Nevertheless, local retailers remain scattered throughout the national territory, which results in greater travel distances, increasing CO2 emissions. Therefore, we carried out an additional analysis considering two groups of four municipalities. The first group contains the municipalities with the lowest SVI and the second group with the highest SVI municipalities for each of the four regions considered (Figure 6).

**Figure 6**

*OF variation when municipalities group switches from groups*



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The second analysis (Figure 6) shows that switching from the location of facilities on the low to locating steel plants in the high SVI group results in a social index increase, with a lower variation in the other dimensions, favoring the establishment of facilities in the most vulnerable municipalities.

## 5 Conclusion

This study proposed an innovative and strategic solution for sustainable steel production by formulating and solving a multi-objective, multi-level, multi-modal, multi-product, and multi-period model for sustainable SCND. The model includes particular features of the steel process and technological production routes allowing a country-level analysis that can balance financial, competitiveness, eco-efficiency, and social responsibility factors for new entrant steel networks in the presence of pre-existing competing chains. The proposed optimization model was solved through a GA metaheuristic devised to solve the problem efficiently, providing numerous distinct solutions to a Pareto frontier. The experiments of Section 4.3 confirmed that indeed there is a trade-off among the three proposed objective, mapping the relationship of the objectives. The experiments of the Section 4.4 showed how changes in the production technology impacts the objectives differently. In Section 4.5, we learn that the environmental objective is much more sensitive to the change of the transportation mode than the other objectives. And finally, in Section 4.6, the result shows that when the optimization model is executed with high SVI candidate locations as input, the output solutions tend to have higher social index.

This study presents some delimitations concerning data and methods. We adopted only one option for the production route in steel plants, while there may be plants with more than one or a combination of different technological processes. The parameters used to quantify the environmental impact are limited to a few indicators, while a product life cycle assessment could be employed. Concerning the social index, the assumptions for selecting locations are comprised of several metrics that also incorporate qualitative aspects. In order to make the proposed model even more complete in terms of practical applications, future research may consider the inclusion of uncertainties in the model, specially regarding the product demand per time period, using Fuzzy Logic, for example.

## References

ANTT (Brazilian National Agency of Land Transportation), 2012. National Inventory of Atmospheric Emissions from Rail Cargo Transport. Brasilia- Brazil. [in Portuguese].

Arampantzi, C., & Minis, I. (2017). A new model for designing sustainable supply chain networks and its application to a global manufacturer. Journal of Cleaner Production,

156, 276-292. Doi: https://doi.org/10.1016/j.jclepro.2017.03.164

Ates, S. A. (2015). Energy efficiency and CO2 mitigation potential of the Turkish iron and steel industry using the LEAP (long-range energy alternatives planning) system. Energy, 90, 417-428. Doi: https://doi.org/10.1016/j.energy.2015.07.059

Barbosa-Póvoa, A. P., da Silva, C., & Carvalho, A. (2018). Opportunities and challenges in sustainable supply chain: An operations research perspective. European Journal of Operational Research, 268(2), 399-431. Doi: https://doi.org/10.1016/j.ejor.2017.10.036

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. European journal of operational research, 233(2), 299-312. Doi: https://doi.org/10.1016/j.ejor.2013.09.032

Castro Vivas, R., Sant'Anna, A. M. O., Esquerre, K. P. O., & Freires, F. G. M. (2019). Integrated method combining analytical and mathematical models for the evaluation and optimization of sustainable supply chains: A Brazilian case study. Computers & Industrial Engineering, 139, 105670. Doi: https://doi.org/10.1016/j.cie.2019.01.044

Chalmardi, M. K., & Camacho-Vallejo, J. F. (2019). A bi-level programming model for sustainable supply chain network design that considers incentives for using cleaner technologies. Journal of Cleaner Production, 213, 1035-1050. Doi: https://doi.org/10.1016/j.jclepro.2018.12.197

Climate Observatory, 2020. System for estimating greenhouse gas emissions. URL http://plataforma.seeg.eco.br/ (accessed 5.11.20). [in Portuguese].

Climate Watch, 2020. Climate Watch Data. Url: https://www.climatewatchdata.org/ghg-emissions (accessed 30.12.21).

CNT (National Confederation of Transport), 2019. Statistical Bulletin. Brasilia. [in Portuguese].

Conejo, A. N., Birat, J. P., & Dutta, A. (2020). A review of the current environmental challenges of the steel industry and its value chain. Journal of environmental

management, 259, 109782. Doi: https://doi.org/10.1016/j.jenvman.2019.109782

Devika, K., Jafarian, A., & Nourbakhsh, V. (2014). Designing a sustainable closed-loop supply chain network based on triple bottom line approach: A comparison of metaheuristics hybridization techniques. European Journal of Operational Research, 235(3), 594-615.

Elkington, J. (2013). Enter the triple bottom line. In The triple bottom line (pp. 23-38). Routledge.

EPL (Planning and Logistics Company), 2018. National Logistics Plan Report – 2025. Brasilia. [in Portuguese]

Eskandarpour, M., Dejax, P., Miemczyk, J., & Péton, O. (2015). Sustainable supply chain network design: An optimization-oriented review. Omega, (United Kingdom) 54, 11-32. 54, Doi: https://doi.org/10.1016/j.omega.2015.01.006

Gen, M., Altiparmak, F., & Lin, L. (2006). A genetic algorithm for two-stage transportation problem using priority-based encoding. OR spectrum, 28(3), 337-354. Doi: https://doi.org/10.1007/s00291-005-0029-9

Hasanbeigi, A., Arens, M., Cardenas, J. C. R., Price, L., & Triolo, R. (2016). Comparison of carbon dioxide emissions intensity of steel production in China, Germany, Mexico, and the United States. Resources, Conservation and Recycling, 113, 127-139. Doi: https://doi.org/10.1016/j.resconrec.2016.06.008

IABr (Brazil Steel Institute), 2018. Sustainability Report. Rio de Janeiro. [in Portuguese].

IABr (Brazil Steel Institute), 2019. The Steel Industry in Numbers. Rio de Janeiro. [in Portuguese].

IABr (Brazil Steel Institute), 2021. URL: http://www.acobrasil.org.br [in Portuguese].

IPEA (Institute for Applied Economic Research), 2020. Atlas of Social Vulnerability. URL http://ivs.ipea.gov.br (accessed 3.27.20). [in Portuguese].

Kadziński, M., Tervonen, T., Tomczyk, M.K., Dekker, R., 2017. Evaluation of multi-objective optimization approaches for solving green supply chain design problems. Omega (United Kingdom) 68, 168–184. Doi: https://doi.org/10.1016/j.omega.2016.07.003

Khan, A.S., Khalid, Q.S., Naeem, K., Ahmad, R., Khan, R., Saleem, W., Pruncu, C.I., 2021. Application of exact and multi-heuristic approaches to a sustainable closed loop supply chain network design. Sustain. 13, 1–25. Doi: https://doi.org/10.3390/su13052433

Khorasani, S. T., & Almasifard, M. (2018). The development of a green supply chain dual-objective facility by considering different levels of uncertainty. Journal of Industrial Engineering International, 14, 593-602.

Khoshfarman Borji, M., Sayadi, A. R., & Nikbakhsh, E. (2023). A Novel Sustainable Multi-objective Optimization Model for Steel Supply Chain Design Considering Technical and Managerial Issues: a Case Study. Journal of Mining and Environment, 14(1), 295-319.

Macowski, D.H., Bonfim-Rocha, L., Orgeda, R., Camilo, R., Ravagnani, M.A.S.S., 2020. Multi-objective optimization of the Brazilian industrial sugarcane scenario: a profitable and ecological approach. Clean Technol. Environ. Policy. Doi: https://doi.org/10.1007/s10098-019-01802-0

Mc Loughlin, K., Lewis, K., Lascelles, D., & Nudurupati, S. (2021). Sustainability in supply chains: reappraising business process management. Production Planning & Control, 1-34. Doi: https://doi.org/10.1080/09537287.2021.1884764

Ministry of Environment, Brazil, 2013. National Inventory of Atmospheric Emissions by Road Motor Vehicles: Base year 2012. Brasília. [PtBr].

Moreno-Camacho, C. A., Montoya-Torres, J. R., Jaegler, A., & Gondran, N. (2019). Sustainability metrics for real case applications of the supply chain network design problem: A systematic literature review. Journal of cleaner production, 231, 600-618. Doi : https://doi.org/10.1016/J.JCLEPRO.2019.05.278

Mota, B., Gomes, M.I., Carvalho, A., Barbosa-Povoa, A.P., 2018. Sustainable supply chains: An integrated modeling approach under uncertainty. Omega (United Kingdom) 77, 32–57. Doi: https://doi.org/10.1016/j.omega.2017.05.006

Nielsen, H. (2017). Productive efficiency in the iron and steel sector under state planning:

The case of China and former Czechoslovakia in a comparative perspective. Applied Energy, 185, 1732-1743. Doi: https://doi.org/10.1016/j.apenergy.2015.12.125

Noh, J., & Kim, J. S. (2019). Cooperative green supply chain management with greenhouse gas emissions and fuzzy demand. Journal of Cleaner Production, 208, 1421-1435. Doi: https://doi.org/10.1016/j.jclepro.2018.10.124

Resat, H. G., & Unsal, B. (2019). A novel multi-objective optimization approach for sustainable supply chain: A case study in packaging industry. Sustainable production and consumption, 20, 29-39.

Rezapour, S., Zanjirani Farahani, R., & Drezner, T. (2017). Strategic design of competing supply chain networks for inelastic demand. Journal of the Operational Research Society, 62(10), 1784-1795. Doi: https://doi.org/10.1057/jors.2010.146

Sahebjamnia, N., Fathollahi-Fard, A.M., Hajiaghaei-Keshteli, M., 2018. Sustainable tire closed-loop supply chain network design: Hybrid metaheuristic algorithms for large-scale networks. J. Clean. Prod. 196, 273–296. Doi: https://doi.org/10.1016/j.jclepro.2018.05.245

Sarkar, B., Omair, M., & Choi, S. B. (2018). A multi-objective optimization of energy, economic, and carbon emission in a production model under sustainable supply chain management. Applied Sciences, 8(10), 1744.

Seydanlou, P., Jolai, F., Tavakkoli-Moghaddam, R., & Fathollahi-Fard, A. M. (2022). A multi-objective optimization framework for a sustainable closed-loop supply chain network in the olive industry: Hybrid meta-heuristic algorithms. Expert Systems with Applications, 203, 117566.

SICETEL (National Union of Ferrous Metals Drawing and Rolling Industries), 2019. Steel Market Analysis. São Paulo. [in Portuguese].

Sindifer (Sindicato da Indústria do Ferro no Estado de Minas Gerais), 2019. Annual Statistics. Belo Horizonte. Brazil.

Tosarkani, B. M., & Amin, S. H. (2018). A possibilistic solution to configure a battery closed-loop supply chain: multi-objective approach. Expert systems with applications, 92, 12-

26. Doi: https://doi.org/10.1016/j.eswa.2017.09.039

Tseng, M. L., Islam, M. S., Karia, N., Fauzi, F. A., & Afrin, S. (2019). A literature review on green supply chain management: Trends and future challenges. Resources, Conservation and Recycling, 141, 145-162. Doi: https://doi.org/10.1016/j.resconrec.2018.10.009

UN (United Nations), 2015. Transforming Our World: the 2030 Agenda for Sustainable Development.

Usiminas, 2020. 4Q19 Earnings Release. [in Portuguese].

Vafaeenezhad, T., Tavakkoli-Moghaddam, R., & Cheikhrouhou, N. (2019). Multi-objective mathematical modeling for sustainable supply chain management in the paper industry. Computers & Industrial Engineering, 135, 1092-1102.

Yadav, V. S., Tripathi, S., & Singh, A. R. (2019). Bi-objective optimization for sustainable supply chain network design in omnichannel. Journal of Manufacturing Technology Management, 30(6), 972-986.

Zarbakhshnia, N., Soleimani, H., Goh, M., & Razavi, S. S. (2019). A novel multi-objective model for green forward and reverse logistics network design. Journal of Cleaner Production, 208, 1304-1316. Doi: https://doi.org/10.1016/j.jclepro.2018.10.138

Zhang, S., Lee, C. K. M., Wu, K., & Choy, K. L. (2016). Multi-objective optimization for sustainable supply chain network design considering multiple distribution channels. Expert Systems with Applications, 65, 87-99.

Zhang, X., Zhao, G., Qi, Y., & Li, B. (2019). A robust fuzzy optimization model for closed-loop supply chain networks considering sustainability. Sustainability, 11(20), 5726. Doi: https://doi.org/10.3390/su11205726