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A simulation-based optimization model for balancing economic profitability and working capital efficiency using system dynamics and genetic algorithms

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ABSTRACT

Economic uncertainty has been increasing, as evidenced by recent fluctuations in global markets and unpredictable economic indicators such as volatile demand, stock market fluctuations, and unpredictable interest rates. Economic profitability and working capital efficiency are pivotal indicators of a business's financial health, both of which are adversely impacted by economic uncertainty. However, these metrics may diverge as distinct objectives drive them. There exists a gap in the literature regarding effective strategies for managing the trade-off between these metrics under economic uncertainty. This study addresses this gap by introducing a simulation-based optimization model that integrates system dynamics simulation and genetic algorithms. The proposed model aims to balance economic profitability and working capital efficiency within inventory management under partial trade credit. A recent real case study demonstrates the model's applicability and reveals its superiority over conventional system dynamics simulation modeling. With its capacity to inform strategic and tactical decision-making, this model emerges as a valuable tool for supply chain and financial managers seeking to ensure financial stability amidst economic volatility.

1. Introduction

In recent years, businesses have intensified their efforts to enhance their capabilities in response to increased competition. A strategic avenue receiving notable attention is the effective management of supply chain (SC) networks [1,2]. Supply chain management (SCM) involves the seamless integration of suppliers, manufacturers, distributors, and customers, ensuring the smooth flow of both physical goods and financial resources throughout the network [3,4]. This integration is pivotal as it enables organizations to optimize not only operational performance but also financial health [5].

However, the seamless integration of SC members is increasingly challenged by rising economic uncertainty. As illustrated in Fig. 1, the level of economic uncertainty, indicated by The World Uncertainty Index, has been steadily increasing, with its most significant surge occurring at the onset of the Coronavirus pandemic. This surge in economic uncertainty brings about volatile demand patterns, posing challenges for SC members in accurately forecasting demand. Consequently, this unpredictability often results in either excess inventory or stockouts, both of which undermine working capital efficiency and economic profitability. Furthermore, uncertain economic conditions tend to tighten credit markets, making it harder for businesses to secure financing. This, in turn, limits investment opportunities, constrains growth, increases borrowing costs, and prolongs payment cycles from customers. These combined factors underscore the critical importance of mitigating the impact of economic uncertainty on both working capital efficiency and economic profitability, which serve as vital indicators of a business's financial health.

Although working capital efficiency and economic profitability are both adversely impacted by economic uncertainty, they may diverge as distinct objectives drive them. While economic profitability strives to maximize returns, working capital efficiency focuses on minimizing tied-up capital [6,7]. Therefore, striking a balance between these two objectives is essential to optimize the financial health of a business in the presence of economic uncertainty. This balance requires navigating challenges such as volatility in demand and interest rates. To address these challenges, SC members should proactively plan for possible scenarios and identify the optimal inventory and financial decisions for each scenario to navigate economic uncertainty while balancing economic profitability and working capital efficiency.

Despite the recognized importance of economic profitability and working capital efficiency [9–11], there exists a gap in the literature regarding effective strategies for managing the trade-off between these metrics under economic uncertainty. This study addresses this gap by developing a simulation-based optimization (SBO) model that integrates system dynamics simulation with a genetic algorithm. The system dynamics simulation assesses how changes in economic parameters affect the financial performance of the SC, while the genetic algorithm identifies the optimal values for inventory and financial

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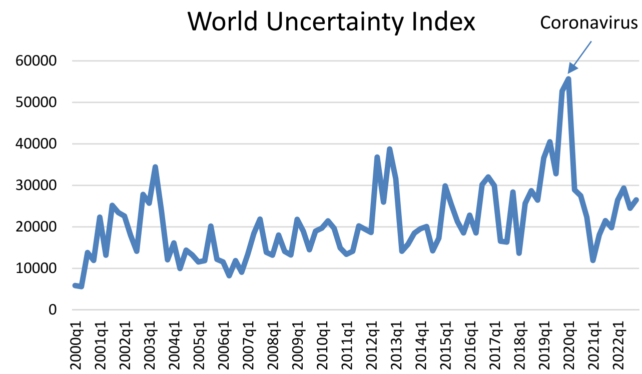


Fig. 1. World uncertainty index from 2000 to 2023. Data obtained from [8].

decisions, offering a novel approach to address the complexities of decision-making within SCs in uncertain economic environments.

The subsequent sections of this paper are structured as follows: Section 2 presents a comprehensive review of the literature, followed by a discussion on model assumptions and the stock management problem in Section 3. The proposed SBO model is detailed in Section 4, with a case study illustrating its applicability in Section 5. Finally, concluding remarks and avenues for future research are outlined in Section 6.

2. Literature review

This study encompasses three major research domains: inventory management under partial trade credit, SC modeling under economic uncertainty, and working capital management in SCs. Therefore, the literature review is organized accordingly. These research strands are integrated to address the trade-off between economic profitability and working capital efficiency in the presence of economic uncertainty and partial trade credit among SC members.

2.1. Inventory management under partial trade credit

Partial trade credit emerges as a prevalent financing solution within SCs, wherein a supplier extends credit to a buyer, allowing the latter to defer part of the payment for received goods or services to a later scheduled time [12]. In the context of partial trade credit, managing accounts receivable and accounts payable becomes integral to inventory management.

Table 1 provides a summary of inventory management under partial trade credit literature. The gaps in the literature are now considered. Firstly, the share of cash payment and trade credit in the literature are considered as given rather than being optimized. Kumar Ghosh et al. [13], Sharma et al. [14], Mahata [15], and Teng [16] developed economic order quantity (EOQ) models to determine the optimal inventory policies for retailers that offered partial trade credit to customers given the share of cash payment and trade credit. Sharma and Mandal [17], Tiwari et al. [18], and Li et al. [19] developed EOQ models to identify the optimal inventory decisions for retailers who were offered partial trade credit by their suppliers given the share of cash payment and trade credit.

Secondly, many models focus on a single objective, such as cost minimization or profit maximization, as the dominant objective function. For instance, Huang and Hsu [20] and Wu and Chan [21] developed EOQ models aiming to minimize total costs for retailers offering partial trade credit to customers. Similarly, Tsao et al. [22], Tiwari et al. [23], and Kreng and Tan [24] designed economic production quantity (EPQ) models to determine optimal replenishment policies for SC members receiving partial trade credit from their suppliers. Badakhshan and Ball [25] integrated SBO and mixed integer linear programming to maximize economic value added for a manufacturer receiving partial trade credit from suppliers. Despite these efforts, much of the current literature lacks studies that effectively manage the trade-off between economic profitability and working capital efficiency through the development of multi-objective models.

Thirdly, certain studies on inventory management under partial trade credit have addressed uncertainty. For instance, Mahata et al. [26] and Tiwari et al. [18] focused on demand uncertainty, while Badakhshan et al. [27] considered both demand and lead time uncertainties. However, there is a notable gap in the literature regarding uncertainties in macroeconomic parameters, such as long-term and short-term interest rates.

Finally, much of the literature has relied on analytical modeling approaches. However, there is an underrepresentation of SBO modeling, which is known to be more efficient in capturing nonlinearities, delays, and feedback loops in the physical and financial flows of SCs [28–30]. SBO provides a more accurate representation of real-world conditions, making it particularly effective for decision-making in inventory management under partial trade credit situations [25].

Existing inventory management models incorporating partial trade credit suffer from four limitations: failure to optimize trade credit and cash payment allocation, overlooking the economic profitability-working capital efficiency trade-off, disregarding macroeconomic uncertainty, and underutilizing SBO modeling. To address these gaps in the literature, we develop an SBO model that aims to manage the trade-off between economic profitability and working capital efficiency while incorporating macroeconomic uncertainty. Moreover, the developed SBO model identifies the optimal shares of trade credit and cash payment in the SC.

2.2. Supply chain modeling under economic uncertainty

Literature related to SC models under economic uncertainty is extensive as the economic uncertainty encompasses uncertainty in microeconomic parameters such as demand and also macroeconomic parameters such as short-term interest rates.

Many studies have focused primarily on addressing microeconomic uncertainties [35–43]. For instance, Chen et al. [41] and Jabbarzadeh et al. [40] considered demand uncertainty in SC planning problems. Mohebalizadehgashti et al. [42] considered the unit cost and price uncertainties in a SC network design problem. Badakhshan and Ball [39] and Arıkan [44] considered demand and lead time uncertainties in an inventory management problem. Rekabi et al. [36] and Ouhimmou et al. [43] considered demand uncertainty in the SC network design problem. Goodarzi et al. [37] considered demand and cost uncertainties for green supplier evaluation and optimal order allocation. Gupta et al. [35] considered demand and price uncertainties when developing an analytic hierarchy process framework for criteria classification in food SCs.

Few studies have addressed uncertainties in both microeconomic and macroeconomic parameters simultaneously [45,46]. Longinidis and Georgiadis [45] and Badakhshan and Ball [25] explored uncertainties in both macroeconomic and microeconomic parameters within the SC network design problem. Marchi et al. [46] focused on demand uncertainty and investment uncertainty, respectively, within the context of inventory planning.

However, notably absent from existing research is a study that addresses the trade-off between economic profitability and working capital efficiency within inventory management under partial trade credit problem, while considering both microeconomic and macroeconomic uncertainties. This study aims to fill this gap in the literature. The macroeconomic factors under scrutiny include the expected return of the market, risk-free rate of interest, short-term interest rate, and long-term interest rate, alongside the microeconomic demand parameter. Through this comprehensive approach, the study seeks to discern the impact of macroeconomic and microeconomic uncertainties on economic profitability and working capital efficiency, thereby aiding in managing the trade-off between these two crucial financial performance indicators.

Table 1
Inventory management under partial trade credit literature.

Author/s	Modeling approach	Model objectives	Uncertain parameters	Decision variables
Sharma and Mandal [17]	Analytical	Min Total cost	–	Replenishment cycle time (T) Inventory depletion time
Tsao et al. [22]	Analytical	Min Total cost	–	T
Kumar Ghosh et al. [13]	Analytical	Max Total profit	Time of advance payment Share of advance payment	T Order quantity (Q)
Tiwari et al. [23]	Analytical	Max Total profit	Production cost Setup cost Holding cost	T Selling price
Sharma et al. [14]	Analytical	Max Total profit	Demand Expiration date	T, Q
Khan et al. [31]	Analytical	Max Net profit	–	T Percentage of cycle length with positive stock level
Tiwari et al. [18]	Analytical	Min Total cost	Demand	Q Maximum backorder
Mahata et al. [26]	Analytical	Max Total profit	Demand	Credit period T
Li et al. [19]	Analytical	Max Total profit	Demand	T Selling price Time period with no shortages
Wu and Chan [21]	Analytical	Min Total cost	Expiration date	T, Q
Feng et al. [32]	Analytical	Min Total cost	–	T, Q
Taleizadeh et al. [33]	Analytical	Max Total profit	–	T, Q Maximum shortage level Demand coverage from stock
Mahata [15]	Analytical	Min Total cost	–	T, Q
Kreng and Tan [24]	Analytical	Max Total profit	–	T, Q
Teng [16]	Analytical	Min Total cost	Default risk	T, Q
Huang [34]	Analytical	Min Total cost	–	T, Q
Huang and Hsu [20]	Analytical	Min Total cost	–	T, Q
Badakhshan et al. [27]	Simulation-based optimization	Min cash flow bullwhip Min Bullwhip effect Min Total cost	Demand Lead time	Inventory parameters Selling price Unit cost
This study	Simulation-based optimization	Max Economic Profitability Max Working capital efficiency	Demand Macroeconomic parameters	Share of cash payment Share of trade credit Selling price Unit cost Inventory parameters

2.3. Working capital management in supply chains

Working capital management aims to enhance operational efficiency by overseeing inventory, accounts receivable, and accounts payable processes [47]. A key performance indicator commonly used to assess the effectiveness of working capital management is the cash conversion cycle (CCC), which measures the time it takes for a company to convert invested capital into customer payments [48]. Table 2 offers an overview of the literature on working capital management in SCs. There are notable limitations in the existing literature.

Primarily, many studies adopt an empirical approach to CCC measurement across diverse industries [49–55]. For instance, Kroes et al. [50] examined gender diversity and compensation among SCM executives in publicly traded US firms, focusing on how CCC impacts executive pay differentials. Pant et al. [49] suggest that over-reliance on relational capital through the interconnected SC and social networks

Table 2
Literature on working capital management in SCs.

Author/s	Research approach	Research objective(s)	Working capital metric
Kroes et al. [50]	Empirical	Investigating the impact of CCC on executive pay differentials	Cash conversion cycle (CCC)
Pant et al. [49]	Empirical	Studying the impact of relational capital on CCC	CCC
Badakhshan and Ball [56]	Simulation Machine learning	Minimizing CCC for upstream SC members	CCC
Tangsucheeva and Prabhu [57]	Analytical modeling	Measuring the cash flow bullwhip	CCC
Lind et al. [53]	Empirical	Investigating the impact of financial crisis 2007–2008 on working capital efficiency in an automobile SC	CCC
Banomyong [52]	Empirical	Measuring working capital efficiency in a global shrimp SC	CCC
Theodore Farris and Hutchison [58]	Descriptive	Identifying the effective strategies for improving working capital efficiency in SCs	CCC
Hofmann and Kotzab [48]	Conceptual model building	Introducing a metric for measuring the efficiency of the SC working capital management	Collaborative CCC
Ruyken et al. [54]	Empirical	Choosing the right cash to cash cycle for SC members	CCC
Talonpoika et al. [55]	Empirical	Measuring the working capital efficiency for industries that receive advance payment	Modified CCC including upfront collection
Badakhshan et al. [59]	Simulation-based optimization	Managing the trade-offs between conflicting CCC minimizations for SC members	CCC
This study	Simulation-based optimization	Managing the trade-off between economic profitability and working capital efficiency	Modified CCC including upfront collection and payment

can increase CCC for firms. Lind et al. [53] empirically assessed CCCs in an automotive SC during 2006–2008, while Banomyong [52] analyzed CCCs using balance sheets from a global shrimp SC. However, there is a shortage of research leveraging SBO, a powerful tool for capturing working capital dynamics and determining optimal policies.

Furthermore, existing studies lack a metric for quantifying CCC among SC members when partial trade credit is involved. Although Talonpoika et al. [55] proposed a novel metric to measure CCC for SC members receiving partial trade credit from customers, there is no research providing a metric for those who receive partial trade credit from their customers and offer partial trade credit to their suppliers.

Previous studies on working capital management in SCs face two main limitations: underutilization of SBO modeling and the absence of a metric for quantifying CCC among SC members engaged in both receiving and offering partial trade credit. To address these gaps, we introduce an SBO model that formulates working capital dynamics through system dynamics simulation and employs a genetic algorithm to optimize policies. Additionally, we propose a new metric for measuring CCC among such SC members.

2.4. Literature review summary

After reviewing three research strands related to this study–inventory management under trade credit, SC modeling under economic uncertainty, and working capital management in SCs–we identified five gaps: (1) failure to optimize trade credit and cash payment allocation, (2) overlooking the trade-off between economic profitability and working capital efficiency, (3) disregarding macroeconomic uncertainty, (4) underutilizing SBO modeling, and (5) absence of a metric for quantifying the CCC for SC members who receive and offer partial trade credit. To address these gaps, our study develops an SBO model. This model aims to manage the trade-off between economic profitability and working capital efficiency while incorporating macroeconomic uncertainty. Additionally, it introduces a new metric to measure the CCC for SC members who receive and offer partial trade credit and identifies the optimal shares of trade credit and cash payment in the SC.

3. Problem definition and assumptions

3.1. Stock management problem

The stock management problem refers to the issue of controlling a system state or stock to meet certain system objectives [60]. This stock management structure can be found in various application domains, such as inventory management, capital investment, and human resources. In this study, the stock management problem is utilized to address an inventory management issue within a two-echelon SC,

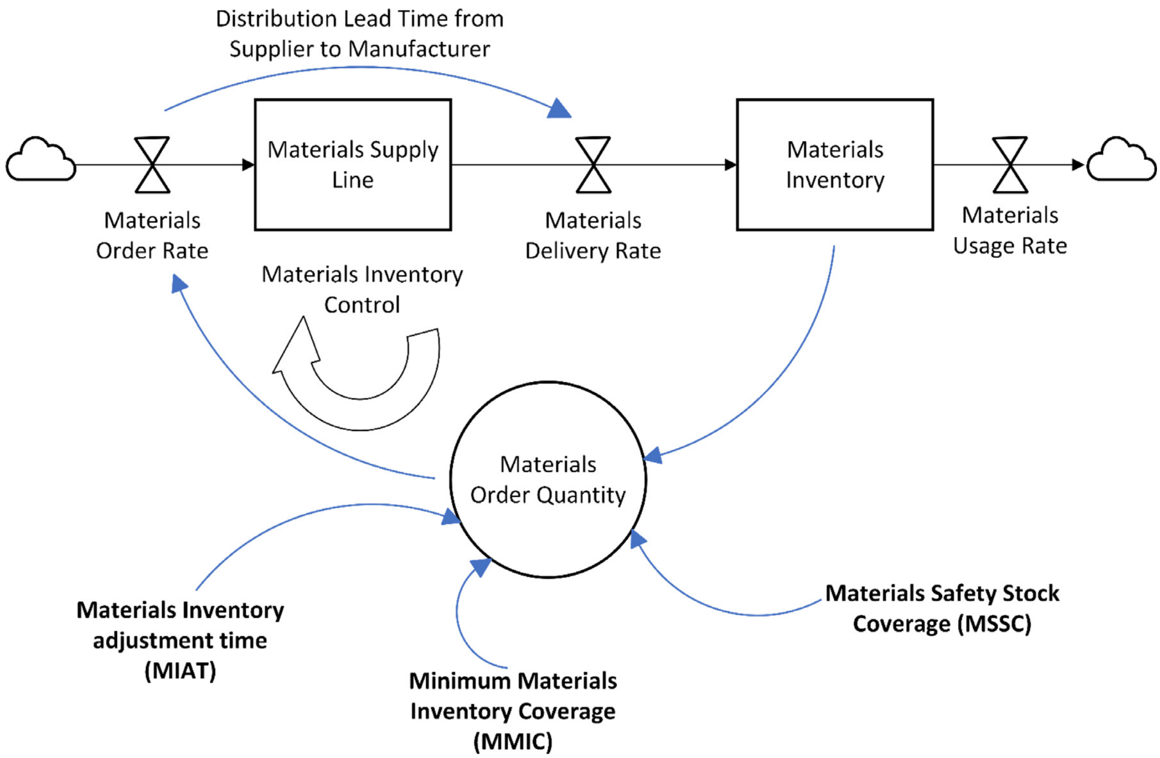


Fig. 2. Stock and flow model of materials inventory management.

comprising a manufacturer and a distribution center (DC). A supplier with unlimited capacity provides raw materials to the manufacturer.

Fig. 2 displays the stock and flow model of materials inventory management. The objective of the model is to specify a sufficient materials order rate to replenish used materials from the inventory and maintain adequate inventory levels to ensure a high service level for the production line.

The stock and flow model incorporates dynamics in the physical flow from three perspectives: Firstly, it addresses delays in physical flow, including distribution lead time between raw material suppliers and manufacturers. Secondly, it includes the materials inventory control feedback loop, which adjusts the materials order quantity based on the materials inventory level. A higher materials inventory results in a lower materials order quantity. Thirdly, it formulates non-linear relationships between controllable inventory decision parameters, such as materials inventory adjustment time, and other model variables by incorporating these parameters into the materials order quantity module.

Fig. 3 illustrates the stock and flow model of product inventory management. The model has two objectives: (1) specifying an adequate production start rate to ensure timely replenishment of products shipped from the manufacturer to the DC and to maintain sufficient manufacturer inventory to fulfill DC orders, and (2) specifying a sufficient order rate for the DC to replace shipped products from DC to the customer and to maintain adequate DC inventory for fulfilling customer orders.

The model incorporates production lead time at the manufacturer and distribution lead time between the manufacturer and DC. It also includes inventory control and DC inventory control feedback loops, which adjust the manufacturer and DC inventories, respectively. A higher inventory results in lower production, and a higher DC inventory leads to lower DC order quantity.

The model formulates non-linear relationships between controllable inventory decision parameters, such as inventory adjustment time, and other model variables by incorporating these parameters into the production and DC order quantity modules.

3.2. Economic uncertainty

The economic cycle concept is applied to model economic uncertainty, which encompasses stagnation, boom, and recession as categories. In our model, five uncertain parameters illustrate the uncertainty in the economic environment: (1) customer demand, (2) expected return of the market, (3) risk-free rate of interest, (4) short-term interest rate, and (5) long-term interest rate [45,61].

During a boom period, economic prosperity leads to increased purchasing power of customers, resulting in excessive demand for products and services. The expected return of the market rises as optimistic investors increase their investment in companies present in the stock market. The risk-free rate of interest, typically the interest rate of a governmental bond, falls as the risk of default diminishes. Consequently, financial institutions charge lower short-term and long-term interest rates. Conversely, during a recession period, these parameters move in the opposite direction. In a stagnation period, it is assumed that the past shapes the future due to minor deviations in the value of parameters compared to the preceding period [45].

The scenario analysis approach is utilized to delineate economic uncertainty, as illustrated in Fig. 4. Initially, during the current period, there is no economic uncertainty, leading to a single scenario branch for the first year. However, with the commencement of the second period, three potential conditions–boom, stagnation, and recession–emerge, generating three distinct scenarios. Each scenario is defined by a specific set of constant parameter values.

3.3. Financial flow modeling

In this section, we expand upon the inventory management model introduced in Section 3.1 by integrating the financial flow alongside the physical flow. Fig. 5 displays the stock and flow model of the modified cash conversion cycle. The model incorporates financial flow dynamics including payment lead time and controllable financial decision parameters such as collection policy to measure the modified cash conversion cycle.

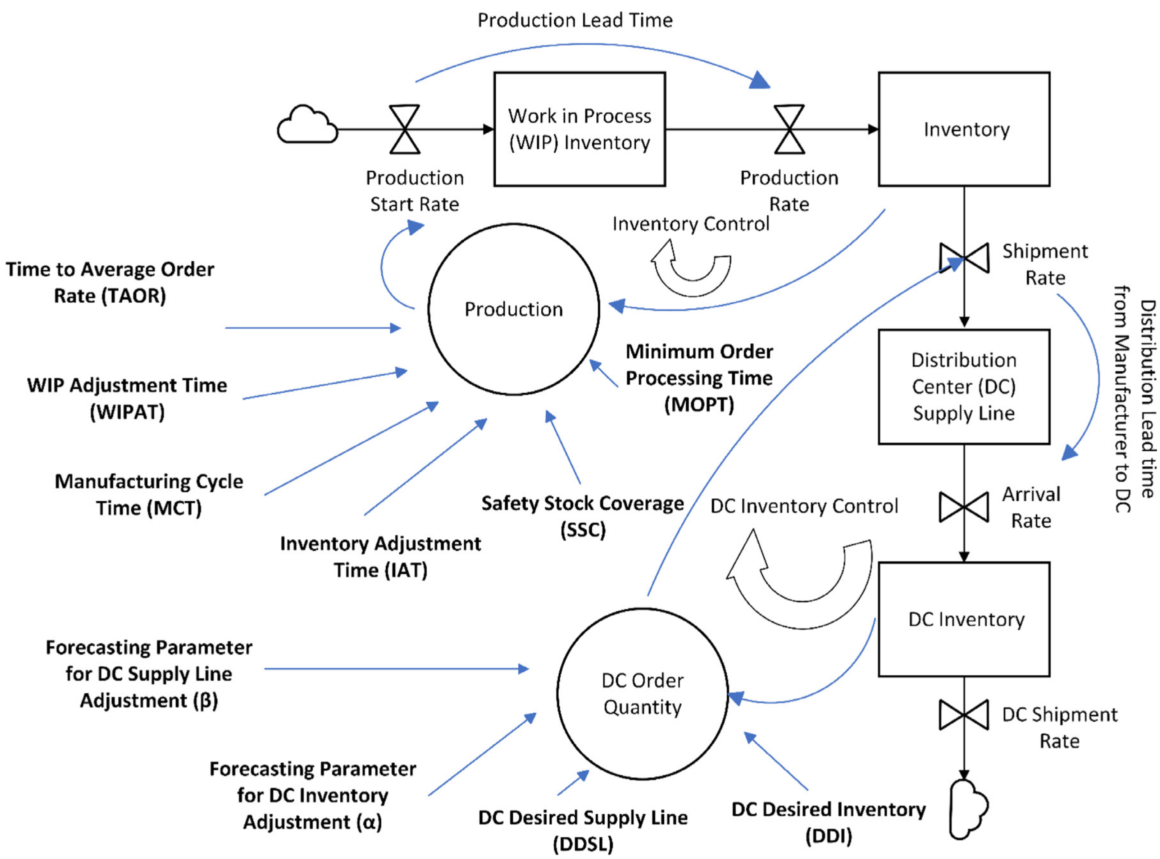


Fig. 3. Stock and flow model of product inventory management.

Fig. 6 illustrates the stock and flow model of economic value added. It integrates controllable financial decision parameters such as the new stock parameter into the weighted average cost of capital and net operating profit after tax modules to measure the economic value added.

Since the DC is owned by the manufacturer, financial transactions in this SC involve payments from the customer to the manufacturer and payments from the manufacturer to the supplier. The collection policy (m) (1) specifies the portion of the order value that must be collected upfront from the customer, while the payment policy (n) (1) represents the share of the raw materials order cost that needs to be paid in advance by the manufacturer to the supplier. The remaining raw materials order cost, payable by the manufacturer to the supplier, is recorded as payable accounts (4). Inventory value (5) determines the worth of inventory held by both the manufacturer and the DC.

Given that the manufacturer makes advance payments to the supplier and receives advance payments from the customer, the cash conversion cycle (CCC) may not fully capture working capital efficiency. To address this limitation, we introduce two additional metrics: Customer Advance Financing Interval (CAFI) (6) and Supplier Advance Financing Interval (SAFI) (7). CAFI represents the average number of days a company can finance its operations using advance payments from customers before delivering the product or service, while SAFI represents the average number of days a company finances its suppliers' operations by making advance payments before goods or services are received.

These metrics are integrated with the original components of the CCC, including days inventory outstanding (DIO), days sales outstanding (DSO), and days payable outstanding (DPO), to formulate a modified cash conversion cycle (mCCC) (8). This modification provides a more comprehensive measure of working capital efficiency.

$$0 \le m, n \le 1 \tag{1}$$

$$Cash = INTEGRAL(Cash\ Inflow - Cash\ Outflow) \tag{2}$$

$$Receivable\ Accounts = INTEGRAL(Receivable\ Accounts\ Inflow - Receivable\ Accounts\ Outflow) \tag{3}$$

$$Payable\ Accounts = INTEGRAL(Payable\ Accounts\ Inflow - Payable\ Accounts\ Outflow) \tag{4}$$

$$Inventory\ Value = INTEGRAL(Inventory\ value\ Inflow - Inventory\ Value\ Outflow) \tag{5}$$

$$CAFI = \frac{Average\ Advance\ Payments\ from\ Customers}{\frac{Revenue}{365}} \tag{6}$$

$$SAFI = \frac{Average\ Advance\ Payments\ to\ Supplier}{\frac{COGS}{365}} \tag{7}$$

$$Modified\ Cash\ Conversion\ Cycle = DIO + DSO + SAFI - DPO - CAFI \tag{8}$$

The income statement is a financial document that outlines a company's revenues and expenses over a specified period, typically a fiscal year. Eqs. (9) to (14) detail the components of the income statement. Net sales (9) are determined by multiplying the shipment rates to customers by the sales price. Earnings before interest and taxes (EBIT) (10) are computed by subtracting the cost of goods sold (COGS) (11), depreciation, and administrative expenses from net sales.

To calculate depreciation (12), the sum-of-years'-digits method, a form of accelerated depreciation, is utilized [62]. It is assumed that fixed assets are depreciated over two years (104 weeks), which aligns with the simulation time frame. Administrative costs (13) are determined by multiplying the administrative constant, set at 0.01, by net sales. These costs include expenses such as rent and utilities that pertain to the entire business rather than specific business units.

Net operating profit after taxes (NOPAT) (14) is computed by multiplying EBIT by the term (1 - Tax Rate). NOPAT is then allocated among

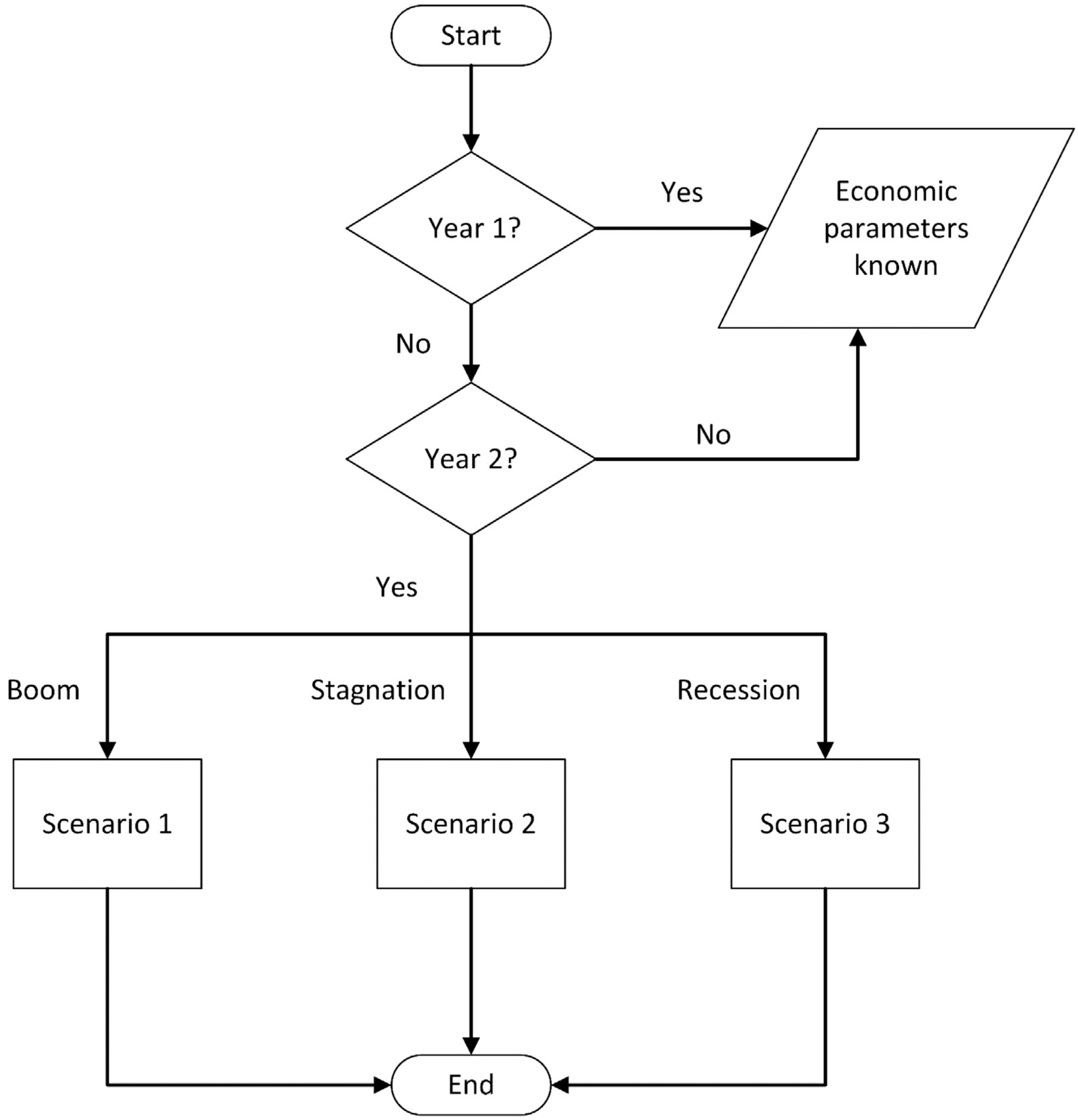


Fig. 4. Scenario tree for economic uncertainty.

dividends, working capital, and retained earnings. Dividends (15) are calculated as the product of NOPAT and the profit distribution policy (16), which is determined by senior management. The working capital policy (17) specifies the portion of NOPAT allocated to working capital. Finally, any remaining NOPAT is added to retained earnings (18).

$$Net\ Sales = Sales\ Price \times DC\ Shipment\ Rate \tag{9}$$

$$EBIT = Net\ Sales - COGS - Depreciation - Administrative\ Costs \tag{10}$$

$$COGS = Unit\ Cost \times Shipment\ Rate \tag{11}$$

$$Depreciation = \frac{104 - Time + 1}{\underbrace{(1 + 2 + \cdots + 104)}_{5460}} \times (Original\ Value\ of\ Fixed\ Assets - Salvage\ Value) \tag{12}$$

$$Administrative\ Costs = Administrative\ Constant \times Net\ Sales \tag{13}$$

$$NOPAT = EBIT * (1 - Tax\ Rate) \tag{14}$$

$$Dividends = NOPAT \times Profit\ Distribution\ Policy \tag{15}$$

$$0 \leq Profit\ Distribution\ Policy \leq 1 \tag{16}$$

$$0 \leq Working\ Capital\ Policy \leq 1 \tag{17}$$

$$Retained\ Earnings = INTEGRAL(Retained\ Earnings\ Inflow) \tag{18}$$

The level of equity (19) increases through stock value inflow (20), determined by the new stock rate and unit stock value. Short-term liabilities (21) and long-term liabilities (22) decrease due to the payment of short-term interest expenses and long-term interest expenses, respectively. Invested capital (23) accumulates financing from short-term liabilities, long-term liabilities, and equity.

The weighted average cost of capital (WACC) (24) reflects the required return on invested capital. It is computed by multiplying the cost of debt (25) and the cost of equity (26) by their proportional weights and summing the results. Unlike the cost of debt, determining the cost of equity can be challenging, as there is no explicit value for the return required by equity investors [45]. Therefore, the capital asset pricing model (CAPM) is utilized as a substitute.

The CAPM calculates the expected return for assets, particularly stocks, by considering the time value of money and risk. The risk-free rate of interest, typically the yield on government bonds like

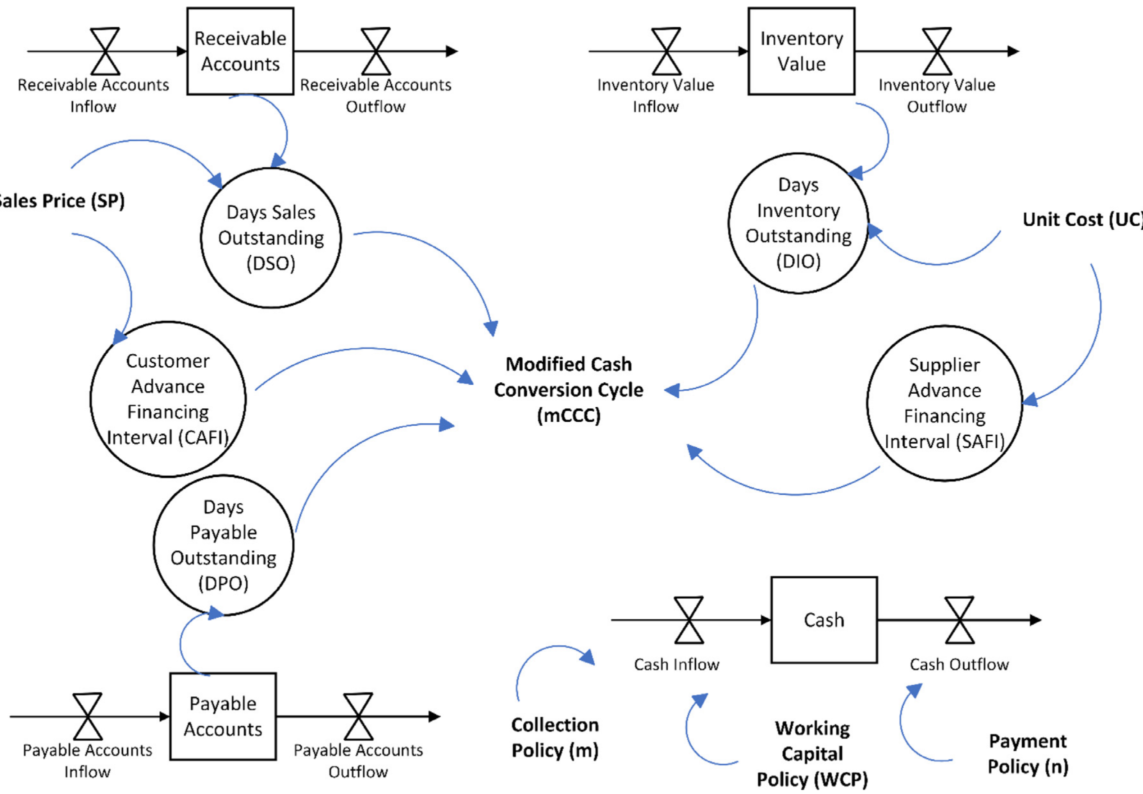


Fig. 5. Stock and flow model of modified cash conversion cycle (mCCC).

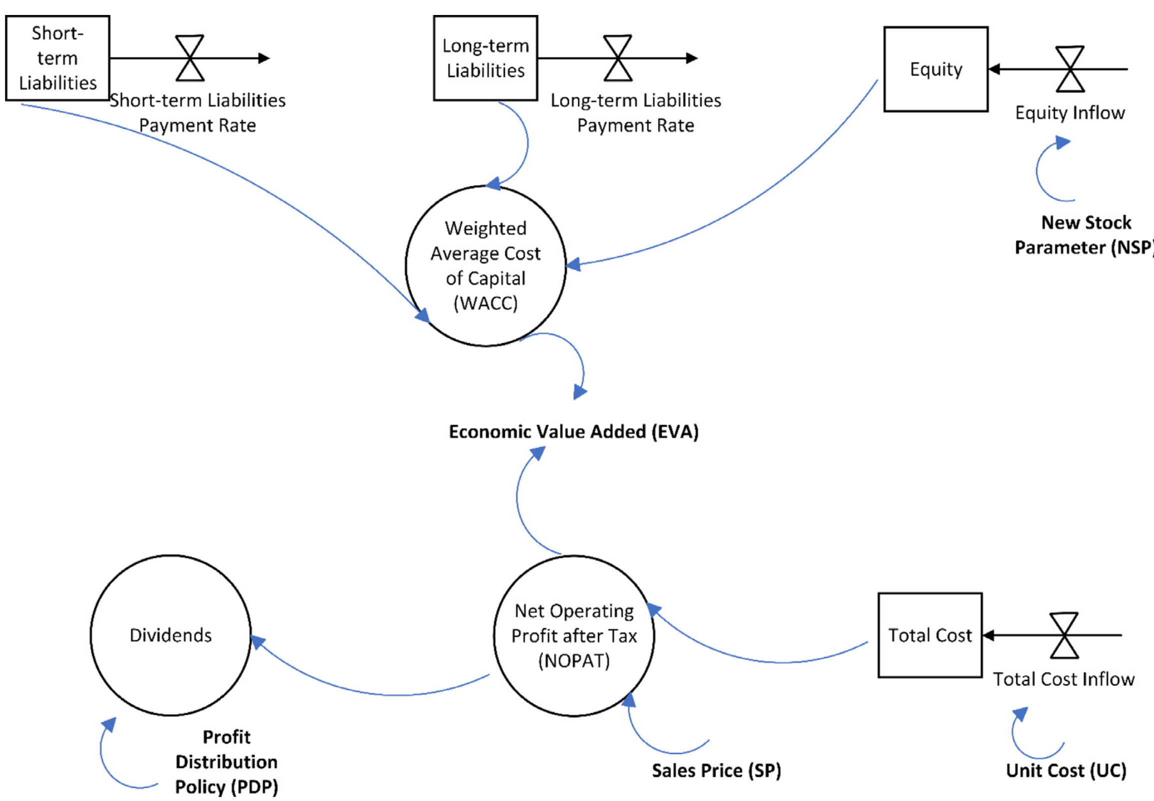


Fig. 6. Stock and flow model of economic value added (EVA).

U.S. Treasuries, accounts for the time value of money, while the risk premium represents compensation for assuming additional risk. The risk measure (β) indicates the level of systematic risk in an asset.

Economic value added (EVA) (27) is determined by subtracting the cost of invested capital from NOPAT.

$$Equity = INTEGRAL(Stock\ Value\ Inflow) \tag{19}$$

$$Stock\ Value\ Inflow = New\ Stock\ Rate \times Unit\ Stock\ Value \tag{20}$$

$$Short\ term\ Liabilities = Integral(-Short\ term\ Interest\ Expenses) \tag{21}$$

$$Long\ term\ Liabilities = Integral(-Long\ term\ Interest\ Expenses) \tag{22}$$

$$Invested\ Capital = Integral(Short\ term\ Liabilities + Long\ term\ Liabilities + Equity) \tag{23}$$

$$WACC = \frac{Equity}{Invested\ Capital} \times Cost of\ Equity + \frac{Short-term\ Liabilities + Long\ term\ Liabilities}{Invested\ Capital} \times Cost\ of\ debt \times (1 - Tax\ Rate) \tag{24}$$

$$Cost\ of\ Debt = \frac{Short\ term\ Liabilities}{Short\ term\ Liabilities + Long\ term\ Liabilities} \times Short\ term\ Interest\ rate + \frac{Long\ term\ Liabilities}{Short\ term\ Liabilities + Long\ term\ Liabilities} \times Long\ term\ Interest\ rate \tag{25}$$

$$Cost\ of\ Equity = Risk\ free\ Rate\ of\ Interest + (Expected\ Return\ of\ the\ Market - Risk\ free\ Rate\ of\ Interest) \times \beta \tag{26}$$

$$EVA = NOPAT - WACC \times Invested\ Capital \tag{27}$$

Although system dynamics simulation models are generally considered more robust than other types of simulation models, they still require validation through various tests. Three validation tests, including the model structure test, boundary adequacy test, and extreme condition test, were employed to validate the developed system dynamics simulation model.

The model structure test evaluates whether the structure of the model accurately reflects the structure of the system being modeled [63]. In our model, each element corresponds to a real-world counterpart in the physical and financial flows of the studied SC.

The boundary adequacy test assesses whether the model's boundaries align with the intended purpose of the model [63]. Given that the objective of our model is to manage the trade-off between economic profitability and working capital efficiency for the studied SC, all factors affecting economic value added (EVA) and modified cash conversion cycle (mCCC) have been incorporated into the model.

The extreme condition test, one of the validation tests for system dynamics models [60], examines whether the model behaves appropriately given extreme input values. For instance, it verifies if the model responds correctly when faced with significant deviations in input parameters. In our developed model, mCCC and EVA exhibit significant growth when the sales price per unit of the product, a key input, experiences a substantial increase.

4. Inventory management under partial trade credit model optimization

4.1. Multi-objective modeling of the inventory management under partial trade credit model

Economic profitability and working capital efficiency are vital indicators of a business's financial health. Economic profitability aims to maximize the overall profitability of the SC while working capital efficiency focuses on minimizing tied-up capital within the SC. In this study, the financial performance of the developed inventory management under the partial trade credit model is optimized by minimizing the working capital efficiency metric (mCCC) and maximizing the economic profitability metric (EVA). These metrics may move in different directions because actions that improve EVA, such as increasing inventory levels to meet higher demand, may increase mCCC by tying up more capital in inventory. Conversely, actions that decrease mCCC, such as tightening credit terms to reduce accounts receivable days, may negatively impact EVA by diminishing sales volume or customer satisfaction. Therefore, while both metrics are crucial for assessing financial performance, they represent different aspects of the business and require trade-offs to optimize overall financial health. The objective functions are denoted as follows:

$$Objective\ functions \begin{cases} Max\ EVA = Max\ \mu_{EVA} \\ Min\ mCCC = Min\ \mu_{mccc} \end{cases}$$

where $\mu_{EVA} = \frac{\sum_{t=0}^{T} EVA}{T}, \mu_{mCCC} = \frac{\sum_{t=0}^{T} mCCC}{T}$

$Input\ (Decision\ parameters) = WIPAT, MCT, IAT, MOPT, SSC, TAOR, m, MIAT, MSSC, MMIC, NSP, n, PDP, SP, UC, WIPAT, WCP$

And $Output = \mu_{EVA}, \mu_{mCCC}$

Subject to:

$$0.25 \le WIPAT \le 10, 5 \le MCT \le 15, 5 \le IAT \le 15, 0.25 \le MOPT \le 10, 0.25 \le SSC \le 10, 5 \le TAOR \le 15, 0 \le m \le 1, 5 \le MIAT \le 15, 0.25 \le MSSC \le 10, 0.25 \le MMIC \le 10, 0 \le NSP \le 1, 0 \le n \le 1, 0 \le PDP \le 0.50, 7 \le SP \le 12, 3 \le UC \le 6, 0 \le WCP \le 0.50, 0 \le \alpha \le 1, 0 \le \beta \le 1, 0 \le DDI \le 30000, 0 \le DDSL \le 35000 \tag{28}$$

$\alpha = forecasting\ parameter\ for\ inventory\ adjustment$: denote the aggressiveness of the distributor in bridging the gap between the desired and current inventory.

$\beta = forecasting\ parameter\ for\ supply\ line\ adjustment$: denote the level of consideration of the distributor to the inventory on-orders at the time of order placement.

$m = collection\ policy$: denotes the portion of sales that must be collected upfront from the customer.

$n = payment\ policy$: denotes the share of the raw materials purchase that is required to be paid in advance to the supplier.

DDI: denote the desired inventory by the distributor.

$DDSL$: represent the desired inventory on order by the distributor.

$IAT = The\ inventory\ adjustment\ time$: represents the time period over which the manufacturer seeks to bridge the gap between the desired and current inventory of finished products.

$MIAT = The\ materials\ inventory\ adjustment\ time$: represents the time period over which the manufacturer seeks to bridge the gap between desired and current inventory of the raw materials.

$MSSC = The\ materials\ safety\ stock\ coverage$: represents the time period over which the manufacturer maintains materials safety stock coverage to hedge against volatility in desired production.

$SSC = The\ safety\ stock\ coverage$: represents the time period over which the manufacturer would like to maintain a safety stock coverage in order to meet any variations in distributor's demands.

$MMIC = The\ minimum\ materials\ inventory\ coverage$: represent the minimum materials inventory required by the manufacturer.

$MOPT = The\ minimum\ order\ processing\ time$: denotes the minimum time required by the manufacturer to process and ship a distributor order.

$PDP = The\ profit\ distribution\ policy$: denotes the dividends that is required to be paid to the shareholders.

$SP = The\ sales\ price$: The price per tonne of product which is paid to the distribution center by the customer.

$TAOR = The\ time\ to\ average\ order\ rate$: denotes the time period over which the distributor demand forecast is adjusted to actual customer's orders.

$UC = The\ unit\ cost$: denotes the production cost and distribution cost per tonne of product.

$WIPAT = The\ WIP\ adjustment\ time$: represents the time required for the manufacturer to adjust its WIP inventory to its desired level.

$MCT = The\ manufacturing\ cycle\ time$: represents the average delay time of the production process for the products from start until completion of the product.

$NSP = New\ stock\ parameter$: represents the growth rate in the stock units.

$WCP = Working\ capital\ policy$: represents the share of NOPAT dedicated to the working capital.

The first objective is to maximize EVA, while the second objective aims to minimize mCCC. These objectives are formulated as the means of performance indicators over the simulation period. The decision parameters include controllable inventory and financial decisions, which are highlighted in Figs. 2 and 4.

4.2. Multi-objective simulation-based optimization

Multi-objective optimization is a method applied to solve problems containing conflicting objectives that may not be formulated to a common scale of cost or benefit [64]. To solve problems with multiple objectives, a non-dominated set of optimal solutions is obtained. Then, the decision maker chooses the optimal solution based on their preferences [65]. Non-dominated solutions form a set of different points in a frontier called Pareto optimal. These solutions do not have superiority over one another but dominate all other solutions. Specifically, a solution S_1 dominates another solution S_2 if S_1 is significantly better than S_2 in at least one optimization objective, and where S_1 is no worse than S_2 regarding all optimization objectives [65].

In this study, the weighted sum method, one of the most widely used methods for multi-objective optimization [66], is utilized to construct the Pareto optimal frontier for maximizing EVA and minimizing mCCC. In this method, multi-objectives are transformed into a single objective by multiplying each objective function by a weighting factor and aggregating all weighted objective functions [67]. The weight of an objective is chosen in proportion to its relative importance [68]. In a multi-objective optimization problem with m objectives, denoted by $w_i(i = 1, \dots, m)$, if $\sum_{i=1}^{m} w_i = 1$ and $0 \le w_i \le 1$, the weighted sum represents a convex combination of objectives [69]. Thus, each solution obtained by single objective optimization corresponds to a point on the Pareto optimal frontier. By adjusting the weighting factors (w_i), different optimal solutions can be determined through single objective optimization. These optimal solutions collectively form the set of non-dominated solutions represented on the Pareto optimal frontier. Using the weighted sum method, the multi-objective model presented in Eq. (28) is transformed into a single-objective model as follows:

$$New\ Objective = w_1 \times \mathrm{Max}\ \mu_{EVA} + w_2 \times \mathrm{Min}\ \mu_{mCCC} w_1 + w_2 = 1 \quad (29)$$

To solve the transformed single-objective optimization model, we employ a simulation-based optimization (SBO) approach. SBO integrates an optimization algorithm directly into a simulation model, aiming to enhance its performance by determining optimal values for its decision parameters [70]. This approach iteratively explores the decision space, taking into account system dynamics and constraints, to find solutions that optimize the specified objective function.

The SBO framework, illustrated in Fig. 7, operates as an iterative process. It typically begins with an optimization algorithm generating initial values for the decision parameters of the simulation model. Subsequently, the simulation model is executed using these values to assess system performance. The resulting performance measures are then fed back into the optimization algorithm for analysis. Based on this feedback, a new set of decision parameters is generated and fed back into the simulation model for further evaluation [71]. This iterative cycle continues until a user-defined stopping criterion is met, such as reaching a specified number of evaluations [72]. The iterative nature of this process allows for refinement of the decision parameters, leading to improved optimization results.

Genetic algorithms (GAs) are computational algorithms inspired by Darwinian evolutionary theory, often summarized as "survival of the fittest" [73]. In a genetic algorithm, a population of candidate solutions to an optimization problem evolves toward a better solution through selection, crossover, and mutation operators [74]. Genetic algorithms employ a fitness function to assess the quality of each solution relative to the optimization objective [75]. Unlike analytical optimization, genetic algorithms do not rely on derivative information, making them well-suited for numerically generated data. They exhibit the capability to escape local minima and can optimize both continuous and discrete parameters, particularly the former [76].

In this study, GAs are chosen as the optimization method due to their suitability for handling continuous decision parameters and their ability to optimize objective functions that rely on measurements from simulation models rather than explicit mathematical formulations. The decision parameters in our model are continuous, making GAs well-suited for exploring the solution space efficiently. Furthermore, the objective function presented in Eq. (29) is not explicitly available but is derived from measurements obtained during simulation runs.

The fitness function of the GA defined by Eq. (30) evaluates the quality of each candidate solution. It incorporates measurements of the simulation model's performance indicators, i.e., economic profitability (EVA) and working capital efficiency (mCCC). By iteratively evaluating candidate solutions using the fitness function, the GA guides the search towards optimal or near-optimal solutions that balance the trade-off between EVA maximization and mCCC minimization.

$$Fitness\ Function = w1 \times \mu_{EVA} - w2 \times \mu_{mCCC} w1 + w2 = 1 \quad (30)$$

In this study, we develop an SBO framework that integrates a genetic algorithm and system dynamics simulation. The framework begins by generating initial values for inventory and financial decision parameters, as presented in Eq. (28), using the genetic algorithm. These values are then utilized to run the system dynamics simulation model, evaluating system performance based on the fitness function outlined in Eq. (30). Subsequently, the performance feedback is incorporated back into the genetic algorithm, which generates a new set of inventory and financial decision parameters. These parameters are then inputted into the system dynamics simulation model for evaluation. This iterative process continues until the stopping criterion, set to 300 generations, is reached.

5. A case study

This section conducts numerical experiments to illustrate the practicality of the proposed model. The dataset used in this case study was initially introduced in [5,45]. The Initial data required for running the simulation model are detailed in Tables 3 and 4. Table 3 delineates five parameters that predominantly signify economic uncertainty, all of which are incorporated into the scenario tree structure depicted in Fig. 4. Scenario 1 indicates a booming economy with higher demand, lower interest rates, and higher returns on investments. Scenario 2 represents a stagnant economy with no changes in demand, interest rates, and returns on investments. Scenario 3 displays an economy in recession with declining demand, higher borrowing costs, and lower returns on investments.

Table 4 presents the balance sheet at the beginning of the simulation period. It includes essential information such as the original and salvage values of fixed assets, denoted in relative money units. Additionally, key financial parameters such as the administrative constant (0.01), tax rate (30% per year), beta coefficient (unity), and stock value (7 money units per unit stock) are outlined.

5.1. Scenario 1

Scenario 1 portrays a boom occurring in the second year of the simulation, characterized by increased customer demand and an upturn in the expected return of the market. Additionally, there is a decrease in the risk-free rate of interest, short-term interest rate, and long-term interest rate.

To evaluate the impact of these changes on model performance, the system dynamics (SD) simulation model must be initialized to a

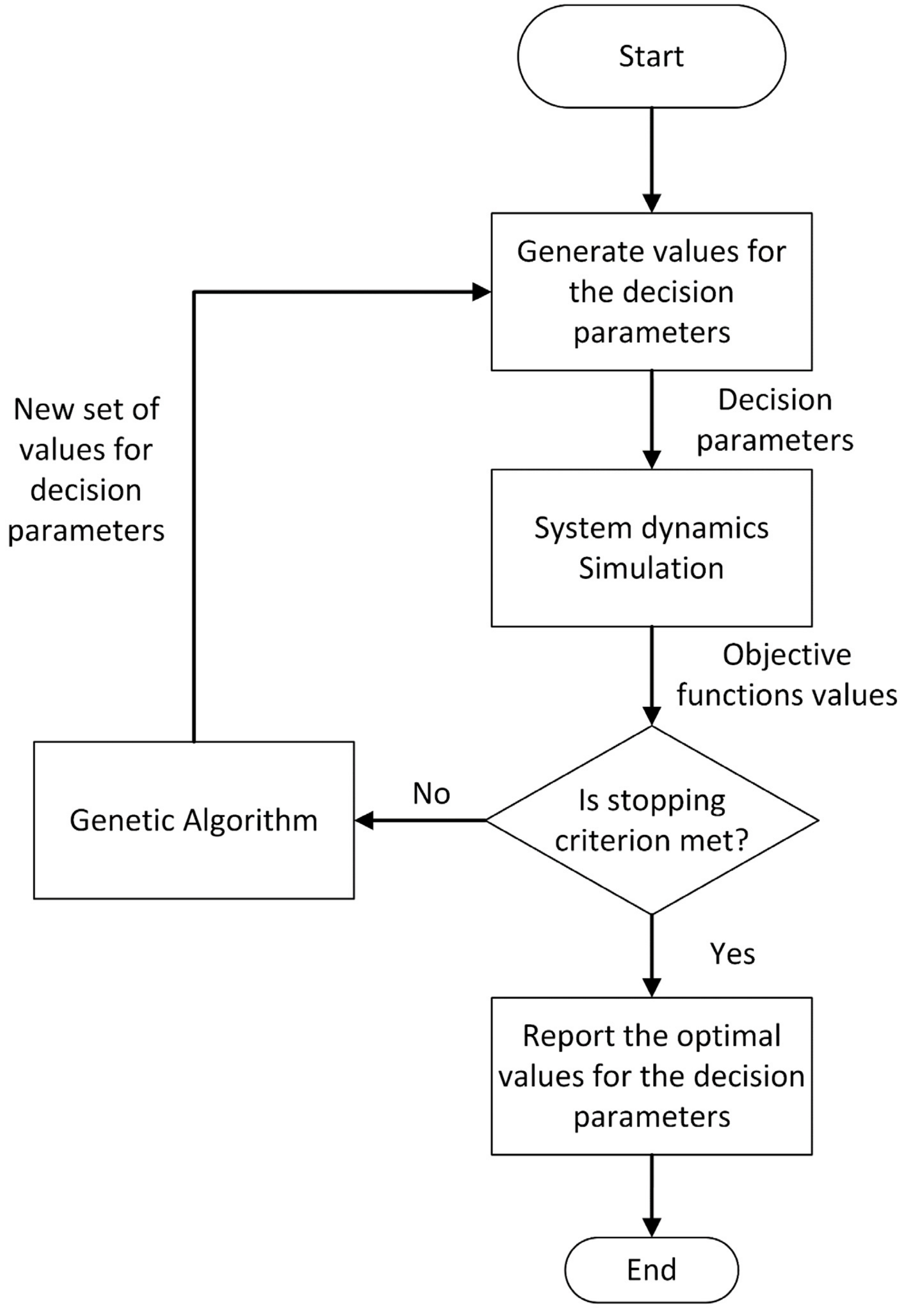


Fig. 7. SBO process.

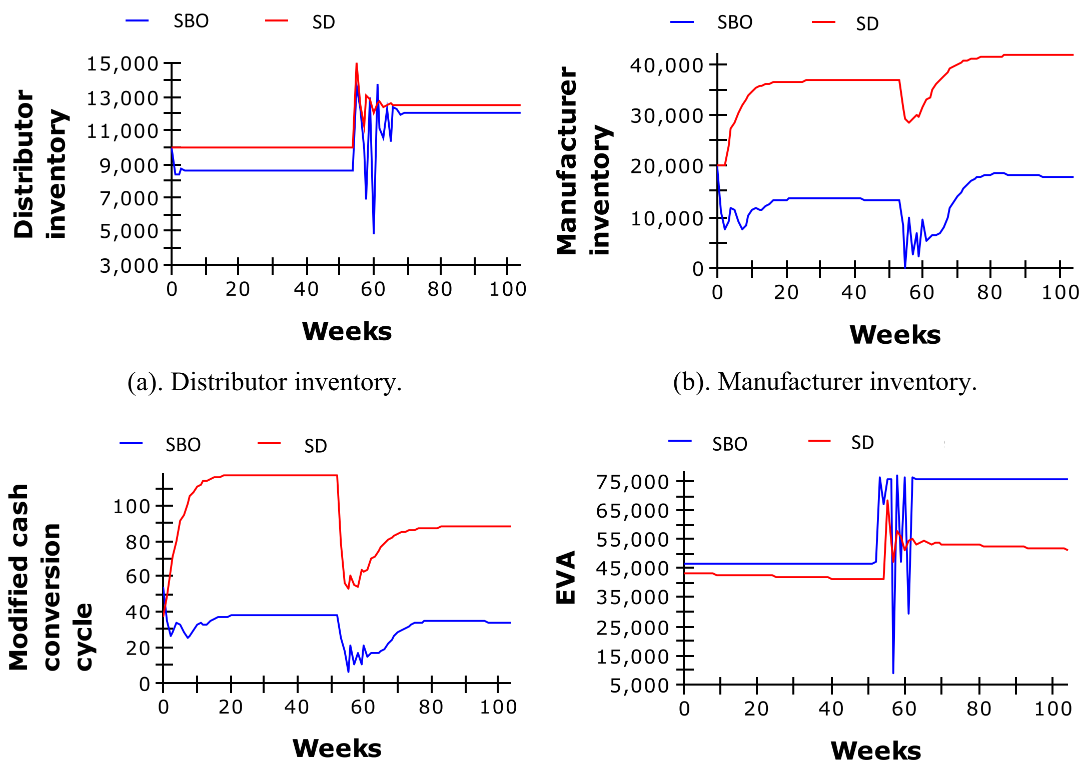
Table 3
Customer demand and financial parameters related to economic scenarios.

Scenario	Parameter									
	$CD^{[s]}_{t=0}$	$CD^{[s]}_{t=53}$	$STR^{[s]}_{t=0}$	$STR^{[s]}_{t=53}$	$LTR^{[s]}_{t=0}$	$LTR^{[s]}_{t=53}$	$r^{[s]}_{f_{t=0}}$	$r^{[s]}_{f_{t=53}}$	$r^{[s]}_{m_{t=0}}$	$r^{[s]}_{m_{t=53}}$
S_1	10 000	15 000	7.00	5.60	4.00	3.00	2.50	2.00	5.00	6.00
S_2	10 000	10 000	7.00	7.00	4.00	4.00	2.50	2.50	5.00	5.00
S_3	10 000	5000	7.00	8.40	4.00	5.00	2.50	3.00	5.00	4.00

balanced equilibrium. This ensures an accurate assessment of the effects of both microeconomic and macroeconomic parameters on the model's behavior [60].

During initialization, all model stocks, including inventories and supply lines, are set to their desired values. Additionally, the expected order rate is aligned with the customer order rate, facilitating a stable starting point for the simulation.

In Scenario 1, depicted in Fig. 8(a)–(d), the dynamics of inventory, modified cash conversion cycle (mCCC), and Economic Value Added (EVA) for the SC members obtained from System Dynamics (SD) simulation model were analyzed over two years spanning 104 weeks. During this scenario, a surge in customer demand occurred in the second year, prompting the distributor to increase orders to the manufacturer. As a result, the inventory level peaked at 15,000 units of product by



(a). Distributor inventory. (b). Manufacturer inventory.

(c). Modified cash conversion. (d). Economic Value.

Fig. 8. SD and SBO models performances in scenario 1.

Table 4
Balance sheet at the beginning of simulation time (t=0).

Account	Relative money units
A.1. Assets	170,000
A.1.1. Tangible assets	170,000
A.1.2. Intangible assets	0
A.2. Current assets	70,000
A.2.1. Cash	29,968
A.2.2. Receivable accounts	28,000
A.2.3. Inventory	10,032
A.2.4. Prepaid expenses(Advance payments to supplier)	2,000
A. Total assets	240,000
B.1. Equity	130,000
B.1.1. Common stock	80,000
B.1.2. Retained earnings	50,000
B..2. Debt	110,000
B..1. Short-term liabilities	45,000
B.2.1.1. Advance payments from customers	3,000
B.2.2.2. Other short-term liabilities	42,000
B.2.2. Long-term liabilities	65,000
B. Total debt and equity	240,000

Table 5
Impact of population size on fitness function.

Population size	Fitness value			
	Worst (Min)	Best (Max)	Mean	Standard deviation
150	59 615.64	59 723.68	59 642.37	38.28
200	59 596.38	59 684.24	59 625.40	25.36
250	59 487.80	59 537.51	59 514.29	14.62
300	59 422.11	59 453.62	59 433.72	6.42
350	59 422.11	59 448.23	59 431.51	6.21

week 55, reflecting the distributor's efforts to meet the heightened demand. Subsequently, the distributor's inventory stabilized at a new equilibrium of 12,742 units by week 70.

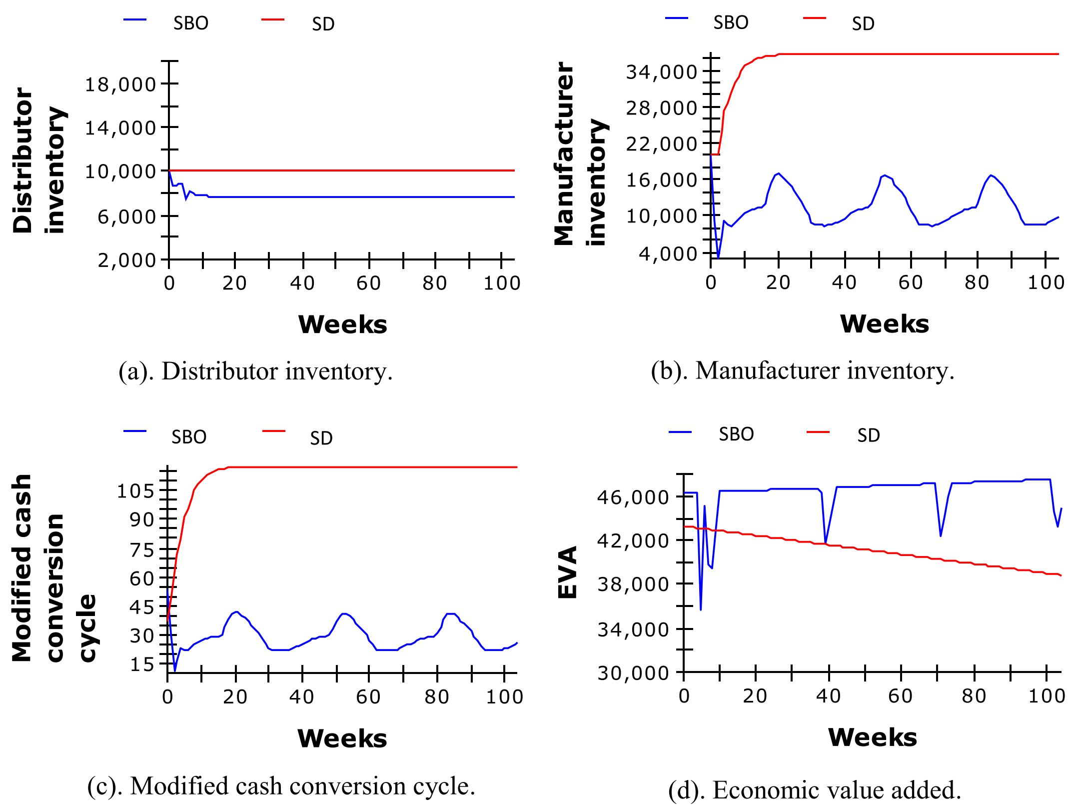
Meanwhile, the manufacturer experienced a decrease in inventory following the demand surge. However, by week 58, the manufacturer's inventory began to rise again, reaching a new equilibrium of 41,635 units by week 80.

The dynamics of the modified cash conversion cycle (mCCC) mirrored those of the manufacturer's inventory, given its substantial inventory levels within the SC. At the start of the second year, mCCC experienced a sharp decline due to reduced inventory accumulation, ultimately stabilizing at 87 days by week 80. In terms of Economic Value Added (EVA), there was a notable increase at the beginning of the second year, primarily driven by the reduction in manufacturer inventory levels and subsequent sales growth. EVA leveled off at £51,716 by week 100, signifying the impact of inventory management strategies on financial performance.

To implement the SBO methodology, the parameters for the Genetic Algorithm (GA) are configured as follows: a population size of 300, crossover and mutation rates set at 0.8 and 0.1, respectively. The values for $w1$ and w2 in the fitness function of the GA, as presented in Eq. (30), are both set to 0.5, signifying equal importance for mCCC minimization and EVA maximization. To determine the optimal population size, various population sizes were tested, with the algorithm executed 15 times for each size. The outcomes, detailed in Table 5, indicate that increasing the population size enhances both the mean and the standard deviation of the fitness function until the optimal solution, achieved at a population size of 300, is reached.

For each scenario, the SBO process is executed 15 times with the predefined GA parameters, and the optimal fitness value is determined. Subsequently, the simulation system is run using the decision parameters derived from the SBO model that yielded the best fitness value.

Fig. 8(a)–(d) depict the outcomes of the SBO model. Following the implementation of the SBO methodology, notable changes are observed



(a). Distributor inventory. (b). Manufacturer inventory.

(c). Modified cash conversion cycle. (d). Economic value added.

Fig. 9. SD and SBO models performances in scenario 2.

in the inventory levels of both the distributor and the manufacturer. The distributor's inventory exhibits a consistent decrease, stabilizing at 11,864 units of products from week 75 onwards, contrasting with the SD model where it levels off at 12,743 units during the same period.

Similarly, the manufacturer's inventory experiences a significant reduction post-SBO. While the manufacturer's inventory peaks at 20,000 units of products after employing SBO, it reaches 41,635 units in the SD model. Furthermore, the manufacturer's inventory level at week 80 is 18,487 units post-SBO and continues to decline, whereas in the SD model, it remains constant at 41,635 units from week 80 onwards.

This reduction in the manufacturer's inventory levels leads to a considerable decline in the cash-to-cash cycle. Post-SBO implementation, the cash conversion cycle oscillates between 6 and 38 days, decreasing from 33 days at week 80 onwards. In contrast, the SD model shows fluctuations in the range of 36 to 114 days and maintains stability at 87 days from week 80 onwards.

Regarding EVA, post-SBO results closely follow the pattern observed in the SD model. Furthermore, the EVA reaches an equilibrium level of £75,789 after SBO, whereas in the SD model, it reaches £49,832 by the end of the simulation period.

5.2. Scenario 2

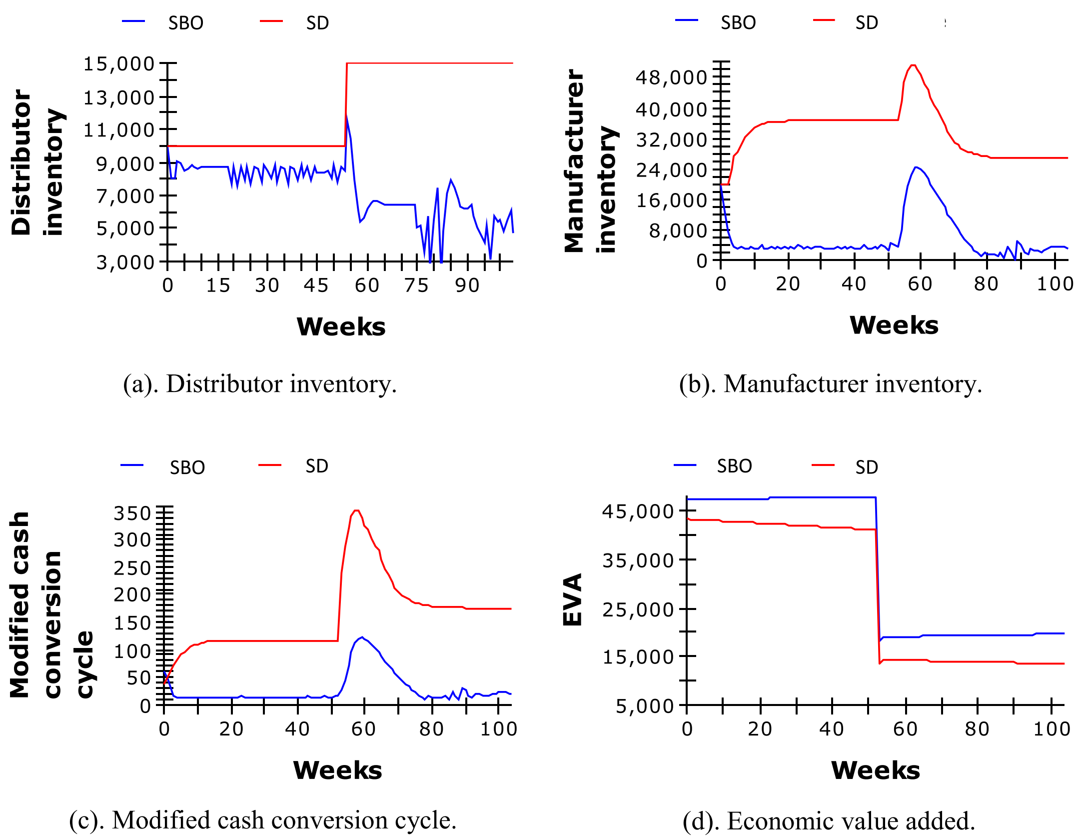
Scenario 2 depicts a period of stagnation in the second year of the simulation, resulting in stability in customer demand, expected return of the market, risk-free rate of interest, short-term interest rate, and long-term interest rate. Fig. 9(a)–(d) illustrate the inventory, cash-to-cash cycle, and EVA dynamics for the SC members under scenario 2, obtained from running the SD simulation model over two years (104 weeks). With customer demand remaining stable throughout the simulation, the system maintains its equilibrium state over time. The manufacturer's inventory and the cash conversion cycle exhibit a goal-seeking pattern, reaching equilibrium by week 10. Meanwhile, the EVA experiences a linear decrease as invested capital increases proportionally, reflecting the stable demand and resulting in a consistent trajectory.

The application of the SBO methodology to scenario 2, using the GA parameters and fitness function defined in scenario 1, yielded significant changes in inventory levels, as depicted in Fig. 9(a)–(d). Following the implementation of SBO, the distributor's inventory level experienced a notable reduction, stabilizing at 7613 units from week 10 until the simulation's conclusion. In contrast, the inventory level remained at 10,000 units throughout the simulation in the SD model. Similarly, the manufacturer's inventory level saw a substantial decrease post-SBO. While the SD model maintained a stable inventory of 36,600 units at week 10, the inventory oscillated between 8567 and 18,246 units from week 10 onwards after employing SBO.

The substantial reduction in the manufacturer's inventory level, resulting from the application of SBO, had a notable effect on the cash-to-cash cycle. Post-SBO implementation, the cash conversion cycle fluctuated between 22 and 43 days from week 10 until the simulation's conclusion. In contrast, the SD model maintained a stable cash conversion cycle of 117 days during the same period. Additionally, the EVA exhibited oscillations ranging from £39,948 to £46,347 after the implementation of SBO from week 10 onwards, attributed to the reduction in the manufacturer's inventory. Conversely, in the SD model, the EVA started at £43,892 and decreased to £38,621 by week 104.

5.3. Scenario 3

In Fig. 10(a)–(d), the dynamics of inventory, mCCC, and EVA for the SC members in scenario 3 are depicted, derived from the SD simulation model spanning two years (equivalent to 104 weeks). Initially, the distributor's inventory remains constant at 10,000 units until the end of the first year. However, at the onset of the second year, the distributor's inventory experiences a surge, peaking at 15,000 units, and maintains



(a). Distributor inventory.

(b). Manufacturer inventory.

(c). Modified cash conversion cycle.

(d). Economic value added.

Fig. 10. SD and SBO models performances in scenario 3.

stability until the simulation concludes due to a decline in customer demand.

The manufacturer's inventory demonstrates a goal-seeking pattern before the commencement of the second year, achieving its target of 36,700 units by week 10. Subsequently, it undergoes significant growth, reaching 50,448 units by week 60. However, between weeks 60 and 80, there is a decline in inventory levels before stabilizing at a new equilibrium of 26,569 units by week 80.

The mCCC mirrors the pattern observed in the manufacturer's inventory, peaking at 364 days by week 60 and converging to a new equilibrium level of 175 days by week 80. The EVA experiences a plunge at the beginning of the second year due to reduced customer demand, reaching £13,569 by the simulation's end.

The SBO methodology for scenario 3 is applied using the GA parameters and fitness function established in scenario 1, with results depicted in Fig. 10(a)–(d). Notably, the SBO methodology yields significant reductions in distributor inventory. Post-implementation, the distributor's maximum inventory reaches 11,227 units by week 53, contrasting with the steady 15,000 units maintained in the SD model during the second year.

Furthermore, the SBO implementation results in a notable decrease in manufacturer inventory. After employing the SBO, manufacturer inventory peaks at 2524 units by week 60, compared to the peak of 50,448 units in the SD model during the same period. Between weeks 80 and 100, manufacturer inventory fluctuates between 2705 and 3819 units in the SBO model, contrasting with the stable 26,569 units observed in the SD model.

Moreover, the SBO significantly reduces the cash-to-cash cycle, given its dependency on SC member inventories. Post-implementation, the cash conversion cycle ranges from 15 to 125 days, compared to the SD model's fluctuation between 48 and 364 days.

Regarding EVA, the SBO model reflects a substantial reduction at the start of the second year, attributed to declining customer demand. However, EVA values in the SBO model during the second year exceed those of the SD model. Specifically, in the second year, EVA stabilizes at around £20,000, contrasting with £14,500 in the SD model.

5.4. Pareto optimal frontiers

To provide decision-makers with a portfolio of alternative optimal inventory and financial decisions to manage the trade-off between minimizing mCCC and maximizing EVA, we employ the weighted sum method to generate the Pareto efficient frontiers. Figs. 11–13 illustrate the Pareto optimal frontier for EVA versus mCCC in scenarios 1–3. These results are determined by specifying the weighting factors for objective functions, which could be selected based on the decision-maker's preferences. To achieve non-dominated solutions, each single objective optimization problem is formulated using Eq. (30) by selecting weighting factors w1 and w2 within the interval [0, 1], summing up to 1. Each point in this frontier corresponds to a different combination of inventory and financial decision parameters.

Table 8. Optimal decision parameters of two non-dominated solutions in Scenario 3

To gain a deeper understanding of the model's decision-making process, we examined two solutions within each scenario. These solutions offer contrasting approaches: Solution 1 prioritizes minimizing mCCC, while Solution 101 focuses on maximizing economic value added.

Tables 6–8 show the optimal inventory and financial decisions corresponding to these solutions. In Solution 1 across all scenarios, a notable strategy involves collecting a significant portion of the customer order value upfront, evident from the high value of parameter m, such as $m = 0.96$ in scenario 1. Conversely, a considerable portion of materials purchases is made on credit, as indicated by the low value of parameter n, for example, $n = 0.08$ in scenario 1. This approach aims to reduce accounts receivable while increasing accounts payable, thereby

Table 6
Optimal decision parameters of two non-dominated solutions in Scenario 1.

Parameter Solution	W_{CCC}	W_{EVA}	m	IAT	DDI	β	$MIAT$	$MSSC$	$MMIC$	$MOPT$	NSP	n
Solution 1	1	0	0.96	13.37	25,341	0.27	6.10	4.16	3.94	0.28	0	0.08
Solution 101	0	1	0.52	13.39	27,028	0.35	8.35	5.25	9.44	9.74	0	0.23

Parameter Solution	PDP	SSC	SP	$TAOR$	α	$DDSL$	MCT	UC	$WIPAT$	WCP	μ_{mCCC}	μ_{EVA}
Solution 1	0.50	0.32	9.29	14.42	0.47	14,158	5	4.08	3.15	0.50	1	33,471
Solution 101	0.50	3.77	11.96	10.42	0.81	7,179	5	3.06	4.42	0.50	362	74,243

Table 7
Optimal decision parameters of two non-dominated solutions in Scenario 2.

Parameter Solution	W_{CCC}	W_{EVA}	m	IAT	DDI	β	$MIAT$	$MSSC$	$MMIC$	$MOPT$	NSP	n
Solution 1	1	0	0.91	8.66	2,362	0.31	5.23	5.52	6.97	0.25	0	0.09
Solution 101	0	1	0.37	12.86	21,722	0.14	13.43	6.90	8.92	9.48	0	0.42

Parameter Solution	PDP	SSC	SP	$TAOR$	α	$DDSL$	MCT	UC	$WIPAT$	WCP	μ_{mCCC}	μ_{EVA}
Solution 1	0.50	0.25	11.31	14.11	0.45	1,999	5	5.93	6.92	0.50	0	21,218
Solution 101	0.50	8.28	11.28	12.91	0.54	22,342	5	3.01	4.98	0.50	467	41,665

Table 8
Optimal decision parameters of two non-dominated solutions in Scenario 3.

Parameter Solution	W_{CCC}	W_{EVA}	m	IAT	DDI	β	$MIAT$	$MSSC$	$MMIC$	$MOPT$	NSP	n
Solution 1	1	0	0.91	10.06	1,381	0.48	5.94	5.75	5.24	0.28	0.0005	0.12
Solution 101	0	1	0.37	12.67	11,031	0.08	8.97	6.40	7.75	7.94	0	0.58

Parameter Solution	PDP	SSC	SP	$TAOR$	α	$DDSL$	MCT	UC	$WIPAT$	WCP	μ_{mCCC}	μ_{EVA}
Solution 1	0.44	0.33	10.27	13.94	0.42	3,514	5	5.87	2.48	0.50	2	$-4,675$
Solution 101	0.50	4.29	11.52	9.99	0.27	5,085	5	3.54	3.23	0.50	291	14,215

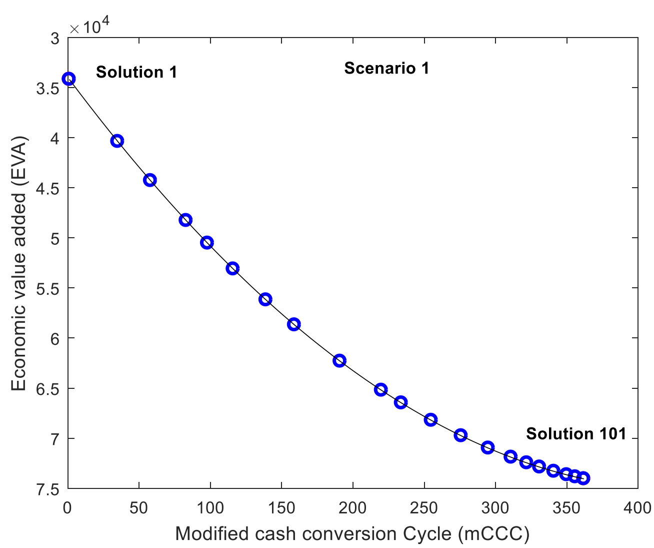


Fig. 11. Pareto optimal frontier illustrating the trade-off between EVA and mCCC in scenario 1.

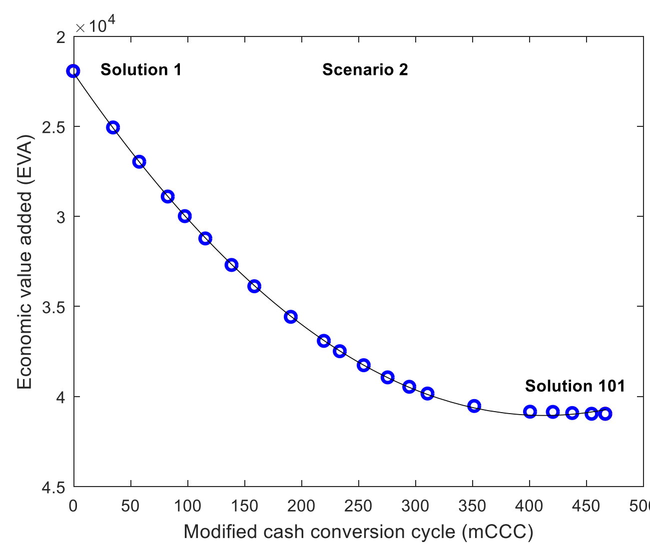


Fig. 12. Pareto optimal frontier illustrating the trade-off between EVA and mCCC in scenario 2.

lowering the mCCC. These findings align with the conclusions drawn by Nobanee and Al Hajjar [77] and Kolias et al. [78].

To minimize the cash-to-cash cycle, reducing inventory levels, including materials and finished and unfinished goods, is a common strategy [79]. Therefore, in Solution 1, inventory decision parameters such as safety stock coverage (SSC), materials safety stock coverage (MSSC), minimum order processing time (MOPT), minimum materials inventory coverage (MMIC), inventory adjustment time (IAT), materials inventory adjustment time (MIAT), WIP adjustment time

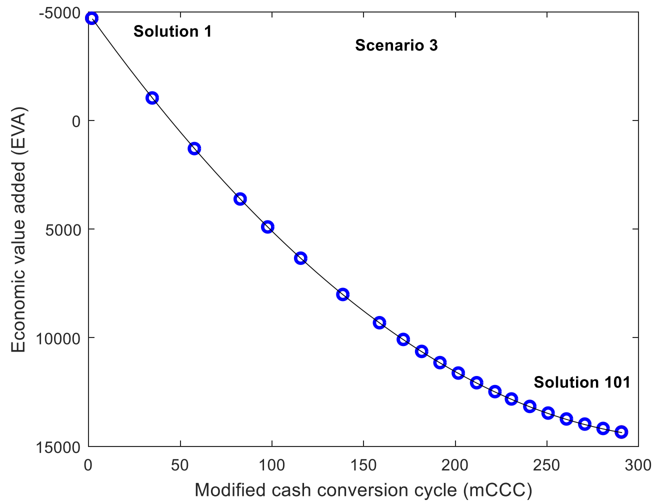


Fig. 13. Pareto optimal frontier illustrating the trade-off between EVA and mCCC in scenario 3.

(WIPAT), and time to average order rate (TAOR) are set lower than those recommended in Solution 101.

In contrast, Solution 101 across all scenarios prioritizes a substantial profit margin. For instance, in scenario 1, the sales price (SP) is set at 2.91 times greater than the unit cost (UC), aiming to maximize operating profit. Moreover, to optimize Economic Value Added (EVA), Solution 101 advocates allocating 100 percent of the Net Operating Profit After Tax (NOPAT) to working capital and dividends, with parameters set to WCP = 0.5 & PDP = 0.5. Conversely, in the face of economic recession, Solution 1 proposes reducing the share of dividends from 50% to 44% of NOPAT and allocating the remaining 6% to retained earnings. This aligns with the findings of Lee et al. [80], suggesting that firms with greater retained earnings demonstrate increased resilience to economic downturns.

In terms of inventory decisions for the distribution center, Solution 1 across all scenarios proposes reducing the desired inventory (DDI) to mitigate overall inventory levels. For scenarios 2 and 3, Solution 1 recommends a lower desired supply line level (DDSL), considering high levels unnecessary given demand stability and shrinkage. However, in scenario 1, Solution 1 suggests a higher level for finished products within the supply line to meet increased customer demand. Additionally, the forecasting parameters for inventory adjustment (α) and supply line adjustment (β) reflect the distribution center's policy on bridging the gap between desired and current inventory and supply levels, respectively. A high α indicates an aggressive inventory adjustment policy, while a high β suggests accounting for all orders in the supply line when deciding on upstream orders [71].

In terms of inventory decisions for the distribution center, Solution 1 across all scenarios proposes reducing the desired inventory (DDI) to mitigate overall inventory levels. For scenarios 2 and 3, Solution 1 recommends a lower desired supply line level (DDSL), considering high levels unnecessary given demand stability and shrinkage. However, in scenario 1, Solution 1 suggests a higher level for finished products within the supply line to meet increased customer demand. Additionally, the forecasting parameters for inventory adjustment (α) and supply line adjustment (β) reflect the distribution center's policy on bridging the gap between desired and current inventory and supply levels, respectively. A high α indicates an aggressive inventory adjustment policy, while a high β suggests accounting for all orders in the supply line when deciding on upstream orders [71].

The inventory adjustment parameter (α) and end customer demand demonstrate a positive correlation, indicating that they move in the same direction. As end customer demand increases or decreases, the inventory adjustment parameter (α) similarly adjusts, reflecting the responsiveness of inventory levels to changes in demand. This relationship underscores the dynamic nature of inventory management, as adjustments are made in response to market demand fluctuations [81].

When prioritizing mCCC minimization, a negative correlation emerges between end customer demand and supply line adjustment forecasting parameters (β). This suggests that a greater emphasis is placed on orders within the supply line when demand decreases. This observation aligns with a well-established principle in SCM, wherein decreasing demand tends to increase the risk of excess inventory, as discussed in previous studies (e.g., [82,83]).

As anticipated, scenario 3 exhibits the lowest EVA values, attributed to recessionary economic conditions during the second year. Furthermore, EVA values in scenario 2 are lower than those in scenario 1, aligning with the stagnation experienced in the second year, resulting in stable end customer demand.

6. Concluding discussion

Economic profitability and working capital efficiency are crucial indicators reflecting a business's financial health. Despite their significance, these indicators often pursue divergent objectives. Economic profitability aims to maximize a business's profit while working capital efficiency seeks to minimize the capital tied up in a firm. Additionally, economic uncertainty can significantly impact both economic profitability and working capital efficiency.

To effectively manage the trade-off between economic profitability and working capital efficiency amidst economic uncertainty, this study develops a simulation-based optimization (SBO) model that integrates system dynamics simulation and genetic algorithms. The developed model utilizes economic value added (EVA) to gauge economic profitability and the modified cash conversion cycle (mCCC) to assess working capital efficiency.

6.1. Theoretical contribution

This paper contributes to three distinct research domains: inventory management under partial trade credit, supply chain (SC) modeling under economic uncertainty, and working capital management in SCs. Previous studies in these domains have overlooked several critical aspects, leading to five main gaps: (1) failure to optimize trade credit and cash payment allocation, (2) neglecting the trade-off between economic profitability and working capital efficiency, (3) disregarding macroeconomic uncertainty, (4) underutilizing SBO modeling, and (5) lacking a metric for quantifying the CCC for SC members receiving and offering partial trade credit. To address these gaps, this study develops an SBO model to manage the trade-off between economic profitability and working capital efficiency while incorporating macroeconomic uncertainty. The model introduces a new metric to quantify the CCC for SC members involved in partial trade credit transactions and identifies optimal trade credit and cash payment shares in the SC.

Utilizing real case study data from [5,45], this study initially assigns equal importance to conflicting objectives: minimizing mCCC and maximizing EVA. Subsequently, we compare the performance of the SBO approach against that of system dynamics (SD) simulation across three economic scenarios.

The first scenario simulates a boom in the second year, characterized by increased customer demand and market expected return, coupled with decreased risk-free, short-term, and long-term interest rates. Implementing the SBO approach leads to notable reductions in inventory levels held by SC members, namely the distributor and manufacturer, as well as a decrease in the modified cash conversion cycle. Additionally, the EVA of the SC experiences a significant 52% increase, rising from £49,832 to £75,789.

In the second scenario, which assumes stagnation in the second year of the simulation, resulting in stability in customer demand, expected market return, and interest rates, the implementation of the SBO approach leads to a substantial reduction in inventory levels across the SC. Additionally, there is a notable decrease in the modified cash conversion cycle. The economic value added (EVA) of the SC experiences a 20% increase, rising from £38,621 to £46,347.

In the third scenario, which assumes a recession in the second year of the simulation, characterized by a decrease in customer demand and market return, alongside an increase in risk-free, short-term, and long-term interest rates, the implementation of the SBO resulted in a notable reduction in inventory levels across the SC. Additionally, there was a significant decrease in the modified cash conversion cycle. Furthermore, the economic value added (EVA) of the SC experienced a substantial 36% increase, rising from £14,768 to £20,057.

To facilitate decision-making and offer a range of optimal inventory and financial strategies, addressing the trade-off between conflicting objectives such as minimizing mCCC and maximizing EVA, the weighted sum method is utilized to generate Pareto efficient frontiers. From these frontiers, two solutions are selected in each scenario for further analysis of their optimal decision parameters. This detailed analysis provides insight into the decision-making process of the model. Finally, decision makers choose the optimal inventory and financial strategies based on the relative importance assigned to mCCC minimization and EVA maximization.

6.2. Managerial implications

SCs aim to meet customer demand efficiently while minimizing the costs associated with holding inventory. However, finding the right balance between inventory levels and shipment rates is paramount. To aid SC managers in navigating this delicate balance, we present an SBO model.

Our model is designed to achieve two primary objectives simultaneously: minimizing inventory levels by minimizing the modified cash conversion cycle (mCCC) and maximizing the shipment rate to customers by maximizing the economic value added (EVA) of the SC. By effectively managing these objectives, our model aims to enhance SC's working capital efficiency and economic profitability.

Additionally, minimizing the cash conversion cycle aids in reducing the cost of capital and accelerating cash flow within the SC. This optimization extends to improving receivables, payables, and inventory levels, ultimately contributing to a more agile and financially robust SC.

Furthermore, effective SC planning requires a holistic approach that considers both physical and financial flows. Integrating financial decision parameters, such as collection and payment policies, into SC planning models provides a comprehensive understanding of financial dynamics. Collaboration between SC and financial managers is essential for estimating uncertain economic parameters, such as short-term interest rates, and allocating necessary financial resources to implement recommended solutions.

In summary, our SBO model offers a comprehensive solution for balancing inventory levels and shipment rates while optimizing overall SC performance. Active collaboration between SC and financial managers ensures the effective allocation of resources and enhances decision-making capabilities in the face of economic uncertainty.

6.3. Limitations and future work

This study is subject to several limitations. Firstly, while our SBO model effectively manages the trade-off between economic profitability and working capital efficiency under economic uncertainty, it overlooks other critical trade-offs, such as the balance between working capital efficiency and credit solvency. Future research should explore these additional dimensions of trade-offs. Secondly, while we account for uncertainty in certain financial parameters like interest rates, future studies could broaden this scope to include other influential factors such as tax rates in SC inventory and working capital management problems.

Thirdly, extending our model to treat fixed assets as endogenous variables rather than constants, or integrating leaseback arrangements for fixed assets into the calculation of invested capital, could provide a more comprehensive understanding of capital management within SCs. Fourthly, future investigations could delve into the implications of a two-part trade credit policy, where some SC members receive full trade credit from suppliers while offering partial trade credit to their customers. Lastly, exploring alternative optimization algorithms beyond the genetic algorithm employed in this study could offer insights into managing the trade-off between economic profitability and working capital efficiency. Comparing the performance of different algorithms against the GA presented here would be a valuable area for further research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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