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ORIGINAL RESEARCH

Viable supply chain with vendor-managed inventory approach by considering blockchain, risk and robustness

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Abstract
This research shows a Viable Supply Chain with Vendor Managed Inventory approach by considering Blockchain, Risk, and Robustness. We embedded Blockchain Technology (BCT) to improve SC agility. To tackle risk and robustness, we suggest a new objective function with the weighted expected value, worst case, and Entropic Value at Risk for considering risk and robustness under different scenarios. This model is Mixed-Integer Linear Programming, and GAMS-Bonmin is utilized to solve it. The case study of this research is on the Pharmacy industry. We compare problems in the situation with BCT and without BCT. The results show that the cost function of the main problem without BCT is greater than the same problem with BCT, and its gaps are 0.61%. Finally, the cost function increase by increasing the conservative coefficient and decreasing the resiliency coefficient. The cost function reduces by increasing the confidence level. We change the scale of the problem and define problems. By increasing the scale of the problem, the solution time increased.

Keywords Viable supply chain · Vendor managed inventory · Blockchain · Risk · Robustness

1 Introduction

The Viable Supply Chain (VSC) is a new concept in the SC area that considers sustainability, agility and resiliency (cf. Fig. 1) (Ivanov, 2020; Lotfi, Nazarpour, Gharehbaghi, Sarkhosh, & Khanbaba, 2022c). Managers pay more attention to the resiliency and flexibility of SC regarding COVID-19. Resilience SC means the capacity to recover quickly after disruption (Lotfi, Kargar, Hoseini, et al., 2021b). In addition, the requirements of governments and

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Fig. 1 Concept of viability (Ivanov, 2020; Lotfi, Safavi, et al., 2021)

people that apply sustainability and green concept make better performance and improve the environmental behavior of the SC. The vital point of agility is to deliver products and services as soon as possible with minimum delay and satisfy demand. The best agility inventory method is Vendor Managed Inventory (VMI) approach. The VMI approach is where the manufacturer, vendor (or supplier) takes control of the seller's or retailer's inventory management decisions (Fakhrzad & Lotfi, 2018). It means that suppliers are responsible for optimizing the inventory. Therefore, defining VSC with the VMI approach by considering risk and robustness is the best way to consider resiliency, sustainability and agility. Although, using novel technology like Blockchain Technology (BCT) and Internet of Things (IoT) increases agility and sustainability (Kouhizadeh et al., 2021; Ruel, El Baz, Ivanov, & Das, 2021).

BCT help to clear transaction between the pillar of SC and decrease variable cost. Therefore, applying VMI and BCT in VSC improves performance and increases SC resiliency for disruption and demand fluctuation (Lotfi, Safavi, et al., 2021b).

The main contribution and motivation of this study are as follows:

1. VSC with VMI approach,
2. Considering risk and robustness,
3. Applying BCT in VSC as an agility approach.

We try to design a novel VSC that applies the VMI approach and BCT together. Further, we pay more attention to the VMI approach as the best way to manage the inventory system to improve costs. Also, applying BCT is an excellent way to provide agility for this SC to create transparency in the transaction. In addition, we want to embed environmental and social impact in this research. As a result, VSC is the best method for sustainability, resiliency, and agility. Finally, the importance and necessity of proposing this research and gap research are understood. As a result, we suggest a systematic and mathematical model for designing the best SC for managing inventory, assets, and transparency in the transaction by considering risks and robustness. Regarding disruptions, we should evaluate risk and robustness for decreasing fluctuation and robustify the model against a complex situation.

We organized this paper as follows. Section 2 reviews related work SC and VMI and shows gap research in this scope. In Sect. 3, we determine a VSCVMI approach. In Sect. 4, the findings and results of the proposed model with sensitivity analysis are explained. In Sect. 5, the managerial insights are presented. In Sect. 6, the conclusion and outlook are drawn.

2 Related work

In this section, we survey related work about VMI in SC. The researchers develop many contributions to this issue. However, there are many research gaps in this issue; we suggested a VSC with VMI approach by considering BCT, Risk, and Robustness (VSCVMIBRR).

2.1 Application of VMI in SC

PRAMUDYO and Luong (2017) proposed a VMI problem in one vendor-one retailer with stochastic demand. They embedded Simulation–Optimization using Genetic Algorithm (SOGA) to solve the model. They analyzed the effects of holding costs on vendors, retailers, and lost sales. Fakhrzad and Lotfi (2018) developed a green SC with VMI and backorder policy and compared it with the traditional inventory. Because the model is nonlinear programming, they used ε-constraint for small scale and the Non-Dominated Sorting Genetic Algorithm (NSGA-II) approach for large scale. Weraikat et al. (2019) improved the performance of a pharmaceutical SC through a VMI system. They suggested the VMI approach to enhance the inventory of medications in hospitals.

Gharaei et al. (2019) presented a SC under penalty, green, and quality control policies and a VMI with a consignment stock agreement. They proposed an optimal batch-sizing policy in an integrated multiproduct-constrained supply chain. They utilized the outer approximation with equality relaxation and the Augmented Penalty Algorithm (APA) for optimal batch sizing. Wettasinghe and Luong (2020) presented a VMI policy with emergency orders. They studied two approaches; approach one used the concept of demand rate, while approach two was based on total demand received during the cycle. Jamshidpour Poshtahani and Pasandideh (2020) designed a SC with a green VMI problem. They suggested a bi-objective multiproduct with a single-vendor single-buyer based on the economic production quantity (EPQ) model. They added Green House Gas Emissions (GHGs) as a second objective function. They implemented Lp-metric, Goal attainment and multi-choice goal programming with utility function (MCGP-U).

De Giovanni (2021) proposed using Artificial Intelligence (AI) in a dynamic brick-and-mortar SC to improve the efficiency of VMI. They used a SC game with Stackelberg format to obtain optimal cost between players. Gharaei, Karimi, and Hoseini Shekarabi (2021) proposed a VMI with joint replenishment planning for SC. They used generalized Benders Decomposition (BD) under the separability approach to solve the model. They used a penalty approach to penalize the supplier if the inventory products exceeded the certain upper bound by the VMI contract. Weißhuhn and Hoberg (2021) developed a VMI approach with smart replenishment systems and Internet-of-Things technology. They model with a single manufacturer and multi-customers. Maximum inventory, capacity and acceptable levels are constraints of this model.

Najafnejhad et al. (2021) explained VMI policy in a single vendor and multiple retailers. They generated an upper bound for inventory based on a penalty. They used Imperialist Competitive Algorithm (ICA) to solve the model. Ashraf and Shahid (2021) suggested a multiobjective VMI system with interval type-2 fuzzy demand and order quantities. They applied NSGA-II with EKM (Enhanced Karnink-Mendel) algorithm. In other works of Ashraf et al. (2021), they developed a model and solved it with Particle Swarm Optimization. Turken, Geda, and Takasi (2021) studied a situation in which a single vendor and multiple buyers with multiple products under various environmental impacts and considered a cap-and-trade regulation.

Lotfi, Kargar, Rajabzadeh, Hesabi, and Özceylan(2022a, b, c) proposed a hybrid fuzzy and Data-Driven Robust Optimization (DRO) for resilience and sustainable healthcare SC with the VMI approach. They applied the VMI approach in health care and showed the model's performance in a situation without the VMI method. Wang et al. (2022) utilized a VMI in SC coordination based on commitment-penalty contracts with bilateral asymmetric information. In other research, Benrqya (2022) suggested combining cross-docking and VMI in a retail supply chain. Mahdavisharif, Kazemi, Jahani, and Bagheri (2022) developed a pricing and inventory policy for non-instantaneous deteriorating items in VMI systems. They applied a Stackelberg game theory approach to solving the problem.

2.2 Application of VMI in CLSC

POURSOLTAN et al. (2021) studied a Closed-Loop Supply Chain (CLSC) under VMI with learning. They utilized a novel metaheuristic algorithm to solve the model.

Keshavarz-Ghorbani and Pasandideh (2021) optimized a CLSC under the VMI contract and learning. They applied Fibonacci, GA, IWO, and MFO algorithms to solve the model.

3 Research gap

We surveyed the literature review and found that there is no research VSC with VMI considering risk and robustness approach by applying BCT as an agility approach. Based on the research gap that we show in Table 1, the innovation and aims of this research are:

1. VSC with VMI approach,
2. Considering risk and robustness,
3. Applying BCT in VSC as an agility approach.

4 Problem statement

In this model, we survey viable SC with a VMI approach by considering BCT, risk and robustness, including vendors and buyers. Running a BCT network decreases variable costs (Lotfi, Safavi, et al., 2021b). BCT improves information sharing and run smart contract. As a result, BCT changes sustainable parameters, including economic, environmental, and sociality. Therefore, we should utilize this novel technology in our inventory management to raise the productivity of SC. Eventually; we suggested VSCVMIBRR based on this scope:

1. Resilience strategy: we present a resilience strategy through order resiliency
2. Sustainable strategy: we present emission, energy, and employment constraints,
3. Agile strategy: we add BCT as an agile strategy.

Table 1 Survey on related work

Reference	Type	Objective	Constraints	SC		Uncertainty	Viability				Methods	Case study	Conditions
				Vendor	Retailer (buyer)		Resiliency	Sustainability	Agility	Risk			
Pramudyo & Luong (2017)	SC	Cost	–	Single	Single	stochastic	–	–	–	–	SOGA	NE	–
Fakhrzad & Lotfi (2018)	GSC	Cost											
CO_2	Warehouse Capacity, Number Of Orders	Single	Multi	–	–		–	–	ϵ-constraint, NSGA-II	NE	Backorder		
Weraikat et al. (2019)	SC	Cost											
	Capacity, Fifo, Shortage	Single	Single	–	–		–	–	Solver	Hospitals	–		
Gharaei et al. (2019)	GSC	Cost	–	Single	Multi	Stochastic constraint	–		–	–	APA	Numerical example (NE)	Quality control policies and a VMI with consignment stock agreement
Jamshidpour Poshtahani & Pasandideh (2020)	GSC	Cost											
CO_2	Capacity, Budget, Warehouse Capacity, Order	Single	Single	Stochastic	–		–	–	Lp-metric, Goal attainment, MCGP-U	NE	–		
Wettasinghe & Luong (2020)	SC	Cost	–	Single	Single	Probably	–	–	–	–	Differentiation	NE	Emergency orders
Gharaei et al. (2021)	SC	Cost	–	Single	Single	Stochastic	–	–	–	–	BD	NE	–

Table 1 (continued)

Reference	Type	Objective	Constraints	SC		Uncertainty	Viability				Methods	Case study	Conditions
				Vendor	Retailer (buyer)		Resiliency	Sustainability	Agility	Risk			
De Giovanni (2021)	SC	Cost	–	Single	Single	Stochastic	–	–	–	–	Differentiation	NE	Stackelberg Game
Poursoltan et al. (2021)	CLSC	Cost	–	Single	Single	Probably	–	–	–	–	Metaheuristic	NE	Learning
Weißhuhn & Hoberg (2021)	SC	Cost	Maximum inventory, Capacity, Acceptable levels	Single	Multi	–	–	–	–		–	NE	–
Keshavarz–Ghorbani & Pasandideh (2021)	CLSC	Cost	–	Single	Single	–	–	–	–	–	Fibonacci, GA, IWO, MFO	NE	Learning
Najafnejhad et al. (2021)	SC	Cost	Order	Single	Multi	–	–	–	–	–	ICA	NE	–
Ashraf & Shahid (2021)	SC	Cost	Warehouse space	Single	Single	Interval type-2 fuzzy	–	–	–	–	NSGA-II	NE	–
Ashraf et al. (2021)	SC	Cost	Warehouse space	Single	Single	Interval type-2 fuzzy	–	–	–	–	PSO	NE	–
Turken et al. (2021)	SC	Cost	Carbon trade	Single	Multi	–	–		–	–	Lagrange Relaxation (LR)	NE	–
Lotfi, Kargar, Rajabzadeh and et al. (2022a, 2022b, 2022c)	SC	Cost	Carbon trade	Multi	Multi	Fuzzy							
DRO			–	–	–	Iran	–						
This research	SC	Cost	Resiliency in orders, shortage, sustain-ability	Multi	Multi	Robust Stochas-tic					Commercial Solver	Pharmacy	Blockchain

4.1 Assumptions and notation list

- There is a multi-vendor and multi-buyer SC based on the VMI approach,
- There are $|P|$ products,
- The planning horizon is infinite,
- Shortage of demand product is allowed,
- Delivery order time is immediate (Fakhrzad & Lotfi, 2018).

First, indices, parameters, and decision variables are defined as follows.

4.1.1 Indices (sets)

i Index of vendors (supplier) $i \in I = \{1, 2, ..., \bar{i}\}$,
jIndex of buyers $j \in J = \{1, 2, ..., \bar{j}\}$,
p Index of products $p \in P = \{1, 2, ..., \overline{p}\}$,
s Index of scenarios $s \in S = \{1, 2, ..., \overline{s}\}$,

4.1.2 Parameters

D_{jps} Demand at buyer j for product p under scenario s,
Os'_{ip} Ordering cost in vendor i for product p without BCT,
Os''_{ip} Ordering cost in vendor i for product p with BCT,
Or'_{jp} Ordering cost in buyer j for product p without BCT,
Or''_{jp} Ordering cost in buyer j for product p with BCT,
π'_{ip} Backorder time-independent cost in vendor i for product p without BCT,
π''_{ip} Backorder time-independent cost in vendor i for product p with BCT,
$\hat{\pi}'_{ip}$ Backorder cost in vendor i for product p per time unit without BCT,
$\hat{\pi}''_{ip}$ Backorder cost in vendor i for product p per time unit with BCT,
hr'_{jp} Holding cost in buyer j for product p without BCT,
hr''_{jp} Holding cost in buyer j for product p with BCT,
ff_p Space required for product p,
F Total spaces for all products in every transport,
M Total number of orders for all products.
pp_s Probably of scenario s,
λ Coefficient of Resiliency and disruption in order,
e_i CO_2 emission produced in vendor i,
ee CO_2 emission produced for each order,
Em_{is} Maximum CO_2 emission in vendor i under scenario s,
en_i Consumed energy in vendor i,
en Consumed energy for each order,
Eg_{is} Maximum energy in vendor i under scenario s,
o_i Employment and occupation in vendor i,
oo Employment and occupation for each order,
Ocu_{is} Minimum employment and occupation in vendor i under scenario s,
bb The proportion of shortage to order,
α Confidence level α,
fbt The fixed cost of BCT include fix and maintenance cost,
mbt_s The maintenance cost of BCT under scenario s,

β The conservative coefficient,

4.1.3 Decision variables

Binary variables

Xbt Equal 1, if BCT is established in the network; otherwise 0,

Positive variables

Q_{ijps} Order quantity transported from vendor i to buyer j for product p under scenario s,

b_{ijps} Shortage allowed from vendor i to buyer j for product p under scenario s,

Auxiliary (Free) variables

Os_{ip} Ordering cost in vendor i for product p,

Or_{jp} Ordering cost in buyer j for product p,

π_{ip} Backorder time-independent cost in vendor i for product p,

$\hat{\pi}_{ip}$ Backorder cost in vendor i for product p per time unit,

hr_{jp} Holding cost in buyer j for product p,

dd_{ijps} Assigned demand buyer j for vendor i for product p under scenario s,

$CINV_s$ Summation of inventory cost under scenario s,

CBT_s Summation of BCT cost include fix and maintenance cost,

Γ_s Total cost under scenario s,

Z Total cost (objective function).

4.2 Mathematical model

Model (1)–VSCVMIBRR

$$\min\ Z = (1-\beta)\sum_s p_s\Gamma_s + \beta\frac{(\max(\Gamma_s) + EVaR(\Gamma_s))}{2}, \tag{1}$$

subject to:

$$\Gamma_s = CBT_s + CINV_s, \quad \forall s \tag{2}$$

$$CINV_s = \sum_i\sum_j\sum_p\left(\frac{(Os_{ip}+Or_{jp})dd_{ijps}}{q_{ijps}} + hr_{jp}\frac{(q_{ijps}-b_{ijps})^2}{2q_{ijps}} + \frac{\hat{\pi}_{ip}b_{ijps}}{2q_{ijps}} + \frac{\pi_{ip}b_{ijps}dd_{ijps}}{q_{ijps}}\right), \quad \forall s \tag{3}$$

Constraints of BCT

$$CBT_s = fbt.xbt + mbt_s xbt, \quad \forall s \tag{4}$$

$$Os_{ip} = Os'_{ip}(1 - xbt) + Os''_{ip}xbt = Os'_{ip} - (Os'_{ip} - Os''_{ip})xbt, \ \forall i, p \tag{5}$$

$$Or_{jp} = Or'_{jp}(1 - xbt) + Or''_{jp}xbt = Or'_{jp} - (Or'_{jp} - Or''_{jp})xbt, \ \forall j, p \tag{6}$$

$$hr_{jp} = hr'_{jp}(1 - xbt) + hr''_{jp}xbt = hr'_{jp} - (hr'_{jp} - hr''_{jp})xbt, \ \forall j, p \tag{7}$$

$$\hat{\pi}_{ip} = \hat{\pi}'_{ip}(1 - xbt) + \hat{\pi}''_{ip}xbt = \hat{\pi}'_{ip} - (\hat{\pi}'_{ip} - \hat{\pi}''_{ip})xbt, \ \forall i, p \tag{8}$$

$$\pi_{ip} = \pi'_{ip}(1 - xbt) + \pi''_{ip}xbt = \pi'_{ip} - (\pi'_{ip} - \pi''_{ip})xbt, \ \forall i, p \tag{9}$$

Capacity constrain

$$ff_p q_{ijps} \le F, \ \forall i, j, p, s \tag{10}$$

Resiliency constraint in orders

$$\frac{dd_{ijps}}{q_{ijps}} \le \lambda M, \ \forall i, j, p, s \tag{11}$$

Shortage constraint

$$b_{ijps} \le bb \cdot q_{ijps}, \ \forall i, j, p, s \tag{12}$$

Demand assignment constraints

$$dd_{ijps} = \frac{d_{jps}}{|I|} \ \forall i, j, p, s \tag{13}$$

Sustainability constraints (environments, energy consumption, and employment)

$$e_i + ee \sum_j \sum_p q_{ijps} \le Em_{is}, \ \forall i, s \tag{14}$$

$$en_i + en \sum_j \sum_p q_{ijps} \le Eg_{is}, \ \forall i, s \tag{15}$$

$$o_i + oo \sum_j \sum_p q_{ijps} \ge Ocu_{is}, \ \forall i, s \tag{16}$$

Decision variables
$Q_{ijps}, b_{ijps} \ge 0,$

$$Os_{ip}, \ Or_{jp}, \ \pi_{ip}, \ \hat{\pi}_{ip}, \ hr_{jp}, \ dd_{ijps}, \ CINV_s, \ CBT_s, \ \Gamma_s = \text{free} \, \forall i, j, p, s \tag{17}$$

$$xbt \in \{0, 1\} \tag{18}$$

The objective function (1) shows the cost function that contains the weighted expected value, worst case and Entropic Value at Risk (EVaR) for considering risk and robustness. Constraints (2) indicate the summation of inventory costs and establishing a BCT network. Constraints (3) include vendors' ordering, holding, and shortage costs in the VMI approach. Constraints (4) explain BCT's fix and maintenance cost summation. Constraints (5–9) ordering, holding, and shortage costs in running BCT and without BCT. Constraints (10) guarantee that the flow quantity is less than the warehouse capacity. Constraints (11) guarantee resiliency in orders by a coefficient of maximum orders. Constraints (12) show amount of shortage is less than the maximum shortage. Constraints (13) describe demand assignment between vendors. Constraints (14–16) show sustainability (environments, energy consumption and employment) constraints. Constraints (17–18) present flow, shortage decision variables, and BCT establishment. The binary variable aims to select BCT by the model based on parameters. We permit the model to select and establish BCT regarding the volume of demand. The volume of demand helps the model of whether running BCT is economically feasible or not. Therefore, we need to add this binary variable to allow the model to use BCT or not based on the value of parameters in the model.

4.3 Linearizing of max and absolute function

Linearizing the max function and absolute function is as follows:
If $k = \max(\Omega_s)$, therefore, we can replace these constraints with the model $k \geq \Omega_s,\ \forall s$.
If $k = |\Omega_s|$, consequently, we can replace the absolute function with these constraints to the model:$k = \alpha_s + \beta_s,\quad \Omega_s = \alpha_s - \beta_s,\quad \alpha_s, \beta_s \geq 0,\ \forall s.$

4.4 Linearizing of VSCVMIBRR

To decrease the solution time, it is better to change objective function (1) from Nonlinear to Linear Programming (LP) by operational research method in two steps (Lotfi, Kargar, Gharehbaghi, & Weber, 2021a; Mohtashami, Bozorgi-Amiri, & Tavakkoli-Moghaddam, 2021). We can add covariate variable for max function and use formulation EVaR:

Step 1-linearizing of Model 1

$$\min\ Z = (1-\beta)\sum_s p_s\Gamma_s + \beta\frac{(\Omega + EVaR(\Gamma_s))}{2}, \tag{19}$$

subject to:

$$EVaR(\Gamma_s) = \sum_s p_s\Gamma_s + \sum_s p_s\left|\Gamma_s - \sum_s p_s\Gamma_s\right|\sqrt{-2Ln(\alpha)}, \tag{20}$$

$$\Omega \geq \Gamma_s,\ \forall s \tag{21}$$

Constraints (2–17).

Step 2-linearizing of Model 1

$$\min\ Z = (1-\beta)\sum_s p_s\Gamma_s + \beta\frac{(\Omega + EVaR(\Gamma_s))}{2},$$

subject to:

$$EVaR(\Gamma_s) = \sum_s p_s\Gamma_s + \sum_s p_s(va_s + vb_s)\sqrt{-2Ln(\alpha)}, \tag{22}$$

$$\Gamma_s - \sum_s p_s\Gamma_s = va_s - vb_s,\ \forall s \tag{23}$$

$$va_s, vb_s \geq 0,\ \forall s \tag{24}$$

Constraints (2–17), (20).

When linearization is done, the main problem changes from MINLP to LP, and the complexity and solution time (speed of solving) decrease for the commercial solver.

4.5 The complexity of proposed model

The complexity of proposed model is calculated in Eqs. (25) to (28) and includes the number of binary, free, positive variables and numbers of constraints:

$$\text{Binary variables} = 1, \tag{25}$$

$$\text{Positive variables} = |S|(3|I||J||P| + |J||P| + 2), \tag{26}$$

$$\text{Free variables} = 7 + 2|S| + |P|(|I| + 2|J|), \tag{27}$$

$$\text{Constraints} = 6 + |S|(5 + 4|I||J||P| + 3|I|) + |P|(|I| + 2|J|). \tag{28}$$

We can see the number of constraints, positive and free variables dependent on the scenario and suggest scenario reduction algorithms like Fix-and-Optimize and LR to solve and generate the best upper in minimal time.

5 Results and discussion

Based on the case study information, we assigned the parameters described in the notation list. The case study of this research is the pharmaceutical industry. We mine data by meeting with managers (cf. Tables 2, 3).

We applied a computer with this configuration: CPU 3.2 GHz, Processor Core i3-3210, 6.00 GB RAM, and 64-bit operating system. Finally, we solve the mathematical models with the GAMS-Bonmin solver. After solving the model, we received the cost function and determined them in Table 3. We can see that the cost function is 239487.458, and the solution time is 1.521 s (Fig. 2).

5.1 Comparing models

We compare the proposed model in the situation with BCT and without BCT. As can be seen, the cost function of P1-without BCT is greater than P1-with BCT, and its gaps are 0.61% (cf. Table 4 and Fig. 3).

5.2 Variation on the conservative coefficient

This section changes the conservative coefficient (β) between 0 and 100%. The cost function increases by increasing the conservative coefficient (cf. Table 5 and Fig. 4). It means that if decision-makers are conservative and risk-averse or risk-aware, they plan to pay more inventory costs.

5.3 Variation on the resiliency coefficient

This section changes the resiliency coefficient (λ) between 94 and 100%. The cost function increases by decreasing the resiliency coefficient (cf. Table 6 and Fig. 5). As a result, diminishing the resiliency coefficient for orders increases cost.

Table 2 Assign values for parameters

Par	Value	Unit	Par	Value	Unit	Par	Value	Unit
d_{jps}	[(U(50,000,60,000)]*12);	Num	e_i	7.9 o_i	Ton	ff_p	[(U (1,5)]	M^2
Os'_{ip}	[(U (1,5)]	Dollar	ee	0.03	Ton	F	21,000	M^2
Os''_{ip}	0.72 Os'_{ip}	Dollar	Em_{is}	86.9 Ocu_{is}	Ton	M	50	Num
Or'_{jp}	[(U (1,4)]	Dollar	en_i	1	MW	fbt	30,000	Dollar
Or''_{jp}	0.72 Or'_{jp}	Dollar	en	0.01	MW	mbt_s	12*3000	Dollar
π'_{ip}	0	Dollar	Eg_{is}	700	MW	pp_s	$s/(\|S\| *(\|S\|+ 1)/2)$	Per. (%)
π''_{ip}	0.72 π'_{ip}	Dollar	o_i	20	Per %	λ	100	Per
$\hat{\pi}'_{ip}$	3	Dollar	oo	0.05	Per	β	50	Per
$\hat{\pi}''_{ip}$	0.72 $\hat{\pi}'_{ip}$	Dollar	Ocu_{is}	600	Per	α	5	Per
hr'_{jp}	[(U (2,10)]	Dollar	hr''_{jp}	0.72 hr'_{jp}	Dollar	bb	10	Per

Table 3 Number of sets, variables, and constraints of case study

Problem	$\|I\|.\|J\|.\|T\|.\|S\|$	Variables			Constraints	Cost function (Dollars)(Z)	Time (second)
		Binary	Positive	Free			
P1	3.2.5.5	1	510	52	711	239,487.458	1.521

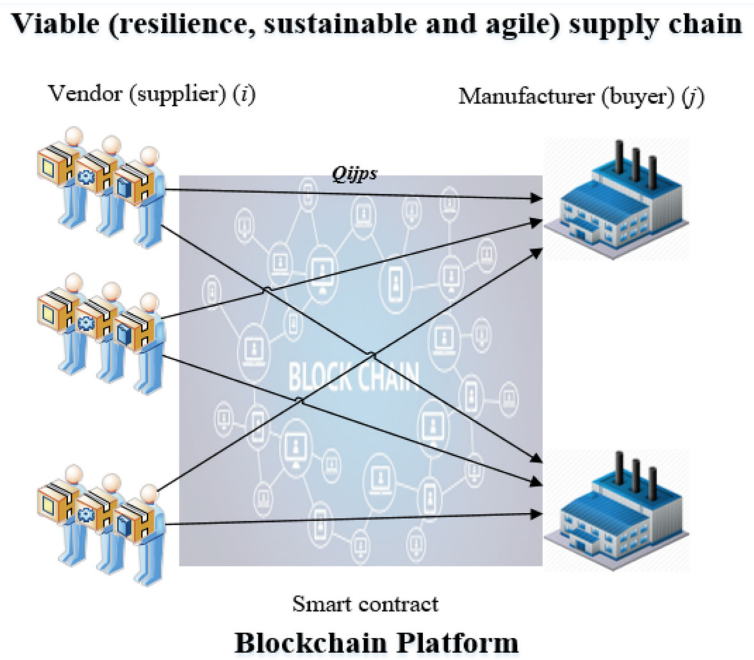

Fig. 2 VSCVMIBRR

Table 4 Compare P1 with BCT and without BCT

Problem	xbt	Cost function (Dollars)(Z)	Gap
P1-with BCT	1	239,487.458	0.61%
P1-without BCT	0	240,954.803	

5.4 Variation in the confidence level

We change the confidence level (α) between 1 and 10%. The cost function decreases by increasing the confidence level (cf. Table 7 and Fig. 6). It means that increasing the confidence level make to increases costs.

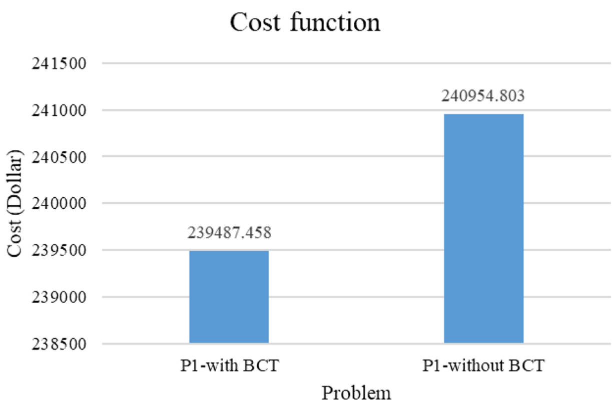

Fig. 3 Compare P1 with BCT and without BCT

Table 5 Variation of conservative coefficient (β)

Conservative coefficient (β)(%)	Cost function (Dollars)(Z)	Cost variation(%)
0	231,832	− 3.2
25	236,203.3	− 1.4
50	239,487.458	0.0
75	241,060.4	0.7
100	241,120.7	0.7

5.5 Variation on the scale of problem

In this section, we change the scale of problem and define problems. Increasing the scale of the problem increased solution time (cf. Table 8, Figs. 7 and 8). We contribute regression between solution time ($Time\ Sol$) and sets in Eq. (29). We found that:

$$SolTime \approx 331.3041 + 38.15222|I| + 17.44289|J| - 131.944|P| + 32.99533|S|,$$

$$R^2(\text{Correlation}) = 0.713874. \tag{29}$$

5.6 Discussion

This section analyzes VSC with VMI by considering blockchain, risk, and robustness in the pharmacy industry. We compare our model with the situation because we do not have BCT. As can be seen, we decrease costs and improve agility and sustainability with the presence of BCT. We did sensitivity analysis on the conservative coefficient, the resiliency coefficient, the confidence level and the scale of problem. The cost function increases by growing the conservative coefficient, decreasing the resiliency coefficient, and increasing the confidence level, and vice versa. This research is developed by Lotfi, Kargar, Rajabzadeh and et al., (2022a, b, c). However, we add the BCT can be utilized in the system and compare this model with Lotfi, Kargar, Rajabzadeh and et al., (2022a, b, c). Previous research has no

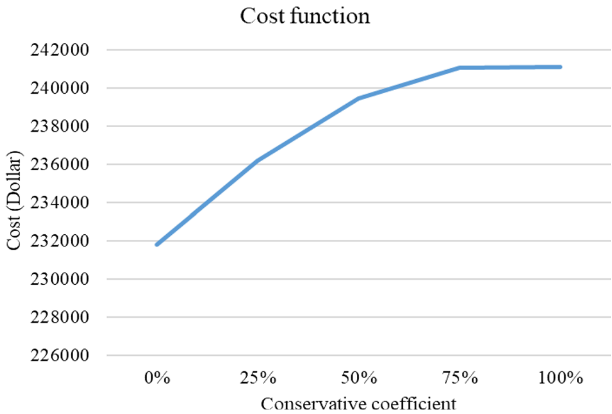

Fig. 4 Variation of conservative coefficient (β)

Table 6 Variation of resiliency coefficient (λ)

Resiliency coefficient (λ)(%)	Cost function (Dollars)(Z)	Cost variation(%)
94	250,021.7	4.4
95	248,171.3	3.6
97	244,587.6	2.1
98	242,852	1.4
100	239,487.458	0.0

research on VSC with VMI approach by considering blockchain, risk, and robustness. As a result, this research tries to cover the research gap and show that using BCT decreases cost and improves SC's performance and agility.

6 Managerial insights and practical implications

This research suggests that the VSC considers sustainability, agility and resiliency together. In line with this concept, we offer sustainability as environmental and social impact, agility and resiliency as the VMI method for inventory and BCT technology for increasing lean production. The VMI approach manages and controls retailers' inventory by vendors or suppliers and is responsible for SC inventory. In addition, BCT clears transaction between SC components and reduce variable costs. Therefore, applying new concepts, including VMI and BCT upgrades agility and resilience for disruption and demand fluctuation in VSC.

SC Managers should do everything to improve the performance of SC. One of them is applying VMI, which decreases the cost of inventory. Running VMI controls inventory by vendors and reduces sustainable pillar-like environmental pollution and energy consumption. We suggest an application of BCT in SC as an agility policy. Utilizing BCT decreases costs, increases agility, and clarifies transactions between SC components. We present a resilience strategy through order resiliency, proposed emission, energy, and employment constraints for sustainability, and adding BCT as an agile strategy. We, as SC managers, should embed

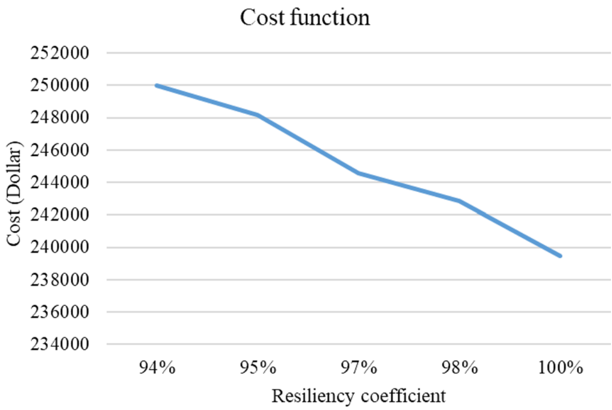

Fig. 5 Variation of resiliency coefficient (λ)

Table 7 Variation of confidence level (α)

Confidence level (α)(%)	Cost function (Dollars)(Z)	Cost variation(%)
1% (99)	239,994.874	0.21
2% (98)	239,812.228	0.136
5% (95)	239,487.458	0
8% (92)	239,117.930	− 0.1543
10% (90)	238,930.439	− 0.2326

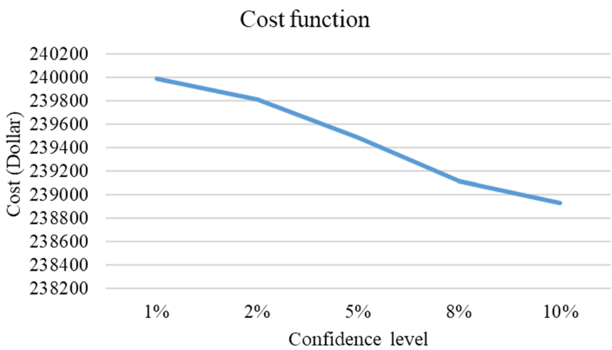

Fig. 6 Variation of confidence level (α)

all tools to improve the viability of SC for the hard situation. We contribute VSCVMIBRR in the healthcare industry like a pharmacy because COVID-19 tremendously affected supply chains.

Table 8 Variation of the scale of problem

Problem	$\lvert I\rvert.\lvert J\rvert.\lvert T\rvert.\lvert S\rvert$	Variables			Constraints	Cost function (Dollars)(Z)	Time (second)
		Binary	Positive	Free			
P1	3.2.5.5	1	510	52	711	239,487.458	1.521
P2	4.3.5.5	1	985	67	1336	322,970.825	25.885
P3	5.4.6.7	1	2702	99	3577	686,822.613	42.665
P4	7.4.6.5	1	2650	107	3581	651,354.345	25.841
P5	6.4.6.7	1	3206	105	4276	708,984.25	30.635
P6	7.5.6.5	1	3310	119	4433	863,380.904	74.515
P7	7.4.6.7	1	3710	111	4975	692,173.942	134.585
P8	7.5.6.7	1	4634	123	6163	–	–

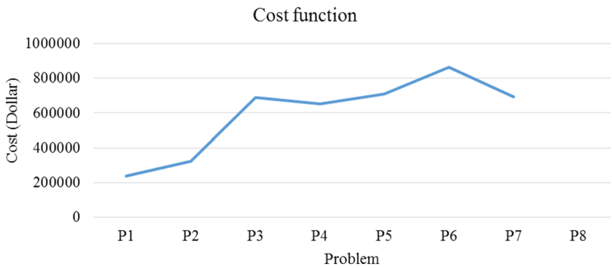

Fig. 7 Variation of the scale of problem

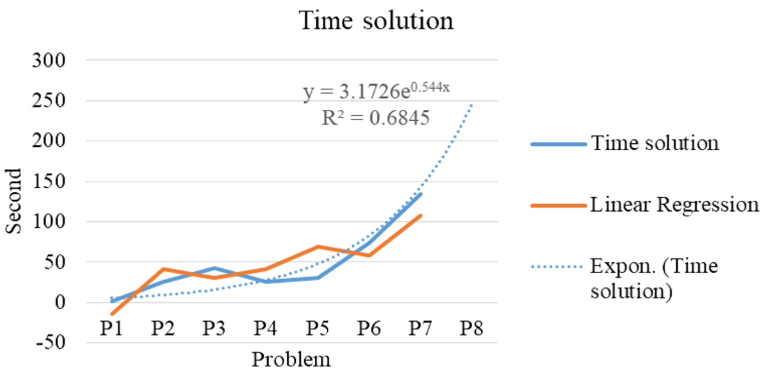

Fig. 8 Variation of the scale of problem

7 Conclusions and outlook

The best strategy that needed to apply by companies in the recent decade for managing and reducing the cost of inventory can be VMI policy. Therefore, we show VSC that used the VMI strategy by considering blockchain, risk, and robustness in healthcare SC. The researcher has not surveyed this subject and can be innovative in this research. We add BCT constraint to show agility in the mathematical model. We propose ordering resiliency as a resilience strategy and offering sustainability pillars of emission, energy, and employment constraints. We generated an objective function that includes weighted expected value, worst case, and EVaR for considering risk and robustness under different scenarios.

The results of this research and managerial insights are as follows:

1. After solving the model, we received cost functions and determined them in Table 3.
2. We compare the proposed model (P1) in the situation with BCT and without BCT. As can be seen, the cost function of P1-without BCT is greater than P1-with BCT, and its gap is 0.61% (cf. Table 4 and Fig. 3).
3. We change the conservative coefficient (β) between 0 and 100%. The cost function increase by increasing the conservative coefficient (cf. Table 5 and Fig. 4).
4. We change the resiliency coefficient (λ) between 94 and 100%. The cost function increase by decreasing the resiliency coefficient (cf. Table 6 and Fig. 5).
5. We change the confidence level (α) between 1 and 10%. The cost function decreases by increasing the confidence level (cf. Table 7 and Fig. 6).
6. We change the scale of the problem and define problems. By increasing the scale of the problem, the solution time increased (cf. Table 8, Figs. 7 and 8).

One of the limitations of this research is solving the model on a large scale. We propose to apply the heuristic and metaheuristic approaches (Khalilpourazari et al., 2021). Adding other objectives can help to satisfy another requirement of researchers and managers. Embedding other tools of coherent risk measure like Conditional Value at Risk (CVaR) or Wang risk measure can tackle risks and uncertainty. Using novel uncertainty like data-driven robust optimization (Khalilpourazari & Hashemi Doulabi, 2021; Khalilpourazari & Pasandideh, 2021; Khalilpourazari et al., 2019; Lotfi, Kargar, Gharehbaghi, et al., 2022a) and neutrosophic optimization technique and learning approach (Mohammadi & Khalilpourazari, 2017) are very interesting for researchers (Ahmad, 2021).

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