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Multiobjective Model to Reduce Logistics Costs and CO_2 Emissions in Goods Distribution

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Abstract. Goods transportation has increased in recent years due to new and more intensive distribution processes, such as door-to-door distribution generated by e-commerce and other marketing and logistics strategies. Transportation processes generates negative impacts in society and environment since it produces traffic jams and pollution. This paper presents a multiobjective model that simultaneously optimizes freight transportation and inventory quantity through collaboration between customers and suppliers, and also considers the distribution process CO_2 emissions. With this model decision makers in logistics can find a suitable combination between logistics costs and pollutants emission reduction. This model is solved using a multiobjective genetic model based on the NSGA II algorithm.

Keywords: goods distribution, multiobjective model, genetic algorithm, collaborative inventory, CO_2 emissions.

1 Introduction

The highly dynamic transportation processes generated by new marketing processes and changes in consumers habits have been studied for several years usually pursuing their optimization through models such as the Traveling Sales Problem (TSP) or the Vehicle Routing Problem (VRP) [1, 2]. However, these transport processes not only impact companies´ economics, but also society and the environment since it generates congestion as well as physical and chemical pollution. Therefore, professionals and academics in this area are interested in the search for processes that will improve both, economics as well as social/environmental conditions for companies and society [3].

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Many authors have argued that collaboration among supply chain participants is one of the main strategies to reduce goods distribution cost, highlighting the Vendor Managed Inventory-VMI as one of the most important ways in which companies can collaborate [4]. Through VMI the inventory quantity for multiple companies can be optimized, allowing for distribution systems configurations with higher efficiency. This effectively reduces costs and transport activities intensity, as a consequence of a better inventory allocation [5]. This can be done with the Inventory Routing Problem -IRP optimization model, which, based on the collaborative inventory, allows transportation and inventory costs to be simultaneously reduced [6].

This paper analyzes the effect that inventory collaboration has on CO_2 emissions in distribution processes. Inventory and transportation in a distribution network are optimized using a multiobjective model with tree objective functions, namely: inventory cost, transport costs and CO_2 emissions. This model is based upon customers and suppliers´ collaboration under the Vendor Managed Inventory (VMI) strategy. In order to analyze the proposed multiobjective model benefits, the results are compared with the single transport optimization process through the Vehicle Routing Problem (VRP).

2 Inventory Collaboration and Optimization

Collaboration in logistics and supply chain is understood as the joining efforts of several organizations seeking superior benefits than those achievable by acting separately. For this, companies cooperate in processes such as transportation, inventory management, storage, facility design, information exchange and other logistics activities [1, 7, 8]. Since many years, supply chain collaboration has been established through approaches such as Quick Response (QR), Efficient Customer Response (ECR), Continuous product Replenishment (CPR), Vendor Managed Inventory (VMI), Planning, Collaborative Forecasting and Replenishment (CPRF) and Centralized Inventory Management, among others [1, 9, 10]. According to Díaz-Batista and Pérez-Armador [11], inventory collaboration produces a lower total annual cost than when companies work individually, generating performance improvements in the entire supply chain [12-14]. The main problem is the inventory allocation and transportation, which has been studied by multiple authors [15-17]. The most used strategy for it is the VMI [18]. The joint assignment of inventory and transportation can be done by using the IRP model [6, 19-23] as well as with multiobjective optimization approaches.

The multiobjective optimization models must be solved using complex procedures, the most widely used methods are: MOGA (Multi- Objective Genetic Algorithm), NSGA y NSGA-II (Nondominated Sorting Genetic Algorithm), SPEA y SPEA2 (Strength Pareto Evolutionary Algorithm), PAES (Pareto Archived Evolution Strategy), PESA (Pareto Envelope-based Selection Algorithm), MO-VNS (Multiobjective Variable Neighbourhood Search), DEPT (Differential Evolution with Pareto Tournaments), MO-TLBO (Multiobjective Teaching-Learning-Based Optimization), MOABC (Multiobjective Artificial Bee Colony), among others [24-28].

3 Related Works

Many authors have studied the effect of using multiobjective approaches to distributions problems. A lot of research in multiobjective transportation problems is available, however much less for models considering inventory and transport together [24]. Some works that integrated transportation and inventory management through multiobjective approaches are:

Seferlis and Pechlivanos [23] propose a model to minimize inventory level and maxmise the difference between generated revenues and associated costs. Chen and Lee [29] presented a four-objective model to optimize profits, safe inventory levels, customer service and robustness under demand uncertainties. By solving a multi-product and multi-time period production/distribution planning decisions problems, Liang [30] minimizes the total costs and total delivery time. Liao et al. [31] proposed a model for Minimizing total costs and maximizing demand satisfaction and response level. Azuma et al. [32] and Azuma et al. [33] present a model aiming to minimize transport and inventory costs using the IRP; Shankar et al. [34] propose a three-echelon capacitated plant location-distribution network in order to minimize total costs and maximize demand fulfillment.

Afshari et al., [35] minimizes the total cost of transportation, establishment/facility location, and inventory management, as well as customer satisfaction in a multi-period, multi-commodity, distribution-service network, Nekooghadirli et al. [36] minimize the costs and the average delivery time. Pasandideh et al. [37] propose a Multi-product multi-period three-echelon model that minimizes total costs and maximizes the amount of product sent to customer. Pasandideh et al. [38] similar to the later work, minimizes the mean and the total cost variance in a Supply Chain network. Zapata [28] and Arango et al [39] presented a multiobjective model to minimize inventory and transport costs, service level and required trips thorugh collaboration in a suppliers and customers network. Arango and Zapata [40] minimize transportation Costs, Inventory Costs and Service Level using the IRP. In most of the before mentioned works, authors were interested only in the companies' economics, since the goal of their research was to improve company performance or customer satisfaction.

Only Zapata [28] and Arango et al. [39] mentioned the reduction of trips required as a measure to mitigate transportation negative impact. Furthermore, these models optimize inventory and transport cost as a sum of both magnitudes, which may result in lower costs for companies but adverse environmental effects, such as an increase in trips or higher pollutants emissions. The model proposed in this article presents a new approach in which inventory and transport costs are treated apart while separately considering CO2 emissions. The aim is to evaluate different transport and inventory relationships and mitigate their environmental effect.

4 Methodology

With the aim of minimizing CO_2 emissions caused by the goods distribution process, a multiobjective model using a VMI background is proposed.

Table 1. Input parameters Customers.

Customer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Demand each Period	32	36	91	52	76	10	85	79	22	36	68	46	55	65	73
Inventory Cost	0.02	0.03	0.03	0.02	0.02	0.03	0.04	0.04	0.02	0.04	0.02	0.02	0.02	0.03	0.02
Initial Inventory	32	72	182	52	152	20	85	79	22	72	136	46	55	65	146
X position	237	180	141	163	282	455	326	235	412	113	266	257	363	158	423
Y position	182	332	388	188	374	296	332	432	488	46	302	23	22	81	95

Supplier			
Production quantity by period	826	X position	312
Inventory cost	0.3	Y position	363
Initial inventory	2042	Number of periods	5

This model includes three objective functions: inventory cost, transportation costs and CO_2 emissions. The result of the multiobjective model in a network conformed by one supplier and 15 customers, to be compared with the single transport optimization obtained by using the Vehicle Routing Problem – VRP. In the optimization processes two distinct genetic algorithms were used: a simple genetic algorithm for solving the VRP and an algorithm based on the NSGA2 for the multiobjective analysis, similar to what is presented in [28, 39, 40].

The emission factor of a typical urban goods distribution vehicle was used to analyze the CO_2 emission effect. The vehicle corresponds to a VAN with an average city emission of e = 190 g of CO_2 / km [41]. This parameter is multiplied by the number of kilometers traveled, in order to calculate the emitted CO_2 gases amount. The formulation for the multiobjective model with three objective functions is presented in Eq. 1 to 4.

$$minimizing\ G(g_1, g_2, g_3), \tag{1}$$

$$g_1 = \sum_{t\in\tau}\sum_{i\in v}\sum_{i\in v}\sum_{k\in K} c_{ij}x_{ij}^{kt}\ , \tag{2}$$

$$g_2 = \sum_{i\in v'}\sum_{t\in\tau} h_i I_i^t + \sum_{t\in\tau} h_0 I_0^t\ , \tag{3}$$

$$g3 = \sum_{t\in\tau}\sum_{i\in v}\sum_{i\in v}\sum_{k\in K} e\cdot c_{ij}\cdot x_{ij}^{kt}\ . \tag{4}$$

Equation (1) is the objective function that seeks to minimize transport costs, where x_{ij}^{kt} is a binary variable that is equal to 1 if the vehicle k has to travel from I to j in period t, and c_{ij} is the corresponding cost. Equation (2) is the functions for minimizing inventory both at the supplierI_0^t and at the customers I_i^t. Equation (3) minimizes the

CO2 emissions calculated as the sum of the distances multiplied by the vehicle CO2 emission factor. This objective function is restricted to the subsequent equations that assure the correct distribution process and correspond to those of the IRP Model according to Archetti et al., [42] and Arango et al. [6].

$$I_0^t = I_0^{t-1} + r_0^{t-1} - \sum_{k\in K}\sum_{i\in v} q_i^{kt-1} \ , \tag{5}$$

$$I_0^t \geq \sum_{k\in K}\sum_{i\in v} q_i^{kt}\, Y_i^{kt} \ , \tag{6}$$

$$I_i^t = I_i^{t-1} + \sum_{k\in K}\sum_{i\in v} q_i^{kt} - d_i^t \ , \tag{7}$$

$$I_i^t \geq 0 \ , \tag{8}$$

$$I_i^t \leq C_i \ , \tag{9}$$

$$q_i^{kt} \leq C_i - I_i^t \ , \tag{10}$$

$$q_i^{kt} \leq C_i Y_i^{kt} \ , \tag{11}$$

$$\sum_{i\in v} q_i^{kt} \leq Q_k \ , \tag{12}$$

$$\sum_{i\in v} q_i^{kt} \leq Q_k Y_0^{kt} \ , \tag{13}$$

$$\sum_{i\in v, i<j} X_{ij}^{kt} + \sum_{i\in v, j<i} X_{ji}^{kt} = 2y_i^{kt} \ , \tag{14}$$

$$\sum_{i\in S}\sum_{j\in S} X_{ij}^{kt} \leq \sum_{i\in S} y_i^{kt} - y_m^{kt} \quad \forall\, subset \ \ S \subseteq V \ , \tag{15}$$

$$q_i^{kt} \geq 0;\ Q_k \geq 0;\ I_i^t \geq 0;\ d_i^t \geq 0;\ C_i \geq 0. \tag{16}$$

For a thoughtful explanation of the restrictions, readers may refer to [6, 42] and [19]. The input parameters are obtained from the 15 customers and one supplier instance proposed by Archetti et al., [42]. In this case, the inventory amount that can be stored in each of the customers was increased, as a strategy to generate a lower distribution costs and a decreased CO_2 Emissions. The input data for location, initial quantity and inventory cost for customers and the supplier, as well as other instance information are presented in Table 1.

5 Results

The multiobjective model, in which the transport costs, inventory costs and CO_2 emission are optimized simultaneously, generates a set of 13 individuals due to the solutions non-dominance.

Table 2. Three objective functions multi-objective model results.

Solutions	Transport cost	CO_2 Emissions	Inventory cost	Total cost
1	3288.4	624.8	445.0	3733.3
2	4982.8	946.7	404.3	5387.1
3	5111.9	971.3	403.7	5515.6
4	3502.8	665.5	413.1	3915.9
5	5427.4	1031.2	403.7	5831.0
6	3902.6	741.5	406.9	4309.5
7	3642.3	692.0	407.5	4049.9
8	4156.1	789.7	404.9	4561.0
9	3304.3	627.8	421.3	3725.5
10	5012.8	952.4	404.2	5417.0
11	4831.7	918.0	404.8	5236.4
12	5692.9	1081.7	403.4	6096.3
13	3580.2	680.2	411.3	3991.5

Table 3. Results comparison for the models.

Model	Total Cost	Transport Cost	Inventory Cost	CO_2 Emissions
VRP.	8918.8	8612.5	306,3	1636,4
Multiobjective.	3733.3	3288.3	445.0	624.8

It is not possible to argue that one of the solutions is better than the others, for that reason, the decision maker, depending on his preference, may choose any of the model produced solutions.

Table 2 shows the results for the 3 optimized objective functions generated by the multobjective algorithm, presenting the CO_2 emissions, inventory, transport and total cost for each individual.

From Table 2 it can be observed that the lower the inventory level, the higher the transport cost and the CO_2 emissions, this as a consequence of an increase in transportation intensity in order to minimize inventory. This behavior is caused because the three-functions multiobjective model searches the best solution for every objective function without excessively increasing the others. In the solutions set produced by the multiobjective model, the individual number 1 is the solution that yields the lower CO_2 emissions, as observed in Table 1. Presented in Fig. 1, individual number 1, allows to serve the customers and satisfy its demand without visiting all customers in every period due to the collaboration between customers and supplier through the VMI. This generates an increase in inventory levels but reduces transportation and CO_2 emissions.

In order to compare these solutions, the distribution problem was solved supplying all customers in each period, what minimizes inventory costs in customers but increases transportation. For that, the Vehicle Routing Problem – VRP was used, assuming that

Inventory

Customer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Period 1	0	167	0	0	0	45	0	0	109	0	0	215	275	0	427
Period 2	158	0	0	253	0	0	183	316	0	128	317	0	0	386	0
Period 3	0	0	288	0	329	0	271	0	0	0	0	0	0	0	0
Period 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Period 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Routes sequence (Routes starts on Depot -0- and ends on it.)

Period 1	0	6	9	15	12	13	2	0	0	0	0	0	0	0	0	0
Period 2	0	4	14	10	1	11	7	8	0	0	0	0	0	0	0	0
Period 3	0	5	3	7	0	0	0	0	0	0	0	0	0	0	0	0
Period 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Period 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 1. Individual 1 generated by the three-functions multiobjective model.

every customer must be served every period, explaining why there is no customers inventory at the each period end, as well as no initial inventory need. For that distribution process, the transport cost is 1722.5 for each period, which corresponds to a total cost of 8612.5 for the 5 periods. This single VRP cost is higher than the transport cost for all individuals generated by the three-functions multiobjective model.

Table 3 presents the comparison of the distribution process with the VRP and individual 1 of the multobjective model, since this is the solution that generates the lower CO_2 Emissions. In Table 3 can be observe that the inventory is lower in the VRP solution, but it generates a higher costs and rises CO2 emissions, making it unattractive for companies and the environment.

The lower inventory cost in the VRP is caused by the transportation intensity that allows minimizing the inventory amounts required in customers facility. However, such intensity directly increases transport costs and the distances, what ultimately causes higher CO_2 emissions. A similar analysis could be made for the other solutions proposed by the algorithm and similar results will be found.

The results allow inferring that the multiobjective model generates solutions that improve the distribution process performance, both in cost and emissions, through evaluating different relationships between transport and inventory assignments. The proposed model results are better than the produced by the well-know VRP. However for a more comprehensive affirmation about the goodness of the multiobjective model, a comparison with more complex routing algorithms as well as trials with more and difficult instances are to be made.

6 Conclusions

In this paper, the collaborative inventory process and its effect on the pollutant gases emission are analyzed from a multiobjective perspective using an optimization model that includes three objective functions: inventory cost, transportation costs and CO_2 emissions, which are optimized simultaneously. This multiobjective model, as expected based on available literature, generates a set of optimal and non-dominated individuals, which achieves better results than the traditional, single transport optimization procedures, since total cost and CO_2 emissions are higher for the VRP. The increase in cost by the VRP model is caused by the inventory reduction at customers what mandates supplying customers every period. This behavior is known as a local optimum, in many cases worse than the global logistics optimization.

Through inventory collaboration it is possible to reduce goods distribution cost, and simultaneously minimize CO2 emissions due to the logistics activity. Based on the results found in this paper, the search for the single and individual optimization of transport or inventory costs generates large increases in logistical costs as well as CO2 emissions, which is neither beneficial for Company nor for the environment. However this conclusion applies only for the specific analyzed case. For a more comprehensive affirmation about the virtue of the multiobjective model, it should be tested with more complex instances, as well as compared with more sophisticated routing algorithms.

As future Work it will be interesting to study the possibility of including other objective functions that evaluates the performance of distribution processes such as Service level, process variability or risk [43]. It would also be interesting to consider distribution networks analysis involving several suppliers, several products and also more than one single Supplier-Customers echelons. Some authors have explored [6, 40, 43-44] these research lines, making their work an interesting starting point.

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