

# Optimizing a bi-objective vendor-managed inventory of multiproduct EPQ model for a green supply chain with stochastic constraints

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#### **Abstract**

In this paper, a bi-objective multi-product single-vendor single-buyer supply chain problem is studied under green vendor-managed inventory (VMI) policy based on the economic production quantity (EPQ) model. To bring the model closer to realworld supply chain, four constraints of model including backordering cost, number of orders, production budget and warehouse space are considered stochastic. In addition to holding, ordering and backordering costs of the VMI chain, the unused storage space cost is also added to the total cost of the chain. To observe environmental requirements and decrease the adverse effects of greenhouse gases emissions (GHGs) on the earth and human's life, green supply chain is utilized to reduce the GHGs emissions through storage and transportation activities in the second objective function. Three multi-objective decision making methods namely, LP-metric, Goal attainment and multi-choice goal programming with utility function (MCGP-U) are implemented in different sizes to solve the presented model as well. Two multi-criteria decision making (MCDM) approach and statistical analysis are applied to compare the outcomes of three proposed solving methods. GAMS/BARON software is utilized to minimize the values of the objective functions. At the end, numerical examples are presented to represent the application of the mentioned methodology. To come up with more insights, sensitivity analysis is executed on the main parameters of proposed model.

**Keywords**: Economic production quantity (EPQ), vendor-managed inventory (VMI), greenhouse gases (GHGs) emissions, stochastic programming, bi-objective non-linear model.

## 1- Introduction

In today's progressively competitive business world, companies are trying to increase customer's satisfaction by reducing their costs and increasing customer's service levels. For instance, accommodating supply with demand, decreasing stock-outs, and increasing customer delivery times would be appropriate in this case. In this way, the success of companies is related to the efficient flow of products to customers, and without coordinated decisions between their members, the success of companies would not be achieved (Fugate, Sahin, & Mentzer, 2006). As a result, the supply chain is used to communicate among supply chain members. In today's global markets, supply chain management (SCM) plays a crucial role to make a long-term cooperative relationship among organizations and companies in order to gain either a tensionless constant source of supply and demand of products, or optimum profit from each other, as well as reliability to achieve better performances and (Simchi-Levi, Kaminsky, Simchi-Levi, & Shankar, 2007).

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Inventory is one of the important factors in SCM. In a supply chain, unpleasant or fluctuating inventory, leads to Bullwhip effect and Double marginalization and eventually undermines supply chain's performance and may even contributes to the failure of companies (Disney, & Towill, 2003). Among several strategies of collaboration and coordination between supply chain (SC) partners, vendor-managed inventory (VMI) has been successfully implemented in many companies (Disney, & Towill, 2002). It has been used widely in recent years because of its profits. It accelerates the supply chain, improve the profitability for both vendors and customers, and remove the effects of bullwhip in supply chain management. The benefits of VMI are well recognized by successful retail businesses such as Wal-Mart, JC Penney, and Dillard Department Stores (Dong & Xu, 2002). Successful VMI implementation in retailing are more observable in the apparel industry. For example, VF Corporation was able to increase the sales of its men's jeans by 20% through the adoption of a replenishment system based on point-of-sales data and VMI principles (Kaipia & Tanskanen, 2013). All of this evidence proves that the potential advantages of the VMI partnerships have a powerful effect and can be mentioned as a significant tool in order to reduce inventory costs for supply chain members and enhance customer service levels (Achabal, McIntyre, Smith, & Kalyanam, 2007).

The gradual increases of global warming and climate change have enforced industries and governments to reduce their greenhouse gases emissions to improve environmental sustainability. Nowadays, several businesses have launched to perform green supply chain management and pay attention to environmental issues and measure their vendors' environmental performance. Inventory management and transportation are the major activities of supply chain that create the significant amount of greenhouse gases emissions in numerous studies. In reality, inventory control is a crucial activity in many types of organization (Tsou, Hsu, Chen, & Yeh, 2010). The inventory management of a company depends on the frequency of it transportation and storage process, so it is one of the main determinants of the greenhouse gases created in supply chain (Schaefer & Konur, 2015). As a result, current research aims to reduce the greenhouse gases emissions released through transportation and storage activities. In recent studies (Büyüközkan, & Cifci, 2013; Bonney, & Jaber, 2011; Zanoni, Mazzoldi, & Jaber, 2014), merging environmental requirements with inventory and logistics systems has been strongly emphasized. A joint consequence among these models is that the efficiency of an inventory policy becomes sensitive when greenhouse gases (GHGs) emissions are considered. On the other hand, extending the traditional EPO model by adding effective constraints and objective function, and taking into account the parameters of model in an uncertain way by using stochastic programming approach, bring the EPQ model closer to real-world conditions.

In the next section, First, a brief review of research done on the effects of implementing VMI policy on whole supply chain is represented, and then some research worked on the environmental effects due to greenhouse gases emissions on inventory management are presented.

#### 2- Literature review

Cetinkaya & Lee (2000) proposed a harmonized inventory and transportation analytical model Applicable in VMI systems. In particular, they considered a vendor who satisfied a sequence of retailers' demand in a particular geographic area. Ideally, these demands must be shipped immediately. Dong & Xu (2002) evaluated the effects of VMI on a supply channel. In a nutshell, they showed that VMI is found to reduce total costs of the channel system and it could increase the profitability of both vendor and buyer in the chain system. Yao, Evers, Dresner (2007) developed an analytical model that examines the effects of supply chain's parameters on cost savings. They used common initiatives, such as VMI system. The results of the model showed that the benefits, in the form of reducing inventory costs, might have been created according to the ratio of product integrity to the supplier's ordering costs to the buyer and the proportion of transportation cost to the buyer. The results also illustrated that vendor and buyer have equal share in the amount of benefits. Razmi, Rad, Sangari (2010) provided a two-echelon supply chain, including single buyer-single supplier assuming that the supplier meets only one buyer as the contract party. They compared the performance of the traditional system with VMI system and showed that VMI is a better approach than the traditional model and causes lower cost in all conditions. Pasandideh, Niaki, & Roozbeh Nia (2010) proposed a two-level economic order quantity (EOQ) model for a single supplier-single retailer in a supply chain under VMI policy. An analytical model has been investigated to examine the impact of important supply chain's parameters on reducing costs in an integrated supply chain under backlogged shortage,

and the results of the analysis have been compared before and after implementation of VMI. Roozbeh Nia, Hemmati Far, & Niaki (2013) introduced fuzzy multi-products, multi-constraints economic order quantity (EOQ), including a single vendor-single buyer under VMI policy with the goal of minimizing total cost of supply chain. Ant colony optimization algorithm were used to find the near optimal solutions. In order to validate the obtained results a genetic algorithm (GA) and a differential evolution were presented. Bakeshlu, Sadeghi, Poorbagheri, & Taghizadeh (2014) presented a biobjective two-echelon single vendor-single retailer model under VMI Policy with shortage. The first objective function was to minimize the inventory costs, and the second objective function aimed to minimize the warehouse space. Limits on the number of orders and budget were also presented to bring the model closer to reality. Particle Swarm Optimization (PSO) metaheuristic algorithm was implemented to solve the model. Sadeghi & Niaki. (2015) presented a bi-objective vendor-managed inventory model under two-echelon consisting of single vendor-multi retailers in which demand was considered fuzzy by using trapezoidal fuzzy number. The first goal was minimizing inventory costs and the second goal minimized the storage space. In this model, Limits on the number of orders and budget were applied in constraints. Non-dominated sorting genetic algorithm-II (NSGA-II), multiobjective evolutionary algorithm (MOEA), and non-dominated ranking genetic algorithm (NRGA) were implemented to solve the model. Park, Yoo, & Park (2016) proposed an inventory routing problem with lost sales under a vendor-managed inventory strategy in a two-echelon supply chain consisting of a single manufacturer and multiple retailers. They used Genetic algorithm (GA) to determine either replenishment times and quantities, or vehicle routes while maximizing the supply chain profits. Alfares & Attia (2017) proposed integration between quality control and inventory control in supply chain management. They presented vendor-managed inventory (VMI) and a consignment stock (CS) partnership with several buyers, and considered three different levels of supply, including VMI-CS system, traditional system, and integrated system. They also considered the cost of inspection errors. The products produced by the vendor were not perfect and the proportion of them was defective and the quality inspection of these items was done by buyers. Han, Lu, & Zhang (2017) proposed an indirect VMI problem in a three-echelon supply chain in which distributors (third-party logistics companies) took responsibility to balance between a vendor (manufacturer) and multiple buyers (manufacturers). They used vertex enumeration algorithm to solve their three-echelon decision making model. Bonny & Juber (2011) examined the importance of inventory control systems to considerate environmental concerns, and presented that the traditional Economic order quantity (EOQ) model does not have enough efficiency to cover some of the inventory models. Roozbeh Nia, Hemmati Far, & Niaki (2015) presented a multi-product single vendor-single buyer economic order quantity model under backorder and green approach. In their model, they used limited-capacity pallets to transport items. To implement the green approach, they used tax costs for greenhouse gas (GHG) and limitation on GHG emissions. In order to find a near optimal solution, the integrated of genetic and imperialist algorithms was proposed, and they also implemented the genetic algorithm to evaluate the results. Jiang, Li, Qu, & Cheng (2015) proposed a green VMI model with considering both environmental and economic goals. They compared their model with traditional VMI model. The impacts of important factors of carbon emissions and carbon cap were examined analytically on the optimal decisions, the carbon emissions and the total costs of supply chain. Karimi, Niknamfar, Pasandideh (2016) merged a two-level newsboy problem (NP) supply chain model with the supplier selection problem. In order to apply the green approach, the greenhouse gas emissions that are released by the various types of selected vehicles were limited. Alvarado, Paquet, Chaabane, & Amodeo (2016) considered the impacts of environmental regulations on businesses and inventory control systems, and provided demand for both manufacturing and remanufacturing, due to differences in costs and emissions of greenhouse gases. They used the Markov decision to solve the model. Mokhtari & Rezvan. (2017) presented a single supplier multi-buyer multi-product model, under the green supply chain and the VMI model. The shortage was allowed in the form of partial backorder, and the goal was to find the amount of economic production and the maximum level of shortage. The total greenhouse gas emissions have been modeled as a green constraint. To solve the model, a decomposition based analytical approach was proposed. Gharaei et al. (2018) presented an Outer Approximation with Equality Relaxation and Augmented Penalty (OA/ER/AP) in order to solve an integrated multi-product multi-buyer green supply chain under the penalty and VMI-CS policies considering real stochastic constraints. Furthermore, the model distinguished between the financial

and non-financial elements of holding costs in which the first and second, included space investment, and the expenditure allocated to physical storage, movement, and security of the products, respectively. Detcharat Sumrit (2019) developed VMI supply chain in healthcare system using fuzzy multi-criteria decision-making approach (MCDM) to determine the best potential supplier which has been performed in one of prominent public hospitals in Thailand as a case study. Three MCDM framework were presented, included Fuzzy Delphi approach to determine the suitable assessment criteria for VMI supplier selection, Fuzzy Step-wise Weight Assessment Ration Analysis (SWARA) method to select the relative importance weight of assessment criteria, and Fuzzy Complex Proportional Assessment of Alternatives (COPRAS) to collate, classify and determine the best allocated supplier. Stellingwerf et al. (2019) investigated VMI as a cooperative policy in order to reduce economic and environmental impacts of transportation, and eventually increased the efficiency of environmental sector of the supply chain. In this study, the Shapley value (a commonly used CGT approach) was used to allocate the financial profits in a way that gives consideration to the partners' contributions to the expenses and carbon dioxide emissions reduction. The method was carried out to assess the distribution of economic and environmental advantages of vendor-managed inventory between collaborative supermarket chains in the Netherlands. Golpîra (2020) introduced a comprehensive integrated model using the VMI strategy formulating a general multi-project multiresource multi-supplier CSC network design with a facility location problem. This paper scheduled the resources of network in terms of timing and delivery associated with determining suitable suppliers and appropriate potential locations confined to only certified facilities in a capacitated system. Taleizadeh et al. (2020) developed a two integrated vendor managed inventory system considering partial backordering and limited warehouse capacity for the buyer along with continuous review and periodic review replenishment policies under stochastic demand. This paper, moreover included the comparison between the new proposed integrated system and traditional retailer managed inventory systems. Among several papers worked on VMI models, the papers are categorized based on different fields of VMI in table 1.

Table 1. Some studies on VMI problem

Studies	Green	Level	Deteriorating	Bi- Objective	Routing Problem	Stochastic programming	Solution method
Akbari		Bi- level	<b>√</b>	Objective	Troblem	programming	GA and PSO
kaasgari et al.		21 10,01					0.14
(2017)							
Bakeshlu et al.		Bi- level		$\checkmark$			PSO
(2014)							
Bazan et al.	$\checkmark$	Bi- level					
(2015)							
Darwish and		Bi- level					KKT
Odah	,	D: 1 1				✓	(O 4 /ED /4 D)
Gharaei et al.	$\checkmark$	Bi- level				V	(OA/ER/AP)
(2018)	$\checkmark$	Bi-level				✓	
Golpira et al. (2017)	•	Di-level				•	
Golpîra (2020)		Multi-level					
Han et al.		Tri- level					VEA
(2017)		111 10 (01					, 2, 1
Hemmati et al.		Bi- level					Exact solution
(2017)							procedure
Jiang et al.	$\checkmark$	Bi- level					
(2015)							
Khan et al.		Bi- level	✓				
(2016)					,	,	
Kleywegt et al.					$\checkmark$	✓	approximation
(2002)		Bi- level	✓				methods
Lee and Kim (2014)		Bi- level	V				
Liao et al.		Bi- level		✓			GA algorithm
(2011)		DI- ICVCI		•			GA aigorialli
Lu et al. (2015)	$\checkmark$	Bi- level				Stochastic	
( <b>2</b> 010)		21 10.01				demand	
Mokhtari and	$\checkmark$	Bi- level					DBA approach
							• •

Table 1. Continued

	<b>C</b>	T1		Continued	D4!	C414* -	G-1-4'
Studies	Green	Level	Deteriorating	Bi- Objective	Routing Problem	Stochastic programming	Solution method
Rezvan (2017)							
Pasandideh et al. (2011)		Bi- level					GA algorithm
Pasandideh et al. (2014)		Bi- level		✓			Lexicographic max-min
Rabbani et al. (2018)			✓				approach SA and Tabu search
Radha and Praveen	✓	Bi- level					GA and KT optimization
Prakash (2016) Rahim et al. (2016)		Bi- level			✓	✓	
Sadeghi et al. (2013)		Bi- level					PSO and GA
Sadeghi et al. (2014)		Tri- level		<b>√</b>			HBA
Sadeghi et al. (2014)		Bi- level		<b>√</b>			NSGA-II
Sadeghi and Akhavan Niaki (2015)		Bi- level		✓			NSGA-II and NRGA
Sadeghi et al. (2016)		Bi- level					Hybrid ICA
Setak and Daneshfar (2014)		Bi- level	✓				
Soni et al. (2018)			✓				
Taleizadeh et al. (2015)		Bi- level	✓				Concavity of the profit functions
Taleizadeh et al. (2020)		Bi- level				Stochastic demand	Efficient algorithms
Tat et al. (2015)		Bi- level	✓				
Xiao and Rao (2016)		Tri- level			✓		Fuzzy GA
Xiao and Xu (2013)		Bi- level					
Yu et al. (2012)		Bi- level	✓			Demand	
Yu et al. (2013)		Bi- level					The hybrid algorithm DP, GA and analytical methods
Zhu et al. (2007)		Tri- level			✓	✓	
Current research	✓	Bi-level	✓			✓	MODM methods

Non dominated sorting genetic algorithm; DBA SA (simulated annealing); (PSO) Partial swarm optimization; (NSGA-II) (Decomposition based analytical); Genetic algorithm (GA); Kuhn Tucker (KT); imperialist competitive algorithm (ICA); Vertex enumeration algorithm (VEA); Karush-Kuhn-Tucker (KKT); dynamic programming (DP); hybrid bat algorithm (HBA); non-dominated ranking genetic algorithm.

Despite many research carried out in the field of VMI, a small number of these studies have considered green supply chain in VMI models with regard to EPQ models, especially within the context of stochastic programming. Also, there are parameters in VMI models that should be considered non-deterministic in order to bring the model closer to reality, but most of the previous studies examined the VMI supply chain under deterministic environment, or considered uncertainty only for a small number of parameters. As a result, as considering VMI supply chain with regard to main parameters can improve this chain, in this research, we try to cover the mentioned gap in previous studies.

In the current research, we have inspired by the works of Pasandideh, Niaki, & Hemmati Far (2014), a bi-objective vendor-managed inventory (VMI) model is proposed to manage the inventory of supply chain with multi-product multi-constraint economic production quantity (EPQ) model and shortage at two-level of supply chain, consisting of single vendor-single buyer under green approach of supply chain. To propose the model closer to reality and make it more practical, various stochastic constraints are considered. The problem is formulated as a non-linear programming model to minimize the total inventory costs of supply chain including holding cost, ordering cost, backordering cost and the cost of unused storage space, and also the emissions of greenhouse gases should be minimized in the second objective function of model. Three exact methods of multi objective decision making are developed to solve the non-linear programming (NLP) optimization. To compare solving methods, two approaches of multiple-criteria decision making (MCDM) methods and statistical analysis are used.

To be more specific, the contribution of this research is that some constraints of model are considered stochastic, also unused storage space cost is added to total inventory costs in the first objective function that these works have not been done in literature related to VMI models. In addition, we consider green approach in the second objective function of our model, which aims to minimize greenhouse gases emissions in the two processes of storage and transportation. As a result, a combination of stochastic programming, green supply chain management (GSCM), vendor-managed inventory (VMI), and a bi-objective mathematical model is considered in this paper, which has not been attended in similar studies. Furthermore, we have implemented different solving methods and compared them one another that other researchers have not done in the same literature.

The overall structure of the remainder of the research is organized as follows. The third section, describes the problem and assumptions in more details. In the fourth section, the bi-level mathematical model is formulated as a non-linear programming. In the fifth section, solution methods and some numerical examples are presented. In the sixth section, computational results and comparisons are presented. Also, the sensitivity analysis is implemented in section 6 to investigate the effect of changes of the important parameters on the mentioned problem, and conclusions are presented in section 7.

#### 3- Problem definition

This study is relevant to a green supply chain with multi-products multi-constraints using the EPO model. A bi-objective model at a two-echelon supply chain includes single vendor-single buyer under VMI policy is proposed. To make the model more practical, the shortage is allowed and backordered. Orders are carried by trucks from vendor to buyer. Therefore, fossil fuels which released from the trucks cause significant amount of greenhouse gases emissions during transportation process. In addition, considerable amounts of greenhouse gases are released while holding products in warehouse. As a result, in this paper, we focus on reducing the greenhouse gases emissions that are released through transportation and storage activities in the second objective function to make a kind of green supply chain (GSC). An additional cost for unused storage space is also added to the total cost of VMI system including ordering, holding and backordering costs. The objective of this paper is to determine order quantities of products, total amount of each product shipped by each truck and the maximum backorder level per cycle, such that the total cost of VMI system and greenhouse gases emissions are minimized, while the mentioned constraints are satisfied. The number of orders and the capacity of trucks are also limited. Because there is no definitive sight for some data in real-world, in this research, we use stochastic programming to create more realistic answers. Thus, some constraints of model including maximum total allowable backordering cost, maximum allowable number of orders, total production budget and total storage space available for all products are considered stochastic.

### 3-1- Assumptions

The following assumptions are used for the mathematical formulation of the model:

- (a) There is a multi-product single vendor-single buyer supply chain with several trucks.
- (b) Shortage is allowed for all products and backordered.
- (c) Orders are shipped by trucks with limited capacity.

- (d) Lead time is assumed zero.
- (e) The selling prices of all products in the planning horizon are fixed (discounts are not allowed).
- (f) The production rate for all products is continuous and finite.
- (g) The rate of customer's demand for all products is deterministic and permanent.
- (h) The time-independent fixed backorder cost per unit and the linear backorder cost per unit per time are limited and considered stochastic to be closer to reality.
- (i) Total storage space available for all products in the vendor's warehouse is limited and considered stochastic to become more realistic.
- (j) To bring the model closer to reality, budget constraint is considered stochastic.
- (k) The total number of orders for all products is limited and stochastic.
- (l) The buyer's order quantity of an item is limited by upper and lower bounds.
- (m) The cost of unused storage space is added to the EPQ inventory system costs.

### 4- Problem formulation

Pasandideh et al. (2014) studied the vendor-managed inventory problem at a two echelon supply chain system, consisting of a vendor and a buyer in which the vendor is responsible to manage the buyer's inventory. They considered the multi-product economic production quantity under three constraints of storage capacity, number of orders and available budget. In the current study, their model is developed to minimize the total inventory cost of the VMI chain, including ordering, holding, backordering and unused storage space costs in the first objective function, while another new objective function is added to create a kind of green supply chain (GSC) in which greenhouse gases emissions released through storage and transportation activities should be minimized. Four new stochastic constraints are also added to bring the model closer to real-world supply chain. The stochastic constraints include limitation on the backordering cost, number of orders, storage space and available production budget. Before presenting the mathematical model, we will introduce the indices, parameters and decision variables of proposed model.

#### **4-1- Notations**

Index and sets	
I	Set of trucks $(i \in I)$
J	Set of products $(j \in J)$
<b>Parameters</b>	
$L_{j}$	Lower bound on the order quantity of product <i>j</i>
$U_j$	Upper bound on the order quantity of product <i>j</i>
$D_{j}$	Buyer's demand rate of product <i>j</i>
$P_{j}$	Vendor's production rate of product <i>j</i>
$C_{j}$	Variable production cost for each unit of product <i>j</i>
$\pi_1$	Fixed backorder cost per unit (time independent)
$\pi_2$	Linear backorder cost per unit per time unit
$A_{jS}$	Vendor's fixed ordering cost per unit of product j
$A_{jB}$	Buyer's fixed ordering cost per unit of product j
$h_{jB}$	Holding cost per unit of product j stored in buyer's warehouse in a period
F	Maximum available storage space for all products
$f_i$	Space occupied by each unit of product <i>j</i>
MABC	Maximum total allowable backordering cost
Norder	Maximum allowable number of orders
Budget	Total available budget to produce products
W	Unused storage space cost (per unit)
$cap_i$	Capacity of truck <i>i</i> to transport products from vendor to buyer
$\gamma_0$	Fixed amount of greenhouse gases emissions in holding products in warehouse

$\gamma_{j}$	The variable amount of greenhouse gases emissions in holding					
	product <i>j</i> in warehouse					
$ heta_0$	The fixed amount of greenhouse gases emissions in transporting					
	products when trucks are empty					
$ heta_i$	The variable amount of greenhouse gases emissions in transporting					
	products by truck i					
TOC	Total ordering cost of products					
THC	Total holding cost of products					
TBC	Total backordering cost of products					
TUC	Total cost of unused storage space					
$TB_{VMI}$	Total cost of buyer's inventory in the VMI chain					
$TS_{VMI}$	Total cost of vendor's inventory in the VMI chain					
$TC_{VMI}$	Total cost of the VMI chain					
$TA_{GHG}$	Total amount of greenhouse gases emissions					
Variables						
$Q_{j}$	Order quantity of product <i>j</i>					
$Z_{ij}$	The amount of product $j$ shipped by truck $i$					
$b_j$	Maximum backorder level of product $j$ in a cycle of the VMI chain					

According to the above description of notations, the problem is formulated as a mathematical model in the next subsection.

#### 4-2- The buver's and vendor's total cost of VMI chain

In the EPQ model with shortage under the VMI policy, the vendor (supplier) is responsible for managing and controlling the inventory by specifying the time and quantities of order, and lead time. As a result, all costs of the VMI chain including the cost of ordering, holding, backordering and unused storage space are paid by the vendor and the buyer does not play any role in paying the costs of VMI chain. Referring to Pasandideh et al. (2014), we have:

$$TB_{VMI} = 0 (1)$$

$$TS_{VMI} = TOC + THC + TBC + TUC (2)$$

Referring to Tersine (1993), the total ordering cost, total holding cost and total backordering cost are formulated in the next subsection.

### 4-2-1- Total ordering cost (TOC)

The total ordering cost of product j includes the vendor's and buyer's ordering cost according to the number of cycles and obtained by:

$$TOC = \sum_{j \in J} \left( \frac{D_j A_{jS}}{Q_j} + \frac{D_j A_{jB}}{Q_j} \right) \tag{3}$$

#### 4-2-2- Total holding cost (*THC*)

The buyer's total holding cost of products due to the upper area of the inventory graph and the number of cycles per year is as follows:

$$THC = \sum_{j \in J} h_{jB} \left( \frac{\left[ Q_j \left( 1 - \frac{D_j}{P_j} \right) \right]^2}{2Q_j \left( 1 - \frac{D_j}{P_j} \right)} \right)$$

$$\tag{4}$$

### 4-2-3- Total backordering cost (TBC)

Due to the permissibility of shortages in the form of backlogged, its costs is divided into two dependent and independent of time categories. Independent annual shortage cost is determined based

on the amount of shortage in a cycle and the number of cycles, but the time-dependent shortage cost is obtained according to the lower area of the inventory graph and the number of annual cycles. Therefore, the annual total backordering cost of products is as follows:

$$TBC = \sum_{j \in J} \left( \frac{\pi_2 b_j^2}{2Q_j \left( 1 - \frac{D_j}{P_j} \right)} + \frac{\pi_1 b_j D_j}{Q_j} \right)$$
 (5)

#### 4-2-4- Total unused storage space cost (*TUC*)

Referring to Khalilpourazari (2016), unused storage space cost is considered as follows:

$$TUC = w \left( F - \sum_{j \in J} \left( f_j Q_j \left( 1 - \frac{D_j}{P_j} \right) - b_j \right) \right)$$
 (6)

# 4-3- Total amounts of greenhouse gases (GHGs) emissions ( $TA_{GHG}$ )

Referring to Jiang et al. (2015), to make a type of green supply chain (GSC), the total amounts of GHGs emissions can be formulated as follows:

$$TA_{GHG} = \left(\gamma_0 + \sum_{j \in J} \gamma_j \left(\frac{\left[Q_j \left(1 - \frac{D_j}{P_j}\right)\right]^2}{2Q_j \left(1 - \frac{D_j}{P_j}\right)}\right) + \theta_0 + \sum_{i \in I} \sum_{j \in J} \theta_i Z_{ij} \frac{D_j}{P_j}\right)$$
(7)

 $\theta_0 + (\theta_i \times Z_{ij})$  is the amount of greenhouse gases emissions when product j is shipped by the truck i,  $\theta_0$  is the amount of greenhouse gases emissions when truck is empty, and  $\theta_i$  is the variable factor of greenhouse gases emissions in transporting products, which depends on the fossil fuels quantity released by truck i and orders quantity of product j shipped by truck i.  $\gamma_0$  +

$$\gamma_{j}\left(\frac{\left[Q_{j}\left(1-\frac{D_{j}}{P_{j}}\right)-b_{j}\right]^{2}}{2Q_{j}\left(1-\frac{D_{j}}{P_{j}}\right)}\right)$$
 is The amount of greenhouse gases emissions in holding product j in warehouse,

 $\gamma_0$  is the fixed amount of greenhouse gases emissions,  $\gamma_j$  is the variable factor of greenhouse gases

emissions in holding product j in warehouse, and  $\frac{\left[Q_j\left(1-\frac{D_j}{P_j}\right)-b_j\right]^2}{2Q_j\left(1-\frac{D_j}{P_j}\right)}$  is the average of inventory in

warehouse.

### 4-4- Total costs of VMI chain and amounts of GHGs emissions

Based on equations (1) to (7), the total costs of VMI chain as first objective function, and total amounts of GHGs emissions as second objective function are as follows:

$$TC_{VMI} = TB_{VMI} + TS_{VMI}$$

$$= min \sum_{j \in J} \left( \frac{D_{j}A_{jS}}{Q_{j}} + \frac{D_{j}A_{jB}}{Q_{j}} \right) + \sum_{j \in J} h_{jB} \left( \frac{\left[ Q_{j} \left( 1 - \frac{D_{j}}{P_{j}} \right) \right]^{2}}{2Q_{j} \left( 1 - \frac{D_{j}}{P_{j}} \right)} \right)$$

$$+ \sum_{j \in J} \left( \frac{\pi_{2}b_{j}^{2}}{2Q_{j} \left( 1 - \frac{D_{j}}{P_{j}} \right)} + \frac{\pi_{1}b_{j}D_{j}}{Q_{j}} \right) + w \left( F - \sum_{j \in J} \left( f_{j}Q_{j} \left( 1 - \frac{D_{j}}{P_{j}} \right) - b_{j} \right) \right)$$

$$(8)$$

$$TA_{GHG} = \left(\gamma_0 + \sum_{j \in J} \gamma_j \left(\frac{\left[Q_j \left(1 - \frac{D_j}{P_j}\right)\right]^2}{2Q_j \left(1 - \frac{D_j}{P_j}\right)}\right) + \theta_0 + \sum_{i \in I} \sum_{j \in J} \theta_i Z_{ij} \frac{D_j}{P_j}\right)$$
(9)

#### 4-5- The mathematical model

Referring to economic production quantity model (EPQ) (Tersine, 1993), in this section, based on Equations. (1) to (9), the multi-item multi-constraint bi-objective EPQ model under green VMI policy becomes:

$$\begin{split} Z_{1} &= min \sum_{j \in J} \left( \frac{D_{j} A_{jS}}{Q_{j}} + \frac{D_{j} A_{jB}}{Q_{j}} \right) + \sum_{j \in J} h_{jB} \left( \frac{\left[ Q_{j} \left( 1 - \frac{D_{j}}{P_{j}} \right) \right]^{2}}{2 Q_{j} \left( 1 - \frac{D_{j}}{P_{j}} \right)} \right) \\ &+ \sum_{j \in J} \left( \frac{\pi_{2} b_{j}^{2}}{2 Q_{j} \left( 1 - \frac{D_{j}}{P_{j}} \right)} + \frac{\pi_{1} b_{j} D_{j}}{Q_{j}} \right) + w \left( F - \sum_{j \in J} \left( f_{j} Q_{j} \left( 1 - \frac{D_{j}}{P_{j}} \right) - b_{j} \right) \right) \end{split}$$

$$Z_{2} = min\left(\gamma_{0} + \sum_{j \in J} \gamma_{j} \left(\frac{\left[Q_{j}\left(1 - \frac{D_{j}}{P_{j}}\right)\right]^{2}}{2Q_{j}\left(1 - \frac{D_{j}}{P_{j}}\right)}\right) + \theta_{0} + \sum_{i \in I} \sum_{j \in J} \theta_{i} Z_{ij} \frac{D_{j}}{P_{j}}\right)$$

$$(11)$$

$$prob\left\{\sum_{j\in J}\left(\frac{\pi_{2}b_{j}^{2}}{2Q_{j}\left(1-\frac{D_{j}}{P_{j}}\right)}+\frac{\pi_{1}b_{j}D_{j}}{Q_{j}}\right)\leq MABC\right\}\geq\alpha\tag{12}$$

$$prob\left\{\sum_{j\in J} \left(f_j Q_j \left(1 - \frac{D_j}{P_j}\right) - b_j\right) \le F\right\} \ge \alpha \tag{13}$$

$$prob\left\{\sum_{j\in J}\left(\frac{D_{j}}{Q_{j}}\right)\leq Norder\right\}\geq \alpha$$
 (14)

$$prob \left\{ \sum_{j \in J} (C_j Q_j) \leq Budget \right\} \geq \alpha$$

$$L_j \leq Q_j \leq U_j$$

$$b_j \leq Q_j$$

$$Q_j \leq \sum_{i \in I} Z_{ij}$$

$$Y_j \in J$$

The first objective function (1) aims to minimize the total cost of VMI chain including ordering cost, holding cost, fixed and linear backordering costs and unused storage space cost, respectively. The second objective in Equation (11) aims to minimize the total amounts of GHGs emissions, including the amounts of greenhouse gases emissions in holding products in warehouse and the amounts of greenhouse gases emissions in transporting products by trucks from vendor to buyer, respectively. Equation (12) is a stochastic backordering costs constraint, where we assume that the backordering costs follow a normal distribution with mean  $\mu_{MABC}$  and standard deviation  $\sigma_{MABC}$ . To put it another way, this constrain becomes:

$$\sum_{j \in J} \left( \frac{\pi_2 b_j^2}{2Q_j \left( 1 - \frac{D_j}{P_j} \right)} + \frac{\pi_1 b_j D_j}{Q_j} \right) + Z_{\alpha} \sigma_{MABC} \le \mu_{MABC}$$

$$(22)$$

Where,  $Z_{\alpha}$  is the upper  $\alpha$ -percentile point of the standard normal distribution. In equation (13) storage space constraint is considered stochastic, because in some cases, the supplier tends to lease warehouse to storage his products, but there may be uncertainty in the amount of storage space for storing products or the supplier may be the owner of the warehouse and tends to produce other products and store them in storage, in addition to the current products or he may be desirable to use part of the warehouse space for other activities, such as production besides storing products, there are uncertainty in the above conditions. Therefore, the storage space constraint can be considered stochastic, and similar to the previous constraint it becomes:

$$\sum_{j \in I} \left( f_j Q_j \left( 1 - \frac{D_j}{P_j} \right) - b_j \right) + Z_{\alpha} \sigma_F \le \mu_F \tag{23}$$

In equations (14) and (15) budget and the number of orders constraints are considered stochastic and similar to equation (12) we have:

$$\sum_{j \in I} (C_j Q_j) + Z_{\alpha} \sigma_{Budget} \le \mu_{Budget}$$
 (24)

$$\sum_{j \in I} \left( \frac{D_j}{Q_j} \right) + Z_{\alpha} \sigma_{Norder} \le \mu_{Norder}$$
 (25)

Equation (16) indicates the bounds on the buyer's order quantity of product j. Equation (17) ensures that the maximum backorder level of product j in a cycle should be equal or less than the quantity of the buyer's orders. Equation (18) guarantees that jth product carried by m trucks should be more than or equal to the buyer's order quantity of product j. Equation (19) indicates the limited capacity of trucks. Equations (20) and (21) limit the decision variables of the model. The goal is to find the economic order quantity of product j ( $Q_j$ ), the maximum backorder level of product j ( $Q_j$ ), and the

total amount of product j shipped by truck i ( $Z_{ij}$ ), in a cycle of VMI chain, such that the total cost of the VMI chain in the first objective described in equation (10), and the total greenhouse gases emissions in the second objective function given in equation (11) are minimized, while the model constraints are satisfied.

### 5- The proposed solution methods

In numerous decision-making problems in real environment, we will be faced with a variety of goals and criteria, and all these goals and criteria could be proposed in the multi-criteria decision making space. A multi-objective optimization problem is a subset of a multi-criteria decision making in an uncountable (continuous) space. The proposed model in section 4.5 is a constrained multi-objective problem. Multi-objective problems are relevant to the optimization of multiple (vector of objectives), conflicting, and incommensurable objective functions issue to limit exposing the application of multi-objective optimization problems. Since both objective functions aim to minimize the problem, the multi-objective optimization problem can be formulated as follows:

$$\min\{F_1(x), F_2(x), \dots, F_k(x)\}\tag{26}$$

$$X \in \mathbb{R}^n \tag{27}$$

Subject to:

$$X \in x$$
 (X is a feasible set; X is unrestricted in sign) (28)

$$k \ge 2$$
 (The number of objectives) (29)

Where k determines the number of objectives by assuming that k is equal or more than 2, and the set x is the feasible set of decision vectors. In order to optimize different and sometimes conflicting objective functions simultaneously, there are two general approaches: It can be used by combining the values of different objective functions and obtaining a fitness value, and eventually converting the problem into a single-objective function, or it is possible to use Pareto optimal solution to obtain answers that optimize the objective functions in a way that guarantee the rationality of a decision. There are different methods to solve multi-objective optimization problems such as multi-objective decision making (MODM) techniques, non-dominated sorting genetic algorithm-II (NSGA-II), multi-objective particle swarm optimization (MOPSO), strength Pareto evolutionary algorithm (SPEA-2), etc. In this research, MODM techniques are used to convert the multiple objectives into a single objective optimization problem.

#### 5-1- MODM techniques

Generally, approaches used in multi-objective decision-making methods are based on the time and type of information received from decision makers, and are classified into four categories: in the first category, there are methods that don't receive information from decision makers during the resolution process, the LP metrics, global criteria, the Maxi-Min and the Filtering/displaced ideal solution (DIS) are placed in this category. The approach used in the second category consists of the goal programming, the lexicography/preemptive optimization, converting objectives into constraints, the goal attainment and the utility function that begins by getting initial information from the decision maker before solving the problem. In the third category, the analyst obtains information from the decision maker, interactively during the problem solving process, including Geoffrion method and satisfactory goals method. In the fourth category information, the preferences of decision maker for different solution methods will be achieved at the final stages of the resolution process, consists of the multi-criteria simplex method, the minimum deviation method, and the De Novo programming. In this section, there are three multi objective decision making (MODM) techniques, including LP-metrics, Goal attainment and Multi-choice goal programming with utility function. All of these methods are solved by a non-linear programming solver (i.e., Baron Solver) in Gams software.

### 5-1-1- Goal attainment

In this section, goal attainment method of Gembicki (1994), which is the modified form of the goal programming method is utilized to solve the multi-objective problem. In this technique, similar to the

goal programming method, the desirable solution is affected by the vector of goal and the vector of weighting specified by the decision maker. In contrast to the interactive multi-objective methods, Goal attainment technique is a one-stage approach which works with fewer variables. Thus, compared to other methods, this method has less computational complexity. Consequently, due to the high capability of this method in terms of computational time, it is one of the best MODM methods to solve our green VMI supply chain problem in the form of nonlinear program. Goal attainment technique has been successfully implemented to solve a number of real-world multi-objective optimization problems in reliability optimization (Azaron et al., 2007a), project management (Azaron et al., 2007b) and production systems (Azaron et al., 2006), and we use this technique to solve the stochastic green VMI supply chain problem. This method demonstrates a set of designed goals  $F^* =$  $\{F_1^*, F_2^*, \dots, F_k^*\}$  which is associated with a set of objectives,  $F(x) = \{F_1(x), F_2(x), \dots, F_k(x)\}$ . This method involves setting up a goal and weight,  $b_i$  and  $w_i$  ( $w_i \ge 0$ ), for i=1,2, for the two introduced objective functions. The  $w_i$  described the relative under-attainment of the  $b_i$ . For under-attainment of the goals, a smaller  $w_i$  is related to the more significant objectives. When  $w_i$  reaches 0, then the objective function associated with, must be fully satisfied or the associated objective function value should be less than or equal to its goal  $b_i$ . The general mathematical formulation of this method obtained by:

$$\min Z$$
 (30)

Subject to:

$$F_i(x) - w_i Z \le b_i \tag{31}$$

$$i = 1, 2, \dots, k \tag{32}$$

$$X \in x$$
 (x is a feasible set; X is unrestricted in sign) (33)

k is the number of objectives,  $F_i(x)$  is the ith objective function, Z is the free variable of the problem that indicates the maximum objective deviation from the goal and must be minimized,  $w_i$  is the normalized weight of the ith objective function, so that  $\sum_{i=1}^k w_i = 1$ , and  $b_i$  is the ideal solution for the ith objective function. In fact, this method is a min-max method that minimizes the maximum objective deviation from the goal. The optimal solution using this formulation is sensitive to b and w. According to the values for b, it is possible that the optimal solution is not influenced remarkably by W.

### 5-1-2- Multi-Choice Goal Programming with Utility Function (MCGP-U)

We use multi-choice goal programming with utility function (MCGP-U) technique, which is a combination of multi-Choice Goal programming and utility function approaches to solve the multiobjective problem presented by Chang (2011) for the first time. This method, presented a novel theory of level achieving in the utility functions to substitute the aspiration level with scalar value in classical goal programming (GP) and multi-choice goal programming (MCGP) for multiple objective problems. Also, this method can be used as measuring tools to give assistance to decision makers make the best/suitable policy associated with their goals with the highest level of utility obtained. Moreover, it can improve the practical utility of MCGP in solving more real-world decision/management problems. It is for the first time that we use this technique to solve a multiobjective stochastic green VMI supply chain problem. In this method, according to the type of objective functions of problem, left linear utility function (LLUF) and right linear utility function (RLUF) are used. In this research based on the objective functions, we use LLUF to formulate MCGP-U. Therefore, we have:

$$\min Z = \sum_{i=1}^{k} [w_i(d_i^+ + d_i^-) + \beta_i f_i^-]$$
(34)

Subject to:  

$$\lambda_{i} \leq \frac{g_{i,max} - y_{i}}{g_{i,max} - g_{i,min}}$$

$$i = 1,2, ..., k$$

$$f_i(x) - d_i^+ + d_i^- = y_i$$
  $i = 1, 2, ..., k$  (36)

$$g_{i,min} \le y_i \le g_{i,max}$$
  $i = 1, 2, ..., k$  (37)  
 $\lambda_i + f_i^- = 1$   $i = 1, 2, ..., k$  (38)

$$\lambda_i + f_i^- = 1$$
  $i = 1, 2, ..., k$  (38)

$$d_i^+, d_i^-, f_i^-, \lambda_i \ge 0$$
  $i = 1, 2, ..., k$  (39)

 $X \in x$  (x is a feasible set; X is unrestricted in sign) (40)

Where  $d_i^+$  and  $d_i^-$  are the positive and negative deviations attached to the *i*th goal.  $w_i$  and  $\beta_i$  are weights attached to deviations  $d_i^+$ ,  $d_i^-$  and  $f_i^-$ .  $y_i$  is the continuous variable with a range of interval values  $g_{i,min} \leq y_i \leq g_{i,max}$ ,  $g_{i,max}$  and  $g_{i,min}$  are the upper and lower bounds of  $y_i$ .  $\lambda_i$  is the utility value of the *i*th goal and k is the number of objective functions.

### 5-1-3- Linear Programming-metrics method (LP-metrics)

As the model proposed by current study is a multi-objective, non-linear programming model with conflicting objective functions, it was decided to apply the LP-metrics method that is useful and simple in execution introduced by Zeleny (1982), Duckstein & Opricovic (1980) and Szidarovszky et al. (1986). So far, several multi-criteria decision making (MCDM) methods have been developed and investigated to solve multi-objective problems with inconsistent objective functions. One of the reasons we used the LP-metrics method is that LP-metrics approach is one of the well-known methods and widely used for solving the problems of this kind. In the Linear Programming (LP)-metrics method, a multi-objective problem is solved by optimizing each objective function separately, and then converting the problem to a single-objective optimization. By using LP-metrics method, the difference between any present solutions and the optimal solution are minimized (Branker et al., 2008). The mathematical formulation of this method is defined by:

$$\min Z = \left(\sum_{i=1}^{k} w_i \left| \frac{F_i(x) - F_i^*}{F_i^*} \right|^p \right)^{1/p}$$
 (41)

Subject to:

$$X \in x$$
 For  $1 \le p \le \infty$  (42)

(x is a feasible set; X is unrestricted in sign)

k represents the number of objective functions,  $F_i(x)$  is the ith objective function,  $F_i^*$  presents the ideal solution for optimizing the ith objective function.  $0 \le w_i \le 1$  ( $\sum_{i=1}^k w_i = 1$ ) represents the relative weight of components involved in the objective function (Mirzapour et al., 2011). The value of  $w_i$  are given by decision maker's measures. p is a parameter that controls the deviation of the objective function from the ideal solution. There are different values for p values 1, 2 or p0 are usually considered for it. The value of p1 demonstrates the type of metric. For p1, we obtain the Manhattan metric and for p1, we obtain the Tchebycheff metric. In this study, we consider p1. Whatever the amount of p1 is considered lower, the problem shows the lower sensitivity to the difference from the optimal level. According to the above mathematical formulation mentioned, single objective function of our model (p2) can now be formulated by:

$$\min Z = w_1 \times \frac{F_1 - F_1^*}{F_1^*} + w_2 \times \frac{F_2 - F_2^*}{F_2^*}$$
(43)

By considering this single objective function and our model constraints, a single-objective, non-linear programming model can be acquired and solved by a non-linear programming solver (i.e., Baron Solver) in Gams software. It is noted that the  $F_1$  and  $F_2$  minimize the first and second objective functions, respectively.  $F_1^*$  and  $F_2^*$  are the ideal solution for optimizing the first and second objective functions, respectively.  $w_1$  and  $w_2$  represent the relative weights of the first and second objective functions, respectively.

### 6- Computational results, comparisons and sensitivity analysis

In this section, first, three mentioned approaches are implemented on a set of 30 test problems, and then are compared in terms of the three comparison criteria, including the first objective function, the second objective function, and computational time (CPU time). Afterward, statistical analysis and MCDM approach that aim to specify significant differences among the proposed algorithms are applied. Finally, sensitivity analysis is investigated.

### **6-1- Comparison results**

Referring to Roozbeh Nia et al. (2015), different dimensions and parameter values of the numerical example are used to solve the model presented in table 2 and table 3, respectively. It should be noted that we use uniform distribution to produce data in table 3. In order to evaluate and compare three proposed methods, 30 test problems in different sizes are designed and three mentioned methods are implemented to obtain solutions in terms of three considered evaluation criteria that shown in table 4. The results in this table show that in average, LP-metrics, MCGP-U, and Goal attainment have the best performance in terms of the first objective function, the second objective function, and CPU time criteria, respectively. Note that the solving methods are implemented using GAMS/Baron software (win32, 24. 1. 2) on a pc with 2.2 GHz Intel Core 2 Duo CPU, and 4 GB of RAM memory. In addition, the performance of methods in the first and second objective function and CPU time is shown in figures 1, 2, and 3, respectively.

**Table 2.** Numerical examples with different dimensions

Numerical examples	i, j	Numerical examples	i, j
1	20,60	16	10,55
2	20,50	17	10,55
3	20,90	18	10,55
4	20,90	19	10,50
5	20,80	20	5,50
6	20,80	21	5,50
7	20,80	22	20,120
8	10,70	23	20,120
9	10,70	24	20,115
10	10,70	25	20,115
11	10,65	26	20,115
12	10,65	27	20,110
13	10,60	28	20,110
14	10,60	29	15,100
15	10,60	30	15,100

Table 3. Parameters and values

Parameters	values
$L_j$	Uniform (5,40)
$U_{j}$	Uniform (100,700)
$D_j$	Uniform (800,1700)
$A_{jS}$	Uniform (20,40)
$A_{jB}$	Uniform (20,50)
$h_{jB}$	Uniform (12,20)
$C_{j}$	Uniform (10,30)
$P_{j}$	Uniform (2000,10000)
$f_{j}$	Uniform (1,8)
$cap_i$	Uniform (270,1000)
$ heta_i$	Uniform (10,40)
$\gamma_j$	Uniform (20,50)

Table 4. Results of numerical examples solved by GAMS

Solving	LP metric			Goal attainment			MCGP-U		
method Numerical	$Z_1$	$Z_2$	CPU	$Z_1$	$Z_2$	CPU	$Z_1$	$Z_2$	CPU Time
examples	21	$\mathbf{z}_2$	Time (s)	21	<i>L</i> <sub>2</sub>	Time (s)	$z_1$	<i>L</i> <sub>2</sub>	(s)
champies			Time (b)			Time (b)			(5)
1	497503.819	41956.909	0.713	497281.207	42023.300	0.293	497544.298	41953.717	2.419
2	285225.148	6421494.787	156.973	2660482.216	6410977.367	30.452	285225.017	6421429.249	233.586
3	285225.188	6420006.530	356.142	2633906.054	6411036.490	20.333	285224.986	6419922.346	1.577
4	285225.092	6419956.811	403.04	2630605.951	6411027.797	30.385	285224.986	6419913.709	126.591
5	444007.422	5375525.963	89.018	1325442.241	5366821.106	23.012	444007.258	5375471.623	151.51
6	470392.037	5376561.796	29.018	5644908.302	5367796.179	21.312	470376.651	5376557.854	251.507
7	390761.542	5519270.829	32.86	10446190	5507671.460	6.067	390761.449	5519272.216	1015.507
8	294533.779	2312938.579	15.192	1239844.509	2301869.429	0.828	294533.277	2312924.400	10.383
9	465801.677	2309756.074	11.804	1406817.431	2301949.524	0.711	465801.565	2309752.004	6.5
10	598948.419	2455511.201	2.774	3947421.679	2449238.167	1.04	598948.528	2455510.755	275.009
11	599573.964	2365862.119	4.295	1359547.566	2359980.999	1.223	599573.882	2365862.595	44.463
12	609400.659	2366186.028	8.172	1325927.326	2360397.351	1.161	609401.068	2366182.614	3.23
13	588196.451	2215253.818	7.178	1151763.518	2209510.370	0.929	588196.661	2215252.907	0.286
14	632183.901	2473558.371	4.933	1260565.547	2468433.514	0.851	632184.288	2473556.389	11.308
15	819956.754	2472378.858	7.037	1509162.383	2467737.941	0.844	819957.055	2472377.968	136.53
16	827321.593	2227418.254	3.611	1438533.321	2223334.743	0.86	827319.093	2227431.574	63.071
17	929322.380	2816967.189	8.291	2625414.644	2812859.743	0.948	2816977.586	929319.509	5.127
18	1083425.026	2817132.655	4.758	1852411.734	2812859.743	0.694	1083425.328	2817131.660	4.214
19	1074836.123	2548684.732	4.13	1884736.185	2544782.500	0.615	1074837.274	2548681.978	6.629
20	1074843.897	2549628.538	2.337	1903194.241	2545715.201	0.82	1074837.154	2549638.583	5.667
21	1211859.410	1388304.383	2.158	2197318.814	1380857.711	0.719	1211859.675	1388304.094	1.831
22	1566046.920	11454140	261.82	3300667.421	11450030	129.392	1566046.964	11454140	4.084
23	1121775.034	11033200	261.402	2857830.085	11031120	45.781	1121775.157	11033200	3.259
24	1110984.63	10802680	148.221	2607595.457	10800680	48.69	1110984.753	10802670	4.982
25	800249.448	10375600	27.691	1441142.69	10371450	19.729	800250.010	10375560	2.666
26	324858.316	10808010	618.25	1618208.364	10800640	41.734	500000.534	10803330	6.147
27	345709.184	10087640	806.314	1658671.977	10080510	2.143	500002.521	10083210	4.218
28	703409.567	10466280	242.618	1378994.486	10461130	3.103	2228247.130	10461220	2.833
29	770031.498	7814799.983	30.625	1495752.920	7808788.46	0.941	770038.555	7814770.875	8.383
30	1026810.535	7814274.665	47.173	1900040.943	7807700.871	29.796	1026817.473	7814247.727	2.842
Average	117.6039	5398879	718233.2	15.97426	5392795	2293562	77.39358	5337518	838941.9

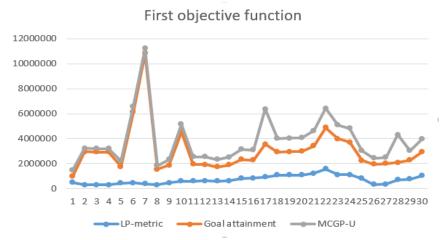


Fig 1. Results of LP-metrics, Goal attainment and MCGP-U methods in first objective function

### Second objective function

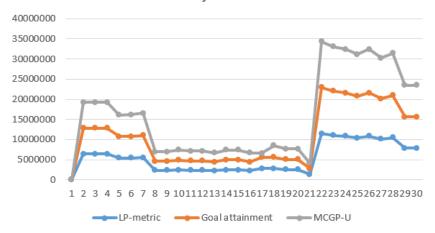


Fig 2. Results of LP-metric, Goal attainment and MCGP-U methods in second objective function

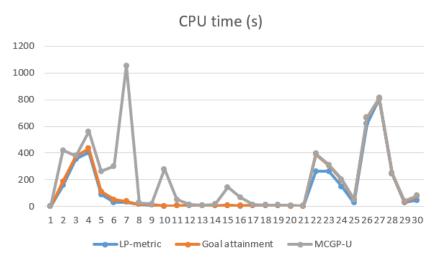


Fig3. Results of LP-metric, Goal attainment and MCGP-U methods in CPU time (s)

### 6-1-1- Comparison based on MADM technique

In this section, the technique for order preference by similarity to ideal solution (TOPSIS) is employed to compare three solving methods by using the first objective function, the second objective function and CPU time criteria, in order to find a method with the best performance.

#### 6-1-1-1 The technique for order preference by similarity to ideal solution (TOPSIS)

The technique for order preference by similarity to ideal solution which first was introduced by Hwang & Yoon (1981) and developed by Yoon (1987) and Hwang et al. (1993), is one of the multicriteria decision-making methods which is used to rank a set of alternatives, and choose the best alternative which have the farthest distance from the negative-ideal solution and the shortest distance from the positive-ideal solution. Positive-ideal solution seeks to minimize the cost criteria or maximize the profit criteria. On the other hand, the negative-ideal solution seeks to maximize the cost criteria or minimize the benefit criteria. The TOPSIS method consists of six steps which are explained below.

Table 5. The means of results prepared by algorithms

	$Z_1$	$Z_2$	CPU time (s)
LP-metric	718233.2	5398879	117.6039
Goal attainment	2293562	5392795	15.97426
MCGP-U	838941.9	5337518	77.39358

#### 1. The first step

To compare the alternatives LP-metrics, Goal attainment and MCGP-U, the means of four criteria presented in table 5, should be normalized using Euclidean norm which calculated in equation (44).

$$n_{ij} = \frac{r_{ij}}{\sqrt[2]{\sum_{i=1}^{3} r_{ij}^2}}$$
  $j = 1,2,3$  (44)

Where i and j are the indices related to the alternatives and attributes, respectively.  $n_{ij}$  is a normalized score for ith alternatives and jth attributes,  $r_{ij}$  is the score for the ith alternatives, according to the jth attributes. The normalized values are presented in table 6.

Table 6. The normalized values  $Z_1$   $Z_2$  CPU time (s)

LP-metric	0.282146273	0.579756846	0.830017474
Goal attainment	0.900988662	0.579103518	0.112742136
MCGP-U	0.32956473	0.573167615	0.546223584

### 2. The second step

According to the weights assigned to the attributes in table 7, the normalized scores are weighted, in which the equal weights are considered for three attributes.

Table 7. The weighted normalized values

	$Z_1$	$Z_2$	CPU time (s)
LP-metric	0.094048758	0.193252282	0.276672491
Goal attainment	0.300329554	0.193034506	0.037580712
MCGP-U	0.10985491	0.191055872	0.182074528

### 3. The third step

Positive-ideal and negative-ideal solutions are calculated based on the normalized weighted values, so that  $A^+$ =[0.094048758, 0.191055872, 0.037580712] is the best value of the jth attribute among all alternatives and  $A^-$ =[0.300329554, 0.193252282, 0.276672491] is the worst value of the jth attribute among all alternatives.

### 4. The fourth step

The Euclidean distances of each alternative from the positive-ideal and negative-ideal solutions are shown in table 8 which calculated as follows:

$$d_i^+ = \sqrt{\sum_{j=1}^3 (v_{ij} - v_j^+)^2}$$
  $i = 1,2,3$  (45)

$$d_i^- = \sqrt{\sum_{j=1}^3 (v_{ij} - v_j^-)^2}$$
  $i = 1,2,3$  (46)

Where,  $d_i^+$  is the Euclidean distances of each alternative from the positive-ideal solutions,  $d_i^-$  is the Euclidean distances of each alternative from the negative-ideal solutions,  $v_{ij}$  is the normalized weighted values,  $v_j^+$  is the vector of the best values of each attribute, and  $v_j^-$  is the vector of the worst values of each attribute.

**Table 8.** The distance of alternatives from the positive-ideal and negative-ideal solutions

	Positive-ideal solutions	Negative-ideal solutions
LP-metric Distance	0.239101868	0.206280796
Goal attainment Distance	0.206290286	0.239091878
MCGP-U Distance	0.145355761	0.212683307

#### 5. The fifth step

Finally, in order to rank alternatives, the closeness index  $(CL^+)$  for each alternative is calculated in table 9 by using equation (47).

$$CL^{+} = \frac{d_{i}^{-}}{d_{i}^{-} + d_{i}^{+}} \tag{47}$$

 $CL^+$  determines the closeness of each alternative from the ideal solution, so the alternative with the highest  $CL^+$  has the best performance and should be selected as the best alternative. As  $CL^+$  for LP-metrics, Goal attainment and MCGP-U are 0.463154, 0.536824, and 0.594023, respectively, it can be concluded that MCGP-U has better efficiency than Goal attainment and LP-metrics, and Goal attainment has better performance than LP-metrics. It should be noted that bigger values of the three mentioned criteria are preferred.

Table 9. Results of TOPSIS method

	LP-metrics		Goal attainment		MCGP-U
TOPSIS	0.463154	<u>≤</u>	0.536824	<u> </u>	0.594023

#### 6-1-2- Statistical analysis

In this section, the differences between the three presented methods in terms of the means of the employed criteria are statistically investigated. For each criterion, a single-factor analysis of variance (ANOVA) is utilized to test the equality of the means of criterion gained by the methods against the inequality of the means in order to specify whether there are significant differences between the solution methods in terms of the employed criteria when the standard deviations are uncertain. In each experiment, the two hypotheses are:

$$\begin{cases}
H_0: \mu_1 = \mu_2 = \mu_3 \\
H_1: \mu_1 \neq \mu_2 \neq \mu_3
\end{cases}$$
(48)

On the one hand, the null hypothesis in (48), representing the equality of the means of the methods in terms of a particular criterion, indicates no significant differences between them. On the other hand, the opposite situation is speculated by alternative hypothesis in (48). In this paper, the MINITAB software is employed to execute the Tukey's test. Three ANOVA experiments are designed according to the data results in Table 4, each for one criterion.

#### 6-1-2-1- First objective function criterion

Table 10 provided the outputs of the single-factor analysis of variance by the Tukey's multiple comparison tests for the first objective function  $(Z_1)$  criterion.

**Table 10.** Single-factor analysis of variance by the Tukey's multiple comparison tests for the first objective function criterion

Source	DF	Adjusted SS	Adjusted MS	F-value	p-value	Test result
Method	2	$4.74418 \times 10^{13}$	$2.37209 \times 10^{13}$	18.71	0.000	null
Error	87	$1.10292 \times 10^{14}$	$1.2677 \times 10^{12}$			hypothesis
Total	89	$1.57734 \times 10^{14}$				is rejected
			Confidence			
			level = 95%			

According to table 10, the p-value resulted from ANOVA, is less than 0.05. This implies that null hypotheses of equality of the first objective function is rejected at 95% confidence level, and significant differences are existed between the performances of LP-metrics, Goal attainment and MCGP-U methods in terms of the first objective function. In this case, when the solution methods generate significantly different outcome, in order to find out how the solution methods vary from each other, a post hoc analysis, such as the Tukey's multiple comparison test is performed (Montgomery et al., 1973). Table 11 displays the ranking of the solution methods in terms of the first objective function, according to the results of Tukey's test.

**Table 11.** Ranking the solution methods in terms of the first objective function criterion

		-			=	
Method	N	Mean	Rank	St Dev	95% CI	Grouping
Goal	30	2306679	3	1835059	(1898094,2715264)	A
attainment						
LP-metrics	30	707947	1	336925	(299362,1116532)	В
MCGP-U	30	832679	2	567635	(424094,1241264)	В

According to the results obtained by table 11, LP-metrics and MCGP-U are in the same group and Goal attainment is different from them. That means there is no significant difference between the LPmetrics and MCGP-U in terms of the first objective function, but significant differences are existed between the Goal attainment and two other solution methods in terms of the first objective function. Also, since lower value of the first objective function is preferred, the results of table 11 indicate that LP-metrics has remarkably the best performance in terms of the first objective function criterion among the mentioned solution methods. The results of the Tukey's multiple comparison tests in an analogical manner are expressed in figures 4 and 5. Figure 4 depicts the lower and upper limits of the criteria generated by each solution method presented in box plots. Basically, if the boxes do not cross each other, a significant difference is existed between the solution methods. According to figure 4, since significant overlap exists between the boxes related to LP-metrics and MCGP-U, there is no significant difference between them, but, as no overlap is observed between the boxes of the Goal attainment and two other mentioned solution methods, significant differences are existed between the Goal attainment and two other mentioned solution methods in terms of the first objective function criterion. According to figure 5, if an interval does not contain zero, the corresponding methods are significantly different. As a result, Goal attainment is significantly different from LP-metrics and MCGP-U in terms of the first objective function criteria, but there is no significant difference between LP-metrics and MCGP-U in terms of the first objective function criterion. It can be concluded that LP-metrics and MCGP-U are in the same group.

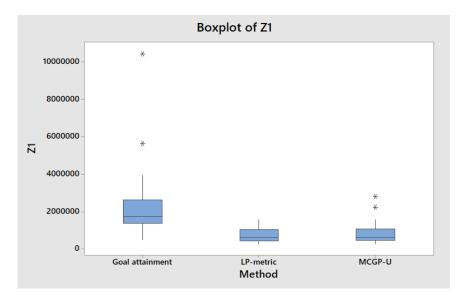


Fig 4. Boxplot of the average of the first objective function of the solution methods

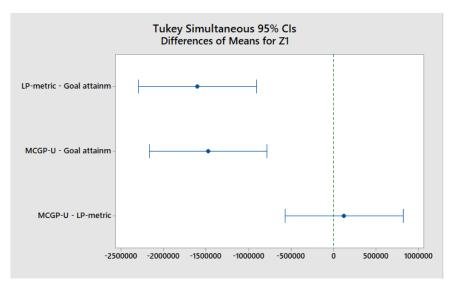


Fig 5. Tukey's simultaneous 95 percent intervals for the first objective function comparison

### 6-1-2-2- Second objective function criterion

Table 12 provided the outputs of the single-factor analysis of variance by the Tukey's multiple comparison test for the second objective function  $(Z_2)$  criterion.

**Table 12.** Single-factor analysis of variance by the Tukey's multiple comparison tests for the second objective function criterion

		1	unction criterion			
Source	DF	Adjusted SS	Adjusted MS	F-value	p-value	Test result
Method	2	73447785230	36723892615	0.00	0.997	null
Error	87	$1.12971 \times 10^{15}$	$1.29645 \times 10^{13}$			hypothesis
Total	89	$1.12798 \times 10^{15}$				is not
						rejected
			Confidence			
			level = 95%			

According to table 12, the p-value resulted from the ANOVA is more than 0.05, expressing that null hypotheses of equality of the first objective function is not rejected at 95% confidence level, and significant differences are not existed between the performances of LP-metrics, Goal attainment and

MCGP-U methods in terms of the second objective function. Table 13 displays the ranking of the solution methods in terms of the second objective function, according to the results of Tukey's test.

<b>Table 13.</b> Ranking the solution methods in terms of the second objective
--

Method	N	Mean	Rank	St Dev	95% CI	Grouping
Goal	30	5312298	2	3580247	(4005683,6618912)	A
attainment						
LP-metrics	30	5318366	3	3580219	(4011751,6624981)	A
MCGP-U	30	5254960	1	3641052	(3948345,6561574)	A

Based on the results obtained by table 13, all of the solution methods are in the same group and that means there is no significant difference between them. Also, since lower value of the second objective function is preferred, the results of table 13 indicate that MCGP-U has remarkably the best performance in terms of the second objective function criterion among the mentioned solution methods. Figures 6 and 7 express the results of the Tukey's multiple comparison tests in an analogical manner. According to figure 6, since the boxes cross each other, a significant difference is not existed between the solution methods. According to figure 7, since an interval contains zero, there is no significant difference between the three methods in terms of the second objective function criterion.

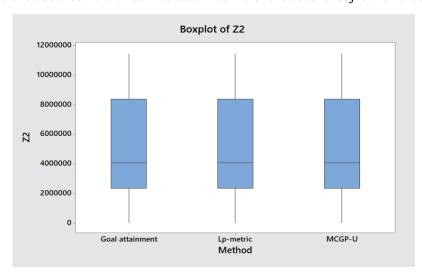


Fig 6. Boxplot of the average of the second objective function of the solution methods

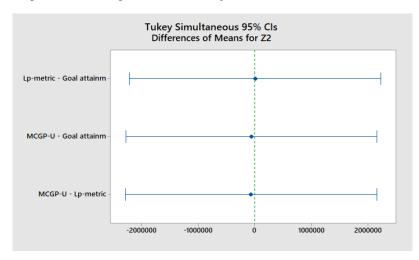


Fig 7. Tukey's simultaneous 95 percent intervals for the second objective function comparison

#### 6-1-2-3- CPU time criterion

Table 14 provides the outputs of the single-factor analysis of variance by the Tukey's multiple comparison tests for the CPU time criterion.

**Table 14.** Single-factor analysis of variance by the Tukey's multiple comparison tests for the CPU time criterion

Source	DF	Adjusted SS	Adjusted MS	F-value	p-value	Test result
Method	2	166560	83280	3.20	0.046	null
Error	87	2264653	26030			hypothesis
Total	89	2431214				is rejected
			Confidence			

Confidence level = 95%

According to table 14, p-value resulted from the ANOVA is less than 0.05 indicating that null hypotheses of equality of the CPU time is rejected at 95% confidence level, and significant differences exist between the performances of LP-metrics, Goal attainment, and MCGP-U methods in terms of the CPU time. So, the Tukey's multiple comparison test is performed to find out how the solution methods vary from each other. According to the results of Tukey's test, table 15 displays the ranking of the solution methods in terms of the CPU time

**Table 15.** Ranking the solution methods in terms of the first objective function criterion

Method	N	Mean	Rank	St Dev	95% CI	Grouping
Goal	30	15.51	1	26.47	(-43.03, 74.06)	A
attainment						
LP-metrics	30	120.0	3	198.9	(61.4, 178.5)	В
MCGP-U	30	79.9	2	194.5	(21.3, 138.4)	A,B

According to the results obtained by table 15, LP-metrics and MCGP-U are in the same group, whereas Goal attainment and MCGP-U are in the same group. That means there is no significant difference between the LP-metrics and MCGP-U function in terms of CPU time criterion. Also, significant differences are not existed between the Goal attainment and MCGP-U in terms of CPU time, but there are significant differences between the Goal attainment and LP-metrics, and they are not in the same group. Also, since lower value of the CPU time is preferred, the results of table 15 indicate that Goal attainment has remarkably the best performance in terms of the CPU time criterion among the mentioned solution methods. Figures 8 and 9, express the results of the Tukey's multiple comparison tests in an analogical manner. According to figure 8, since significant overlap exists between the boxes related to LP-metrics and MCGP-U, there is no significant difference between them. Also, figure 8 shows that there is no significant difference between Goal attainment and MCGP-U. In contrast, based on figure 8, as no overlap is observed between the boxes of the Goal attainment and LP-metrics, significant differences are existed between them in terms of the CPU time criterion. Figure 9, expresses the same conclusion as well as figure 8.

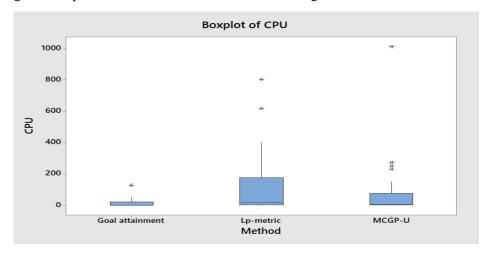


Fig 8. Boxplot of the average of the CPU time of the solution methods

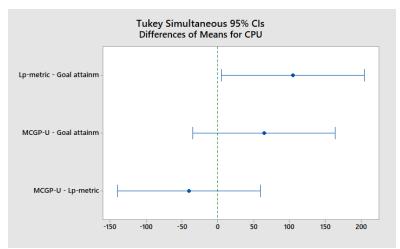


Fig 9. Tukey's simultaneous 95 percent intervals for the second objective function comparison

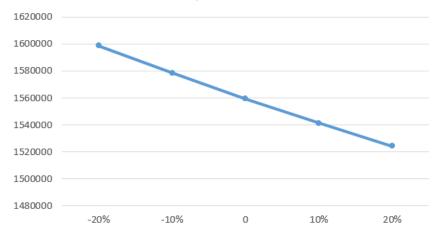
### 6-3- Sensitivity analysis

In this section, sensitivity analysis is used to investigate the effects of some changes of parameters of model on the first and second objective functions. For this purpose, changes in parameters including:  $\mu_{Norder}$ ,  $\sigma_{Norder}^2$ ,  $\mu_F$ ,  $\sigma_F^2$ ,  $\mu_{MABC}$  and  $\sigma_{MABC}^2$  are evaluated at -20%, -10%, +10%, +20% rates. GAMS software is used to perform sensitivity analysis. The results are presented in table 16 and figures 10-21.

**Table 16.** Results of sensitivity analysis

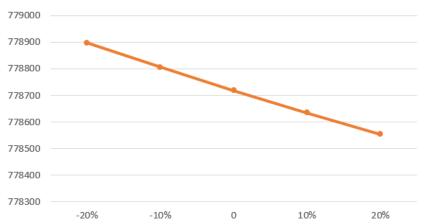
Parameters	Change (%)	$Z_1$	$Z_2$
	-20	1598655.273	778897.631
	-10	1578420.159	778805.635
$\mu_{MABC}$	0	1559373.196	778718.743
, MADC	+10	1541380.499	778634.769
	+20	1524262.642	778553.457
	-20	1559363.608	778718.719
	-10	1559363.464	778718.124
$\sigma^2_{MABC}$	0	1559373.196	778718.743
	+10	1559391.427	778718.801
	+20	1559395.934	778718.845
	-20	1559373.196	778718.743
	-10	1559373.195	778718.739
$\mu_F$	0	1559373.196	778718.743
• •	+10	1559373.196	778718.743
	+20	1559373.196	778718.743
	-20	1559373.195	778718.739
	-10	1559373.193	778718.730
$\sigma_{\scriptscriptstyle F}^2$	0	1559373.196	778718.743
r	+10	1559373.196	778718.743
	+20	1559373.196	778718.743
	-20	1559373.194	778718.742
	-10	1559373.196	778718.743
$\mu_{Norder}$	0	1559373.196	778718.743
r Noraer	+10	1559373.196	778718.743
	+20	1559373.196	778718.743
	-20	1559373.193	778718,730
	-20 -10	1559373.196	778718.730
$\sigma_{Norder}^2$	0	1559373.196	778718.743
Norder	+10	1559373.196	778718.743
	+20	1559373.196	778718.738

# First objective function



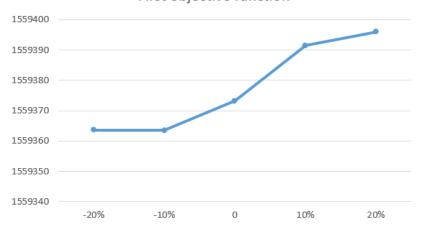
**Fig 10.** Change in first objective function value by the changes in  $\mu_{MABC}$ 





**Fig 11.** Change in second objective function value by the changes in  $\mu_{MABC}$ 

First objective function



**Fig 12.** Change in first objective function value by the changes in  $\sigma_{MABC}^2$ 

# Second objective function

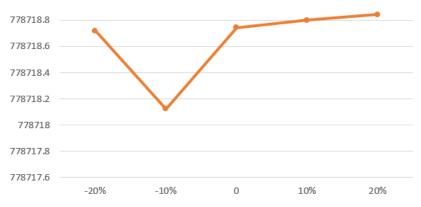


Fig 13. Change in second objective function value by the changes in  $\sigma^2_{MABC}$ First objective function

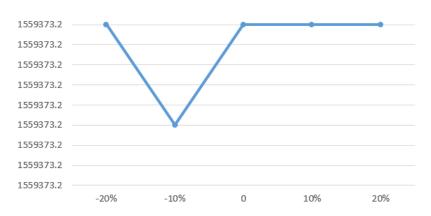


Fig 14. Change in first objective function value by the changes in  $\mu_F$ 

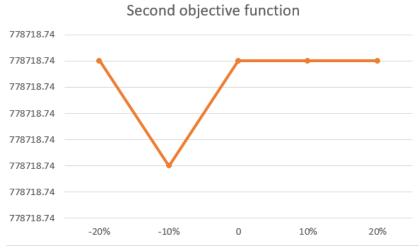
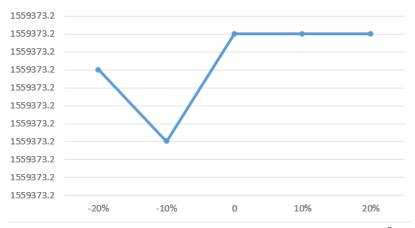


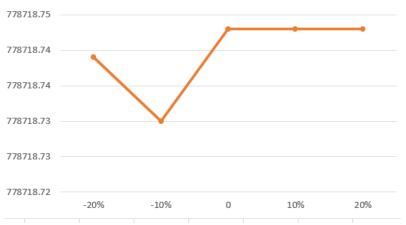
Fig 15. Change in second objective function value by the changes in  $\mu_F$ 

# First objective function



**Fig 16.** Change in first objective function value by the changes in  $\sigma_F^2$ 

# Second objective function



**Fig 17.** Change in second objective function value by the changes in  $\sigma_F^2$ 

# First objective function

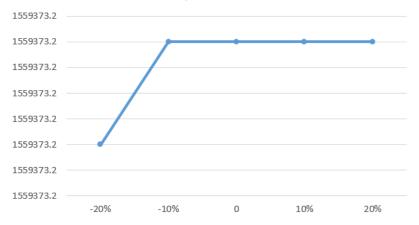
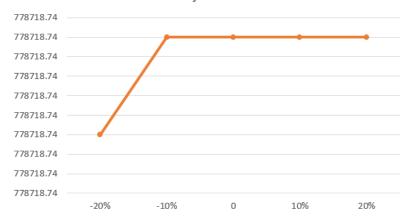
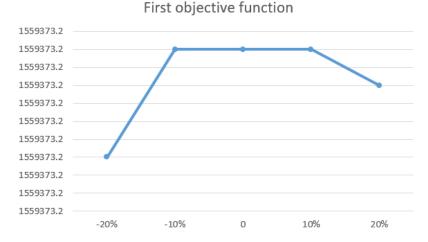


Fig 18. Change in first objective function value by the changes in  $\mu_{\textit{Norder}}$ 

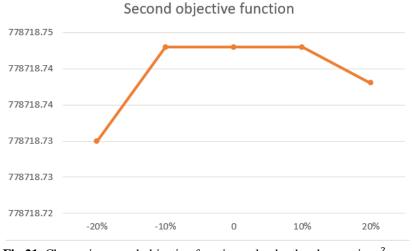
#### Second objective function



**Fig 19.** Change in second objective function value by the changes in  $\mu_{Norder}$ 



**Fig 20.** Change in first objective function value by the changes in  $\sigma_{Norder}^2$ 



**Fig 21.** Change in second objective function value by the changes in  $\sigma_{Norder}^2$ 

According to table 16, figures 10-21 and the results of the sensitivity analysis, if we change the value of the mean of maximum allowable backordering cost ( $\mu_{MABC}$ ) parameter in the range of -20 to +20 percent, we will have a significant impact on the values of the first and second objective functions. In such a way, If the value of this parameter increases, the amount of the first and second objective functions will be reduced. In other words, there is an inverse relationship between the mean of maximum allowable backordering cost ( $\mu_{MABC}$ ) parameter and the first and second objective

functions. Another important parameter examined to specify its effects on the values of the first and second objective functions, is the variance of maximum allowable backordering cost  $(\sigma_{MABC}^2)$ . If the value of the variance of maximum allowable backordering cost  $(\sigma_{MABC}^2)$  parameter is changed in the range of -20 to +20 percent, it will display different procedures, such that if the value of  $\sigma_{MABC}^2$ increases, the value of the first objective function will be reduced, but the effect of changes of the values of  $\sigma_{MABC}^2$  on the second objective function is completely different, so that the increase in  $\sigma_{MABC}^2$  values in the initial runs, leads to a decrease in the value of the second objective function, but in the subsequent runs, the trend is completely inverse. Therefore, increasing the value of  $\sigma_{MABC}^2$  parameter, leads to an increase in the value of the second objective function. So, we can say that there is an inverse relationship between the  $\sigma_{MABC}^2$  parameter and the first objective function, while about the second objective function, in the initial runs, the relation is inverse and in the subsequent runs there is a direct relation between them. The two other important parameters acting completely different from the other parameters are the mean of maximum storage space  $(\mu_F)$  and the variance of maximum storage space  $(\sigma_F^2)$ . The effects of the changes in these two parameters in the range of -20 to +20 percent on the two objective functions are completely the same. Changes in these two parameters have vibrational effects on the values of the first and second objective functions, and they do not have a stable trend. In the initial run, the increase of the two mentioned parameters reduces the values of the first and second objective functions, but over time, increasing the values of these two parameters will not have any effect on the first and second objective functions. The other examined parameter is the mean of maximum number of orders ( $\mu_{Norder}$ ). Increasing the value of this parameter will have the same effect on the first and second objective functions and leads to fluctuations in the values of the objective functions, such that the increase in the value of the  $\mu_{Norder}$ parameter initially increases the first and second objective functions values, but in subsequent runs, it does not have any effect on the values of the objective functions. Therefore, by increasing the value of the  $\mu_{Norder}$  parameter, the values of the first and second objective functions increase and then their values are constant and without any changes. The last parameter we examined, is the variance of maximum number of orders  $(\sigma_{Norder}^2)$  parameter, which changes of this parameter have vibrational effects on the values of the first and second objective functions. If we increase the value of the  $\sigma_{Norder}^2$ , initially the values of both objective functions will be increased. In the subsequent runs, it has no effect on the first and second objective functions, and in the end runs, the reverse effect is between this parameter and objective functions. As a result, it can be said that among the parameters considered in the sensitivity analysis, the  $\mu_{MABC}$  and  $\sigma_{MABC}^2$  parameters have significant effects on the first and second objective functions. In other words, the first and second objective functions are more sensitive to changes in the two mentioned parameters than others, while there is no logical relation between changes in other examined parameters and objective functions.

### 7- Conclusions

In this paper, a bi-objective multi-item multi-constraint economic production quantity model for a two-echelon single vendor-single buyer green supply chain under vendor-managed inventory policy was proposed to minimize the total cost of the VMI chain and greenhouse gases emissions, where backordering shortages were allowed. Our model offered the green policy, compared to the model propose by Pasandideh et al. (2014), aimed to reduce greenhouse gases emissions presented in second objective function. In other word, GHGs emissions released through transporting orders by trucks and holding them in warehouse must be reduced. In addition, more technical and physical constraints were presented to bring our mathematical model closer to reality using stochastic programming. The biobjective non-linear programming was solved by GAMS software using three multi-objective decision making (MODM) methods, namely LP-metrics, Goal attainment and MCGP-U. To show the application of the solution methods, 30 numerical examples with different sizes were proposed in terms of first and second objective functions criteria as well as CPU Time criterion. Statistical analysis and MCDM technique were used to compare and analyze the performance of proposed methodology. The results derived from TOPSIS demonstrated that MCGP-U has better efficiency than Goal attainment and LP-metrics, and Goal attainment has better performance than LP-metrics in terms of the first objective function, the second objective function and CPU Time criteria. In addition, the results of statistical analysis showed that in terms of the first objective function criterion,

significant differences are existed between the performances of LP-metrics, Goal attainment and MCGP-U methods. Based on Tukey's multiple comparison tests, there was no significant difference between LP-metrics and MCGP-U, but significant differences were existed between the Goal attainment and two other solution methods. In terms of the second objective function criterion, significant differences were not existed between the performances of LP-metrics, Goal attainment and MCGP-U methods, while significant differences were existed between the performances of LP-metrics, Goal attainment and MCGP-U, in terms of the CPU time.

As a future research, the following suggestions are presented:

- (a) Considering some main parameters of the problem to be fuzzy or uncertain, could be worthwhile.
- (b) Developing either exact methods, or meta heuristic algorithms, such as NSGA-I, NCGA and MOPSO algorithms to solve the bi- objective NLP model would be effective.
- (c) To make the model more applicable, inflation and discount could be added to the model.
- (d) Pricing policies and the impact of greenhouse gases on end-customers could be considered.
- (e) The shortage could be used in the form of lost sales.
- (f) The economic order quantity model could be investigated, instead of economic production quantity model.
- (g) Multi-echelon supply chain, such as one vendor-one buyer, one vendor-multi buyer, multi-vendor one-buyer and multi-vendor multi distributing centers, and multi-vendor in VMI system could be examined.

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