Blockchain acceptance rate prediction in the resilient supply chain with hybrid system dynamics and machine learning approach

Abstract

In today's era, the importance and implementation of blockchain networks have become feasible as it improves the resilience of the supply chain network at all levels by clarifying information and creating security in the network, improving the speed of response, and gaining the trust of customers. This paper aims to investigate the behavior of the blockchain acceptance rate (BAR) in the home appliances flexible supply chain in Iran using. system dynamics (SD), which is used to better define the relationships between the variables of the model that are non-linearly connected. Through simulating the behavior of the BAR in the long term in the supply chain, whilst conducting sensitivity analysis, policy design, and validation, this model will be implemented for the years 2020 to 2030. Additionally, post-simulation, blockchain acceptance behavior will be assessed by having simulated data considered as input for studied Multi-Layer Perceptron (MLP) and Vector Regression (SVR) (data that have the highest correlation with BAR). The acceptance rate behavior function is estimated with the help of machine learning methods to have the best function behavior and prediction for the data of 2020-2022 since the prediction function is compared to daily real data obtained these years. The results show that in 2030, the BAR will be around 0.6 if the COVID-19 outbreak impact is medium, and if the considered policy designs are implemented, this rate will reach a maximum of 0.8. So paying attention to the creation and design of policies can achieve positive implications for increasing the resilience of the supply chain in the long run. Findings suggest that the SD-MLP method is better than the SD-SVR method as it has less error and can estimate the behavior of the BAR function better.

Keywords: Blockchain, Function prediction, System dynamics, MLP, SVR

1 Introduction

With the advent of emerging AI and I4.0 technologies, and In order to mitigate risks, increase efficiency and reduce the costs of procurement and sourcing operations in supply chains, it is necessary to create a secure technological platform for suppliers, manufacturers, distributors, and customers of a supply chain to allow them to efficiently and effectively operate so as to create a dynamic network. For this purpose, supply chain networks (SC) have been created, which include different stages in an SC of meeting the needs of customers from the beginning of the SC cycle (primary raw material) to the end or even to recycling the product. So that their time and expenses are in the most optimal state [1]. On the other hand, traditional supply chain networks need to be transformed to increase resilience along the network. So that if the network faces problems such as floods, earthquakes, or as in recent years, the spread of COVID-19, these networks can adapt and respond with agility to the new environmental conditions [2]. For this purpose, resilient supply chain (RSC) networks have been formed which provide a stable structure when operating in difficult and volatile situations, especially when the supplier may not be able to meet their customer demand and/or there is a disruption in the SC transportation network [3].

In this regard, different modeling techniques have been adopted over the past several decades. For example, Markley and Davis (2007) used graph theory to provide a model and interpretive structural modeling to find interrelationships to have more resilience in the supply chain [4]. Lockamy (2014) assessed the risk of supplier shortages for an automotive foundry supplier based in the United States and found that Bayesian networks can be effectively used to help managers make decisions about current and potential suppliers [5]. Torabi et al. (2015) developed a two-stage probabilistic hybrid stochastic programming model to create supplier resilience under operational risk and disruption to address the supplier selection and order allocation problem. In order to create a flexible supply base under operational risks and disruption, findings showed a significant effect of considering natural events on the supply chain's levels [6].

More recent studies included additional dimensions. For example, Saenz et al. (2018) investigated the role of resilient management in the SC where they presented a framework that captured the dynamics of supply chain flexibility and related supply chain portfolio design to supply chain vulnerabilities [7]. Parkouhi et al. (2019) considered two dimensions of resilience enhancer and resilience reducer for selecting and segmenting suppliers where they used the Gray DEMATEL technique to determine the degree of importance of the criteria for each of these two dimensions. This helped them determine the score of each supplier based on each dimension; with the backup buffer as the most critical enhancer and the supplier's capacity restriction being the most important reducer [8].

Also, it is important to note that the most critical resilient enhancer and reducer criteria for selecting and segmenting suppliers ie., backup supplier and lack of excess capacity possessed, can only be useful after the critical incident has occurred. Although these two policies are very important in times of crisis, their implementation across an SC can still disrupt due to the lack of coordination and transparency between inter- and intra- organizations. For this purpose, a technological platform that can proactively maintain sufficient security throughout the network; one that creates the necessary transparency for all participants in the network so that they can take the necessary measures in critical situations with agility in the shortest time and with the least risk be created A resilient technological platform, enabled through blockchain, an emerging technology which is a distributed database of records or a shared public/private ledger of all digital events executed and communicated among individuals partaking in the blockchain can help transform SC, especially in critical situations [9].

Moreover, in past studies system dynamics (SD) has been used for the supply chain and examined the risk and some latest technology effects on it. But the blockchain network impacts on the supply chain when natural events occur have not been investigated yet [10]. So, this paper aims to address the issue of the behavior of the chief variable in an RSC and show how blockchain acceptance rate (BAR) in an RSC with SD and MLP methods can result in a dynamic network. Since many variables are involved in examining the behavior of the BAR in the RSC, a simulation model has been created that can show the interaction across all the variables resulting in demonstrating the behavior of BAR in the long term. This study has prioritized and identified the most effective variables and their relationships in the RSC according to past studies ([1, 11–14]) for the first time and presented a simulated model of the problem. Also, by presenting the design policies, the theoretical and practical implications that analysts and policymakers can adapt according to the conditions and level of COVID-19 are expressed. In general, the main aim of this paper is to investigate the behavior of BAR in the long term and to examine the behavior of effective variables based on different design policies (i.e., investigating the effects of the exchange rate, inflation, domestic policy, and research and development on the SC variables). Underpinning this, the main contributions of this paper provided for the first time are as follows:

1. Identifying and examining the factors that play a key role in the BAR in an RSC network.
2. Predicting the blockchain acceptance behavior in the network through model simulation with SD using data for 10 years
3. Using MLP and SVR methods to estimate the blockchain acceptance function over the years 2020 to 2022 (optionally also creating an innovative combined SD-MLP and SD-SVR method to estimate function)

The paper is structured as follows. The second section describes the theoretical section, research methodology, whilst in the third section, the design and validation of the blockchain acceptance function /model and the design of policies as applied to the theoretical model are presented, in the fourth part, the implementation of the model for a case study, the evaluation of the model behavior, the evaluation of the results and the sensitivity analysis are done. In the next section, the blockchain acceptance function is finally estimated using machine learning methods and the best method is introduced. Finally, implications, future research, limitations of this research study, and the conclusion are presented.

2 Literature Review

2.1 The role of blockchain

In the blockchain, an agent makes a new transaction to be added to the chain. This new transaction is broadcasted across the SC network for validation and audit. When the majority of nodes in the chain endorse this transaction due to the predetermined rules, this new transaction is added to the chain as a new block. Once the new record is confirmed and added to the blockchain, multiple copies are created and decentralized to create a chain of trust. Decentralization and verification of any falsification of information are the important features of blockchain technology, thus increasing the credibility of information [12].

Blockchains are potentially a comprehensive technology for the organization, design, operation, and overall management of supply chains. Blockchain's ability to ensure the reliability, traceability, and authenticity of the information, along with smart contract relationships for a trust-less environment, all indicate the need for a major rethink in SC and supply chain management. The smart contract, as one of the important features of blockchain technology, provides the possibility of valid transactions without the involvement of third parties [13]. Blockchain-based supply chain networks may need a closed, private, and permissioned blockchain with a restricted number of participants. Four main institutions play a role in blockchain-based supply chains, some of which are not seen in conventional supply chains [10]. Registrars, provide unique identities to people on the network [15]. Standards organizations, which represent standard schemes, such as Fair Trade for Sustainable Supply Chains or blockchain policies and technology requirements. Certifiers who provide certificates to people to participate in the SC network. Participants, including manufacturers, retailers, and customers, must be certified by a registered auditor or certifier to maintain system trust [14, 16].

2.2 RSC – Dynamic networks

Many simulation studies have been conducted on RSC and the role of blockchain in improving the performance of the supply chain structure. In this section, the most important studies are stated. Focusing on RSCs, Sawik (2022) presented a model to minimize production costs and maximize estimated demand using a multi-portfolio approach and stochastic models with scenario-based mixed integer programming (MIP) to solve the model. The model allowed calculation of the amount of extra inventory required to reduce risk level, which is used as the excess capacity for building more resilience in the SC as trade-off to, the amount of production, and the supply of parts by the factory and suppliers [17].

Similarly, Piprani et al. (2022) showed that natural events increase SC risks [18]. Taleizadeh et al. (2022) evaluated resilience variables and pricing decisions to optimize an SC where they used two-level planning and the Stackelberg game model to calculate the amount of inventory backup buffer. As part of this modeling, the authors considered preventive and recovery policies at the same time, and found that maintaining a contingency stock strategy is highly recommended, but considering multiple suppliers and additional reserve capability is not almost always preferred to reduce the negative effect of disruptions in the case study [11]. Hosni et al. (2021), using a multi-objective nonlinear model, maximized profit, minimized facilities, and carbon dioxide, and considered both green and RSC criteria [19]. Also, Arian et al. (2021) used the SD simulation for investigating cutting-edge technology like 3D printing in a home appliances SC. They showed the dynamics behavior of 3D printing over the times. Also, they investigated the personnel skills effects on production in the SC [20]. Moreover, some recent papers like: Aloui et al. (2021), Flynn et al. (2021), Ivanov (2022), Sawik (2022), and Shokouhifar et al. (2022) considered the effects of COVID-19 on different SC. They show that COVID-19 can face the supply chain's irreparable consequences [17, 21–26].

Although blockchain can help to improve and reform the SC, many governments and organizations are not willing to accept it for their reasons [25, 26]. A lot of research has been done on blockchain acceptance in the RSC. In general, these studies have not focused on predicting the acceptance rate of blockchain in an RSC. Although there are studies, Casado-Vara et al. (2018) critically reviewed blockchain technology and smart contracts with potential application to SC management. Due to local and global government, community, and consumer pressures to achieve sustainability goals, they investigated how to implement blockchain to help SC sustainability. They have only used a questionnaire to find the effective criteria of blockchain in the RSC. This study uses previous articles and tries to complete them [27]. Table 1shows the previous studies about RSC and blockchain acceptance rate prediction in SC and their comparison with the present study.

In these two sections, the previous studies were described more fully and finally, the research gap and our contributions were reported. In the literature studies, although they have tried to show the influential variables of blockchain acceptance in RSC, none of the studies have presented long-term behavior for BAR changes. Also, another important difference between this paper and previous studies is that it presents policies that can not only affect the acceptance rate of blockchain but also change other variables. Also, the method used to estimate the acceptance function of the blockchain (SD-MLP and SD-SVR) is another innovative contribution of this paper.

Table 1 The comparison of proposed method with past studies.

Authors	Features and model solution method	The purpose of the model	Case Study
Torabi et al. (2015)	Two-stage probabilistic hybrid dual-objective stochastic programming for RSC	Minimizing costs, Minimizing risk	Numerical examples
Casado-Vara et al. (2018)	Integer combinatorial linear programming, Uncertainty in demand, Cost minimization	Minimizing costs	A European company
Aloui et al. (2021)	Two-stage random mixed integer programming, Demand uncertainty	Minimizing costs	Numerical examples
Taleizadeh et al. (2022)	Two-level programming, Stackelberg game model	Optimizing a sustainable SC considering resilience factors and pricing decisions	Manufacturing cartridges in Iran
Shokouhifar et al. (2022)	Deep learning, Multivariate time series	Demand forecasting, COVID-19 disruptions	Iranian blood donation organization
Alazab et al. (2021)	Investigating the effective BAR factors in SC, Applied structural equation modeling	Finding the key factors for BAR in SC	Industry factory in Jordan
Kamble et al. (2021)	A machine learning approach (Bayesian network), Using the technology acceptance model (TAM) for showing concept of BAR model in SC	Predicting blockchain acceptance rate in SC	Mumbai-Pune and Bangalore –Chennai companies in India
Proposed study	Predicting the BAR function in RSC, Considering the most comprehensive variables of model for simulating, Investigating variables behavior during the time, Analyzing the effective policies during the disruptions, Designing new method based on SD and machine learning	Investigating model behavior based on some policies, predicting BAR in RSC	Home appliance SC

3 Theorizing the research model – RSC and BAR

Since global economic policy uncertainty and domestic political stability have significant positive and negative effects on the banks and business of countries' profitability, so the adjustment of the plans for making the far-reaching positive change can develop trade, reduce inflation, increase exchange rate, and improve supply chain structure [28]. In this regard, political risk stability was investigated in this study as a policy. This paper shows that the total transactions by smart contracts (since political stability is caused by constructive communications between all levels of the SC), the BAR, the number of blocks, backup buffer, and inventory can be increased based on improving political risk in the RSC. In general, after analyzing the impact of COVID-19 on the subsystems presented in the simulation model, it can be concluded that to face the disruption, there is a need to explain the policies that cause resistance to chain disruptions.

Also, there are lots of studies that identified the effective criteria for an RSC and BAR. Sachin et al. (2021) have investigated the possibility of blockchain acceptance in the SC using the Bayesian method. They defined blockchain technology as a dynamic capability that must be possessed by organizations to remain competitive. They identified the most effective influencing factors in blockchain acceptance behavior and tried to use them to predict the probability of blockchain acceptance in their organization by company managers [29]. But since the acceptance of blockchain depends on many factors and the changes of each factor can cause many changes in the blocking process, its prediction requires dynamic tools to include non-linear dependence between variables. SD is one of those tools that consider the non-linear relationships between variables to show variable behavior in the long term. None of the previous studies have used SD to investigate BAR behavior. Table 2 shows the list of variables and their direct relationships that have been established in past research. In general, although previous studies have examined one or two

Table 2 Relationships between variables in previous studies.

Variables	Relation to other variables	Studies
Backup buffer	RSC, Response time, Number of supplier, Vehicles	[9, 12, 20, 30, 31]
BAR	Security, Information sharing, Transactions, Collaborative integration, The number of blocks, Total costs, R& D	[14, 27, 29, 32]
Confirmed transactions	Main inventory, Smart contracts, Investments	[16, 33]
Personnel skills	R& D, Training, Total costs	[7, 13]

variables in RSC and blockchain influencing variables in the SC, none of them have comprehensively explored all the behaviors of RSC variables in terms of blockchain.Also, this study has another interesting output that can help predict the BAR rate function. According to the purpose of this study, policies have been designed to increase the resilience of the supply chain, especially in the event of a crisis. On the other hand, since the SC is being studied in Iran and this country in the last decade encountering all the policies examined in this paper, the necessity of designing these policies have multiplied. Table 3 shows these policies and how they affect the SC.

Table 3 Review of policies in the SC in past studies.

Policy	Relation with SC	Source
Exchange rate	Exchange rate risk can show the company's risk tolerance in transactions and outsourcing.	[34–36]
Inflation	The inflation rate can have a significant impact on contracts and transactions. It also affects inventory changes.	[37–39]
R&D	R&D increases the innovation of companies and strengthens the speed of acceptance of new technology.	[40, 41]
Domestic political stability	Domestic policies can be influential in some domestic decisions such as accepting or rejecting a technology, systematic change or relations with other countries, and sanctions issues.	[28, 42, 43]

4 Research Design

This paper addressed the behavior of the BAR in the RSC during the time by using the new method as shown in Fig. 1. There are several stages to this model. In this model, there are many variables in determining the acceptance rate of blockchain in the RSC. As the variables have non-linear relationships with each other, so the best way is to use the SD simulation. Therefore, in the first stage, the boundary of the system is determined, and the most important variables are identified within the boundary, and the relationships between them are determined according to past literature and experts' opinions. In the second step, a stock-flow diagram is drawn for the relationships between the variables. According to the variables, this chart has three types of stocks (accumulation mode), flow (rate variables), and auxiliary variables (internal and external), which can be used to formulate the model according to the relationships between the variables. In the third stage, after the implementation of the model, the results that show the behavior of each of the variables in the long term (in this model, 2020-2030) are reported. Also, in the fourth step, its results are evaluated to determine the validity of the model. This evaluation consists of two stages, first is the sensitivity analysis, which examines whether the behavior of the other variables is reasonable or not for changing one of the external variables and keeping the rest of the variables constant and another is to compare the results of the model with the variables that behavior is already available (reference modes. In this study, backup buffer, profitability, and main inventory), which can evaluate how similar the past behavior of the model is to the actual behavior. In addition, the simulated model can provide them with the necessary information to examine the conditions in the future by managers and politicians who want to develop policies that take into account the natural factors that may occur. In this paper, during three scenarios for the Covid-19 pandemic (low, medium, and sharp scenarios), several different policies are evaluated according to the case sample.

In the next step, machine learning methods are used to improve the accuracy of predictions and model behavior. So that after receiving the results from the SD model, the correlation of the main variables is calculated with BAR. So, given that machine learning methods, are trained using past historical data to predict future behavior based on this training, this paper uses these methods to improve the BAR function for 2020-2022. The amount of input data for prediction with MLP and SVR is determined in two ways. Firstly, because the past behavior of some variables (such as backup buffer, total transactions, and main inventory) is available, real data is used for these features, and secondly, for features that real data are not available, their simulation data is used. After checking the errors of each method, the most effective function is specified. The detail of these stage has been expressed below. Fig. 1 shows the flowchart of all the steps of the paper. All of the steps are explained below.

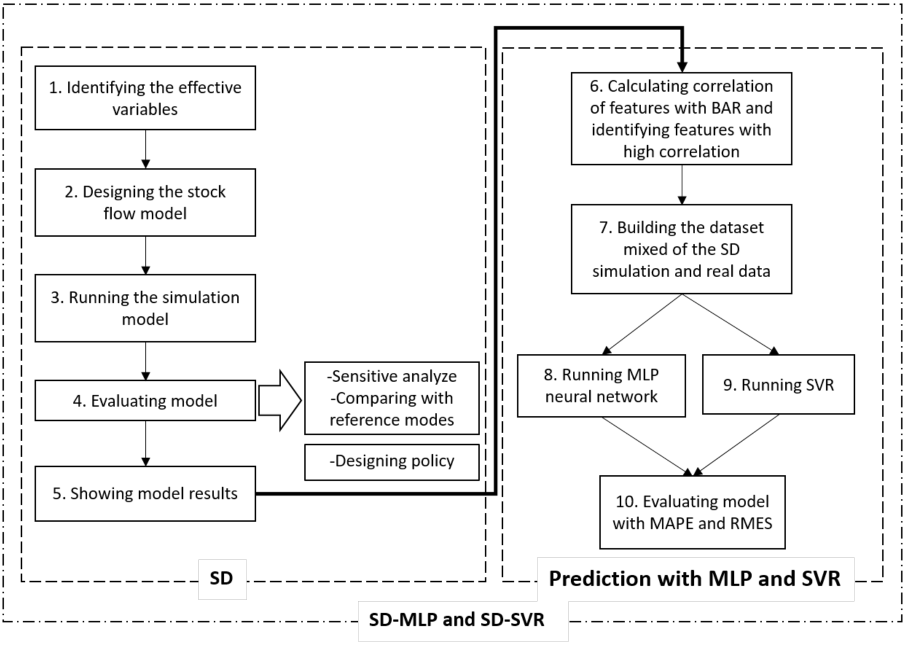


Fig. 1 The methodology flowchart of the study

4.1 Stage one: system dynamics model design

The SD model is an interdisciplinary subject based on system science and management science that can reveal the intrinsic motivation of a complex system and perform optimization methods [44]. SD is an approach to understanding the nonlinear behavior of complex systems over time using feedback loops. This method was introduced by [41] in the book industrial dynamics and spread rapidly. The main roots of this method come from systems theory, which is a modern approach to management theories. This method has two main differences from statistical methods in solving problems. First, unlike statistical methods, it does not intend to limit variables. Dynamic analysis of systems tries to analyze all the elements involved in the phenomenon's behavior in a closed boundary. Second, all relationships are considered, including the feedback loop. Although the causal loop diagram is an effective tool for showing feedback relations, it cannot quantify for simulating models. So the best way to formulate simulation models is using the "stock-flow" diagrams. Also, the other limitations of causal loop diagrams is their inability to show the variable structure of the state and flow of systems. Stocks and flows, along with feedback, are two main concepts in the theory of dynamic systems.

For example, Meadows (1972) designated a global model for investigating industries, pollution, population, and other significant factors using the SD model. From its birth in the 1950s, the SD model became widely used globally and acquired more comprehensive development as an outcome in the fields of policy development, project management, learning organization, logistics and supply chains, and a company's strategic areas. The standard SD approach is as follows: first, determine the problems and define the boundaries of the system; second, make a dynamic hypothesis, find the formulation, and carry out the simulation test; and eventually, complete the policy design and evaluation. Each causal loop in SD models must have at least one stock; otherwise, no cumulative will occur. Also, just the flow can change the stock value since all variables change. As SD theory has grown, the application scope has widened to include industry, finance, medical science, education, resources, the environment, real estate, and other fields. Stock variables are the accumulations that determine the state of the system. Also, they provide data that can decide based on them. Stock variables also create delays by accumulating the difference between the input flow to a process and the output flow from them. For example, the factory inventories, or the number of staff are the sample of stock variables [45].

Indeed, investigators can develop possible policies according to the analysis and simulation outcomes provided by the SD model. Moreover, SD can reflect the complex relationship between enormous numbers of variables in immense systems. Thus, it is broadly used in complex nonlinear systems, and it can make better mid- or long-term predictions [45]. Fundamentally, there are five different types of variables for an SD model: stock variables, flow variables, rate variables, auxiliary variables, and constant variables. The stock variable is defined by Eq. 1.

$$Stock(t) = S(t_0) + \int (inflow(t) - outflow(t))dt \tag{1}$$

where $Stock(t)$ is the accumulation value of stock variables at t moment, which is illustrated by stocks in feedback diagrams. $Inflow(t)$ or $outflow(t)$ are the types of flow variables (they can change the rate of stock variable). Also, $S(t_0)$ is the initial value of the stock variable. As it turns out, flow variables are derived from the instantaneous changes of the stock variable [46].

4.2 Stage two: Multi-Layer Perceptrons (MLP) for estimation BAR function

MLP is a class of artificial neural networks. An MLP includes at least three layers of nodes: an input layer, a hidden layer, and an output layer. Excluding the input nodes, per node is a neuron that employs a non-linear activation function [47]. MLP utilizes a supervised learning method named feedback for training. Its multiple layers and nonlinear activation differentiate MLP from a linear perceptron. Indeed, it can determine data that are not linearly detachable. Basically, the output activation $s^{(l+1)}$ layer $l + 1$ is derived by the input activation $s^{(l)}$, as it is indicated in Eq. 2.

$$\mathrm{s}^{(\mathrm{l}+1)}=\sigma(\mathrm{w}^{(\mathrm{l})}\mathrm{s}^{(\mathrm{l})}+\mathrm{b}^{(\mathrm{l})}) \tag{2}$$

Where l corresponds to s specific layer, $w^{(l)}$ and $b^{(l)}$ designate the weight and bias at layer l, and σ denotes the nonlinear activation operation (e.g. sigmoid, hyperbolic tangent, rectified linear units) function. For an m layer multi-layer perceptron, the first input layer is $s^l = x$ while the last output layer is (Eq. 3).

$$\mathrm{h_{w,b}}\left(\mathrm{x}\right) = \mathrm{s}^{(\mathrm{m})} \tag{3}$$

The b bias and w weights in equation 3 are recognized by supervised training using a back-propagation algorithm to approximate an anonymous input-output relation (Del Frate et al., 2007) [48]. The objective function is to minimize the distinction between the predicted outputs and the expected outputs (Eq 4).

$$\mathrm{J}_{(\mathrm{w,b,x,y})} = \frac{1}{2}||\ \mathrm{h_{w,b}}(\mathrm{x}) - \mathrm{y}||^2 \tag{4}$$

4.3 Stage three: Support Vector Regression (SVR) for estimate BAR function

SVR is a robust approach for creating a classifier for regression and classification first presented by Vladimir Vapnik and his research team in 1992 [49]. The SVR algorithm makes a decision limit, known as the hyperplane, between two classes that allow anticipating labels from one or more feature vectors. This decision limit is oriented such that it is as far as possible from the closest data points from each of the classes. These closest points are named support vectors. Due to a labeled training dataset, $Z \equiv \left(x_1, y_1\right), \left(x_2, y_2\right), \ldots, \left(x_B, y_n\right)$, $x_1 \in R^d$ and $y_i \in (-1, +1)$. The optimal hyperplane can then be described as Eq.(5):

$$wx^T + b = 0 \tag{5}$$

where w is the weight vector, x is the input feature vector, and b is the bias. The hyperplanes would be defined by Eq.(6) and Eq.(7) respectively:

$$wx_i^T + b \geq +1 \text{ if } y_i = 1 \tag{6}$$

$$wx_i^T + b \leq -1 \text{ if } y_i = -1 \tag{7}$$

The purpose of training an SVR algorithm is to obtain w and b so that the hyperplanes separate the data and maximize the margin $1/\|w\|^2$. Initially suggested to build a linear classifier, the SVR algorithm would be applied to model higher dimensional or nonlinear models utilizing the kernel function [50, 51]. For example, in a non-linear problem, the kernel function would be used to present extra dimensions to the raw data and turn it into a linear problem in finding higher dimensional space. The kernel function would present faster computations that require calculations in high dimensional space. The kernel is an internal product, which would be linear or nonlinear (Polynomials), Radial-Basis Function (RBF), and the Sigmoid. It is described as Eq.(8):

$$K(x, y) =< f(x), f(y) > \tag{8}$$

4.4 Step four: Proposed method: SD-MLP and SD-SVR

After SD simulation, the BAR is calculated. This paper for improving the behavior uses the MLP and SVR methods to estimate the best function for BAR in the RSC. In this regard, data that they have obtained from SD simulation during the time (2020-2030), are the input for MLP and SVR. For improving the relationships between BAR and other variables, correlation is used. Some variables that have a low correlation (lower than 0.3), are omitted. So the function is estimated based on the effective variables. Table 5 shows the correlation between BAR and other decision variables.

5 Research Methodology

In this paper, Stella Architect software for drawing and Vensim PLE x32 for formulating are used. The model structure includes three subsystems; the BAR, RSC, and personnel skills. Table 4 shows the value of simulations variables. The primary values of data have been collected based on the average of experts' opinions for 50 home appliances companies in Iran and data on companies' figures. The initial value for the stock variables and parameters are assumed at the beginning of 2020, and the simulation is performed over 4000 days (10 years).

Data resources

The data used in this paper is taken from asstra.com/industries/household-appliances-and-electronics/, clicktrans.com/transport/household-appliances/, www.amar.org.ir/english/Statistics-by-Topic/Household-Expenditure-and-Income, islamicmarkets.com/publications/blockchain-technology-and-islamic-capital-markets-in-iran, and www.blockchain.com/charts/ sites.

Table 4 Values used for variables and parameters in the simulation

Variable	Initial value	Unit
Maximum of supplier in network	856	Number
Maximum inventory per day	23000	Number
Average of each vehicle's capacity	3.5	Ton
Main inventory	1007	Number
Backup buffer	108	Number
The number of blocks	100301	Number
Total costs	801000	Dollar
National event rate	0.3	
Cost of storage	250000	Dollar
Production costs	12985	Dollar
Average salary per staff	2600	Dollar
Work time	9	Hour
Total transactions	100874	Number
Average block creation time	0.42	Hour
Personnel	415	Number
Increasing inventory rate	0.6	
Using probability of inventory per day	0.4	

5.1 Model assumptions

Model time period: The developed model was run from 2020 to 2030 daily. The developed model was simulated in three-month time steps in 2020-2030 by calculating reserves, flows, and converters in each time step adopted for the entire simulation phase. The model was then tested for 2 years from 2020 to 2022 to compare the model's simulated results with historical data of key variables obtained from the home appliance factory. Main inventory, backup buffer, personnel skill, number of blocks, the total number of transactions, and confirmed and unconfirmed transactions. The duration of this simulation was more than 10 years so that the long-term dynamics of the system under the influence of alternative intervention scenarios could be recorded.

- Scope of the model: The boundary of the model was determined according to the policies of the intelligent RSC. Factors such as mining costs, energy consumption, and other factors specific to blockchain are considered outside the system boundary. Because the goal is to check the acceptance rate of blockchain in the SC. Therefore, they are not considered in the model.

- Model development parameters and input data: To enable the simulation, the model includes the identification of all relevant parameters, including initial stock values at the start of the simulation, and almost all initial stock values are 2020 data (Table 4), except the investment that is the observed data for 100 days from the beginning of 2020. Inventory, buffer, numbers of suppliers, vehicles, and related to the SC figures are obtained or calculated based on appliance factory data. Where data were not available, assumptions were made based on current literature and expert suggestions from stakeholders in the study reported in Sachin et al. (2021) [29]. There are relationships between these subsystems. In past studies, this relation is investigated. After simulating the behavior of the BAR in the SC, machine learning is used to improve the behavior of its function so that it can estimate the best function according to the data obtained from the SD. In this paper, SD-MLP and SD-SVR are proposed.

5.1.1 Dataset Normalization

The dataset should be normalized since the features intended for BAR prediction do not have the same unit and range. The method which is applied for normalization in this paper is mean-normalization. Eq.(9) represents the mean-normalization formula.

$$\|f_i\| = \frac{f_i - \mu_i}{\max(f) - \min(f)}. \tag{9}$$

Where f_i is the i^{th} feature, μ_i is the average of i^{th} feature in the corresponding period and $\|f_i\|$ is a normalized feature of f_i [35].

In Table 5 personnel skills and main inventory have a low correlation with BAR (they are lower 0.3), so they are removed from the regression estimation equation. The MLP and SVR can help SD to be modified the behavior function.

Table 5 The correlation between BAR and decision variables

Variable	Correlation
Confirmed transactions	0.991525
Total transactions	0.979279
Number of unconfirmed transactions	0.991525
The number of blocks	0.942144
Total costs	0.962897
Main inventory	0.121484
Backup buffer	0.997216
SC resilience	0.997216
Customer response speed	0.996946
Personnel skills	0.056297
Profitability	0.962897

6 Model description

The BAR SD model is an integrated model containing three joint subsystems that interact to build the behavior over time of the system. Variables in one subsystem impact variables in other subsystems. The part below focuses on separate subsystems to enable a thorough analysis of the interrelationships between variables and the structural and behavioral assumptions of the model.

6.1 Subsystem 1: Blockchain acceptance rate concept in RSC

As mentioned in previous studies [16, 20, 41, 52, 53], many effective variables are effective in improving SCR, and these variables in turn affect other variables. Also, due to the introduction of blockchain as a new technology in the SC, knowledge and training of personnel are prioritized because skilled personnel is needed for the implementation of this technology. So another subsystem that can help improve the structure of the RSC is employee training [15]. On the other hand, one of the modulating factors of blockchain technology is the costs that are spent on providing infrastructure, equipment, and training. So the effects of these costs are discussed in the model. In general, the implementation of this subsystem in the SC helps to reduce risk, the speed of responding to customers, quality, and resilience, thus amplifying the RSC subsystem [27, 54]. The BAR subsystem illustrates the interrelationships between the area and output of blockchain and the variables influencing these (Fig. 2). Total transactions, confirmed transactions, unconfirmed transactions, the number of blocks, and total costs are proposed as stocks for this subsystem and interconnected through various variables. In our model, the BAR is supposed to depend on the total transactions and confirmed transactions. The total transactions are determined by the number of smart contracts per day, company trust rate, and investments.

The total costs are supposed to be approximately 8 billion dollars in the first year of simulation. This figure allows close-to-reality simulation of BAR growth dynamics, given historical data on the total production, storage, blockchain cost, and transportation over 2020–2022 in the case study area.

Smart contracts are affected by the performance of investments. The confirmed transactions increase the number of blocks. Also, in the model, the confirmation probability of transactions plus the rejection probability of transactions is considered equal to one. Besides, the average transaction confirmation time is 30 minutes.

As shown in Equation 10, the BAR is obtained from the number of approved transactions per total transaction. Approved transactions at each stage of the RSC depend on a number of factors, and one transaction is approved when all participants in the network approve it.

$$Blockchain\ acceptance\ rate = \frac{Confirmed\ transaction}{All\ transactions} \tag{10}$$

On the other hand, if a new transaction in the network is indicated by x, it can be said that the probability of its acceptance depends on all participants in the network. If a new transaction with a_1 is considered at the supplier stage, with a probability a_2 at the manufacturer stage, with a_3 probability at the distributor stage, and with a_4 probability at the customer stage, the probability of accepting a new transaction is as equation 11.

$$\begin{gathered} P(\text{ confirmed transaction } \mid a_1, a_2, a_3, a_4) = \\ \frac{P(a_1, a_2, a_3, a_4 \mid \text{ confirmed transaction }) \times P(a_1, a_2, a_3, a_4)}{P(\text{ confirmed transaction })} \end{gathered} \tag{11}$$

If all four transactions are members of approved transactions at each stage, then x is approved. Also, since the SC is resilient, each of a_1. a_2, a_3, a_4 depends on other factors that must first be identified (such as unforeseen natural events) that cause inventory shortages, increase service time, and incompatibility of partners, etc. For example, if b_1 is the first effective factor (e.g. interoperability) in the supplier stage (a_1), then the probability that the effective factors will continue to affect a1 is equation 3. Similar to this probability will be obtained for a_2, a_3, and a_4 (Eqs. 11 and 12).

$$P(a_1 \mid b_1, \ldots) = \frac{P(b_1, \ldots \mid a_1) \times P(b_1, \ldots)}{P(a_1)} \tag{12}$$

All in all, in this paper, to predict the BAR and examine the variables affecting it, information about several companies (home appliances) with their characteristics will be collected in a specific time period. This section is said for understanding the concept of BAR in the RSC.

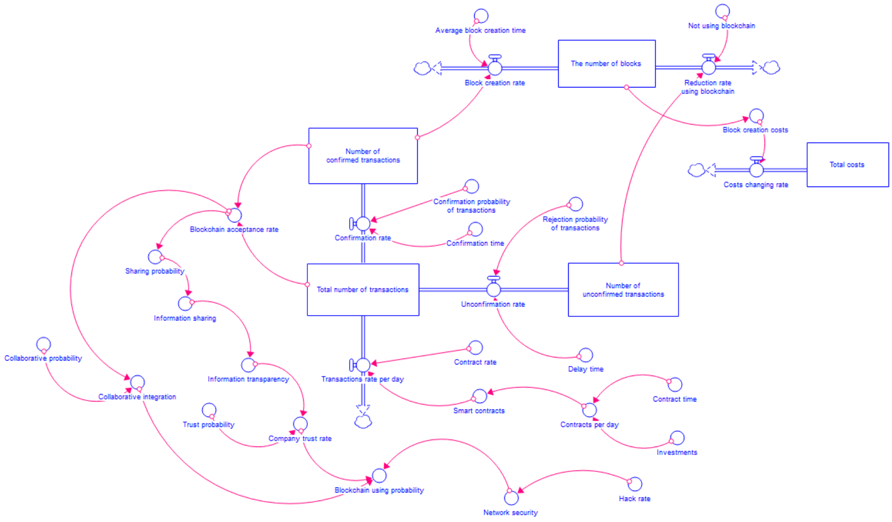


Fig. 2 Blockchain acceptance rate subsystem

6.2 Subsystem 2: RSC

Fig. 3 depicts the RSC subsystem and how this can influence the BAR. In the factory, the parts are supplied by the supplier, which forms the main initial stock of the factory, but a support buffer is also considered to deal with the risk and possible natural accidents. For all participants in the network to know about the incident earlier when natural events occur, and if, for example, one supplier fails to provide service, another one is available in the network and covers the demand, the blockchain network is used. In addition to helping to increase the security of the SC network, this network can increase the speed of decision-making and risk management when problems occur. Increasing blockchain acceptance reduces risk and improves crisis management, which ultimately contributes to the stability and resilience of the SC.

The rate of natural disasters was investigated for two years 2020-2022. The average number of days that factories were involved in natural events such as Corona, breakdowns of transport machines, political risks and excessive inflation, which caused the bankruptcy of home appliance suppliers or the import of parts, was divided by the total days of the year. So, the rate of natural disasters for the SC of household appliances in Iran was calculated, and this rate was estimated to be 0.32 (Eq. 12). On the other hand, if the withdrawal of the main stock increases or more natural disasters occur, the probability of using the buffer stock increases. Finally, in this subsystem, it can be said that the more resilient the SC is, the greater the trust of the blockchain company. Increasing trust in blockchain, as discussed in the previous subsystem, will increase smart contracts and, as a result, increase the acceptance rate of blockchain in the network.

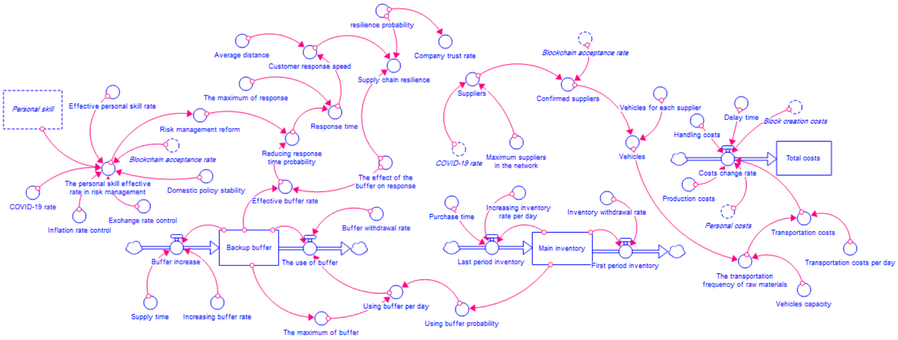


Fig. 3 RSC subsystem

6.3 Subsystem 3: personnel skills

Since the BAR increases with the increase of staff skills and their familiarity with blockchain, this part is very important. In this part, it was shown in the model that the skill of personnel depends on two factors: repetition of daily tasks and training [18]. Also, negligence and incompetence of employees reduce this amount. The three factors learning rate, learning time, and working hours are important in this department. The average working hours in Iran's home appliances factory is 8 hours. The average learning time is two hours. The skill level of the employees was considered as a maximum of 5000 units with the advice of experts. In fact, by increasing the skills of employees, on the one hand, risk and crisis management improves, and on the other hand, human resources cost increase. Therefore, in the model, a maximum rating of 5,000 units is considered for the skills of employees. Fig. 4 shows the stock flow chart for this subsystem.

7 Sensitivity analysis

The dynamic systems approach can test different design policies and evaluate their results over time, so it is a good tool for adapting the model to the real environment. This method, unlike other approaches for system analysis, in addition to breaking down the system into its subsystems, combines subsystems and considers their connections [31]. This capability allows the decision-maker to test his proposed policies in the simulated model before applying them in the real world and to observe its effects and results over long-term periods. In this step, different policies are simulated and the final goal is to investigate the effect of different policies on the behavior of the system. In this method, all variables are kept constant and only the tested variable is changed ±10% to determine the effect it has on other variables.In the following section, BAR and RSC have been analyzed, and the effects that other variables receive if they increase or decrease are reported. In general, the learning staff rate about blockchain is changed by ±10% in the model and its impact on the

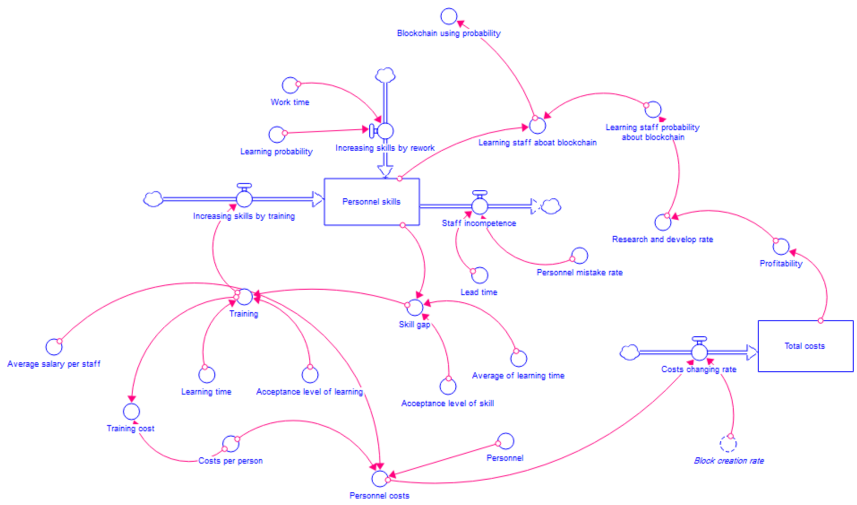
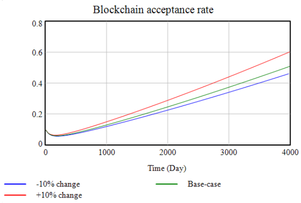
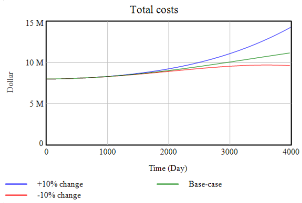


Fig. 4 Personnel skills subsystem

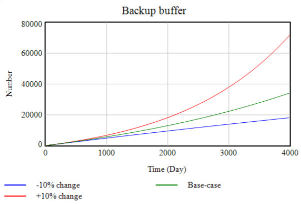
BAR and the total costs due to more/less staff training and more/less usage compared to the base case have been investigated. As shown in Figure 5,a -10% reduction in the personnel training rate will decrease the BAR exponentially, the backup buffer, and total costs. Although blockchain helps the resilience of the SC, it creates costs for the network. Moreover, with a +10% increase in the training rate of personnel, due to the increase in personnel information and the increase in their skills in learning and working with the blockchain network, its acceptance rate in the SC increases, which increases the backup buffer to face the possibility of disruptions in the SC. But the total costs would increase slightly with the BAR in the network, which is justified because the resilience of the SC is much higher than normal. Also, in the continuation of Table 6, there is a kind of sensitivity analysis test based on scenario.



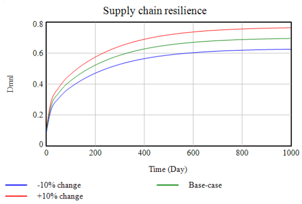
(a) BAR.



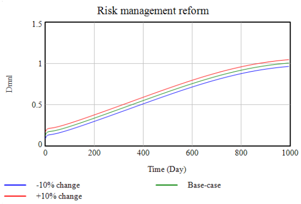
(b) Total costs.



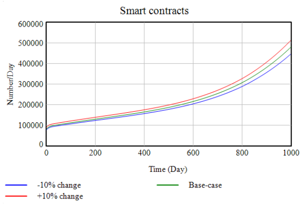
(c) Bachup buffer.



(d) Supply chain resilience.



(e) Risk management reform.



(f) Smart contracts.

Fig. 5 The sensitivity analysis on profitability with the changes in rate of learning staff about blockchain.

8 Policy scenario design and evaluation

The scenario refers to the environmental conditions that occur randomly, and the policy refers to the actions of humans on the model that is under control. Policy design plays a vital role in model evaluation. This usually contains a model simulation with a spectrum of policy parameters utilizing the existing model form, then setting the model structure to investigate the impact of diverse policies on decision-making [54, 55].According to the sensitivity analysis which led to a set of parameters that have most affected the behavior of the model during the time, a set of policy scenarios was designed and simulated between 2020 and 2030 to know how the blockchain rate might alter under distinct circumstances. This step includes several trials with diverse combinations of model parameters, which were synced to investigate the behavior of the model under these changes. Also, Three state of COVID-19 pandemic consider as the scenarios (low, medium, and sharp).

Particularly, Policies with changes in individual parameters chosen in line with current provincial development plans and past studies (e.g. a 10% decrease in the probability of transaction approval for blockchain indicate the lack of cooperation between participants of the smart SC, who have delayed the registration of contracts and their approval in the network.)

In the base-case or business-as-usual Policies (S1), policy interventions were supposed to be absent over the simulation period. Five policy scenarios were then simulated (Table 6). Inflation control increased research and development, political risks, and exchange rate control.

Inflation control (S2): One of the most important factors that cause problems in the SC is the excessive increase in the number of raw materials and prices that happen due to inflation. Considering that Iran has recently been sanctioned, the inflation rate in this country is very high, which has reduced the resilience of the chain. For this reason, companies can greatly contribute to the resilience of the chain by using policies to control internal inflation. If the inflation is 15% more controlled, the smart contracts can be more, so the number of blocks can be more.

Increasing research and development (R&D) (S3): Increasing the skills of employees and their familiarity with modern methods will provide the infrastructure for the implementation of blockchain and also help the resilience of the chain as presented in Table 6. Therefore, policy and research, and development allow companies to increase the speed of implementation of new technologies [18]. So the number of confirmed transactions can increase.

Exchange rate control (S4): Considering that COVID-19 has caused many changes in the exchange rate, especially in developing countries like Iran, it is important to examine the changes in the exchange rate on the variables of the RSC [39]. A 10% increase in the exchange rate affects the purchase, and the sale price of products, and back-up buffer, as well as can disrupt the SC.

Domestic political stability (S5): Since political issues and sanctions, especially for the country of Iran, have provided many problems, including preventing the import of parts and raw materials, this issue is investigated in the simulation model. If policymakers try to decline this risk, they can improve inflation, political risks, exchange rates, and the development of new technologies such as blockchain in the SC [36]. Therefore, the political risk control policy has been considered by 15% change. Moreover, it is examined how this risk can change the behavior of the number of confirmed transactions and, as a result, the BAR in the SC.

Best case (S6): When all three of the above policies are implemented where exchange rate, inflation control, and development research are maximized.

Worst case (S7): The worst case is the Policy in which inflation increases and R&D and inspection rates decrease by 10%-15%, which is likely to happen under the current events, is also stimulated to illustrate the worst case among all simulation scenarios of the model.

8.1 Evaluation Metrics

Due to the assessment model, the error is assessed through Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE) which are proposed as Eq.(13):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_t - \hat{y}_t|}{|y_t|} \times 100 \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\frac{y_t-\hat{y}_t}{y_t}\right)^2}$$

where y_t is the actual values and $\hat{y}_t$ are the forecasted values. In this section, the findings calculated by the deterministic models are demonstrated. The architecture of the model for the primary MLP structure. After SD simulation implementation, the BAR function from 2020 to 2022 is predicted by MLP. It helps the model to have the best behavior in comparison with SD.

The trained MLP model includes 4 layers, each with the same activation function ReLU, and is trained to utilize the Adam algorithm for 300 epochs. The input includes the daily variation of BAR and 9 other dependent variables. The layers contain 1, 2, 5, and 10 neurons hierarchically in the input to the output direction.

For the secondary MLP neural network, the trained MLP model includes 4 layers, each with the same activation function ReLU, and trained employing the Adam algorithm for 700 epochs. The input includes 18 features over the specific period from the previous step. The layers contain 200, 90, 50, and 1 neurons hierarchically in the input to the output direction.

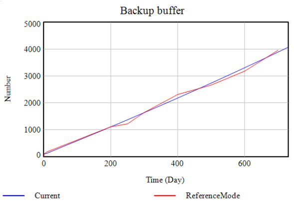
The suggested method is accomplished on a system with the specifications (CPU:2.3GHz core i5, RAM:4GB) which represents does not require a highly trained configuration. Each epoch of primary and secondary neural network learning took 0.05 and 0.2 seconds respectively. Besides, this system has been simulated on the Jupyter notebook which is a strong compiler in Python language.

9 Model testing

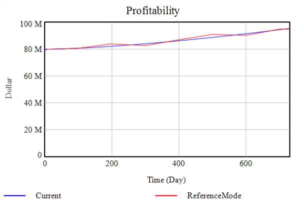
The simulation model was tested using structural and behavioral validity analyses to see if it could adequately depict the structure of the real system and if it could produce behavior that was acceptable in comparison to the patterns seen in reality [52, 56]. For model behavior verification, severe condition and behavior reproduction tests were carried out, whereas conservation of matter, dimensional consistency, and structural verification tests were utilized for model structure evaluation [53, 57].This means that a stock must never go negative and the difference in stock at any point must equal the net flow, which is the sum of inflows minus outflows. The conservation of matter test is used to determine whether the model violates these fundamental physical laws.

A difference in a stock like the number of blocks, for instance, should equal the sum of creation block inflows minus the sum of the reduction rate utilizing blockchain outflows. For example, a stock like the number of blocks will never dip below zero. The purpose of the dimensional consistency test is to examine the model equations for ambiguous parameters and relationships assigned to them as well as to check the measurement units for all variables to diagnose any faults resulting from unit mistakes. Specifically, reinforcing and balancing feedback loops should show the proper polarities and behaviors [58, 59]. Structural verification means that all structural components of the model should produce acceptable behavior as predicted.

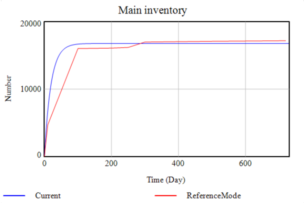
Fig. 6 illustrated the outcomes of behavior replication tests performed by a comparison between model simulation outputs and historical data. The extreme condition test is to examine if the model makes adaptable behavior when extreme values such as zero or infinity are used in model inputs [32]. For instance, if there is no transaction or smart contract inflow, the overall number of transactions, confirmed transactions, unconfirmed transactions, and blocks should all decrease after any possible delays, indicating that the model structure is accurate to the system it represents. Two extreme circumstances, including extreme values for resilience and blockchain-related variables, were employed to assess the model's robustness in this study. For behavior design appraisal, an inconsistency coefficient (Q) was utilized at the ultimate step, after the show passed all past approval examinations, to degree the disparity between the simulated behavior and checked the information of primary factors. The values of Q run from (culminate expectations) to 1 (most noticeably awful forecasts); a demonstration may be respected as great to normal where Q ranges between 0.4 and 0.7 [60]. In this study, three key parameters were chosen for the model behavior pattern validation: main inventory, backup buffer, and profitability. The simulated trends of these variables were compared to their historical data over two years from 2020 to 2022 and reflected in the values of Q.



(a) Bachup buffer.



(b) Profitability.



(c) Main inventory.

Fig. 6 A comparison of the behavior of simulation outputs with historical data

A sensitivity analysis was performed to identify the parameters most likely to influence model behavior. Since the purpose of this model is to analyze how the blockchain behaves under her RSC conditions, the rate of block and inventory change in response to changes in the selected model parameters was evaluated. The results show that the number of confirmed transactions and blocks is the most sensitive to changes in investments per day. Variations in the values of other auxiliary variables which are considered constant, are insignificant to the behavior of the model. Changes in model dynamics corresponding to variations in model parameters of up to 15% indicate that the model has low to moderate sensitivity [61, 62]. This means that a single model parameter alone cannot significantly change the SD represented by the model, which has important implications for the design of policy scenarios in the next step.

10 Results

The simulation results of the base-case or business-as-usual (BAU) and policy intervention scenarios are presented in Fig. 7 for the BAU scenario, the BAR, and the number of blocks in years when natural events (COVID-19) occurred such as in 2021 and 2022. Under this scenario, the BAR and the number of blocks are predicted to plateau around 2030 at approximately 0.61 and 30934700 number, respectively, resulting in a peak in BAR at the same time. This is associated with a peak in transactions and main and buffer inventory availability. Key variables of the model exhibit the "reinforcing to growth" behavior in all scenarios over the simulation period, except for the carrying capacity of production will most likely continue to grow to balance. This upward tendency of blockchain rate will likely contribute to increasing smart contracts in the investments in the future, affecting an RSC, with backup buffer and company trust rate quickly reaching their peaks within the simulation time. Under 'medium COVID-19 outbreak' conditions, the maximum growth in confirmed transactions and the number of blocks is expected to happen under the S6 scenario – reaching approximately 16569100 and 28201731, respectively, by 2030 – when a combination of policies including inflation control, domestic political stability, increasing research and development, and exchange rate is enforced (Table 6).

In scenario S1, the basic state is when the COVID-19 outbreak is medium, the BAR, the number of blocks, and the number of transactions in the RSC are higher than when the COVID-19 outbreak is sharp. According to Fig. 7, the effect of applying policies in the model can be seen and the BAR first declines and then grows. This makes perfect sense as blockchain acceptance in the SC is not yet widespread and is growing. As it is clear from the policies when the worst case is applied because all the policies are in their worst state, the BAR is also in the lowest state, i.e. scenario S7, and when the best policy is applied, it can be seen that the block acceptance rate China will grow to about 80% in 2020. But on the other hand, it can be seen that with the acceptance of blockchain, because the fixed and variable costs of creating blocks are applied to the chain, the total costs will increase in the S6 scenario (the best case). The higher the BAR, the higher the total costs. Also, the total transactions will have an almost balancing behavior (limits to growth) over time. This means that over time the participants that trade in the chain via blockchain and smart contracts are increasing at a lower rate. Also, in Fig. 7 the importance of the backup buffer when the best policy (S6) is applied is clear because the existence of the backup buffer will make the SC more resilient.

Overall, the best scenario with a combination of inflation, domestic political stability, research and development measures, and exchange rate control appears to produce the greatest benefit in the region. This result plays an essential part in confirming the significance of the BAR in the RSC, contributing to encouraging traditional supplier contract change to the smart contract and blockchain technology acceptance in the SC.

Table 6 Policy scenarios for BAR in the SC of household appliances in Iran

Base-case and intervention scenarios with the percentage of change compared to the base-case							
Policy	S_1	S_2	S_3	S_4	S_5	S_6	S_7
Parameters	Base-case (No intervention)	Inflation control	R&D	Exchange rate control	Domestic political stability	Best-case	Worst-case
Confirmed transactions	99000	0%	10%	0%	15%	15%	-15%
Backup buffer	10800	0%	0%	10%	0%	10%	-10%
Number of blocks	10000	15%	0%	0%	0%	15%	-15%
Main inventory	1007	10%	0%	10%	0%	10%	-10%
Total costs	801000	10%	0%	10%	0%	10%	-10%

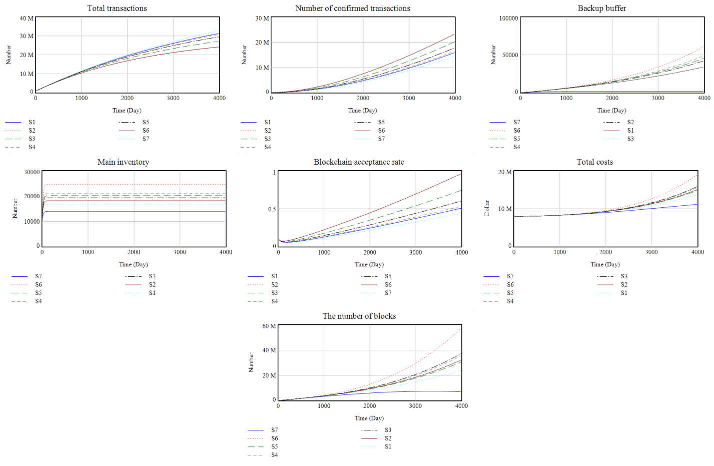


Fig. 7 A comparison of the behavior of simulation outputs with historical data

Table 7 The simulated value of the main variables by 2030 under base-case and policy scenarios

Policy	S_1	S_2	S_3	S_4	S_5	S_6	S_7
Parameters	Base-case (No intervention)	Inflation control	R&D	Exchange rate control	Domestic political stability	Best-case	Worst-case
BAR							
Medium COVID-19 outbreak	0.61	0.68	0.63	0.62	0.66	0.69	0.42
Sharp COVID-19 outbreak	0.32	0.45	0.49	0.39	0.42	0.58	0.233
Low COVID-19 outbreak	0.63	0.7	0.67	0.68	0.75	0.79	0.48
Number of blocks							
Medium COVID-19 outbreak	28201731	32801031	38901511	34701787	39401250	51320092	10440911
Sharp COVID-19 outbreak	18532092	23532659	25536100	29913189	29076126	33023108	6505673
Low COVID-19 outbreak	31007519	357501865	39100412	53300075	57012601	60000800	16050105
Total transactions							
Medium COVID-19 outbreak	30934700	31000574	31000532	31000861	30912460	31002109	31000001
Sharp COVID-19 outbreak	29900420	29983160	30002000	30005100	30101236	30508180	29830100
Low COVID-19 outbreak	31678900	31998600	31998600	31751500	31094319	32007514	31321085

Figure 8 shows a comparison of MLP, SVM and SD-behavior (real) of BAR since 2020 to 2022 which is included 160 backtesting data. It is worth to mention that the backtesting data is not used on training procedure.

Table 8 shows the comparison between SVR and MLP since 2020 to 2022 including 160 backtesting data.

Table 8 MAPE and RMSE for BAR with SD-MLE and SD-SVR methods

Model	**MAPE**	**RMSE**
MLP	0.097195996	0.122225952
SVM	0.171057854	0.306167098

By paying attention to table 8, MAPE and RMSE as proper measurements to compare methods is significantly lower in MLP compared to SVR under similar situation. In general, the behavior of the BAR in the SC of home appliances in Iran was first simulated using the dynamics of the systems. Then, for the years 2020 to 2022, this function was estimated using simulation data for the acceptance rate and other data that had a high correlation with the

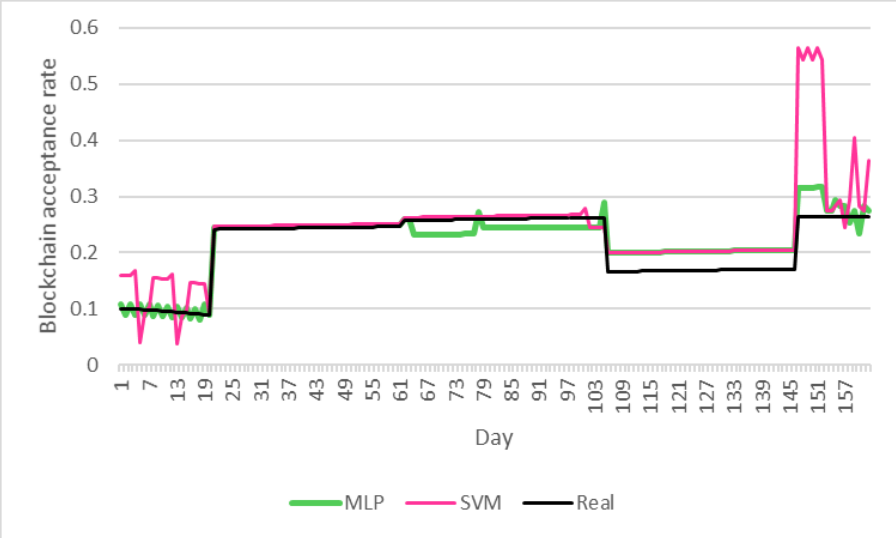


Fig. 8 Trend line in BAR Prediction in MLP and SVR (2020-2022)

acceptance rate using MLP and SVR to obtain a more accurate behavior of the acceptance rate.

10.1 The theoretical and practical policy implications

Reviewing and creating policies can help improve the structure of the SC in the long term and pose positive implications. As shown in Tables 6 and 7, by controlling the exchange rate and the inflation of the purchase and sale prices of products, the costs of buying raw materials, the costs of creating backup buffers, and the cost of keeping goods and transporting them are reduced. Explanation and careful monitoring to prevent the increase of these rates, especially in a situation where a disorder like COVID-19 automatically increases inflation and exchange rates, can help the resilience of the SC. In this study, it was shown that with a 15% increase in inflation control, the backup buffer can be improved by about 20%, and on the other hand, the BAR increases due to the reduction of total costs. This condition is the same for the exchange rate. On the other hand, the policy of increasing research and development leads to more familiarity of the employees with the blockchain, and since the implementation of the blockchain requires familiarity with its mechanism, the exponential growth of these variables was seen in the long-term behavior of the BAR and the variable of the number of blocks (Figure 7).

In addition, as shown in Figure 7,the total number of transactions that take place through the blockchain network increases sharply at first according to the policy, but after a while, it is almost stable. This shows that in the long term, all people in the network do their transactions using smart contracts and in the blockchain network, the amount of transactions reaches its optimal and almost maximum per day. This is confirmed by the BAR after 4000 days, which is close to one. Although at the beginning of blockchain acceptance, there is a decrease in BAR for about 100 days, this rate grows after this period. The reason for this is that it is difficult to provide a suitable platform for the use of blockchain in the SC after the disruption, but after the training of the employees and the learning of all the participants in the chain, this rate will increase.

10.2 The managerial insights

Nowadays due to the COVID-19 outbreak, SC management has undergone many disruptions [43]. Therefore, managers and policymakers are looking to improve the resilience of their SC. This study provided a comprehensive analysis considering the severity of Corona and various policies that can strengthen the SC in the face of this disease. Also, the current research has strong results that can be a panacea to guide managers in improving the resilience of the supply chain. In this section, management insights are expressed based on the results.

- This paper shows that for the resilience of the SC, the most important priorities should be paying attention to the skills of the personnel, their timely and correct training to communicate with new technologies, recognizing and using blockchain to increase the speed of action, transparency, and security in the network. Although using these factors can increase the costs of the entire network, in the long run, it increases the profitability and resilience of the SC.
- Managers can strengthen their supply chain structure by adopting blockchain. As shown in this study, the more blockchain acceptance increases, the more backup buffer, response speed, and inventory in critical situations will increase.
- Also, another policy that makes the system resilient is the policy makers' attention to exchange rates, political risk and inflation (especially in developing countries). As shown in Table 7, controlling these factors helps to minimize the impact of COVID-19 on the SC.

In a smart RSC, profitability, customer satisfaction, and minimizing the effects of disruptions in responding to customer needs have a more prominent priority. In this research, the SC of household appliances in Iran was chosen because political risk, inflation, exchange rate changes, and the effects of COVID-19 on the SC are strongly felt in this country. Therefore, for better management of the chain in this country, the need for full acceptance of blockchain, proper training of employees, and other arrangements that make the RSC is well felt.

11 Conclusion

This study presents an approach based on a whole-of-system view to understand the dynamics of natural events' impacts on SC development using a case study in a home appliance SC in Iran and finding the BAR in that network.

Also, this paper uses simulation data for improving the acceptance function estimation. Indeed, it is a new method based on SD-MLP and SD-SVR. In general, this paper is the first research that simulates the BAR in an RSC and provides a new method for predicting the function behavior.

In a nutshell, a detailed study of the feedback interactions between system components will make it possible to identify the key dynamics that affect blockchains and identify the impact of transformations on system behavior. Test results of the SD model output confirmed its ability to reproduce well the historical behavior of the system it represents. It is worth noting to recognize that while natural phenomena are one of the factors influencing SC, they are not the determinant of SC sustainability. Our model results show that the control of inflation, R&D, exchange rate, and political risks play important roles, and it is these dynamics that drive the RSC. In the current situation, conditions related to smart contract trading may be exacerbated by the conditions of natural events, but applying a range of policy interventions, such as managing inflation, political risks, and exchange rates, can reduce the impact can be greatly minimized. The best-case scenario that allows BAR spending to reach potentially maximum acceptance in SC is a strategy that combines all these guidelines.

For future research, in addition to the approach presented in this study, other methods can be used to make the RSC, such as the optimization approach, robust planning to consider the uncertainty of parameters, and the use of mathematical models considering two dimensions, i.e. profitability and resilience (blockchain costs and smart contracts to increase profitability and reducing unfulfilled demand to increase resilience). It is also possible to use other implementation policies, such as the use of fast production methods such as 3D printing (additive manufacturing) in the blockchain platform to increase the speed of responding to customers. Because 3D printing can reduce SC levels, bring production closer to customers, and thus neutralize the effects of disruption to a large extent. Also, Bayesian Monte-Carlo or robust Bayesian can be suitable methods for future research to find the BAR.

References

[1] H. Adobor. Supply chain resilience: an adaptive cycle approach. International Journal of Logistics Management, 31(3) (2020) 443-463.

[2] P. Centobelli, R. Cerchione, M. Ertz. Managing supply chain resilience to pursue business and environmental strategies. BusinessStrategy and the Environment, 29(3)(2020) 1215–1246.

[3] M. M. de Sá, P. L. de Souza Miguel,R. P. de Brito, S. C. Pereira. Supply chain resilience: the whole is not the sum of the parts. International Journal of Operations and Production Management, 40(1) (2019) 92-115.

[4] M. J. Markley, L. Davis, L. Exploring future competitive advantage through sustainable supply chains. International Journal of Physical Distribution and Logistics Management, 37(9) (2007) 763–774.

[5] A. I. Lockamy. Assessing disaster risks in supply chains. Industrial Management and Data Systems, 114(5) (2014) 755–777.

[6] S. Torabi, M. Baghersad, S. Mansouri. Resilient supplier selection and order allocation under operational and disruption risks. Transportation Research Part E: Logistics and Transportation Review, 79 (2015) 22–48.

[7] M. J. Saenz, E Revilla, B Acero. Aligning supply chain design for boosting resilience. Business Horizons, 61(3) (2018) 443–452.

[8] S. V. Parkouhi, A. S. Ghadikolaei, H. Lajimi. Resilient supplier selection and segmentation in grey environment. Journal of Cleaner Production 207 (2019) 1123–1137.

[9] I. Eyal. Blockchain Technology: Transforming Libertarian Cryptocurrency Dreams to Finance and Banking Realities. Computer, 50(9) (2017) 38–49.

[10] B. Santosh, T. S. Rane, Viral, K Ravi. Stakeholders' involvement in green supply chain: a perspective of blockchain IoT-integrated architecture. Management of Environmental Quality, (2020) 1477-7835. Doi: 10.1108/MEQ-11-2019-0248.

[11] A. Taleizadeh, K. Ahmadzadeh,B. R. Sarker, A. Ghavamifar. Designing an optimal sustainable supply chain system considering pricing decisions and resilience factors. Journal of Cleaner Production, 332 (2022). doi.org/10.1016/j.jclepro.2021.129895.

[12] K. Fanning, D. P. Centers. Blockchain and Its Coming Impact on Financial Services. Journal of Corporate Accounting and Finance , 27(5) (2016) 53–57.

[13] E. Hofmann, U. M. Strewe, N. Bosia, N. Discussion–How Does the Full Potential of Blockchain Technology in Supply Chain Finance Look Like? In Supply Chain Finance and Blockchain Technology, Cham: Springer, (2018) 77–87.

[14] R. B. Rane, S. V. Thakker. Green procurement process model based on blockchain–IoT integrated architecture for a sustainable business. Management of Environmental Quality: An International Journal, (2019) 1477-7835. doi:10.1108/MEQ-06-2019-0136.

[15] Sh. Rajabi, P. Roozkhosh, N. Motahari Farimani. MLP-based Learnable Window Size for Bitcoin price prediction. Applied Soft Computing, 129

(2022). Doi: 10.1016/j.asoc.2022.109584.

[16] S. Saberi, M. Kouhizadeh, J. Sarkis, L. Shen. Blockchain technology and its relationships to sustainable supply chain management. International Journal of Production Research. (2018). doi:https://doi.org/10.1080/00207543.2018.1533261.

[17] T Sawik. Stochastic optimization of supply chain resilience under ripple effect: A COVID-19 pandemic related study. Omega, 109 (2022). doi:doi.org/10.1016/j.omega.2022.102596.

[18] A. Zahid Piprani, N. Jaafar, S. Ali, M. Mubarik, M. Shahbaz. Multi-dimensional supply chain flexibility and supply chain resilience: the role of supply chain risks exposure. Operations Management Research. (2022) https://doi.org/10.1007/s12063-021-00232-w.

[19] A. Hasani, H. Mokhtari, M. Fattahi. A multi-objective optimization approach for green and resilient supply chain network design: A real-life case study. Journal of Cleaner Production, 278 (2021) doi:https://doi.org/10.1016/j.jclepro.2020.123199.

[20] N. Hosseini Arian, A. Pooya, F. Rahimnia, A. Sibevei. Assessment the effect of rapid prototyping implementation on supply chain sustainability: a system dynamics approach. Operations Management Research. (2021) 14:467–493.

[21] A. Aloui, N. Hamani, L. Delahoche. Designing a Resilient and Sustainable Logistics Network under Epidemic Disruptions and Demand Uncertainty. Sustainibility. 13(24) (2021).

[22] B. Flynn, D. Cantor, D. Pagell, K. Dooley, A. Azadegan. From the Editors: Introduction to Managing Supply Chains Beyond Covid-19- Preparing for the Next Global Mega-Disruption. Journal of Supply Chain Management. 57(1). (2021) 3–6.

[23] D. Ivanov. Lean resilience: AURA (Active Usage of Resilience Assets) framework for post-COVID-19 supply chain management. International Journal of Logistics Management. 33(4) (2022) 1196-1217. https://doi.org/10.1108/IJLM-11-2020-0448.

[24] M. Shokouhifar, M. Ranjbarimesan. Multivariate time-series blood donation/demand forecasting for resilient supply chain management during COVID-19 pandemic. Cleaner Logistics and Supply Chain. 5 (2022). https://doi.org/10.1016/j.clscn.2022.100078.

[25] M. Alazab, S. Alhyari, A. Awajan, A. Bahjat Abdallah. Blockchain technology in supply chain management: an empirical study of the factors

affecting user adoption/acceptance. Cluster Comput 24 (2021) 83–101. https://doi.org/10.1007/s10586-020-03200-4.

[26] S. Kamble, A. Gunasekaran, V. Kumar, A. Belhadi, C. Foropon. A machine learning based approach for predicting blockchain adoption in supply Chain. Technological Forecasting and Social Change. 163 (2021). https://doi.org/10.1016/j.techfore.2020.120465.

[27] R. Casado-Vara. Blockchain for Democratic Voting: How Blockchain Could Cast off Voter Fraud. Orient. J. Comp. Sci. and Technol, 11(1) (2018). http://www.computerscijournal.org/?p=8042.

[28] SA. Athari. Domestic political risk, global economic policy uncertainty, and banks' profitability: evidence from Ukrainian banks. Post-Communist Economies, 33(4) (2021) 458-483.

[29] S. Sachin, A. Gunasekaran, V. Kumar, A. Belhadi, C. Foropon. A machine learning based approach for predicting blockchain adoption in supply Chain. Technological Forecasting and Social Change. 163 (2021).

[30] M. Crosby, P. Pattanayak, S. Verma, V. Kalyanaraman. Blockchain Technology: Beyond Bitcoin. Applied Innovation 2 (2016) 6-9.

[31] N. Tsolakis, J. Srai. Mapping supply dynamics in renewable feedstock enabled industries: A systems theory perspective on 'green' pharmaceuticals. Operations Management Research. (2018) 11:83–104. https://doi.org/10.1007/s12063-018-0134-y.

[32] J. Sterman. Business dynamics system thinking and modeling for a complex world. *Boston: McGraw-Hill.* (2000).

[33] D. H. Meadows. The Limits to Growth: a Report for the Club of Rome's Project on the Predicament of Mankind. Universe Books, New York. (1972).

[34] Z. Liu, A. Nagurney. Supply chain outsourcing under exchange rate risk and competition. Omega. 39(5) (2011) 539-549.

[35] S. Das, M. A. Rout. hybridized ELM using self-adaptive multi-population-based Jaya algorithm for currency exchange prediction: an empirical assessment. Neural Comput Appl. (2018) 1-24. doi:https://doi.org/10.1007/ s00521-018-3552-8.

[36] M. Kondoz, D. Kirikkaleli, SA. Athari. Time-frequency dependencies of financial and economic risks in South American countries. The Quarterly Review of Economics and Finance, 79 (2021), 170-181. Doi: 10.1016/j.qref.2020.05.014.

[37] B. R. Sarker, A.M.M. Jamal, Sh. Wang. Supply chain models for perishable products under inflation and permissible delay in payment. Computers and Operations Research. 27(1) (2000) 59-75.

[38] N. Wan, X. Chen. The role of put option contracts in supply chain management under inflation. International Transactions in Operational Research. (2017). https://doi.org/10.1111/itor.12372.

[39] SA. Athari, D. Kirikkaleli, I. Yousaf, S. Ali. Time and frequency comovement between economic policy uncertainty and inflation: Evidence from Japan. Journal of Public Affairs, (2021). Doi: 10.1002/pa.2779.

[40] F. Chan, A. Nayak, R. Raj, A. Yee-Loong Chong, T. Manoj. An innovative supply chain performance measurement system incorporating Research and Development (R&D) and marketing policy. Computers & Industrial Engineering. 69 (2014) 64-70. https://doi.org/10.1016/j.cie.2013.12.015.

[41] J. W. Forrester. Industrial dynamics: a major breakthrough for decision makers. Harv. Bus. Rev. 36(4) (1958).

[42] D. Nepstad, S. Irawan, T. Bezerra, W. Boyd, C. Stickler, J. Shimada. More food, more forests, fewer emissions, better livelihoods: linking REDD+, sustainable supply chains and domestic policy in Brazil, Indonesia and Colombia. Carbon Management. 4(6) (2014) 639-658. https://doi.org/10.4155/cmt.13.65.

[43] SA. Athari, D. Kirikkaleli, TS. Adebayo. World pandemic uncertainty and German stock market: evidence from Markov regime-switching and Fourier based approaches. Quality and Quantity. (2022). https://doi.org/10.1007/s11135-022-01435-4.

[44] Y. Pham, K. Reardon-Smith, R. Deo. Evaluating management strategies for sustainable crop production under changing climate conditions: A system dynamics approach. Journal of Environmental Management. 292 (2021).

[45] G. Li, K. Chenhuan, Y. Wang, H. Yang. System dynamics modelling for improving urban resilience in Beijing, China. Resources, Conservation and Recycling. (2020) 1810-1821.

[46] Y. Sun, N. Liu, J. Shang, J. Zhang. Sustainable utilization of water resources in China: A system dynamics model. *Journal of Cleaner Production*. 142 (2017) 613-625.

[47] G. Box, G. M. Jenkins. Time Series Analysis: Forecasting and Control. Holden-Day. (1976).

[48] O. Berat, S. Mehmet, U. Gudelek, A. Murat, O. Oglu. Financial time series forecasting with deep learning : A systematic literature review: 2005–2019. Applied Soft Computing. 90 (2020). doi:https://doi.org/10.1016/j.asoc.2020.106181.

[49] I. Guyon, B. Boser, V. Vapnik. Automatic capacity tuning of very large vc-dimension classifiers. In NIPS. Morgan Kaufmann. (1992) 147–155.

[50] T. Hastie, R. Tibshirani, J. Friedman. The elements of statistical learning: data mining, inference and prediction.2nd ed. Springer. (2009). http://www-stat.stanford.edu/tibs/ElemStatLearn/

[51] S. Haykin. Neural Networks: A Comprehensive Foundation. Prentice Hall. (1999).

[52] Y. Li, Y. Q. Chen, I. Podlubny, Stability of fractional-order nonlinear dynamic systems: Lyapunov direct method and generalized Mittag-Leffler stability, Comp. Math. Appl., 59 (2010) 1810-1821.

[53] B. Ruskey, E. Rosenberg, Minimizing Risk in Bayesian Supply Chain Networks, Computers and Industrial Engineering, 2022.

[54] F. Tian. An Agri-food Supply Chain Traceability System for China Based on RFID and Blockchain Technology. 13th International Conference on Service Systems and Service Management (ICSSSM). (2016).

[55] A. R. Sai, J. Buckley, B. Fitzgerald, A. Legear. Taxonomy of centralization in public blockchain systems: A systematic literature review. Information Processing and Management. 58(4) (2021).

[56] S. A. Abeyratne, R. P. Monfared, Blockchain Ready Manufacturing Supply Chain Using Distributed Ledger, International Journal of Research in Engineering and Technology. 5 (9) (2016) 1–10.

[57] B. Tukamuhabwa, M. Stevenson, J. Busby, M. Zorzini. Supply chain resilience: definition, review and theoretical foundations for further study. International Journal of Production Research. 53(18) (2015) 5592-5623.

[58] P. Suryawanshi, P. Dutta. Optimization models for supply chains under risk, uncertainty, and resilience: A state-of-the-art review and future research directions. Transportation Research Part E. 157 (2022). Doi: 10.1016/j.tre.2021.102553.

[59] M. Javed, M. Hasan, R. Khan. Future of bitcoin in India: Issues and challenges. Journal of Statistics and Management Systems. Journal Abbreviation. 10 (2020) 142-149.

[60] E. Remington, W. Seth Egger, M. Devika, A. Jing. Dynamical Systems Perspective on Flexible Motor Timing. celpress reviews. 2018.

[61] D. Tapscott, A. Tapscott. How Blockchain Will Change Organizations. MIT Sloan Management Review. 58(2) (2017).

[62] H. Min. Blockchain technology for enhancing supply chain resilience, Business Horizons. 62(1) (2019) 35-45.