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Robust Optimization Theory for CO₂ Emission Control in Collaborative Supply Chains

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Abstract. Global sourcing in complex assembly production systems entails the management of potentially high variability and multiple risks in costs, quality and lead times. Additionally, current strategies of many companies or environmental regulatory frameworks impose - or will impose - on industries worldwide to take control, among others, of CO₂ emissions and related costs generated in supply, production and distribution. Strategic planning should therefore manage multifaceted risks in order to prevent high-costly re-planning. This work addresses the problem of simultaneously controlling CO₂ emission, production and transportation costs in supplier-manufacturer echelons. The problem is addressed by using the robust optimization theory applied to network strategic planning. A non-collaborative scenario in which each manufacturer independently selects its suppliers is compared to a scenario in which all the supply-chain actors aim to minimize production, transportation and CO₂ emission costs. Computational experiments on realistic instances show positive effects of collaboration on costs, especially in more constrained tests.

Keywords: Supply chain management, Supplier selection, Robust optimization, Sustainability, Collaboration.

1 Introduction

Supplier selection is a critical sourcing process with huge impacts on cost, time, and quality performance of manufacturing companies. The implementation of global sourcing programs offers companies to gain significant competitive advantages. However, these programs also expose Original Equipment Manufacturers (OEMs) to multifaceted risks (e.g., late deliveries, financial instability, environmental disasters or

negative impacts, security, and safety issues) and hidden costs that make supply chain more vulnerable to supply chain disruptions or poor supplier performance.

Optimization models for supplier selection (mainly deterministic) have been proposed in the literature but a few of them included operational risks. Operational risks are related to uncertainties in customer demand, supply, and cost, and are opposed to disruption risks which are related to natural or man-made disasters [1]. As pointed out in [2, 3], (operational) risk management approaches can be divided into four categories: risk avoidance aims at eliminating the source of risk; risk mitigation reduces the probability of potential risks; risk sharing, in which cooperation contracts and insurances can be used to share risk with other parties; risk adoption, which is a passive risk taking strategy. Only in the recent years disruptions and uncertainty have been introduced and modeled in formulations including supplier selection (see, e.g., [4]). Beyond the competitiveness, supplier selection hugely impacts on sustainability performance of companies. However, quantitative models for supplier selection still require further research on criteria sets and integration of social and environmental dimensions [5]. In this work we study a robust approach in supply-chain strategic planning dealing with uncertainties in costs which are the uncertain price paid for CO₂ emission during production process.

Green supplier selection requires solid environmentally-oriented metrics, collaborative relationships across the supply chain and real-life scenario testing even though the literature seems to demonstrate a raising interest which however is still relatively low [6]. CO₂ emissions can be an effective and clear metric to be embedded in decision making. This is demonstrated by the recent development of models integrating CO₂ in multiple criteria analysis such as Analytic Network Process (ANP) [7], fuzzy multi-objective linear programming and Analytic hierarchy process (AHP) [8]. Multicriteria decision models for supplier selection in collaborative networks (in particular ANP) have been introduced [7, 9] but risks and uncertainty issues have not been addressed. At industry level, the inclusion of CO₂ emissions in supply chain management and in particular in supplier selection is particularly significant for companies relying on energy-intensive processes such as automotive suppliers and manufacturers [10, 11] or transportation and chemical/pharmaceutical industry [5]. Indeed, regulatory frameworks based on carbon taxation or cap-and-trade mechanisms have been already introduced in many countries worldwide [12]. In the future, companies will have to cope with these regulations *de facto*, internalizing the cost of their greenhouse gas emissions. This can also lead to improved environmental performance and cost energy savings involving suppliers [10]. On the other hand, the level of taxation or the trade pricing mechanisms may represent an additional risk factor because of the uncertainty in trends and fluctuations of CO₂ prices (see, for example, [12, 13]).

The objective of this paper is threefold: first, the CO₂ emission cost for companies is integrated into an optimization model to support decision making for supplier selection in addition to production and transportation costs. Second, uncertainty is addressed by using the robust optimization theory, thus exploring several risk scenarios. Third, the impact of collaboration between suppliers and an OEM on the performance of these supply chain echelons is estimated. As exemplary case study, computational tests are carried out on the basis of an instance envisioned for an automotive supply chain [14]. Our approach, which entails robust optimization

modeling in operational risks, according to [3], is a risk mitigation strategy which anticipates risks and develops contingency plans. The proposed approach has been selected because optimization allows decision-makers to simultaneously minimize multiple cost components that can be parameterized in scenarios with different constraints. Robust optimization then includes uncertainty in model parameters, thus embedding risk management issues. In our model, multiple supply chain variables and parameters are included and uncertain CO₂ emission cost levels (i.e., trade prices or taxation) are considered as a risk factor. To our best knowledge this is the first optimization model for supplier selection using robust optimization theory and internalization of CO₂ emission costs by comparing collaborative and non-collaborative settings.

The paper is structured as follows. Section 2 presents the suppliers-OEM manufacturing network of the two supply chain echelons. The robust optimization model and the collaboration aspects are introduced in Section 3. Computational results are presented and discussed in Section 4. Conclusions follow.

2 Manufacturing Network

The manufacturing network consists of a two echelon production-distribution network serving a customer demand clustered in country demand areas. The general (physical) network configuration is presented in Fig. 1.

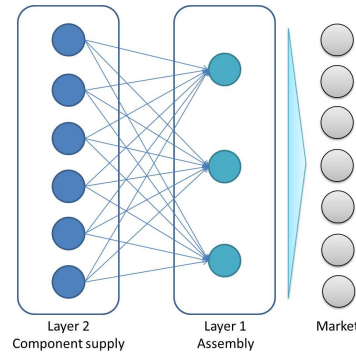


Fig. 1. Multiechelon production – distribution network.

The central echelon (layer 1) of the modeled supply chain considers the final assembly stage of the production. This layer represents all the final assembly plants controlled by a focal company (OEM). The upstream layer (layer 2) is represented by the suppliers of the main components that have to be assembled into the final products. Fig. 1 shows that potentially all the suppliers can provide all the assembly plants with the components and that all assembly plants can produce all the final products and serve the market. However, constraints regarding supply and assembly options have to be met as hereinafter explained.

Usually OEMs (the layer 1) establish supply contracts with a subset of suppliers in order to provide the required production levels and serve the final customers with an agreed service level. More sophisticated strategies could involve partnerships and collaboration between suppliers and/or a single OEM's assembly plant or sets of OEM's plants.

In the modeled network, three assembly plants can produce and deliver at least one of three final products to the market. Each product consists of three major components. The OEM's assembly plants can be supplied by a set of six (competing) suppliers. Suppliers produce specific components. Suppliers, components and product assembly options are specified in Table 1.

Table 1. Component supply and product assembly options.

Supplier (S_i)	Component (C_i)	Product assembly options (P_i)
S_1	C_1	$P_1 = C_1 + C_2 + C_3$
S_2	C_1	
S_3	C_2	
S_4	C_2	$P_2 = C_1 + C_2 + C_4$
S_5	C_3 and C_4	
S_6	C_3 and C_4	$P_3 = C_1 + C_3 + C_4$

Each supplier operates in a specific country. Each country is characterized by specific CO₂ emission levels depending on the location and manufactured components. Suppliers and assembly plants are connected by a multimodal transport network across which road, rail or sea transport services are provided.

The main CO₂ emission parameters for production and transportation are summarized in Table 2 and 3. The CO₂ emission standard parameters for component production are presented in Table 2. These CO₂ emission levels have been estimated by elaborating on the data of a case study of the automotive industry¹. In our elaboration, CO₂ emission levels at suppliers' production sites are limited to the lowest (ideal) levels across the countries considered. According to the different locations of sites in the network, in the worst cases, the CO₂ emission levels can be up to approximately 200% and 270% higher than the standard values considered in Table 2 for the components.

Table 2. CO₂ emissions and cost parameters of production of components.

Components	CO ₂ Emission (tCO ₂ /unit) ^a
C_1	0.102
C_2	0.022
C_3	0.05
C_4	0.1

^a Estimate of standard CO₂ emissions in the countries with the lowest emissions per unit manufactured in the network.

The production costs are both fixed and variable. Fixed production costs range in the interval 1.80-4 mEUR while the variable costs of components respectively range

¹ <http://publications.lib.chalmers.se/records/fulltext/136639.pdf>

in the intervals 26.5-300 EUR. Transportation costs are specified in Table 3. The carbon price considered is 10 EUR/tCO₂ (see, for example, the 2020 ETS price projections presented in [13]). The considered network costs concern the supply costs and transportation costs between the selected suppliers' sites and assembly plants.

Table 3. CO₂ emissions and cost parameters of transport.

Transport mode	CO ₂ Emission (gCO ₂ /tKm) ²	Transport cost (EUR/tKm) ³
Road ^a	93.1	0.14
Rail	17.4	0.11
Sea	101	0.009

^a Road, semi-trailer truck with a GCW of 40 tonnes, large volumes, road diesel

^b Short-sea shipping, Ro-Ro

3 Robust Optimization Approach

Robust optimization is used in mathematical programming to deal with uncertain parameters. With respect to stochastic programming, where some parameters are known through their distribution probability, in robust optimization the parameters are known only through their bounds of variability.

In integer programming, the robust optimization [15] can be defined over cost parameters, constraint parameters (e.g., product weights, arc traveling times, etc.), and known terms (e.g. customer demand values, plant capacities, etc.). The robust optimization aims to find a solution which is feasible and “good” over all the variation scenarios of unknown terms. In particular, some approaches are aimed to find the best solution in the worst case. Our approach is inspired by the work of [15], where robustness is considered inside the mathematical model and a parameter called “robustness budget” will let decide the degree of coverage amongst unexpected events. In the studied case, the unknown parameters are the CO₂ emission costs.

The studied problem can be formulated over a graph $G(N,A)$ where multiple commodities k should be delivered from suppliers to OEM's assembly plants using arcs (i,j) . The goal is to minimize the overall production transportation and CO₂ emission costs over a time horizon T . The single time period is denoted with t . The parameters are as follows:

d_{ikt}	Demand
fp_{ikt}	Activation cost
cp_{ikt}	Unit production cost
h_{ikt}	Unit holding cost in inventories at node i
IC_{ikt}	Inventory capacity
PC_{ikt}	Production capacity
ep_{it}	Emission factor at node level: the grade of emission of node i with respect to the reference country

² http://www.developpement-durable.gouv.fr/IMG/pdf/Information_CO2_ENG_Web-2.pdf

³ http://ec.europa.eu/ten/transport/studies/doc/compete/compete_report_en.pdf

ep_k	Unit emission cost for product k (Reference country at time 0)
et_k	Emission cost/Km (rail at time 0 =1)
c_{ijkt}	Unit travel cost for production k
ft_{ijkt}	Arc activation cost for production k
et_{ijt}	Emission factor at arc level: the grade of emission of arc (i,j) with respect to the reference arc

The variables are as follows:

v_{ikt}	quantity of product k manufactured in node i in period t
z_{ikt}	1 if k is manufactured in i at time t , 0 otherwise
x_{ijkt}	quantity of product k flowing in arc (i,j) in period t
u_{ijkt}	1 if k is flowing in arc (i,j) in period t , zero otherwise
s_{ikt}	inventory level of product k in node i in period t , $t \in [0, T]$.

We first describe the non-robust deterministic model. The objective function to be minimized is:

$$z = \sum_{i \in N} \sum_{k \in K} \sum_{t \in T} [z_{ikt} fp_{ikt} + v_{ikt} (cp_{ikt} + ep_k ep_{it}) + s_{ikt} h_{ikt}] + \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} [u_{ijkt} ft_{ikt} + x_{ijkt} (c_{ijkt} + et_k et_{ijt})] \quad (1)$$

The constraints on flow balancing are:

$$\sum_{j \in \Delta^+(i)} x_{ijkt} + v_{ikt} - \sum_{j \in \Delta^-(i)} x_{ijkt} + s_{ik(t-1)} - s_{ikt} = d_{ikt} + \beta_{kk'} \sum_{(k,k') \in B \circ M} (v_{ik't} - s_{ik'(t-1)} + s_{ik't}) \forall i, k, t \quad (2)$$

The constraints on capacity are:

$$s_{ikt} \leq IC_{ikt} \quad \forall i, k, t \quad (3)$$

$$v_{ikt} \leq PC_{ikt} z_{ikt} \quad \forall i \in O^k, k, t \quad (4)$$

$$x_{ijkt} \leq AC_{ijkt} u_{ijkt} \quad \forall i, j, k, t \quad (5)$$

Other constraints are:

$$s_{ik0}, s_{ik(-1)} = 0 \quad \forall i, k \quad (6)$$

$$v_{ikt}, x_{ikt}, s_{ikt} \text{ positive integer; } z_{ikt}, u_{ijkt} \text{ binary} \quad (7)$$

Robust optimization protects against all the possible occurrences of the uncertain values inside given bounds. Here robustness is introduced against the variation of costs of CO₂ emissions for production nodes. The emission factor ep_{it} over time is not fixed and may vary inside the interval $[ep_{it}, ep_{it} + \Delta ep_{it}]$ for $i \in N' \subseteq N$, $t \in [1, \dots, T]$.

Subset N' and A' contain the nodes for which the unknown variability is considered. Let $\Gamma \leq |N'| T$ be the “budget of robustness” for emission variability intervals of production. Γ can be explained as the maximum number of variable intervals that are allowed to vary at their maximum and for which robust solution is guaranteed to be feasible. The model considering Γ robustness is named “robust counterpart”. The new objective function z' of the robust counterpart model is:

$$z' = z + \max_{\{S_0: S_0 \leq \Gamma, S_0 \leq \Gamma\}} \left\{ \sum_{i \in N, t \in T} \Delta e p_{it} \sum_{k \in K} v_{ikt} e p_k \right\}$$

By using duality theory, the formulation can be rewritten as a standard mixed-integer linear programming (MILP) model adding variables and constraints to hold robust terms and removing the min – max form [15]:

$$z' = z + \Gamma z_0 + \sum_{i \in N, t \in T} p_{it}$$

The complete model would then be:

$$\begin{aligned} & \min z' \\ & \text{s.t (2), (3), (4), (5), (6), (7) and} \end{aligned}$$

$$z_0 + p_{it}^0 \geq \Delta e p_{it} \sum_{k \in K} e p_k v_{ikt} \quad \forall i \in N, t \in [1..T] \quad (8)$$

$$z_0, p_{it} \geq 0 \quad (9)$$

4 Computational Results and Discussion

The computational experiments have been conducted on two different scenarios: first, a non-collaborative scenario in which each OEM's assembly plant (layer 1 of Fig. 1) run the optimization separately and sequentially in order to identify the suppliers leading to locally optimal solutions. In the second scenario, a collaborative decision is made between all the OEM's assembly plants of the layer 2 simultaneously in order to jointly select the suppliers minimizing the global system costs. The multi-period model runs over 10 years. The robustness is applied to the CO₂ emission cost of the suppliers' production nodes in order to investigate variability and risks of CO₂ cost impact for production in different countries by focusing on the supplier selection problem. A nominal level of demand and capacity is used in a first experiment (Experiment 1). In the Experiment 2, the demand is supposed to increase by 5% yearly. However, in the non-collaborative scenario, it is also assumed that the suppliers and carriers allocate no more than 75% to each assembly plant. In the Experiment 3, the demand is the nominal one (Experiment 1) but the supplier's production capacity allocated to an OEM's plant is up to 33% in order to be able to potentially cover with 100% of capacity the demand of all the three OEM's assembly plants. The computational results are presented in Table 4.

In the Experiment 1, the total cost savings resulting from the collaboration at OEM level (approximately 3% in robust and non-robust solutions) moderately support the need for integrated sourcing solutions between assembly sites. In this experiment, the most relevant contribution to cost savings derives from reduced production costs whereas the impact of the variability of CO₂ emission costs is negligible. The effects of collaboration on cost reduction are amplified when the demand increases and capacity allocation decisions are more constrained (Experiments 2 and 3). In particular, production, transportation and CO₂ emission costs significantly decrease.

Especially in the Experiment 2, the cost savings are quite significant and higher than the Experiment 3, which however exhibits positive results.

Table 4. Comparisons between the non-collaborative and collaborative scenarios.

<i>Experiment 1: Nominal demand and capacity</i>	<i>Non-collaborative scenario (KEUR)</i>	<i>Collaborative scenario (KEUR)</i>	<i>Var. %</i>
Production cost	2,695,705	2,545,705	-5.56
CO ₂ Emission cost from production	13,974.10	13,974.10	0.00
Transportation	2,418,167	2,418,167	0.00
CO ₂ Emission cost from transport	3,027.10	3,027.10	0.00
Total costs without robustness	5,130,873	4,980,873	-2.92
Total costs with robustness	5,256,640	5,106,640	-2.85
Robustness contribution ($\Gamma = 1$)	125,767	125,767	0.00
<i>Experiment 2: Increased demand; reduced supplier capacity allocation in non-collaborative scenario</i>			
Production costs	4,117,944	3,268,599	-20.63
CO ₂ Emission costs from production	21,519.58	18,901.30	-12.17
Inventory costs	583,500	956,250	+63.88
Transportation costs	3,893,614	3,159,373	-18.86
CO ₂ Emission cost from transport	4,728.39	3,986.67	-15.69
Total costs without robustness	8,621,306	7,407,111	-14.08
Total costs with robustness	8,814,982	7,577,223	-14.04
Robustness contribution ($\Gamma = 1$)	193,676	170,112	-12.17
<i>Experiment 3: Nominal demand; reduced supplier capacity allocation in non-collaborative scenario</i>			
Production costs	2,837,585	2,545,705	-10.29
CO ₂ Emission costs from production	15,155.07	13,974.1	-7.79
Transportation costs	2,526,145	2,418,167	-4.27
CO ₂ Emission cost from transport	3,206.29	3,027.1	-5.59
Total costs without robustness	5,382,092	4,980,873	-7.46
Total costs with robustness	5,518,488	5,106,640	-7.45
Robustness contribution ($\Gamma = 1$)	136,396	125,767	-7.79

The collaborative supplier selection based on global cost optimization not only entails important cost savings but produces also a positive effect on risk management related to emission costs. In fact, in the last two experiments, the contribution of the robustness budget emerges in terms of reduction in the budget allocated to the variability of CO₂ cost on the basis of the same demand for suppliers (approximately -12 and -8%). Although the total cost of the robust optimization is higher than the non-robust one, the effects of the occurrence of the worst cases may definitely be more harmful in non-robust solutions.

5 Conclusions

This work contributes to the research on collaborative supply chains under risk conditions with consideration of CO₂ emissions by embedding a robustness budget for CO₂ cost uncertainty in the optimization approach for supplier selection, in both collaborative and non-collaborative settings.

The work is inspired by realistic instances and can be useful for: (i) industrial managers, in order to innovate procurement decision-making processes by considering supply-chain partnerships and budgets for uncertainty of variable CO₂ prices or taxes that has, or will have, to be considered according to current or future regulatory frameworks; (ii) policy makers, in order to adjust and test the impacts of variable CO₂ emission trading prices, different pricing mechanisms, carbon taxation schemes or collaboration incentives for supply chain actors.

Test runs are executed over a test instance envisioned in a previous work [14]. We find that the simultaneous, joint decision of OEMs on the selection of the suppliers leads to a cost reduction which varies depending on the experimental setting. When capacity constraints are less tight and the demand does not vary, a reduction in production cost is observed whereas transportation and CO₂ emission costs are substantially unvaried. However, the effects of collaboration on cost reduction are amplified when the demand increases and capacity allocation decisions are more constrained. Therefore, collaboration benefits the environmental performance of the sourcing process. In fact, in the non-collaborative approach, suppliers sequentially reserve production capacity to OEMs requesting the components. This entails a not optimal allocation strategy. Nominal demand levels in the constrained scenario of capacity allocation produce positive but less significant effects. Robust optimization leads to reduced total costs in all the tests with respect to non-collaborative settings. This entails the possibility to allocate a budget for risks related to CO₂ emissions cost uncertainty from variable trade prices or taxation that can be fully absorbed by the cost benefits from collaboration.

This work has the following limitations: collaboration is not considered horizontally among suppliers and carriers, respectively. Furthermore, transaction costs, which are not considered in the model yet, may lower the potential gain of the collaborative scenario. Future research tasks will aim to identify further instances and additional complexities of the real-life decision-making processes such as, e.g., scarce resources and their impact on collaboration settings. Moreover, the model will be extended to an entire supply chain and possibly integrated with simulation in order to embed dynamicity.

References

1. Tang, C.S.: Perspectives in Supply Chain Risk Management. *Int. J. Prod. Econ.* 103, 451--488 (2006)
2. Mullai, A.: Risk Management System: a Conceptual Model. In: Zsidisin, G. A., Ritchie, B. (Eds.), *Supply Chain Risk*, pp. 83--101. Springer, NewYork (2008)

3. Hahn, G.J., Kuhn, H.: Value-Based Performance and Risk Management in Supply Chains: a Robust Optimization Approach. *Int. J. Prod. Econ.* 139, 135--144 (2012)
4. Sawik T.: Joint Supplier Selection and Scheduling of Customer Orders under Disruption Risks: Single vs. Dual Sourcing. *Omega-Int. J. Manage. S.* 43, 83--95 (2014)
5. Brandenburg, M., Govindan, K., Sarkis, J., Seuring, S.: Quantitative Models for Sustainable Supply Chain Management: Developments and Directions. *Eur. J. Oper. Res.* 233, 299--312 (2014)
6. Genovese, A., Koh, S.C.L., Bruno, G., Esposito, E.: Greener Supplier Selection: State of the Art and Some Empirical Evidence. *Int. J. Prod. Res.* 51, 2868--2886 (2013)
7. Theißen, S., Spinler, S.: Strategic Analysis of Manufacturer-Supplier Partnerships: An ANP Model for Collaborative CO2 Reduction Management. *Eur. J. Oper. Res.* 233, 383--397 (2014)
8. Shaw, K., Shankar, R., Yadav, S.S., Thakur, L.S.: Supplier Selection Using Fuzzy AHP and Fuzzy Multi-Objective Linear Programming for Developing Low Carbon Supply Chain. *Expert Sys. Appl.* 39, 8182--8192 (2012)
9. Verdecho, M.J., Alfaro-Saiz, J.J., Rodríguez-Rodríguez, R.: An Approach to Select Suppliers for Sustainable Collaborative Networks. In: Camarinha-Matos, L.M., Boucher, X., Afsarmanesh, H., Collaborative Networks for a Sustainable World. PRO-VE 2010. IFIP AICT, vol. 336, pp. 304--311. Springer, Berlin Heidelberg (2010)
10. Lee, K.-H.: Integrating Carbon Footprint into Supply Chain Management: The Case of Hyundai Motor Company (HMC) in the Automobile Industry. *J. Clean Prod.* 19, 1216--1223 (2011)
11. Lee, K.-H.: Carbon Accounting for Supply Chain Management in the Automobile Industry. *J. Clean Prod.* 36, 83--93 (2012)
12. World Bank: State and Trends of Carbon Pricing 2014. World Bank, Washington, DC (2014)
13. Capros et al.: EU Energy, Transport and GHG Emissions, Trends to 2050, Reference Scenario 2013. Publications Office of the European Union, Luxembourg (2014)
14. Liotta, G., Stecca, G., Kaihara, T.: Optimisation of Freight Flows and Sourcing in Sustainable Production and Transportation Networks. *Int. J. Prod. Econ.* 164, 351--365 (2015)
15. Bertsimas L., Sim, M.: Robust Discrete Optimization and Network Flows. *Math. Program., Ser. B* 98, 49--71 (2003)