"OPTIMIZATION OF MULTI-COMMODITIES CONSUMER SUPPLY CHAINS FOR-PART I-MODELING"

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ABSTRACT

This study and its companions (Part II, Part III) will concentrate on optimizing a class of supply chain problems known as Multi-Commodities Consumer Supply Chain (MCCSC) problem. MCCSC problem belongs to Production-Distribution (P-D) planning category. It aims to determine facilities location, consumers' allocation and facilities configuration to minimize total Cost (C_T) of the entire network. These facilities can be manufacturer units (MUs), Distribution Centres (DCs) and Retailers/End-users (REs) but not limited to them. To address this problem, three major tasks should be undertaken. At the first place, a Mixed Integer Non-Linear Programming (MINP) mathematical model is developed. Then, system's behaviors under different conditions will be observed using a simulation modeling tool. Finally, the most optimum solution (minimum C_T) of the system will be obtained using a multi-objective optimization technique. Due to the large size of the problem and the uncertainties in finding the most optimum solution, integration of modeling and simulation methodologies is proposed followed by developing new approach known as GASG. It is a genetic algorithm on the basis of granular simulation which is the subject of the methodology of this research. In part II, MCCSC is simulated using Discrete-Event Simulation (DES) device within an integrated environment of SimEvents and Simulink of MATLAB® software package followed by a comprehensive case study to examine the given strategy. Also, the effect of genetic operators on the obtained optimal/near optimal solution by the simulation model will be discussed in part III.

Keywords: Supply Chain, Genetic Algorithm, Optimization, Simulation, Discrete Event System

1. INTRODUCTION

Supply Chain (SC) is defined as an effective coordination and integration of activities undertaken by several infrastructures; such as suppliers, manufacturers, distributors and retailers; from the procurement of raw material to the distribution of final products to the customer (Beamon, 1998; Shapiro, 2007; Gupta and Maranas, 2003). These activities are mainly categorized based on the business divisions namely marketing, distribution, planning, manufacturing and purchasing (Gupta and Maranas, 2003), where effective integration of them will be considered as the primary objective of supply chain management (Winser *et al.*, 2011). A typical SC is depicted in **Fig. 1**.

Due to the violated global market, SC organizations are highly at risk and significantly responsible for their strategic and operational decision makings in different levels. Consequences of even an insignificant error that leads massive damages are undeniable IBM, 2012. Therefore, for a better risk management cost savings and revenue growing, it is essential to have a smarter supply chain. It can be achieved through exploiting the optimization approaches.

Production and Distribution (P-D) planning are two main optimization problems which have been investigated in the context of supply chain for nearly two decades. Materials assembly and/or transformation into final commodity is focused on in the first network, while transforming commodities from manufacturing plants to distribution centres and then delivering to retailers (end-users) is considered in the second network (Fahimnia *et al.*, 2012).

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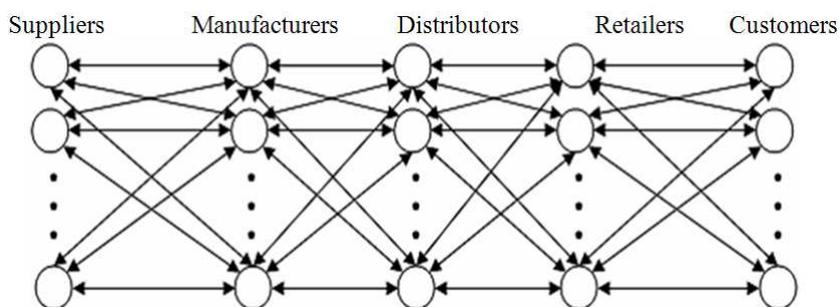
Fig. 1. A typical supply Chain

Analyzing the existing mutual relationship between production and distribution problems can be better dealt with in an integrated manner (Park *et al*., 2007). Many studies have been conducted and a large number of algorithms and methodologies have been developed (Papageorgiou, 2009; Fahimnia *et al*., 2012) accordingly. However, it is still a flourishing research area. This is mainly because of the following two reasons (Persson and Olhanger, 2002):

- Maximizing the outstanding indicator of any Supply Chain Network (SCN); SC value added performance
- Managing the market response in a fairly quick possible time span through lowering lead time

An integrated P-D problem typically consists of Manufacturing Units (MU), Distribution Centres (DC), Warehouses (W) and Retailers (R). It mainly deals with simultaneous management of the information flows as well as optimization of the decision variables of various functions to obtain the best output.

Due to an extremely large number of decision variables subject to different constraints, analyzing the P-D problem is become very complicated. So that, optimal/near optimal solution is hardly obtained. Also, varying these constraints over a time makes the system dynamic. This attribute beside the stochastic nature of the SC, will amplify the difficulties associated with this type of problem. Hence, it is essential to develope a comprehensive model which should be fairly efficient and cost-effective.

This study is mainly focused on developing an intelligent methodology to optimize multi commodities consumer supply chain (MCCSC) problem.

Due to the extent of the work and to facilitate presentation, this study is divided into three parts as bellow.

Part I

Optimization of multi-commodities consumer supply chains (Modeling): entails design, modeling and optimization procedure of a SC system with different family commodities which will be performed with respect to their particularities and constraints. Hence, a new methodology-GASG-is developed through which outputs of the simulation phase, simultaneously with the control of granularity, will be utilized as input of the optimization phase. This methodology will be discussed in details later in this study.

In order to reduce unexpected complexity, (e.g., supply, demand, process. Lalmazloumian and Wong (2012) and diversity in MCCSC problems, system's behavior is then modeled mathematically. Moreover, cost functions and equations are presented. To examine the efficiency of the presented model, simulation approach is chosen which will be demonstrated (using MATLAB®) in part II. It will facilitate the GA application in problem optimization (part III) that leads to validating the quality of the solution.

Part II

Optimization of multi-commodities consumer supply chains (Simulation Modeling): investigates the SC system as an event-driven problem. SC is a perfect environment where via using simulation approaches especially Discrete-Event Simulation (DES), reproduction and evaluation of what-if scenarios can be examined and optimality level and the robustness of the proposed strategy can be predicted.

A simulation modeling of the developed mathematical model (part I) is created within an integrate environment of SimEvents and Simulink toolboxes of MATLAB®. Furthermore, a typical three echelons SC is exploited on the basis of which, a comprehensive case study- 10 commodities C, 10 R, 1 DC and 1 MU is described (100 interrelated variables subject to a number of constraints). The advantage of SimEvents is highlighted in simulating the passing entities (orders and stock) through a network of different modules; queues, servers, gates, switches. over a particular instant of time.

Part III

Optimization of multi-commodities consumer supply chains (Genetic Algorithm Application and Results): demonstrates the particularities of the GA employed to optimize the problem. Results from simulation phase are treated as input of this phase. Additionally, the genetic operators such as selection, cross over and mutation used within the GA are presented.

Generating the model will yield an algorithm to intelligently search for optimized solutions out of feasible solutions. The feasible solutions are in the form of chromosomes which act within the constraints. This mechanism will be introduced in the 3rd part of this study. Besides, it can reduce the systems size to the most prominent features in order to simplify application of GA for their optimization. Finally, the results of the proposed methodology-GASG- is presented.

This study is structured as following. Section 2 reviews the literatures done in the last decade on optimization P-D problems in particular multi-commodities supply chain. Section 3 provides the problem statement followed by mathematical formulations of the developed model in section 4. Next, Small application of the proposed model demonstrates in section 5. The paper is finalized by a summary of the obtained results in section 6.

2. LITERATURE REVIEW

Several studies have been conducted to investigate various level of decision making in Bhatnagar *et al.* (1993) in a fairly review on Multi-Plant Coordination problems in SC categorized the integration of decision making in SCNs into three main categories namely:

- Supply and Production(S-P) planning
- Production and Distribution (P-D) planning
- Inventory and Distribution (I-D) planning

Production-distribution planning problems outweigh others in terms of their importance and effectiveness in global optimization in SCM (Lee *et al.*, 2002; Yimer and Demirli, 2010; Fahimnia *et al.*, 2012).

Optimization of P-D planning problems in the SC has attracted the focus of many studies through different approaches; including (1) multiple run of deterministic models, (2) simulation of deterministic models, or (3) stochastic programming (Tsiakis and Papageorgiou, 2008; Eppen *et al.*, 1989), over different planning horizon in the literature. Also, modeling and analyzing of such systems have been carried out for many years within the integrated planning structure, using

deterministic or stochastic methods. However, due to a wide range of dynamic behaviors in SN they become so complicated. Consequently, the refereed methodologies are not applicable and popular to be used separately in optimization problems. Hence, simulation approaches are preferably used in presence of having inappropriate and invalid values for evaluation (Lee *et al.*, 2002). To this end, a number of surveys were reviewed in the next section. The findings pointed out that the following gaps in P-D optimization problem analysis.

- Independent problem analysis of modelling and simulation
- Integrated problem analysis of modelling and simulation
- Low complexity of case studies used for simulation

2.1. Independent Analysis of P-D Problems in Modelling and Simulation

Vidal and Goetschalckx (2001) presented a non-convex optimization tactical global SC model. The heuristic solution algorithm was utilized to maximize the after tax profits in Transfer Pricing problem (TP). In the developed model, decision variables considered as transfer prices and the transportation costs allocation. With four suppliers located in four countries, having four warehouses through which the final product was delivered to the customers. The parameters optimization was not fulfilled simultaneously but sequentially through different functions.

A multi variable production model of three-echelon supply driven chain (**Fig. 2**) was studied by Xiao *et al.* (2012) within uncertain quality environment. Also, the most suitable supply coordination mechanism on the basis of a fuzzy set was provided. The stability of the analytical production control model was independently analyzed and formulated by providing a numerical example. However, a number of simplified assumptions limit its applicability in practical situations. It was simulated for a three echelon SC with three suppliers and one DC for single product over a period of 120 weeks.

Similarly, Waldemarsson *et al.* (2013) proposed a multi-site, multi-period MILP P-D problem in Forestry industry (**Fig. 3**). Over a planning horizon of one year (with monthly periods consideration), the problem was aimed to maximize the total supply chain profit.

The profit function was considered through entire SN from procurement and production to transportation of pulp products and the use of energy in pulp industry. The mathematical model was formulated using CPLEX approach via AMPL programming language.

Fig. 2. An analytical production model of supply-driven chain (Xiao *et al*., 2012)

Fig. 3. Illustration of the supply chain for Sodra Cell

Fig. 4. Network configuration of the provided case study (Tsiakis and Papageorgiou, 2008)

An analysis of seven scenarios was conducted with 5 pulp mills being able to produce 15 products at each site. Even though, there was hard effort to develop such mathematical model but it was restricted only to the represented scenario not being a general model.

From the above reviewed researches, it is concluded that both approaches have been appropriately reflected their advantages in a specific problem. However, independent deployment of them has some drawbacks too. The cons and pros of analytical and simulation modeling is perfectly summarized by Nolan and Sorverign (1972).

Hence, integration of both approaches leads to efficiency enhancement to a higher level alongside diminishing their shortcomings. Therefore, in section 2.2 examples of an integrated approach are included.

2.2. Integrated Analysis of P-D Problems in Modelling and Simulation

Using a hybrid method, Lee *et al*. (2002) presented an integrated P-D model combining the analytical and simulation models to satisfy the retailer's demand subject to capacity and inventory balance uncertainties. Thus, through utilizing the outputs from optimization procedure, the value of the inputs in simulation solution are tuned. The production system used in the simulation includes two shops having three machine centers with one machine plus one input and output buffer. In addition, the distribution system was simulated with two warehouses and three retailers. Despite the fact that this study has focused on integration of modeling and simulation in P-D systems, the solutions of phases were obtained independently.

Tsiakis and Papageorgiou (2008) addressed optimal design and operation of a multi-product, multi-echelon global production and distribution network (**Fig. 4**) under operational and functional uncertainties. The resulting MILP model was aimed to minimize the total annualized cost of network including both infrastructure and operating costs. However, the proposed model was utilized in long-term planning horizon to address strategic and tactical supply design. The SCN demonstrated in the simulation part contains six MPs in which six types of products are produced, but only one product family may be manufactured at a time. Also, six DCs are fully connected and interrelated to the eight corresponding CZs and considered in the proposed SCN.

An integrated mathematical model is developed by Y. Huang *et al*. (2010) for strategic planning of multi-location-layer bioethanol supply chain management (**Fig. 5**). The objective function in the proposed multistage MILP model minimizes the total supply chain costs over the planning horizon (1 year), subject to the demand uncertainty. Eight types of feedstock resources in a low-carbon fuel making procedure were considered over average five locations in California US.

Yimer and Demirli (2010) proposed a two-phase multi-product and multi plant supply chain, depicted in **Fig. 6**, under capacity limitations. The MILP model was developed to cover assembling and distribution scheduling of the finished products in phase 1. Subsequently, based on the output from phase 1, component fabrication and raw material procurement were formulated in phase 2. These two models were generated on the basis of the Build-To-Order (BTO) strategy to minimize the aggregate cost in each subsystem accordingly. In addition, since the obtained search space in phase 1 was so sophisticated including too many possible solutions, GA was chosen to apply to the methodology. As a numerical test, two supply plants, four distribution centers and six retailers were considered in the supply chain.

2.3. Simulation Analysis of P-D Problems with Low Complex Case Studies

Zamarripa *et al*. (2012) analyzed a two stage complex stochastic programming model considering both internal and external sources of uncertainty. Using GA, they demonstrated how to minimize firstly, the total cost of the SC and secondly, the buyer's expenses. In this research as a subsequence of their previous research (Zamarripa *et al*., 2012); uncertainty sources were formulated as the competition behavior of several SCs. The proposed model was tested on the SCN with only two products and four DCs over the planning horizon of three months. However, the model is useful tool for the similar problem with small size and low complexity.

Aliev (2007) developed a Fuzzy integrated multi-period and multi-product P-D model with uncertain demand (soft constrain) and capacity parameters in a production environment. The fuzzy decision variables are obtained through solving the optimization problem using Genetic Algorithm approach with main objective of maximizing the overall profit. The SCN considered in the case study as illustrated in **Fig. 7**, consists of two Manufacturing Plants (MPs), two Distribution Centers (DCs), two Customer Zones (CZs) and two kinds of products. Although, the developed model is supposed to be applied on multi-products, only two product families are considered in the case study, which point to an important limitation of the study.
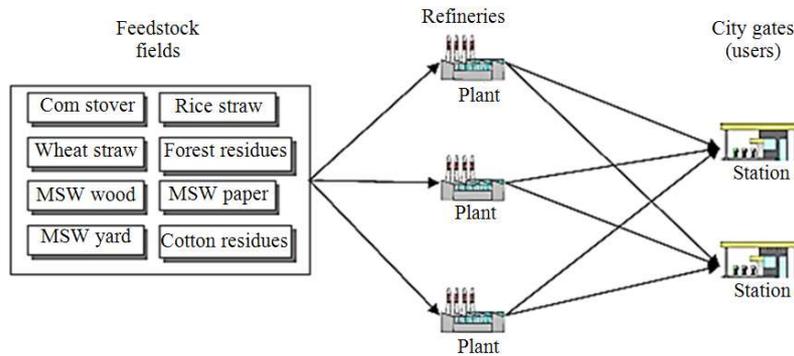
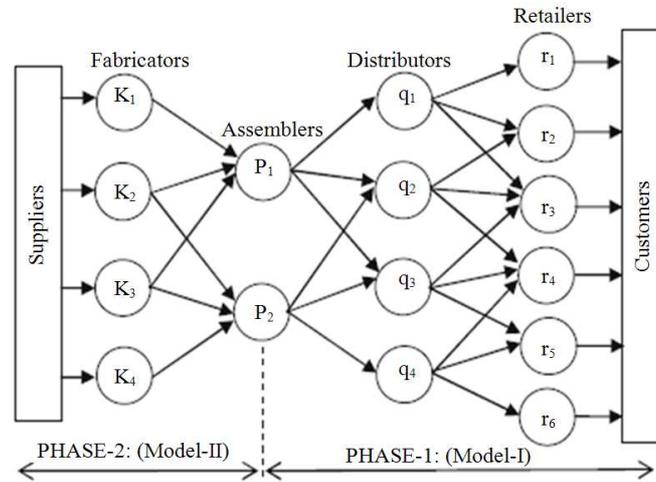**Fig. 5.** A snap shot of a bioethanol supply chain (Huang *et al*., 2010)

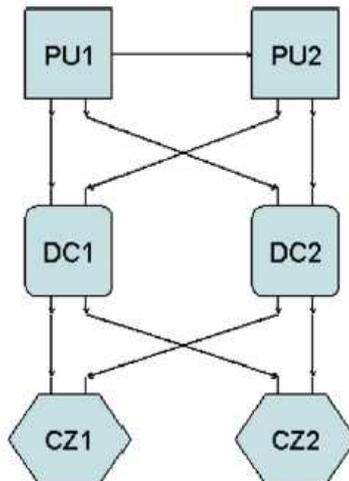**Fig. 6.** A BTO supply chain network structure (Yimer and Demirli, 2010)

Fig. 7. Supply Chain Network considered for simulation of the proposed model (Aliev, 2007)

A two-echelon supply network model (**Fig. 8**) was proposed by Fahimnia *et al.* (2009) in which multiple production plants and distributions of items were used in the first echelon. In the second echelon, multiple warehouses and distribution of products from warehouses to the end-user were considered. It targets to minimize the sum of the production costs (regular and over-time), inventory holding costs, direct and indirect transportation costs and backlogging costs subject to the following prioritized constraints: (1) capacity constraints; (2) demand and shortage constraints; (3) balanced constraints at stack buffers; (4) warehouses and end-users constraints via using multi-objective Genetic Algorithm. The proposed model was validated in the SCN with four MPs, four products family where they were directly distributed between the five end-users through six pre-established warehouses. This case study is exactly the same as the one in the previous publication of author in 2008.

A multi-product multi-period aggregate P-D problem with trans-shipment was proposed by Torabi and Moghaddam (2012). Using fuzzy logics programming approach, two objective functions total profit maximization and manufacturing lead time minimization were optimized, subject to demand constraints.The developed model was formulated for J number of Manufacturing Sites (MS), I types of products and L retailers over T periods of planning horizon in two distinct scenarios. In the former, it was assumed that products shipment between MSs is not permitted and there are no relationships between MSs; while in the later, mutual connections between MSs were existed and later products shipment between MSs was taken place as it is illustrated in **Fig. 9**. However, in the provided case study, only three types of products manufactured in four MSs demanded from seven SRs (customers) over medium planning horizon of three months, are considered.

A multi-site multi-product supply chain planning was presented by Mitra *et al.* (2008) in multi-objective Pareto sense including uncertain demand and machine up-time factors using Fuzzy mathematical programming. The proposed model was formulated for both with and without minimum run length restriction, based on the mid-term planning model of McDonald and Karimi (1997), which results in LP and MILP problems respectively to minimize the entire supply chain costs. Also, this model was evaluated through a real scenario for 1 year planning horizon with two production locations (S1, S2) connecting to two markets (M_1 and M_2), producing 34 family products (P_1-P_{34}), with single raw material supplier in each production unit. So that, S1 produces family product 1 to 23

(P_1-P_{23}) and S2 manufactures the other 10 family products P_{24}-P_{34} respectively.

Chen and Li (2013) presented a multi-objective inventory optimization problem model. A so-called grey system theory was integrated with meta-heuristic mathematical method-GA approach to overcome SCN uncertainties. Under demand uncertainty, with the aim of SC total cost minimization a two stages model was developed. The proposed model then was generalized for multi-suppliers providing a product or a service to a single subsequent unit. Also, it was simulated through a case study with two final product manufactures, one distribution center, nine production center and 11 external suppliers.

A Closed-Loop Supply Chain (CLSC) network (**Fig. 10**) model was investigated by Qiang *et al.* (2013). The main contribution of this research was developing SN considering W material suppliers, N manufactures and M retailers subject to demand and yield uncertainties which are formulated through a finite-dimensional variation inequality. Also, it was assumed that the manufacturers are in charge of collecting the recycled product directly from the demand market. However, in the provided numerical example two raw material suppliers, two manufacturers and two retailers were considered.

Using the concept of Agile Manufacturing with a focus on companies' capability of operating in a competitive environment within unstable market dealing with changes in uncertainty, Pan and Nagi (2013) designed a multi-echelons multi-periods SCN under demand uncertainty as result of multiple customers. As it is shown in **Fig. 11**, this problem is formulated as Lagrangian relaxation-based heuristic to obtain the optimal solution with four echelons containing three companies in each level, with one end-user having one type of demand for three periods of time. Considering production and transportation capacity limits, the main objective was to minimize the total lead costs including fixed alliance costs between two companies, production, raw material holding, finished products holding and transportation costs.

Overall, in all of the reviewed studies, not only modeling and simulation has been executed in two separate modules, but also all the applied scenarios were so simple. Owing to this fact, the complexity level of the problem downgrades and it becomes less practical. As a result, one cannot tackle with P-D problems in various levels of detail.
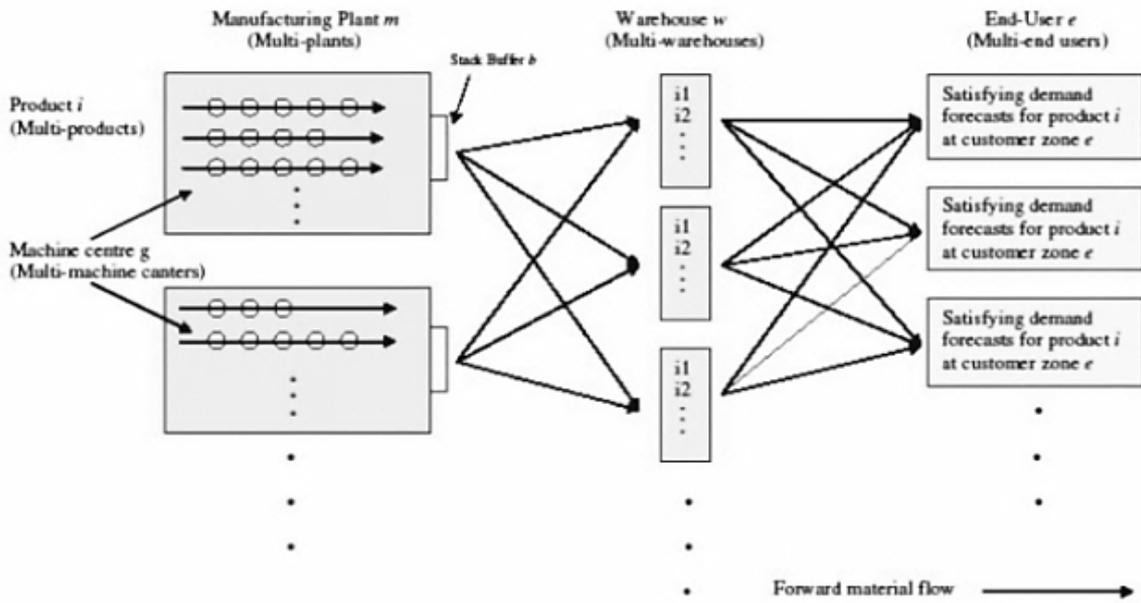
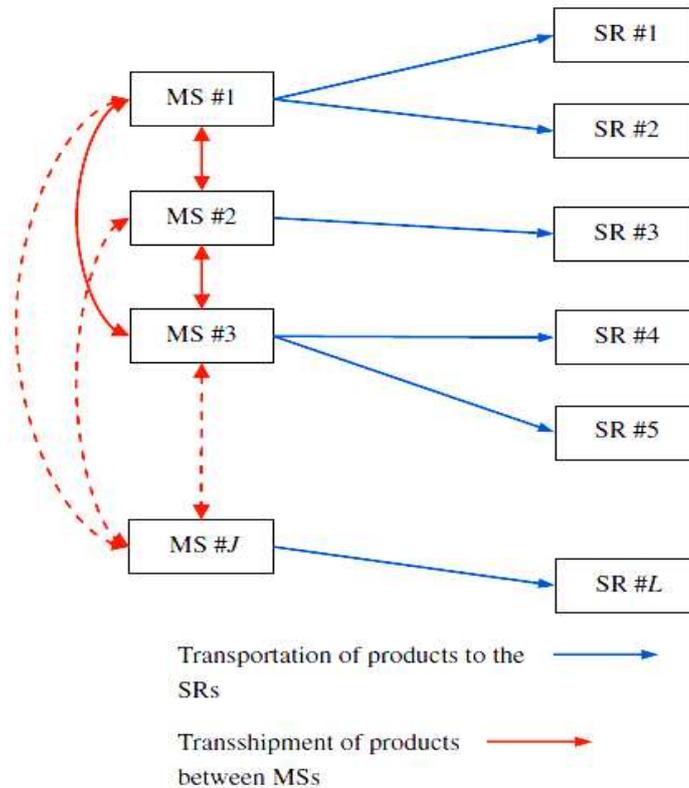**Fig. 8.** The proposed two-echelon supply network (Fahimnia *et al.*, 2009)

Fig. 9. An example of parallel multi-site manufacturing system (Torabi and Moghaddam, 2012)
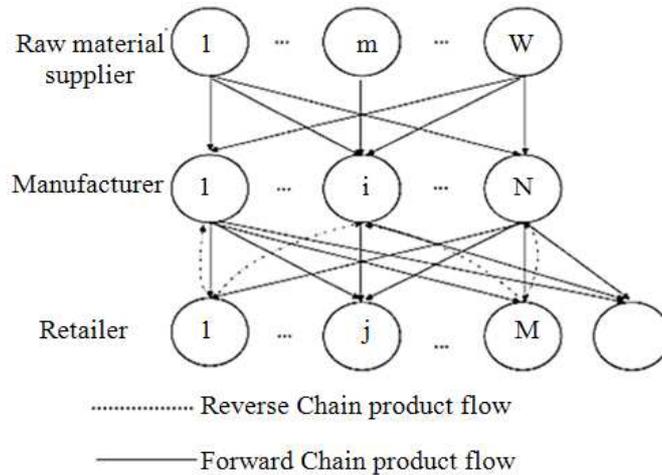
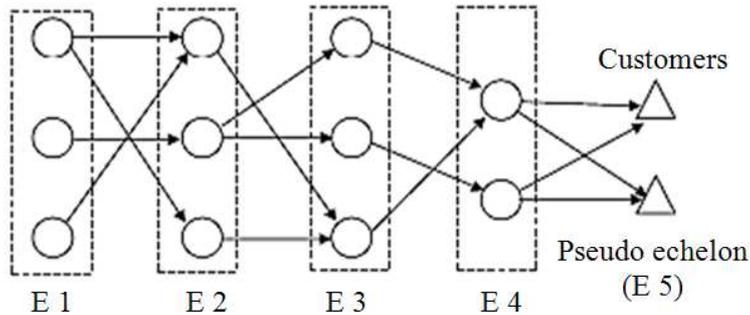**Fig. 10.** Closed-loop supply chain (Qiang *et al.*, 2013)

Fig. 11. Four-echelons supply chain network (Pan and Nagi, 2013)

Also, the possibility of generalizing models with respect to their applicability decreases. This translates into less efficient model. Moreover, granularity has been ignored since the existing problems have not been complex enough to raise its importance.

As it was observed in the literature, a number of potential solutions for this type of problems with similar size and complexity exist. Examples include Chartniyom *et al.* (2007); Mohd-Lair *et al.* (2007); Aliev (2007); Papadimitratos *et al.* (2008); Ferreira *et al.* (2008); Fahimnia *et al.* (2009) and Dellino *et al.* (2010). However, in these examples predominantly one mathematical optimization engine i.e., Genetic Algorithm (GA), Fuzzy Logics, Neural Networks (NNs), Simulating Annealing (SA), Tabu Search (TS) or combination of two of them in conjugation with simulation were utilized. Also, It is notified that in these researches, optimization and simulation are either applied separately in (Dellino *et al.*, 2010; Aliev, 2007;

Papadimitratos *et al.*, 2008) or used distinctly as validation tools (Solon *et al.*, 2009) without considering the granularity of the model (Dellino *et al.*, 2010). Hence, a new methodology will be discussed in this study.

3. PROBLEM STATEMENT

In this section, a Multi-Commodity Consumer Supply Chain (MCCSC) optimization problem is developed. MCCSC is aimed to determine where to locate facilities (DC) and how to allocate customers (R) to facilities so to minimize total costs via non-linear programming techniques with single objective. Due to the large size of the problem on one hand and the uncertain circumstances in finding the most optimum solution on the other hand, integration of modeling and simulation methodologies is utilized. Genetic Algorithm (GA) is deployed as a systematic approach (Holland, 1975) to resolve this issue.

It works based on principles natural selection and genetics to evolve better solutions through multiple consecutive generations. As a global search method, GAs can be used for combinatorial optimization problems where the number of possible solutions increases exponentially with respect to the number of decision variables. The advantage of GAs over similar methodologies is the fact that no information about gradient of the optimized objective function (local minimum/maximum) would be necessary. This is a significant point since acquiring any such information in combinatorial optimization problems is a rigorous task.

4. GASG-METHODOLOGY

GAs as a global search method, when implemented appropriately, will converge to a small set of optimal/near optimal solutions within the last generations. This convergence results in GAs operators to be ineffective through the last generation. This is due to the fact that the chromosomes in the last generations are very similar. Therefore, an evaluator is necessary to ensure quality of the solution. This evaluator can be introduced as a simulation module which is incorporated in conjunction with the optimization process and incorporates the natural variation of the process. An overview of this methodology is depicted in **Fig. 12**.

According to the literature review, it was concluded that the researchers and practitioners are attempting to enhance the decision-making in industrial SCNs toward the optimal developments of infrastructures and planning with uncertainties. However, it is observed that the granularity of problems is greatly ignored in both simulation and evaluation phases. Thus, in this research, the focus would be more on considering granularity as a key issue in optimization of large scale problem in a controlled manner.

Hence, GASG, where the output of modeling phase will be treated as the input of the **S**imulation phase, simultaneously with the control of **G**ranularity will be used as a methodology in developing the model for this study. This translates into ensuring the validity of the solution. In the case of this study, the integrated simulation approach is described to improve the network' total cost using SimEvents-designed to simulate Discrete Event Systems (DES)-that is embedded in Simulink ®. This enables engineers to take advantage of integrating data processing, computing tools and visualization both in MATLAB and Simulink®. More details about how to evaluate the result will be presented in part II -Optimization of Multi-Commodities Supply Chains- GA Application and Results.

GASG optimization paradigm will dominate the following problems:

- An algorithm that does not cover the whole search space
- An algorithm that gets consistently trapped at the local optima

In addition to the above advantages, through GASG the proposed methodology will be successfully implemented. So, an integrated GA optimization engine will validate the quality of the solution simultaneously with a simulation module that is incorporated as fitness function evaluator. In other words, the output variables of optimization problem are considered as simulation model performance measures which are naturally quantitative. Therefore, GA ability to search through the complete set of configurations of the system for a static set of input data will be combined with the simulation's ability to validate any combination of input data for a set of configurations. Finally, through well-defining the granularity that describes the level and the size of the units in the model (Bollen *et al*., 2007) which is a critical decision parameter in the system, optimization/validation will be done.

4.1. Validation of the Proposed Optimization Paradigm

The vast majority of the problems in SCM are solved through deploying the mathematical programming approaches. The mathematical approaches are as: (1) deterministic, (2) stochastic, (3) economic and (4) simulation approaches, (5) Fuzzy-based, (6) scenario-based and (7) hybrid approaches (Lalmazloumian and Wong, 2012).

In this study the proposed optimization paradigm and the quality of the solutions obtained from the previous step will be validated through simulation approach.

Simulation, as a powerful tool is extensively utilized in modeling, analyzing and validating of complex systems. Accurate analysis and visualization of alternatives are also possible through simulation (Tumay, 1995). Supply chain Networks problems are no exception to that. Due to time dependency of this type of problems that make them dynamic, complexity and uncertainty can be analyzed perfectly, by means of simulation tools (Persson and Araldi, 2009).

Discrete-event driven simulation is the most powerful tool to deal with supply chain problems because of the dynamic entity of SNs.
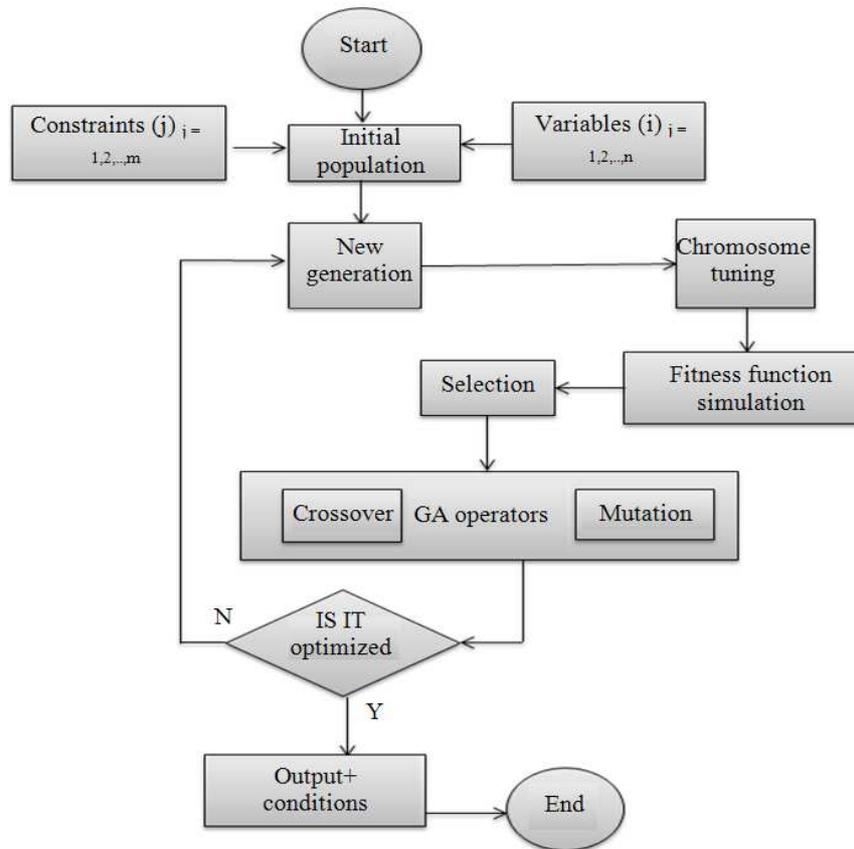
Fig. 12. A framework of GASG methodology

Examples of such simulation tools include: SIMPROCESS (Swegles, 1997), AUTOMODE, ARENA (Persson and Araldi, 2009) and MATLAB (Fahimnia *et al.*, 2012).

SIMPROCESS is a hierarchical modeling tool that combines process mapping, discrete-event simulation and Activity Based Costing (ABC) with a user-friendly interface. AUTOMODE (Automotive Model-Based Development) and ARENA (developed by Rockwell Automation) are well-designed for discrete-event simulation. However, MATLAB software package provides the user with both optimization and Simulation Toolboxes. In this work, the programming part (optimization module using GA) will be generated in MATLAB programming environment (m.file). Subsequently, the output of this step will be treated as the input of simulation through Sim-Event simulation toolbox. The superiority of MATLAB comparing to other existing software packages is a number of

predefined mathematical functions. This feature gives users the capability of retrieving necessary functions to apply mathematical operations on model's equations or inequalities. More details about SimEvents functionality will be explained in part II of this study.

5. THE CASE STUDY PRIMARY SCENARIO

In this section, a typical three layers medium term planning model for a supply chain is presented. These three stages are commonly: Manufacturer (factory), Distribution Center and Retailer. The first and the most upstream stage 1 has one facility (factory) which feeds into stage 2 that is a Distribution Center (DC). As it is shown in **Fig. 13**, it is assumed that finished goods can be delivered either directly from manufacturer to retailer or indirectly form manufacturer to DC and then to retailer.
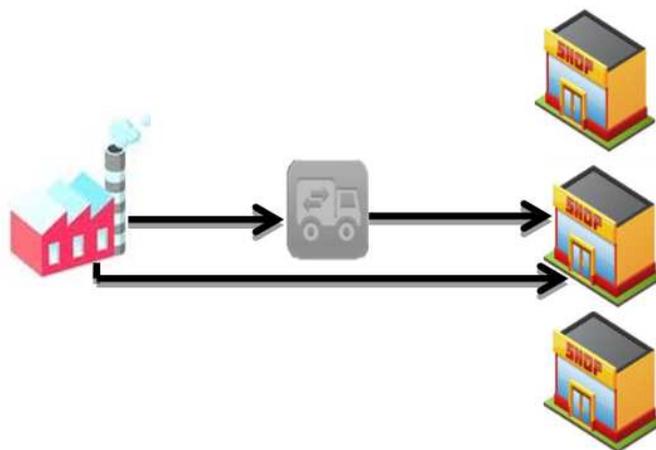
Fig. 13. Three layers supply chain system

Moreover, due to the assumed transportation policies, reverse transportation cycle would also be considered in development procedure of this model.

Also, the number of retailer-zones and demand forecasts for each product is available at end-users. In addition, the number, location and the capacity of DCs are known. The main objective function in this study is obviously the cost function. It minimizes the sum of the following costs:

- Production costs
- Holding costs
- Packaging costs
- Transportation costs
- Retailer variable/fixed costs

More details about the objective function are presented in section 6.

It is assumed that a factory works 24 h (around the clock); so that weekly production capacity available is $24 \times 7 = 168$(hr). Also, there are 10 lines of product families F_1, F_2, …, F_{10}. The demand forecasts for the period of one month (four weeks) are known (e.g., will be randomly generated 100 to 5000). The problem's parameters and input data, the subscripts and superscripts are denoted as bellow:

- The subscript t (t = 1,..,4) refers to week t
- The subscript j (j = 1,..,10) refers to product family j
- The subscript r (r = 1,..,5) refers to retailer r
- The subscript s (s = 1, 2, 3) refers to stage s
  - s = 1 refers to the Manufacturing Unit (MU)
  - s = 2 refers to the Distribution Center (DC) and
  - s = 3 refers to the retailer

- The subscript p refers to production parameters
- The subscript m refers to transportation parameters
- The subscript r refers to operations taken in the store

The demand for product family j = 1,2,…,10, at the manufacturer level (s_1) by the end of week t = 1,…,4, is denoted as D_{1jt}. The demand for product family j = 1,2,…,10, at the retailer level (s_3) by the end of week t = 1,…,4, is denoted as D_{3jt}. Moreover, the product costs and average times are given:

- c_j^p = The cost to produce one unit of family j in the factory
- $\acute{p}_j^p$ = The average time to produce one unit of family j in the factory. (It will be assigned later as the minimum run length of product family j in week t have not been determined yet)

5.1. Objective Functions

As in many supply chain optimization problems is addressed; the main objective function will minimize the aggregate of the following costs: (1) production costs; (2) packaging costs; (3) holding costs; (4) transportation costs- either directly from factory to retailer or indirectly from factory through distribution center to the retailer; (5) backordering costs. As it was mentioned before, it is assumed that all transportation times are identical and equal to 1 week; hence, if y_{2jt} (y_{3jt}) are transported in week t from factory to DC (retailer), then they will be delivered at their destination in week t+1. The same procedure is true once z_{2jt} is transported form DC to retailer. The total system cost will be minimized through the entire planning horizon, using the following objective function (1):

$$\sum_{t=1}^{4}\sum_{j=1}^{10}C_j^p x_{jt} + \sum_{t=1}^{4}\sum_{j=1}^{10}\ddot{C}_{jt}^p x_{1jt} + \sum_{t=1}^{4}\sum_{j=1}^{10}C_{20}^m y_{2jt} +$$

$$\sum_{t=1}^{4}\sum_{j=1}^{10}C_{03}^m y_{3jt} + \sum_{t=1}^{4}\sum_{j=1}^{10}C_{023}^m z_{jt}$$

$$+\sum_{t=1}^{4}\sum_{j=1}^{10}h_{1t}^p q_{2it}$$

$$+\sum_{t=1}^{4}\sum_{j=1}^{10}h_{2t}^p q_{2jt} + \sum_{t=1}^{4}\sum_{j=1}^{10}C_3^r v_{3jt}$$

Transportation cost if indirect delivery method chose; from factory to Distribution Centers (DC) and then to the end-user; is consisted of two sub costs: delivery cost from factory to DC by $\sum_{t=1}^{4}\sum_{j=1}^{10}C_{20}^m y_{2jt}$ and by $\sum_{t=1}^{4}\sum_{j=1}^{10}C_{023}^m z_{jt}$ delivery from DC to the end-user (retailers). Otherwise, if the end products delivered directly by retailer form factory it would only include $\sum_{t=1}^{4}\sum_{j=1}^{10}C_{03}^m y_{3jt}$.

In order to obtain the optimal or near optimum solution of the above equation, the costs in regards to weights and penalty should also be considered. Moreover, subject to the implied conditions, there is a possibility for backordering costs to be considered. The variables in regards to each cost of the objective function are separately identified in the following sections.

5.1.1. Holding Costs

h_{1t}^p = The inventory holding cost in factory for one unit of any type in week t

h_{2t}^p = The inventory holding cost in DC for one unit of any type in week t

hc_{1jt}^p = The holding capacity at factory for product family j in week t

hc_{2jt}^p = The holding capacity at DC for product family j in week t

5.1.2. Packaging Costs

$\ddot{c}_t^p$ = The cost of material for producing one container (with m×n×o dimension) at week t.

l_{1jt}^p = Labor/hour for loading/unloading the container for product family j in the factory at week t.

λ_j^p = Number of units of product family j fitted in the container.

λ^c = The volume of the container

5.1.3. Transportation Costs

w = (1,2,3) refers to the type of truck whether it is small, medium or large respectively.

l_{1wt}^m = labor/hour cost for loading/unloading the containers for any type of products to the trucks w at factory at week t (truck loading and unloading cost of container $/ container).

λ_w^m = The volume/ of truck w.

c_{20w}^m = The cost of moving one unit of any type from factory to DC with truck w.

c_{03w}^m = The cost of moving one unit of any type from factory to retailer with truck w.

c_{023w}^m = The cost of moving one unit of any type from DC to retailer with truck w.

τ = The transportation time from the factory to DC, from the factory to retailer and from the DC to retailer; e.g.; it can be assumed that all transportation times are identical and equal to 1 week.

5.1.4. Retailer Fixed and Variable Costs

c_3^r = Labor/hour cost of container loading/unloading of one unit of any type to the self in the store.

λ_{jt}^r = The capacity of shelf for product family j in week t.

sc_{3jt} = The unit shortage cost of product family j at retailer in week t.

5.1.5. Weight and Penalty Costs

α = The penalty cost of one unit of any type demand shortage

5.1.6. Decision Variables

The objective is to minimize the total production costs, holding costs, transportation cost, tardiness costs (e.g.; lost items, late items …) and the penalty costs for delivery over the planning horizon (e.g.; four weeks). In addition, controlling the granularity factor will be significantly effective in enhancing the optimization procedure:

x_{jt} = Number of units of family j produced at factory during week t.

x_{1j0} = Number of units of family j packed and loaded in the container at factory at time 0.

x_{1jt} = Number of units of family j packed and loaded in the container at factory at time t.

x_{1j4} = Number of units of family j packed and loaded in the container at factory by the end of the planning horizon (week 4).

y_{2jt} = Number of units of family j transported from factory to DC in week t.

y_{3jt} = Number of units of family j transported from factory to retailer in week t.

z_{jt} = Number of units of family j transported from DC to retailer in week t.

q_{2j0} = Number of units of family j being held in storage at DC at time 0.

q_{3jt} = Number of units of family j being held at storage at DC at the end of week t.

v_{2jt} = Number of units of family j that have not yet arrived at DC in week t.

v_{2j4} = Number of units of family j that have not been delivered to DC by the end of the planning horizon (week 4).

$\dot{q}_{2jt}$ = Number of units of family j being left at DC at the end of week t.

$\dot{q}_{2j4}$ = Number of units of family j being left at DC at the end of the planning horizon (week 4).

v_{3j0} = Number of units of family j that have not yet arrived at the retailer at time 0.

v_{3jt} = Umber of units of family j that have not arrived yet at the retailer by the end of week t.

v_{3j4} = Number of units of family j that have not been delivered to the retailer by the end of the planning horizon (week 4).

$\dot{v}_{3jt}$ = Number of units of family j being left at retailer's shelf at the end of week t.

$\dot{v}_{3j4}$ = Number of units of family j being left retailer's shelf at the end of the planning horizon (week 4).

G = Granularity of the problem- the size of the minimum unit transferring through the container.

The focus would on the last 50 m of SC. It deals with all systems, subsystems, activities and information flows from MU; once a product is produced; to DC and from DC to RE. Therefore, based on the orders that have received by DC from RE, the products will transport to DC and allocate to the particular retailer. When an order is preceded an inventory level must be updated and a total cost of the order should be calculated at the end of the net. Minimizing the total cost is a primary objective which leads retailers remains competitive in the global market. For instance, having maximum order and stock levels of 5000 randomly generated the total cost of the entire supply network using equatioan 1 can be calculated which is shown in **Fig. 14 and 15** are illustrating the total costs of the net in 3 dimensions. The number of weeks, products and the costs are denoted as x, y and z coordinates respectively. As it is observed, total cost can be reported in two granular trends: (1) cost of each family product per week and (2) cost of each order per week.
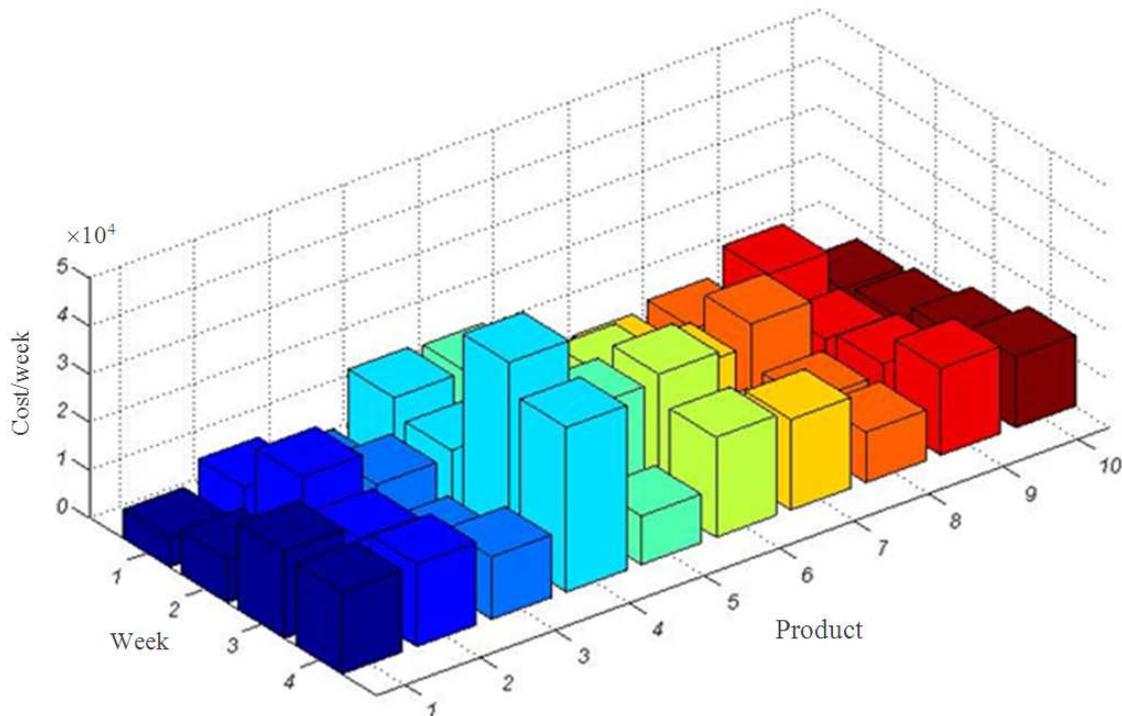

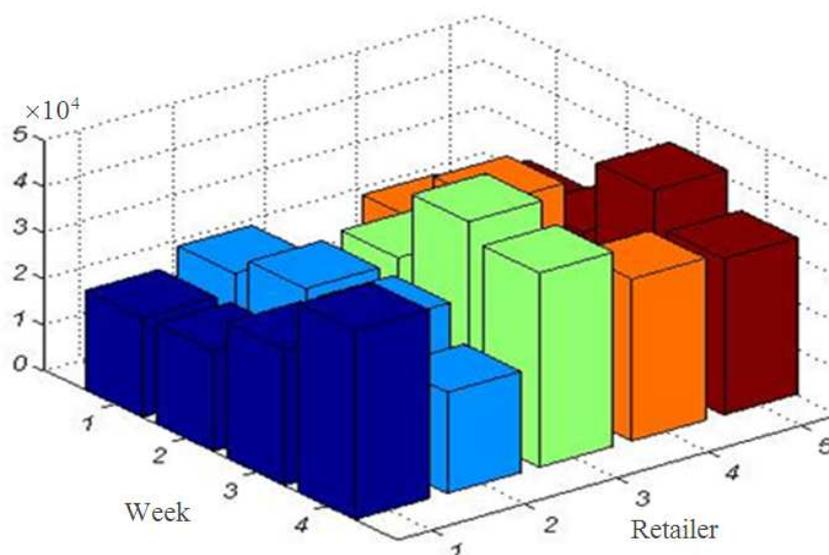**Fig. 14.** Total costs of 10 products/4 weeks

Fig. 15. Total costs of 10 products/5 retailer/4 weeks

6. CONCLUSION

In this study, out of the existing methodologies in addressing MCCSC problems, GASG was selected due to its integrated, appropriate and effective nature. This methodology can be used for optimization of single or multi-objective P-D problems in a controlled environment. It will be capable of being applied on large scale problems with various scenarios. Also, on the basis of the desired application, the problem can be analyzed through different granular levels.

Due to the dynamic nature of SNs, discrete event-driven simulation tool will be used in part II to simulate the system's behavior. There are a number of well-designed simulations tools such as SIMPROCESS, AUTO MODE, ARENA and MATLAB® used in SC model simulation. Since MATLAB® provides the user with optimization and simulation (SimEvents and Simulink) toolboxes, as well as user-friendly interfaces for data evaluation; it will be utilized for the purpose of predicting the outputs of the given strategy. He programming part will be executed in C packaging language linked with MS Excel as the programming interface. C-Programming language is the most popular middle language used in implementation of business oriented applications and easy to compile in any operating systems. Numerical results will also be provided in part II. In order to validate the robustness of the algorithm, historical data of the SC and demand forecast will be collected from the local supplier. Finally, the developed program will be applied on it to optimize the entire SCN for the midterm planning horizon.

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