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Using Simulation-Optimization to Integrate Financial and Product Flow Planning in Supply chains

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Abstract

Researchers have increasingly focused on the impact of financial flow on planning decisions in supply chain networks, especially due to rising costs and concerns about funding and resource allocation in the post-Covid era. This study introduces a simulation-optimization model that integrates financial and physical flows in supply chain planning. The model combines mixed-integer linear programming and simulation-based optimization through an iterative process. Financial performance is measured using the economic value added (EVA) index. To evaluate its effectiveness, the proposed model is compared with conventional SBO and MILP approaches on a test problem from recent literature. Results indicate that the proposed simulation-optimization model achieves higher EVA compared to the SBO model and demonstrates greater robustness to economic uncertainty than the MILP approach.

Keywords: Simulation-optimization; simulation-based optimization (SBO); Economic value added; Cash flow management

1. Introduction

The efficient management of the supply chain (SC) is a crucial requirement for organizations to thrive in a highly competitive environment. SC management involves connecting the participants in the product or service value chain by modeling the flows of physical, financial, and information resources. The SC system can be complex, encompassing autonomous entities such as suppliers, manufacturers, and retailers, as well as various processes like procurement, production, and distribution. Uncertainties can arise from both internal factors, like distribution lead time, and external factors, like customer demand (Spiegler et al., 2016). Effective management of this complex system requires making various planning decisions, all of which are influenced by the allocation of financial resources. In other words, the availability of financial resources is crucial for implementing these planning decisions (Hossain et al., 2022). For example, opening a new facility in the SC depends on explicit funding mechanisms. Furthermore, optimizing planning decisions can lead to cost savings, such as optimizing inventory decisions that free up financial resources for other decisions like expanding production capacity. Therefore, incorporating the financial aspect in SC planning models ensures the availability of financial resources and offers opportunities for saving resources

(Hofmann et al., 2023; Yousefi and Pishvaee, 2018).
To address these challenges, we propose a simulation-optimization framework that integrates financial flow modeling into SC planning problems. The simulation-optimization methodology is chosen due to its ability to combine the advantages of simulation and optimization. Optimization models can determine the optimal SC decisions, but incorporating complexities such as nonlinear relationships, delays, and feedback loops in cash and physical flows significantly increases their computational cost. On the other hand, simulation models are effective in capturing the complexities of the SC, but they cannot provide optimal decisions. Therefore, simulation-optimization emerges as a powerful approach for tackling complex SC problems (Badakhshan and Ball, 2021).
The remainder of the paper is structured as follows: Section 2 presents the literature review. Section 3 describes the problem description and the proposed simulation-optimization approach. The model formulation is elaborated in Section 4. Section 5 demonstrates the applicability of the proposed model through a case study. Finally, Section 6 concludes the paper and provides directions for future research.

2. State of the art

2.1. Using Simulation-optimization modelling for SC management

Simulation-optimization modelling encompasses the combination of simulation and optimization approaches, which can be classified into two main categories. The first category involves hybrid models where simulation and optimization approaches are integrated into a single model. The second category involves hybrid modelling, where independent simulation and optimization models are constructed, and a feedback structure is established to integrate the solution strategy. Hybrid models can further be divided into simulation-based optimization (SBO) and optimization-based simulation models. SBO involves incorporating optimization algorithms into simulation models to determine optimal values for decision parameters, while optimization-based simulation focuses on computing optimization model parameters using simulation or sampling of the optimization model scenarios.
A review of simulation-optimization modelling studies in SC management has identified two gaps in the literature. Firstly, most studies utilized discrete-event simulation (DES) as the simulation approach in simulation-optimization models, neglecting the potential of system dynamics (SD) simulation for tactical and strategic decision making in SCs. To address this gap, this study employs SD as the simulation technique in a simulation-optimization model.
Secondly, existing SBO models primarily optimize the performance of simulation systems by identifying optimal values for decision parameters, overlooking the optimization of decision variables within the simulation models. To address this gap, this study presents a simulation-optimization framework that integrates an SBO model, consisting of system dynamics and genetic algorithm, and an optimization model using mixed-integer linear programming (MILP). The developed model framework optimizes production and distribution decision variables, as well as inventory and financial decision parameters within the SD simulation model.
This study contributes to the literature on simulation-optimization modelling for SC management in two ways. Firstly, it employs SD as a simulation technique, which is more efficient than DES for tactical and strategic decision making. Secondly, it determines optimal values for both decision variables and decision parameters of a simulation model, going beyond previous studies that focused solely on decision parameters.

3. Problem description and modelling approach

We consider a general SC (SC) that comprises four stages: (1) suppliers, (2) production center, (3) distribution centers, and (4) retailers. The flow of the SC starts with suppliers providing raw materials to the production center, where products are manufactured and then distributed to retailers through distribution centers. Retailers are responsible for meeting customers' demands. In the opposite direction, customers pay for the products they purchase from the retailers. The distribution centers and retailers are owned by the production center and share a common profit. The focus is on a single product and multiple time periods in this SC system. The suppliers can fulfill the entire production center's order, while both the production center and distribution centers have limited capacities. The production center, which owns the distribution centers and retailers, has access to long-term and short-term loans.

To maximize the economic profitability of the SC, we have developed a simulation-optimization model that determines the optimal values for various decisions. These decisions include the amount of raw material to be purchased from suppliers, the production rate at the production center, the number of suppliers and distribution centers needed, the inventory levels at SC facilities, the flow of products in the network, the level of short-term and long-term liabilities, the level of equity, the level of fixed and current assets, the level of cash, the price of the product, and the profit distribution policy. The simulation-optimization model consists of an optimization module and a simulation-based optimization (SBO) module, which are integrated to identify the optimal decisions.

The optimization module is a mixed-integer linear programming (MILP) model that aims to maximize the economic value added (EVA). It determines the structure of the SC, including the decision to open or close distribution centers and the selection of suppliers. It also determines the optimal amount of raw material to be purchased from each supplier, the production rate, inventory levels, the flow of products, liabilities, equity, assets, and cash levels within the SC.

In the SBO module, the structure of the SC determined by the optimization module is incorporated into a system dynamics (SD) simulation model. The SBO framework, which combines the genetic algorithm with the SD simulation model, is used to identify the optimal values for the product price, cash, profit distribution policy, and inventory levels at SC facilities. This framework iterates between the optimization module and the SBO module to refine the optimal solution.

The SBO model inputs the optimal values obtained from the optimization module into the MILP model to determine new optimal values for the decision variables. The SBO model is then run again to obtain a new optimal solution, which includes the product price, cash, profit distribution policy, and inventory levels. The process continues iteratively until the termination criterion is met, comparing the EVA obtained in each iteration to ensure improvement.

The information gathered from the optimization-SBO model is used to examine if the current solution provides a higher EVA than the previous iteration. If the termination criterion is satisfied, the solution suggested by the optimization-SBO model is accepted. Otherwise, the problem is revised for further resolution by the optimization-SBO model in subsequent iterations. This revision involves adjusting the feasible intervals of controllable parameters such as price, desired inventory levels, and cash.

4. Simulation-optimization model

The simulation-optimization model that has been developed consists of two main modules: an optimization module and a simulation-based optimization module. Firstly, we provide an explanation for each of these modules, detailing their individual components and functionalities. Subsequently, we present the framework that outlines the integration of these two modules, illustrating how they work together to achieve the desired outcomes. This framework is adopted from Badakhshan and Ball (2023).

4.1. Optimization model

The goal of the optimization model is to maximize the economic value added (EVA) index, as indicated by equation (1). The EVA is calculated based on the net operating profit after tax (NOPAT) stated in the income statement. The weighted average cost of capital (WACC) is a metric that represents the actual expenses associated with the various capital sources utilized by the company, as discussed by Ogier et al. (2004).

$$Max\ EVA_t = \sum_{t=1}^{T}[NOPAT_t - (WACC_t)IC_t] \quad (1)$$

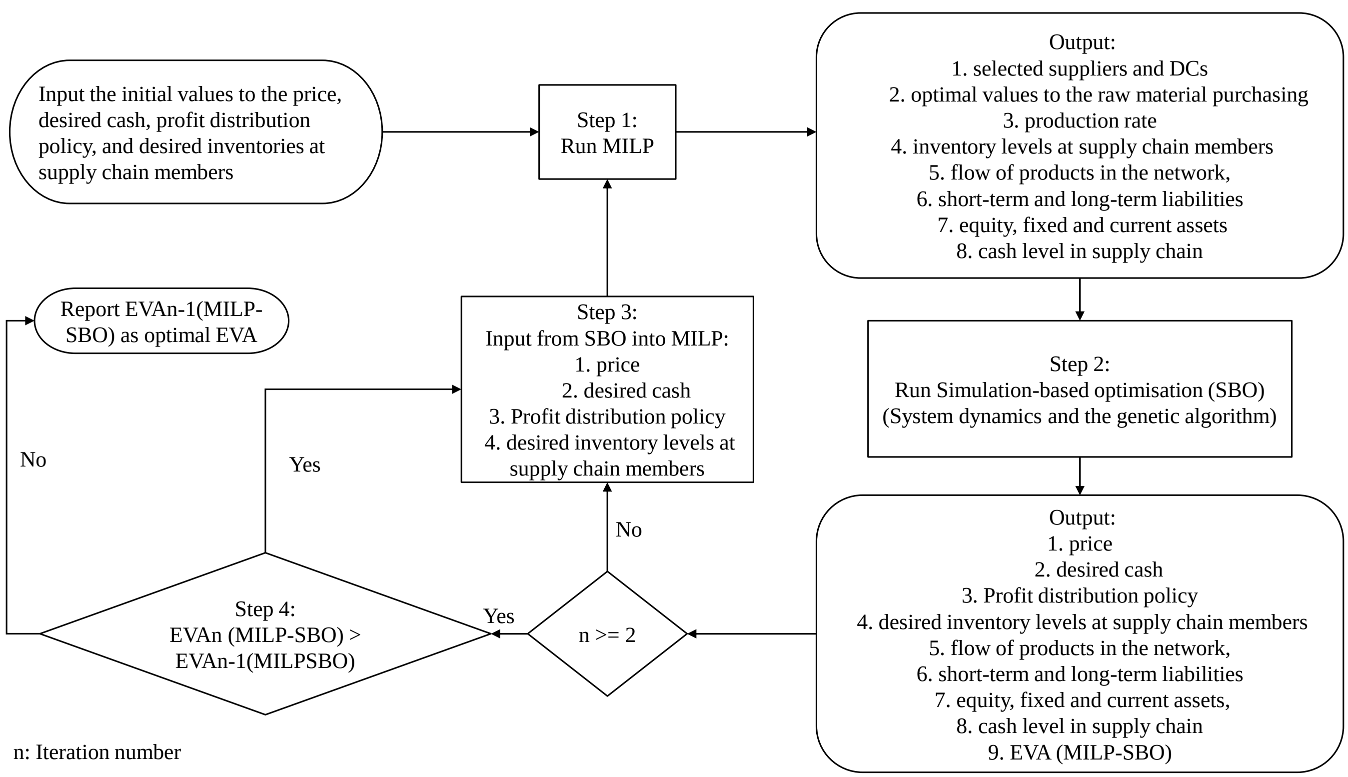


Figure 1. Optimization-SBO data exchange (adopted from Badakhshan and Ball , 2023).

The calculation of the weighted average cost of capital (WACC) (equation 2) involves multiplying the cost of debt (CD) and the cost of equity (CE) by their respective proportional weights, and then summing the results. The cost of debt represents the average of the interest rates associated with short-term and long-term liabilities. On the other hand, the cost of equity consists of three components. The first component is the risk-free rate of interest (r_{f_t}), which represents the return on investing capital in a risk-free asset like government bonds. The second component is the difference between the expected return of the stock market (r_{m_t}) and the risk-free rate (r_{f_t}), reflecting the additional return for investing in a risky asset such as stock market bonds. The third component is the risk measure (β), which indicates the level of systematic risk present in an asset. The invested capital (IC) (equation 3) represents the accumulation of funds from both debt and equity financing.

$$WACC_t = \left(\frac{E_t}{IC_t}\underbrace{(r_{f_t} + (r_{m_t} - r_{f_t})\beta)}_{Cost\ of\ equity}\right) + \left(\frac{STL_t + LTL_t}{IC_t}\underbrace{\left(\frac{STL_t}{TL_t}STR_t + \frac{LTL_t}{TL_t}LTR_t\right)}_{Cost\ of\ debt}(1 - tr_t)\right) \quad (2)$$

$$IC_t = STL_t + LTL_t + E_t \quad \forall t. \quad (3)$$

To determine the net operating profit after tax (NOPAT) (4), the earnings before interest and taxes ($EBIT$) is multiplied by the complement of the tax rate (tr). EBIT represents the gross income of the company and is calculated by subtracting the total cost (TC) from the net sales (NTS). The revenue of the SC (SC) (6) is obtained by multiplying the sales quantities of each retailer by the price and summing up the outcomes.

$$NOPAT_t = EBIT_t(1 - tr_t) \quad \forall t. \quad (4)$$

$$EBIT_t = NTS_t - TC_t \quad \forall t. \quad (5)$$

$$NTS_t = \sum_{r=1}^{R} SR_{rt}pri_t \quad \forall t. \quad (6)$$

The overall cost of the SC (7) comprises various components, including the production cost at the production center (PC), transportation cost between centers (TRC), inventory holding cost at centers (HC), fixed costs of the centers (FC), cash holding cost (CC), and the cost of raw material purchased from suppliers (RMC). Equation 8 illustrates the operating cost at the production center, which is calculated by multiplying the production rate (PR) by the unit production cost (upc). The operating costs encompass expenses related to the activities involved in producing final products. The transportation cost (TRC) (9) includes the cost of transporting goods from the supplier to the manufacturer (tc), from the manufacturer to the distributor (tcc), and from the distributor to the retailer (tcd). Equation 10 represents the inventory holding cost incurred by the manufacturer, distribution centers, and retailers. This cost includes the holding cost of raw materials (hr) and the holding cost of the product (hp) at the production center, as well as the holding cost of safety stock at the distribution centers and retailers. The unit holding cost of raw material is set at 10% of the raw material price, while the unit holding costs of the product at the production center (hp), distribution centers (ho), and retailers (hs) are also set at 10% of the product price.

$$TC_t = PC_t + TRC_t + HC_t + FC_t + CC_t + RMC_t + DPR_t \quad \forall t. \quad (7)$$

$$PC_t = upc_tPR_t \quad \forall t. \quad (8)$$

$$TRC_t = \sum_{s=1}^{S} tc_{st}X_{st} + \sum_{d=1}^{D} tcc_{dt}SC_{dt} + \sum_{r=1}^{R}\sum_{d=1}^{D} tcd_{drt}SDI_{drt} \quad \forall t. \quad (9)$$

$$HC_t = hr_t\left(\frac{FIR_t + FIR_{t-1}}{2}\right) + hp_t\left(\frac{FIP_t + FIP_{t-1}}{2}\right) + \sum_{d=1}^{D} ho_{dt}\left(\frac{FIO_{dt} + FIO_{dt-1}}{2}\right) + \sum_{r=1}^{R} hs_{rt}\left(\frac{FIS_t + FIS_{t-1}}{2}\right) \quad \forall t. \quad (10)$$

The fixed cost (11) encompasses all the expenses incurred by a member of the SC (SC), such as employee salaries, that are not dependent on the quantity of goods and services provided by the member. For distribution centers, this cost is determined by multiplying the fixed cost (fcd) by a binary variable indicating the activity status of the distribution center. However, the fixed costs of the production center (fcp) and retailers (fcr) are not multiplied by the binary variable, as it is assumed that they are fixed in their respective locations. Companies hold cash as a means to pay their suppliers for services rendered and to cover unexpected expenses that may arise. The cash holding cost (12) represents the opportunity cost of holding cash instead of investing it in more profitable options, such as purchasing stock. This cost is calculated by multiplying the unit cash cost (ucc) by the average cash amount during the period. The raw material cost (13) corresponds to the expense incurred from purchasing raw materials from various suppliers. It is determined by multiplying the quantity purchased (X) by the unit price of each raw material (rmc). Depreciation (DPR), as shown in constraint (14), is calculated by multiplying the value of fixed assets by the depreciation rate (dr).

$$FC_t = \sum_{d=1}^{D} fcd_{dt} Y_{dt} + fcp_t + \sum_{r=1}^{R} fcr_{rt} \quad \forall t. \tag{11}$$

$$CC_t = ucc_t \left(\frac{CS_t + CS_{t-1}}{2} \right) \quad \forall t. \tag{12}$$

$$RMC_t = \sum_{s=1}^{S} X_{st} rmc_{st} \quad \forall t. \tag{13}$$

$$DPR_t = dr_t FA_t \quad \forall t. \tag{14}$$

4.1.2. Constraints

Constraint (15) represents the equation that governs the inventory level of raw material in the production center over time. It states that the inventory at the current period is determined by adding the remaining inventory from the previous period, the amount of raw material purchased from suppliers, and subtracting the quantity consumed for manufacturing final products.
Similarly, constraint (16) defines the available inventory of products in the production center at the end of a specific period. It is calculated by summing the inventory at the end of the previous period, the production rate during the current period, and subtracting the quantity of products transported from the production center to the distribution centers within the same period.

$$FIR_t = \sum_{s=1}^{S} X_{st} - PR_t o_t + FIR_{t-1} \quad \forall t. \tag{15}$$

$$FIP_t = PR_t - \sum_{d=1}^{D} SC_{dt} + FIP_{t-1} \quad \forall t. \tag{16}$$

Constraints (17) and (18) express the relationship between inventory levels at distributors and retailers. They indicate that the inventory at each member of the SC is determined by adding the incoming flow of products from the higher-level echelon, the remaining inventory from the previous time period, and subtracting the outgoing flow of products to the lower-level echelon.

$$FIO_{dt} = SC_{dt} - \sum_{r=1}^{R} SDI_{drt} + FIO_{dt-1} \quad \forall d, t. \tag{17}$$

$$FIS_{rt} = \sum_{d=1}^{D} SDI_{drt} - SR_{rt} + FIS_{rt-1} \quad \forall r, t. \tag{18}$$

Constraint (19) ensures that the quantity of products transported from each retailer is limited to the demand of the end customers or less.

$$SR_{rt} \leq d_{rt} \quad \forall r, t. \tag{19}$$

Constraint (20) ensures that the total number of products sold to end customers is equal to the total number of products sent to the retailers. Constraint (21) states that the total number of products shipped to the retailers should be equal to the total number of products sent to the distribution centers.

$$SR_{rt} = \sum_{d=1}^{D} SDI_{drt} \quad \forall r, t. \tag{20}$$

$$\sum_{r=1}^{R} SDI_{drt} = SC_{dt} \quad \forall d, t. \tag{21}$$

Constraint (22) guarantees that there is at least one active supplier during each period. Constraint (23) ensures that there is at least one open distribution center during each period.

$$\sum_{s=1}^{S} Z_{st} \geq 1 \quad \forall t. \tag{22}$$

$$\sum_{d=1}^{D} Y_{dt} \geq 1 \quad \forall t. \tag{23}$$

Constraints (24)-(27) mandate that the inventory levels at the production center, distribution centers, and retailers must exceed the predetermined safety stock levels, also referred to as the desired inventories (DI), which are determined by the SBO model.

$$DIRM_t \leq FIR_t \leq caprm_t \quad \forall t. \tag{24}$$

$$PDI_t \leq FIP_t \leq cap_t \quad \forall t. \tag{25}$$

$$Y_{dt} DDI_{dt} \leq FIO_{dt} \leq Y_{dt} capd_{dt} \quad \forall t, d. \tag{26}$$

$$RDI_{rt} \leq FIS_{rt} \leq capr_{rt} \quad \forall t, r. \tag{27}$$

Constraint (28) regulates the production rate of the production center, ensuring that it does not surpass the available production capacity and remains above zero.

$$0 \leq PR_t \leq prcap_t \quad \forall t. \tag{28}$$

Constraint (29) presents the fundamental equation of the balance sheet, which highlights the equivalence between assets and the combination of equity (E) and debts. The assets encompass both fixed assets (FA) and current assets (CA), while the debts consist of both short-term liabilities (STL) and long-term liabilities (LTL).

$$FA_t + CA_t = E_t + STL_t + LTL_t \quad \forall t. \tag{29}$$

The value of fixed assets (FA) at the end of each period (30) is calculated by summing up the fixed assets of all SC (SC) members and subtracting the depreciation amount.

$$FA_t = \sum_{d=1}^{D} DFAV_d Y_{dt} + PCFAV_t + \sum_{r=1}^{R} RFAV_{rt} - DPR_t \quad \forall t. \tag{30}$$

Constraint (31) formulates the current assets (CA) which is composed of cash (CS), receivable accounts (RA), and inventory value (INR).

$$CA_t = CS_t + RA_t + INR_t \quad \forall t. \tag{31}$$

Constraint (32) demonstrates the cash availability, which is calculated by combining the total amount of loans ($STL + LTL$), newly issued stocks, and the operating profit that can be accessed as cash. The portion of the operating profit that cannot be accessed as cash is accumulated in the receivable accounts (RA) (33).

$$CS_t = css_t NOPAT_t + NIS_t + CS_{t-1} \quad \forall t. \tag{32}$$

$$RA_t = (1 - css_t)\, NOPAT_t + RA_{t-1} \; \forall t. \tag{33}$$

Constraint (34) represents the value of inventory, which is calculated by multiplying the sales price of each member by their respective inventory levels, and then summing up the results.

$$INR_t = FIR_t\, rmv_t + \left(FIP_t + \sum_{d=1}^{D} FIO_{dt} Y_{dt} + \sum_{r=1}^{R} FIS_{rt} \right) pri \quad \forall t. \tag{34}$$

Constraint (35) computes the equity value (E) at a given period by summing up the accumulated equity from the previous period, the net operating profit after tax ($NOPAT$) that remains undistributed to shareholders, and the value of newly issued stocks.

$$E_t = (1 - PDP_t) NOPAT_t + E_{t-1} + NIS_t \quad \forall t. \tag{35}$$

Constraint (36) ensures that the cash level at the end of each period is greater than the safety cash level known as desired cash level determined by the SBO model.

$$DCS_t \le CS_t \quad \forall t. \tag{36}$$

4.2. Simulation-based optimization model

The optimization model discussed in section 4.1 overlooks the dynamic aspects of the SC, such as non-linearities, delays, and feedback loops present in both physical and financial flows. Incorporating these dynamics into the optimization model transforms it into a non-linear model, which substantially increases the computational time required. To address this, SBO (System Dynamics-based Optimization) proves to be more effective in capturing the SC dynamics. Therefore, we have devised an SBO model that combines System Dynamics simulation with a Genetic algorithm. The purpose of this SBO model is to determine the optimal values for inventory and financial decision parameters that are disregarded in the initial optimization model.

4.2.1. *System Dynamics Simulation*

System Dynamics (SD) simulation provides a more realistic representation of the physical and financial flows within the studied SC (SC). It considers the dynamic nature of these flows from three perspectives, enhancing the accuracy of the model. Firstly, SD simulation considers the delays in both physical and financial flows, which include distribution lead time between SC members, production lead time at the manufacturer, and payment lead time. In this study, distribution and production lead times are assumed to be 1 week, while the payment lead time is set to 4 weeks. Secondly, SD simulation incorporates feedback loops, such as the material inventory control loop, which adjusts the material order quantity based on the current inventory level. This means that higher material inventory levels result in lower material order quantities, creating a self-regulating feedback mechanism. Lastly, SD simulation formulates non-linear relationships between the decision parameters and variables by integrating the physical and financial decision parameters. This ensures that the model captures the complex interactions and dependencies present in the SC, resulting in more accurate and realistic outcomes.

4.2.2. *Genetic Algorithm (GA)*

The Genetic Algorithm (GA) is utilized in the SD simulation model to determine the optimal values for the inventory and financial decision parameters. Unlike analytical optimization methods, GAs do not rely on derivative information, making them suitable for handling numerically generated data. They possess the ability to escape local minimums and are effective in optimizing both continuous and discrete parameters, with a particular emphasis on continuous parameters in this study.

The GA is a well-suited approach for optimizing the SD simulation model as it integrates seamlessly with the continuous inventory and financial decision parameters. Figure 2 illustrates the System Dynamics-Based Optimization (SBO) framework, which combines the SD simulation and GA. The SBO process initiates with the optimization algorithm, namely the GA, generating initial values within the feasible ranges for the inventory and financial decision parameters. The SD simulation model is then executed using these generated values to evaluate the system's performance, specifically measured by the mean of the Economic Value Added (EVA). The performance measures obtained from the simulation are fed back into the optimization algorithm, which generates a new set of inventory and financial decision parameters. These parameters are then inputted into the simulation model for evaluation, and the iterative process continues. The SBO process iterates until a user-defined stop criterion is met. In this study, the stopping criteria are set at 300 generations, meaning the iterative process will be performed for a specified number of evaluations or until the maximum number of generations is reached.

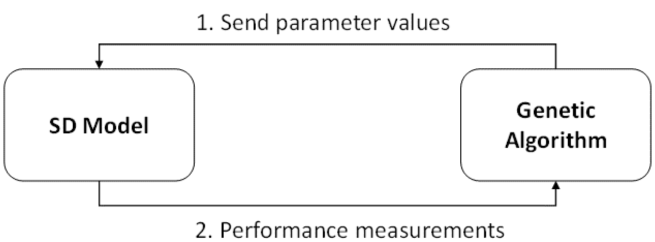


Figure 1. SBO framework (adopted from Badakhshan and Ball , 2023).

4.3. Integrating optimization and SBO models

Optimization models can determine the optimal values for decision variables, but they may not effectively capture the dynamics of SC (SC). On the other hand, System Dynamics-Based Optimization (SBO) models excel at considering SC dynamics and identifying optimal values for decision parameters, but they may not directly determine the optimal values for decision variables. By integrating optimization and SBO models, we can leverage the strengths of both approaches. In the integrated framework, the recommendations from the optimization model and the decisions obtained from the SBO model are combined to determine key aspects such as the quantity of raw material to be purchased, the production start rate, and the shipment rates throughout the network.

The material delivery rate (37) in this integrated model is determined by the desired material order rate from the SD simulation model and the material order rate suggested by the optimization model. The production start rate (38) is influenced by the desired production rate, feasible production based on material availability from the SD model, and the production rate recommended by the optimization model. The manufacturer's shipment rate ($\boldsymbol{MSR_d}$) (39) is determined by considering the maximum shipment rate to each distributor, the desired shipment rate of each distributor, and the shipment rate suggested by the optimization model.

The number of products shipped from each distribution center to each retailer ($\boldsymbol{DSR_{dr}}$) (40) is a function of the desired shipment rate determined by the optimization model, the maximum shipment rate, and the distributor's inventory obtained from the SD simulation model. The sale rate of each retailer ($\boldsymbol{RSR_r}$) (41) is calculated based on factors such as customer demand, the retailer's inventory level, and the sale rate obtained from the optimization model. By integrating optimization and SBO models, we can optimize decision parameters while considering SC dynamics, resulting in a more comprehensive approach to decision-making in the SC.

$$Production\ start\ rate = Min\begin{pmatrix} Desired\ production\ start\ rate, \\ Feasible\ production\ from\ material, PR_t \end{pmatrix} \tag{38}$$

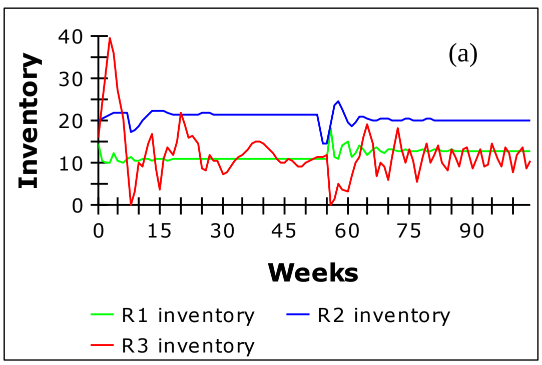
$$MSR_d = Min\begin{pmatrix} Maximum\ shipment\ rate_d, \\ Desired\ shipemnt\ rate_d, SC_{dt} \end{pmatrix} \quad \forall d. \tag{39}$$

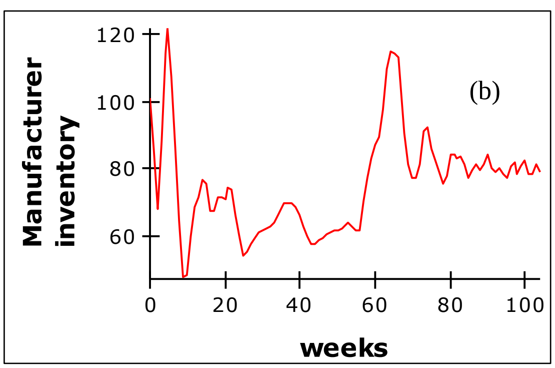
$$DSR_{dr} = Min\begin{pmatrix} Retailer\ order_r, Distributor\ inventory_d, \\ SDI_{drt} \end{pmatrix} \quad \forall r, d. \tag{40}$$

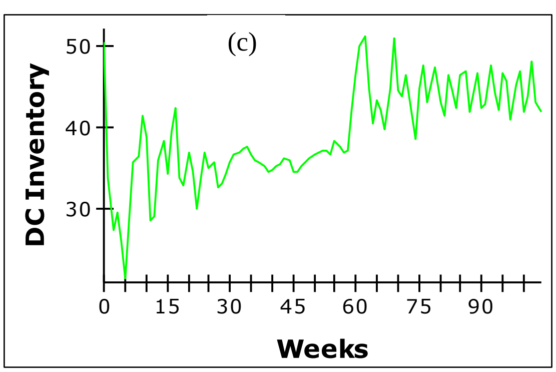
$$RSR_r = Min(d_{rt}, Retailer\ Inventory_r, SR_{rt}) \quad \forall r. \tag{41}$$

5. Results and Discussion

The benefits of the optimization-SBO model are examined by conducting empirical tests and comparing it with both the SBO and optimization methods. The numerical experiment is conducted on a scaled-down scenario, including three customer zones, retailers, and distributors, one production center, two suppliers, and a total of two one-year periods. The inventory and cash dynamics resulting from the SBO and optimization-SBO models are depicted in Figures 3(a)-(d) and 4(a)-(d), respectively. By utilizing optimal values for raw material order quantity, production rate, and shipment rate between SC members within the SD simulation model, the optimization-SBO approach proves to be more efficient in managing the cash and inventory of SC members. The implementation of optimization-SBO leads to a reduction in inventory peaks and a decrease in the oscillation range of inventory levels for SC members. Additionally, the inflow and outflow of cash in the optimization-SBO model are lower compared to the SBO model. The optimization-SBO model's lower inventory and cash levels contribute to decreased inventory and cash costs compared to the SBO model. As a result, the optimization-SBO model achieves an EVA of £38,045, which is 16% higher than the EVA obtained from the SBO model, amounting to £32,840. Through empirical testing, the optimization-SBO model demonstrates superior performance by effectively managing inventory and cash, leading to improved financial outcomes for the SC.







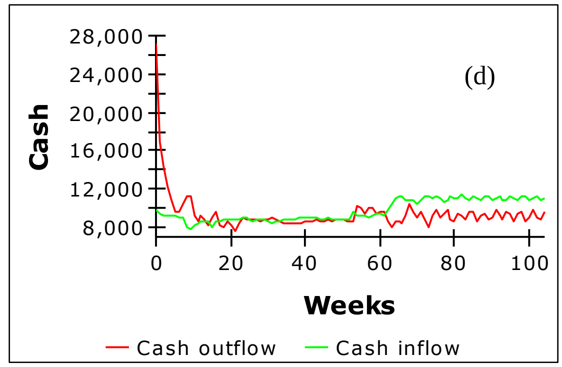
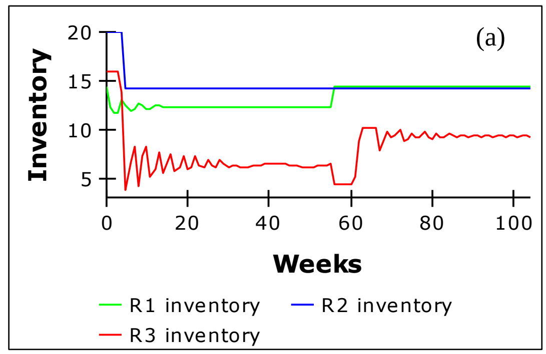
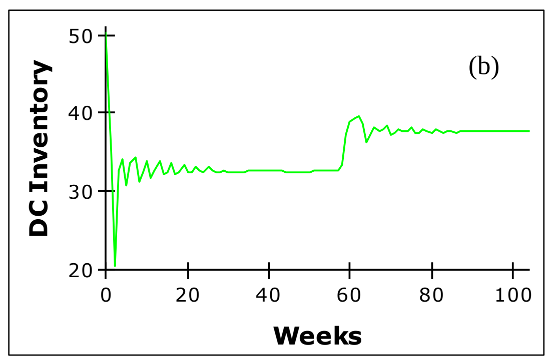
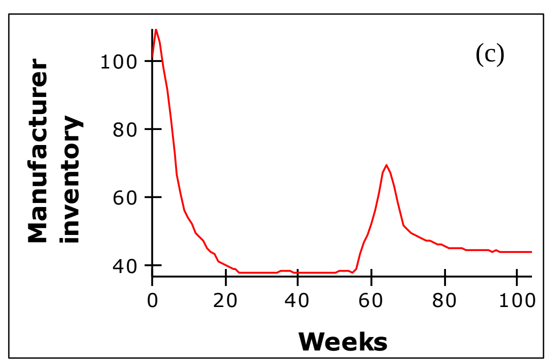


Figure 2. Inventory and cash dynamics for the SC members obtained from SBO model.







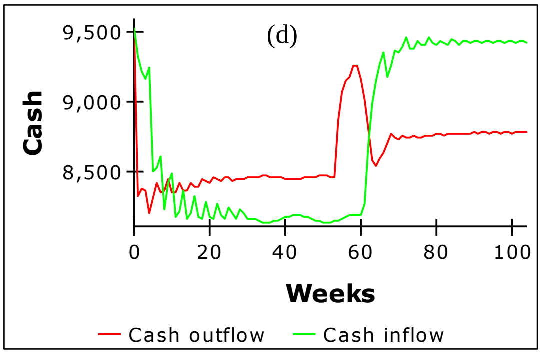


Figure 3. Inventory and cash dynamics for the SC members obtained from SBO model.

To compare the performance of the optimization-SBO and SBO models with the optimization model, a series of 10 random realizations of macroeconomic parameters, including short-term interest rate, long-term interest rate, risk-free rate of interest, and expected return of the market, are generated uniformly by varying these parameters within the range of [-15%, +15%]. These generated parameters are then utilized as inputs for the optimization, SBO, and optimization-SBO models to calculate the EVA for each model and realization. The resulting EVAs from all models for each realization are presented in Table 1.

The average EVA obtained from the optimization model is 17% higher than the SBO model and 1.2% higher than the optimization-SBO model. This disparity arises because the optimization model disregards the dynamics of inventory and cash in the SC, unlike the SBO and optimization-SBO models. Consequently, the recommended cash and inventory levels at SC members by the optimization model are lower than the levels recommended by the SBO and optimization-SBO models.

In terms of variability, the standard deviation of EVAs obtained from the optimization-SBO model is 61% lower than that of the SBO model and 95% lower than that of the optimization model. This indicates that the optimization-SBO model exhibits greater robustness against fluctuations in macroeconomic parameters compared to both the SBO and optimization models. This advantage stems from the fact that the optimization-SBO model identifies optimal values for inventory and financial decision parameters (as shown in Eq. (38)) and utilizes the minimum function to ensure the feasibility of production and distribution values (as shown in Eq. (39)-(43)). On the other hand, the SBO model only determines optimal values for inventory and financial decision parameters, while the optimization model solely identifies optimal values for production and distribution values without considering the dynamics of physical and financial flows in the SC.

Table 1. Sensitivity analysis on the models

No. of realization	MILP model	SBO model	MILP-SBO model
1	39964	32893	37993
2	39626	32901	37870
3	39979	32667	37953
4	37070	32574	37922
5	38070	32543	38003
6	37651	32750	38074
7	37565	32808	37904
8	40123	32984	38016
9	37235	33111	37919
10	37061	32703	38068
Mean	38434.4	32793.4	37972.2
Standard deviation	1252.41	163.97	62.99

The number of iterations required to fulfill the stopping criterion, which is defined as no improvement in the EVA value obtained from the optimization-SBO model, is presented in Table 2. In each iteration, the GA was executed 15 times. The findings demonstrate that the maximum number of stopping iterations is three. However, it is important to note that proving the rapid convergence of the EVA obtained from the optimization-SBO model for all test outcomes is not feasible since the GA is a stochastic search algorithm, meaning its results can vary due to its inherent randomness.

Table 2. Convergence of EVA obtained from optimization-SBO model.

Iteration number	Fitness value			
	Worst (Min)	Best (Max)	Mean	Standard deviation
1	35951	36674	36548	47.29
2	37163	37794	37658	26.24
3	37956	38084	38045	10.34
4	37956	38076	38023	9.67

Table 3 presents the results of comparing the EVA values obtained from the optimization-SBO model with those obtained from the optimization and SBO models. The optimization-SBO approach demonstrates superior performance over the SBO approach by effectively reducing the levels of cash and inventory within the SC (SC).

Table 3. EVA obtained from optimization-SBO model.

EVA (GBP)	Number of iterations	Percentage difference between the optimization-SBO and MILP models	Percentage difference between optimization-SBO and SBO models
38045	3	-1.89%	+15.85%

6. Conclusions

By incorporating the financial aspect of SC management (SCM) into SC planning models, the availability of financial resources for implementing planning decisions can be ensured, leading to potential savings in financial resources (Hofmann et al., 2023). To address this, we have developed a simulation-optimization framework that integrates financial flow modeling into an SC planning problem. This methodology combines simulation and optimization techniques to determine optimal SC decisions while accounting for complexities such as nonlinear relationships, delays, and feedback loops that exist in both financial and physical flows within SCs.

Previous literature on simulation-optimization in SCs has focused solely on optimizing the decision parameters of simulation models, without providing optimal values for the decision variables within these models. To bridge this gap, our study introduces a simulation-optimization model that identifies optimal values for both decision variables (e.g., product flows among SC members and production rates) and decision parameters (e.g., payables and receivables policies) within the simulation model. By employing this developed simulation-optimization model, we were able to significantly reduce inventory levels for SC members and the amount of cash held within the SC. Additionally, the EVA of the SC increased by approximately 16%, from £32,840 to £38,045.

In this study, we utilized System Dynamics (SD) simulation, but future research could explore the performance of optimization-SBO models that incorporate other simulation techniques. Furthermore, the developed optimization-SBO model in this study could be extended to incorporate multi-objective optimization, allowing for the consideration of multiple performance criteria in SC planning problems.

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