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A bi-objective model for scheduling green investments in two-stage supply chains

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ABSTRACT

Investing in green technologies to increase sustainability in supply chains has become a common practice for two reasons: the first is directly related to the defense of the environment and people's health to smooth the emissions of pollutants; the second is the increasing consumer awareness of green products. Despite the higher costs of producing with green technologies and processes, there is also a higher markup on the price of products which rewards the former costs. This study proposes a mathematical model for scheduling green investments over time in a two-stage supply chain to minimize the impact of production on the environment and the economic costs deriving from the investment. The resulting bi-objective model has nonlinear constraints and is solved using a commercial solver. Given its complexity, we propose an upper-bound heuristic and a lower-bound model to reduce the optimality gap attained at a given time limit. Tests on synthetic instances have been conducted, and an example demonstrates the applicability and efficacy of the proposed model.

1. Introduction and literature review

Clean technologies can help reduce environmental impact or improve efficiency and productivity. According to several criteria, the objectives for investing in green technology can be categorized. Among them, the following can be found: (i) Source reduction, where the objective is to lessen waste and pollution by altering patterns of consumption and production; (ii) Sustainability, where the aim is to meet societal needs by using techniques that can be used indefinitely in the future so that natural resources are not harmed or depleted; (iii) Innovation, when the goal is to create alternatives to existing technologies when those technologies are environmentally detrimental; (iv) Cradle-to-cradle Design, which calls for making products that can be recycled or reused, ending the cradle-to-grave cycle that most manufactured products experience; (v) Viability, which focuses on the establishment of economic activity hubs that prioritize environmental products and technologies.

In this paper, we concentrate on the first of these goals, i.e., Source Reduction, in the quest to minimize the emissions produced by production plants/facilities. In an attempt to solve this strategic problem comprehensively, we also try to trade off the latter objective with another still important goal. In fact, generally, an investment in green technologies, besides the benefits in reducing the impact on the environment, carries additional costs related to, e.g., properly using and coordinating these new technologies with the resources currently existing in a (production) plant. This is the second main feature that we concentrate on, trying to define a way of modeling and minimizing such additional costs. Therefore, our proposal/contribution is a bi-objective model which poses the simultaneous minimization of (i) the emissions associated with production facilities when investments in green technologies, under a limited budget, have to be scheduled overtime producing a positive effect on the environment and (ii) the costs associated with such investments.

Several papers in the literature deal with green investments and green technologies. A classification system for green technologies is presented by Guo et al. [16]. Investments in cleaner technologies are addressed in Sengupta [29] in terms of incentives to invest and pricing strategy. Government subsidies are analyzed by Li et al. [23] under the cap-and-trade mechanism. The problem is studied in a two-echelon supply chain and modeled as a Stackelberg game. Game theory is also applied by Bian et al. [4] to determine the effects of subsidy policies on the manufacturer and the consumer. Coordination mechanisms are studied by Zhang and Yousaf [45]; an application to the petroleum industry is used to demonstrate the efficacy of two-part tariff contracts and how to select between taxes and subsidies. An empirical study based on historical data is presented by Siedschlag and Yan [31]; they

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show the relations between the dimension of the company and the industry sector and green investments. Knobloch and Mercure [19] provide a model for technology adoption; in this framework, companies are modeled as agents with various behaviors, and the problem is solved using Monte Carlo simulations. To find the best investment-production plan, Liu et al. [24] solve a matching process between a manufacturer with a limited investment budget and a green technology supplier using a Stackelberg model. Zhang et al. [47] examine green investments made by manufacturers in a competitive market with a single common retailer. Wang et al. [35] simulate a supply network with one supplier and one retailer using a game-theoretic approach and explore who should invest in green technologies in a decentralized supply chain under uncertain demand. Demand uncertainty is also assumed by Wang and Song [38] to investigate the pricing policies for a dual-channel supply chain with green investment and sales efforts. Here the manufacturer produces both green and non-green products and sells the former using direct channels and the latter using retail channels. Considering the selling prices of these two kinds of products, sales effort and green level as decision variables, the authors propose three models where the manufacturer and the retailer maximize their expected profits in centralized, decentralized, and collaborative scenarios. Wang et al. [39] analyze the implications of vertical strategic interactions for green technology investment in a supply chain and find that the retailer closer to the customer is the more effective undertaker for green technology investment. According to Wang et al. [37], who concentrate on the interaction between the supplier's choice of online channel format and the e-tailer's green investment strategy, the e-tailer would only go green when the efficiency of the upstream investment is high, despite the online channel format.

Yang et al. [44] investigate the green investment of two competing manufacturers in a supply chain based on price and quality competition and analyze the effect of green investment on the quality level of the product. Zhang et al. [46] develop a game-theoretical model to study green investment choice decisions of two horizontally differentiated firms in the presence of quality competition in a duopoly market. Shi et al. [30] investigate clean technology investment in a competitive environment for a supply chain formed by one manufacturer and two retailers. Wu et al. [40] investigate green technology investment decisions in a closed-loop supply chain with government subsidies. In their two-period model, Dong et al. [9] study the strategic investment for green product development in a supply chain. A two-period model is developed in which either the retailer or the manufacturer could decide to invest in green product development in the second period. In order to analyze how customer environmental awareness and regulatory pressure affect supply chain profits and emissions, Cheng et al. [8] devise a differential game model. Li et al. [21] examine the effects of customer green awareness and product substitutability on supply chain profitability, social welfare, and environmental performance. Heydari et al. [17] analyze the green channel coordination problem in a two-echelon supply chain where demand is a function of the retailer price and the product's green quality in a green supply chain under consumer environmental awareness. Moon et al. [27] investigate an investment problem in a supply chain for fresh agricultural products considering different investment scenarios. The supply chain is then coordinated using a combined strategy of cost-sharing and revenue-sharing contracts. Wang et al. [36] study a supply chain network design problem with environmental investment decisions in the design phase and propose a multi-objective optimization model capturing the trade-off between the total cost and the environmental influence.

In a multi-level supply chain with a single firm, operational management issues are addressed by Benjaafar et al. [3] using low-carbon factors. Taking into account both cost and carbon footprint, they examined how inventory decisions affect carbon emissions. Toptal et al. [33] investigate order quantity and investment in carbon emission reduction under various emission regulations. Dong et al. [10] analyze the viability of supply chain coordination through various contracts and study the sustainability investment in sustainable products with emission regulation in a two-level supply chain. Chen and Hu [7] discuss how retailers should invest in green technology and manage their warehouses in light of the cap-and-trade emissions policy. Gharaei et al. [13] develop an integrated supply chain model under penalties with green, quality control policies while taking into account the tax cost of greenhouse gas emissions. In a two-echelon supply chain, Ghosh and Shah [14] investigate the effects of greening costs and customer sensitivity toward green apparel. To coordinate the green channel, they suggest a two-part tariff contract between the manufacturer and the retailer. To analyze pricing and greening strategies in a two-echelon supply chain and to suggest a contract to manage the decentralized dual-channel green supply chain, Li et al. [20] present a Stackelberg game model. Ma et al. [26] propose six different models to analyze the pricing strategies for sustainable products in a two-stage supply chain with two competitive producers and one retailer. The interaction between upstream and downstream firms when they choose green investments is also studied. Andic et al. [1] use an empirical analysis method to analyze the dynamics between upstream and downstream firms in the supply chain when the firms adopt a more environmentally aware attitude. Yan et al. [42] show how upstream green investment efficiency can affect downstream competition intensity and the degree of the prisoner's dilemma in a dual-channel supply chain.

In Li et al. [22] the authors study a green investment problem of a sustainable supply chain with one manufacturer and one retailer. The manufacturer may adopt blockchain to possibly raise customers' green sensitivity level. The study compares the supply chain performance with and without blockchain, each in combination with and without emotional fairness concerns of the customers. Sun et al. [32] study the strategy of green investment for manufacturers and material suppliers in a two-echelon supply chain to identify the optimal green investment strategy under a government subsidy policy. An evolutionary game theory model is developed between a population of suppliers and a population of manufacturers under a government subsidy mechanism. The study by Huang et al. [18] investigates the effects that carbon policies and green technologies may have on the integrated inventory of a two-echelon supply chain considering carbon emissions during production, transportation, and storage processes. Three carbon emissions policies (limited total carbon emissions, carbon taxation, and cap-and-trade) are considered in the study. Yang et al. [43] model the environmental responsibility behaviors of both the manufacturer and consumers to study the dual-channel structure strategy of a green manufacturer and examine its environmental performance under fuzzy uncertainties.

To meet customer demand in a remanufacturing environment with green investment, Sarkar and Bhuniya [28] suggest a model that focuses on the flexibility of production rate under the multi-retailer-based supply chain. In this study, the manufacturer produces using both new and used raw materials. A two-echelon green supply chain comprising a risk-averse manufacturer and a risk-neutral retailer, where the retailer is the leader and the manufacturer is the follower, is studied by Bai and Wang [2] with the goal of increasing the level of green investment, the green degree of products, and reduce the impact of risk aversion on green investment. A Stackelberg game model of green investment decision-making among companies is constructed by Wu et al. [41] by taking into account the scenarios of the supplier's alone green investment and the manufacturer and the supplier's joint green investment. Analysis of the impact of green uncertainty company choices and a comparison of green investment decision-making strategies are provided. Feng et al. [12] define green supply chain innovation as innovation practices by manufacturers that apply emergent digital technologies to integrate environmental concerns into supply chain management activities. Cao et al. [5] consider an agri-food supply chain consisting of a cooperative, an enterprise, and environmentally sensitive consumers. Consumer demand for green agri-food depends on products' sales price and greenness. According to the study, the degree of greenness is decided by both the cooperative and the enterprise's greening efforts, and each party's efforts cannot fall below a particular level in compliance with the requirements of applicable laws and regulations on green agri-food and the environment. The best choices made by each entity in a centralized and decentralized system are investigated using a game-theory model. Liu et al. [25] study the issue of investment decisions and coordination in a green agri-food supply chain. To solve this problem, they propose a specific supply chain structure where Big Data and blockchain are applied.

Using a Stackelberg game model, Golmohammadi and Hassini [15] investigate cooperative investments made by a buyer and a supplier to increase the capacity of the supplier. They examine both buyer-led and supplier-led scenarios and demonstrate that the actors exhibit opportunistic behavior toward investment in both contexts. When the buyer determines that the supplier is willing to invest in the buyer-led game, he/she refrains from making any direct contributions to capacity improvement. Falcone [11] debate why taking on a wide range of difficulties is necessary for a successful transition away from a long-established regime that is built on deeply ingrained production and consumption practices. In fact, the establishment of necessary investment projects is still seen as having a high degree of complexity and unpredictability in the transition toward sustainability. In order to hasten this transition and ensure a level playing field between the traditional and green economies, the paper shows how green financing can play a critical role in this regard. In Wang and Wang [34], a port, a shipping firm, and a forwarder make up a maritime supply chain. To cut down on emissions of pollutants, the port and shipping companies decide on particular green investments. The authors propose three vertical alliance strategies for the shipping companies: no alliance, alliance with the port, and alliance with the forwarder.

Regarding the cited literature, our contribution is to put forth a nonlinear model that can determine the best investment plan taking into account the time-varying cost of emissions and the relationships between investments and emissions over time. The proposed model is nonlinear. To expedite its resolution we provide an algorithm to find a starting upper bound and a lower bounding model. Computational results reveal that the model can produce meaningful results compared to the scenario of investing all the budget at the beginning of the planning period without a correct scheduling strategy.

The rest of the paper is organized as follows. Section 2 contains the definition of the problem and its mathematical formulation. Section 3 defines the starting initial solution algorithm and the lower-bound proposals. Section 4 shows the experimental campaign and, finally, in Section 5, we draw some conclusions.

2. Problem definition and mathematical formulation

In the following, we formally describe the problem under consideration and the proposed mathematical formulation. Given is a supply chain network modeled as a graph $G = (N, A)$, where N and A are the set of nodes and arcs, respectively. The graph is bipartite and, therefore, N is the union of two partite sets, i.e., the set S of suppliers and the set F of facilities, that is, $N = S \cup F$. The set A of arcs models connections among pairs of nodes belonging to the Cartesian products $S \times F$. Given customer demand, supply capacities, and a budget (denoted with B) to be invested in environmental protection, the goal is to decide how to invest B over time to minimize CO_2 emissions and investment costs while respecting demand and capacities. The sets and parameters are:

- S: the set of supplies;
- F: the set of facilities;
- T: the set of time periods defining the time horizon;
- j: index for facilities;
- k: index for suppliers;
- D: the total demand of customers;
- s_{kt}: the supply capacity of supplier $k \in S$ at time $t \in T$;
- B: the available budget for the (green) investments in the facilities;
- c_{jt}: capacity of facility $j \in F$ at time $t \in T$,
- $\tilde{\phi}_j$: constant of the inverse relationship between the total investment made until a certain time period in facility $j \in F$ and the cost of CO_2 emissions per unit of product at the same time in j,
- $\bar{\phi}_j$: CO_2 emission cost in facility $j \in F$ without investments,
- $\bar{\rho}_t$: unit cost of an investment made at time $t \in T$ in a facility;
- L_{min}: the minimum amount of products to be sent from suppliers to a facility.

The decision variables are:

- x_{kjt}: flow of products from supplier $k \in S$ to facility $j \in F$ at time $t \in T$;
- z_{jt}: investment in environmental protection in facility $j \in F$ at time $t \in T$;
- ϕ_{jt}: cost of CO_2 emissions per unit of product associated with facility $j \in F$ at time $t \in T$;
- ρ_t: total cost of the investments made at time $t \in T$ in all the facilities;
- y_{jt}: binary variable that holds 1 if an investment has been made until time $t \in T$ in facility $j \in F$, and holds 0 otherwise.

The objective function measures the total cost of CO_2 emissions produced by plants plus the total cost associated with investments as follows:

$$\min \sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\phi_{jt}x_{kjt} + \sum_{t\in T}\rho_t. \tag{1}$$

Variables ϕ_{jt} and ρ_t are defined in the following constraints.

Constraint (2),

$$\rho_t = \sum_{j\in F}\sum_{\tau=t}^{T}\bar{\rho}_t z_{jt}(1-\alpha)^{\tau-t},\ \ \forall\, t\in T, \tag{2}$$

defines the investment cost made at time $t \in T$. We assume that a certain investment made at time t in plant j, say z_{jt}, in addition to budget consumption, requires acquiring resources to use and/or implement the purchased technology. These resources produce, in each time period from t to T, a cost $\bar{\rho}_t z_{jt}$, where $\bar{\rho}_t$ is the unit investment cost. The latter is time-indexed since it can vary over time in such a way that $\bar{\rho}_t \geq \bar{\rho}_{t-1}$, with $t = 2, \ldots, T$. This is because technologies may suffer from obsolescence during the time horizon considered. The cost associated with an investment quota z_{jt} in facility j at time t is not constant over time. In fact, the (external and/or additional) resources consumed and generating such costs tend to (i) yield a return on these investments over time and (ii) produce a learning-by-doing effect; together, these factors tend to decrease the investment cost over time with a decay modeled by the term $(1-\alpha)^{\tau-t}$, with $\tau = t, \ldots, T$, where α is a parameter ranging from 0 (no cost reduction is produced over time) to 1 (the cost is completely rewarded in the first period). When the investment is made at time $\tau = t$ its cost is at its full rate $\bar{\rho}_t$ and, for increasing values of t, it decreases, tending to zero.

To figure out the behavior of (2), we report and display two examples. In the first case, $\hat{\rho}_t$ does not decrease over time, so we assume a cost decrease factor $\hat{\rho}$ constant over time and equal to 1, i.e, $\hat{\rho}_t = \hat{\rho}\cdot\hat{\rho}_{t-1} = \hat{\rho}_{t-1}$, with $t = 2, \ldots, T$. In the second example, we consider a cost decrease factor $\hat{\rho}$ equal to 0.8, i.e., $\hat{\rho}_t = \hat{\rho}\cdot\hat{\rho}_{t-1} = 0.8\hat{\rho}_{t-1}$, with $t = 2, \ldots, T$. The different values of $\bar{\rho}_t$, and ρ_t are shown in Figs. 1 and 2, respectively, considering $\alpha = 0.1$.

Constraint (3) limits investments to the available budget B,

$$\sum_{j\in F}\sum_{t\in T} z_{jt} = B. \tag{3}$$

This constraint ensures that green investments must be made within the time horizon T and can be distributed over time. The rationale of this assumption is that green investments may encompass different areas/

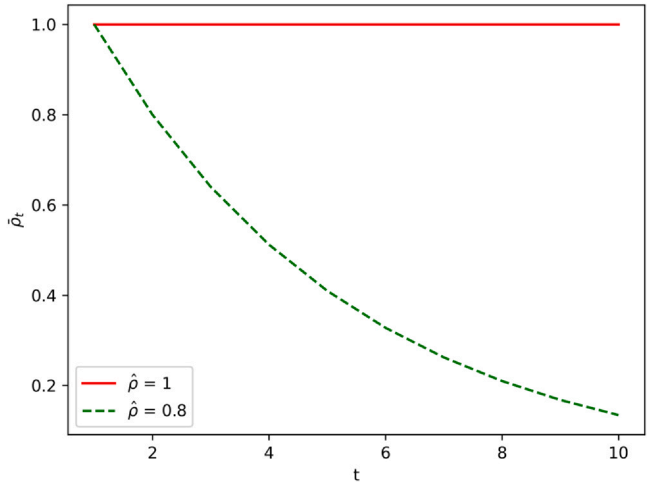

Fig. 1. $\bar{\rho}_t$ with different $\hat{\rho}$ factors.

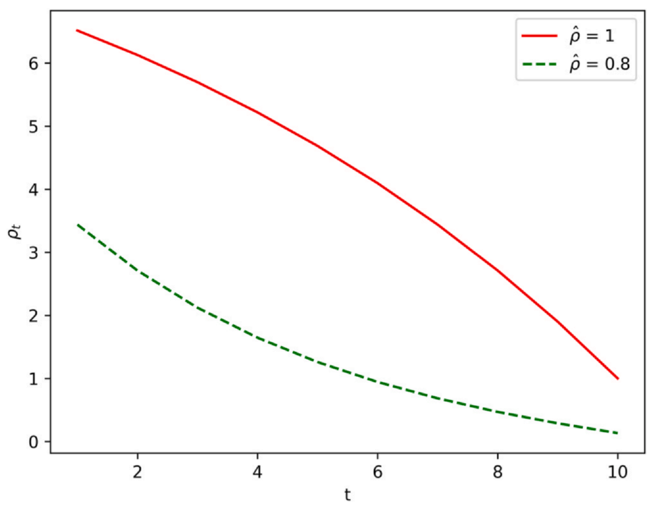

Fig. 2. ρ_t with different $\hat{\rho}$ factors.

parts of the plants, and therefore, they can be carried out in different time periods and, also, differently distributed over time among the plants.

A further limitation is that the initial investment cannot be very close to zero but should be greater than or equal to a minimum value B_{min}. This is formulated in by Constraints (4) and (5):

$$\sum_{\tau=1}^{t} z_{j\tau} \geq y_{jt} B_{min}, \quad \forall\, j \in F, \forall\, t \in T. \tag{4}$$

$$B y_{jt} \geq \sum_{\tau=1}^{t} z_{j\tau}, \quad \forall\, j \in F, \forall\, t \in T. \tag{5}$$

Constraint (4), imposes that if $y_{jt} = 1$, then $\sum_{\tau=1}^{t} z_{j\tau} \geq B_{min}$, as requested, while Constraint (5) imposes that if y_{jt} holds 0 then $\sum_{\tau=1}^{t} z_{j\tau} = 0$. Indeed, when $y_{jt} = 0$, by the definition of this variable, the sum of investments made in plant j until time t must be zero, which is implied by the above constraint. Furthermore, if $y_{jt} = 1$, then we have $B \geq \sum_{\tau=1}^{t} z_{j\tau}, \ \forall\, j \in F, \forall\, t \in T$.

To make $\sum_{\tau=1}^{t} z_{j\tau}$ consistent when $y_{jt} = 1$, we introduce Constraint (6), reported below, that implies that $\sum_{\tau=1}^{t} z_{j\tau}$ will be greater than zero in case $y_{jt} = 1$. Indeed, Constraint (6) defines the relation between investment quotas until time $t \in T$ in facility $j \in F$ and CO_2 emissions per unit of flow at time t in the same facility, that is,

$$\phi_{jt} = y_{jt} \frac{\hat{\phi}_j}{\sum_{\tau=1}^{t} z_{j\tau} + y_{jt} - 1} + \bar{\phi}_j (1 - y_{jt}), \quad \forall\, j \in F, \forall\, t \in T. \tag{6}$$

It says that if no investment has been made in plant j until time t, i.e., $y_{jt} = 0$, then $\phi_{jt} = \bar{\phi}_j$, that is, the CO_2 emission cost per unit of product reaching facility j at time t without any green intervention. In case $y_{jt} = 1$ then $\phi_{jt} = \frac{\hat{\phi}_j}{\sum_{\tau=1}^{t} z_{j\tau}}$ and it appears to be worthwhile to have invested until time t unless one pays an infinite value of ϕ_{jt}, which is not what the minimum function aims at.

Constraint (7) says that the overall flow of products over time must be equal to the customer demand, i.e.,

$$\sum_{k \in S} \sum_{j \in F} \sum_{t \in T} x_{kjt} = D. \tag{7}$$

We assume that market demand D is aggregated and should be met within the end of the planning period. Disaggregated demands for each time period and costs associated with possible storage of products in the plant over the planning horizon are not taken into account in our model; this is because the latter copes with a strategic problem and, therefore, tactical and operational phases, hierarchically subordinate, are to be taken into account afterward, possibly in a separate successive optimization phase.

Constraints (8) and (9) are capacity constraints. In particular, (8).

$$\sum_{j \in F} x_{kjt} \leq s_{kt}, \ \forall\, k \in S, \forall\, t \in T, \tag{8}$$

imposes that the amount of supply, from each supplier $k \in S$, should not exceed the amount s_{kt} at each time $t \in T$. Constraint (9).

$$\sum_{k \in S} x_{kjt} \leq c_{jt}, \quad \forall\, j \in F, \forall\, t \in T, \tag{9}$$

imposes that the total flow entering facility $j \in F$ at each time $t \in T$ should not be greater than the capacity c_{jt} of facility j at that time.

To ensure that when no flow has been directed to facility j until time t no investment has been made in j until that time, we add the following Constraint (10):

$$\sum_{k \in S} \sum_{\tau=1}^{t} x_{kj\tau} \geq y_{jt} L_{min}, \quad \forall\, j \in F, \forall\, t \in T. \tag{10}$$

Indeed, if no flow is sent to a facility j until time t, we cannot assume that a learning-by-doing process or rewarding mechanism is going on in that plant; therefore, when the first term in (10) is zero, then y_{jt} must be zero. In contrast, when the first term is positive, y_{jt} can be either zero (in this case there is no restriction on the flow sent in j) or $y_{jt} = 1$ implying that

$$\sum_{k \in S} \sum_{\tau=1}^{t} x_{kj\tau} \geq L_{min}, \quad \forall\, j \in F, \forall\, t \in T,$$

which means that to consider an investment acceptable in j at least an amount L_{min} of products must be routed from suppliers to j.

Constraint (11),

$$\begin{aligned} y_{jt} &\geq y_{j,t-1}, \quad \forall\, j \in F, \forall\, t \in T, \\ y_{j0} &= 0, \qquad \forall\, j \in F. \end{aligned} \tag{11}$$

imposes that variable y_{jt} is a step variable and, therefore, once it assumes value 1 at a certain time t, the latter remains fixed to 1 until the end of the time horizon. A border condition is needed for this recursive definition, and, therefore, we put $y_{j0} = 0$.

The following remaining constraints define the domains of the variables, i.e.,

$$
\begin{aligned}
&x_{kjt} \geq 0, && \forall\, k \in S, \forall\, j \in F, \forall\, t \in T,\\
&z_{jt} \geq 0, && \forall\, j \in F, \forall\, t \in T,\\
&\phi_{jt} \geq 0, && \forall\, j \in F, \forall\, t \in T,\\
&\rho_{t} \geq 0, && \forall\, t \in T,\\
&y_{jt} \in \{0, 1\}, && \forall\, j \in F, \forall\, t \in T.
\end{aligned}
$$

3. Starting feasible solution and lower bound

In order to solve the problem, as detailed in the next section, we will use a commercial solver. As our model is non-linear and non-convex, in the following, we describe a heuristic algorithm to find an initial feasible solution and a lower-bound linear model to enhance its solution performance.

3.1. Starting feasible solution

To provide a starting feasible solution to the solver in a reasonable running time, we devised a fast algorithm, namely Algorithm 1, as follows. Initially, flows are sequentially allocated from suppliers to facilities, and then investments are activated in the facilities consistently with the flows; then, the remaining variables y_{jt}, ϕ_{jt}, and ρ_t are set to guarantee feasibility.

Algorithm 1. Upper bound algorithm.

```
Set x^u_{ijt}, z^u_{jt}, y^u_{jt}, phi^u_{jt}, \rho^u_t <- 0
Set s^r_{kt} <- s_{jt}; c^r_{jt} <- c_{jt} \forall k \in S, \forall j \in F, \forall t \in T
Set x^r_{jt} <- 0, D^r <- D
Set NF <- \emptyset
Set \mathcal{T} = {{1,...|T|}, {2,...(|T|-1)}, ..., {|T|, 1, ...(|T|-1)}}
for \bar{T} \in \mathcal{T} do
    for t \in \bar{T} do
        for k \in S, j \in F do
            Set maxflow <- min{s^r_{k,t}, c^r_{j,t}, D^r}
            if maxflow = 0 then
                continue
            x^s_{kjt} <- maxflow
            NF <- NF \cup (k, j, t)
            D^r <- D^r - maxflow
            s^r_{kt} <- s^r_{kt} - maxFlow
            c^r_{j,t} <- c^r_{j,t} - maxFlow
            if D^r = 0 then
                break
        if D^r = 0 then
            break
    for (k, j, t) \in NF do
        z^s_{jt} <- z^s_{jt} + B/|NF|
        for \tau \in {t, ... |T|} do
            y^s_{j\tau} <- 1
Compute \phi^s_{jt} using Equation (6)
Compute \rho^s_t using Equation (2)
Compute UB using Equation (1)
```

3.2. Lower bound

In this section, we derive a linear program that provides a lower bound to the optimal solution value of the nonlinear program defined in Section 2. Let us use Constraint (6) by substituting ϕ_{jt} in the objective function. We obtain

$$\min \sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\left[\hat{\phi}_{jt}\frac{x_{kjt}}{\sum_{\tau=1}^{t} z_{j\tau}+y_{jt}-1}y_{jt}+\bar{\phi}_{jt}x_{kjt}(1-y_{jt})\right]+\sum_{t\in T}\rho_t. \tag{12}$$

Let us use Constraint (5) to minorize the objective function as follows:

$$
\begin{aligned}
&\sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\left[\hat{\phi}_{jt}\frac{x_{kjt}}{\sum_{\tau=1}^{t} z_{j\tau}+y_{jt}-1}y_{jt}+\bar{\phi}_{jt}x_{kjt}(1-y_{jt})\right]+\sum_{t\in T}\rho_t \geq\\
&\sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\left[\hat{\phi}_{jt}\frac{x_{kjt}}{\sum_{\tau=1}^{t} z_{j\tau}+y_{jt}-1}\frac{\sum_{\tau=1}^{t} z_{j\tau}}{B}+\bar{\phi}_{jt}x_{kjt}(1-y_{jt})\right]+\sum_{t\in T}\rho_t \geq\\
&\sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\left[\hat{\phi}_{jt}\frac{x_{kjt}}{B}+\bar{\phi}_{jt}x_{kjt}-\bar{\phi}_{jt}x_{kjt}y_{jt}\right]+\sum_{t\in T}\rho_t.
\end{aligned}
\tag{13}
$$

Consider now Constraint (7):

$$\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} x_{kjt} = D.$$

If we denote $\pi = |S||F||T|$, we can rewrite D as follows:

$$\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \frac{D}{\pi} = D \tag{14}$$

which, in turn, means that

$$\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} x_{kjt} = \sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \frac{D}{\pi},$$

that can be extended to the following set of relations

$$\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} y_{jt}x_{kjt} \le \sum_{k\in S}\sum_{j\in F}\sum_{t\in T} x_{kjt} = \sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \frac{D}{\pi}. \tag{15}$$

Now, let

$$\tilde{\phi} = \max_{j,t} \bar{\phi}_{jt}.$$

Using the latter in (15) we have:

$$\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \bar{\phi}_{jt} y_{jt}x_{kjt} \le \sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \tilde{\phi}x_{kjt} = \sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \tilde{\phi}\frac{D}{\pi}. \tag{16}$$

Changing the signs in (16) we have:

$$-\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \bar{\phi}_{jt} y_{jt}x_{kjt} \ge -\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \tilde{\phi}x_{kjt} = -\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} \tilde{\phi}\frac{D}{\pi}. \tag{17}$$

Now we can use (17) to minorize (13) as follows:

$$\sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\left[\hat{\phi}_{jt}\frac{x_{kjt}}{B} + \bar{\phi}_{jt}x_{kjt} - \bar{\phi}_{jt}x_{kjt}y_{jt}\right] + \sum_{t\in T}\rho_t \ge$$

$$\sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\left[\hat{\phi}_{jt}\frac{x_{kjt}}{B} + \bar{\phi}_{jt}x_{kjt} - \tilde{\phi}\frac{D}{\pi}\right] + \sum_{t\in T}\rho_t.$$

Therefore, the overall lower-bound model is as follows:

$$\min \sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\left[\hat{\phi}_{jt}\frac{x_{kjt}}{B} + \bar{\phi}_{jt}x_{kjt} - \tilde{\phi}\frac{D}{\pi}\right] + \sum_{t\in T}\sum_{j\in F}\sum_{\tau=t}^{T}\bar{\rho}_t z_{jt}(1-\alpha)^{\tau-t} \tag{18}$$

$$\begin{aligned}
&\sum_{k\in S}\sum_{j\in F}\sum_{t\in T} x_{kjt} = D, && \\
&\sum_{j\in F} x_{kjt} \le s_{kt}, && \forall\, k\in S, \forall\, t\in T,\\
&\sum_{k\in S} x_{kjt} \le c_{jt}, && \forall\, j\in F, \forall\, t\in T,\\
&\sum_{j\in F}\sum_{t\in T} z_{jt} = B, && \\
&\sum_{\tau=1}^{t} z_{j\tau} \ge y_{jt}B_{min}, && \forall\, j\in F, \forall\, t\in T,\\
&By_{jt} \ge \sum_{\tau=1}^{t} z_{j\tau}, && \forall\, j\in F, \forall\, t\in T,\\
&\sum_{k\in S}\sum_{\tau=1}^{t} x_{kj\tau} \ge y_{jt}L_{min}, && \forall\, j\in F, \forall\, t\in T,\\
&y_{jt} \ge y_{j,t-1}, && \forall\, j\in F, \forall\, t\in T,\\
&y_{j0} = 0, && \forall\, j\in F,\\
&x_{kjt} \ge 0, && \forall\, k\in S, \forall\, j\in F, \forall\, t\in T,\\
&z_{jt} \ge 0, && \forall\, j\in F, \forall\, t\in T,\\
&0 \le y_{jt} \le 1, && \forall\, j\in F, \forall\, t\in T.
\end{aligned} \tag{19}$$

4. Computational results

4.1. Case study

To see how the model behaves, before presenting extensive computational results, we show how the solution can be shaped in a specific case study, properly adapting to our model the instance used in Caramia and Stecca [6] and Wang et al. [36], and inspecting its sensitivity to parameters. The latter (considering similar assumptions made in the literature) are chosen as follows:

- $|S| = 6$, $|F| = 8$, $|T| = 5$, $D = 60000$,
- $s_{kt} = 6000$, $\forall\, k\in S$, $\forall\, t\in T$,
- $c_{jt} = 4500$, $\forall\, j\in F$, $\forall\, t\in T$,
- $\hat{\phi}_j \in \{0.5835, 58.35\}$,
- $\bar{\phi}_j \in \{0.5835, 58.35, 116.7\}$,
- $\alpha \in \{0, 0.1, 0.5\}$,
- $\hat{\rho} \in \{0.8, 1.0\}$.

Fig. 3 plots $\Sigma_{k\in S, j\in F}x_{kjt}$ over $t = 1, \ldots, 5$ when $\hat{\rho} = 0.8$ and $\hat{\rho} = 1$ ($\alpha = 0.1$, $\hat{\phi} = \bar{\phi} = 0.583$), showing an increase in late shipments.

Fig. 4, reports the value of the variable ρ_t for the same scenario.

Remarkable is the investment schedule, reported in Figure 5 where the sum of investments in the facilities (that is, $\Sigma_{j\in F}z_{jt}$) is plotted on the y axis over time for different values of $\hat{\rho}$. In this particular case, a large part of the investments is postponed toward the end of the planning period.

Changing parameters $\hat{\phi}$, $\bar{\phi}$, and α, induce a different schedule, and, in Figs. 6 and 7, investments are shown to be anticipated with respect to the previous settings.

Further analysis has been conducted to detail the behavior of the two model objectives. To this end, we set a parameter $\eta \in [0,1]$ to weigh the two terms of the objective function as follows:

$$\min \bar{Z} = \eta \sum_{k\in S}\sum_{j\in F}\sum_{t\in T}\phi_{jt}x_{kjt} + (1-\eta)\sum_{t\in T}\rho_t = \eta Z' + (1-\eta)Z''. \tag{20}$$

The values of Z', Z'', and $\bar{Z}$ are plotted for different values of η in Fig. 8 when $\hat{\rho} = 0.8$, $\alpha = 0.1$, $\hat{\phi} = \bar{\phi} = 0.5835$. As can be inferred from the chart, the behavior of Z is consistent: as soon as η increases, that is, more emphasis is placed on the cost of emissions, $\bar{Z}$ tends to decrease. It becomes clear how the decision about when and where to invest the green budget and produce is not trivial and can change remarkably while changing these parameters.

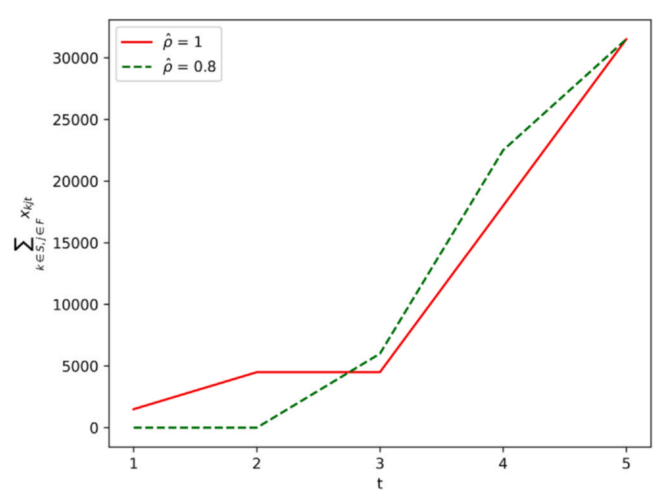

Fig. 3. Quantity $\Sigma_{k\in S, j\in F}x_{kjt}$ over time for different $\hat{\rho}$ factors, for $\alpha = 0.1$, $\hat{\phi} = \bar{\phi} = 0.583$.

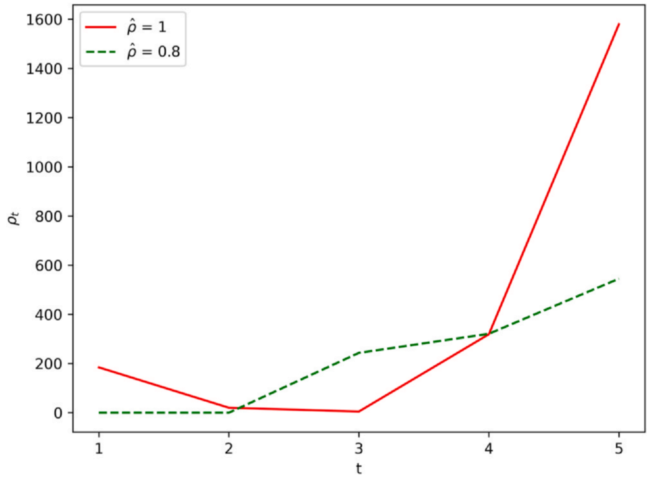

Fig. 4. ρ_t variable with different $\hat{\rho}$ factors, for $\alpha = 0.1$, $\hat{\phi} = \bar{\phi} = 0.583$.

4.2. Experimental analysis on synthetic instances

Test instances have been designed to investigate the experimental complexity of the non-linear model. Instances were generated by changing the size of the network, demand, budget, and parameters such as investment cost (see Table 1). Parameters s_{kt}, $\forall\ k \in S$, $t \in T$, and c_{jt}, $\forall\ j \in F$, $t \in T$, have been generated uniformly at random between 100 and 150. The sizes of the network are $|S|$, $|F| \in \{5, 10, 15, 20, 30\}$, the number of time periods $|T| = 10$; $\bar{\rho}_t = 1,\ \ \forall\ t \in T$; $\hat{\rho} \in \{0.8, 1\}$, $\alpha = 0.1$.

The non-linear model and the lower bound have been coded in GUROBI™ release 9.1.2. The solver has the specific functionality to solve problems containing non-convexity and has been enabled to get the upper bound and the lower bound values as inputs. The upper bound algorithm has been implemented in Phyton. In particular, the upper bound is given to GUROBI as starting values for the variables. The machine used for the experiments is equipped with a processor Intel(R) Xeon(R) Gold 6136 CPU 3.00 GHz with 48 cores and 256 GB RAM. A time limit was set to 1800 s

The results (reported in Table 2) show how the model exploits both the starting upper bound and the lower bound to produce enhanced solutions. In particular, 24 times out of the 30 instances, the model is able to find the optimal solution. In the remaining 6 instances the optimality gap remains limited ranging from 2 % to 26 %. For all the

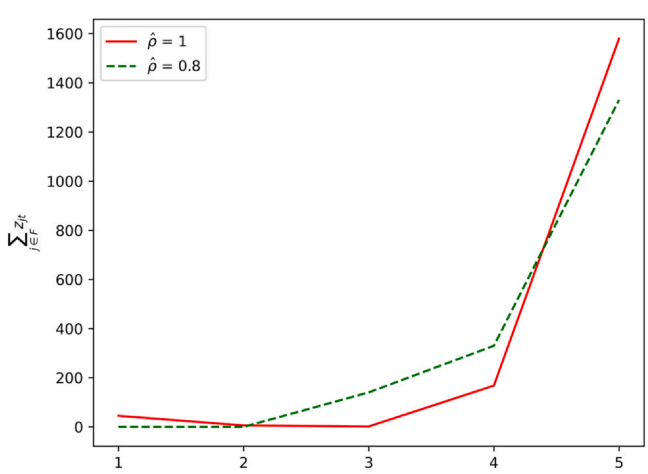

Fig. 5. Investment quotas over time for different $\hat{\rho}$ factors, for $\alpha = 0.1$, $\hat{\phi} = \bar{\phi} = 0.583$.

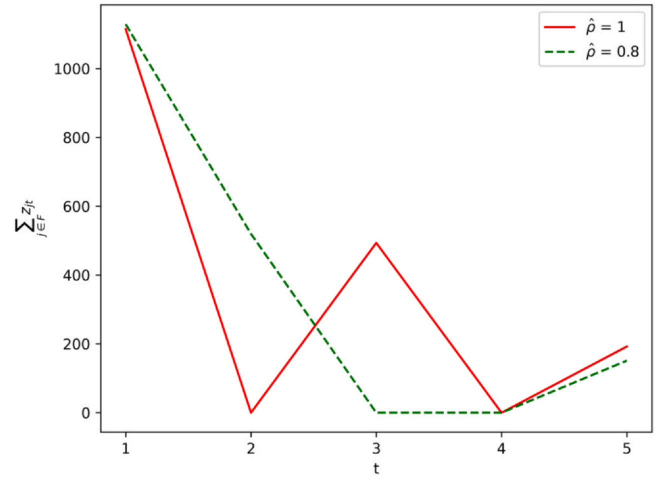

Fig. 6. Investment quotas over time with different $\hat{\rho}$ factors, for $\alpha = 0$, $\hat{\phi} = 58.35$, $\bar{\phi} = 116.7$.

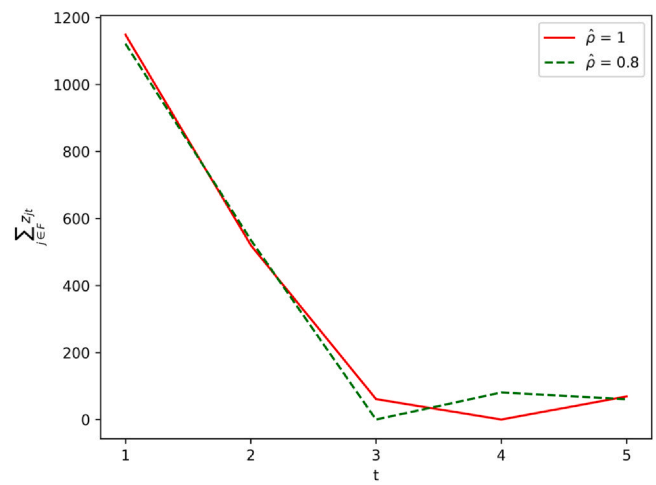

Fig. 7. Investment quotas over time with different $\hat{\rho}$ factors, for $\alpha = 0.5$, $\hat{\phi} = 58.35$, $\bar{\phi} = 116.7$.

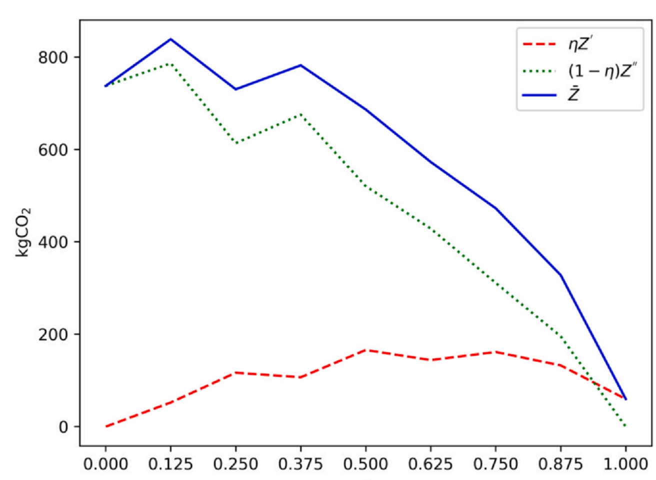

Fig. 8. Z', Z'', and Z values.

Table 1
Instance parameters. $\hat{\phi}_j = \hat{\phi}$ and $\bar{\phi}_j = \bar{\phi}$, $\forall\, j \in F$.

ID	$\|S\|$	$\|F\|$	T	B	D	$\hat{\phi}$	$\bar{\phi}$	$\hat{\rho}$
I1	5	5	10	1000	1000	1000	1000	1.0
I2	5	5	10	1500	500	500	500	1.0
I3	5	5	10	500	1500	1500	1500	1.0
I4	10	10	10	2000	2000	2000	2000	1.0
I5	10	10	10	3000	1000	1000	1000	1.0
I6	10	10	10	1000	3000	3000	3000	1.0
I7	15	15	10	3000	3000	3000	3000	1.0
I8	15	15	10	4500	1500	1500	1500	1.0
I9	15	15	10	1500	4500	4500	4500	1.0
I10	20	20	10	4000	4000	4000	4000	1.0
I11	20	20	10	6000	2000	2000	2000	1.0
I12	20	20	10	2000	6000	6000	6000	1.0
I13	30	30	10	6000	6000	6000	6000	1.0
I14	30	30	10	9000	3000	3000	3000	1.0
I15	30	30	10	3000	9000	9000	9000	1.0
I16	5	5	10	1000	1000	1000	1000	0.8
I17	5	5	10	1500	500	500	500	0.8
I18	5	5	10	500	1500	1500	1500	0.8
I19	10	10	10	2000	2000	2000	2000	0.8
I20	10	10	10	3000	1000	1000	1000	0.8
I21	10	10	10	1000	3000	3000	3000	0.8
I22	15	15	10	3000	3000	3000	3000	0.8
I23	15	15	10	4500	1500	1500	1500	0.8
I24	15	15	10	1500	4500	4500	4500	0.8
I25	20	20	10	4000	4000	4000	4000	0.8
I26	20	20	10	6000	2000	2000	2000	0.8
I27	20	20	10	2000	6000	6000	6000	0.8
I28	30	30	10	6000	6000	6000	6000	0.8
I29	30	30	10	9000	3000	3000	3000	0.8
I30	30	30	10	3000	9000	9000	9000	0.8

Table 2
Table detailing the results for all the instances; starting upper bound value (UB), GUROBI solution value (ObjVal), lower bound found by GUROBI (LBG), and our lower bound (LB). Gap NL indicates the Gap found by GUROBI after 1800 s while Gap* column indicates the best optimality gap found considering the maximum between the two lower bounds for each instance. For the GUROBI solution, both the first term (Z') and the second term (Z'') of the objective function are reported.

ID	UB	Z'	Z''	ObjVal	LBG	LB	Gap NL	Gap*
I1	2000	1000	1000	2000	1000	2000	0.50	0.00
I2	1667	167	1500	1667	1500	1667	0.10	0.00
I3	5000	4500	500	5000	500	5000	0.90	0.00
I4	4000	2000	2000	4000	2000	4000	0.50	0.00
I5	3333	333	3000	3333	3000	3333	0.10	0.00
I6	10,000	9000	1000	10,000	1000	10,000	0.90	0.00
I7	6000	3000	3000	6000	3000	6000	0.50	0.00
I8	5000	500	4500	5000	4500	5000	0.10	0.00
I9	15,000	13,500	1500	15,000	1500	15,000	0.90	0.00
I10	8000	4000	4000	8000	4000	8000	0.50	0.00
I11	6667	667	6000	6667	6000	6667	0.10	0.00
I12	38,000	18,299	3892	22,191	2000	20,000	0.91	0.10
I13	18,000	7500	8700	16,200	6000	12,000	0.63	0.26
I14	10,000	1000	9000	10,000	9000	10,000	0.10	0.00
I15	63,750	30,649	6668	37,317	3000	30,000	0.92	0.20
I16	2000	1000	134	1134	134	1134	0.88	0.00
I17	1667	167	201	368	201	368	0.45	0.00
I18	5000	4500	67	4567	67	4567	0.99	0.00
I19	4000	2000	268	2268	268	2268	0.88	0.00
I20	3333	333	403	736	403	736	0.45	0.00
I21	10,000	9000	134	9134	134	9134	0.99	0.00
I22	6000	3000	403	3403	404	3403	0.88	0.00
I23	5000	500	604	1104	605	1104	0.45	0.00
I24	15,000	13,500	201	13,701	203	13,701	0.99	0.00
I25	8000	4000	537	4537	540	4537	0.88	0.00
I26	6667	667	805	1472	808	1472	0.45	0.00
I27	38,000	18,000	638	18,638	275	18,268	0.99	0.02
I28	18,000	6202	1913	8114	819	6805	0.90	0.16
I29	10,000	1000	1208	2208	1211	2208	0.45	0.00
I30	63,750	33,063	897	33,960	408	27,403	0.99	0.19

instances, our lower bound was able to improve on the GUROBI lower bound.

In 18 cases out of 30 instances, the solver has improved the initial upper bound value. In 12 instances out of 30, the starting solution found by the proposed heuristic was equal to the value of the proposed lower bound value, which proves their effectiveness.

5. Concluding remarks

In this paper, we proposed a mathematical model used to decide optimal green investments over time in a two-stage supply chain. The objective of the model is to minimize the costs of emissions and investments. Although the current literature on green investments is mostly focused on the strategic impact of investments, in our approach a time dimension is exploited. In this way, investment decisions can take into account technology costs and investment costs that vary over time. The resulting model is non-linear and non-convex. It is solved by a commercial solver on a set of synthetic instances, showing the complexity of the model. An initial upper bound and a lower bound based on linear programming are proposed to enhance the performance of the model. Future work will be devoted to analyzing the green finance model in a cap-and-trade scenario.

Ethics approval

The authors declare that the submitted work is original and has not been published elsewhere in any form or language. Moreover, this article does not contain any studies with human participants or animals performed by the authors.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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