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Multi-objective green supply chain optimization with a new hybrid memetic algorithm using the Taguchi method

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Abstract The aim of most supply chain optimization problems is to minimize the total cost of the supply chain. However, since environmental protection is of concern to the public, a green supply chain, because of its minimum effect on nature, has been seriously considered as a solution to this concern. This paper addresses the modeling and solving of a supply chain design for annual cost minimization, while considering environmental effects. This paper considers the cost elements of the supply chain, such as transportation, holding and backorder costs, and also, the environmental effect components of the supply chain, such as the amount of NO_2, CO and volatile organic particles produced by facilities and transportation in the supply chain. Considering these two components (cost and environmental effects), we propose a multi-objective optimization problem. In this model, the facilities and transportation options have a capacity constraint and, at each level of the chain, we have several transportation options with different costs. We utilize a memetic algorithm in combination with the Taguchi method to solve this complex model. We also propose a novel decoding method and priority based algorithm for coding the solution chromosome. The performance of the proposed solution method has been examined against the hybrid genetic Taguchi algorithm (GATA) on a set of numeric instances, and results indicate that the proposed method can effectively provide better results than previous solution procedures.

1. Introduction

In a broad sense, a green supply chain refers to the management between the facility operation, transportation and environmental effects of all facilities in a supply chain, i.e. the environment protection constraint is brought into facility location and allocation. *Its purpose is to add environment protection consciousness into production and transportation, in order to improve the competitive edge of the supply chain regarding environmental effects*.

The growing awareness of supply chain environmental aspects is now greatly recognized by academic and industrial communities [1]. Srivastava [2] defines a green supply chain as "integrating environmental thinking into supply chain management, including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers, as well as the end of life management of the product after its useful life".

Researchers have divided greenness into two types. Some consider green designs for products [3] and others have placed emphasis on green operations. Green operation includes topics such as reverse logistics, network design [4,5], and waste management [6,7]. However, our research has a different idea regarding "greenness". More specifically, we are interested in environmental investment decision making in the supply chain design phase, and in taking precautions against environmental pollution.

A green supply chain is a logistic network that guarantees the product delivery from manufacturer to customer in an environmentally friendly manner. To reach this goal, companies should invest in design and planning to optimize their logistic network, while accounting for the trade-off between cost and environmental effects [8,9].

Noci [10] pointed out that companies should construct efficient management policies in supply chains. *In fact, they*

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should balance cost and environmental effects throughout the entire supply chain.

Pagell et al. [11] *proposed that supply chain managers need to balance cost reduction and innovation, while maintaining good environmental performance and a green supply chain*. In recent years, many researchers have proposed mathematical models to solve problems considering environmental effects. One of the first works was by Zhou et al. [12], which proposed a goal programming model to calculate the sustainability of continuous processes in a supply chain.

Guillen-Gosalbez and Grossmann [1] addressed the design and planning of supply chains, and proposed a bi-objective stochastic mixed integer non-linear program that simultaneously minimizes cost and environmental impact for a given probability level for a liquid material supply chain. The same authors [13] also developed a spatial branch and bound method that extends the specific structure of the prior problem and guarantees that the obtained results are a global solution that minimizes the problem objective function.

The supply chain problem is usually considered as a single objective problem, or can be converted to a single objective using weighting method [14,15]. Modeling a supply chain, considering environmental effects as a separate objective besides cost and customer satisfaction is another influential trend worthy of study. Comparing that with a single objective, it is more reasonable in terms of actual applications. Multi-objective optimization is utilized in a variety of decision making problems [16–18]. In recent years, multi-objective supply chain optimization has been considered by many researchers. For example, Paksoy et al. [19] modeled a supply chain to minimize total cost, prevent more CO_2 gas emissions and encourage customers to use recyclable products. They proposed different transportation choices between echelons, according to CO_2 emissions. Mincirardi et al. [20] proposed a multi-objective model to minimize solid waste in a supply chain. Alçada-Almeida et al. [21] addressed a multi-objective programming approach to identify the locations and capacities of hazardous material incineration facilities, and balance social, economic, and environmental impacts. Wang et al. [22] studied a multi-objective optimization model that captures the trade-off between total cost and environmental influence.

In this paper, we study an integrated supply chain with five tiers that delivers products from suppliers to customers. In this supply chain, we have several transportation options that transport products to downstream facilities. All facilities and transportation options have capacity constraints.

In some prior papers, manufacturers and warehouses have capacity constraints, but in this paper, we assume that each transportation option also has a capacity and we cannot always use the transportation option with the least cost and pollution effects. Thus, according to the amount of transported products and distance between facilities, we need to choose the best transportation options. The model of this paper is multi-objective. We have one objective that focuses on total cost minimization, which consists of transportation, raw material, holding, fixed, backorder and variable costs. The second objective is to minimize the amount of 3 gases, consisting of NO_2, CO and volatile organic particles produced by facilities and transportation means. In this paper, we assume that in addition to supply chain facilities, such as manufacturers, warehouses and distribution centers, transportation options also emit different amounts of dangerous gases, such as NO_2, CO and volatile organic particle.

We first model the supply chain mathematically, and next propose a novel coding method that produces a feasible solution. Utilizing this coding method, all generated solutions are feasible and we do not need to check the feasibility of solutions. We also use the memetic algorithm in combination with the Taguchi method to solve the model and reduce computational efforts.

The rest of paper is organized as follows: Section 2 gives an explanation of problem assumptions. In Section 3, we propose the mathematical model with its constraints, and Section 4 explains the solution approach. Section 5 presents a discussion of the results and, finally, Section 6 concludes the paper.

2. Problem statement

Before the mathematical model is proposed, we provide a verbal description of the model. In this model, we deal with allocation of facilities and transportation options. We consider a 5 tire supply chain consisting of suppliers, manufacturers, warehouses, distribution centers and customers. At the first level, the proposed model assigns each manufacturer, warehouse, distribution center and customer to suppliers, manufacturers, warehouses and distribution centers, respectively. Between each layer, we have several transportation options, such as trucks, trains, planes and etc. According to the distance between facilities and the amounts of dangerous gases produced using a specific transportation option, the proposed model allocates a transportation option to each open facility. In this model, we have two objectives. The first objective intends to minimize the total cost of the supply chain, which consists of several components, and the second objective attempts to minimize the environmental effects of the supply chain.

Since the second objective is the amount of produced gases, based on liter units, and we do not have the means to convert one liter of dangerous gas, such as nitrogen monoxide, to an equivalent amount of expenditure, we can not combine these two objective functions and propose a single objective based on cost or amount of dangerous gas production.

Other assumptions made in the problem are as follows:

- Raw materials are more than one type and the manufacturer provides them from several suppliers.
- Manufacturers, warehouses, distribution centers and transportation options have capacity constraints. If the demand of the supply chain is greater than the total capacity, we confront it with the backorder cost.
- Manufacturers and warehouses have a fixed lead time.
- Each supplier can fulfill the demand of more than one manufacturer.
- The demand of each warehouse can be satisfied by more than one manufacturer.
- The demand of each distribution center can be satisfied by more than one warehouse.
- The demand of each customer can be satisfied by more than one distribution center.
- The transportation options available to facilities in different tiers are not identical.
- Each transpiration option has a predetermined rate of hazardous gas production.
- Manufacturers, warehouses and distribution centers have predetermined rates of hazardous gas production.
- A periodic review inventory replenishment policy is assumed for warehouses and distribution centers.

2.1. Environmental effects

Nowadays, the major threat to the environment is posed by traffic that emits a wide variety of pollutants; principally,

Table 1: Notations regarding the function of cost and environmental effect functions.

Environmental impact function	PN	The amount of nitrogen oxide produced in supply chain (liter)
	PC	The amount of carbon monoxide produced in supply chain (liter)
	PO	The amount of volatile organic produced in supply chain (liter)
Cost function	RC	Total cost of purchasing raw materials from suppliers
	FC	Fixed costs of opened facilities
	VC	Variable costs of opened facilities
	TC	Transportation costs
	HC	Holding inventory costs in warehouses and distribution centers
	BC	Backorder cost

carbon monoxide (CO), nitrogen oxide (NO_2), and volatile organic (VOCs), which have an increasing impact on environmental conditions. Furthermore, industrial facilities impact an environment by producing these dangerous gases. Environmental effects are a major risk to health and are estimated to cause approximately 2 million premature deaths worldwide per year. For these reasons, we should establish a supply chain with this requirement; that minimum amounts of dangerous gases should be produced. In the environmental effects of a supply chain, several components are involved. Each facility and transportation option produces dangerous gases based on its operation type. This paper supposes that each facility produces a predetermined amount of gas in proportion to its demand handling. For transportation, this means the amount of produced gas is a function of distance and the number of products carried by them. Appendix gives the gas emission rate of different transportation options.

3. Mathematical model

In this section, we describe the mathematical model. As previously stated, our model has two objectives and each objective is divided into several components. Table 1 shows the components of each objective.

The following notations are used in the model formulation:

Sets:

- C set of customers,
- D set of distribution centers,
- W set of warehouses,
- M set of manufacturers,
- TM set of transportation options for manufacturers,
- TW set of transportation options for warehouses,
- TD set of transportation options for distribution centers,
- I set of suppliers producing raw material, type i,
- J set of suppliers producing raw material, type j.

Parameters:

- dem_c demand of customer c with mean μ_c and standard deviation σ_c,
- dem_f demand of facility $f \in \{m, w, d\}$,
- cr_m^i unit raw material cost from supplier of type i to manufacturer m,
- cr_m^j unit raw material cost from supplier of type j to manufacturer m,
- c_{mw}^{tm} unit transportation cost from manufacturer m to warehouse w with transportation option tm,
- c_{wd}^{tw} unit transportation cost from warehouse w to distribution center d with transportation option tw,
- c_{dc}^{td} unit transportation cost from distribution center d to customer c with transportation option td,
- $dis_{ff'}$ distance between facility $f \in \{m, w, d\}$ and facility $f' \in \{w, d, c\}$,
- fc_f fixed cost of opening facility $f \in \{m, w, d\}$,
- lt_m lead time of facility $f \in \{m, w\}$,
- vc_f unit variable cost per unit for facility $f \in \{m, w, d\}$,
- inv_f expected inventory at facility $f \in \{w, d\}$,
- nrr^i number of units of raw material of type i required to produce one unit of the product,
- nrr^j number of units of raw material of type j required to produce one unit of the product,
- p penalty cost per unit of customer demand if it is not fulfilled,
- ca_f the capacity of facility $f \in \{m, w, d\}$,
- $ca^{f'}$ capacity of transportation option $f' \in \{tm, tw, td\}$,
- G_N^f rate of released nitrogen oxide to produce/handle one unit of product in facility $f \in \{m, w, d\}$,
- G_C^f rate of released carbon monoxide to produce/handle one unit of product in facility $f \in \{m, w, d\}$,
- G_O^f rate of released volatile organic to produce/handle one unit of product in facility $f \in \{m, w, d\}$,
- $G_N^{f'}$ rate of released nitrogen oxide per one unit of distance for transportation option $f' \in \{tm, tw, td\}$,
- $G_C^{f'}$ rate of released carbon monoxide per one unit of distance for transportation option $f' \in \{tm, tw, td\}$,
- $G_O^{f'}$ rate of released volatile organic per one unit of distance for transportation option $f' \in \{tm, tw, td\}$.

Variables:

$$x_m \begin{cases} 1 & \text{if manufacturer } m \text{ is opened} \\ 0 & \text{otherwise} \end{cases}$$

$$x_w \begin{cases} 1 & \text{if warehouse } w \text{ is opened} \\ 0 & \text{otherwise} \end{cases}$$

$$x_d \begin{cases} 1 & \text{if distribution center } d \text{ is opened} \\ 0 & \text{otherwise} \end{cases}$$

- x_{mw}^{tm} quantity of products shipped from manufacturer m to warehouse w by transportation option tm;
- x_{wd}^{tw} quantity of products shipped from warehouse w to distribution center d by transportation option tw;
- x_{dc}^{td} quantity of products shipped from distribution center d to customer c by transportation option td;
- x_m^i quantity of raw material transported to manufacturer m from supplier that produce raw material type I;
- x_m^j quantity of raw material transported to manufacturer m from supplier that produce raw material type j.

With respect to the above notations, the multi-objective model can be formulated as follows:

$$f_1 = FC + VC + TC + RC + BC + HC, \tag{1}$$

$$FC = \sum_m fc_m \cdot x_m + \sum_w fc_w \cdot x_w + \sum_d fc_d \cdot x_d, \tag{2}$$

$$VC = \sum_m vc_m \cdot dem_m + \sum_w vc_w \cdot dem_w + \sum_f vc_d \cdot dem_d, \tag{3}$$

$$TC = \sum_m \sum_w \sum_{tm} x_{mw}^{tm} \cdot c_{mw}^{tm} \cdot dis_{mw} + \sum_w \sum_d \sum_{tw} x_{wd}^{tw} \cdot c_{wd}^{tw} \cdot dis_{wd} + \sum_d \sum_c \sum_{td} x_{dc}^{td} \cdot c_{dc}^{td} \cdot dis_{dc}, \tag{4}$$

$$RC = \sum_s \sum_m x^i_{sm} \cdot cr^i_{sm} + \sum_s \sum_m x^j_{sm} \cdot cr^j_{sm}, \tag{5}$$

$$BC = \left[\sum_c dem_c - \sum_d \sum_c \sum_{td} x^{td}_{dc}\right] \cdot p, \tag{6}$$

$$HC = \sum_w h_w \cdot inv_w + \sum_d h_d \cdot inv_d, \tag{7}$$

$$f_2 = PN + PC + PO, \tag{8}$$

$$\begin{aligned} PN = {} & \left(\sum_i \sum_m x^i_m \cdot G^m_N + \sum_j \sum_m x^j_m \cdot G^m_N \right. \\ & \left. + \sum_w dem_w \cdot G^w_N + \sum_d dem_d \cdot G^d_N\right) \\ & + \left(\sum_m \sum_w \sum_{tm} x^{tm}_{mw} \cdot G^{tm}_N \cdot dis_{mw} \right. \\ & + \sum_w \sum_d \sum_{tw} x^{tw}_{wd} \cdot G^{tw}_N \cdot dis_{wd} \\ & \left. + \sum_d \sum_c \sum_{td} x^{td}_{dc} \cdot G^{td}_N \cdot dis_{dc}\right), \end{aligned} \tag{9}$$

$$\begin{aligned} PC = {} & \left(\sum_i \sum_m x^i_m \cdot G^m_C + \sum_j \sum_m x^j_m \cdot G^m_C \right. \\ & \left. + \sum_w dem_w \cdot G^w_C + \sum_d dem_d \cdot G^d_C\right) \\ & + \left(\sum_m \sum_w \sum_{tm} x^{tm}_{mw} \cdot G^{tm}_C \cdot dis_{mw} \right. \\ & + \sum_w \sum_d \sum_{tw} x^{tw}_{wd} \cdot G^{tw}_C \cdot dis_{wd} \\ & \left. + \sum_d \sum_c \sum_{td} x^{td}_{dc} \cdot G^{td}_C \cdot dis_{dc}\right), \end{aligned} \tag{10}$$

$$\begin{aligned} PO = {} & \left(\sum_i \sum_m x^i_m \cdot G^m_O + \sum_j \sum_m x^j_m \cdot G^m_O \right. \\ & \left. + \sum_w dem_w \cdot G^w_O + \sum_d dem_d \cdot G^d_O\right) \\ & + \left(\sum_m \sum_w \sum_{tm} x^{tm}_{mw} \cdot G^{tm}_O \cdot dis_{mw} \right. \\ & + \sum_w \sum_d \sum_{tw} x^{tw}_{wd} \cdot G^{tw}_O \cdot dis_{wd} \\ & \left. + \sum_d \sum_c \sum_{td} x^{td}_{dc} \cdot G^{td}_O \cdot dis_{dc}\right). \end{aligned} \tag{11}$$

Objective Function (1) minimizes the total costs within the supply chain. Objective Function (8) minimizes the produced dangerous gases, such as NO_2, CO and Volatile organic. Relation (2) determines the fixed cost of the supply chain based on opened facilities. Relation (3) calculates the amount of variable cost based on the demand of each facility. Relation (4) computes the transportation cost according to the distance and amount of the transported product by each transportation option. Relation (5) calculates the raw material cost. Relation (6) determines the penalty cost for the unsatisfied demand of each customer and Relation (7) determines holding cost based on the inventory level of warehouses and distribution centers. Relation (9) calculates the amount of produced NO_2. We consider that the amount of NO_2 produced by each facility is calculated, based on its release rate of nitrogen oxide and its demand. With the same procedure, Relations (10) and (11) calculate the amount of produced CO and volatile organic gases, respectively.

$$dem_m = \sum_{tm} \sum_w x^{tm}_{mw} \quad \forall m, \tag{12}$$

$$dem_w = \sum_{tw} \sum_d x^{tw}_{wd} \quad \forall w, \tag{13}$$

$$dem_d = \sum_{td} \sum_c x^{td}_{dc} \quad \forall d, \tag{14}$$

$$inv_w = \frac{dem_w}{2} + z_\alpha \cdot \sigma_w \cdot \left(\frac{\sum_m \sum_{tm} x^{tm}_{mw} \cdot \sqrt{lt_m}}{dem_w}\right) \quad \forall w, \tag{15}$$

$$inv_d = \frac{dem_d}{2} + z_\alpha \cdot \sigma_d \cdot \left(\frac{\sum_w \sum_{tw} x^{tw}_{wd} \cdot \sqrt{lt_w}}{dem_d}\right) \quad \forall d, \tag{16}$$

$$\sigma_w = \frac{\sum_w \sum_{tw} \sum_d \sigma_d \cdot x^{tw}_{wd}}{dem_w}, \tag{17}$$

$$\sigma_d = \frac{\sum_d \sum_{td} \sum_c \sigma_c \cdot x^{td}_{dc}}{dem_d}, \tag{18}$$

$$\sum_{tm} \sum_w x^{tm}_{mw} \le ca_m \cdot x_m \quad \forall m, \tag{19}$$

$$\sum_{tw} \sum_d x^{tw}_{wd} \le ca_w \cdot x_w \quad \forall w, \tag{20}$$

$$\sum_{td} \sum_d x^{td}_{dc} \le ca_d \cdot x_d \quad \forall d, \tag{21}$$

$$x_m \le \sum_{tm} \sum_w x^{tm}_{mw} \quad \forall m, \tag{22}$$

$$x_w \le \sum_{tw} \sum_d x^{tw}_{wd} \quad \forall w, \tag{23}$$

$$x_d \le \sum_{td} \sum_c x^{td}_{dc} \quad \forall d, \tag{24}$$

$$\sum_i x^i_m = dem_m \cdot nrr^i \quad \forall m, i, \tag{25}$$

$$\sum_j x^j_m = dem_m \cdot nrr^j \quad \forall m, j, \tag{26}$$

$$\sum_m \sum_{tm} x^{tm}_{mw} = dem_w \quad \forall w, \tag{27}$$

$$\sum_w \sum_{tw} x^{tw}_{wd} = dem_d \quad \forall d, \tag{28}$$

$$\sum_d \sum_{td} x^{td}_{dc} \le dem_c \quad \forall c, \tag{29}$$

$$\sum_m \sum_w x^{tm}_{mw} \le ca^{tm} \quad \forall tm, \tag{30}$$

$$\sum_w \sum_d x^{tw}_{wd} \le ca^{tw} \quad \forall tw, \tag{31}$$

$$\sum_d \sum_c x^{td}_{dc} \le ca^{td} \quad \forall td. \tag{32}$$

Eqs. (12)–(14) determine the demand of each facility. Constraints (15) and (16) also calculate the inventory level that each warehouse and distribution center must hold. Since the demand of the facility is not served by only one facility, and more than one manufacturer or warehouse can supply the demand of a warehouse or a distribution center, in these constraints, we used a weighting method to determine the lead time for each facility. Eqs. (17)–(18) also show that the standard deviation of demand for warehouses and distribution centers is defined as the weighted average of the standard deviation of demands assigned to them. Eqs. (19)–(21) ensure that we cannot assign a demand to a facility that is higher than its capacity. Eqs. (22)–(24) assure that if a facility does not supply any facility at its lower level, it will be closed and its binary variable is equal to zero. Constraints (25) and (26) guarantee that the total raw material shipped from suppliers to a manufacturer can not be greater than the manufacturer demand, according to the required raw material for one product unit. Eqs. (27)–(28) ensure that the amount of product transported from a manufacturer and a warehouse must be equal to warehouse and distribution center demand, respectively. But, in this model, distribution centers are allowed to not serve the percentage or total demand of a customer. Eq. (29) shows this assumption. Finally, Constraints (30)–(32) are capacity constraints on transportation means, which prohibit assigning more than their capacity to the transportation means.

The aforementioned supply chain model is NP-hard, within which it is difficult to find the optimal point accurately [23]. We have also capacity constraints for facility and transportation means that make the problem more complex. For these reasons, we use a meta heuristic method to solve the model and find the near optimum solution.

4. Solution approach

4.1. Memetic algorithm

The memetic was proposed by both the Darwinian principle of natural evolution and Dawkins' notion of a meme. The Memetic Algorithm (MA) was first introduced by Moscato and Norman [24], where he viewed MA as being close to a form of population-based hybrid Genetic Algorithm (GA) coupled with an individual learning procedure capable of performing local refinements. In the last few years, many researchers have become more attracted to this methodology as a way out of some limitations present in other approaches. MAs were used in a variety of optimization problems, such as supply chain [25], scheduling [26], and partitioning problems [27], respectively. In this paper, we utilize a memetic algorithm and propose a modified coding method, and priority based decoding methods to solve the supply chain model, as detailed below.

4.2. Coding method

In this paper, we divide the supply chain into 5 sections; two sections for the manufacturer, according to the number of raw material types needed to produce one unit of product (in this case, we assume 2 types of raw material), and the 3 remaining sections are assigned to warehouses, distribution centers and customers, respectively. Figure 1 shows these sections and a primary solution coding for a problem with 3 manufacturers, 4 warehouses, 5 distribution centers and 8 customers, with 3 transportation options in each layer.

For decoding this chromosome, we modified the method proposed by Gen and Chen [28] that does not need a repair mechanism. In this approach a solution is represented by a $|k| \cdot |j|$ matrix, where k depicts the number of sources and j indicates the number of demand centers. Then, solutions are encoded as arrays of size $|k| + |j|$, in which the position of each cell represents the sources and depots, and the value in cells represents the priorities. In this paper, we modified this method and encoded the solution as an array of size $|j|$. Furthermore, the value of cells in the proposed array can be zero, if a cell value is zero, the demand of the cell is not satisfied and we have backorder costs. For example, the value of the first cell in Section 5 is zero, and the demand of customer one is not satisfied. Algorithm 1 shows the modified decoding method.

Algorithm 1.

Inputs

dem_j= the demand of node j

cap_i=the capacity of source i

cat_k=the capacity of transportation means available between source i and node j

$c(k,i,j)$= the cost of transporting one unit product from source i to demand node j by transportation mean k

Output

$X(k,i,j)$=the number of the product transported by mean k from source i to demand node j

while($\mathbf{max}(cat_k(:))>0$ *and* $\mathbf{max}(cap_i(:))>0$ *and* $\mathbf{max}(A(:))>0$)

j^*=**argmax**$\{A(j)|A(j)>0\}$ " find the maximum priority in solution chromosome"

(k^*,j^*)=**argmin**$\{c(k,i,j^*)|\ c(k,i,j^*)>0\}$ " find the minimum cost in matrix c for node j"

d=**min**$\{dem(j^*),cap(i^*),cat(k^*)\}$

$dem(j^*)= dem(j^*)-d$

$cap(i^*)= cap(i^*)-d$

$cat(k^*)= cat(k^*)-d$

if$(dem(j^*)=0)$ **then** $A(j^*)= 0$

if$(cap(i^*)=0)$ **then** $c(:,i^*,:)= 0$

if$(cat(k^*)=0)$ **then** $c(k^*,:,:)= 0$

$X(k^*, i^*, j^*)=d$

end of loop

END

4.3. Fitness function

In this paper, we have two different objectives; the first calculates the total cost of the supply chain and the second determines the amount of produced gases. For fitness evaluation, there are different types of weighting method, such as the random-weight approach proposed by Murata et al. [29], the Bang–Bang Weighted (BBW) and the dynamic weighted [30]. In this paper, we examine 2 types of weighting method; dynamic weight and random weight. The weighted objective is shown in Eq. (33)

$$Z = \sum_i w_i \cdot f_i^{nor}. \qquad (33)$$

	Manufacturer no.			Manufacturer no.			Warehouses no.				Distribution centers no.					Customers no.							
	1	2	3	1	2	3	1	2	3	4	1	2	3	4	5	1	2	3	4	5	6	7	8
	Section 1			Section 2			Section 3				Section 4					Section 5							
Priority	2	1	3	2	1	3	2	4	1	3	4	2	1	3	5	0	8	2	7	3	5	4	0

Figure 1: Modified priority based coding method.

The advantage of random weight is that it gives the algorithm a trend to demonstrate a variable search direction, enabling it to sample the solution space uniformly over the entire frontier. The random weight, w_i, for objective function i is calculated by the following formula, where r_i is a random number for the ith objective function.

$$w_i = \frac{r_i}{\sum_i r_i}. \quad (34)$$

Dynamic weight is proper for bi-objective problems. In this weighting method, we use Eq. (35), where t denotes the iteration index, and R the weight change frequency, the amount of R varies between 100 and 200 according to problem specifications [29].

$$w_1 = |\sin(2\pi \cdot t \cdot R)| \qquad w_2 = 1 - w_1. \quad (35)$$

Since the dimensions of the objective functions are different, we normalize the value of each objective. Eq. (36) used to normalize the objective values.

$$f_i^{nor} = \frac{f_i}{\max(f_i)} \quad i = 1 \cdots n. \quad (36)$$

Based on the fitness values, the solutions with the best fitness function value are passed on to the next population for elite protection. The other solutions of the next population are generated through an evolutionary procedure and improvement method.

4.4. Crossover method

In this paper, we utilize the Taguchi method in crossover procedure. Two chromosomes are selected and all combinations of their genes are produced according to the Taguchi table design. To produce a combination of two parents, according to the Taguchi table, if the value of the gene in the Taguchi table is equal to 1, we use the value of parent 1, otherwise, we use the value of parent 2 in combination. Then fitness value of all combinations is calculated and the combination with the best fitness function is passed to the next population. Figure 2 shows the crossover procedure.

According to Figure 2, parents 1 and 2 are selected to produce one chromosome for the next population. Total combinations of genes of two chromosomes are performed in 32 experiments, according to the Taguchi design, for 23 factors in 2 levels. In Figure 2, the "exp21" with the best fitness function is selected for passing to the next population. This crossover method is done until the next population is built completely.

4.5. Improvement method

In this paper, we utilize an improvement function to modify the solution in order to gain a solution with a better fitness function. The improvement function starts from a new solution, generated at random by some other algorithms. Subsequently, it iterates, using a transition at each step, based on the neighborhood of the current solution. The newly generated solution turns out to be the current solution in the next step if it has a better fitness value than the current solution. The whole process is sketched in Algorithm 2.

Table 2: Instances design.

	Instances number				
	1	2	3	4	5
Supplier type	2	4	4	4	4
Manufacturers	3	4	8	6	6
Warehouses	4	7	10	12	12
Distribution centers	5	7	12	12	16
Customers	16	21	25	35	39
Transportation for warehouses	3	4	3	5	6
Transportation for distribution	3	3	4	5	5
Transportation for customers	3	4	6	6	4

Algorithm 2: Improvement method.

Procedure Local-Search-Engine (current)
while (Criterion)
new solution= Generate Neighbor(current)
if (*Fitness(newsolutions)* < *Fitness(current)*) **then**
current =new solution
end if
until TerminationCriterion() ;
end

5. Results and discussion

5.1. Test instances

We present the results obtained by implementation of the proposed memetic algorithm to solve various test instances. Five test instances of several sizes have been taken to examine the effectiveness of the proposed method on large, as well as small, data sets. The problems design is detailed in Table 2. The required parameters for these instances are generated randomly using uniform distribution at proper intervals.

5.2. Parameters tuning

In this paper, the algorithms were coded in Matlab and implemented on a core 2 due PC running at 2.4 GHz. The results are sensitive to algorithm parameters. Hence, it is required to perform repeated simulations to find suitable values for the parameters. Optimal parameter combinations for different methods are experimentally determined by conducting experiments with different parameter settings. In

	Section 1			Section 2			Section 3				Section 4					Section 5							
Parent 1	2	1	3	2	1	3	2	4	1	3	4	2	1	3	5	0	8	2	7	3	5	4	0
Parent 2	3	2	1	2	3	1	4	1	3	2	5	2	3	1	4	0	5	0	7	8	6	3	2

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	fitness value
exp1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.952193
exp2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	0.929765
exp3	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	0.966065
exp4	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	0.959772
exp5	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	0.906155
exp6	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	0.989116
exp7	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2	0.995333
exp8	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	0.918088
exp9	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	0.907355
exp10	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	0.998803
exp11	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2	0.942791
exp12	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	0.975898
exp13	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	0.992317
exp14	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	0.987212
exp15	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1	0.996336
exp16	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	0.929676
exp17	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	0.971004
exp18	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	0.99011
exp19	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2	0.98742
exp20	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	0.98286
exp21	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	0.903521
exp22	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	0.990614
exp23	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2	2	1	2	1	0.962793
exp24	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	0.95726
exp25	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	0.973819
exp26	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	0.950822
exp27	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1	0.986483
exp28	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	0.914024
exp29	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	0.965714
exp30	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	0.959299
exp31	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2	0.951337
exp32	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	0.924462

exp21	3	1	1	2	1	1	2	4	3	3	5	2	1	1	5	0	5	2	7	8	5	3	0

Figure 2: Selection procedure with Taguchi design.

Table 3: Factors and their levels.

Factor	Levels	Values
A (crossover probability)	5	0.6, 0.65, 0.7, 0.75, 0.8
B (mutation probability)	3	0.01, 0.012, 0.014
C (population size)	4	100, 200, 300, 400

this paper, we assumed that the crossover probability (P_c) is selected between 0.6 and 0.8, in steps of 0.05, and other parameters, such as mutation probability (P_m), are selected between 0.01 and 0.014, by step .002, and the population size is selected between 100 and 400, with step size 100. Based on this assumption, we conduct a full factorial design to obtain the best combination of parameters. A full factorial experimental study is tackled, whose factors and respective levels and values are shown in Table 3.

To investigate the significant difference of the analyzed levels of factors, the analysis of variance (ANOVA) as a common statistical procedure is utilized. The results of experiments which have been analyzed by means of a three-way ANOVA with interactions are summarized in Table 4.

Table 4: Analysis of variance for weighted objective function.

Source	*DF*	*SS*	*MS*	*F*	*p*-value
A	4	0.2272	0.0568	12.0032	0.00
B	2	0.3857	0.1928	40.7514	0.00
C	3	0.4321	0.1440	30.4389	0.00
AB	8	0.1351	0.0169	3.57072	0.00
AC	12	0.2161	0.0180	3.80708	0.00
BC	6	0.1561	0.0260	5.50161	0.00
ABC	24	0.0057	0.0002	0.05084	0.00
Error	120	0.5678	0.0047		
Total	179	2.1260			

The last column of Table 4 indicates that the *p*-values of all main effects and their interactions are zero, and all factors and two-way interactions, and the only three-way

Table 5: Optimum value for algorithm parameters.

Parameters	Optimal value
P_m	0.012 or 0.014
P_c	0.65
Population size	200

Table 6: Comparison of performance of random and dynamic weights.

Instance no.	Random weight		Dynamic weight	
	Average value objective 1	Average value objective 2	Average value objective 1	Average value objective 2
1	10.55180614	27740.37968	10.55087054	27742.88593
2	12.09223266	31673.67998	12.33127719	31705.65464
3	12.40878685	32405.89137	12.5422946	32463.37882
4	12.61783607	32860.08868	12.65972052	32875.80287
5	12.74644465	33137.49248	12.77578009	33168.7175

interaction, are significant at each α-level. For this matter, we have to find the best level of each factor to propose the best combination of algorithm parameters. To reach this goal, the Student–Newman–Keuls (SNK) range test is used [31]. The SNK is often referred to as post hoc analysis, which is usually concerned with uncovering patterns in subsets of the sample. The SNK procedure compares pairs of level means for a statistically significant factor and then ranks the group means. Table 5 shows the results obtained by SNK for the best combination of algorithm parameters.

5.3. Results on test instances

In order to show the privilege of the proposed method, we have accomplished a comparative analysis on results obtained by implementation of the proposed method and a hybrid of the genetic algorithm with the Taguchi (GATA) algorithm. In order to find the best weighting method, we first compared the results obtained by random weight and dynamic weight. Table 6 shows the results of this comparison.

From Table 6, it is clear that random weight obtains better results than dynamic weight. For this reason, we run all instances with random weight, and Table 7 shows all results gained by running the proposed method and GATA for each instance.

From Table 7, it is obvious that the proposed method provides lower average cost in comparison with GATA in both objective functions. Because we normalize the value of the objective function, the value of fitness (weighted objective function) has a tendency to be equal to 1. Hence, in each run, the values of the best (minimum) fitness and the worst (maximum) fitness of the population get close to each other. This continues

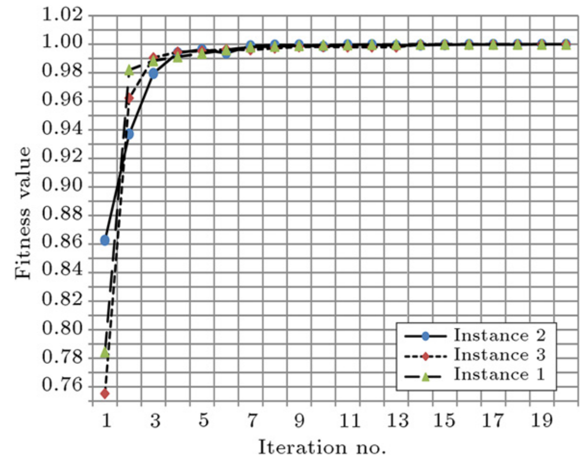

Figure 3: Convergence trends of the proposed algorithm.

Table 8: Percentage contribution of different types of costs (instance 1).

No. of customers	Average cost	*RC*	*FC*	*VC*	*TC*	*HC*	*BC*
20	27740.379	20.81	2.26	4.42	55.2	8.81	8.5
25	27742.568	16.92	2.3	5.41	56.51	8.63	10.23
30	28062.354	18.57	2.41	5.86	55.4	7.23	10.53
35	28157.842	19.54	2.08	6.32	53.2	7.53	11.33

until the fitness of all solutions in the population is identical. Convergence of the proposed algorithm for instances 1–3 is shown in Figure 3.

To realize the impact of the number of customers on the total cost of the supply chain, we run the model on instances with several customers. Table 8 gives the results of running the model on instance 1 with several customers. We also show the contribution of each cost in the total cost, in Table 8. From the results, it is obvious that the transportation cost is the major portion of the total cost, and raw material costs are ranked second. The fixed cost of opened facilities and holding costs comprise the lower proportion compared to the costs mentioned above. Because of capacity constraint we have backorder costs, and some customer demands are not satisfied.

It is worthy to mention that the proposed algorithm gets very close to the optimal solution at a much lower iteration number in comparison with GATA. As shown in Figure 4a, the value of objective 1 reaches its optimum value in iteration number 9. Objective 2 also gains its best value in the 9th iteration, for instance 1, as shown in Figure 4b. The convergence of GATA for instance 1 is also shown in Figures 4c and 4d for objectives 1 and 2, respectively. It is obvious that the

Table 7: Comparison of performance of the proposed algorithm and GATA.

Instance no.	Proposed method						GATA					
	Best value objective 1	Average value objective 1	Best value objective 2	Average value objective 2	Average fitness	CPU time (s)	Best value objective 1	Average value objective 1	Best value objective 2	Average value objective 2	Average fitness	CPU time (s)
1	10.5252	10.5518	27684.8989	27740.3797	0.9936	198.6	11.7943	12.0632	28576.3615	29127.8639	0.9726	178.12
2	12.0439	12.0922	31483.6379	31673.6800	0.9953	213.14	12.4337	12.6254	35995.0820	36189.1634	0.9774	198.05
3	12.3207	12.4088	32175.8095	32405.8914	0.9946	246.32	13.5570	13.7615	35417.0366	36022.1627	0.9840	226.79
4	12.5421	12.6178	32814.0846	32860.0887	0.9964	274.3	14.4124	14.6090	33182.6943	33277.1185	0.9861	246.87
5	12.6078	12.7464	32846.8767	33137.4925	0.9976	302.12	12.9926	13.0154	34789.5306	35135.1257	0.9927	287.73

Table 9: Demand of customers in Instance 1.

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$	$C11$	$C12$	$C13$	$C14$	$C15$	$C16$
Demand	12	140	150	160	170	180	190	100	110	120	130	140	150	160	170	180

Table 10: Customers allocation to each distribution center and transportation option.

		$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$	$C11$	$C12$	$C13$	$C14$	$C15$	$C16$
	$D1$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	$D2$	0	0	150	0	0	0	0	0	0	0	0	140	0	110	0	0
$TD1$	$D3$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	$D4$	0	0	0	0	0	0	0	0	0	0	130	0	0	0	0	0
	$D5$	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0
	$D1$	0	140	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	$D2$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$TD2$	$D3$	12	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0
	$D4$	0	0	0	0	0	0	0	0	0	30	0	0	0	50	0	0
	$D5$	0	0	0	78	0	142	0	0	0	90	0	0	20	0	0	0
	$D1$	0	0	0	0	0	0	0	0	0	0	0	0	60	0	0	0
	$D2$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$TD2$	$D3$	0	0	0	0	170	0	0	0	0	0	0	0	0	0	0	180
	$D4$	0	0	0	0	0	0	190	0	0	0	0	0	0	0	0	0
	$D5$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

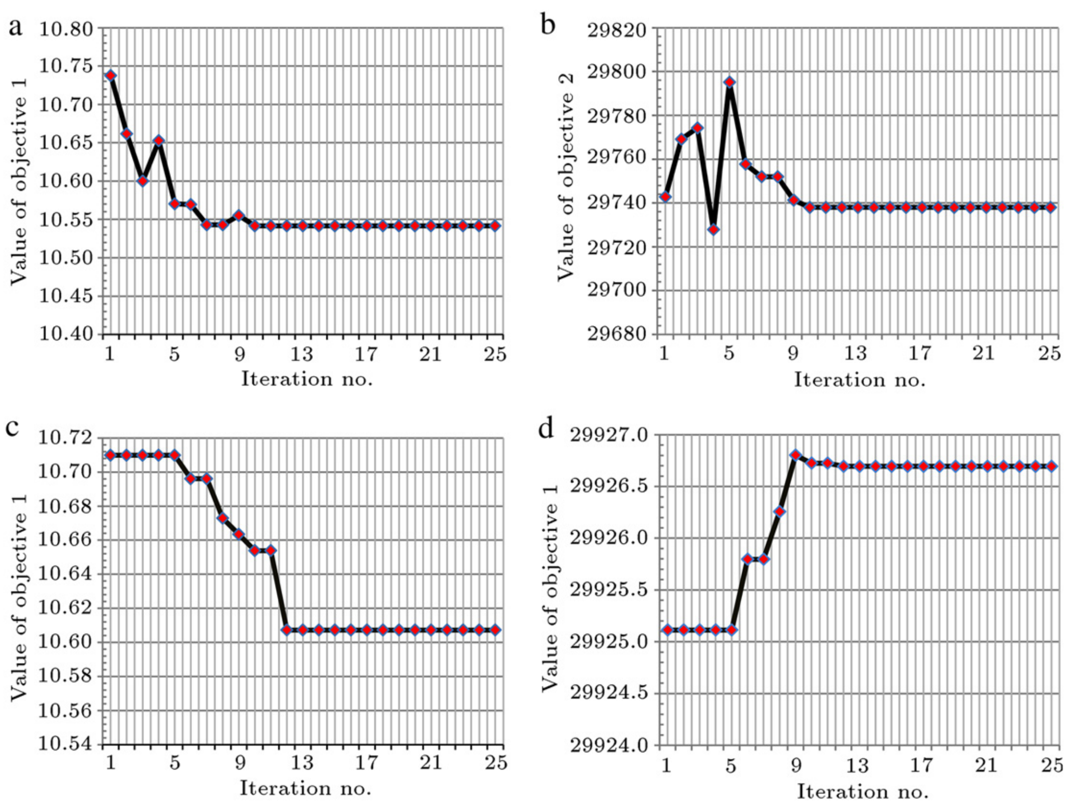

Figure 4: Convergence trends of the proposed algorithm and GATA for each objective function.

convergence of the proposed method is much higher than GATA and prior methods in the literature.

After reviewing the results from a computational perspective, it should be explained how the supply chain manager can use the obtained results from the model. In instance 1, we assumed that the capacity of distribution centers, warehouses and manufacturers was 200, 600 and 900 units, respectively, and the demand of each customer was as mentioned in Table 9.

Table 10 shows the number of products transported from distribution centers to customers by each transportation option. In this case, the supply chain could not satisfy the demand of some customers, such as C8, C9, C15, and this matter

Table 11: Warehouse allocation to each manufacturer and transportation option.

		$W1$	$W2$	$W3$	$W4$
$TM1$	$M1$	0	0	0	0
	$M2$	0	0	300	600
	$M3$	0	600	0	0
$TM2$	$M1$	0	0	0	0
	$M2$	0	0	0	0
	$M3$	0	0	300	0
$TM3$	M1	0	0	0	0
	$M2$	0	0	0	0
	$M3$	0	0	0	0

Table 12: Distribution center allocation to each warehouse and transportation option.

		$D1$	$D2$	$D3$	$D4$	$D5$
$TW1$	$W1$	0	0	0	0	0
	$W2$	0	0	0	0	0
	$W3$	0	0	0	0	400
	$W4$	0	0	0	0	0
$TW2$	W1	0	0	0	0	0
	$W2$	0	0	400	0	0
	$W3$	0	0	0	0	0
	$W4$	0	400	0	200	0
$TW3$	W1	0	0	0	0	0
	$W2$	200	0	0	0	0
	$W3$	0	0	0	200	0
	$W4$	0	0	0	0	0

leads to backorder costs. Tables 11 and 12 also show the amount of products transported to distribution centers and warehouses by each transportation option, respectively. For example, 400 products are shipped from warehouse 3 to distribution center 5 by transportation option 1.

It is obvious that all allocations mentioned in Tables 10–12 are feasible and pass all constraints in the model. These allocations minimize the amount of dangerous gases and the total cost of the supply chain simultaneously.

6. Conclusion

This paper studied a problem of a supply chain at a tactical level, where all facilities and transportation options have a capacity constraints. We also consider the environmental effects of the facilities and transportation options in the supply chain as an objective function, in addition to the total cost function, considering that these components of the supply chain bring the model closer to reality. In regard to the problem with these specifications, computational effort is very complicated. Thus, in order to overcome this complexity, we utilized the Taguchi method in combination with the memetic algorithm and proposed a modified antibody priority based coding and selecting method to avoid spending a lot of time and cost on problem optimization. An increase in convergence and a decrease in average cost are the results of using Taguchi in combination with the memetic algorithm. The results of extensive computational tests indicated that the proposed method is both effective and efficient for a wide variety of problem sizes and structures.

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Appendix

Transportation options can be divided in two categories. First is the road transportation option, and second is the nonroad transportation option; each category in turn having several options. For example, in the road category, we have several transportation options, such as automobiles, heavy trailers and semi-heavy trailers. Airplanes and locomotives are categorized as nonroad transportation. In this paper, we assume that at each level of the supply chain, several transportation options exist, according to their specifications, such as motor volume and fuel. Table 13 shows the emission rates of dangerous gases.

Table 13: Emission rate of dangerous gases.

Road transportation				
Rated power	CO (g/bhp-h)	HC (g/bhp-h)	NO_2 (g/bhp-h)	PM (g/bhp-h)
25 < hp	8.5	1	6.9	0.4
175 =< hp <= 750	8.5	1	5.8	0.16
hp = 751+	8.5	1	6.9	0.4
Locomotive				
Type	CO (g/bhp-h)	HC (g/bhp-h)	NO_2 (g/bhp-h)	PM (g/bhp-h)
Line-haulduty-cycle	11.5	0.3	5.5	2.2
Switchduty-cycle	12.4	0.6	8.1	2.4
Aircraft				
Type	CO (g/kN)	HC (g/kN)	NO_2 (g/kN)	PM (g/kN)
TF	118	19.6	40	24
T8 with ro above 26.7 kN	118	19.6	32	24
T8, TF newly manufactured (above 26.7 kN)	118	19.6	32	21

g/bhp-h: grams per brake horsepower-h.
g/kN: grams per kilonewton.
TF: all turbofan and turbojet aircraft engines except engines of Class T3, T8, and TSS.
T8: all aircraft gas turbine engines of the JT8D model family.
Switch: locomotives with four or six axles.
Line-haul: locomotives move between two major cities or ports, especially those more than about 1500 km or 1000 miles apart.

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