A GREEN FINANCE BI-OBJECTIVE MODEL IN A THREE STAGE SUPPLY CHAIN

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ABSTRACT
In this paper, we study a novel green financing model for a three-stage supply chain. The model considers nonlinear relations among CO_2 emissions, budget spent for emission control, and quantity of products moved towards and worked in the facilities. Moreover, the model, besides the minimization of CO_2 emissions, aims at balancing the commodity flow over the different facilities. The latter objective is represented by the linear combination of two quadratic penalty functions: one associated with the arc flows and the other with the entering flows at the facilities, respectively. The model is solved on both synthetic instances and a realistic network, demonstrating its effectiveness as a tool for strategically supporting green financing decisions in supply chains.

KEYWORDS: CO_2 emissions, Green Supply Chain Optimization, Green Financing.
MSC: 90C29 Multi-objective and goal programming, 90B06 Transportation, logistics and supply chain management

RESUMEN
En este artículo, estudiamos un nuevo modelo de financiación verde para una cadena de suministro de tres etapas. El modelo considera relaciones no lineales entre las emisiones, el presupuesto gastado para el control de emisiones y la cantidad de productos que se mueven hacia las instalaciones y se trabajan en ellas. Además, el modelo, como segundo objetivo, pretende equilibrar el flujo de mercancías entre las diferentes instalaciones. Este último objetivo está representado por la combinación lineal de dos funciones de penalización cuadráticas: una asociada a los caudales de arco y otra a los caudales de entrada a las instalaciones, respectivamente. El modelo se resuelve tanto en instancias sintéticas como en una red realista, lo que demuestra su eficacia como herramienta para apoyar estratégicamente las decisiones de financiación verde en las cadenas de suministro.

PALABRAS CLAVE: Emisiones de CO_2, optimización de la cadena de suministro, finanzas verdes.

1. INTRODUCTION AND LITERATURE REVIEW

Climate change requires the integration of different approaches both for designing and operating supply chain networks and to reach the demanding green targets. In these settings, Green Supply Chain Management (GrSCM) and Green Supply Chain Network Design (GrSCND) require a rethinking in organization and collaboration settings. New models for GrSCND, considering structural elements

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such as green corridors (see, e.g., [5]) and multiple objective functions, are worth considering. GrSCND is a recent but more and more studied research topic as witnessed, e.g., by the review in [20]. The extensive review in [1] classifies pressures, practices, and performance of GrSCM, emphasizing the importance of financial performance measures and their impacts on practices within GrSCM. Under this viewpoint, green finance plays an important role in defining strategies for CO_2 emission control and decarbonization of complex systems. Researchers analyzed relations between green financing and social behavior like in [7, 19]. However, there are still a few attempts to formalize relations between green financing decisions and operational decisions in green supply chains. In addition, CO_2 emission control is often accounted for only partially in supply chains, mainly for transport problems and most of the time in a linear way. It is evident how, in several situations, emissions should be more realistically dealt with considering both production and transportation factors as well as considering nonlinear models.

In this paper, we try to follow this direction when it comes to three-layered supply chains. In the literature, there are only a few cases where emission control in GrSCND is modeled by means of nonlinear functions as reported in the following. In [18], a nonlinear function is used to model warehouse emissions that depend on the warehouse volume; the problem is solved by means of a Lagrangian approach. A similar method is used in [12] where the relations between emissions and vehicle weight are assumed to be concave. [21] consider two minimum objectives for a Green Supply Chain, namely cost and emissions. The relationship between budget and emissions is nonlinear because of the availability of different technologies, discretely modeled, having different costs and unitary emissions. In [6], the relations among emissions, budget for green financing, and quantity are nonlinear and continuous. The model has a single objective while quadratic constraints relate the budget used for green and non green investments.

The above analysis of the literature, therefore, shows that investigating the nonlinear effects of operations over carbon emissions represents a gap that deserves to be addressed. The model proposed in this paper, which is an attempt to close this gap, is a bi-objective one and foresees the use of a financial budget aimed at both mitigating emissions associated with transportation and production facilities, and balancing flows over the facilities (and, in turn, over the network). This is quite an important aspect since it allows for global and local optimization measures of the emissions over a three-echelon supply chain with inbound logistics and handling operations at the intermediate levels. Indeed, even though emissions could be globally minimized over the whole chain, we must also consider fairness in distributing the emissions themselves over the network. Having a solution associated with an overall minimum emission of CO_2 which comprises only a subset of the facilities does not represent an equitable distribution of the pollutants over the territory. The need for an equitable distribution of the flow in a solution is studied in several other logistic problems comprising possible negative impacts of the operations on the environment as it happens, for instance, in hazardous transportation problems (see, e.g., [4]).

The mathematical model proposed is solved on both synthetic instances and a realistic network, demonstrating its effectiveness as a tool for strategically supporting green financing decisions in supply chains where both global emission minimization and flow balancing over the facilities are sought.

The reminder of the paper is organized as follows. Section 2. details the formulation of the GrSCD problem. Section 3. discusses computational results and, finally, Section 4. reports 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 by means of a graph $G = (N, A)$, where N is the set of nodes and A is the set of arcs. The set N is formed by the union of three sets: the set S of suppliers, the set F of facilities, and the set C of customers, i.e., $N = S \cup F \cup C$. The arc set A models links among pairs of nodes belonging to the Cartesian products $S \times F$ and $F \times C$. Given the customer demands, the supply and the facility capacities, and a budget b, the goal is to decide the investment in environmental protection to minimize the CO_2 emissions associated with servicing clients. Figure 1 depicts the G graph.

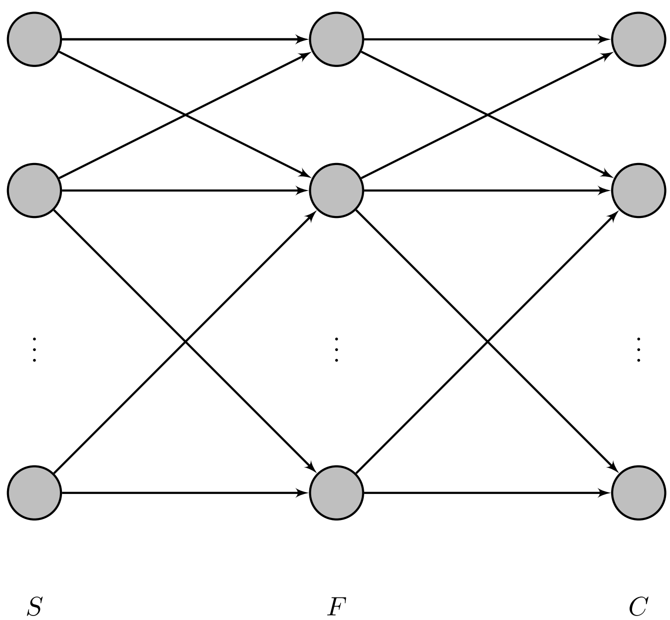

Figure 1: A generic network representing a three-stage supply chain

Let us define the problem formulation. The sets and parameters are:

- S: the set of supplies;
- F: the set of facilities;
- C: the set of customers;
- N: the set of nodes of the supply network;
- k: index for suppliers;
- j: index for facilities;

- c: index for customers;
- i, i': indices for generic nodes of the supply network;
- d_c: the demand of customer $c \in C$;
- s_k: the supply capacity of supplier $k \in S$;
- r_j: capacity consumed by handling a unit of product in facility $j \in F$;
- b: whole budget available to design the supply network;
- b^v: part of the budget b available for green investments on transportation;
- ch_j: the unit handling capacity installation cost in facility $j \in F$;
- cap_j^f: the product handling capacity of facility $j \in F$;
- cap^v: the capacity of a generic vehicle used for transportation;
- β_1, β_2: weight of CO_2 and congestion in objective function, with $0 \leq \beta_1 \leq 1$, and $\beta_2 = 1 - \beta_1$;
- β^p, β^v: weights for production and transportation congestion contributions, with $0 \leq \beta^p \leq 1$, and $\beta^v = 1 - \beta^p$.

The decision variables are:

- $x_{i,i'}^p$: the flow of product $p \in P$ from node $i \in N$ to node $i' \in N$;
- z_j: the environment protection investment in facility $j \in F$;
- v: level of green investment on the fleet of vehicles;
- u_j: the amount of products worked in facility $j \in F$;
- $w_j(z_j, u_j)$: CO_2 emissions caused by a facility $j \in F$, as a function of the environment protection investment z_j and the amount of flow of products u_j to be worked by that facility j;
- $q_{ii'}(v, x_{i,i'})$: CO_2 emissions generated by the flow of products $x_{i,i'}$ on arc $(i, i') \in A$ as a function of the level of green investment v on the fleet of vehicles;
- Γ^p congestion measure for production;
- Γ^v congestion measure for transport.

The objective function f minimizes both the CO_2 emissions and a measure of the congestion in production and transportation. As detailed in (2.1), the objective function is formed by the sum of four components, namely, f_1, f_2, f_3, and f_4. f_1 accounts for the emissions caused by the travels of vehicles from suppliers to customers to service demands whilst f_2 considers the emissions caused by the activities carried out at each production facility; f_3 penalizes the congestion caused by concentrating operations in a small number of facilities; finally, f_4 penalizes the transport congestion along traveling arcs.

$$\begin{aligned}\min f &= \min\left[\beta_1\left(f_1+f_2\right)+\beta_2\left(f_3+f_4\right)\right]\\ &= \min\left[\beta_1\left(\sum_{(i,i')\in A} q_{ii'}(v,x_{i,i'})+\sum_{j\in F} w_j(z_j,u_j)\right)+\beta_2\left(\beta^P\Gamma^p+\beta^v\Gamma^v\right)\right]\end{aligned} \tag{2.1}$$

In the literature, transport CO_2 emission functions, like f_1, are modeled considering different factors such as travel, weather, vehicle-related, roadway, traffic, and driver [22]. Comprehensive white box models for truck emissions are treated in [2], where factors such as engine speed, mass, and power, affect emissions. The comparative analysis reported in [8] analyzes different methods, such as the MEET and COPERT III [17] in which emissions are considered mainly dependent on the vehicle type and the distance traveled, with correction factors based on polynomial functions (of second order or greater) considering velocity, load, acceleration, and power. The works of [3] and [10] survey different operations research applications of MEET and COPERT III models in the road and maritime transportation. The surveys highlight how a linear estimation of emissions is often not sufficient to effectively model green problems. The above-mentioned measures of CO_2 emissions (caused by transportation) are in general dealt with operational problems; a very important example is the case of the nonlinear dependency of emissions from vehicle velocity and load considered in the operative pollution routing problem introduced by [9]. However, nonlinearities are less often considered in literature within network design models. In this paper, to consider the strategic problem of investing a budget b for green purposes, we propose a function that transforms levels of green investments in the fleet of vehicles into coefficients representing emissions per unit of full truckload traversing an arc. These coefficients are assigned to each arc and are dependent on the length of the latter and on the amount of budget invested to this end. To determine the overall impact of the CO_2 emissions caused by the transportation activities, each coefficient must be multiplied by the ratio between the flow of commodity traversing that arc and the capacity of a transport mean. This implies the hypothesis that the fleet of vehicles considered in our model is homogeneous, i.e., all vehicles have the same capacity cap^v.

Further pursuing the rationale hidden behind function f_1, we note that for a given flow $\bar{x}_{ii'}$ on arc (i,i'), a larger green investment v in the fleet of vehicles will lead to lower CO_2 emissions; consequently, in the long-term, the CO_2 emissions associated with $q_{ii'}(v,\bar{x}_{ii'})$ will be lower. At the same time, given a green investment level $\bar{v}$, larger flows $x_{ii'}$ of goods flowing on arc (i,i') will cause larger $q_{ii'}(\bar{v},x_{ii'})$ values. Therefore, f_1 can be defined as follows:

$$f_1=\sum_{(i,i')\in A} q_{ii'}(v,x_{ii'})=\sum_{(i,i')\in A}\rho_{ii'}\left(b^v-v\right)\frac{x_{ii'}}{cap^v}. \tag{2.2}$$

where $\rho_{ii'}$ is a parameter allowing the transformation of the quantity $(b-v)$ from money to CO_2 emissions per unit of full truckload on arc (i,i'). Note that the ratio $\frac{x_{ii'}}{cap^v}$ defines the number of full truckload transports; the fractional part of the ratio identifies a less than truckload transport and the CO_2 emissions of the latter are, therefore, given by the corresponding fraction of $\rho_{ii'}(b^v-v)$.

The term f_2, modeling the CO_2 emissions caused by the production activities carried out in each facility, is more complex since it considers both the number of products worked in each facility and

the level of green investment made in each such facility. Roughly speaking, in our model, we consider the CO_2 emissions in a production site dependent upon two factors: the greater the flow of processed products in a facility, the greater the CO_2 emissions, and the greater the investment made in green technology, the lower the CO_2 emitted in the environment.
More formally, for a given amount of worked products $\bar{u}_j$ in a facility j, larger environmental investment values z_j will lead to lower CO_2 emissions; consequently, in the long-term, the CO_2 emission in a facility $j \in F$ for handling product $p \in P$, denoted as $w_j(z_j, \bar{u}_j)$, will be lower. At the same time, given a green investment level $\bar{z}_j$ at facility j, larger flows of products u_j in facility j will cause larger $w_j(\bar{z}_j, u_j)$ values. A similar approach has been addressed by [21] and [6]. These applications follow several studies where emissions are accounted for in relation to the number of products worked, see, e.g., [11], and in relation to green investments, see e.g., [14] and [13]. Therefore, f_2 can be defined as follows:

$$f_2 = \sum_{j \in F} w_j(z_j, u_j) = \sum_{j \in F} \phi_j \left(b - z_j\right) u_j, \tag{2.3}$$

where ϕ_j is a parameter allowing the transformation of the quantity $(b - z_j)$ from money to CO_2 emissions per unit of worked product in j.
The penalties representing congestion terms in the objective function are $f_3 = \Gamma^p$, and $f_4 = \Gamma^v$, respectively. As we know, CO_2 has global effects and if we consider only the minimization of a measure of the total CO_2 emitted, local operations could be inefficiently planned. In the proposed model, therefore, we introduce the second objective of balancing the allocation at both facility sites, through the term f_3, and traveling arcs, through the term f_4.
The set of constraints (SC) of the problem is as follows:

$$\begin{array}{lr}
\sum_{k \in S} x_{kj} - \sum_{c \in C} x_{jc} = 0, & \forall j \in F, \\
\sum_{j \in F} x_{jc} = d_c, & \forall c \in C, \\
\sum_{j \in F} x_{kj} \leq s_k, & \forall k \in S, \\
\sum_{k \in S} r_j x_{kj} \leq cap_j^f, & \forall j \in F, \\
\sum_{k \in S} x_{kj} = u_j, & \forall j \in F, \\
\sum_{j \in F} (z_j + ch_j u_j) + v = b, & \forall j \in F, \\
\left(\sum_{k \in S} x_{kj}\right)^2 \leq \Gamma^p, & \forall j \in F, \\
\left(x_{i,i'}\right)^2 \leq \Gamma^v, & \forall (i,i') \in A, \\
x_{i,i'} \geq 0, & \forall (i,i') \in A, \\
u_j \geq 0, & \forall j \in F, \\
z_j \geq 0, & \forall j \in F, \\
b^v \geq v \geq 0, & \\
\Gamma^p, \Gamma^v \geq 0. &
\end{array} \tag{2.4}$$

The first constraint models the mass conservation, i.e., the amount of flow entering node j must outflow the same node, $\forall j \in F$. The second constraint imposes that client demands must be satisfied. The third constraint warrants that, for every product $p \in P$, the amount of supply, from each supplier $k \in S$, should not exceed its supply capacity s_k^p. The fourth constraint imposes that the processing required for handling all the products in facility $j \in F$ should not exceed the capacity cap_j^f of facility j. The fifth constraint considers the number of products worked in a facility. The sixth constraint models the limitation on the available budget and limits the overall investment associated with both the CO_2 emissions reduction equipment and the installed capacity in a facility. The seventh constraint limits the penalty for production to the square of flow entering each facility. The eighth constraint limits the penalty for transportation to the square of flow per traveling arc. The remaining constraints define the domains of the variables.

To underline the different purposes of the two objectives defined in (2.1), we used a gadget supply chain network with 3 suppliers, 3 production sites, and 3 demand areas. The toy instance is solved twice: the first time by considering the CO_2 emission term only ($\beta_1 = 1$) and the second time by considering the penalty minimization term only ($\beta_1 = 0$). From the first to the second run, the CO_2 emissions pass from 20620.9 Kg to 37102 Kg. However, if we consider the balancing of flows on arcs and at production sites, from the first to the second run, we obtain a variation of the total standard deviation from 156.5 to 2.9. Figures 2 and 3 depict the different allocation of flows when the two objectives are activated. In particular, Figure 2 reports only those arcs with no null flows (along with their values). Over each facility node, the value of variable u_j is reported as well. The solution of the second run, as depicted in Figure 3, uses, differently from the other scenario, all the arcs and it is possible to see how leveled the resulting flows are. Also, the flows entering the facilities are totally balanced.

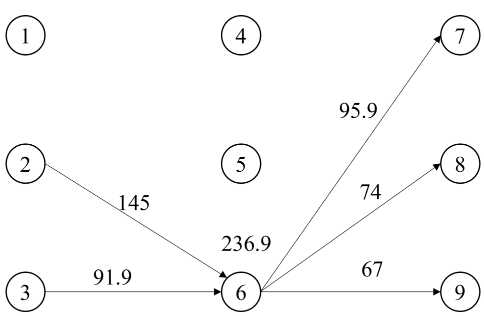

Figure 2: Example network: allocation of flows with $\beta_1 = 1$

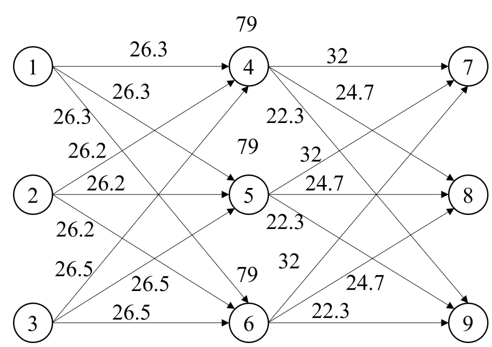

Figure 3: Example network: allocation of flows with $\beta_1 = 0$

3. COMPUTATIONAL ANALYSIS

Computational experiments have been designed to investigate the behavior of the model in relation to the two objectives over different instances. Parameters have been generated according to what is reported in Table 1. In particular, the transport emission ρ is set to be compatible with the literature findings in [15, 16] considering a full truck fuel consumption and emission of 0.33 km/L and 2.621 kg CO_2/L, respectively. ϕ_j is computed accordingly to [6].

Table 1: Parameter setting

parameter	value
d_c	uniform(50, 100) [units]
cap_j^f	uniform(120, 240) [units]
s_k	uniform(50, 100) $\cdot \lceil \frac{\lvert C\rvert}{\lvert S\rvert} \rceil$ [units]
r_j	1
b	1000 [k€]
b^v	0.5b [k€]
ch_j	0.001 [k€]
cap^v	100 [units]
$dist_{ii'}$	uniform(800,1200) [km]
ρ	0.867 [kg CO_2 vehicle/km]
$\rho_{ii'}$	$\frac{\rho}{cap^v} dist_{ii'}$ [kg CO_2/unit k€]
ϕ_j	0.000167 [kg/unit k€]

Instances have been generated and classified by size. Small size instances have $|S| = 5$, $|F| = 5$, and $|C| = 5$; large instances have $|S| = 30$, $|F| = 30$, and $|C| = 30$. The model has been coded and solved by means of the GUROBI™ solver release 9.15 using Python API. The solver has the specific functionality (which must be enabled) to solve problems containing non-convexity. This flag allowed us to solve all the generated instances. The machine used for the experiments is equipped with a processor Intel® Core™ i7-1260P CPU 2100Mhz with 12 cores and 32GB RAM. A time limit was set to 600 seconds.

In each test, we considered different values of $\beta_1 \in \{1.00, 0.75, 0.50, 0.25, 0.00\}$ (recall that $\beta_2 = 1-\beta_1$). The weights for production and transport penalties β^p and β^v are set to 0.5.

Results are detailed in Tables 2 and 3 for small and large size instances, respectively. The results show that the model can be easily solved in both the two scenarios. As for the large set, most of the time all the running time limit is consumed. However, the optimality gap is less than 1%. To better evaluate the impact of the penalty on the solution, the standard deviation of the flow on arcs - denoted by $\delta(p)$ - and the standard deviation of the flow received by the facilities - denoted by $\delta(v)$ - are reported in the tables. It is easy to see how the two objectives can be tuned to balance the penalty and the total emissions of the supply chain.

The two objectives can also be compared by plotting the total CO_2 (TotCO2) and the total penalty $\Gamma^p + \Gamma^v$ (TotGamma) over different values of β_1 (see Figures 4 and 5).

Table 2: Computational results for a network with $|S| = 5$, $|F| = 5$, and $|C| = 5$

β_1	1.00	0.75	0.50	0.25	0.00
v	500.00	500.00	500.00	500.00	124.48
optVal	28,374.28	23,737.38	16,805.84	9,726.28	2,319.70
gap	0.00	0.00	0.00	0.00	0.00
runTime	0.04	0.49	0.11	0.11	0.04
Γ^p	33,856.00	6,526.34	4,329.64	4,329.64	4,329.64
Γ^v	33,856.00	2,407.08	1,082.41	659.52	309.76
$\Gamma^p + \Gamma^v$	67,712.00	8,933.42	5,412.05	4,989.16	4,639.40
CO_2^p	3,958.91	4,820.18	4,945.23	4,945.23	4,532.58
CO_2^v	24,415.37	25,340.75	25,960.42	26,476.16	49,797.53
$\delta(p)$	68.12	29.93	0.00	0.00	0.00
$\delta(v)$	34.36	19.00	15.22	11.13	2.46
$CO_2^p + CO_2^v$	28,374.28	30,160.93	30,905.66	31,421.39	54,330.11
$\delta(p) + \delta(v)$	51.24	24.47	7.61	5.57	1.23

Table 3: Computational results for a network with $|S| = 30$, $|F| = 30$, and $|C| = 30$

β_1	1.00	0.75	0.50	0.25	0.00
v	500.00	500.00	500.00	500.00	0.00
optVal	188189.02	144073.45	97477.75	50399.31	2638.41
gap	0.00	0.00	0.00	0.00	0.00
runTime	1.34	600.27	600.24	600.16	24.50
Γ^p	54084.19	7649.38	5563.60	5265.92	5265.92
Γ^v	43530.81	4134.95	1486.68	1242.55	10.89
$\Gamma^p + \Gamma^v$	97615.00	11784.33	7050.27	6508.47	5276.81
CO_2^p	34501.96	35628.78	35735.79	35752.61	35146.67
CO_2^v	153687.06	154505.10	155694.58	156081.94	378788.60
$\delta(p)$	59.51	25.21	7.71	0.00	0.00
$\delta(v)$	14.69	10.84	8.82	8.48	0.50
$CO_2^p + CO_2^v$	188189.02	190133.88	191430.37	191834.55	413935.28
$\delta(p) + \delta(v)$	37.10	18.02	8.26	4.24	0.25

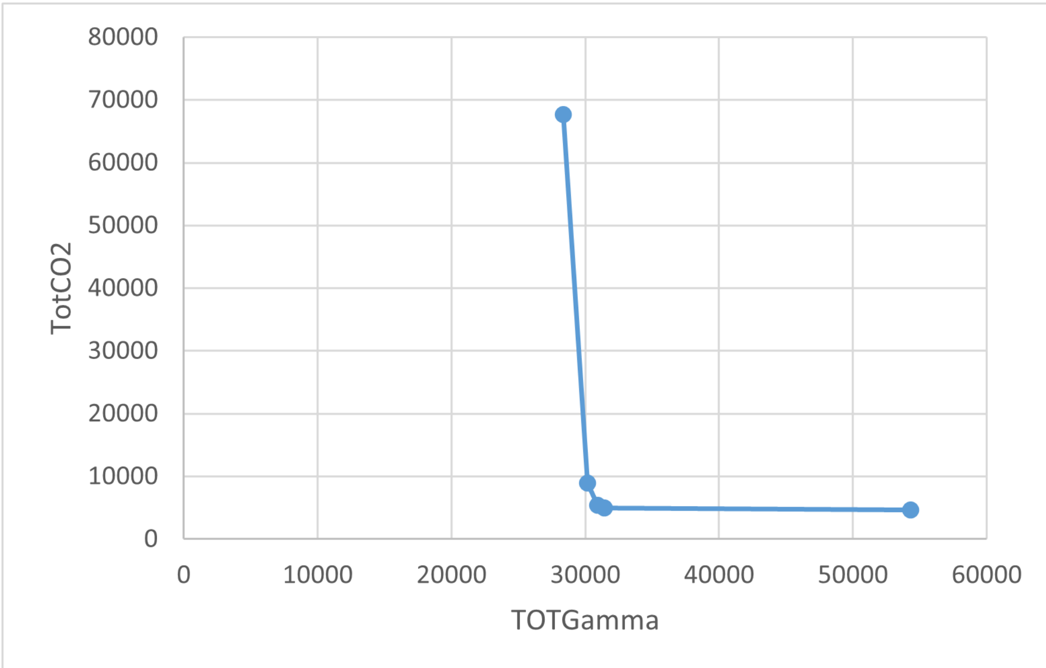

Figure 4: Pareto front for a small size instance

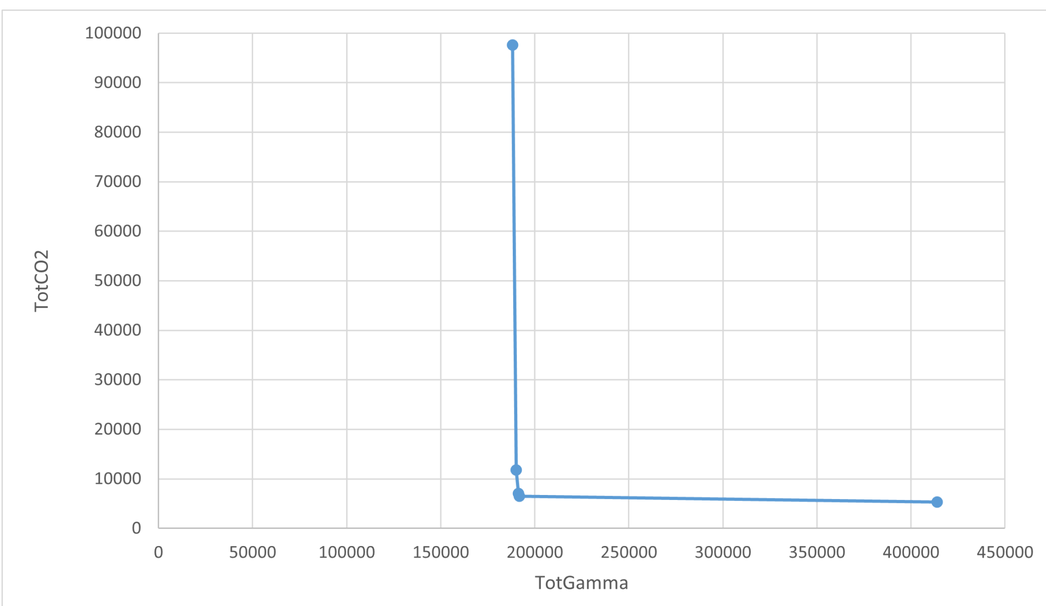

Figure 5: Pareto front for a large size instance

3.1. Tests on a realistic case study

A third instance set has been developed taking into account the real case study presented in [21] and [6]. This test set considers $|S| = 6$, $|8| = 5$, $|C| = 12$, and a budget of 1800 k€. We computed distances between network nodes using the geodesic distance. Investigating the results obtained for this test set, it appears clear the impact of the penalties associated with flow balancing (both on arcs and in the facilities). These indicators are represented by Γ^p and Γ^v values and by the standard deviations $\delta(p)$ and $\delta(v)$. Detailed results are depicted in Table 4. Here, β^p is set to 0.5. A set of instances with different β^p values is also solved and the results are detailed in Table 5. The Pareto front of the two objective functions over different β_1 values is shown in Figure 6.
Further scenario analysis is performed by varying the available budget that can be spent for emission control. In this case, it is important to highlight the potential CO_2 reduction. Thus, for each instance, the maximum emission obtained when no budget is invested in emissions control is used to compute the CO_2 reduction obtained for each level of budget $b \in \{900, 1800, 2700, 3600, 4500\}$. The results for this scenario are detailed in Table 6, and CO_2 reduction is plotted against total penalty TotGamma $= \Gamma^p + \Gamma^v$ in Figure 7.

Table 4: Computational results for a network with $|S| = 6$, $|F| = 8$, and $|C| = 12$

β_1	1.00	0.75	0.50	0.25	0.00
v	900.00	900.00	900.00	900.00	0.00
optVal	17,466,506.46	20,283,063.47	19,328,737.63	16,337,049.17	10,406,250.00
gap	0.00	0.00	0.00	0.00	0.00
runTime	0.06	3.49	0.82	0.75	1.33
Γ^p	36,000,000.00	22,914,342.25	25,000,000.00	20,250,000.00	20,250,000.00
Γ^v	36,000,000.00	18,306,789.94	9,000,000.00	4,081,295.06	562,500.00
$\Gamma^p + \Gamma^v$	72,000,000.00	41,221,132.19	34,000,000.00	24,331,295.06	20,812,500.00
CO_2^p	995,587.20	1,013,090.88	1,010,016.00	1,017,230.40	949,595.40
CO_2^v	16,470,919.26	19,160,805.05	20,647,459.26	27,834,023.70	116,049,518.36
$\delta(p)$	1,500.00	590.85	866.03	0.00	0.00
$\delta(v)$	1,322.88	1,150.20	1,027.40	783.35	353.55
$CO_2^p + CO_2^v$	17,466,506.46	20,173,895.93	21,657,475.26	28,851,254.10	116,999,113.76
$\delta(p) + \delta(v)$	1,411.44	870.52	946.71	391.68	176.78

Table 5: Computational results for the real case network for different β^p values

β^p	1.00	0.75	0.50	0.25	0.00
v	900.00	900.00	900.00	900.00	900.00
optVal	20,360,782.91	20,360,782.91	19,328,737.63	17,318,546.89	14,779,794.55
gap	0.00	0.00	0.00	0.00	0.00
runTime	0.72	0.17	0.86	2.23	2.00
Γ^p	20,250,000.00	20,250,000.00	25000000.00	25,000,000.00	50,128,051.42
Γ^v	20,250,000.00	20,250,000.00	9000000.00	8,038,078.92	6,970,640.69
$\Gamma^p + \Gamma^v$	40,500,000.00	40,500,000.00	34,000,000.00	33,038,078.92	57,098,692.11
CO_2^p	1,017,230.40	1,017,230.40	1,010,016.00	1,010,016.00	980,012.63
CO_2^v	19,454,335.41	19,454,335.41	20,647,459.26	21348518.58	21608935.77
$\delta(p)$	0.00	0.00	866.03	866.03	1,387.77
$\delta(v)$	1,224.74	1,224.74	1,027.40	988.95	971.04
$CO_2^p + CO_2^v$	20,471,565.81	20,471,565.81	21,657,475.26	22,358,534.58	22,588,948.40
$\delta(p) + \delta(v)$	0.00	306.19	946.71	958.22	971.04

Table 6: Results for the real case network for different b values

b [k€]	900	1,800	2,700	3,600	4,500
v	450	900	1,350	1,350	2,250
optVal	13,193,455.08	19,328,737.63	24,742,354.95	24,742,354.95	35,438,603.75
gap	0.00	0.00	0.00	0.00	0.00
runTime	0.18	0.88	0.32	0.32	0.21
Γ^p	20,250,000.00	25,000,000.00	25,000,000.00	25,000,000.00	23,810,636.44
Γ^v	5,062,500.00	9,000,000.00	9,000,000.00	9,000,000.00	13,855,619.70
CO_2^p	509,967.90	1,010,016.00	1,513,521.00	1,513,521.00	2,524,982.11
CO_2^v	13,220,692.26	20,647,459.26	30,971,188.90	30,971,188.90	49,519,097.31
$\delta(p)$	0.00	866.03	866.03	866.03	681.86
$\delta(v)$	866.03	1,027.40	1,027.40	1,027.40	1,075.93
$CO_2^p + CO_2^v$	13,730,660.16	21,657,475.26	32,484,709.90	32,484,709.90	52,044,079.43
$\delta(p) + \delta(v)$	433.01	946.71	946.71	946.71	878.89
$\Gamma^v + \Gamma^p$	25,312,500.00	34,000,000.00	34,000,000.00	34,000,000.00	37,666,256.14
maxCO_2	26,982,464.53	42,377,078.53	63,565,617.79	84,023,909.37	101,743,594.60
Δ CO_2	13,251,804.36	20,719,603.27	31,080,907.90	51,539,199.47	49,699,515.17

4. CONCLUSIONS

In this paper, we studied a novel model for green financing on a three-stage supply chain. The model considers nonlinear relations among CO_2 emissions, budget spent for emission control, and number of products moved towards and worked in the facilities. Besides the objective of minimizing CO_2

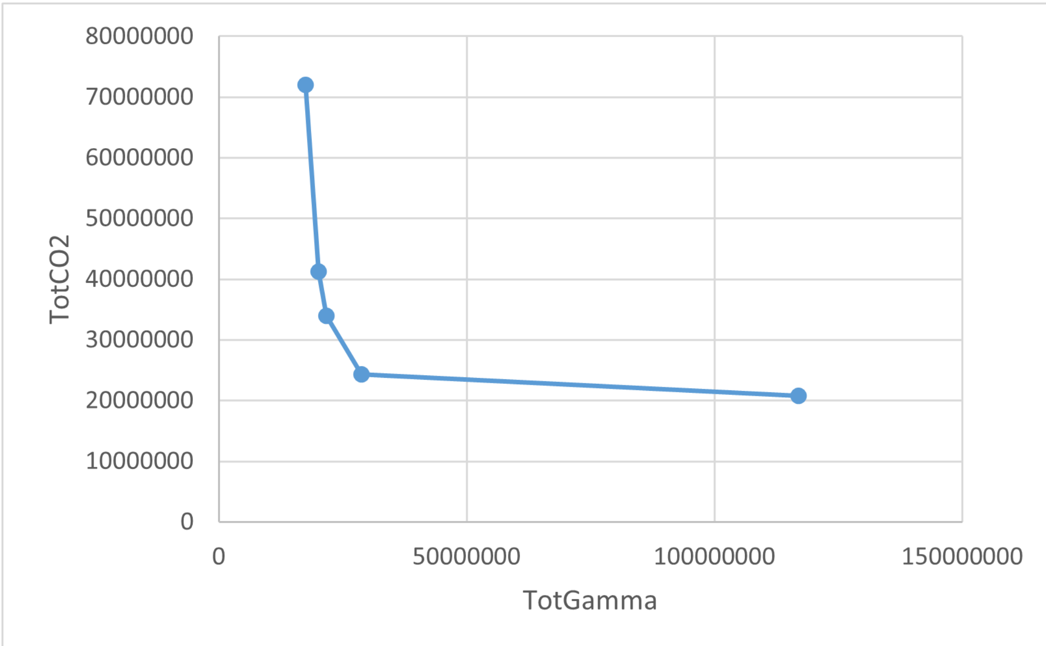

Figure 6: Pareto front for the case study instance

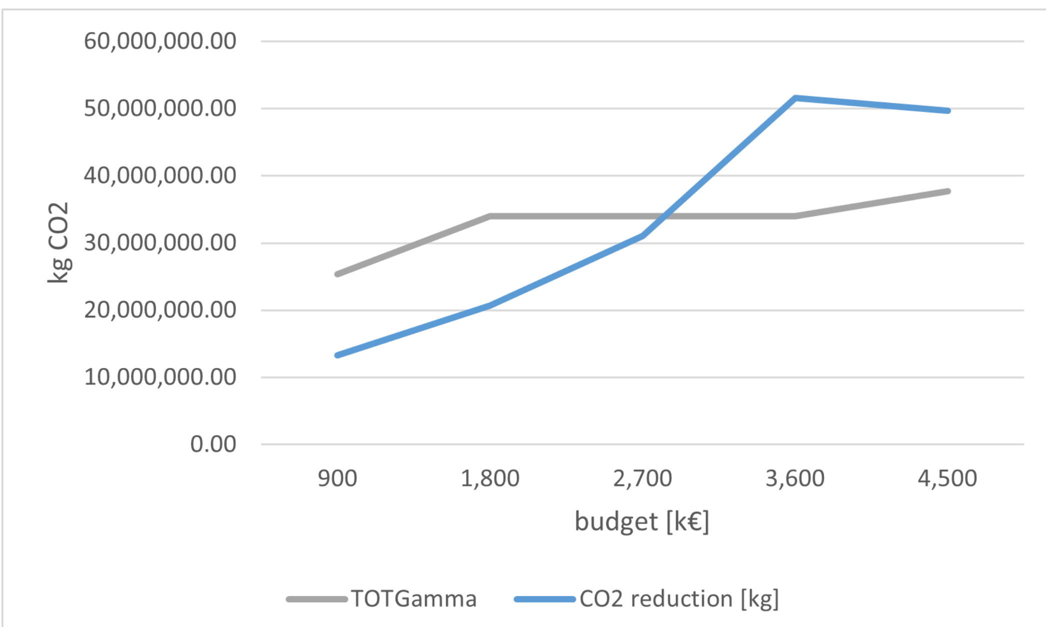

Figure 7: Plot of CO_2 reduction and total penalty over different budget values for the case study instance

emissions, commodity flow balancing is considered as a second objective and is represented by means of two quadratic penalty functions of the flows on arcs and at the entering facilities, respectively.

The model is solved both on synthetic instances and on a realistic network, with the aim to test the computational effort to find solutions and verify the behavior of the bi-objective model in different scenarios. For the real case instance, a quantification of the potential emissions reduction based on the available budget for green financing is computed. The model resulted to be effective on both small and large instances and, therefore, in our opinion, it may be useful in supporting green financing decisions in real supply chains. Future work will be devoted to extending the model to multi-product and multi-period environments.

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