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A SIMULATION-BASED OPTIMIZATION APPROACH TO INTEGRATED CASH AND MATERIAL FLOW PLANNING WITHIN A SUPPLY CHAIN

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ABSTRACT

The aim of this research is to develop a simulation-based optimization (SBO) approach in order to model the material and cash flow planning decisions through a supply chain. SBO approach composed of both simulation and optimization models which transform information repetitively until optimal solution sets are achieved. Particularly, in this research, system dynamics (SD) and multi-objective optimization are used as simulation and optimization techniques, respectively. The proposed SBO model is seeking to minimize total cost and cash conversion cycle whilst maximizing inventory turnover of supplier and manufacturer. The developed model is implemented in Powersim studio 10 which contributes integrated modeling of hybrid simulation-optimization models. The data of a wheel rig supply chain employed to validate the proposed SBO model. Pareto optimal solutions are provided by the aid of genetic algorithm. The results show that SBO yields to considerably better solutions in comparison to SD modelling approach.

Keywords: Genetic algorithm, Multi-objective optimization, Simulation-based optimization, Supply chain management, System dynamics

State of the literature

- Simulation-based optimization is a hybrid approach which is applied for various decisions in supply chains
- Optimization techniques are used for finding optimal planning decisions in supply chains
- System dynamics is utilized for modeling of dynamism and interrelationships through the supply chains

Contribution of this paper to the literature

- This study considers cash and material flow through the supply chain, simultaneously
- Simulation-based optimization is employed in order to deploy advantages of system dynamics and multi objective optimization approaches
- The proposed hybrid approach diminishes time required for acquiring optimal solutions, remarkably.

INTRODUCTION

Supply chain optimization is crucial for manufacturing companies to retain economic viability in the current highly competitive global marketplace (Grossmann, 2005; Neiro & Pinto, 2004; Wassick et al., 2012). The complex networks of supply chains are composed of several actors that strive toward different purposes which in most cases are in conflict with each other. Due to multiple performance measures, supply chain decision making is much more complex than treating it as a single objective optimization problem (Aslam et al., 2011). The optimization of supply chains often addresses the situation in which the interest is to find sets of model specification that lead to optimal output performance(April et al., 2003).

The supply chain network is represented by various facilities such as suppliers, manufacturers, distributors, and retailers and different flows (i.e. financial, information and material flows) connecting these facilities. Due to significant interactions between financial and material flows, it is necessary to consider the simultaneous optimization of these flows as well as inventory planning decisions in order to achieve an effective solution. The problem studied in this research is an integrated financial and material flow optimization problem in a wheel ring supply chain. The goal is to minimize holding and backlog cost as well as reducing cash conversion cycle while maximizing inventory turnover. However, the complexity of integrated planning imposes significant computational load into mathematical programming models. This drawback has motivated the researchers to use system dynamics (SD) which is able to capture the dynamic behavior of the concerned system and model the nonlinear interrelationships between the system elements. However, SD as a descriptive decision making tool can only simulates the system's behavior for each distinct policy and/or scenario and is unable to find the optimum decisions and policies. To be benefited from the advantages of both descriptive (e.g. SD) and prescriptive (e.g. mathematical optimization) decisions making tools while preventing the shortcomings of them, the simulation-based optimization approach is introduced in the recent literature. Simulation- based optimization (SBO) is an emerging field which integrates optimization methods into simulation analysis (Nikolopoulou & Ierapetritou, 2012).By the aid of this methodology decision maker can conveniently approach the complex problems such as the one studied in this research without concerning about the shortcomings of traditional optimization and simulation methods.

In this paper a novel SBO framework is proposed for integrated optimization of financial and material flows within a supply chain. In the developed approach SD modelling is used as an effective simulation engine which is able to simulate the future behavior of the complex systems based on its inherent casual-loop structure. On the other hand a multi-objective optimization model is employed as an efficient optimization engine in the proposed framework in which the optimum decision is found and prescribed to decision maker. To demonstrate the efficiency of the developed approach, the method is applied to a cost, cash conversion cycle minimization and inventory turnover maximization problem in a real-life supply chain system and the results are compared with those generated by scenario making in traditional system dynamics model.

The remainder of the paper is organized as follows. Literature review on analytical and simulation approaches as well as the hybrid simulation-optimization methodologies employed in the area of supply chain planning problems is given in Section 2. Section 3 presents the developed simulation-based optimization model including the SD and mathematical programming sub-models. The usefulness of the proposed SBO model is investigated through Section 4 by the aid of the data extracted from the studied case. Finally, Section 5 concludes this paper as well as defining some general future research directions.

Literature review

Supply chain planning problems have been modeled by both analytical-based and simulation-based methods in addition to hybrid approaches. This section, presents a number of important research works existed in the relevant literature based on the aforementioned categories.

System dynamics models for supply chain management

Since system dynamics is known as an efficient approach which can appropriately consider the supply chain complexities, researchers have used this descriptive method for variety of supply chain planning decisions. Hafeez et al.(1996) pointed out that SD is an efficient tool to model supply chain management problems. They propose a SD model for identifying the optimal inventory policies in a steel supply chain network.

A large number of applications on SD modeling published in the literature are related to bullwhip effect and the strategies used to decreasethis phenomenon across the supply chain. Berry & Naim (1996) developed a SD model of a PC supply chain for modeling of bullwhip effect and proposed information sharing as an efficient tool for decreasing mentioned effect. Anderson et al.(2000) presented a SD model for modeling of bullwhip effect in machine tool supply chain and stated demand volatility decreases efficiency of workforce; therefore, companies must seek suitable policies for demand forecasting. Disney & Towill (2003)introduce E-commerce as an effective tool for decreasing bullwhip effect in supply chain. Another popular issue which has been modeled by SD is inventory planning/management. Larsen et al., (1999) recognized optimal policies for inventory management in case of a European restaurant supply chain. Inventory planning/ management in manufacturing supply chains is examined by (Helo, 2000; Holweg & Bicheno, 2002; Minegishi & Thiel, 2000). Naim (2006) by considering time value of money describes a SD model for inventory planning in supply chain. SD modeling is also utilized for strategic issues in supply chain. Disney & Towill (2002) design structure of a vendor managed inventory supply chain. Vlachos et al.(2007) present a SD model for a closed-loop supply chain and evaluate long-term policies of capacity planning by profitability indexes. Hybrid modeling of SD and fuzzy approach is also used for supply chain modeling. Wangphanich et al., (2010) propose a hybrid

SD-Fuzzy approach for modeling of a beverage supply chain in which demand is forecasted by fuzzy approach.

Optimization approaches for supply chain management

Most of the models have been proposed for SCM formulation are in the form of mixed integer programming (MIP) models with several assumptions (Yan et al., 2003). Azaron et al. (2008) propose a MINLP model for supply chain configuration under uncertainty. The objective functions include minimizing total cost and financial risk. Goal attainment technique is utilized for acquiring Pareto-optimal solutions. Yimer & Demirli (2010) present a MILP model with the purpose of minimizing aggregate costs whilst maximizing the customer satisfaction. The authors used a genetic algorithm (GA) to solve the problem. Altiparmak et al.(2006) describe a MILP model for designing a plastic products supply chain. The objective of study was to minimize total cost also maximize the customer service level and the capacity utilization balance for the distribution centers. The authors compared the performance of the proposed GA with a simulated annealing algorithm, and results showed that GA outperformed SA with regard to quality of Pareto- optimal solutions. Pishvaee et al.(2010) present a MINLP model for configuration of a closed-loop supply chain in order to minimize total cost and maximize responsiveness of forward and reverse networks. Multi-objective memetic algorithm (MOMA) is used to solve the model. According to importance of sustainable development, Pishvaee et al. (2014) propose a multi-objective possibilistic programming model to cope with sustainable supply chain network design under uncertainty. They have also developed a Benders decomposition algorithm to solve the model. For an overview of issue, challenges and optimization opportunities present in manufacturing supply chain systems, the reader can consult with Aslam et al. (2011).

Hybrid approaches for supply chain management

Unfortunately, using simulation alone is not sufficient to provide optimal solutions, therefore, simulation is not a real optimization tool and an extra step is needed- a step that incorporate simulation and optimization (Fu et al., 2005). This technique, as we know, is SBO, whereby simulation models are integrated with meta-heuristic search algorithms. SBO is the process of obtaining optimal system settings from sets of decision variables, i.e., input parameters, where the objective functions are evaluated through the output results of the simulation model (Ólafsson & Kim, 2002). Komoto et al.(2011) propose a hybrid simulation-optimization approach for supply chain configuration problem in which discrete event simulation (DES) and multi objective optimization are integrated to minimize the total cost and environmental impacts while maximizing the delivery performance. A genetic algorithm is used to generate the corresponding Pareto optimal solutions. Ding et al., (2005) develop toolbox ONE comprises simulation and optimization models of enterprise networks of automotive and textile industry. Ding et al., (2008, 2009) propose a simulation optimization methodology composed of GA and DES for design of production-distribution network in textile and automotive supply chains, respectively. Duggan (2008)demonstrates the applicability of combining SD and MOO. He presents a simplified version of the well-known beer game developed by Sterman(1989). In this study, a two echelon supply chain, consisting of a wholesaler and a retailer, is modeled. The aim of the optimization is to investigate the trade-offs between the two conflicting minimization objectives: wholesaler cost and retailer cost that is solved by GA. Aslam et al.(2014) combines SD and MOO for inventory management problem in a manufacturing supply chain. MOO consists of minimization of work in process (WIP) and work in process coverage as well maximizing delivery rate. Author uses NSGA- II algorithm for problem solving.

The review of the literature shows that most of the works in the area of supply chain planning only consider the material flow through the supply chain while cash flow which plays a crucial role in the performance of SCs is usually ignored. The optimization approaches in the literature are unable to appropriately model the dynamism and complex nonlinear relationships through the supply chain. On the other hand the SD based models which can consider the complex relationships are not capable to find the optimal decisions and policies. Here, a SBO framework is proposed to cope with a tactical-level supply chain planning problem considering both the material and cash flow simultaneously. The proposed SBO model employed a SD model beside an optimization model and is capable to handle complex nonlinear relationships while finding the optimum planning decisions.

Supply chain planning problem definition and formulation

The problem of supply chain management arises a supplier provides a product to the production site which supplies market with unspecified demand quantity of final product. The challenge is to determine unit cost, sales price, inventory adjustment time and production preparation time for supplier and manufacturer to use so as to minimize inventory cost (contains holding and backlog costs) and cash conversion cycle, which is the average days required to convert a rial (Iran's currency) invested in raw material into a rial collected from a customer, while maximizing inventory turnover for mentioned members.

The origin for all activities in the supply chain is the predefined probabilistic demand of the market which is a uniform distribution function between 900,000 to 1,200,000 products per season. The supply chain network is order-driven, meaning that the production of product occurs only when supply chain entity requests it. The supplier is used as source for steel rolls, which is then transformed into final product at production site. Production site can store excess amount of products at warehouse to satisfy unforeseen orders. The members in the supply chain network and the information, material and cash flow examined in this work are illustrated in Fig.1.

In model developed, unsatisfied demand is assumed to be carried over to the next planning period (backlog) and also partial order fulfillment is allowed. We assume that limited supply of products from production site is available and holding and backlog costs within given time planning period (daily) are known. The shipping delays in the network are taken into account in production rate of supplier and manufacturer.

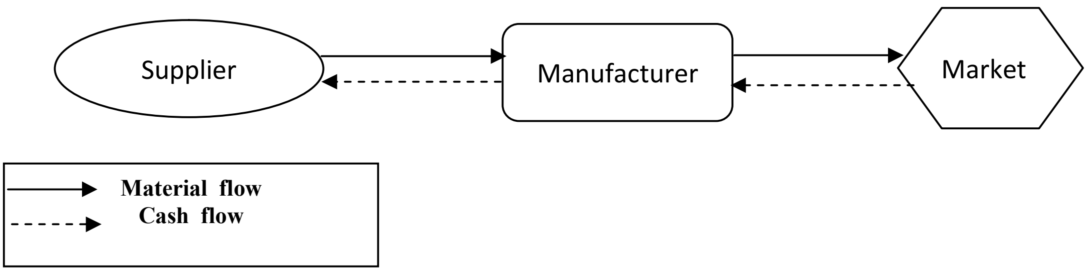

Fig. 1. The structure of concerned supply chain network

Optimization model

An integrated production and financial planning optimization model of the entire supply chain was developed. Given the seasonal demand for manufacturer, the goal of the integrated production and financial planning problem is to ascertain (i) unit cost (ii) sales price (iii) production preparation time and, (iv) inventory adjustment time for supplier and manufacturer, so that conflicting objectives are satisfied over the planning horizon.

The objective of the integrated problem is to minimize inventory cost and cash conversion cyclealso maximize inventory turnover for members individually. The multi objective model includes production and financial constraints of supplier and manufacturer. The extended integrated multi objective model is as follows.

$$\textit{Obj. Fun.} \quad Min(SCC), Min(MCC), Min(SCCC), Min(MCCC), Max(IT), Max(IT1) \tag{1}$$

Subjectto:

$$\alpha_1 \leq PPT \leq \alpha_2 \tag{2}$$
$$\alpha_3 \leq MPT \leq \alpha_4 \tag{3}$$
$$\beta_1 \leq SIAT \leq \beta_2 \tag{4}$$
$$\beta_3 \leq MIAT \leq \beta_4 \tag{5}$$
$$\gamma_1 \leq SPU \leq \gamma_2 \tag{6}$$
$$\gamma_3 \leq SPU1 \leq \gamma_4 \tag{7}$$
$$\delta_1 \leq UC \leq \delta_2 \tag{8}$$
$$\delta_3 \leq UC1 \leq \delta_4 \tag{9}$$

The objective functions shown in Eq. (1) minimize total costs which includes holding and backlog cost, cash conversion cycle as well maximizes inventory turnover of supplier and manufacturer. The production and financial parameters, which are exogenous parameters of SD model, are modeled by constraints (2) –(9). Eq. (2) and Eq. (3) define feasible intervals of production preparation time for supplier and manufacturer, respectively. Limitation of inventory adjustment time for supplier and manufacturer are described by Eq. (4) and Eq. (5), severally. Eq. (6) and (7) describe feasible intervals of sales price for supplier and manufacturer, respectively. Eq. (8) and Eq. (9) represent severally limitation of unit cost for manufacturer and supplier.

System dynamics model

The first step in the modeling process of SD approach is to construct the causal diagrams. Strong interrelationships between variables causes a loop in which variables influence one another (Özbayrak et al., 2007).

There are two loops in Fig. 2, one controlling the inventory and the second one controlling the backlog of orders for supplier. Both loops show that the manufacture inventory has a counteractive effect on the manufacturer inventory adjustment. Therefore, when inventory is low the inventory adjustment will be high. Other represented variables have positive influence on each other which finally leads to counteracting loops which hold balance in backlog and inventory level for supplier. The same loops exist for manufacturer.

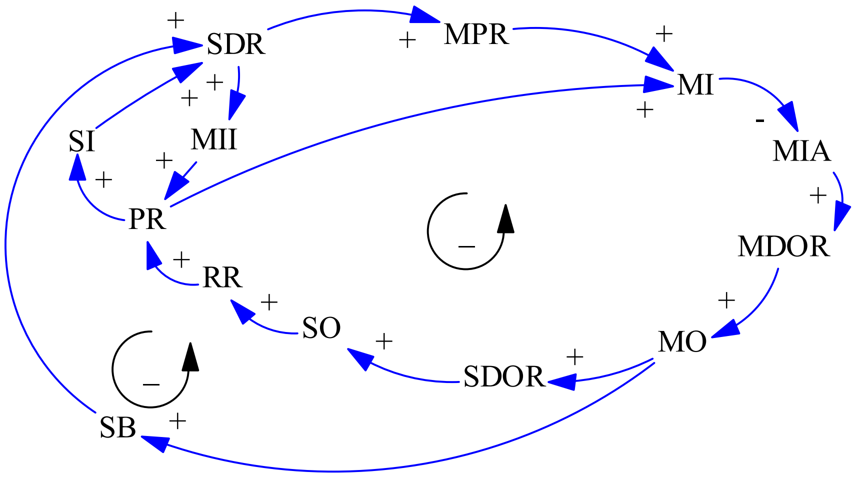

Fig. 2. Supplier-manufacturer influence diagram

We develop the SD model of a wheel rig supply chain including supplier and manufacturer. In SD discipline, the model is presented as a stock-flow diagram that captures interrelationships among the variables (Sterman, 2000). The stock-flow diagram is translated into a system of differential equations, which is then solved via numerical simulation (Georgiadis & Michaloudis, 2012). The embedded mathematical equations are divided into state equations, which integrate the net flow into a stock, and rate equations, explaining the inflows and outflows among the stocks as functions of time. Fig. 3, illustrates stock-flow diagram of wheel ring supply chain. The SD model is developed using Powersim Studio 10 software package and consists of two modules: manufacturing model module (which contains material flow and inventory cost objective function); and financial model module (which contains cash flow as well cash conversion cycle and inventory turnover objective functions).

Table 1. Notations used in the optimization and SD models

Notation	Definition	Notation	Definition
CD	Customer demand	PPT	Production preparation time
SDOR	Supplier desired order rate	MPT	Manufacturer preparation time
MDOR	Manufacturer desired order rate	SDR	Supplier delivery rate
SO	Supplier order	MDR	Manufacturer delivery rate
MOR	Manufacture order rate	PR	Production rate
RR	Receive rate	MPR	Manufacturer production rate
SRM	supplier raw material	SI	Supplier inventory
MII	Manufacturer in transit inventory	MI	Manufacture inventory
SB	Supplier backlog	COGSR	Cost of goods sold rate
MB	Manufacturer backlog	SIAT	Supplier inventory adjustment time
SIA	Supplier inventory adjustment	DSI	Desired supplier inventory
SNI	Supplier net inventory	StoC	Stockout cost
Stc	Stock cost	SCC	Supplier cumulative cost
SDOR	Supplier desired order rate	SPU	Supplier sales price per unit

UC	**Unit cost**	**SAR**	**Supplier accounts receivable**
SRE	**Supplier revenue**	**SIV**	**Supplier inventory value**
MP	**Manufacturer price**	**SDIO**	**Supplier days inventory outstanding**
SAP	**Supplier accounts payable**	**COGS**	**Cost of goods sold**
SDPO	**Supplier days payable outstanding**	**SCCC**	**Supplier cash conversion cycle**
IT	**Inventory turnover**	**SDSO**	**Supplier days sale outstanding**

In SD models, the general mathematical representation of stocks and flows is given by the following equations:

$$\boldsymbol{Stock(t)} = \int_{\boldsymbol{t0}}^{\boldsymbol{t}} [\boldsymbol{Inflow(t) - outflow(t)}]\boldsymbol{dt} + \boldsymbol{Stock(t0)} \quad \textbf{(10)}$$

$$\boldsymbol{Inflow(t), Outflow(t)} = \boldsymbol{f(Stock(t), E(t), P)} \quad \textbf{(11)}$$

Where, E any exogenous variables and P system parameters.

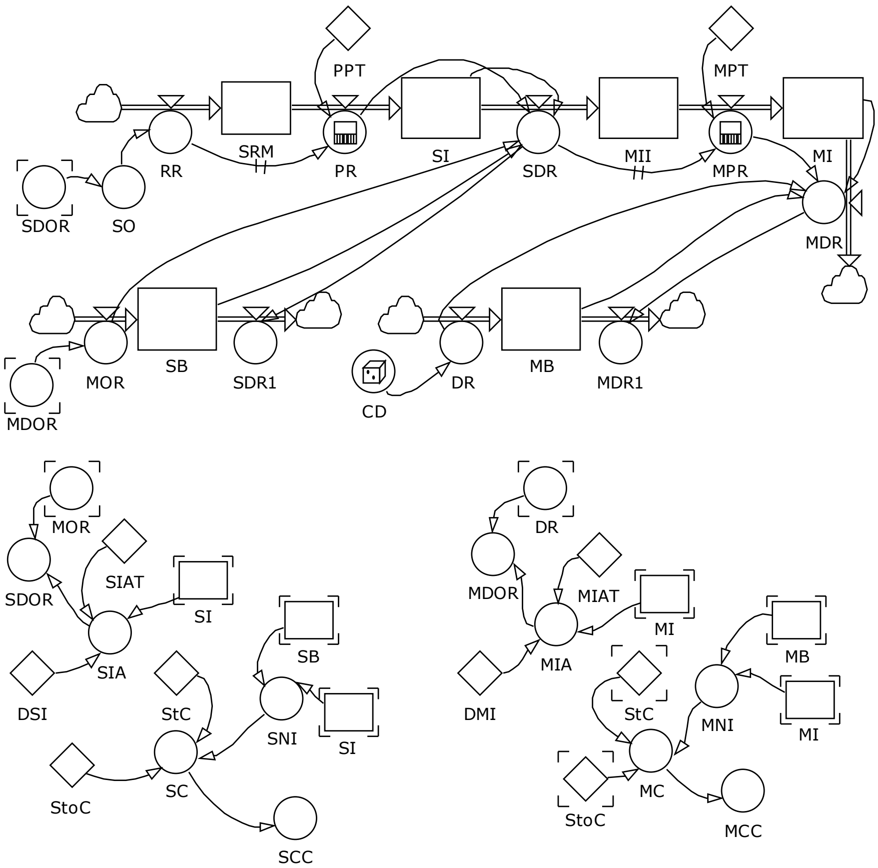

Fig. 3. Stock and flow diagram forproduction model

Equations of manufacturing model are presented as follow:

SO=Max(SDOR,0) **(12)**

PR=DELAYMTR(RR,PPT,1,900000) **(13)**

MOR=Max(MDOR,0) **(14)**

MPR=DELAYMTR(SDR,MPT,1,900000) **(15)**

SB=SDR-MOR **(16)**

MB=MDR-DR **(17)**

CD=RANDOM(900000,1200000,0.3) **(18)**

$$SIA=\frac{DSI\text{-}SI}{SIAT} \quad (20)$$
$$SNI=SI\text{-}SB \quad (21)$$
$$SCC=IF(SNI>0, SNI*StC, ABS(SNI)*StoC) \quad (22)$$

According to Fig. 3, supplier places order to upper level (ironstone suppliers) that is defined in Eq. (12) Supplier order is determined by supplier desired order which is explained in detail in the following. Thereafter, supplier produces steel rolls with a rate is described in Eq. (13) and satisfies manufacture order which is calculated in Eq. (14). Manufacture produces final product with a rate is represented in Eq. (15). Both supplier and manufacturer have backlog which is calculated from difference of order rate and delivery rate in Eq. (16) and Eq. (17), respectively. Customer demand is defined by Eq. (18). As shown in Eq. (20) supplier inventory adjustment is determined by inventory gap (difference of desired inventory and inventory) divided by inventory adjustment time. Supplier net inventory is calculated from difference of supplier inventory and supplier backlog in Eq. (21). Then Eq. (22) calculates cumulative cost (which is tried to be minimized) by multiplying stock or stockout cost by supplier net inventory.

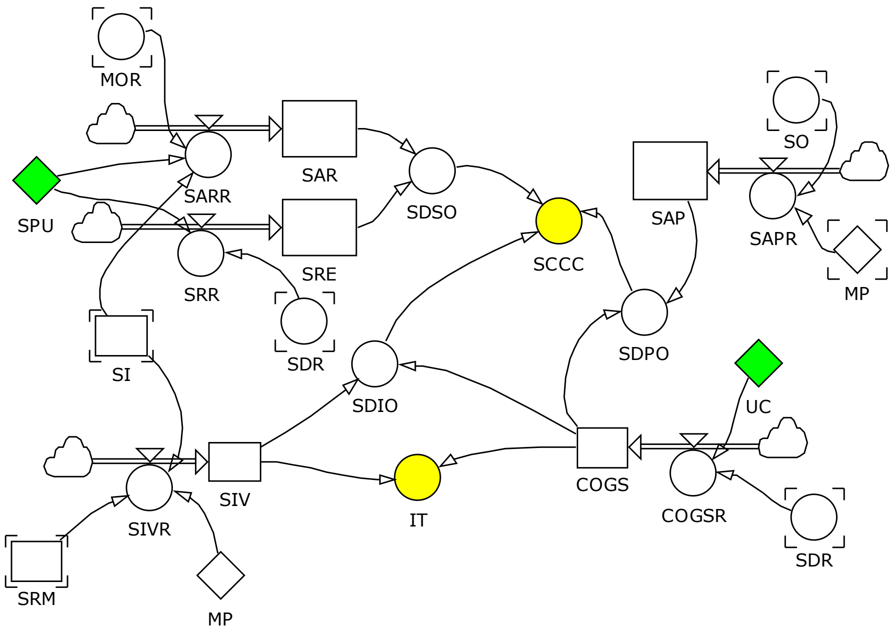

Fig. 4. Stock and flow diagram for financial model of supplier

Equations of financial model are as follow:

$$SARR=Min(SPU*MOR, SPU*SI) \quad (23)$$
$$SRR=SPU*SDR \quad (24)$$
$$SIVR=(SPU*SI+MP*SRM) \quad (25)$$
$$SAPR=MP*SO \quad (26)$$

$$COGSR=UC*SDR \tag{27}$$

$$SDSO=\frac{SAR}{\frac{SRE}{365}} \tag{28}$$

$$SDIO=\frac{SIV}{\frac{COGS}{365}} \tag{29}$$

$$SDPO=\frac{SAP}{\frac{COGS}{365}} \tag{30}$$

$$SCCC=SDIO+SDSO-SDPO \tag{31}$$

$$IT=\frac{COGS}{SIV} \tag{32}$$

According to Fig. 4, supplier accounts receivable rate which is a minimum function of multiplication of sales price per unit by supplier delivery rate and manufacturer order rate is determined in Eq. (23). As shown in Eq. (24) supplier revenue rate is calculated by multiplying sales price per unit by supplier delivery rate. As, supplier inventory includes raw material and steel rolls inventory, supplier inventory value rate is determined by sum of raw material and products value in Eq. (25). Supplier accounts payable is calculated from multiplying supplier order by raw material price in Eq. (26) Cost of goods sold is defined by Eq. (27) from multiplying unit cost of a single product by supplier delivery rate.

Cash conversion cycle, which is tried to be minimized, is defined by Eq. (31) is calculated by sum of days sales outstanding and days inventory outstanding which are given by Eq. (28) and Eq. (29)minus days payable outstanding which is defined by Eq. (30). By Eq. (32) inventory turnover, which is tried to be maximized, is determined by cost of goods sold divided by inventory value. The same financial model exists for manufacturer.

Proposed simulation-based optimization approach

The idea in this paper is to illustrate efficiency of SBO for the solution of the SCM problem in comparison with SD approach. As previously described, SBO consists of building independent optimization and simulation models of the supply chain and integrating the solution strategy. The connection of the two models is shown in Fig. 5. In this work, we first initialize the optimization model and use its output (parameter values) as an input to the simulation model. Then, the output of simulation model (values of optimization objectives) is fed to the optimization model and this procedure continues iteratively until desired results are obtained or in other words, stop criterion is fulfilled.

The coupling of the multi objective optimization model with the simulation model is achieved through the following variables: (i) production preparation time (PPT, MPT), (ii) inventory adjustment time (SIAT, MIAT), (iii) unit cost (UC, UC1), (iv) sales price per unit (SPU, SPU1), (v) cumulative cost (SCC, MCC), (vi) cash conversion cycle (SCCC, MCCC), (vii) inventory turnover (IT, IT1). According to Fig. 5, procedure is started by generating an initial solution for the first four solution sets which are exogenous variables of SD model then simulation is run and objective functions are determined and fed into optimization model. Considering initial values, the algorithm then generates a new set of decision variables for evaluation. This process is iterated until stop criterion (generating 300 generation which equals 4360 simulation run) is fulfilled. Finally, optimal solution sets are presented at the end of process.

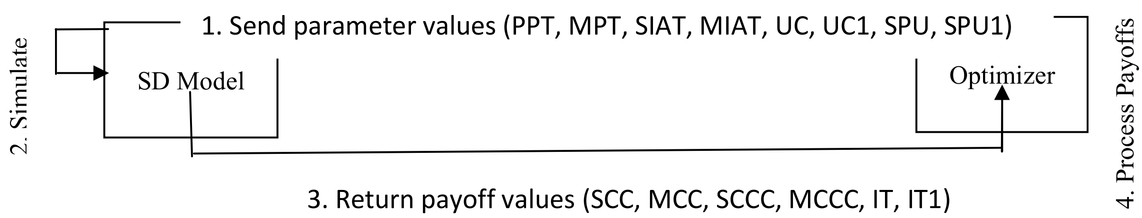

Fig. 5. Simulation-based optimization procedure

Model implementation and evaluation

In this section, the proposed SBO and SD approaches are applied to a small scale supply chain management problem. The supply chain network in this work contains a supplier who provides early product (steel rolls) to a production site. The production site transforms steel rolls into final product (wheel rig) and delivers to market (an automobile manufacturer). The early products are stored until an order from the production site is received and early products are then delivered. Production site can order early products from supplier and then store it in an input storage. Early products are transformed into final products which are stored in order to be delivered to market (automobile manufacturer). The market has a predefined demand rate which is a uniform distribution function between 900,000 to 1,200,000 final products per season. The delivery of final product from the production site is generated by the predefined market demand.

The optimization model is a multi- objective optimization includes six objective functions and boundaries of parameter values which are illustrated through Eq. (33) - (41). The eight parameter values boundaries have been determined at experts and managers consensus sessions based on their subjective knowledge. According to Saipa Wheel rig (SWC) and Isfahan Mobarakeh Steel (IMS) managers opinions, equal weights are given to objective functions. Powersim studio 10 software is used to implement the model and solution approaches and all the empirical experiments are carried out by a Pentium dual-core 2.66 GHz computer with 4 GB RAM.

$$\text{Obj. Fun.} \quad Min(SCC),\ Min(MCC),\ Min(SCCC),\ Min(MCCC), Max(IT),\ Max(IT1) \tag{33}$$

Subject to:

$$2 \leq PPT \leq 4 \tag{34}$$

$$1 \leq MPT \leq 2 \tag{35}$$

$$7 \leq SIAT \leq 30 \tag{36}$$

$$3 \leq MIAT \leq 30 \tag{37}$$

$$139000 \leq SPU \leq 142000 \tag{38}$$

$$216000 \leq SPU1 \leq 219000 \tag{39}$$

$$127000 \leq UC \leq 130000 \tag{40}$$

$$205000 \leq UC1 \leq 212000 \tag{41}$$

As it is obvious, SD is a scenario-based approach which is seeking to find optimal solutions by experimenting different scenarios. Drawbacks of SD approach can be enumerates as (i) considerable time required for scenario making and experimenting (ii) incapability in experimenting possible scenarios when variables are continuous. Considering mentioned drawbacks, using SBO approach which excludes mentioned drawbacks seems inevitable. Some of solutions generated by SBO approach and SD scenario making are presented in Table 2 and Table 3. As it is obvious, SBO has generated more suitable solutions in shorter time comparing SD. Moreover, Objective functions values of 24 solution sets generated by SD and SBO are compared in Fig. 6 –11. According to Fig. 6 –7, supplier and manufacturer costs fall dramatically by using SBO methodology. Optimal values of cash conversion cycle, which is tried to be minimized, and inventory turnover, which is tried to be maximized, for both members is illustrated in Fig. 8 – 11. Considering Fig. 6 –11, Show that solutions were generated by SBO fulfil objective functions more effectively in comparison with SD solutions also SBO solutions are less volatile while SD solutions fluctuate significantly.

Table 2.Model input parameters

Parameter name	Solution 1		Solution 2		Solution 3		Solution 4	
	SD	SBO	SD	SBO	SD	SBO	SD	SBO
PPT (day)	2	2.15	2	2.47	2	2.31	3	2.39
MPT (day)	1	1.46	1	1.52	2	1.68	2	1.51
SIAT (day)	10	13.12	20	10.16	10	11.26	20	10.8
MIAT (day)	7	22.08	15	19.75	15	16.6	7	20.28
SPU (rial)	139,130	140,999	139,130	140,511	139,130	139,974	139,130	140,695
UC (rial)	128,000	127,840	128,000	128,510	128,000	129,767	128,000	128,953
SPU1(rial)	216,536	216,924	216,536	217,858	216,536	216,287	216,536	218,100
UC1(rial)	209,632	208,753	209,632	208,488	209,632	207,975	209,632	209,230

Table 3. Objective functions

Objective function	Solution 1		Solution 2		Solution 3		Solution 4	
	SD	SBO	SD	SBO	SD	SBO	SD	SBO
SCC (m rial)	1580	19	1067	2	1164	5	7237	13
MCC (m rial)	3532	23	1703	11	248	0.3	1458	17
SCCC (day)	- 65.63	-73.40	-78.93	-67.24	-67.28	-69.16	-60.01	-68.55
MCCC(day)	61.81	25.78	29.26	27.67	43.69	33.10	37.99	26.61
IT (m rial)	4.05	4.19	4.45	3.90	4.09	4.07	3.50	3.99
IT1 (m rial)	1.38	1.43	1.48	1.42	1.35	1.39	1.36	1.43

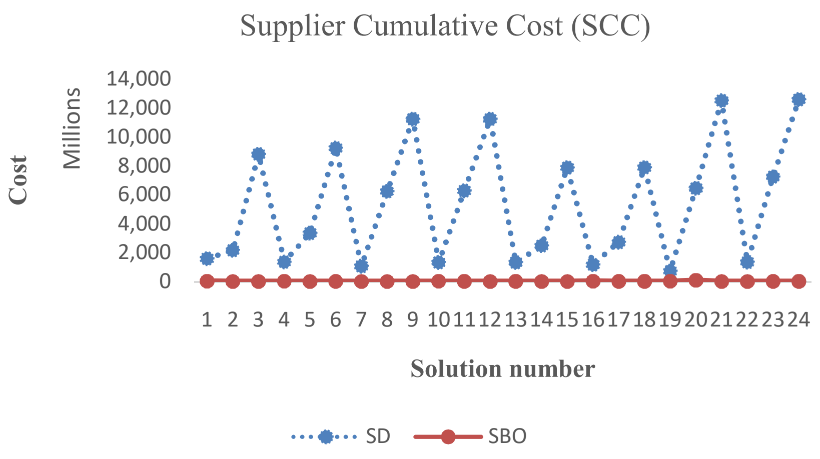

Fig. 6. Comparing SD and SBO for SCC minimization

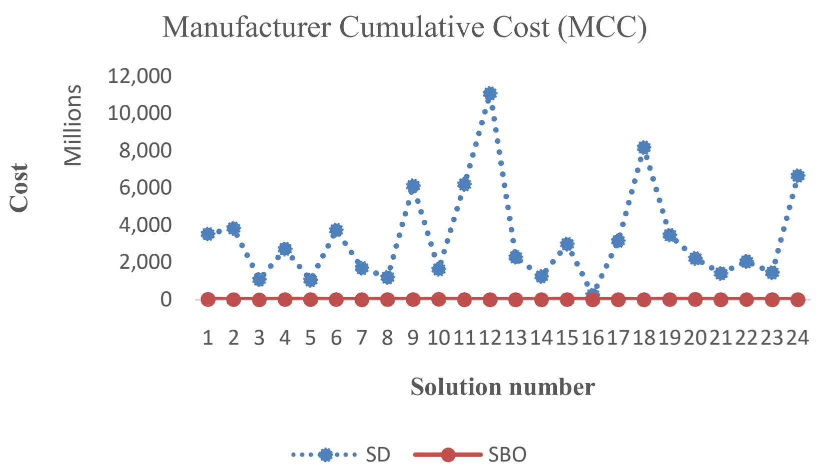

Fig. 7. Comparing SD and SBO for MCC minimization

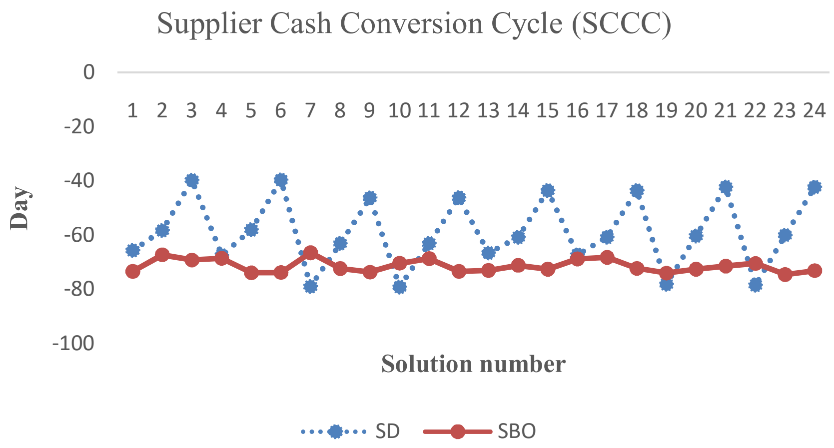

Fig. 8. Comparing SD and SBO for SCCC minimization

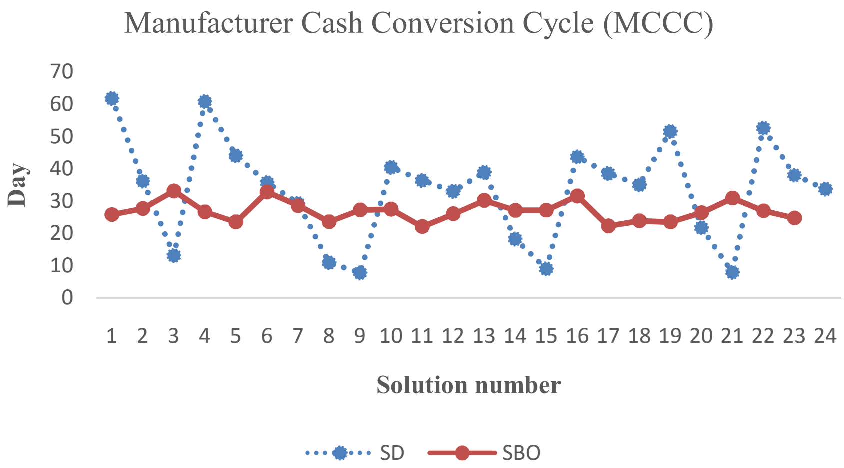

Fig. 9. Comparing SD and SBO for MCCC minimization

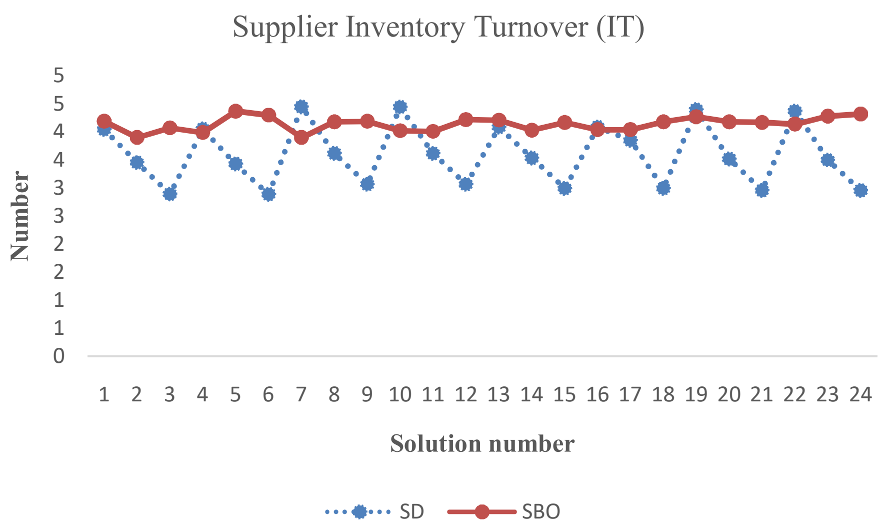

Fig. 10. Comparing SD and SBO for IT maximization

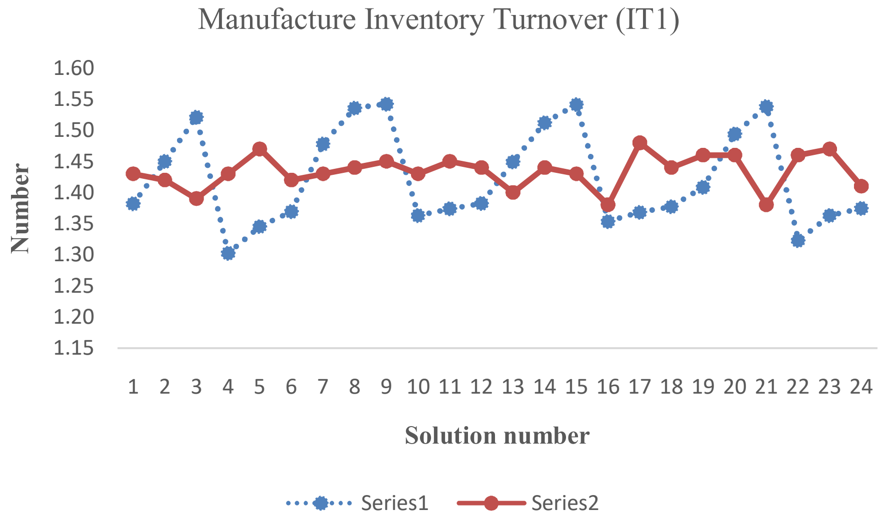

Fig. 11. Comparing SD and SBO for IT1 maximization

Choosing optimal solution

The results of SBO are different solution sets that make a trade-offs between objective functions. Now, Pareto optimal fronts for performance measures are obtained pairing. Pareto optimal front for cumulative cost of supplier and manufacturer which includes solutions number 8, 18, 21 is presented in Fig. 12. Fig. 13,illustratesPareto optimal front for cash conversion cycle of manufacturer and supplier which includes solutions number 8,13,18,20 and 24. Pareto optimal front for inventory turnover of supplier and manufacturer which contains solutions number 1,8,13,17,18 and 22 is shown in Fig. 7.

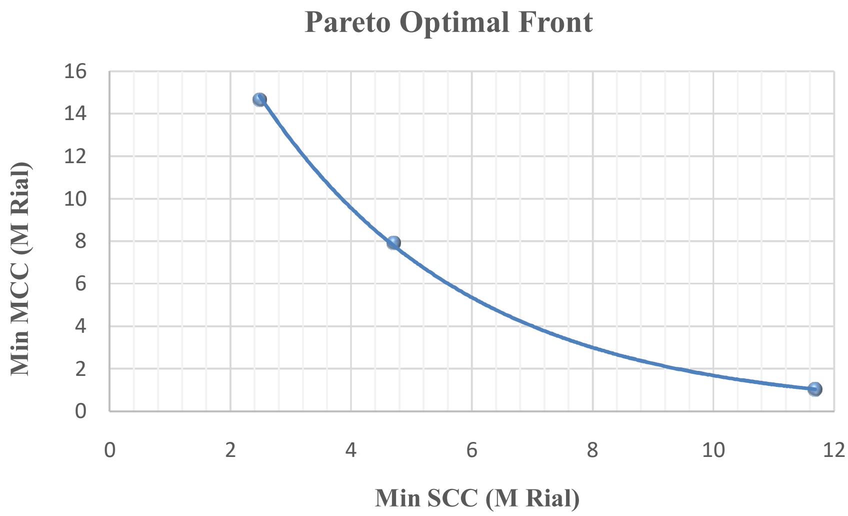

Fig. 12. Pareto optimal front of cost

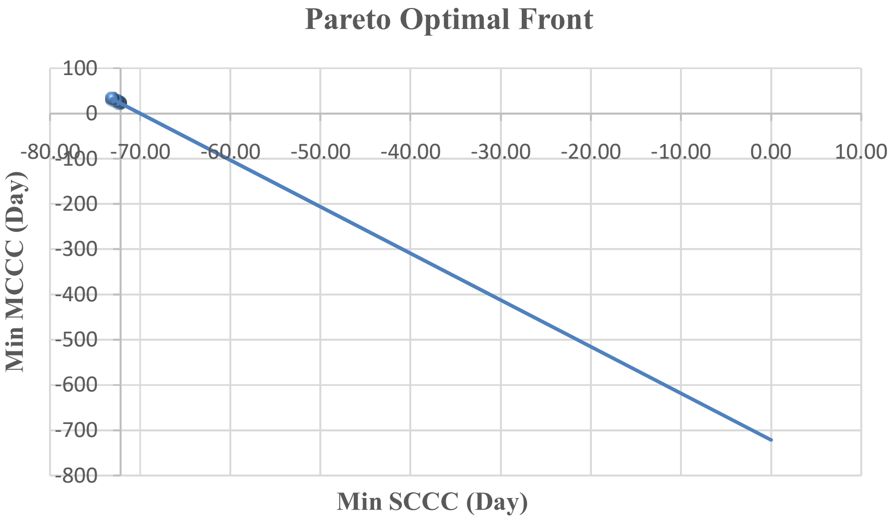

Fig. 13. Pareto optimal front of cash conversion cycle

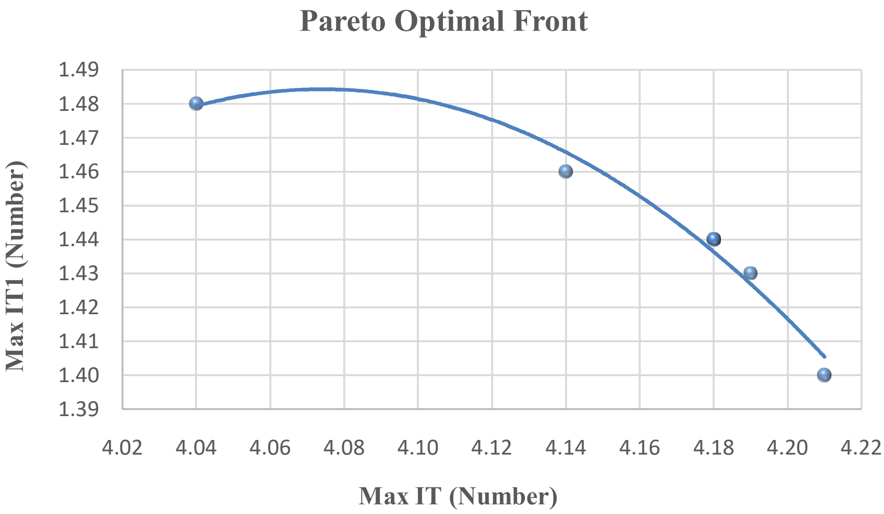

Fig. 13. Pareto optimal front of inventory turnover

With reference to the presented optimal fronts, solutions number 8 and 18 are found in all three optimal fronts. Comparing solution number 8 and 18, induces inventory turnover and cash conversion cycle are approximately equal in two solutions while cumulative costs of manufacturer and supplier are completely different with each other. Now it is time for high-level information leads decision maker to choose optimal solution. As it is clear, if decision maker prefers manufacturer objectives chooses solution 18 otherwise solution 8 will be chosen.As managerial discussion, we can recommend managers to implement following actions: (1) identifying methods of cost reduction (2) decrease in production preparation times and (3) increase in inventory adjustment times. By applying proposed measures inventory costs and cash conversion cycles fall dramatically also inventory turnovers rise significantlyfor both members.

Table 4. The analyze of optimal solutions

Parameter name	Optimal parameter value		Objective function	Objective function payoff	
	Solution 8	Solution 18		Solution 8	Solution 18
PPT	2.19	2.2	SCC	2,485,794	11,683,773
MPT	1.40	1.34			
SIAT	12.69	12.69	MCC	14,644,066	1,022,238
MIAT	23.76	26.22			
UC	128,467	128,545	SCCC	-72.35	-72.27
UC1	208,817	206,996	MCCC	23.54	23.15
SPU	140,384	140,381	IT	4.18	1.44
SPU1	217,818	218,915	IT1	4.18	1.44

CONCLUSIONS

Taking into consideration the existing solution approaches has been utilized by researchers, a hybrid approach has been proposed to efficiently find solution of the variables related to the operational/ tactical level of the supply chain management. The presented approach relies on the development of independent simulation and optimization models which are then coupled in an iterative procedure.

Reasons of utilizing proposed approach are as following: (i) reducing time required for acquiring optimal solution. As, underlying problem contains six objective functions using MOO or scenario making in SD model separately for solving the model takes a considerable time while hybrid approach decreases time needed dramatically. (ii) Integrating advantages of SD and MOO includes capturing interrelationships by SD model and Prioritizing objective functions by MOO simultaneously. (iii) Incapability of SD approach in experimenting possible scenarios especially when variables are continuous and (iv) necessity of presenting decision variables in objective functions in MOO whereas hybrid approach absolves model from mentioned constraint.

As the presented approach is able to provide reasonable solutions in a shorter time than SD and MOO, it can be used for modeling of complex networks such as supply chains or other systems which contain multiple conflicting objectives. In addition, the problem formulation can be extended in the future to include other decisions in the supply chain such as distribution and transportation planning.

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