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# A dual-channel network design model in a green supply chain considering pricing and transportation mode choice

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**Abstract** A green supply chain with a well-designed network can strongly influence the performance of supply chain and environment. The designed network should lead the supply chain to efficient and effective management to meet the efficient profit, sustainable effects on environment and customer needs. The proposed mathematical model in this paper identifies locations of productions and shipment quantity by exploiting the trade-off between costs, and emissions for a dual channel supply chain network. Due to considering different prices and customers zones for channels, determining the prices and strategic decision variables to meet the maximum profit for the proposed green supply chain is contemplated. In this paper, the transportation mode as a tactical decision has been considered that can affect the cost and emissions. Lead time and lost sales are considered in the modeling to reach more reality. The developed mathematical model is a mixed integer non-linear programming which is solved by GAMS. Due to NP-hard nature of the proposed model and long run time for large-size problems by GAMS, artificial immune system algorithm based on CLONALG, genetic and memetic algorithms are applied. Taguchi technique is used for parameter tuning of all meta-heuristic algorithms. Results demonstrate the strength of CLONALG rather than the other methods.

**Keywords** Supply chain network design · Mathematical model · Greenhouse gases emissions · Pricing · Artificial immune system · CLONALG

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## Introduction

### Supply chain network design

In today's competitive business world, enterprises are confronting the growing markets, increasing expectations of customers and new relationship ways and channels with customers. Therefore, to satisfy the customer expectations and increase the capability of competitiveness against competitors, companies need to analyze their working styles and relations with their customers. For these reasons, supply chain management (SCM) has been considered as an important necessity. Therefore, an appropriate design of the supply chain network is needed to synchronize facilities more efficiently in order to increase the productivity of the supply chain and to obtain customers satisfaction. Supply chain network design tries to construct the most efficient and effective supply chain due to the operating environment of companies (Samadhi and Hoang 1998). The prominent status of supply chain network design in the early 1970s was considered (see, e.g. Geoffrion and Graves 1974). A supply chain network totally comprises suppliers, plants, distribution centers (DCs), retailers along with their markets and systems, sub systems, operations, activities and relations among the facilities (Shapiro 2007).

Supply chain network design is classified as strategic decision problems which are used to make the supply chain more efficient in their long term operations and activities. Therefore, it needs to be optimized (Gumus et al. 2009). The design decisions at the strategic level determine the open facilities with their locations and their relations. At the operational level, decisions comprise setting up distribution channels, determining the amount of products manufacturing, the inventory level and the quantity of materials or products which should be transported between the facilities.

It is important that the design decisions not be taken without investigating the operational ones and their effects (Lee and Billington 1992).

## Green supply chain

Awareness about the necessity of the protection of the environment is rapidly increasing. Worldwide environmental problems such as air pollution, toxic substance usage, global warming, the loss of non-renewable resources and water are threats to our modern life style. Therefore, to protect the environment and the earth, some of organizations use green principles. These green principles have been applied to a lot of scientific and industrial areas comprising supply chain management. To use the green principles in supply chains, a new concept has been emerged in the last few years which is called green supply chain management (GSCM) (Markovits-Somogyi et al. 2009). Numerous research have been published in recent years in the field of green supply chain (see for example Bai and Sarkis 2010; Diabat and Govindan 2011; Eltayeb et al. 2011; Hsu and Hu 2008; Kumar et al. 2011; Yeh and Chuang 2011). A comprehensive review on the area of green supply chain management is presented by Min and Kim (2012) which comprises more than five hundred papers. As a sub set of green supply chain, green logistic is reviewed by Dekker et al. (2012). They considered the transportation activities as the most visible aspect of supply chains affecting the environment. They modeled a mathematical operational research model with the ability of choosing the mode of transportation, since each mode has different cost, time and environmental effects. Le and Lee (2013) have used transportation and vehicle selection in supply chains for different modes and vehicles when $CO_2$ emission is considered. Many researches have been used transportation modes in their supply chain and we have used these studies for choosing transportation modes (see, e.g. Khalifehzadeh et al. 2014; Rajabalipour Cheshmehgaz et al. 2014).

To balance the environmental and economic concerns in supply chain network design, improving environmental quality should be considered as a cost function which comes at total supply chain cost (Quariguasi Frota Neto et al. 2009). Therefore, the aim of these trades-off between environmental and economic issues are to determine those solutions which increase the total cost if environmental damage will be decreased. These solutions are known as eco-efficient.

Greenhouse gases (GHG) emissions are known as one of the most environmental pollutants. To design green supply chain networks, different strategies can be used to model the GHG emissions in the mathematical models such as GHG cap, tax on generation of the GHGs, GHG offset as a trading scheme in supply chains, GHG management by using life cycle assessment (LCA) or modeling the total GHG emitted as an objective function and try to minimize it. LCA is a methodology that measures the environmental performance during the life cycle of the products. Carbon offset strategy as a trading scheme in supply chains allows the plants or supply chains to achieve the threshold of GHG emissions (Giarola et al. 2012). GHG emissions cap to impose mandatory targets as a green legislation is a kind of strategy that enforces that supply chains to control their GHG emission. Here, in this study to cap the GHG emissions a mandatory target is set as a green regulation constraint in the mathematical modeling. Some of studies try to minimize their GHG emissions as an objective function when there is no difference between green and economic goals.

## Dual-channel supply chain design

Nowadays, development of rapid accessibility to information technology has changed purchasing behavior of customers, especially purchasing products directly from plants along with purchasing products indirectly from distribution centers (NPD Group 2004). On the other hand, manufacturers consider direct channel more accurately than previous methods. For example, about 68 % of manufacturers of consumer goods are creating their online selling (direct channel) (Forrester Report 2000) (for more examples see Xu et al. 2012). Rajabalipour Cheshmehgaz et al. (2013) have presented a model to minimize the indirect shipment to increase the flexibility of the supply chain. Also, Hiremath et al. (2013) defined three channels as very slow, slow and fast movement to improve the flexibility. They classified their delivering channels based on nature of demands. Fast moving items have their especial strategy to be stocked and delivered by regional DCs. Slow moving items are stocked in central DCs and very slow items are stocked in plants with in-house storage facilities.

One of the important issues in dual-channel supply chain design is determining price competition between the channels (Xu et al. 2012). Customers of direct channel usually have higher expectations from those who purchase from indirect channel. Therefore, total allowable delivery lead time of direct channel is not longer than the indirect one. Ernst and Young (2001) have shown that two-thirds of companies choose different prices for their channels, however in some industries, trend is to charge low prices for direct channels. Amini and Li (2015) have considered pricing concept by using selling price ration in their model.

Dual-channel supply chains can be implemented in those industries with the ability of attracting customers directly in addition to indirect channel. Designing dual-channel for supply chains can be used for products with two kinds of customers, who link to supply chains directly via internet and who purchase products indirectly. As a real case, Yezheng and Zhengping (2012) have been studied a dual-channel supply chain in a free riding problem with coordination strategy in revenue sharing. Yu et al. (2015) have been a dual-channel supply chain network design for fresh agri-products.

### Motivation

However, a wide range of studies have been dedicated to green supply chain along with its network design and dual-channel in supply chains separately. According to related literature and the best of our knowledge, our recent study is trying to enter a new area by integrating the concepts of green supply chain and dual-channel networks into supply chain network design.

In this study, the concept of green supply chain is considered in two ways as follows; the first way is to choose transportation mode between facilities in each channel which is related to the amount of greenhouse gases (GHGs) emissions, and the second one is to restrict the total amount of emissions to be lower than significant allowable amount which is usually determined by law or green organizations. In this study, other aspects of supply chain network design such as production, pricing, lost sales and its penalty, capacity constraints and lead time are also considered. Here, the mathematical formulation presented by Pishvaee and Rabbani (2011) for direct and indirect shipment is used as our base model for designing the proposed dual-channel supply chain network model. They developed a profitably supply chain network design mathematical model without considering any environmental and green concepts. They considered lead time and capacity constraint in their modeling. According to Table 1, we consider transportation mode choice and their impacts on GHG emissions in our model.

Some related studies in the field of green supply chain network design and dual-channel design are compared with ours in Table 1. According to this Table, channel structure is classified as single and dual-channels. As it seems most of designed mathematical models are classified in the single channel group. Previous studies almost employed the concepts of single channel, forward flow and capacity constraint in their models. Besides, a few studies considered GHG emissions in their modeling for different modes of transportation activities (see Jamshidi et al. 2012; Mallidis et al. 2012). In addition, pricing as an important concept in green supply chain network design is only considered by Guillén-Gosálbez and Grossmann (2010). The concept of pricing can play an important role in dual-channel supply chains especially when trade-offs between environmental and economic issues are considered.

Costumers can be classified into two groups, those who prefer ordering from indirect channel and those who prefer buying from direct one. These two groups usually have different expectations in product price and delivery lead time. On the other hand, developing technologies in transportation modes along with restrictions for GHG emissions in laws and changing demands of customers to buy products from those supply chains that produce fewer emissions are some of motivations to design dual-channel green supply chains considering GHG emissions, delivery lead time with different modes in transportation activities and pricing decisions for channels to maximize the total profit of supply chain. The concepts of lost sales and capacity constraints are also considered in the production process.

Since capacitated facility location problems are introduced as NP-complete problems and most of supply chain network design problems can be reduced to them, it can be concluded that supply chain network design problems belong to NP-hard problems class (Davis and Ray 1969). Therefore, heuristic and meta-heuristic algorithms can be employed to match the complexity of NP-hard problems. Finally, the proposed model is solved by GAMS and according to NP-hard nature of the presented problem and long run time, an artificial immune system algorithm based on CLONALG and Taguchi method is applied. Then, to validate the obtained results, other population-based algorithms such as genetic and Memetic algorithms are taken into accounts. Melo et al. (2009) in the field of supply chain network design (SCND) has reviewed the solution approaches for single objective problems. They declared that about 45 % of the SCND models are solved by specific algorithms and heuristic solutions based on heuristic and meta-heuristics which are the most popular solution approaches. In the end, a numerical example is used and the results obtaining from solution approaches are compared. Most parameters of the proposed model in all test problems in the numerical example are generated randomly with the range of parameters presented in recent literature (Pishvaee and Rabbani 2011).

The reminder of the manuscript is organized as follows: in the next part, Problem definition and formulation, assumptions of the model and mathematical model formulation are presented. In Solving methodology Section, artificial immune system based on CLONALG for problems with long run time as the solving method is presented. To express more explicitly, some experimental results are implemented in Experimental results Section. Finally, some concluding remarks are provided in Conclusion Section.

## Problem definition and formulation

Today, by increasing the sensitivity of the governments and nations about the environmental issues in economical and non-economic activities, the concept of greening is growing fast. On the other side, competition to interest customers by rapid delivering and direct connection with them has become significant. Thus, developing dual-channel green supply chains can join these goals together. In this study,

**Table 1** Comparison of literature of dual-channel network design and supply chain network design with our model

| Article | Channel structure | Objective function | Network flow | Model specifications | | | | | | | | | Modeling and solving | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Green and environmental concepts | GHG emission strategy | Pricing | Production | Transportation modes | Lead time | Lost sale | Capacity constraint | Inventory | Modeling Method | Solution Approach |
| Guillén-Gosálbez and Grossmann (2010) | Single | Multi | Forward | * | LCA | * | | | | | * | * | Stochastic | $\varepsilon$−C |
| Jamshidi et al. (2012) | Single | Multi | Forward | * | O.F. | | * | * | * | | * | * | Stochastic | MA |
| Pishvaee and Razmi (2012) | Single | Multi | F&R | * | | | | | | | * | | Fuzzy | FMOP |
| Pishvaee et al. (2012) | Single | Multi | Forward | * | | | * | | | | * | | Fuzzy | FMOP |
| Chaabane et al. (2012) | Single | Multi | Closed-loop | * | Cap | | | | | | * | * | Deterministic | LINGO |
| Mallidis et al. (2012) | Single | Single | Forward | * | O.F. | | * | * | | | * | | Deterministic | LINGO |
| Wang et al. (2011) | Single | Multi | Forward | * | O.F. | | | | | | * | | Deterministic | NNCM |
| Hugo and Pistikopoulos (2005) | Single | Multi | Forward | * | LCA | | | | | | * | | Deterministic | GAMS |
| Giarola et al. (2012) | Single | Single | Forward | * | Offset | | | | | | * | | Stochastic | GAMS |
| Elhedhli and Merrick (2012) | Single | Single | Forward | * | O.F. | | | | | | | | Deterministic | LR |
| Pinto-Varela et al. (2011) | Single | Multi | Forward | * | LCA | | | | | | * | * | Fuzzy | FMOP |
| Corsano et al. (2011) | Single | Single | Forward | * | | | | | | | * | | Stochastic | GAMS |
| Büyüközkan and Berkol (2011) | Single | Single | Forward | * | O.F. | | | | | | | | Deterministic | LINDO |
| Pishvaee et al. (2012) | Single | Multi | Forward | * | | | * | * | | | * | | Fuzzy | FMOP |
| Kara and Onut (2010) | Single | Single | Reverse | * | | * | * | | | * | * | | Stochastic | GAMS |
| Pishvaee and Rabbani (2011) | Single | Single | Forward | | | | | | * | | * | | Deterministic | LINGO |
| Tunali et al. (2011) | Single | Single | Forward | | | | | | | | * | | Stochastic | Simulation |
| Sousa et al. (2008) | Single | Single | Forward | | | | | | | | * | * | Deterministic | ILOG |
| Cardoso et al. (2013) | Single | Single | Closed-loop | | | | | | | | * | * | Stochastic | GAMS |
| Fahimnia et al. (2015) | Single | Multi | Forward | * | Tax | | * | * | | | * | * | Deterministic | NICE |
| Fahimnia et al. (2015) | Single | Multi | Forward | * | Tax | | * | * | | | * | * | Deterministic | NICE |
| Xu et al. (2012) | Dual | Single | Forward | | | * | | | * | | | | Deterministic | — |
| Yu et al. (2015) | Dual | Multi | Forward | | | | * | | | | * | | Fuzzy | FMOTPA |
| Hsieh et al. (2014) | Dual | Multi | Forward | | | | | | * | | | | Stochastic | NSGA-II |
| Amini and Li (2015) | Dual | Single | Forward | | | * | * | | * | | | * | Stochastic | GAMS |
| **Our Study** | **Dual** | **Single** | **Forward** | ***** | **Cap** | ***** | ***** | ***** | ***** | ***** | ***** | | **Deterministic** | **GAMS-CLONALG** |

*F&R* Forward & Reverse, *$\varepsilon$ -C* $\varepsilon$-Constraint, *MA* Memetic Algorithm, *FMOP* Fuzzy Multi-Objective Programming, *NNCM* Normalized Normal Constraint Method, *LR* Lagrangian Relaxation, *LCA* Life Cycle Assessment, *O.F.* Objective Function, *Cap* GHG Cap Strategy, *Offset* GHG Offset Strategy, *NICE* Nested Integrated Cross Entropy, *FMOTPA* Fuzzy Multi-Objective Two-Phase Algorithm

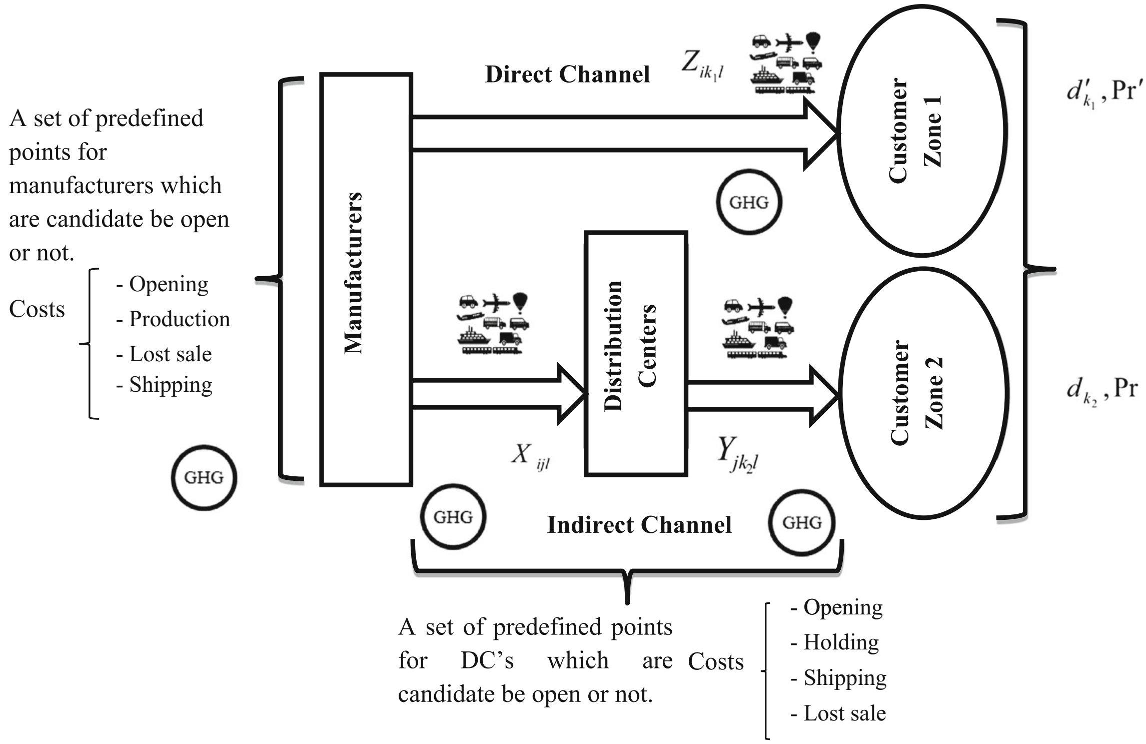


**Fig. 1** Illustration of the proposed supply chain

a single-product, two-echelon green supply chain network including plants and distribution centers (DC's) is considered. To design this network, greenhouse gases emission, as an environmental issue, with regard to economic aspects are investigated. Markets to sell the products are significant and predefined. Figure 1 shows the proposed supply chain with its characteristics. The important feature of the supply chain is being dual-channel. Markets are classified into two groups. First one comprises those customers (customer zone 1) which order directly to plants as direct channel (on-line ordering). Plants deliver the ordered products through this channel. The second group (customer zone 2) is those customers which order indirectly to the supply chain. Therefore, their demand will be satisfied by distribution centers through the indirect channel.

The following assumptions are the features which are used to design the proposed supply chain.

1. The supply chain is single-product.
2. The supply chain is composed of two echelons; plants and distribution centers.
3. Two kinds of channels are considered. Direct channel links plants to customer zone 1. On the opposite side, indirect channel links distribution centers to customer zone 2.
4. Each market has determined demand which depends on the selling price of products in both channels.
5. There is a lead time constraint to deliver products to markets for both channels.
6. Plants and distribution centers have capacity constraints.
7. Unsatisfied demands for both channels are considered as lost sales.
8. Manufacturing and shipping activities within supply chain emit greenhouse gases (GHG).
9. Different transportation modes are considered for products shipping. Greenhouse gases emissions depend on the chosen transportation mode.
10. The supply chain is legally bounded to comply with greenhouse gases emissions law. Therefore, the GHG emissions must not exceed the legal threshold.
11. Determining selling price of products in each channel is a tactical decision. Therefore, each channel, based on its pricing function, has its unique selling price which depends on the selling price of another channel.

Due to the mentioned features of the proposed supply chain, profit maximization of designing a dual-channel green supply chain with regard to transportation and pricing issues is as follows: Strategic decision for the proposed supply chain is to determine which facilities (plants and distribution centers) are open. There are a set of predefined points for plants and distribution centers to determine the positions of open facilities. Tactical decision is to specify the amounts of products which should be dispatched through the channels considering transportation mode and selling price of products in that channels.

## Mathematical model formulation

The following notations are used to formulate the mathematical model of the proposed problem.

*Indices*

- $i$ Candidate locations for plants $i = 1, \ldots, I$
- $j$ Candidate locations for distribution centers $j = 1, \ldots, J$
- $k_1$ Predefined locations for zone one customers (direct channel) $k_1 = 1, \ldots, K_1$
- $k_2$ Predefined locations for zone two customers (indirect channel) $k_2 = 1, \ldots, K_2$
- $l$ Transportation modes $l = 1, \ldots, L$

*Parameters*

- $d_{k_2}$ Demand of customer $k_2$ received from indirect channel
- $d'_{k_1}$ Demand of customer $k_1$ received from direct channel
- $f_i$ Fixed cost of opening plant $i$
- $g_j$ Fixed cost of opening distribution center $j$
- $p_{ijl}$ Unit transportation cost from plant $i$ to distribution center $j$ by using transportation mode $l$
- $q_{jk_2l}$ Unit transportation cost from distribution center $j$ to customer $k_2$ by using transportation mode $l$
- $r_{ik_1l}$ Unit transportation cost from plant $i$ to customer $k_1$ by using transportation mode $l$
- $c_i$ Per unit production cost for each product at plant $i$
- $h_j$ Per unit holding cost for each product at distribution center $j$
- $m_i$ Maximum capacity of plant $i$
- $n_j$ Maximum capacity of distribution center $j$
- $\theta_i$ Penalty per unit lost sale for plant $i$
- $\beta_j$ Penalty per unit lost sale for distribution center $j$
- $lt_{jk_2l}$ Lead time from distribution center $j$ to customer $k_2$ using transportation mode $l$
- $ls_{ik_1l}$ Lead time from plant $i$ to customer $k_1$ using transportation mode $l$
- $\tau_{k_2}$ Maximum permissible lead time to deliver the ordered product to customer $k_2$
- $\tau'_{k_1}$ Maximum permissible lead time to deliver the ordered product to customer $k_1$
- $u_i$ Greenhouse gases emissions from production per unit of product at plant $i$
- $u'_{ik_1l}$ Greenhouse gases emissions from transportation per unit of product from plant $i$ to customer $k_1$ using transportation mode $l$
- $ug_{ijl}$ Greenhouse gases emissions of transportation per unit of product from plant $i$ to distribution center $j$ using transportation mode $l$
- $us_{jk_2l}$ Greenhouse gases emissions from transportation per unit of product from distribution center $j$ to customer $k_2$ using transportation mode $l$
- $Emis_l$ Emissions from using typical transport units of mode $l$
- $D_{ijl}$ Distance between plant $i$ and distribution center $j$ using transportation mode $l$
- $D'_{jk_2l}$ Distance between distribution center $j$ and customer $k_2$ using transportation mode $l$
- $Dg_{ik_1l}$ Distance between plant $i$ and customer $k_1$ using transportation mode $l$
- $\Psi$ Maximum permissible greenhouse gases emissions

*Variables*

- $X_{ijl}$ Quantity of products shipped from plant $i$ to distribution center $j$ using transportation mode $l$
- $Y_{jk_2l}$ Quantity of products shipped from distribution center $j$ to customer $k_2$ using transportation mode $l$
- $Z_{ik_1l}$ Quantity of products shipped from plant $i$ to customer $k_1$ using transportation mode $l$
- $\mathrm{Pr}'$ Per unit selling price of each product in direct channel
- $\mathrm{Pr}$ Per unit selling price of each product in indirect channel
- $V_i$ 1 if an open plant is located in candidate location $i$; 0 otherwise
- $W_j$ 1 if an open distribution center is located in candidate location $j$; 0 otherwise

Due to above notations, mathematical model of the dual-channel green supply chain network design can be formulated as follows.

$$
\begin{aligned}
Max\ Z = & \sum_i \sum_{k_1} \sum_l \mathrm{Pr}' Z_{ik_1l} + \sum_j \sum_{k_2} \sum_l \mathrm{Pr}\, Y_{jk_2l} \\
& - \sum_i f_i V_i - \sum_j g_j W_j - \sum_i \sum_j \sum_l \left(c_i + p_{ijl}\right) X_{ijl} \\
& - \sum_j \sum_{k_2} \sum_l \left(h_j + q_{jk_2l}\right) Y_{jk_2l} \\
& - \sum_i \sum_{k_1} \sum_l \left(c_i + r_{ik_1l}\right) Z_{ik_1l} \\
& - \sum_i \sum_{k_1} \theta_i \left(d'_{k_1} - \sum_l Z_{ik_1l}\right) \\
& - \sum_j \sum_{k_2} \beta_j \left(d_{k_2} - \sum_l Y_{jk_2l}\right) \qquad (1)
\end{aligned}
$$

$$\sum_{i}\sum_{l} Z_{ik_1l} \le d'_{k_1} \qquad \forall k_1 \tag{2}$$

$$\sum_{j}\sum_{l} Y_{jk_2l} \le d_{k_2} \qquad \forall k_2 \tag{3}$$

$$\sum_{k_2}\sum_{l} Y_{jk_2l} \le \sum_{i}\sum_{l} X_{ijl} \qquad \forall j \tag{4}$$

$$Y_{jk_2l} lt_{jk_2l} \le Y_{jk_2l}\tau_{k_2} \qquad \forall j, k_2, l \tag{5}$$

$$Z_{ik_1l} ls_{ik_1l} \le Z_{ik_1l}\tau'_{k_1} \qquad \forall i, k_1, l \tag{6}$$

$$\sum_{k_1}\sum_{l} Z_{ik_1l} + \sum_{j}\sum_{l} X_{ijl} \le V_i m_i \qquad \forall i \tag{7}$$

$$\sum_{i}\sum_{l} X_{ijl} \le W_j n_j \qquad \forall j \tag{8}$$

$$\sum_{i}\sum_{j}\sum_{k_1}\sum_{l} u_i\left(X_{ijl} + Z_{ik_1l}\right) + \sum_{i}\sum_{j}\sum_{l} ug_{ijl}X_{ijl} + \sum_{i}\sum_{k_1}\sum_{l} u'_{ik_1l}Z_{ik_1l} + \sum_{j}\sum_{k_2}\sum_{l} us_{jk_2l}Y_{jk_2l} \le \Psi \tag{9}$$

$$X_{ijl}, Y_{jk_2l}, Z_{ik_1l}, \mathrm{Pr}, \mathrm{Pr}' \ge 0 \qquad \forall i, j, l, k_1, k_2 \tag{10}$$

$$V_i, W_j \in \{0, 1\} \qquad \forall i, j \tag{11}$$

Equation (1) ensures the objective function of the proposed model which maximizes the total profit of supply chain. Revenue of the supply chain comprises of total sale of the supply chain in direct and indirect channels. Cost of supply chain includes fixed opening cost of plants and distribution centers, production cost at plants, transportation cost from plants to distribution centers, distribution centers to customers and plants to customers, holding cost at distribution centers and penalty of lost sales at plants and distribution centers. Constraints (2) and (3) illustrate that plants and distribution centers try to meet all demands of customers of direct and indirect channels respectively, but lost sales are possible in both channels. Constraint (4) assures flow balance at distribution centers. It means that quantity of received products from plants must not be lower than quantity of products sent to customers within indirect channels at each distribution center.

Constraint (5) ensures that all products are delivered to customers of indirect channel with maximum permissible lead time. Constraint (6) assures that all products are delivered to customers of direct channel with maximum permissible lead time. Constraint (7) shows capacity constraint of plants. Constraint (8) illustrates the capacity constraint of distribution centers. Constraint (9) is related to environmental constraint of supply chain. According to this constraint, greenhouse gases emissions of the supply chain activities must not exceed the legal threshold. Constraint (10) shows non-negative variables and Constraint (11) assures the binary ones.

In dual-channel networks, prices in channels can effect on customers demand. The price of each channel can move the customers to other channel because of difference between prices in channels. In fact, due to the competition between channels to interest the customers, different prices between channels have to be determined. Thus, the demand for each channel is a variable depends on the prices of both channels. The cooperative pricing strategy is defined where the members of the supply chain coordinate on determining the optimal price. This optimal price can increase the total profit of the supply chain and also the profit of each member. To maximize the total profit of the supply chain the optimum value for prices of both channels is needed.

For the deterministic demand of customers, $d'_{k_1}$ is demand function of direct channel (Eq. (12)), While $d_{k_2}$ denotes demand function of indirect channel (Eq. (13)).

$$d'_{k_1} = \alpha - \lambda'_{k_1} Pr' + \gamma_2 Pr \qquad \forall k_1 \tag{12}$$

$$d_{k_2} = \alpha - \lambda_{k_2} Pr + \gamma_1 Pr' \qquad \forall k_2 \tag{13}$$

where, $\lambda'_{k_1}$ and $\lambda_{k_2}$ present the elasticity of price on another channel and substitutability between channels for each customer, $\gamma_1$ and $\gamma_2$ are the price-demand elasticity of direct and indirect channels, respectively. Notation $\alpha$ depicts the market scale for the products. Being more sensitive, it seems that $\gamma_1$ should be greater than $\gamma_2$ for customers of zone one. Therefore, we assume$\gamma_1 > \gamma_2$. To estimate the amounts of parameters for the elasticity of channels, market scale of the product and historical market data are used. Thus, based on different available prices, the amount of demand for each channel is registered. Finally, to estimate the elasticity parameters based on Eqs. (12) and (13) regression is implemented for the acquired historical data.

To evaluate emissions of transportation activities ($u'_{ik_1l}$, $ug_{ijl}$ and $us_{jk_2l}$) between nodes of supply chain, emissions of transportation mode $l\,(Emis_l)$ and distances between nodes with regard to selected transportation mode $l$ ($D_{ijl}$,$D'_{jk_2l}$ and $Dg_{ik_1l}$) are used. Therefore, Eqs. (14), (15) and (16) can be defined as follows.

$$u'_{ik_1l} = Emis_l \times Dg_{ik_1l} \qquad \forall i, k_1, l \tag{14}$$

$$ug_{ijl} = Emis_l \times D_{ijl} \qquad \forall i, j, l \tag{15}$$

$$us_{jk_2l} = Emis_l \times D'_{jk_2l} \qquad \forall j, k_2, l \tag{16}$$

In this study, to estimate the average emissions for trucks and vehicles using to transport the products through the points, MOBILE 6.2 computer model software developed by the U.S. Environmental Protection Agency (EPA) is used (see MOBILE6 Vehicle Emission Modeling Software http://www.epa.gov/otaq/m6.htm). Vehicle type/size, vehicle age and accumulated mileage, fuel used, ambient weather and maintenance conditions and type of driving are some of factors that effect on the amount of GHG emissions for each vehicle. Also, gas and diesel are considered as the fuel.

Due to above mathematical formulation, the dual-channel single-objective green supply chain network design model is a mixed-integer non-linear mathematical programming (MINLP) model. The presented model can be implemented in various industries with the ability of attracting customers directly in addition to indirect channel, especially those ones that are known as pollutant industries with high GHG emissions and deal with legal restriction such as automotive, casting the industrial parts, cement industries and so on.

## Solving methodology

In recent years, evolutionary algorithms have been used to supply chain network design optimization problems (see Pishvaee et al. 2010a). Also, according to NP-hard nature of supply chain network design problems, solving large instances efficiently within rational time is a difficult work (Aras and Aksen 2008). Therefore,, the proposed model is solved by GAMS and according to NP-hard nature of the presented problem and long run time, an artificial immune system algorithm based on CLONALG and Taguchi method is applied. To validate the obtained results genetic and Memetic algorithms are taken into accounts.

### Artificial immune system (AIS)

Our body defends against foreign attacks by a complicated hierarchical arrangement of molecules, cells and organs which is called immune system. This system always monitors the body by searching and removing malfunctioning cells and foreign elements which cause diseases. Each of these elements that can be recognized by the immune system is named antigen. Each immune cell has some receptor molecules on its surface which discriminates between antigens and safe cells or elements. One of the main features of each antibody is its affinity which defines as binding strength to the discovered antigen. Then, the antibody cells mature and proliferate into a new kind of cells which are known as plasma cells or terminal cells. Clones are generated during the proliferation or cell division process. These clones are progenies which belong to a single cell (de Castro and Von Zuben 2002). Since, the most active secretors of the antibody cells are plasma ones, clone generation is taken into account to achieve the state of the plasma cells.

Bersini and Varela (1991) and Farmer et al. (1986) are the first ones who introduced immune systems. Only about one decade later, Forrest et al. (1994) (on negative selection) and Kephart (1994) published their first papers on AIS in 1994. Cutello and Nicosia's (2002) and De Castro and Zuben's (2002) research (on clonal selection) became notable in 2002. In 2008, Dasgupta and Nino (2008) published their book on Immunological Computation. They presented a summary of up-to-date works related to immunity-based techniques and also described a wide variety of applications. Clonal selection algorithm (CLONALG), negative selection algorithm, immune network algorithms and dendritic cell algorithms are the common techniques which are used in immunological theories that explain the function and behavior of the immune systems.

AIS is successfully used to solve different kinds of complicated optimization problems comprising traveling salesman problem (de Castro and Von Zuben 2002), machine loading problem (Chan et al. 2005), flow shop scheduling (Kumar et al. 2006), economic load dispatch (Panigrahi et al. 2007) and supply chain network design (Tiwari et al. 2010).

### Clonal selection algorithm (CLONALG)

CLONALG is a AIS-based technique which refers to clonal selection principle along with other main features comprising proliferation and differentiation on provocation of cells with antigens; generating new random genetic changes which is known as diversification of antibody patterns by a process which is called affinity maturation; and removing those differentiated lymphocytes (immune cells) that holding antigenic receptors with low affinity (de Castro and Von Zuben 2002). Here, in optimization problems the concept of the affinity is equal to fitness function evaluation and constraint satisfaction. Therefore, constraints are presented by antigens and constraint satisfaction is related to affinity. On the other hand, the higher the constraint satisfaction, the more is the affinity. Between two antibodies (solutions) with satisfied constraints, one with better value of objective function gain larger affinity.

At the beginning, a pool of antibodies (a population of random feasible solutions) is generated. Then, antigens are introduced to the antibodies randomly and affinity is evaluated for all of the antibodies. Antibodies with higher affinity generate more off-spring and maturate with a lower rate of hyper mutation. The maturation process is comprising of two steps; one, through random genetic changes with a related affinity rate and two, through elimination of those differentiated immune cells (clones) with lower affinities value of their. The above process will be repeated until definite stopping criteria are satisfied.

More details about the proposed CLONALG are investigated as follows. Figure 2 shows the flowchart of the solving method.

#### *The encoding schema*

Here we have used an encoding schema which is a combination of both, binary and integer variables. For more explicitly,

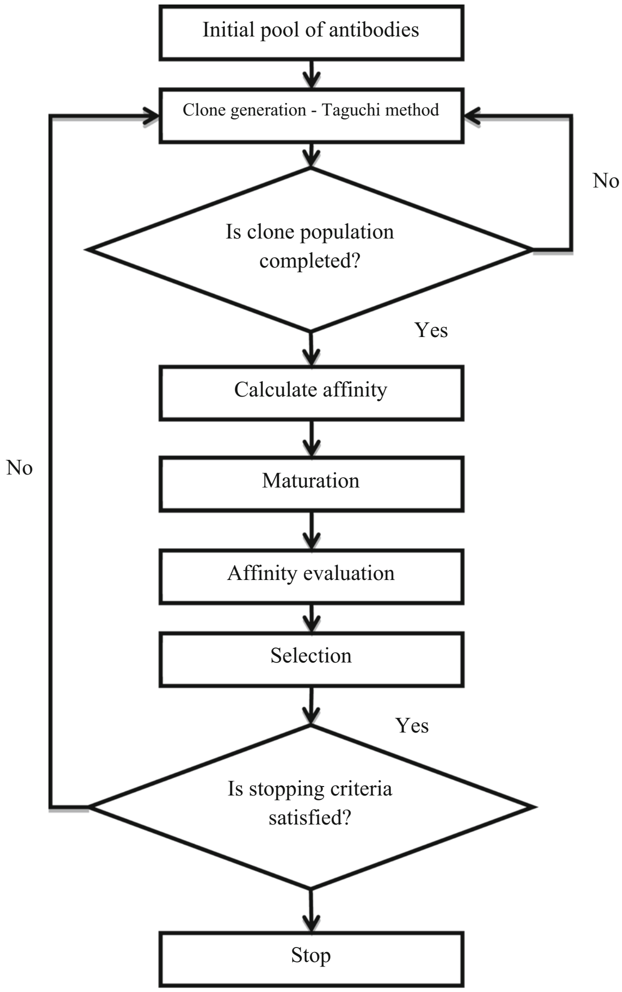


**Fig. 2** Flowchart of CLONALG

a network with 2 plants, 3 DCs, 4 transportation modes and 5 customers for each channel is considered. Figure 3 shows the encoding schema for our proposed problem. The first two receptor cells are binary and they show the plants are opened (value 0) or closed (value 1). Then, five two-receptor cells are the DCs, customers of zone 1, transportation mode which are selected for each plant, the quantity of products shipped to DCs and customers of zone 1, respectively. Next three receptor cells are binary and they show the DCs are opened or closed. Then, 3 three-receptor cells are the customers of zone 2, transportation mode which are selected for each DC and the quantity of products shipped customers of zone 2, respectively. The last two receptor cells present the price of products for direct and indirect channel.

*Initial pool of antibodies (initialization)*

The procedure generates antibodies to reach the defined population randomly. Here, the initial population is considered equal to 100 antibodies. Each antibody is composed of real and integer values.

*Fitness function (affinity evaluation)*

To evaluate the affinity of antibodies with antigens, it is necessary to use a fitness function. The fitness function will present that the higher the affinity of one antibody with antigens is, the higher is the fitness function of the antibody with the better the value of objective function. The fitness function is used to be maximized while the objective function is also considered to be maximized. In this research, a transformation function ($\omega_{ab} = Z_{ab}/Z^{*}$) is employed as the fitness function, where, $\omega_{ab}$ is the fitness value of antibody $ab$, $Z_{ab}$ demonstrates the value of objective function for antibody $ab$, and the best value of objective function which is found by the solution procedure during the solving is named as $Z^{*}$.

*Clone generation*

To carry out the clone generation process, antibodies are sorted based on their affinities. The number of clones for each antigen is derived from equation $N_c = \sum_{i=1}^{n} round\left(\frac{\beta N}{i}\right)$, where, $N_c$ shows the total amount of generated clones for the antigen, $\beta$ is a multiplying factor which is considered equal to one, $N$ the total number of antibodies (in this study it is considered equal to 100). To produce better clones, Taguchi

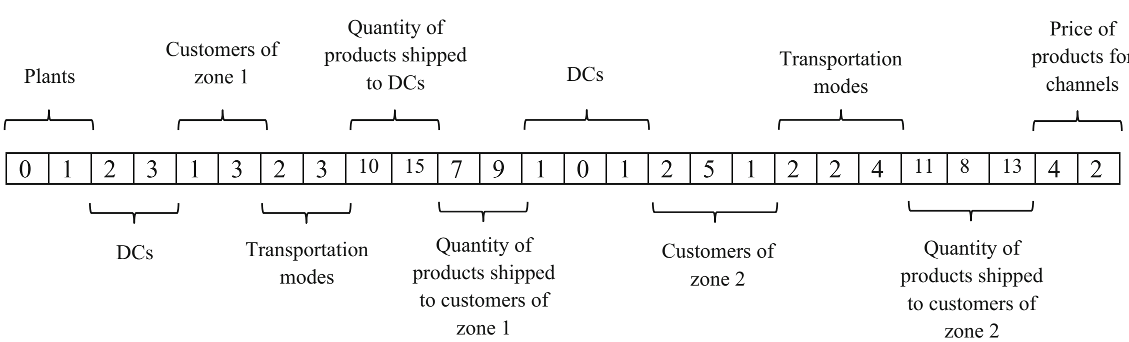


**Fig. 3** Encoding schema for the proposed problem

method is applied to investigate the large numbers of decision variables with a small number of experiments. Here, two antibodies are selected randomly and the optimal level of each decision variable (factors) will be determined by Taguchi method. Level 1 is equal to the values of factors of first antibody and the related values of the second antibody are defined as level 2. The value of factor $f$ at level $l$ is computing by equation $Val_{fl} = \sum_i \phi_i \; \forall i$, where $i$ is the number of experiment. The optimal level of each factor is the one that presents higher $Val_{fl}$.

*Maturation*

In the maturation process, as a similar method with what mutation operator acts in genetic algorithm the antibodies will be maturated (Goldberg 1989). The difference lies in the higher fitness values of antibodies concluded the lower rate of mutation. For maturation process in this study, single-point mutation is employed.

*Selection*

Due to maturation process, for selection we use "roulette wheel mechanism" just the same as what is used in "genetic algorithm". This mechanism based on its randomness nature allows the solving procedure to diversify more and avoid local solutions. This process is done after sorting the antibodies due to their fitness values. Therefore, the higher the fitness value of an antibody is, the higher is the probability of selection.

*Experimental results validation method*

To validate the experimental results, we used genetic and Memetic, two population-based algorithms. To prepare fare conditions to compare between these algorithm and CLONALG, Taguchi technique is applied for both.

## Experimental results

To solve the proposed dual-channel green supply chain network design, GAMS 23.7.3 optimization software is used. Also, artificial immune system (AIS) based on CLONALG is applied for the large-size problems when the running time is huge. The obtained results are compared with MA and GA algorithm on twenty five test problems, when Taguchi technique is used for parameter tuning of all meta-heuristic algorithms. In the field of supply chain network design, Tiwari et al. (2010) has used artificial immune system (AIS) for a supply chain network design with multiple shipping. Fahimnia et al. (2013) and Yeh (2006) have applied genetic algorithm and Memetic algorithm for this field, respectively.

### Test instances

In this section, we present the results derived from solving various test instances by CLONALG. Three dimensions of the sizes of the test problems ($i$, $j$ and $k_2$) are selected in the range of those test problems which are presented in the recent literature (Pishvaee and Rabbani 2011; Yeh 2005; Gen et al. 2006). The size of parameter $k_1$ is considered as equal to $k_2$. The size of parameter $l$ is selected in the range of test problems presented by Tiwari et al. (2010). All the parameters of the proposed model in all test problems which are identified with one asterisk in Table 2 are generated randomly with the range of parameters presented in recent literature (Pishvaee and Rabbani 2011). The values of parameters identified with two asterisks are in the range of the same ones in research of (Liu et al. 2010). The values of emissions of transportation modes for those parameters are marked with three

**Table 2** The value of parameters for the proposed model

| Parameter | Range | Parameter | Range |
|---|---|---|---|
| ${\lambda'_{k_1}}^{**}$ | ∼ Uniform (8, 12.5) | $n_j{}^*$ | ∼ Uniform (2200, 3200) |
| ${\tau'_{k_1}}^{*}$ | ∼ Uniform (10, 14) | $\beta_j{}^*$ | ∼ Uniform (25, 50) |
| $\lambda_{k_2}{}^{**}$ | ∼ Uniform (8, 12.5) | $p_{ijl}{}^*$ | ∼ Uniform (8, 12) |
| $\tau_{k_2}{}^*$ | ∼ Uniform (10, 14) | $ug_{ijl}{}^{***}$ | ∼ Uniform (500, 800) |
| $f_i{}^*$ | ∼ Uniform (2,800,000, 3,500,000) | $q_{jk_2l}{}^*$ | ∼ Uniform (8, 12) |
| $c_i{}^*$ | ∼ Uniform (10, 15) | $us_{jk_2l}$ | ∼ Uniform (400, 900) |
| $m_i{}^*$ | ∼ Uniform (3000, 4500) | $lt_{jk_2l}{}^*$ | ∼ Uniform (6, 12) |
| $\theta_i{}^*$ | ∼ Uniform (40, 100) | $r_{ik_1l}{}^*$ | ∼ Uniform (10, 18) |
| $u_i$ | ∼ Uniform (100, 250) | ${u'_{ik_1l}}^{***}$ | ∼ Uniform (1000, 2100) |
| $g_j{}^*$ | ∼ Uniform (2,200,000, 2,600,000) | $ls_{ik_1l}{}^*$ | ∼ Uniform (10, 16) |
| $h_j{}^*$ | ∼ Uniform (8, 12) | $\Psi$ | ∼ 5.44 million tons |

* The values are in the range of those used by Pishvaee and Rabbani (2011)
** The values are in the range of those used by Liu et al. (2010)
*** The values are derived from (http://www.ntmcalc.se/index.html, February 12, 2011)

**Table 3** Results of numerical example

| Problem size $i \times j \times k_1 \times k_2 \times l$ | Pr. | CLG Obj. value | | SD | SD/Obj. Ave. | GAMS Obj. value | Er. (%) | CLG Ave. time (s) | GAMS time (s) |
|---|---|---|---|---|---|---|---|---|---|
| | | The best | Ave. | | | | | | |
| $5 \times 15 \times 10 \times 10 \times 5$ | $P_{1-1}$ | 43,387,257 | 42,986,098 | 361,766.5 | 0.008416 | 44,588,336 | 3.59 | 9 | 16 |
| | $P_{1-2}$ | 40,653,308 | 40,518,576 | 101,207.4 | 0.002498 | 41,466,011 | 2.28 | 10 | 15 |
| | $P_{1-3}$ | 44,171,394 | 44,044,999 | 792,668.5 | 0.017997 | 44,810,199 | 1.71 | 8 | 17 |
| | $P_{1-4}$ | 42,473,355 | 41,715,306 | 544,938.6 | 0.013063 | 42,846,658 | 2.64 | 8 | 20 |
| | $P_{1-5}$ | 44,876,842 | 42,838,573 | 2,050,342.5 | 0.047862 | 44,884,716 | 4.56 | 9 | 17 |
| $10 \times 30 \times 50 \times 50 \times 5$ | $P_{2-1}$ | 101,984,258 | 100,866,961 | 1,122,138.4 | 0.011125 | 102,125,050 | 1.23 | 14 | 1012 |
| | $P_{2-2}$ | 101,992,461 | 100,989,408 | 2,196,334.3 | 0.021748 | 101,997,804 | 0.99 | 12 | 1055 |
| | $P_{2-3}$ | 101,558,335 | 101,006,667 | 420,207.7 | 0.00416 | 101,582,899 | 0.57 | 13 | 1041 |
| | $P_{2-4}$ | 97,773,354 | 97,519,535 | 1,555,282.3 | 0.015948 | 98,979,657 | 1.48 | 15 | 1001 |
| | $P_{2-5}$ | 98,081,978 | 97,256,765 | 1,629,701.3 | 0.016757 | 101,359,499 | 4.05 | 15 | 1210 |
| $15 \times 40 \times 60 \times 60 \times 8$ | $P_{3-1}$ | 256,687,988 | 256,309,799 | 395,757.2 | 0.001544 | 256,985,554 | 0.26 | 21 | 11,214 |
| | $P_{3-2}$ | 255,780,909 | 255,219,283 | 397,212.7 | 0.001556 | 255,833,807 | 0.24 | 21 | 11,122 |
| | $P_{3-3}$ | 255,895,040 | 255,820,219 | 165,946.1 | 0.000649 | 255,958,117 | 0.05 | 21 | 10,154 |
| | $P_{3-4}$ | 255,948,547 | 255,752,896 | 484,390.0 | 0.001894 | 255,995,039 | 0.09 | 22 | 11,587 |
| | $P_{3-5}$ | 255,650,808 | 255,606,583 | 49,777.1 | 0.000195 | 255,657,990 | 0.02 | 22 | 11,896 |
| $20 \times 50 \times 80 \times 80 \times 8$ | $P_{4-1}$ | 447,551,905 | 445,530,041 | 1,436,501.9 | 0.003224 | 449,664,303 | 0.92 | 35 | 43,250 |
| | $P_{4-2}$ | 447,959,618 | 446,436,447 | 1,235,447.1 | 0.002767 | 448,666,611 | 0.50 | 31 | 43,550 |
| | $P_{4-3}$ | 448,348,658 | 447,652,383 | 1,468,015.4 | 0.003279 | 448,834,671 | 0.26 | 40 | 43,228 |
| | $P_{4-4}$ | 447,424,197 | 445,908,784 | 1,110,439.3 | 0.00249 | 447,634,434 | 0.39 | 42 | 43,095 |
| | $P_{4-5}$ | 446,126,083 | 445,573,812 | 515,914.6 | 0.001158 | 448,975,603 | 0.76 | 39 | 43,665 |
| $40 \times 70 \times 100 \times 100 \times 10$ | $P_{5-1}$ | 708,885,605 | 708,031,596 | 691,822.6 | 0.000977 | 709,865,002 | 0.26 | 102 | 43,272 |
| | $P_{5-2}$ | 708,916,903 | 708,651,213 | 517,228.9 | 0.00073 | 708,978,445 | 0.05 | 92 | 43,101 |
| | $P_{5-3}$ | 707,966,336 | 707,611,488 | 286,385.9 | 0.000405 | 708,441,665 | 0.12 | 112 | 43,754 |
| | $P_{5-4}$ | 708,215,605 | 707,952,043 | 187,935.3 | 0.000265 | 708,653,625 | 0.10 | 121 | 43,247 |
| | $P_{5-5}$ | 708,603,078 | 708,059,647 | 557,377.5 | 0.000787 | 708,855,861 | 0.11 | 115 | 43,140 |

*Pr.* Problem, *Er.* Error, *CLG* CLONALG

asterisks in Table 2 are derived from the source of networks for transport and environment (see http://www.ntmcalc.se/index.html, February 12, 2011). Some research use different transportation modes with regard to their GHG emissions (Dekker et al. 2012; Mirzapour Al-e-hashem et al. 2013). The value of maximum permissible greenhouse gases emissions ($\Psi$) is also derived from (Zhao et al. 2012) and equal to 5.44 million tons.

To compare the results which are obtained by GAMS 23.7 to those from CLONALG, Table 3 is presented. The percentage of error as a comparison criterion along with standard deviation (SD) and the ratio of the standard deviations per averages of objective function values are computed to illustrate the comparison between the results of two solving methods. These criteria are also employed by Pishvaee and Rabbani (2011) to compare their heuristic solution approach with the results of LINGO 8 in a supply chain network design with direct and indirect shipment model. The percentage of error is calculated by Eq. (17). The value of objective which is obtained by GAMS is mentioned by $Z_G$, while $Z_C$ shows the value of objective obtained with CLONALG.

$$Error\% = \frac{Z_G - Z_C}{Z_G} \times 100 \tag{17}$$

Due to Table 3, twenty five test problems are run. For each size, the best and average values of CLONALG with the average of run times are presented. Standard deviation per average of objective function of CLONALG is also computed to assess the stability of obtained solutions.

Due to Table 3, computational run time of GAMS for the size of $10 \times 30 \times 50 \times 50 \times 5$ in $P_{2-1}$ is about 1012 s, while the computational run time of CLONALG is about 14 s with about 1.23 % in error. As the numerical example shows, the errors of the solutions are in the range of 0.02–4.56 % for the five problems in five different test sizes. Usually the largest error for meta-heuristic algorithms are obtained in the large-size problems (see Ebrahim et al. 2009; Pishvaee

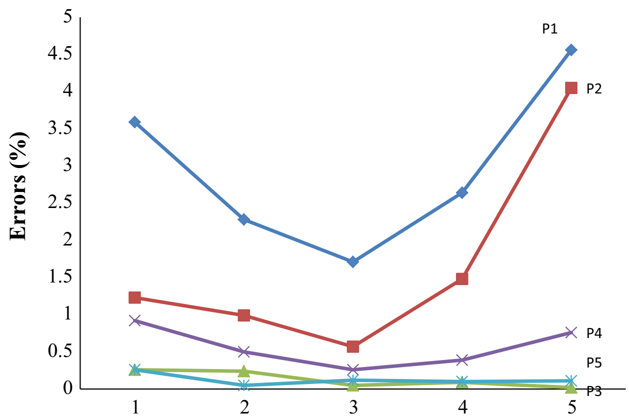


**Fig. 4** Errors (%) of the CLONALG solutions

et al. 2010b), however the largest error for CLONALG is occurred on the small-size of the proposed test problems. On the other hand, for the test problems with the size of $20 \times 50 \times 80 \times 80 \times 8$ and $40 \times 70 \times 100 \times 100 \times 10$ GAMS could not reach the best solution in about 12 hours. Therefore, the best solution which is obtained by GAMS in 12 hours is reported in Table 3.

Computational run times with the error of the solutions are the two important criteria which are reported in Table 3 as a comparison between the solutions obtained from GAMS and CLONALG, while they are used to evaluate the efficiency and stability of CLONALG. Computational run times for small-sizes are close but for large-sizes the gap changes to be very significant. For the largest size, the running time of CLONALG to obtain a near optimal solution is only 121 seconds, while GAMS after about 12 hours reported the best obtained solution with only 0.01 % error in comparison with CLONALG. Also, Fig. 4 shows the error (%) in all test problems. The largest amount of this criterion is 4.56 % for problem $P_{1-5}$ and the test size $5 \times 15 \times 10 \times 10 \times 5$. On the opposite side, the smallest amount of errors is 0.02 % and it is occurred in problem $P_{3-5}$ and the test size $15 \times 40 \times 60 \times 60 \times 8$. Due to Fig. 4, it can be concluded that the errors of large-size problems (i.e. $P_{3-*}$, $P_{4-*}$ and $P_{5-*}$) are smaller than 1 %. On the other hand, it can be concluded that the difference between the run times of large-size problems for two solving methods becomes significantly larger.

Due to Table 3 and Fig. 4, it can be concluded that since the computational run times of CLONALG, especially in large-size problems, are significantly lower than the computational run times which are obtained by GAMS, while the errors of the CLONALG solutions are in a narrow acceptable range, using CLONALG meets the requirements and is adequate to reach near optimal solutions.

## Parameter setting

In meta-heuristic algorithms parameter setting has significant effects of their performance which should be investigated with regard to the conditions of the problem. Taguchi is a method for robust parameters design that minimizes the effects of causes of variations to improve the quality of products or solutions. Here, orthogonal array (OA) and the signal-to-noise ratio (S/NR) are implemented as two significant tools used in Taguchi method. By using the orthogonal array, the effects of different parameters on the performance characteristic of the proposed problem in a condensed set of experiments can be tested. In each process the parameters that can be controlled have been determined. Then, the levels of varying for these parameters must be determined. The levels for these parameters include minimum, maximum and current value. Therefore, the difference between the minimum and the maximum levels for a parameter be large, more values should be tested. Otherwise, if it be small, fewer values can be tested. Taguchi et al. (2000) have been described more details on orthogonal arrays and Taguchi method.

In this study, three level orthogonal array which is known as $L_n(2^{n-1})$ is used. Where, the number of experimental runs is equal to $n = 2^k$; $k$ is defined as a value greater than

**Table 4** The design and noise factors for parameter tuning based on Taguchi method

| Design factors | Algorithms | | | Levels | | | Noise factors | levels | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CLG | GA | MA | Level 1 (low) | Level 2 (medium) | Level 3 (high) | | Level 1 (low) | Level 2 (medium) | Level 3 (high) |
| PS | √ | √ | √ | 75 | 100 | 125 | No. of plants | 5 | 15 | 40 |
| NI | √ | √ | √ | 50 | 100 | 150 | No. of DCs | 15 | 40 | 70 |
| CR | √ | √ | √ | 0.6 | 0.7 | 0.8 | No. of CZ1 | 10 | 50 | 100 |
| MR | √ | √ | √ | 0.1 | 0.3 | 0.5 | No. of CZ2 | 10 | 50 | 100 |
| | | | | | | | No. of TRM | 5 | 8 | 10 |
| OA | $L_9$ ($3^4$) | $L_9$ ($3^4$) | $L_9$ ($3^4$) | | | | $L_{18}$ ($3^5$) | | | |

*PS* Population size, *NI* number of iterations, *CR* Crossover rate, *MR* Mutation rate, *CLG* CLONALG, *TRM* Transportation modes, *CZ1* Customer zone 1, *CZ* Customer zone 2

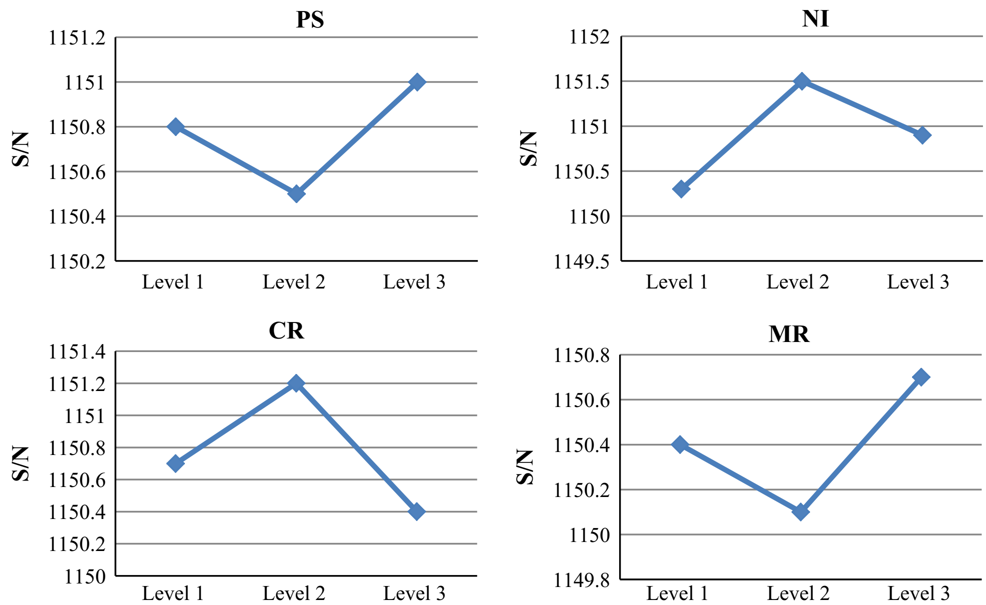


**Fig. 5** S/N ratio plot of the factors for each level for CLONALG

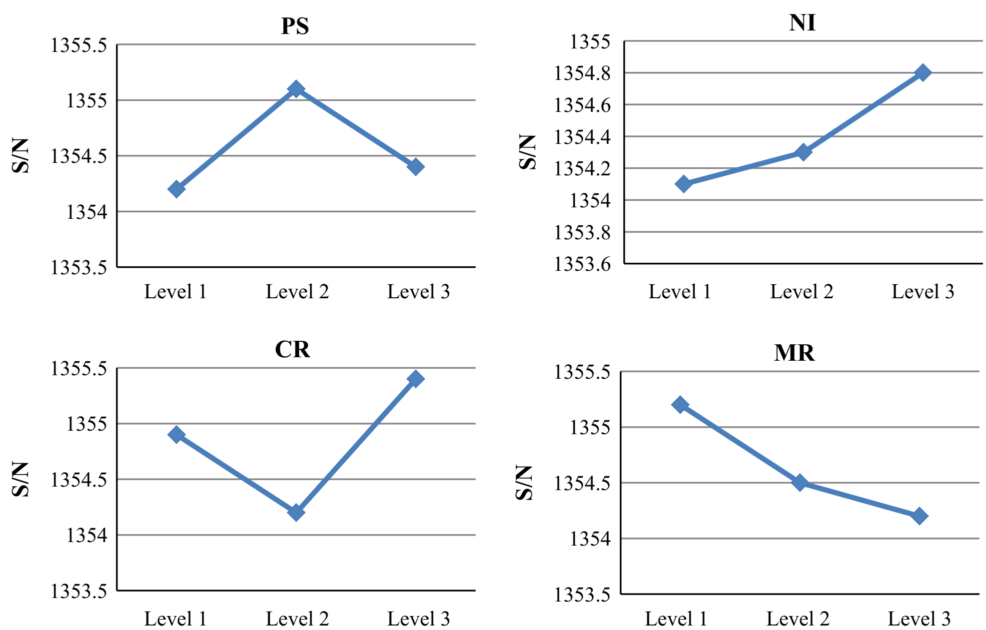


**Fig. 6** S/N ratio plot of the factors for each level for GA

1 and 2 is the number of levels. The S/NR measures how the response varies relative to the target value due to different noise conditions. Thus, at the first stage, we use the S/NR to determine those control factors that reduce variability. At the second one, we determine those control factors that move the mean to target and have small or no effect on the S/NR.

Here, we have used the reference values for some of parameters of our model from the similar papers (see Table 2). We used Taguchi method for CLONALG in clone generation step and the tuning of the parameters of this algorithm. Two antibodies are selected randomly and the optimal level of each decision variable (factors) will be determined by Taguchi method. Level 1 is equal to the values of factors of first antibody and the related values of the second antibody are defined as level 2 (for more details see Tiwari et al. (2010)). Table 4 shows the design and noise factors for parameter tuning based on this method for CLONALG, GA and MA algorithms. Finally, Figures 5, 6, 7 show S/N ratio for each level of the design factors for CLONALG, GA and MA algorithms, respectively.

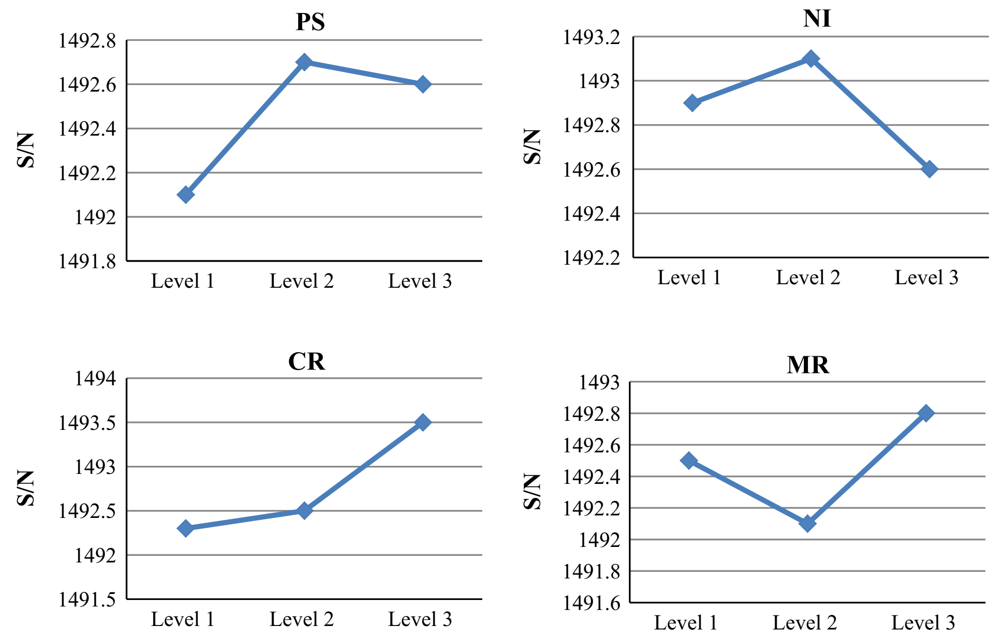


**Fig. 7** S/N ratio plot of the factors for each level for MA

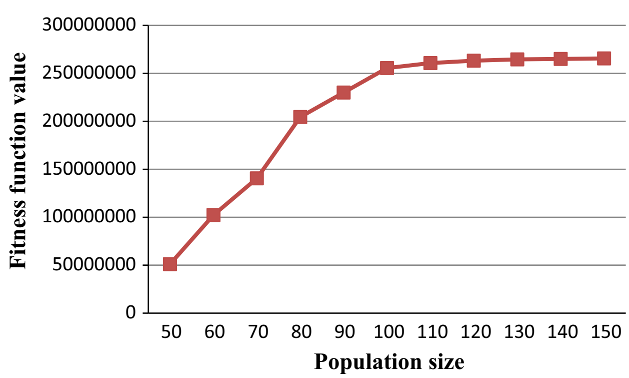


**Fig. 8** The effect of population size on the performance of CLONALG

Finally, we investigated the effect of varying the parameters of CLONALG such as population and mutation. At the first, the population size is varying in the range of 100 ± 50. The results on the value of fitness function have been shown by Fig. 8. Due to Fig. 8, improving the fitness function value for the population sizes greater than 100 is decreasing. At the second, the value of mutation is varying from 0.1 to 0.5 for the problems $P_{5-1}$ to $P_{5-5}$. The results are studied in Table 5. These test runs show that the total benefit of the supply chain will decrease, if the probability of the mutation increases.

## Comparison of the performance of the meta-heuristic solving methods

After parameter setting and determining the level of factors, to investigate the effectiveness and efficiency of CLONALG, all test problems solved with other meta-heuristic methods and the results are reported in Table 6. According to the best and gap values, the advantage of CLONALG over GA and MA is quietly obvious, however the computational time of GA and MA are better. Also, the performance of CLONALG based on average values dominates the other algorithms.

**Table 5** Results of varying the amount of mutation

| Problem | Mutation= 0.1 | | 0.2 | | 0.3 | | 0.4 | | 0.5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Ave. benefit | SD/ Obj. Ave. | Ave. benefit | SD/ Obj. Ave. | Ave. benefit | SD/ Obj. Ave. | Ave. benefit | SD/ Obj. Ave. | Ave. benefit | SD/ Obj. Ave. |
| $P_{5-1}$ | 700,258,414 | 0.000164 | 68,955,821 | 0.000171 | 685,224,788 | 0.000192 | 652,855,001 | 0.000201 | 625,748,957 | 0.000251 |
| $P_{5-2}$ | 702,100,045 | 0.000652 | 66,988,440 | 0.000677 | 65,442,411 | 0.001481 | 64,528,412 | 0.001684 | 601,478,541 | 0.002441 |
| $P_{5-3}$ | 69,851,770 | 0.000302 | 68,840,579 | 0.000404 | 67,418,952 | 0.000784 | 65,438,748 | 0.001201 | 63,518,742 | 0.002658 |
| $P_{5-4}$ | 70,528,892 | 0.000174 | 68,120,547 | 0.000225 | 647,145,022 | 0.000541 | 62,597,100 | 0.000698 | 60,175,985 | 0.000985 |
| $P_{5-5}$ | 703,288,415 | 0.000225 | 70,154,785 | 0.000362 | 68,102,585 | 0.000452 | 63,159,802 | 0.000741 | 62,847,852 | 0.000804 |

**Table 6** Comparison of CLONALG, GA and MA

| Pr. | CLONALG | | | | | CA | | | | | MA | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Best | Ave. | SD | Gap (%) | T (s) | Best | Ave. | SD | Gap (%) | T (s) | Best | Ave. | SD | Gap (%) | T (s) |
| P1-1 | **43,387,257** | 42,986,098 | 361,766.5 | 0.0 | 9 | 40,784,021.58 | 40,406,932.12 | 384,857.979 | 6.00 | 6 | 40,784,021.6 | 40,784,021.6 | 381,299.578 | 6.00 | 7 |
| P1-2 | **40,653,308** | 40,518,576 | 101,207.4 | 0.0 | 10 | 39,433,708.76 | 39,303,018.72 | 104,337.526 | 3.00 | 7 | 39,433,708.8 | 39,433,708.8 | 103,991.733 | 3.00 | 7 |
| P1-3 | 44,171,394 | 44,044,999 | 792,668.5 | 2.82 | 8 | 43,287,966.12 | 43,164,099.02 | 808,845.408 | 4.90 | 6 | **45,452,364.4** | 45,322,304 | 770,328.96 | 0.0 | 5 |
| P1-4 | **42,473,355** | 41,715,306 | 544,938.6 | 0.0 | 8 | 41,156,681 | 40,422,131.51 | 562,372.136 | 3.10 | 6 | 40,333,547.4 | 39,613,688.9 | 573,849.119 | 5.04 | 6 |
| P1-5 | 44,876,842 | 42,838,573 | 2,050,343 | 0.50 | 9 | **45,101,226.21** | 43,052,765.87 | 2,040,141.79 | 0.0 | 7 | 45,056,125 | 43,009,713.1 | 2,042,183.98 | 0.10 | 6 |
| P2-1 | **101,984,258** | 100,866,961 | 1,122,138 | 0.0 | 14 | 101,576,321 | 100,463,493.2 | 1,126,644.98 | 0.40 | 10 | 99,544,794.5 | 98,454,223.3 | 1,149,637.73 | 2.39 | 9 |
| P2-2 | **101,992,461** | 100,989,408 | 2,196,334 | 0.0 | 12 | 99,952,611.78 | 98,969,619.84 | 2,241,157.45 | 2.00 | 11 | 98,653,227.8 | 97,683,014.8 | 2,270,676.24 | 3.27 | 10 |
| P2-3 | **101,558,335** | 101,006,667 | 420,207.7 | 0.0 | 13 | 99,019,376.63 | 98,481,500.33 | 430,982.256 | 2.50 | 12 | 98,524,279.7 | 97,989,092.8 | 433,147.996 | 2.99 | 11 |
| P2-4 | **97,773,354** | 97,519,535 | 1,555,282 | 0.0 | 15 | 94,840,153.38 | 94,593,948.95 | 1,603,383.81 | 3.00 | 14 | 89,149,744.2 | 88,918,312 | 1,705,727.46 | 8.82 | 13 |
| P2-5 | **98,081,978** | 97,256,765 | 1,629,701 | 0.0 | 15 | 95,139,518.66 | 94,339,062.05 | 1,680,104.43 | 3.00 | 13 | 94,092,984 | 93,301,332.4 | 1,698,791.14 | 4.07 | 12 |
| P3-1 | **256,687,988** | 256,309,799 | 395,757.2 | 0.0 | 21 | 255,404,548.1 | 255,028,250 | 397,745.93 | 0.50 | 18 | 254,127,525 | 253,753,109 | 399,744.653 | 1.00 | 17 |
| P3-2 | **255,780,909** | 255,219,283 | 397,212.7 | 0.0 | 21 | 254,757,785.4 | 254,198,405.9 | 398,807.932 | 0.40 | 17 | 252,464,965 | 251,910,620 | 402,429.8 | 1.30 | 17 |
| P3-3 | **255,895,040** | 255,820,219 | 165,946.1 | 0.0 | 21 | 244,891,553.3 | 244,819,949.6 | 173,402.403 | 4.30 | 17 | 243,911,987 | 243,840,670 | 174,098.799 | 4.68 | 16 |
| P3-4 | **255,948,547** | 255,752,896 | 484,390 | 0.0 | 22 | 240,591,634.2 | 240,407,722.2 | 515,308.511 | 6.00 | 15 | 226,156,136 | 225,983,259 | 548,200.543 | 11.64 | 15 |
| P3-5 | **255,650,808** | 255,606,583 | 49,777.1 | 0.0 | 22 | 239,289,156.3 | 239,247,761.7 | 53,180.6624 | 6.40 | 17 | 223,256,783 | 223,218,162 | 56,999.6381 | 12.67 | 18 |
| P4-1 | **447,551,905** | 445,530,041 | 1,436,502 | 0.0 | 35 | 442,628,834.05 | 440,629,210.5 | 1,452,479.17 | 1.10 | 30 | 412,972,702 | 411,107,053 | 1,556,783.68 | 7.73 | 31 |
| P4-2 | **447,959,618** | 446,436,447 | 1,235,447 | 0.0 | 31 | 439,000,425.6 | 437,507,718.1 | 1,260,660.31 | 2.00 | 24 | 417,050,404 | 415,632,332 | 1,327,010.85 | 6.90 | 25 |
| P4-3 | **448,348,658** | 447,652,383 | 1,468,015 | 0.0 | 40 | 426,379,573.8 | 425,717,416.2 | 1,543,654.47 | 4.90 | 25 | 409,750,770 | 409,114,437 | 1,606,300.18 | 8.61 | 25 |
| P4-4 | **447,424,197** | 445,908,784 | 1,110,439 | 0.0 | 42 | 416,104,503.2 | 414,695,169.1 | 1,194,020.75 | 7.00 | 29 | 424,426,593 | 422,989,073 | 1,170,608.58 | 5.14 | 26 |
| P4-5 | **446,126,083** | 445,573,812 | 515,914.6 | 0.0 | 39 | 401,513,474.7 | 401,016,430.8 | 573,238.444 | 10.0 | 32 | 400,710,448 | 400,214,398 | 574,387.219 | 10.18 | 35 |
| P5-1 | **708,885,605** | 708,031,596 | 691,822.6 | 0.0 | 102 | 690,454,579.3 | 689,622,774.5 | 710,290.144 | 2.60 | 99 | 688,383,216 | 687,553,906 | 712,427.426 | 2.89 | 100 |
| P5-2 | **708,916,903** | 708,651,213 | 517,228.9 | 0.0 | 92 | 687,649,395.9 | 687,391,676.6 | 533,225.67 | 3.00 | 90 | 686,961,747 | 686,704,285 | 533,759.43 | 3.10 | 85 |
| P5-3 | **707,966,336** | 707,611,488 | 286,385.9 | 0.0 | 112 | 659,116,658.8 | 658,786,295.3 | 307,611.063 | 6.90 | 101 | 661,094,009 | 660,762,654 | 306,690.99 | 6.62 | 105 |
| P5-4 | **708,215,605** | 707,952,043 | 187,935.3 | 0.0 | 121 | 655,099,434.6 | 654,855,639.8 | 203,173.297 | 7.50 | 111 | 651,168,838 | 650,926,506 | 204,399.695 | 8.06 | 114 |
| P5-5 | **708,603,078** | 708,059,647 | 557,377.5 | 0.0 | 115 | 645,537,404.1 | 645,042,338.4 | 611,830.406 | 8.90 | 110 | 626,171,282 | 625,691,068 | 630,752.996 | 11.63 | 105 |
| Ave | 311,076,553 | 310,394,365 | 810,989.6 | 1.66 | 37.96 | 295,948,422 | 295,286,533.2 | 836,458.3 | 3.98 | 33.08 | 290,785,288.1 | 290,156,437.7 | 853,369.14 | 5.51 | 32.8 |

T: Time

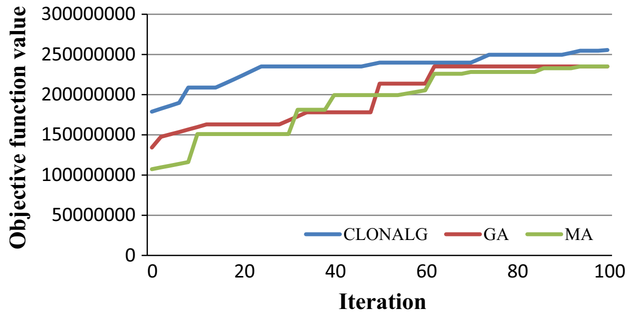


**Fig. 9** Convergence trend for solving algorithm

Figure 9 shows the convergence trends for all meta-heuristic algorithms for problem $P_{3-5}$. It can be concluded that, the convergence trend of CLONALG is higher and the solutions are closer to optimal than the other algorithms. Thus, in summary, it can be claimed that CLONALG can be a competent method for optimizing problems such as the presented model.

For more detailed insights, we investigated the effect of varying the numbers of predefined locations of customers for direct and indirect channels. Problem $P_{3-5}$ as the problem with lowest error is selected and the results of applying solving methods are illustrated by Table 7. Therefore, it can be concluded that moving toward to increasing the demand of the customers of direct channel has more effect on growing the benefit of the supply chain rather than the indirect one. Thus, it is suggested that the management of the supply chain moves toward attract more demand of direct customers. Price elasticity for both channels and their effects on the profit of the supply chain is investigated in Theorem 1.

**Theorem 1** *The effect of the price elasticity of direct channels on the profit of the supply chain is less than that one of indirect channel.*

*Proof* The total profit of the supply chain is calculated by Equation (18).

$$Z = \mathrm{F}_1 + \mathrm{F}_2 - \mathrm{Y} \tag{18}$$

Where, $Z$ is the total profit, $F_1$ and $F_2$ mean the revenue of direct and indirect channels, respectively. The total cost of the supply chain is demonstrated by $Y$ (Cost is independent of the prices). Thus, Equation (18) can be expanded to Equations (19) and (20).

$$Z = \sum_{k_1} d'_{k_1} Pr' + \sum_{k_2} d_{k_2} Pr - Y \tag{19}$$

$$Z = \sum_{k_1} \left(\alpha - \lambda'_{k_1} Pr' + \gamma_2 Pr\right) Pr' + \sum_{k_2} \left(\alpha - \lambda_{k_2} Pr + \gamma_1 Pr'\right) Pr - Y \tag{20}$$

Therefore, we use the derivative of Equation (20) to investigate the effects of price elasticity on the profit of the supply chain in both channels. Equations (21) and (22) show the obtained results.

$$\frac{dZ}{d\lambda'_{k_1}} = -Pr'^2 \Rightarrow \left|\frac{dZ}{d\lambda'_{k_1}}\right| = \left|-Pr'^2\right| = Pr'^2 \tag{21}$$

$$\frac{dZ}{d\lambda_{k_2}} = -Pr^2 \Rightarrow \left|\frac{dZ}{d\lambda_{k_2}}\right| = \left|-Pr^2\right| = Pr^2 \tag{22}$$

**Table 7** Results for different numbers of predefined locations of customers for direct and indirect channel (problem $P_{3-5}$)

| $k_1$ | MTDDC | $k_2$ | MTDDC | CLONALG | | GA | | MA | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Ave. benefit | SD/ Obj. Ave. | Ave. benefit | SD/ Obj. Ave. | Ave. benefit | SD/ Obj. Ave. |
| 50 | 2,650,000 | 80 | 3,312,500 | 298,552,140 | 0.000185 | 229,885,148 | 0.000217 | 279,146,251 | 0.000200 |
| 50 | 2,843,200 | 70 | 2,908,400 | 275,658,921 | 0.000178 | 212,257,370 | 0.000208 | 257,741,091 | 0.000193 |
| 50 | 3,014,000 | 60 | 2,806,500 | 269,985,523 | 0.000155 | 207,888,853 | 0.000182 | 252,436,465 | 0.000167 |
| 50 | 2,881,800 | 40 | 2,505,400 | 244,478,529 | 0.000198 | 188,248,467 | 0.000231 | 228,587,425 | 0.000214 |
| 50 | 2,952,100 | 30 | 2,339,600 | 241,599,802 | 0.000201 | 186,031,847 | 0.000235 | 225,895,815 | 0.000217 |
| 50 | 2,698,400 | 20 | 2,147,700 | 184,550,004 | 0.000512 | 142,103,503 | 0.000599 | 172,554,253 | 0.000553 |
| 80 | 3,554,100 | 50 | 2,668,100 | 315,045,778 | 0.000124 | 242,585,250 | 0.000145 | 294,567,802 | 0.000134 |
| 70 | 3,100,200 | 50 | 2,495,800 | 288,471,104 | 0.000174 | 222,122,750 | 0.000203 | 269,720,482 | 0.000188 |
| 60 | 2,925,100 | 50 | 2,578,800 | 277,859,665 | 0.000225 | 213,951,943 | 0.000264 | 259,798,787 | 0.000243 |
| 40 | 2,614,000 | 50 | 2,511,700 | 258,847,533 | 0.000358 | 199,312,600 | 0.000419 | 242,022,443 | 0.000387 |
| 30 | 2,401,100 | 50 | 2,541,500 | 244,158,896 | 0.000248 | 188,002,350 | 0.000290 | 228,288,568 | 0.000268 |
| 20 | 2,085,700 | 50 | 2,454,200 | 215,447,002 | 0.001258 | 165,894,191 | 0.001472 | 201,442,947 | 0.001359 |

*MTDDC* Mean of total demand of direct channel, *MTDIC* Mean of total demand of indirect channel

Due to trend of companies to charge low prices for direct channels ($Pr' < Pr$) and based on Equations (21) and (22), it can be concluded that the effect of the price elasticity of direct channels on the profit of the supply chain is less than that one in indirect channels.

## Conclusion

In this study, a capacitated single-objective single-product mathematical model is developed to deal with different transportation modes and GHG emissions in a dual-channel green supply chain network design. The proposed model considered network design decisions as strategic decisions and also not only most assumptions of the supply chain network design as tactical decisions, but some more realistic assumptions such as lost sale and its penalty, delivery lead time and pricing. Also in this study, determining different prices for channels and its effects on demand of each channel is considered. Therefore, by these assumptions more complexity is made and a mixed integer non-linear model is obtained. Therefore, this mathematical model is developed to maximize the total profit of the supply chain network design when pricing decisions with trade-off between economic and environmental issues are considered. Also, different transportation modes in both channels of the supply chain are employed, while each mode has its lead time and GHG emission. In this study GHG emissions of transportation and production activities are legally bounded. The proposed model is coded and solved by GAMS. Due to NP-hard nature of the proposed problem and long run time, an artificial immune system algorithm based on CLONALG is applied. The computational results shows those solutions of the solving procedure in comparison with solutions which are obtained by GAMS especially in large-size problems are very close and with an error less than 1%. To investigate the efficiency and effectiveness of CLONALG, GA and MA are taken into accounts. The computational results show that CLONALG dominates the others. Due to the best of our knowledge, the presented study is one of the first researches modeled dual-channel green supply chain network design with regard to pricing decisions of both channels.

For future research, minimization of environmental damages such as GHG emissions in dual-channel network design can be considered as an objective function in a multi-objective model. Also, the concepts of uncertainty such as stochastic demands or fuzzy parameters can be considered as new areas to develop.

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