Hindawi
Mathematical Problems in Engineering
Volume 2021, Article ID 7347389, 18 pages
https://doi.org/10.1155/2021/7347389

Research Article

Viable Supply Chain Network Design by considering Blockchain Technology and Cryptocurrency

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Received 16 July 2021; Accepted 20 October 2021; Published 8 November 2021

Academic Editor: Junyong Zhai

Nowadays, using Blockchain Technology (BCT) is growing faster in each country. It is essential to apply BCT in Supply Chain Network Design (SCND) and is considered by the designer and manager of SC. This research indicates Viable Supply Chain Network Design (VSCND) by applying BCT. A new form of two-stage robust optimization is suggested. Facility locations and activation BCT for VSCND is the first stage of decisions; finally, we determine flow transshipment between components in the next stage. The GAMS-CPLEX is used for solving the model. The results show that running BCT will decrease 0.99% in costs. There is an economic justification for using BCT when demand is high. A fix-and-optimize and Lagrange relaxation (LR) generate lower and upper bound to estimate large scale in minimum time. The gap between the main model and fix-and-optimize is better than the LR algorithm. Finally, this research suggests equipping VSCND by BCT that becomes more resilient against demand fluctuation, sustainable, and agile.

1. Introduction

One of the new discussions in the present age is the Viability of Supply Chain (VSC) in postpandemic adaptation. Ivanov and Dolgui [1] proposed the viability of SC that includes resiliency, sustainability, and agility. They suggested that organizational, informational, technological, financial, and process-functional structure should improve and change as follows:

(1) Organizational (subcontractor and backup supplier, workplace resilience, facility fortification)
(2) Informational (data analytics, visibility, digital twins, supplier portals, blockchain)
(3) Technological (robotics, additive manufacturing, smart manufacturing and warehousing, industry 4.0)
(4) Financial (business-government, revenue management, liquidity reserves)
(5) Process-functional (flexible capacity and sourcing, inventory and capacity buffers, Omnichannel, product diversification, and substitution) [2]

Therefore, using BCT is clearly toward VSC. The BCT can help in the clarity and agility of SC [3]. Smart contract executes contract automatically between layers of SC. After every event happens, such as transactions by customers in retailers, instant settlement and checkout processes are done in all SC layers. This technology runs information sharing, and all components of SC are aware of demands until the end of chain.

Smart contract in BCT runs contracts well between nodes, and financial transaction runs without human intervention. However, establishing BCT in SC needs programming and receiving correct input until giving the correct output. Therefore, it can mitigate risks and transaction costs [4]. Smart contract reduces costs compared to traditional contract and when it runs, tractable and irreversible transactions are established [5]. In the blockchain industry, Ethereum environments can implement smart contracts for SC as well. When a smart contract starts, there is no way to stop it. Thus, this procedure decreases demand fluctuation, raises awareness of demand variation in all SC layers, and decreases bullwhip effects [3]. This subject increases SC's resiliency and sustainability through SC's flexibility by sharing information on transactions and demands, decreasing flow quantity in SC and CO_2 emission, and increasing satisfaction and welfare. Walmart for food supply ecosystem, Ford for supplying cobalt, De Beers for tracking diamond, UPS for tracking logistics, FedEx for tracking shipments are companies that used BCT to add transparency in SC. We should use this technology to manage SC clearly, be resilient against demand, and be sustainable for the future [6, 7]. In Figure 1, we can see the trend of using BCT and the market size of BCT in USA from 2016 to 2028 and the market share of Europe in 2020; it can show that the growth rate is 82.4% from 2021 to 2028. Therefore, we should consider this trend, and every SC that uses this technology can be successful in the future.

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

(1) Applying BCT to increase viability and agility of SCND
(2) Using a new mathematical model for showing the effects of BCT on SCND
(3) Adding resiliency, sustainability, and robustness to VSCND by considering BCT

We organized this paper as follows. In Section 2, we study on related work and show gap research in scope SCND. In Section 3, we determine VSCND mathematical model. In Section 4, the findings and results of the proposed model with sensitivity analysis are explained. In Sections 5 and 6, the managerial insights and conclusion and outlook are determined.

2. Related Work about SCND

Increasing the presence of investors in the cryptocurrency industry has caused other people in the community to be attracted to this industry. This subject has led many researchers to focus on this area, which is described below. Nayak and Dhaigude [9] reviewed and evaluated 178 articles that employed BCT in SCs. They presented that the benefits of BCT include data management, improving transparency, improving response time smart contract management, operational efficiency, disintermediation, immutability, and intellectual property management. Moreover, one of the most important advantages of BCT is increasing SC resiliency, reducing disruptions, helping risk management, and establishing multilayer protection [10].

We surveyed SC by applying BCT with considering the mathematical model and other tools presented below.

Choi [11] proposed global SC operations with air logistics with a mean-variance (MV) approach for risk analysis by applying the BCT era. They utilized their model by helping with the newsvendor problem. Choi and Luo [12] surveyed data quality problems for emerging markets in sustainable fashion SC. Their model includes decentralized SC and implementing BCT to enhance the profit and transparency of SC and increase welfare. They used newsvendor to the model problem and compared the decentralized SCM model with BCT and centralized model. In other works of Choi [11], he proposed BCT for diamond SC. He used BCT for exploring diamonds and compared the traditional model with the BCT platform. He found that using BCT platform can reduce cost and is beneficial to all parties in the luxury SC.

Nayak and Dhaigude [9] suggested a conceptual model for sustainable SC management (SCM) using BCT. They used Interpretive Structural Modeling (ISM) and Matrice d'Impacts Croise's Multiplication Appliquée a UN Classement (MICMAC) to draw a conceptual model, identify factors, and show effects of BCT on SCM. Rahmanzadeh et al. [13] designed a tactical SC planning model with open innovation consideration within a BCT. They proposed using BCT for registering, collecting, and refining ideas in open innovation. They used a fuzzy mathematical model to tackle uncertainty in the home appliances domain. They found that, by spending 1% of the total cost of SC, they can receive good ideas and decrease 41% of the total cost. Dolgui et al. [3] developed multiple logistics service providers by considering a smart contract for flexible flow shop scheduling. They used dynamic control theory for a running model.

Manupati et al. [14] proposed a multiechelon green SC for the production allocation problem by implementing a blockchain approach. They suggested a Mixed Integer Nonlinear Programming (MINLP) for a carbon taxation policy for the greenness of the model. They showed that the distributed ledger-based blockchain approach enables minimizing total cost and carbon emissions. Liu et al. [15] surveyed a green agrifood SC by applying information service based on blockchain and big data (ISBD). They applied Stackelberg's game theory to draw the model and solve investment decision problems. They compared four models, surveyed the freshness of agrifood by BCT, and used BCT for information sharing between producer and retailer. De Giovanni [4] explained that BCT could manage risks and transaction costs. He drew a situation that suppliers and retailers can activate by a traditional online platform or BCT. They removed transaction costs by BCT. Finally, they determined a smart wholesale price and revenue sharing contract to increase coordination between layers. They utilized game theory to solve the model.

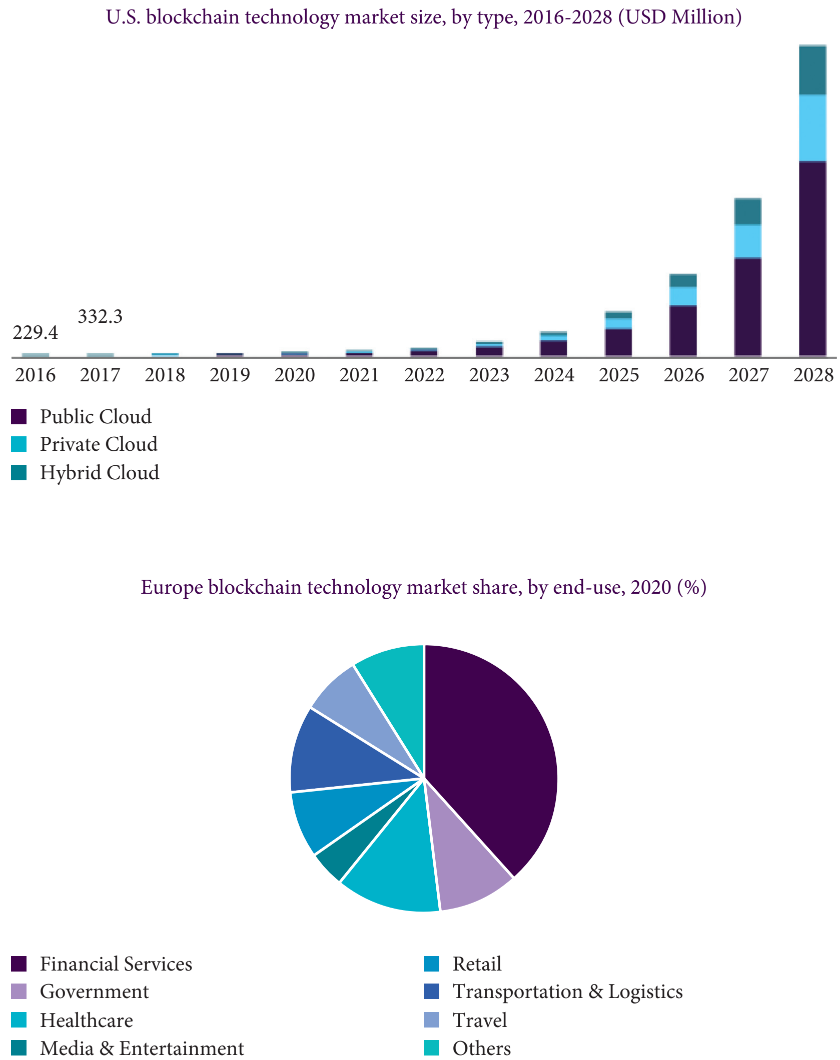

Figure 1: The market size of BCT in the USA and the market share of Europe [8].

Alkahtani et al. [16] considered an e-agricultural SCM with BCT equipment in a cooperative situation. They applied the BCT into the agricultural SCM. Further, a Fuzzy Inference System (FIS) and Analytical Hierarchy Process (AHP) are embedded to show uncertainties in the model. They wanted to maximize profit with advertisement costs constraints and space constraints. As this model was NLP, they employed Karush–Kuhn–Tucker (KKT) to solve the model. They found that the effect of BCT can reduce the costs of SCM. Zhong et al. [17] implemented a Stackelberg game for container shipping lines and surveyed it using blockchain. Their model uses two stages to define the freight rate. They found that entering BCT can regulate the freight rate and improve the price in the container shipping market. The first stage is entering the blockchain or not, and the next step is assigning container shipping lines. They used the Stackelberg game and Cournot game for the second stage to show BCT effects.

We classified the literature review in Table 1 and the application of BCT in SCND. It can be seen that we want to design VSCND by BCT platform, which are not studied yet. We present VSCND through (flexible capacity (resilience strategy), sustainability constraints, and agility (by considering BCT)) for SCND. Finally, we add uncertainty through the robust scenario by defining a new form of the objective function.

3. Problem Description

In this research, we try to design VSCND with considering BCT. The previous section shows a lack of research in resilience and sustainable SC considering BCT. In the present study, we have customers, retailers, manufacturers, suppliers that transact in the BCT environment. The current SC uses BCT and smart contracts and executes contracts automatically between layers of SC. After customers transact in retailers, all payments automatically expand in SC layers, each component withdraws its share at once, and no charge remains in the retailers' accounts. Eventually, we present VSCND through the flexible capacity facility (resilience strategy), sustainability constraints, and agility (by considering BCT) for SCND.

Table 1: Survey of SCND with considering BCT.

Ref.	Problem	Platform	Objectives					Uncertainty	Method	Industry
			Economic	Environmental	Energy	Social	Others			
[11]	SC operations	BCT	✓	—	—	—	—	Probably	Scenario newsvendor + risk	—
[12]	Data quality problems	BCT	✓	—	—	—	—	Probably	Newsvendor	Fashion
[11]	Diamond SC	BCT	✓	—	—	—	—	Probably	Stackelberg game	Diamond
[9]	Sustainable SC	BCT	—	—	—	—	✓	—	ISM + MICMAC	Numerical example (NE)
[13]	Tactical with open innovation	BCT	✓	—	—	—	—	Fuzzy	*MILP	Home appliances
[3]	Flexible flow shop scheduling	BCT	—	—	—	—	✓	—	Dynamic optimal control	NE
[14]	Production allocation problem	BCT	✓	—	—	—	—	—	MINLP + NSGA-II	NE
[15]	ISBD green in agrifood SC	Big data + BCT	✓	—	—	—	—	Probably	Stackelberg game	NE
[4]	SCM	BCT	✓	—	—	—	—	Stochastic	Stackelberg game	NE
[1]	VSC	Digital concept	✓	—	—	—	—	—	Dynamics control approach	—
[2]	VSC	Digital concept	✓	—	—	—	—	—	Dynamic game-theoretic	—
[18]	Sustainable SC	—	✓	✓	—	✓	—	—	MILP, *MOGWO, MORDA, AEC	Aluminum
[19]	Open-CLSC	—	✓	—	—	✓	✓	Robust	MILP + AWT	NE
[16]	E-agricultural SCM	BCT	✓	—	—	—	—	FIS + AHP	NLP + KKT	E-agriculture
[17]	Container shipping lines	BCT	✓	—	—	—	—	—	Stackelberg and Cournot game	NE
[20]	Waste VSC	—	✓	—	—	—	—	Robust	Scenario + risk	Iran
This research	VSCND	BCT	✓	—	—	—	—	New robust stochastic	MILP	Computer

* MILP: Mixed Integer Linear Programming; MOGW: Multiobjective Gray Wolf Optimizer; MORDA: Multiobjective Red Deer Algorithm; AEC: Augmented Epsilon Constraint; AWT: Augmented Weighted Tchebycheff.

In Figure 2, we used Ethereum smart contract technology that pays at once after payment of customers. We want to consider BCT instead of a traditional transaction. Therefore, using BCT enables reducing variable costs. We draw a model that can select applying traditional transactions with higher variable costs or select BCT with lower variable costs. Still, there are fix and maintenance costs for establishing BCT.

Hence, we need this assumption is as follows.

Assumption 1

(i) All demands should be prepared, and the shortage is not permitted (agility)

(ii) Flow and capacity constraints are active in forwarding SC (agility)

(iii) A BCT is used for payment in layers of SC decreasing variable cost (agility)

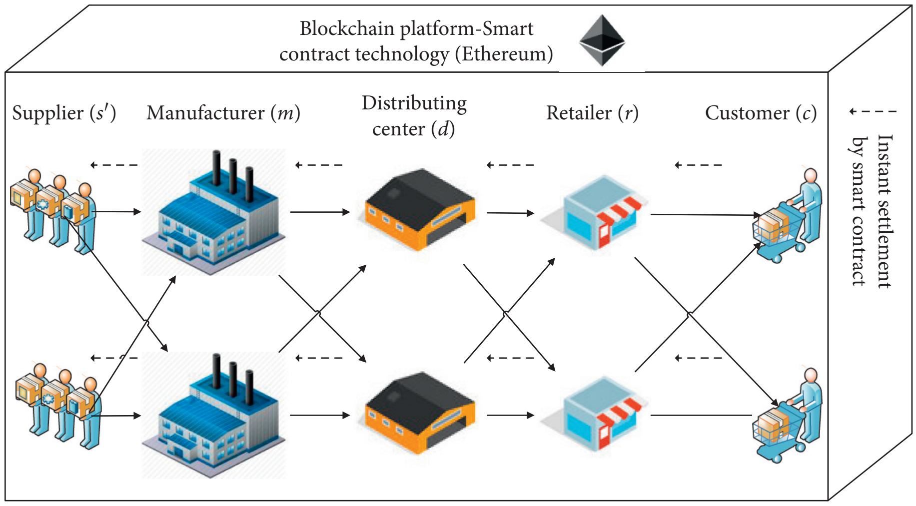

FIGURE 2: VSCND with considering BCT.

(iv) Sustainability constraints include emission and energy consumption are defined (sustainability)

(v) Flexible scenario-based capacity for the facility is as resilience strategy (resiliency)

(vi) Using robust stochastic programming to cope with fluctuation of demand (resiliency) [2, 21]

(vii) Variable cost after activating BCT is less than that without BCT

3.1. Model 1: VSCNDBCT

$$\min Z = (1-\lambda)\left(\sum_s p_s\Gamma_s + z_\alpha \sum p_s\left|\Gamma_s - \sum_s p_s\Gamma_s\right|\right) + \lambda \max\left(\Gamma_s\right), \tag{1}$$

$$\Gamma_s = \mathrm{FC} + \mathrm{VC}_s, \tag{2}$$

$$\mathrm{FC} = \mathrm{FCF} + \mathrm{FCBT}, \tag{3}$$

$$\mathrm{FCF} = \sum_{s'} fs_{s'} xs_{s'} + \sum_m fm_m xm_m + \sum_d fc_d xd_d + \sum_r fr_r xr_r, \tag{4}$$

$$\mathrm{FCBT} = fbt \cdot xbt + \sum_t \sum_s mbt_{ts} xbt, \tag{5}$$

$$\mathrm{VC}_s = \mathrm{VC1}_s(1 - xbt) + \mathrm{VC2}_s xbt = \mathrm{VC1}_s - \left(\mathrm{VC1}_s - \mathrm{VC2}_s\right)xbt, \quad \forall s, \tag{6}$$

$$\mathrm{VC1}_s = \sum_p \sum_t \left(\sum_{s'} \sum_m vsm_{s'mpts} qsm_{s'mpts} + \sum_m \sum_d vmc_{mdpts} qmd_{mdpts} + \sum_d \sum_r vdr_{drpts} qdr_{drpts} + \sum_r \sum_c vrc_{rcpts} qrc_{rcpts}\right), \quad \forall s, \tag{7}$$

$$\mathrm{VC2}_s = \sum_p \sum_t \left(\sum_{s'} \sum_m vsm'_{s'mpts} qsm_{s'mpts} + \sum_m \sum_d vmc'_{mdpts} qmd_{mdpts} + \sum_d \sum_r vdr'_{drpts} qdr_{drpts} + \sum_r \sum_c vrc'_{rcpts} qrc_{rcpts}\right), \quad \forall s, \tag{8}$$

subject to the following.

Flow quantity constraints:

$$\sum_{r} qrc_{rcpts} \geq d_{cpts}, \quad \forall c, p, t, s, \tag{9}$$

$$\sum_{d} qdr_{drpts} = \sum_{c} qrc_{rcpts}, \quad \forall r, p, t, s, \tag{10}$$

$$\sum_{m} qmd_{mdpts} = \sum_{r} qdr_{drpts}, \quad \forall d, p, t, s, \tag{11}$$

$$\sum_{s'} qsm_{s'mpts} = \sum_{d} qmd_{mdpts}, \quad \forall m, p, t, s. \tag{12}$$

Resiliency strategy (flexible capacity based on scenarios):

$$\sum_{c} qrc_{rcpts} \leq \rho_r \text{Capr}_{rpts} xr_r, \quad \forall r, p, t, s, \tag{13}$$

$$\sum_{r} qdr_{drpts} \leq \rho_d \text{Capd}_{dpts} xd_d, \quad \forall d, p, t, s, \tag{14}$$

$$\sum_{d} qmd_{mdpts} \leq \rho_m \text{Capm}_{mpts} xm_m, \quad \forall m, p, t, s, \tag{15}$$

$$\sum_{m} qsm_{s'mpts} \leq \rho_{s'} \text{Caps}_{s'pts} xs_{s'}, \quad \forall s', p, t, s. \tag{16}$$

Sustainability strategy (allowed emission and energy consumption):

$$\sum_{p} \left(\sum_{s'} \sum_{m} emsm_{s'mpts} qsm_{s'mpts} + \sum_{m} \sum_{d} emmc_{mdpts} qmd_{mdpts} + \sum_{d} \sum_{r} emdr_{drpts} qdr_{drpts} + \sum_{r} \sum_{c} emrc_{rcpts} qrc_{rcpts} \right) \leq \text{EM}_{ts}, \quad \forall t, s, \tag{17}$$

$$\sum_{p} \left(\sum_{s'} \sum_{m} ensm_{s'mpts} qsm_{s'mpts} + \sum_{m} \sum_{d} enmc_{mdpts} qmd_{mdpts} + \sum_{d} \sum_{r} endr_{drpts} qdr_{drpts} + \sum_{r} \sum_{c} enrc_{rcpts} qrc_{rcpts} \right) \leq \text{EN}_{ts}, \quad \forall t, s. \tag{18}$$

Decision variables:

$$\begin{aligned} & xs_{s'}, \\ & xm_m, \\ & xd_d, \\ & xr_r, \\ & xbt \in \{0, 1\}, \quad \forall s', m, d, r, \end{aligned} \tag{19}$$

$$\begin{aligned} & qsm_{s'mpts}, \\ & qmd_{mdpts}, \\ & qdr_{drpts}, \\ & qrc_{rcpts} \geq 0, \quad \forall s', m, d, r, p, t, s. \end{aligned} \tag{20}$$

The objective function (1) minimizes the weighted expected and maximum cost function in each scenario. We proposed this form to increase robustness against demand disruption and consider the worst case. Constraint (2) includes the summation of fix and variable costs. Constraints (3) to (5) include the fix cost of establishing facilities and BCT network in a central server and BCT maintenance. Constraints (6) to (8) indicate the variable cost after establishing facilities without running BCT and considering BCT. Constraints (9) show satisfaction of demand. Constraints (10) to (12) show flow quantity between facilities. Constraints (13) to (16) show resiliency strategy and facility and capacity constraints dependent of scenario. Constraints (17) and (18) show sustainability strategy and total emissions and energy are less than maximum emission and energy. Constraints (19) and (20) are decision variables, and constraints (19) are locations and binary variables and activating BCT. Constraints (20) are positive flow variables.

3.2. Linearization of Max and Absolute Function. We need to change objective function (1) and equation (6) from Mix Integer Nonlinear Programming (MINLP (to Mixed Integer Programming (MIP))) by operational research method. This process decreases the time solution [22, 23].

Linearization of max function and absolute function is as follows.

If $k = \max(\Omega_s)$, then we can replace these constraints with the model $k \geq \Omega_s, \forall s$.

If $k = |\Omega_s|$, then we can replace these constraints with the model $k = \alpha_s + \beta_s, \Omega_s = \alpha_s - \beta_s, \alpha_s, \beta_s \geq 0, \forall s$.

We can change and linearize a binary and a nonnegative variable that is produced.

Suppose $z = Ax$, if A is a nonnegative and positive variable and x is a binary variable. Therefore, we can replace these constraints with the model [24]

$$z \geq 0, \tag{21}$$

$$z \leq Mx, \tag{22}$$

$$z \leq A, \tag{23}$$

$$z \geq A - (1 - x)M. \tag{24}$$

It means that if $x$is zero, z is zero based on equations (21) and (22). If x is 1, then z is A based on equations (23) and (24).

3.3. Linearization of VSCNDBCT. We can write linearization of VSCNDBCT as follows.

Linearization of VSCNDBCT:

$$\min Z = (1-\lambda)\left(\sum_s p_s\Gamma_s + z_\alpha \sum p_s\left(va_s + vb_s\right)\right) + \lambda\delta, \tag{25}$$

subject to

$$\delta \geq \Gamma_s, \quad \forall s, \tag{26}$$

$$\Gamma_s - \sum_s p_s\Gamma_s = va_s - vb_s, \quad \forall s, \tag{27}$$

$$va_s, vb_s \geq 0, \quad \forall s, \tag{28}$$

$$\mathrm{VC}_s = \mathrm{VC1}_s - \eta_s, \quad \forall s, \tag{29}$$

$$\eta_s \leq \left(\mathrm{VC1}_s - \mathrm{VC2}_s\right), \quad \forall s, \tag{30}$$

$$\eta_s \geq \left(\mathrm{VC1}_s - \mathrm{VC2}_s\right) - M\left(1 - xbt\right), \quad \forall s, \tag{31}$$

$$\eta_s \geq 0, \quad \forall s, \tag{32}$$

$$\eta_s \leq M\left(xbt\right), \quad \forall s, \tag{33}$$

constraints (2)–(5) and (7)–(20).

We linearize model (1) by changing MINLP to MIP. When we linearize it, speed solving and the complexity of the model are more straightforward than MINLP in all solvers. We show the complexity of VSCND; the numbers of binary, free, and nonnegative variables and constraints are calculated as follows:

$$\text{binary variables} = \left|s'\right| + |m| + |d| + |r| + 1, \tag{34}$$

$$\text{positive variables} = |p| \cdot |t| \cdot |s|\left(\left|s'\right| \cdot |m| + |m| \cdot |d| + |d| \cdot |r| + |r| \cdot |c|\right) + 3|s|, \tag{35}$$

$$\text{free variables} = 11 + 2|s|, \tag{36}$$

$$\text{constraints} = 10 + 10|s| + |p| \cdot |t| \cdot |s|\left(|c| + 2|r| + 2|d| + 2|m| + \left|s'\right|\right). \tag{37}$$

It can be seen that scenario sets positively affect the number of constraints and positive and free variables and make the model scale grow. Therefore, applying methods that reduce scenarios such as Lagrangian relaxation (LR) and fix-and-optimize helps solve fast in minimum time.

3.4. Lagrangian Relaxation (Lower Bound for Large Scale). Lagrangian relaxation (LR) is an exact method that relaxes complex constraints in a difficult problem, and because of removing constraints, solution time decreases. This method removes complex constraints and adds a penalty to the objective with the Lagrange multiplier. In practice, this relaxed problem can give us a lower bound for minimization and can often be solved more quickly than the main problem [25–27].

Formulation of a MIP and changing to LR form are as follows:

$$Z_{IP} \coloneqq \min c^T x, \tag{38}$$

subject to

$$Ax \geq b, \tag{39}$$

$$Dx \geq d, \tag{40}$$

$$x \text{ integer}. \tag{41}$$

In this step, we remove constraint (39) and add it to objective function (38) with the form of penalty cost and used the Lagrange coefficient for this situation:

$$Z(\lambda) \coloneqq \min c^T x + \lambda(b - Ax), \tag{42}$$

subject to constraints (40) and (41).

We need to find the maximum of λ that minimizes $Z(\lambda)$:

$$Z_D \coloneqq \max_{\lambda \geq 0} Z(\lambda),$$
$$Z(\lambda) \coloneqq \min_{i=1,\ldots,m} \left\{c^T x^i + \lambda^T \left(b - Ax^i\right)\right\}, \tag{43}$$

subject to constraints (40) and (41).

In each iteration, we update λ based on these methods:

$$\begin{aligned}
\lambda^{t+1} &= \lambda^t + \gamma^t \nabla Z\left(\lambda^t\right),\\
\lambda^0 &= 0,\\
t &= 0,\\
\lambda^{t+1} &= \lambda^t + \gamma^t \left(b - Ax^i\right),\\
\lambda^{t+1} &= \max\left\{0, \lambda^t + \gamma^t \left(b - Ax^i\right)\right\},\\
\sum_{t=0}^{\infty} \gamma^t &= \infty,\\
\lim_{t \longrightarrow \infty} \gamma^t &= 0,\\
\gamma^t &= \mu^t \frac{z* - z\left(\lambda^t\right)}{\sum_{i=1}^m \left(b_i - \sum_{j=1}^n a_{ij} x^t\right)^2},\\
\gamma^{t+1} &= \alpha \gamma^t, \quad 0 \leq \alpha \leq 1, T > 1.
\end{aligned} \tag{44}$$

Therefore, based on these steps, the objective function (45) is LR of cost based on objective (25) that relax constraint (9). Figure 3 shows the steps of the LR algorithm that we applied to this research:

$$\min \text{LR obj} = Z + \sum_c \sum_p \sum_t \sum_s ud_{cpts} \left(\sum_r qrc_{rcpts} - d_{cpts} \right), \tag{45}$$

Subject to constraints (1)–(8), (10)–(20) and (26)–(33).

As can be seen, the complexity of the LR algorithm is as follows: binary, positive, and free variables are the same as equations (34)–(36). But constraints change into equation (46). This subject decreases the time solution:

$$\text{constraints} = 11 + 10|s| + |p| \cdot |t| \cdot |s| \left(2|r| + 2|d| + 2|m| + \left|s'\right|\right). \tag{46}$$

3.5. Fix-and-Optimize (Upper Bound for Large Scale). Because this problem is Np-hard, we need an algorithm to decrease the scale of this problem, produce an appropriate upper bound, and solve the model in minimum time. We suggest a new fix-and-optimize algorithm that creates an upper bound based on Figure 4. Relaxation of each constraint makes the upper bound for the objective function and equal to or greater than the amount of the primary objective function [21]. Fixing the binary variables by this method produce an appropriate upper bound. Finally, the objective function of the proposed method is always equal to or bigger than the main model.

This technique produces a close upper bound for the primary model explained in Helber and Sahling [28].

These steps of the new fix-and-optimize are as follows:

(1) Relax binary variables by changing them between zero and one and solve the model (relax constraint (19)).

(2) After solving step 1, we receive a lower bound, and our model is LP form.

(3) Loop:

   (a) Summarize binary variables for each set and round them up
   (b) Solve the model with a new fix binary variable
   (c) If the model obtains optimum value, it is an upper bound, and we save it in a list
   (d) Loop until the difference between two steps is less than 0.001

(4) Sort ascending objective function and report less upper bound objective function.

The complexity of the fix-and-optimize algorithm is as follows: binary variables are removed, and free, nonnegative variables and constraints are the same as equations (35)–(37). This subject decreases the time solution.

4. Results and Discussion

This section had a case study and estimated parameters defined in the notation list by the manager's information from the computer supply chain. We tried to show the performance of the proposed model. The number of sets is presented in Table 2, and amount of parameters are assigned in Table 3. The probability of occurrence is the same, and optimistic, pessimistic, and possible scenarios happen.

We applied a computer with this configuration: CPU 3.2 GHz, Processor Core i3-3210, 6.00 GB RAM, 64-bit operating system. Finally, we solve the mathematical models by GAMS-CPLEX solver.

We drew the potential location for assigning components of VSCND in Iran (c.f. Table 4 and Figure 5). After solving the model, it suggests that we activate BCT and determine the location and flow of SC components. The objective function is 2839008.413, shown in Table 2, and the final location-allocation is drawn in Figure 6. Eventually, we compare the model with BCT and without BCT in Table 5. We can see that without BCT, costs are almost 0.99% greater than with BCT.

4.1. Variation on the Scale of the Main Model. We determine several large-scale problems in Table 6. When the scale of problems increases, the time and cost increase as shown in Figures 7 and 8. As shown in Figure 8, the time solution is exponential and NP-hard on a large scale. Therefore, we need to solve the model by heuristic, metaheuristic [29], and new exact solution in minimum time on a large scale.

4.2. Variation on the Conservative Coefficient. The conservative coefficient (λ) is the number of conservative decision-makers. We change it by varying between 0 and 1 that the conservation of decision-maker has been changed. If the conservative coefficient increases to 1, the cost function

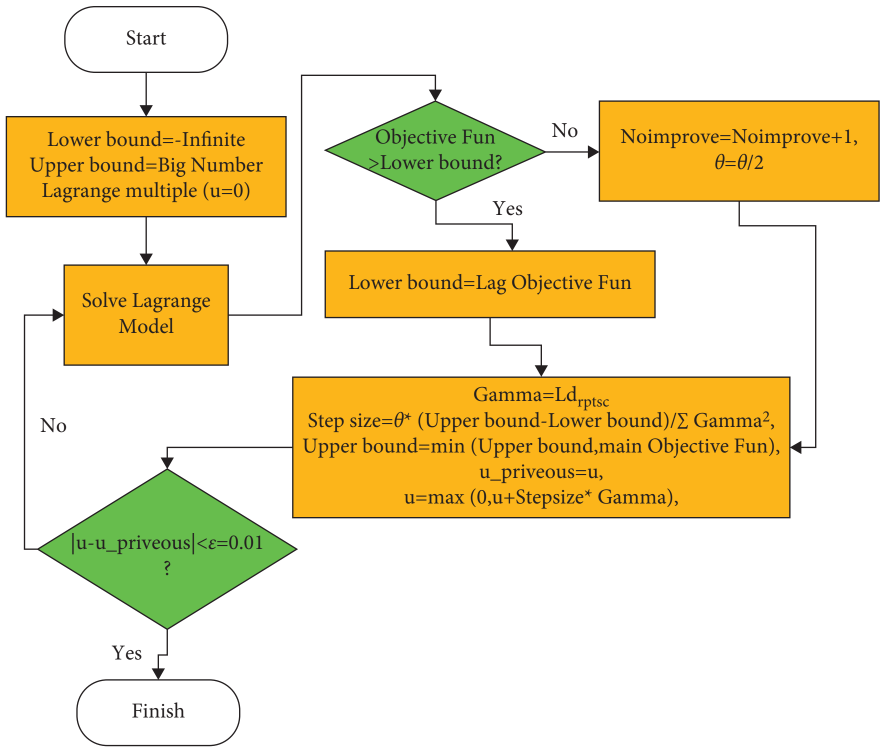

Figure 3: Solution approach for lower bound LR algorithm.

grows in Table 7 and Figures 9 and 10. If λ increases by 25%, the cost will increase by 0.3%, but the time solution does not change significantly.

4.3. Variation on Demand. As shown in Table 8, the application of BCT decreases and is not economical when decreasing demand happens definitely. When demand changes and increases, the cost will grow, and establishing BCT is required to decrease cost (c.f. Figure 11). By reducing 40% for demand, the cost function decreases by 22%, and BCT is not applicable.

4.4. Producing Bounds for the Main Model. We generate lower and upper bounds and compare the main model with the LR algorithm and a new fix-and-optimize strategy (c.f. Table 9). In addition, by relaxing constraint (19) that is LP form, we generate a lower bound for validating the LR algorithm. The comparison of the three methods is determined in Figures 12 and 13. We see that the fix-and-optimize strategy produces a suitable solution with a gap minimum of 10% and the LR algorithm produces a lower bound with a gap of less than 32% for the main model. Also, it can be seen that the cost function of P5 shows a difference between methods for three methods (c.f. Figure 14). We suggest using both approaches, but the fix-and-optimize strategy is better than the LR algorithm for large-scale problems.

5. Managerial Insights and Practical Implications

As managers of the SC, we should move forward to using novel technology in SC to decrease cost and increase resiliency and agility. BCT and cryptocurrency, renewable energy, and Internet of Things are new technologies that all of us need to use to improve the performance of SC. BCT and cryptocurrency are some of the best technologies that can facilitate financial transactions between customers and suppliers. As a result, operational and extra costs have been removed and make SC lean and agile. This research designed a SCND by considering and establishing BCT and cryptocurrency. We apply SC run traditional or consider BCT. Therefore, using BCT enables reducing variable costs. We draw a model that can select BCT with higher variable costs or select BCT with lower variable costs, fix cost, and maintenance costs for establishing BCT. We found that applying cryptocurrency can help SC to attain sustainability by decreasing cost and being agile. When demand is high, using BCT and cryptocurrency is an economic justification. Finally, we design a model for all risk-neutral decision-makers until

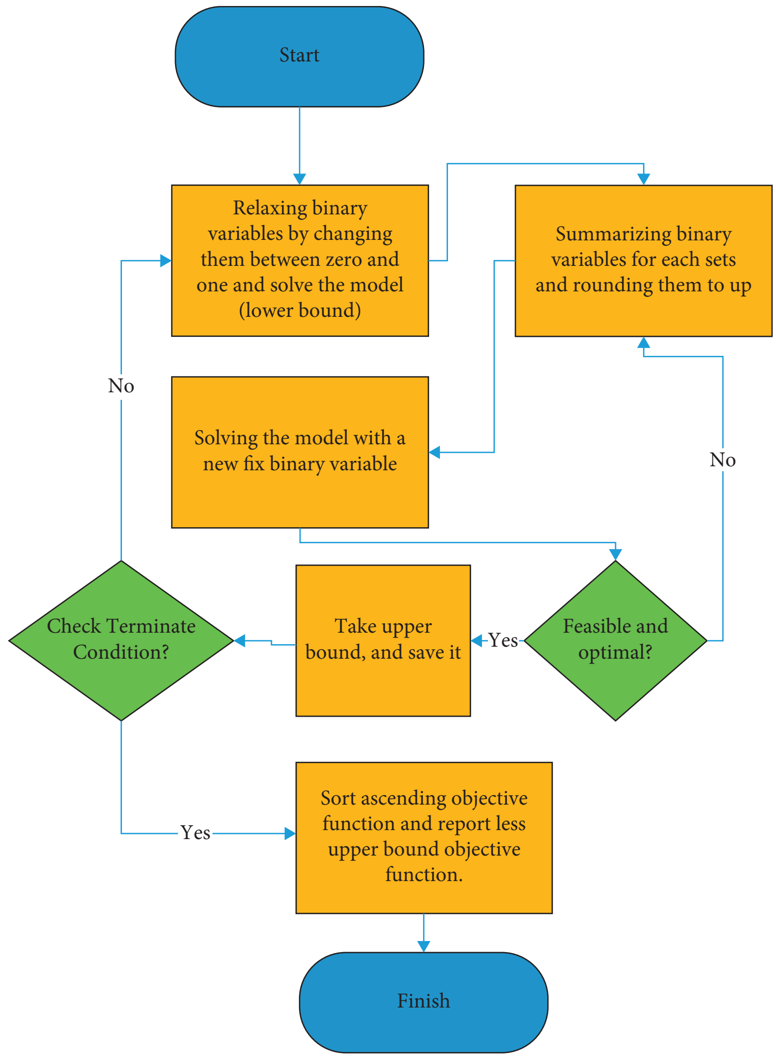

Figure 4: Fix-and-optimize solution approach (upper bound).

Table 2: The number of sets, variables, and constraints.

Problem	$\lvert s'\rvert \cdot \lvert m\rvert \cdot \lvert d\rvert \cdot \lvert r\rvert \cdot \lvert c\rvert \cdot \lvert p\rvert \cdot \lvert t\rvert \cdot \lvert s\rvert$	Binary variable	Positive variable	Free variable	Constraint	Cost function	Time (seconds)
P1-main	3.3.3.3.3.3.3.3	13	981	17	688	2839008.413	1.012

Table 3: Parameters of case study.

Parameters	Value	Unit	Parameters	Value	Unit
dd_{cpts}	[U (2000, 2100)].1000. (s-1)/($\lvert s\rvert$ − 1-).0.2 + 0.9)	Num.	fd_d	[U (80,85)].1000	$
$vsm_{s'mpts}$	U (0.002,0.003)	$/Num.	fr_d	[U(200,210)].1500	$
vmd_{mdpts}	U (0.004,0.005)	$/Num.	fr_r	[U(200,210)].200;	$
vdr_{drpts}	U (0.002,0.003)	$/Num.	fbt	[U(200,210)].200	$
vrc_{rcpts}	U (0.001,0.002)	$/Num.	pp_s	$1/\lvert s\rvert$	%
$vsm'_{s'mpts}$	0.9.U (0.002,0.003)	$	λ	50	%
vmd'_{mdpts}	0.9.U (0.004,0.005)	$	M	10^{500}	-
vdr'_{drpts}	0.9.U (0.002,0.003)	$	$emsm_{s'mpts}$	U (4,5).10^{-4}	Ton/Num.
vrc'_{rcpts}	0.9.U (0.001,0.002)	$	$emmd_{mdpts}$	U (4,5).10^{-4}	Ton/Num.
mbt_{ts}	[U(3,4)].100	$	$emdr_{drpts}$	U (4,5).10^{-4}	Ton/Num.
$esm_{s'mpts}$	U (4,5).10^{-3}	$/Num.	$emrc_{rcpts}$	U (4,5).10^{-4}	Ton/Num.

Table 3: Continued.

Parameters	Value	Unit	Parameters	Value	Unit
emd_{mdpts}	U (4,5).10^{-3}	\$/Num.	$ensm_{s'mpts}$	U (1,2).10^{-4}	MJ/Num.
edr_{drpts}	U (4,5).10^{-3}	\$/Num.	$enmd_{mdpts}$	U (1,2).10^{-4}	MJ/Num.
erc_{rcpts}	U (4,5).10^{-3}	\$/Num.	$endr_{drpts}$	U (1,2).10^{-4}	MJ/Num.
$\mathrm{Caps}_{s'pts}$	[U (5500,6600)].1000	Num.	$enrc_{rcpts}$	U (1,2).10^{-4}	MJ/Num.
Capm_{mpts}	[U (55000,66000)].1000	Num.	EM_{ts}	$50000 \cdot \lvert s'\rvert \cdot \lvert m\rvert \cdot \lvert d\rvert \cdot \lvert r\rvert \cdot \lvert s\rvert$	Ton
Capd_{dpts}	[U (3300,4400)].1000	Num.	EN_{ts}	$70000 \cdot \lvert s'\rvert \cdot \lvert m\rvert \cdot \lvert d\rvert \cdot \lvert r\rvert \cdot \lvert s\rvert$	MJ
Capr_{rpts}	[U (3300,4400)].1000	Num.	$\rho_{s_I} = \rho_m = \rho_d = \rho_r = 90$	%	
fs_{s_I}	[U(200,210)].1000	\$	z_α	0.5	-
fm_m	[U(200,210)].4000	\$		[]: sign	

Table 4: Assigning location for the facility of SC and BCT.

Problem: P1	Variables	City		
Supplier	xs_{s_I}	Yazd 0	Chabahar 1	Behbahan 1
Manufacturer	xm_m	Khorramdareh 0	Zahedan 0	Kashan 1
DC	xd_d	Kashan 1	Kashmar 1	Sanandaj 1
Retailer	xr_r	Tehran 1	Borojerd 1	Khoy 1

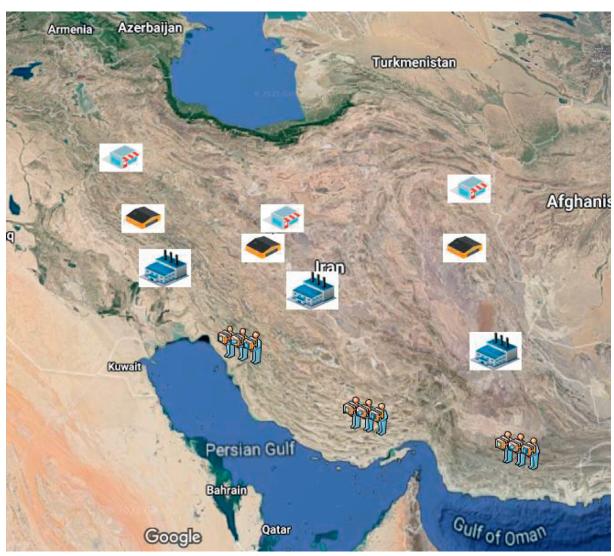

Figure 5: Potential location for the facilities.

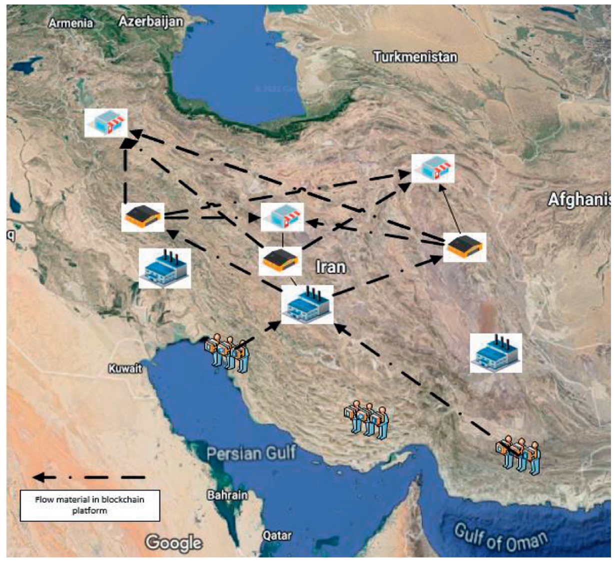

Figure 6: Final location of the SC facility with BCT platform.

Table 5: Compare P1 with BCT and without BCT.

Model	P1-with BCT	P1-without BCT	Gap (%)
Profit	2839008.413	2867283.546	0.99

Table 6: Cost and time solution for different problems.

Prob.	$\vert s'\vert \cdot \vert m\vert \cdot \vert d\vert \cdot \vert r\vert \cdot \vert c\vert \cdot \vert p\vert \cdot \vert t\vert \cdot \vert s\vert$	Binary var.	Positive var.	Free var.	Constraint	Cost function	Time (seconds)
P1	3.3.3.3.3.3.3.3	13	981	17	688	2839008.413	1.012
P2	3.3.3.3.3.3.3.5	13	1635	21	1140	2868628.538	2.857
P3	4.4.4.4.4.4.4.3	17	3081	17	1576	3931302.815	15.437
P4	4.4.4.6.4.4.4.4	19	5132	19	2354	3813256.048	26.237
P5	5.5.5.6.5.5.5.5	22	13765	21	5310	5525665.563	538.483
P6	8.8.8.6.8.8.8.5	31	71695	21	19260	—	—
P7	12.12.12.12.12.12.8.5	49	276495	21	46140	—	—
P8	20.8.8.12.15.15.20.7	49	1050021	25	191180	—	—
P9	30.8.8.12.20.20.30.10	59	3840030	31	636110	—	—
P10	40.8.8.12.30.35.40.15	69	17640045	41	2646160	—	—

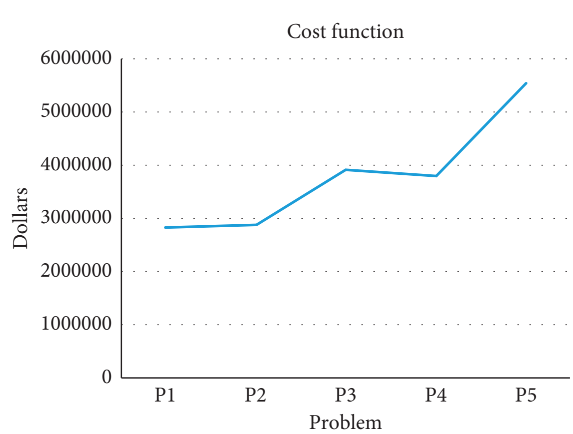

Figure 7: Cost function for problems.

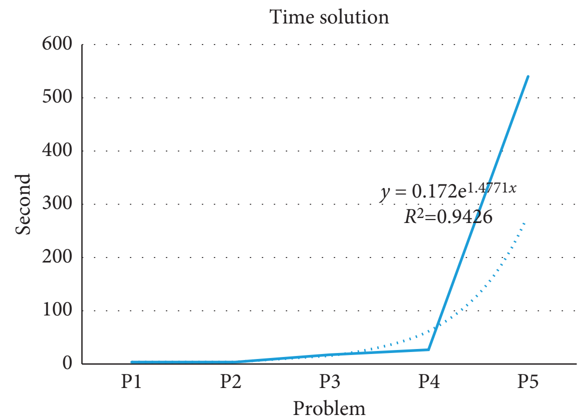

Figure 8: Time solution for problems.

Table 7: Variation on conservative coefficient.

Problem	Conservative coefficient (λ)	Cost function	Time (seconds)	Cost variation (%)
P1	0.00	2822175.206	0.911	−0.59
P1	0.25	3031098.187	1.373	6.77
P1-main model	0.5	2839008.413	1.012	0.00
P1	0.75	2847425.016	1.267	0.30
P1	1.00	2855003.861	0.896	0.56

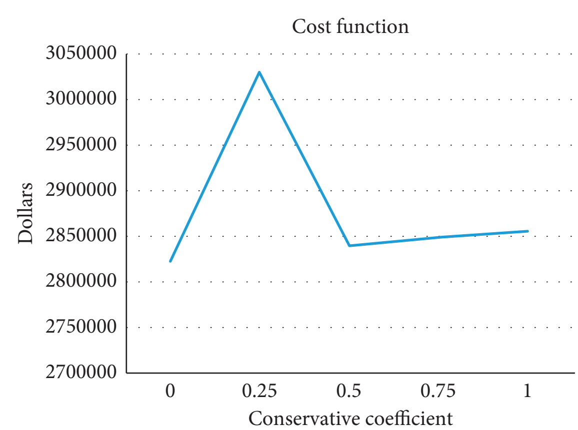

Figure 9: The cost function for variation on conservative coefficient.

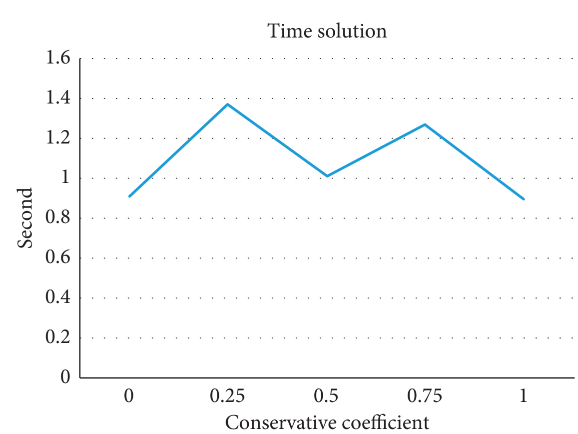

Figure 10: Time solution for variation on conservative coefficient.

Table 8: Variation of demand.

Problem	Variation of demand (%)	Cost function	Time (seconds)	BCT	Cost variation (%)
P1	−50	2208505.182	1.230	No need	−22.21
P1	−40	2065840.501	1.009	No need	−22.21
P1	−20	2381482.610	1.678	Needed	−27.23
P1-main model	0	2839008.413	1.012	Needed	0.00
P1	+20	2954586.691	1.119	Needed	4.07
P1	+40	3072017.106	0.763	Needed	8.21

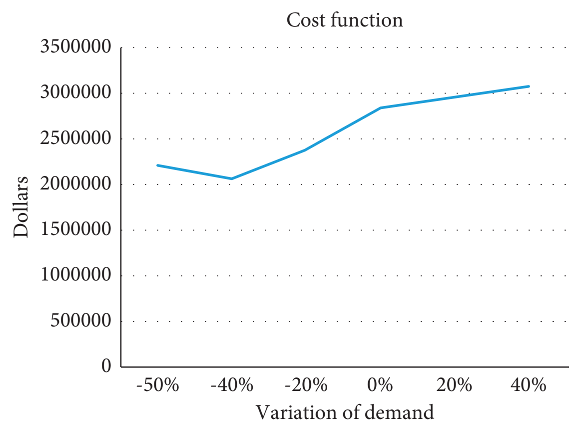

Figure 11: Effects of variation on demand.

Table 9: Comparing three algorithms with the main model.

Problem	LP model lower bound (A)		LR model lower bound (B)		Main model (B)		Fix-and-opt. upper bound (C)		$GAP_1(\%)$	$GAP_2(\%)$
	Cost	Time (seconds)	Cost	Time (seconds)	Cost	Time (seconds)	Cost	Time (seconds)		
P1	1603085.131	0.256	1917317.456	1.544	2839008.413	1.012	2841080.44	0.832	−32.47	0.07
P2	1621637.956	0.342	1938656.333	3.332	2868628.538	2.857	2869908.32	1.108	−30.17	0.04
P3	2696941.848	1.220	2794259.9	22.468	3931302.815	15.437	3941819.72	2.501	−28.92	0.27
P4	2726058.808	0.674	2748952.713	49.748	3813256.048	26.237	3826966.74	30.755	−27.91	0.36
P5	4186057.711	14.921	4479146.692	534.824	5525665.563	538.483	6119280.37	16.347	−18.94	10.74
P6	1.259045 E + 7	456.623	—	—	—	—	1.250087 E + 7	978.651	—	—
P7	2.5671 E + 7	2464.913	—	—	—	—	2.376011 E + 7	40152.25	—	—

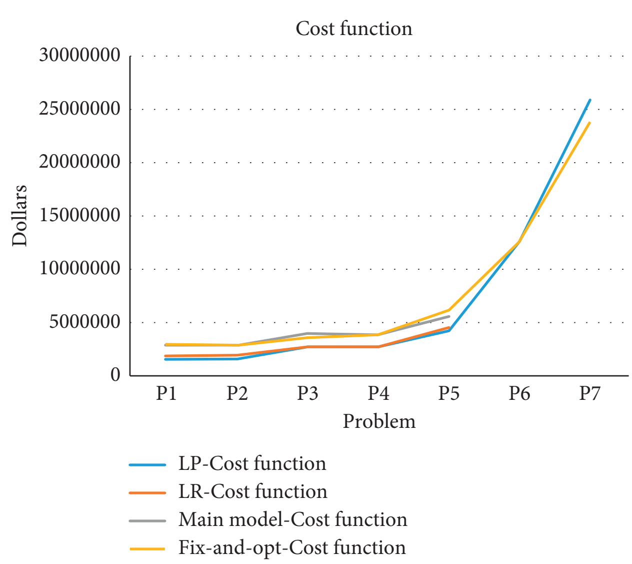

Figure 12: The cost function for models.

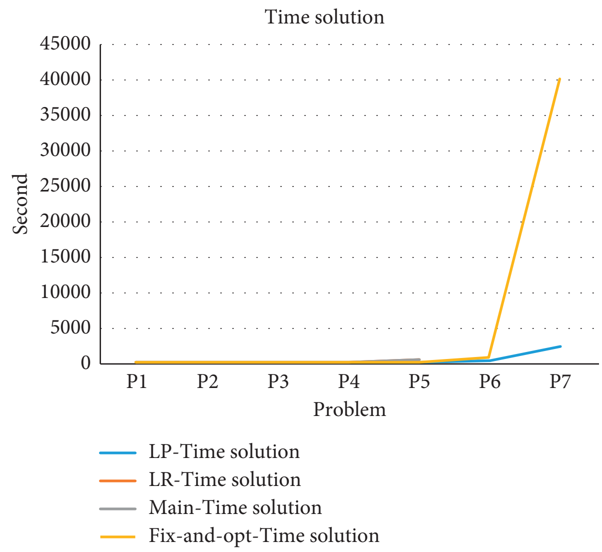

Figure 13: Time solution for models.

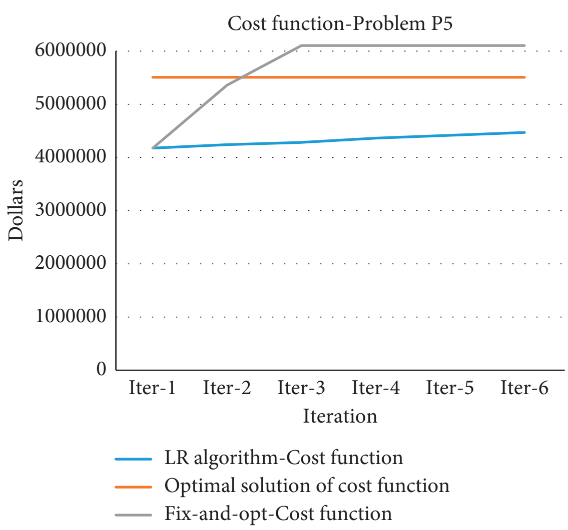

Figure 14: Attaining bounds for problem P5.

risk-averse and cover all spectrum types. We surveyed this model on a large scale and contributed fix-and-optimize and Lagrange relaxation to generate upper and lower bound when the solver cannot solve in logical time.

6. Conclusions and Outlook

Using a novel technology by SC is grown every day. Technologies, such as cryptocurrency and blockchain, make SC agile and lean and decrease operational costs. VSCND applied resiliency, sustainability, and agility by embedding cryptocurrency and BCT. We used a new robust two-stage stochastic MIP for modeling this problem. We utilized GAMS-CPLEX to solve the problem. We found that establishing BCT and cryptocurrency for transaction reduce costs for SC with high demand.

The findings are as follows:

(1) The cost and time increase when the scale of problems increases in Figures 7 and 8.

(2) If the conservative coefficient increases to 1, the cost function grows in Table 7 and Figures 9 and 10. When the conservative coefficient increases by 25%, the cost increases by 0.3%, but the time solution does not change significantly.

(3) The application of BCT decreases and is not economical when decreasing demand happens. When demand increases, it increases the cost function, and establishing BCT is needed for reducing cost (c.f. Figure 11). By reducing 40% of demand, the cost function decreases by 22%, and BCT is not applicable.

(4) We utilize fix-and-optimize and LR to generate lower and upper bound to estimate large scale in minimum time. The results show that the gap between the main model and fix-and-optimize is better than the LR algorithm.

One of the important research limitations is solving the large-scale main model. We propose applying exact algorithms such as benders decomposition, branch and price, branch-and-cut, and metaheuristic algorithms [30, 31]. We can add other resilience, sustainable strategy, and multiobjectives [18, 19] to the model and increase resiliency and sustainability such as backup suppliers and improve node complexity.

Further, we suggest considering robust risk criteria such as Robust Conditional and Entropic Value at Risk (RCVaR and EVaR) [32, 33]. Researchers intend to investigate uncertainty methods such as robust convex and stochastic programming to close to the real world [34]. Using fuzzy and novel robust optimization as a data-driven approach is advantageous for a risk-averse decision-maker in the recent decade. Eventually, we suggest equipping all SC with novel technology such as Internet of Things (IoT) and RFID [35] to increase SC's viability.

Abbreviations

Notation list

Indices

s': Set of suppliers $s' \in \{1, 2, \ldots, S'\}$
m: Set of manufacturers
d: Set of distributing centers (DC) $d \in \{1, 2, \ldots, D\}$
r: Set of retailers $r \in \{1, 2, \ldots, R\}$
c: Set of customers $c \in \{1, 2, \ldots, C\}$
p: Set of products (commodities) $p \in \{1, 2, \ldots, P\}$
t: Set of time periods $t \in \{1, 2, \ldots, T\}$
s: Set of scenarios $s \in \{1, 2, \ldots, S\}$

Parameters

dd_{cpts}: Demand of customer c for commodity p in period $t$on scenario s
$vsm_{s'mpts}$: Variable cost from supplier s' to manufacture m for commodity p in period t on scenario s
vmd_{mdpts}: Variable cost from manufacture m to DC d for commodity p in period t on scenario s
vdr_{drpts}: Variable cost from DC d to retailer r for commodity p in period t on scenario s
vrc_{rcpts}: Variable cost from retailer r to customer c for commodity p in period t on scenario s
$vsm_{s'mpts}'$: Variable cost from supplier s' to manufacture m for commodity p in period t on scenario s with considering BCT ($vsm_{s'mpts} \geq vsm_{s'mpts}'$),
vmd_{mdpts}': Variable cost from manufacture m to DC d for commodity p in period $t$on scenario s with considering BCT ($vmd_{mdpts} \geq vmd_{mdpts}'$),
vdr_{drpts}': Variable cost from DC d to retailer r for commodity p in period t on scenario s with considering BCT ($vdr_{drpts} \geq vdr_{drpts}'$),
vrc_{rcpts}': Variable cost from retailer r to customer c for commodity p in period t on scenario s with considering BCT ($vrc_{rcpts} \geq vrc_{rcpts}'$),
$fs_{s'}$: Activation cost for supplier s'
fm_m: Activation cost for manufacture m
fd_d: Activation cost for DC d
fr_r: Activation cost for retailer r
fbt: Activation cost for running BCT,
mbt_{ts}: Cost of maintenance for BCT in period t on scenario s
$emsm_{s'mpts}$: CO_2 produced for movement from supplier s' to manufacture m for commodity p in period t on scenario s
$emmd_{mdpts}$: CO_2 produced for movement from manufacture m to DC d for commodity p in period t on scenario s
$emdr_{drpts}$: CO2 produced for movement from DC d to retailer r for commodity p in period t on scenario s
$emrc_{rcpts}$: CO2 produced for movement from retailer r to customer c for commodity p in period t on scenario s
$ensm_{s'mpts}$: Energy utilization for movement from supplier s' to manufacture m for commodity p in period t on scenario s
$enmd_{mdpts}$: Energy utilization for movement from manufacture m to DC d for commodity p in period t on scenario s
$endr_{drpts}$: Energy utilization for movement from DC d to retailer r for commodity p in period t on scenario s
$enrc_{rcpts}$: Energy utilization for movement from retailer $r$to customer c for commodity p in period $t$on scenario s
$\mathrm{Caps}_{s'pts}$: Capacity of supplier s' for commodity p in period t on scenario s
Capm_{mpts}: Capacity of manufacture m for commodity p in period t on scenario s
Capd_{dpts}: Capacity of DC d for commodity p in period t on scenario s
Capr_{rpts}: Capacity of retailer r for commodity p in period t on scenario s
p_s: Probably of scenario s
λ: Coefficient of conservative,
M: Very large number,
EM_{ts}: Maximum emission is allowed in period t on scenario s
EN_{ts}: Maximum energy is allowed in period t on scenario s
z_α: Confidence in α level,
$\rho_{s'}$: Availability coefficient of supplier s'
ρ_m: Availability coefficient of manufacture m
ρ_d: Availability coefficient of DC d
ρ_r: Availability coefficient of retailer r

Decision variables

Binary variables

$xs_{s'}$: Equal 1, if supplier s' is established; else 0
xm_m: Equal 1, if manufacture m is established; else 0
xd_d: Equal 1, if DC d is established; else 0
xr_r: Equal 1, if retailer r is established; else 0
xbt: Equal 1, if BCT network is established and activated for SC in the central sever; else 0

Continues variables

$qsm_{s'mpts}$: Flow between supplier s' and manufacture m for commodity p in period t on scenario s
qmd_{mdpts}: Flow between manufacture m and DC d for commodity p in period t on scenario s
qdr_{drpts}: Flow between DC d and retailer r for commodity p in period t on scenario s
qrc_{rcpts}: Flow between retailer r and customer c for commodity p in period t on scenario s

Auxiliary variables

FC: Fixed cost include FC1, FC2, FC3
VC_s: Variable cost includes $\mathrm{VC1}_s$ related to SCND without BCT and $\mathrm{VC2}_s$ related to VSCNDBCT for scenario s
Γ_s: Fixed and variable cost under scenario s
δ: Auxiliary variable for linearizing max function
η_s: Auxiliary variable for linearizing CVaR
va_s, vb_s: Auxiliary variable for linearizing absolute function.

Data Availability

The authors confirm that the data supporting the findings of this study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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