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ORIGINAL RESEARCH

Machine learning-based mathematical model for drugs and equipment resilient supply chain using blockchain

Sachin Yadav[1] · Surya Prakash Singh[2]

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Abstract
The world has been stuck in the prevailing COVID and another pandemic for the last three years which leads to the disruption in the medical equipment, drugs, Liquid Oxygen, and other essential goods supply chain. Essential drugs expire during transportation due to a lack of traceability, transparency, corrupt data, and high documentation works. This mismanagement escalates the disruption and shortages. Meanwhile, blockchain (BC) is the latest cutting-edge technology that comes up with the complete solution to disruption, shortages, fraud, poor quality, burglary in data, lack of transparency, lack of traceability, lack of security, cross-delivery, and adulteration. Therefore, blockchain technology can be seen as an opportunity that introduces resilience to the system. The proposed work focuses on optimising the digital procurement cost for significant supplier selection that keeps transparency, traceability, security, and complete information on the distributed ledger. Here, real-time and other aspects of BC, like authenticity, time, etc., are considered while computing the procurement cost in supplier selection problems. The total cost involved in the digital procurement process hinges on the block's authenticity that comes up through the miner's signals. The probability sampling method is used to generate the data for developing the ML-based model. Machine learning (ML) aggregates the value reported by the miners in real time for developing the authenticity (dependent) variables for supplier selection. Later, this real-time authenticity variable is utilised to formulate the mixed-integer nonlinear programming (MINLP) model for digital procurement problems. This MINLP model reduces the disruption and introduced resilience in the information flow system. Finally, LINGO 19.0 is used for optimising the total cost, and the integrated approach of ML is used for the computation of authenticity factor relationships amongst minors in it.

Keywords Blockchain · Supply chain resilience · Supplier selection · Machine learning

✉ Surya Prakash Singh
surya.singh@gmail.com

Sachin Yadav
sachinyadav.dce@gmail.com

1 Jindal Global Business School, OP Jindal Global University, Sonipat 131001, Haryana, India

2 Department of Management Studies, Indian Institute of Technology Delhi, New Delhi 110016, Delhi, India

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1 Introduction

Practitioners and academicians have been investigating the various crises since 2019 developed due to the COVID-19 pandemic (Suda and Tadrous, 2021) faced by manufacturing organisations. Amidst Covid-19, SC of drugs and other essential equipment is on the utmost in the list of the manufacturing sector (Fegert et al., 2020). Before coming into the shackles of COVID-19, countries like India have faced local riots, farmer's protests, natural calamities (Hosseini et al., 2019) e.g., floods, cyclones and border issues that have disturbed the SC (Cui et al., 2023). However, this time COVID- 19 (Guan et al., 2020; Ivanov & Dolgui, 2021) has broken the spine of the SC. Due to COVID-19 (Adiyoh et al., 2020) outbreaks, the world is struggling with labour shortages (McConnell, 2020), shortage of liquid oxygen and medical equipment, and vaccine crises (Newton et al., 2020; Tabish, 2020). Furthermore, Suda and Tadrous (2021) addressed the uncertain availability of obstacles in the drugs SC that also makes it more disrupted, unbalanced and rigid. Researchers investigated that poor management, lack of supply information, burglary in records and ripple effect, lack of traceability, non-transparency, cyber threat (Creazza et al., 2021), inaccurate quality (Yadav et al., 2017), adulteration (Mackey & Liang, 2011), restamping over expired medications (Rupasinghe, 2018), cross-delivery, and product damage during transportation are the major obstacles.

Trivedi (2021) investigated that in most developing countries, e.g. India, essential medicines and liquid oxygen (PTI, 2021) have been purchased at higher prices than their maximum retail prices. Government agencies investigated that a few testing laboratories and hospitals jointly prepared fake reports of the COVID test (Sunny, 2021) and were involved in medical insurance scam based on artificial and fabricated data resulting in black marketing and black stocking of drugs, and equipment. Rupasinghe (2018) has revealed in his research that the Governments of these countries are incapable and helpless due to the lack of real-time records information, opacity, burglary in data and mismanagement in distribution centres. In addition, Ur Rehman et al. (2011) have proposed the bar code and RFID (FDA, 2004) tag on medications to reduce counterfeiting and authentication of drugs. Wazid et al. (2017) have suggested NFC (Near Field Communication) tags for the verification of medicines.

Governments of various countries (European Medicines Agency & State Food and Drug Administration of China) around the globe have made the traceability of drugs mandatory. In the current stream, Huang et al. (2018) and OPTEL track and trace reported that China had adopted a centralised client–server architecture to authenticate medications for the patient and higher authorities. According to US Food and Drug Administration report, the US Drug SC Security Act (DSCSA) on 27 November 2013 has issued guidelines. It has been made compulsory for the entire country to build up an electronic and interoperable system. This digital platform has successfully identified, authenticated, and tracked the drugs during their distribution during Covid-19. But these alternatives are the temporary solution. These innovative ideas fail when questions arise from research and investigation points of view about the automatic confirmation, tracing, immutability, and security of the drugs and equipment SC worldwide. Various research is being carried out to make drug SC robust, resilient, and easily traceable amidst the rising severe threat to society by counterfeiting drugs. We need an error-proof mechanism for drugs and equipment SC whose hacking might be nearly impossible and will pack with traceability, transparency, immutability, decentralisation and other features.

Finally, (Balakrishnan & Ramanathan, 2021; Tong, 2022) suggested digitization as an alternative to the complexity of SC. Yadav and Singh (2020a) have addressed the characteristics of BCT that will overcome the aforementioned challenges in drugs and medical equipment. This technology is still nascent (Abbas & Sung-Bong, 2019; Yadav & Singh, 2022). BCT has characteristics of immutable data (Liu et al., 2020a, 2020b), transparency (Queiroz et al., 2019), high security (Samad et al., 2022), distributed ledger (Dubey et al., 2020; Yadav & Singh, 2020b), and decentralization (Tseng et al., 2018), immutable (Abbas & Sung-Bong, 2019) which makes the SC more robust and resilient (Yadav & Singh, 2022).

1.1 Research gap

The authors have read out the massive amount of research work in digital SC, drugs and equipment SC. Based on the undermentioned research gap, the authors have analysed and concluded that BCT could be seen as an alternative to achieve resilience in the drugs and equipment SC. Following are the research gap found by the authors:

1. Only various literature theories have been addressed to justify the essentiality of BCT in digital SC.
2. No mathematical model has been developed to show the BCT role in SC.
3. No real-time model is developed for resilient SC through ML.
4. The only quantitative approaches have been addressed from the language programming point of view.

1.2 Research objectives

The research manuscript is robust after introducing the research objective and considering the research gap. The research objectives for procurement problems in drugs and equipment SC are as follows:

- To optimise the overall procurement cost, including BCT cost in real-time.
- To make the model more robust and resilient in real-time by using machine learning for sub-processes transaction validated and authenticated through the miner signal.
- To validate the mathematical model using realistic five different datasets for drugs and equipment procurement problems.

The sequencing of this manuscript is as follows: The first section is the introduction comprised of the research gap, research question and objective. The second section of the literature review explains a detailed description of BCT based on various past work in drugs and equipment SC. After that, the third section comprises the development of the mathematical model, its validation, and the role of machine learning in procurement problems for drugs and equipment SC. The second last section talks about the results and findings based on realistic randomly generated datasets. At last, the manuscript is finished by Sect. 5, which describes the conclusion and future scope.

2 Literature review

A detailed description of this section divides into two subsections of the literature review. These two subsections are as follows: Sect. 2.1 Detailed descriptions based on contemporary drugs and equipment supplier selection and Sect. 2.2, focuses on the marvellous characteristics of BCT and its contribution to achieving resilience in the drugs and equipment SC.

2.1 History of supplier selection based on literature

Supplier selection in procurement problems is the foremost pillar of the manufacturing sector in the dynamic world, therefore, the contribution of efficient supplier selection in real-time (Cavalcante et al., 2019) can't be neglected. Dey et al. (2015) addressed the revenue contribution of raw materials and its procurement process bears more than 60% of the finished product. Lamba and Singh (2019) proposed that disruption and shortages start from the initial level of procurement problems due to incomplete information. Therefore, Kamalahmadi et al. (2022) suggested that a large percentage of manufacturing revenue should be invested in research for eradicating this disruption and ripple effects from the procurement problems in SC. This investment will make the SC robust and resilient. Resilience can't be achieved through efficient supplier selection from the pool (Kaur & Singh, 2017) in the digital SC without optimising the lot-size orders (Lamba & Singh, 2019), fulfilment of buyer's requirements (Aissaoui et al., 2007), quality (Mishra et al., 2018), and eco-friendly products (Mishra & Singh, 2019) in real-time. Kohar and Jakhar (2021) used branch and bound algorithm for finding the least cost vehicle routes to fulfil customer's demands in real-time.

Over the years, a variety of research has been done in the field of drug and equipment supplier selection. Deming (1986) has addressed that the supplier's role as a good partner, in the long run, is significant. The result of a healthy relationship (Faruquee et al., 2021) between supplier and buyer would be positive in terms of high quality (Mehralian et al., 2012), reasonable raw material cost, and strong trust (Faruquee et al., 2021) and loyalty. Zamiela et al. (2022), Kochan et al. (2018) have suggested that resilience is an essential criterion in supplier selection, including order allocation for the procurement problem. Therefore, data resilience (Tucker et al., 2020) cannot be left behind in drugs and equipment SC while selecting efficient suppliers and order allocation in the procurement process. In drugs and equipment SC, choosing the right and efficient supplier from the pool is a highly complex job using the central eight (quality, flexibility, technology, information and communication systems, cost, etc.) and 30 other secondary indicators (environmental risk, delay, etc.). In this research, the TOPSIS technique is used by Sabbaghi (2020). Askaryan et al. (2022) have used the Fuzzy ANP & DEMATEL for prioritising the supplier in resilient drugs SC. Mehralian et al. (2012) have developed a model for the Iranian drug SC by using the Fuzzy TOPSIS methodology. Zamiela et al. (2022) have presented a USA case study for modelling the enablers of resilient healthcare SC in supplier selection by using the rank reversal proximity index method and cluster analysis. Tucker et al. (2020) have suggested a two-stage and multi-stage stochastic programme for reducing the shortfall of medications from resilient SC. Lozano-Diez et al. (2020) have proposed the Logistix optimisation and simulation software methodology for eliminating the shortfall of medicines in the supply network and emphasise on making a robust drug resilient SC.

There is multiple research available in the drugs and equipment literature that emphasise on the importance of information resilience (Askaryan et al., 2022; Balakrishnan & Ramanathan, 2021), transparency (Samad et al., 2022), secured data (Kochan et al., 2018), immutable flow of information in real-time (Ivanov & Dolgui, 2021; Zouari et al., 2020) for procurement problems. Finally, these published literature endorses eliminating disruption (Lücker & Seifert, 2017) and ripple effect (Lozano-Diez et al., 2020) from the drugs and equipment SC while making the procurement decision.

2.2 Contribution of BCT in drugs and equipment resilient SC

In the following decades, a variety of research has been carried out on supplier selection under the criteria of big data (Lamba et al., 2019), Industry 4.0 based on IoT (Lin et al., 2019; Rajput & Singh, 2022), BCT (Yadav & Singh, 2022). Lin et al. (2019) used the probit model for endorsing the IoT in manufacturing plants to improve quality. In previous years, Ivanov et al., 2019a, 2019b have addressed the impact and contribution of BCT, Industry 4.0, in resilient SC (Faruquee et al., 2021) for controlling the effect of ripple, shortages, and disruption. According to Lai et al. (2021), this developing BCT can transform primitive SC into digital SC by eliminating the risk of disruption. They have used the AHP approach on 19 factors to mitigate the disruption and SC risk. Therefore, BCT integrated SC (Lohmer et al., 2020) procurement process is the solution against the rising concern towards disruptions, transparency, security, traceability (Liu, 2022), and ripple effects in drugs and equipment SC businesses. Samad et al. (2022) prioritised the enabler “Real-time connectivity and information flow” over the other twelve enablers using ISM-DEMATEL methodology for justifying the BCT role in SC.

Banerjee & Kharde (2020) have proposed an integrated AHP and TOPSIS approach to prioritise the trust score using the BC platform. Rane & Thakker (2020) suggested that integrated BCT and IoT technologies are the success key for industries and mitigate challenges in terms of transparency, immutable data and security. Dey et al. (2015) has proposed a game-theoretical model for the smart contract through BCT between suppliers, retailers, and firms in SC.

In addition, Liu et al. (2020a, 2020b) have addressed the significant importance of ML while integrating it with BCT for communications and networking systems. They have discussed a few challenges (data processing, scalable operations) and their importance in their research survey. Shahbazi & Byun (2021) have suggested an integrated approach of IoT, ML, and BCT for smart manufacturing and used a private Hyperledger Fabric platform. Cavalcante et al. (2019) proposed the hybrid technique, combining simulation and machine learning for data-driven decision-making support for resilient supplier selection.

Finally, researchers have not yet investigated a real-time mathematical model for ML-based BCT integrated SC for drugs and equipment resilient SC. A brief discussion about past literature has been depicted in Tables 1, 2. The authors found this gap in literature reviews and proposed ML-based MINLP mathematical model for resilient SC. This proposed model will achieve resilience in the drugs and other essential equipment SC and optimizes overall digital procurement cost because ML-based BCT model gives results based on real-time information.

3 Proposed ML model

Initially, this section represents the detailed proposed ML-based supplier model through the framework shown in Fig. 1. Here, the framework depicts the integrated approach of ML for achieving transparency, security, etc., in real-time for the proposed procurement problem using BCT in drugs and equipment resilient SC. The proposed research framework is presented below in Fig. 1.

Table 1 Brief literature review based on supplier selection and digital SC

Authors	Technology used in digital SC and procurement problems				Methodology
	Big Data	IoT	ML	Blockchain	
Yadav and Singh (2020b)	×	✓	×	✓	MCDM
Tong et al. (2022)	×	×	×	×	MCDM + SC
Liu (2022)	×	×	×	✓	Equilibrium Mathematical model
Alam et al. (2021)	×	×	×	×	MCDM + SC
Kochan et al. (2018)	×	×	×	×	Basic mathematical model for SC
Dey (2015)	×	×	×	✓	Game-theoretic model
Lozano-Diez et al. (2020)	×	×	×	×	Logistic optimisation and simulation software for SC
Kaur and Singh (2019)	×	×	×	×	MINLP & MILP for Procurement Problems
Liu et al., (2020a, 2020b)	×	✓	✓	✓	Survey
Shahbazi and Byun (2021)	✓	✓	✓	✓	Multistage quality control model
Banerjee and Kharde (2020)	×	×	×	✓	MCDM + SC
Yadav and Singh (2020a)	×	✓	×	✓	MCDM
Yadav and Singh (2022)	×	✓	×	✓	MILP
Tucker et al. (2020)	×	×	×	×	Two-stage and multi-stage stochastic programme
Samad et al. (2022)	×	×	×	✓	MCDM
Lai et al. (2021)	×	×	×	✓	MCDM
Dubey et al. (2020)	×	×	×	✓	Statistical and theortical analysis
Hosseini et al. (2019)	×	×	×	×	Stochastic bi-objective mixed-integer programming model for SC
Lamba et al. (2019)	✓	×	×	×	MINLP for Supplier Selection
Askaryan et al. (2022)	×	×	×	×	MCDM + SC
Mehralian et al. (2012)	×	×	×	×	MCDM + SC
Zamiela et al. (2022)	×	×	×	×	MCMD
Rajput and Singh (2022)	×	✓	×	×	MINLP

Table 1 (continued)

Authors	Technology used in digital SC and procurement problems				Methodology
	Big Data	IoT	ML	Blockchain	
Rane and Thakker (2020)	×	✓	×	✓	MCDM
Lohmer et al. (2020)	×	×	×	✓	Theoretical Analysis
Kouhizadeh and Sarkis (2018)	×	✓	×	✓	Theoretical Analysis
Ivanov et al. (2019b)	✓	✓	×	✓	Theoretical Framework
Ivanov and Dolgui (2021)	×	✓	×	✓	Theoretical Analysis
Dolgui and Ivanov (2022)	×	✓	×	✓	Theortical Analysis
Cavalcante et al. (2019)	✓	✓	✓	×	Combining simulation and ML
Balakrishnan and Ramanathan (2021)	✓	✓	×	✓	Hypothesis testing
Zouari et al. (2020)	✓	✓	×	✓	Structural equation modelling
Creazza et al. (2021)	×	×	×	✓	One-way ANOVA testing
Faruquee et al. (2021)	×	×	×	✓	Multiple linear regressions for testing the hypotheses
Proposed model	✓	✓	✓	✓	MINLP

Table 2 Indices, variables, and parameters in tabular format

Indicies	Variables		Parameter				
i	x_{ijt}	λ_{ijt}	$\boldsymbol{\pounds}^{\boldsymbol{\alpha}}_{\boldsymbol{ijt}}$	$\mathrm{SC}_{\mathrm{ijt}}$	$N\alpha_{Green_{ijt}}$	$T_{d_{IoT},P}$	$\mathfrak{K}_P$
j	$\boldsymbol{\Theta}_{\boldsymbol{ijt}}$	$\boldsymbol{N}^{\boldsymbol{\alpha}}_{\boldsymbol{ijt}}$	$\boldsymbol{\pounds}^{\boldsymbol{\Psi}}_{\boldsymbol{ijt}}$	D_{it}	$N\alpha_{Red_{ijt}}$	$T_{d_{IoT},O}$	$\mathfrak{K}_O$
t	$\mathrm{Inv}_{\mathrm{it}}$	$\boldsymbol{N}^{\boldsymbol{\Psi}}_{\boldsymbol{ijt}}$	$\boldsymbol{\pounds}^{\boldsymbol{\beta}}_{\boldsymbol{ijt}}$	$\mathrm{PLC}_{\mathrm{it}}$	$N\Psi_{Green_{ijt}}$	$T_{d_{IoT},T}$	$\mathfrak{K}_T$
α	Y_{ijt}	$\boldsymbol{N}^{\boldsymbol{\beta}}_{\boldsymbol{ijt}}$	$\boldsymbol{\pounds}^{\boldsymbol{\lambda}}_{\boldsymbol{it}}$	$\mathfrak{K}_T$	$N\Psi_{Red_{ijt}}$	$T_{d_{IoT},H}$	$\mathfrak{K}_H$
β	W_{it}	$\boldsymbol{N}^{\boldsymbol{\lambda}}_{\boldsymbol{it}}$	€^{α}_{ijt}	$\mathfrak{K}_P$	$N\beta_{Green_{ijt}}$	$N_{IoT,P}$	Truck_Vol
λ	α_{ijt}		€^{Ψ}_{ijt}	$\mathfrak{K}_O$	$N\beta_{Red_{ijt}}$	$N_{IoT,O}$	
ψ	Ψ_{ijt}		€^{β}_{ijt}	$\mathfrak{K}_H$	$N\lambda_{Green_{it}}$	$N_{IoT,T}$	
	β_{ijt}		€^{λ}_{it}	B_S	$N\lambda_{Red_{it}}$	$N_{IoT,H}$	

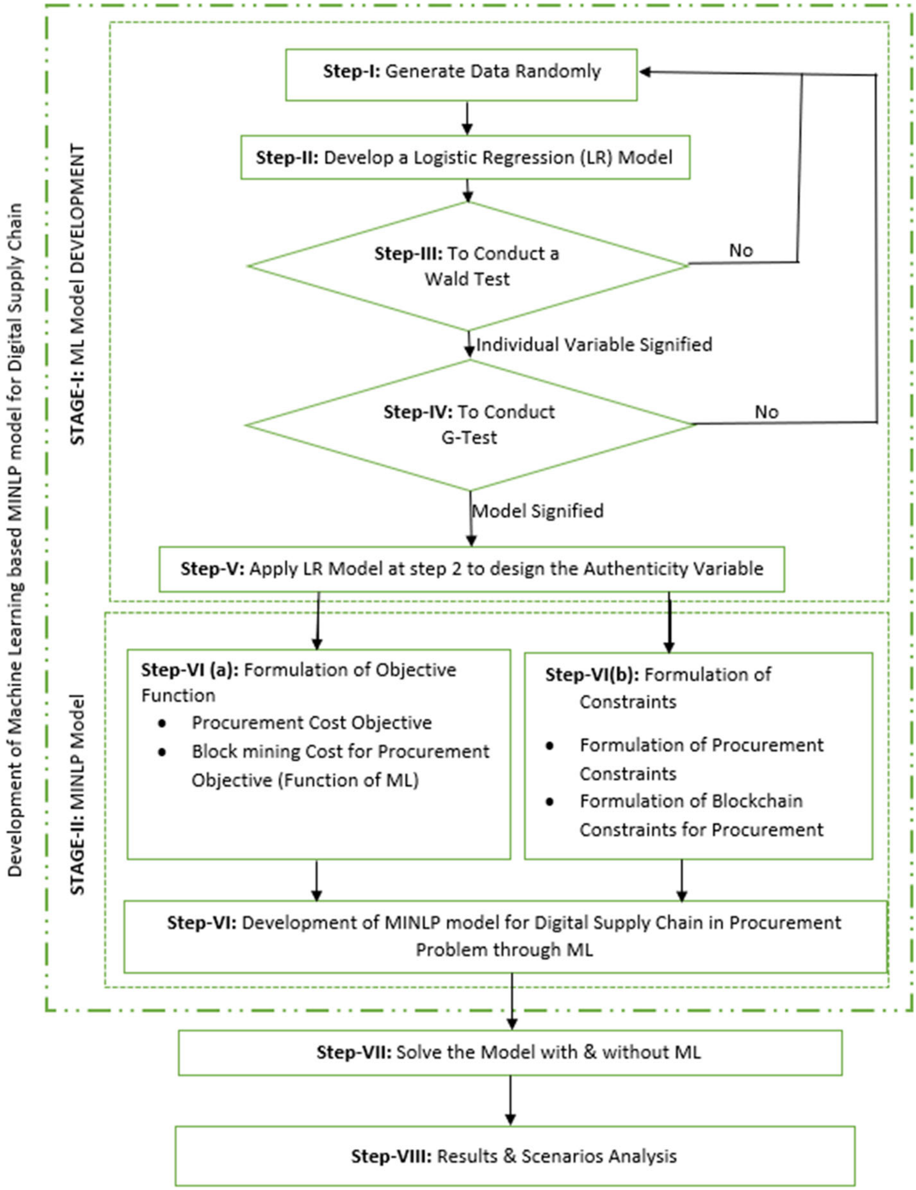

Fig. 1 Flow chart of the ML-based MINLP model for resilient digital SC

3.1 Problem statement

The proposed mathematical model represents the supplier selection for drugs and equipment manufacturing organisations for their resilient SC under multiple periods, multiple suppliers, and multiple products. This research aims to address the optimal total procurement cost for the optimal allocation of suppliers for each period under multiple product delivery. Herein total procurement cost is comprised of the procurement cost, including the cost of BCT. The authors have attempted to achieve a resilient SC through ML by considering real-time information.

3.2 ML model

This section demonstrates the formulation of an ML-based model to compute the authenticity factor. Assumptions and variables to formulate the ML model are discussed below.

3.2.1 Assumptions

The following undermentioned assumptions govern the ML model.

1. The model considers all possibilities like malpractice, biasing, and the influence of a few goons or greedy miners on honest miners and negligence in the mining.
2. ML model run over a randomly generated dataset restricted to 100 values.
3. A case of the miner's 50% green signal and 50% red signal is not considered.

3.2.2 Variables

- Y: Dependent variable (Authenticity factor)
- x_{Red}: Independent variable (Numbers of miners responsible for red signal)
- x_{Green}: Independent variable (Numbers of miners responsible for green signal)
- $\beta_o = Constant$
- $\beta_1 = Coefficientforredsignalindependentvariable$
- $\beta_2 = Coefficientforgreensignalindependentvariable$

3.2.3 ML model formulation

A logistic regression model is developed for the computation of miner authenticity in the procurement model. The entire procedure related to the calculation has been carried out through the machine learning methodology. The significance of the overall developed model and individual independent variable has been verified and computed through G-test with the degree of freedom being two and the Wald test, explained in Eqs. 1 and 2.

ML code is executed in Python. The uploaded dataset and the results of the ML model are depicted in Appendix "H" (Figs. 5 and 6). Equation 3 represents the logistic regression equation result. After validation of the randomly generated dataset for miners' authenticity factor, the same dataset is further used to compute the optimisation cost for the procurement model. As discussed earlier, the authenticity factor is developed by ML and represented in Eq. 3.

$$\mathrm{G-test} = -2 \times \ln\left(\frac{Likelihood\ without\ the\ variable}{Likelihood\ with\ the\ variable}\right) \tag{1}$$

$$\text{Wald test} = \frac{\hat{\beta}}{SE\left(\hat{\beta}\right)},\ \text{where y} = \beta_o + \beta_1 x_{Green} + \beta_2 x_{Red}\ \&\ \text{SE} = \text{Standard Error} \tag{2}$$

$$\text{Expected Value of Authenticity Factor} = \mathrm{E}(\widehat{y}) = \frac{e^{0.7641+0.0751\ x_{Green}-0.0829\ x_{Red}}}{1+e^{0.7641+0.0751\ x_{Green}-0.0829\ x_{Red}}} \tag{3}$$

This developed regression model (Eq. 3) is further deployed to formulate the objective function and constraints for all four procurement processes in terms of respective authenticity factor variables for procurement problems in real-time.

3.3 BCT model

This section demonstrates the formulation of the BCT model to mathematically formulate the objective function and all constraints for drugs and equipment-resilient SC using BC. Assumptions and variables to develop the integrated ML and BCT model are discussed below.

3.3.1 Assumptions considered for supplier selection

- Procurement cost, demand and supplier capacity are known and deterministic.
- Shortages and late deliveries, discounts, and overstock are not allowed.
- Rejected items will not be stored as inventory and will be disposed of immediately. Herein model, this disposed of cost for rejected items is not considered.
- Inventory holding cost is considered only if any chemical/raw material is stocked at tth time for the next (t + 1)th time in the planning horizon.
- Unimodal carriers are permitted for transportation; the volume of the trucks is fixed. Multiple products are allowed for transport in a single truck to fully utilise the container space.
- Transportation cost is independent w.r.t the distance, nature of the roads, and the fuel used in trucks.
- Plant capacity is fixed for all items and varies w.r.t time t.

3.3.2 Assumptions considered for BCT

1. Blocks produced are proportional to their size w.r.t. suppliers, transportation, information about products and others are considered.
2. The block size is less than equal to 10240 KB.
3. Integration of different process information in a block is not allowed.
4. Data for computing the authenticity factor for all processes are uniform and constant.
5. Specification and type of IoT devices are kept constant, and the number is fixed throughout the individual processes for all i, j, t.
6. IoT devices are working with 100% efficiency without breakdown and maintenance throughout all the processes for all i, j, t.

3.4 ML-based Mathematical Model Using BCT

This section integrates ML with BCT to formulate the mathematical model for procurement problems. The list of indices, variables, and parameters to develop the model are as follows.

3.4.1 List of indices

- i = index for Product

- j = index for Supplier
- β = index for the transportation process
- t = index for time
- λ = index for inventory management process
- α = index for the purchasing process
- Ψ = index for the order process

3.4.2 List of decision variables

$\boldsymbol{x}_{ijt}$: lot size procured for the ith product from jth supplier at time t.

$\boldsymbol{\Theta}_{ijt}$: Number of trucks involved for the supply of ith product sent by the jth supplier at time t.

$\mathbf{Inv_{it}}$**:** inventory for ith product available at time t.

$$\boldsymbol{Y}_{ijt}: \begin{cases} 1, & if j^{th} supplier is selected for i^{th} product at time t. \\ 0, & else \end{cases}$$

$$\boldsymbol{W}_{it} = \begin{cases} 1, if i^{th} product is available in inventry section at time t. \\ 0, else \end{cases}$$

$$\mathbf{ijt} = \begin{cases} 1, if minor \geq 51\% gives Green signal for procurement process. \\ 0, else \end{cases}$$

$$\boldsymbol{\Psi}_{ijt} = \begin{cases} 1, if minor \geq 51\% gives Green signal for order process. \\ 0, else \end{cases}$$

$$\boldsymbol{\beta}_{ijt} = \begin{cases} 1, if minor \geq 51\% gives Green signal for transportation process. \\ 0, else \end{cases}$$

$$\boldsymbol{\lambda}_{ijt} = \begin{cases} 1, if minor \geq 51\% gives Green signal for holding process. \\ 0, else \end{cases}$$

$\boldsymbol{N^{\alpha}_{ijt}}$**:** Number of blocks produced during the purchasing process for the ith product from the jth supplier at time t.

$\boldsymbol{N^{\Psi}_{ijt}}$**:** Number of blocks produced during the ordering process for ith product from jth supplier at time t.

$\boldsymbol{N^{\beta}_{ijt}}$**:** Number of blocks produced during the transportation for the ith product from the jth supplier at time t.

$\boldsymbol{N^{\lambda}_{it}}$**:** Number of blocks produced during the Holding process for the ith product at time t.

3.4.3 List of parameters

$\boldsymbol{£^{\alpha}_{ijt}}$: Cost of the unit block while blocks are produced for the purchasing process of ith product from the jth supplier in tth time.

$\boldsymbol{£^{\Psi}_{ijt}}$: Cost of unit block produced during the ordering process of the ith product from the jth supplier in tth time.

$\boldsymbol{£^{\beta}_{ijt}}$: Cost of unit block produced during the transportation process of the ith product from jth suppliers in tth time.

$\boldsymbol{£^{\lambda}_{it}}$**:** Cost of unit block produced during the holding process of the ith lot size for tth to (t + 1)th time.

$€^{\alpha}_{ijt}$: Purchasing Cost for the ith product from the jth supplier in tth time.

$€^{\Psi}_{ijt}$: Order Cost for the ith product from the jth supplier in tth time.

$€^{\beta}_{ijt}$: Transportation Cost for the ith product from the jth supplier in tth time.

$€^{\lambda}_{it}$: Holding cost for the ith product in tth time.

$\mathbf{SC_{ijt}}$: Supplier capacity for the ith product from the jth supplier in tth time.

$\mathbf{D_{it}}$**:** Demand of ith product in tth time.

$\mathbf{PLC_{it}}$**:** Plant capacity of ith product in tth time.

Truck_Vol: Truck Capacity.

$N\alpha_{Green_{ijt}}$: Percentage of green signal required for producing the block in the purchasing process.

$N\alpha_{\text{Re}d_{ijt}}$: Percentage of red signal required for not producing the block in the purchasing process.

$N\Psi_{Green_{ijt}}$: Percentage of green signal for the order process.

$N\Psi_{\text{Re}d_{ijt}}$: Percentage of red signal for the order process.

$N\beta_{Green_{ijt}}$: Percentage of green signal for the transportation process.

$N\beta_{\text{Re}d_{ijt}}$: Percentage of red signal for the transportation process.

$N\lambda_{Green_{it}}$: Percentage of green signal for inventory management process.

$N\lambda_{\text{Re}d_{it}}$: Percentage of red signal for inventory management process.

B_S: Size of Block is constant for the whole procurement problem.

$T_{d_{IoT},P}$: Total time for receiving the information and consumed in data transfer for the procuring process irrespective of i, j, t.

$T_{d_{IoT},O}$: Total time for receiving the information and consumed in data transfer for orders process irrespective of i, j, t.

$T_{d_{IoT},T}$: Total time for receiving the information and consumed in data transfer for the transporting process irrespective of i, j, t.

$T_{d_{IoT},H}$: Total time for receiving the information and consumed in data transfer for holding process irrespective of i, t.

$N_{IoT,p}$: The number of IoT devices installed for the purchasing process irrespective of i, j, t.

$N_{IoT,O}$: The number of IoT devices installed for the order process irrespective of i, j, t.

$N_{IoT,T}$: The number of IoT devices installed for the transportation process irrespective of i, j, t.

$N_{IoT,H}$: The number of IoT devices installed for the holding process irrespective of i, j, t.

$\mathfrak{K}_P$: Average data transfer rate from IoT devices irrespective of device types for the procuring process and irrespective of i, j, t.

$\mathfrak{K}_O$: Average data transfer rate from IoT devices irrespective of device types for the order process and irrespective of i, j, t.

$\mathfrak{K}_T$: Average date transfer rate from IoT devices irrespective of device types for the transportation process and irrespective of i, j, t.

$\mathfrak{K}_H$: Average data transfer rate from IoT devices irrespective of the device type for the holding process and irrespective of i, t.

3.5 Obj function

$$
\begin{aligned}
Z_{\min} = & \sum_i \sum_j \sum_t £_{ijt}^{\alpha} N_{ijt}^{\alpha} \alpha_{ijt} + \sum_i \sum_j \sum_t €_{ijt}^{\alpha} x_{ijt} + \sum_i \sum_j \sum_t £_{ijt}^{\Psi} N_{ijt}^{\Psi} \Psi_{ijt} \\
& + \sum_i \sum_j \sum_t €_{ijt}^{\Psi} Y_{ijt} + \sum_i \sum_j \sum_t £_{ijt}^{\beta} N_{ijt}^{\beta} \beta_{ijt} \\
& + \sum_i \sum_j \sum_t €_{ijt}^{\beta} D_{it} \Theta_{ijt} + \sum_i \sum_t £_{ijt}^{\lambda} N_{it}^{\lambda} \lambda_{it} + \sum_i \sum_t €_{it}^{\lambda} Inv_{it}
\end{aligned}
\tag{4}
$$

3.5.1 Subjective to Constraints:

$$
\mathrm{Inv}_{i,t-1} + \sum_j \boldsymbol{x_{ijt}} = D_{it} + \mathrm{Inv}_{i,t} \quad \forall \text{ i, t} \tag{5}
$$

$$
\boldsymbol{x_{ijt}} \leq SC_{ijt} \quad \forall \text{ i, j, t} \tag{6}
$$

$$
(\mathrm{Inv}_{it}) + \sum_j \boldsymbol{x_{ijt}} \leq PLC_{it} \quad \forall \text{ i, t} \tag{7}
$$

$$
\left(\sum_{k=t}^{T} D_{ik} \right) Y_{ijt} \geq x_{ijt} \quad \forall \text{ i, j, t} \tag{8}
$$

$$
\Theta_{ijt} \geq \frac{x_{ijt} \times Vol_{per_{unit}} of i^{th} PRODUCT}{Truck\_Vol} \quad \forall \text{ i, j, t} \tag{9}
$$

$$
\boldsymbol{N_{ijt}^{\alpha}} \geq \frac{N_{IoT,P} \times \mathfrak{K}_P}{B_S} \times T_{d_{IoT},P} \times \frac{x_{ijt}}{D_{it}} \quad \forall \text{ i, j, t} \tag{10}
$$

$$
\boldsymbol{N_{ijt}^{\Psi}} \geq \frac{N_{IoT,O} \times \mathfrak{K}_O}{B_S} \times T_{d_{IoT},O} \times Y_{ijt} \quad \forall \text{ i, j, t} \tag{11}
$$

$$
\boldsymbol{N_{ijt}^{\beta}} \geq \frac{N_{IoT,T} \times \mathfrak{K}_T}{B_S} \times T_{d_{IoT},T} \times \Theta_{ijt} \quad \forall \text{ i, j, t} \tag{12}
$$

$$
\boldsymbol{N_{it}^{\lambda}} \geq \frac{N_{IoT,H} \times \mathfrak{K}_H}{B_S} \times T_{d_{IoT},H} \times W_{it} \quad \forall \text{ i, t} \tag{13}
$$

$$
W_{it} = \begin{cases} 1, if Inv > 0 \\ 0, if Inv = 0 \end{cases} \quad \forall \text{ i, t} \tag{14}
$$

$$
\alpha_{ijt} \leq \mathbb{C}_{\alpha} \times \left(\frac{e^{0.7641+0.0751 N\alpha_{Green_{ijt}} - 0.0829 N\alpha_{Red_{ijt}}}}{1 + e^{0.7641+0.0751 N\alpha_{Green_{ijt}} - 0.0829 N\alpha_{Red_{ijt}}}} \right) \times Y_{ijt}; \quad \forall \text{ i, j, t} \tag{15}
$$

$$
\Psi_{ijt} \leq \mathbb{C}_{\Psi} \times \left(\frac{e^{0.7641+0.0751 N\Psi_{Green_{ijt}} - 0.0829 N\Psi_{Red_{ijt}}}}{1 + e^{0.7641+0.0751 N\Psi_{Green_{ijt}} - 0.0829 N\Psi_{Red_{ijt}}}}) \right) Y_{ijt}; \quad \forall \text{ i, j, t} \tag{16}
$$

$$
\beta_{ijt} \leq \mathbb{C}_{\beta} \left(\frac{e^{0.7641+0.0751 N\beta_{Green_{ijt}} - 0.0829 N\beta_{Red_{ijt}}}}{1 + e^{0.7641+0.0751 N\beta_{Green_{ijt}} - 0.0829 N\beta_{Red_{ijt}}}} \right) \times Y_{ijt}; \quad \forall \text{ i, j, t} \tag{17}
$$

$$
\lambda_{it} \leq \mathbb{C}_{\lambda} \times \left(\frac{e^{0.7641+0.0751 N\lambda_{Green_{it}} - 0.0829 N\lambda_{Red_{it}}}}{1 + e^{0.7641+0.0751 N\lambda_{Green_{it}} - 0.0829 N\lambda_{Red_{it}}}} \right) \times W_{it}; \quad \forall \text{ i, t} \tag{18}
$$

$$
\alpha_{ijt}, \Psi_{ijt}, \beta_{ijt}, \lambda_{it} = \begin{cases} 1, when 1 \leq \alpha_{ijt}, \Psi_{ijt}, \beta_{ijt}, \lambda_{it} \\ 0, when 0 \leq \alpha_{ijt}, \Psi_{ijt}, \beta_{ijt}, \lambda_{it} < 1 \end{cases}
$$

$¢_{\alpha}$, $¢_{\Psi}$, $¢_{\beta}$, $¢_{\lambda}$ are the arbitrarily constant and used to makeα_{ijt},Ψ_{ijt},β_{ijt}, λ_{it} binary integers.

x_{ijt}, $\mathrm{Inv}_{i,t}$, $\geq$ 0and are integers ∀ i, j , t.

Θ_{ijt}, N_{ijt}^{α}, N_{ijt}^{Ψ}, N_{ijt}^{β}, N_{it}^{λ}, α_{ijt}, Ψ_{ijt}, β_{ijt}, $\lambda_{it} areintegers$∀ I, j, t.

Y_{ijt} Є {0,1}.

W_{it} Є {0,1}.

The authors have proposed an MINLP mathematical model for optimising the total integrated cost. The objective function in Eq. 4 talks about the total cost, including BCT cost, while procuring from multiple suppliers in real-time. The authenticity factor is modelled through ML for considering the real-time signal transmitted by miners for all the individual processes involved in procurement. A standard authenticity factor is represented by Eq. 3. This standard authenticity factor is common for all the sub-processes in this problem. Only purchasing, order, holding, inventory and last transportation processes are considered and addressed in the proposed model. While placing an order from any supplier in each time frame, only purchasing, order, and transportation costs would be considered for that period. Block cost would be accounted for in the individual procurement sub-process if that particular sub-process will get the miner's signals from the BCT system for that period.

Equation 5 represents the inventory balance equation and the first constraint for the mathematical model. In this equation, the constraints tell that for any period, the sum of all demands and availability of inventory is balanced by the sum of previous inventory available for period (t-1) th period and all lot size quantity procured from all suppliers for the ith product.

Here in the mathematical model, two binary variables, $\mathrm{Y_{ijt}}$ and $\mathrm{W_{it}}$ (Eq. 14), are comprised. If at any period t, ith lot size is procured from jth supplier, then $\mathrm{Y_{ijt}}$ is one else zero. If an inventory is available in store for period t, then $\mathrm{W_{it}}$ is one else zero. Similarly, if the material is available in stores before coming on the manufacturing machine line for the upcoming period (t + 1) in period (t), then holding cost will be considered; otherwise, zero inventory cost will be considered.

Equation 6 represents the constraint barrier for the ith lot size product procured for the jth supplier at any period t. In this constraint, the procured ith lot size quantity from the jth supplier may not have been crossed that individual supplier capacity for tth period. Equation (7) explains the capacity constraint for the plant. Here in this constraint, the sum of the availability of inventory in the plant and the material procured from all suppliers at any tth period must be less than the plant capacity for that ith product for tth period. In constraint 8, the model confirms that ith product procured from jth supplier at any tth period; if yes, then $\mathrm{Y_{ijt}}$ is represented by one else by zero for failing the order. Constraint no. 9 is used to account for the number of trucks used to transport procured materials. Transportation cost is the product of the truck required and the unit truck cost. Here the transport capacity of the truck is fixed and constant for all the trucks. It is mandatory to utilise the hundred percentage of truck capacity, and the number of trucks must be in integers.

However, this mathematical model is incomplete without the incorporation of BCT constraints. Therefore, Eqs. 10 to 13 represent the BCT constraints. Constraints 10,11,12,13 are used to compute the number of blocks produced for different sub-processes. Constraints 15,16,17,18 are used to authenticate the transaction for particular i, j, t through the strength of miners for different sub-processes. In constraints 10,11,12,13, the production of the number of blocks depends upon the number of IoT devices installed, data transfer rate and delay time consumed in data transferring during the completion of each sub-process. The number of blocks produced must be an integer in nature. Constraint 10 will give an individual count for the number of blocks if the transaction of ith product is successfully completed from the jth supplier at tth period. Constraint 11 will compute the number of blocks if the transaction for the order process is placed successfully; otherwise, no block will be calculated from this constraint. In the same procedural steps, Eqs. 12 & 13 are explained for computing the number of blocks produced if the transaction of the transportation and holding process are successfully completed for ith product from jth supplier at tth period. Otherwise, zero blocks will be produced for the same transaction. W_{it} has been explained previously, and its dependency is directly proportional to the availability of the stocks in the plant at tth period. W_{it} and Y_{ijt} are essential for computing the number of blocks and for the transaction's authenticity. Constraints 15,16,17,18 represent the authenticity variable for all four processes. The authenticity variable value is assumed to be one for MILP model without ML for all datasets and depicted in Appendix "E". But, the value of authenticity factor for MINLP model based on ML is depicted in Appendix "F" that later on used in constraints 15, 16, 17, 18 for computing the authenticity variable value. The result of these authenticity variables constraints must be binary; without them, it is impossible to compute the real-time cost. These authenticity variables are proportional to the product of the developed logistic regression model through ML, which is explained in-depth before and W_{it} or Y_{ijt} according to the sub-process. These constraints in Eqs. 15,16,17,18 are balanced by an arbitrary constant whose valve is equal to 0.56 according to the strength of the dataset taken for the logistic regression model. Finally, the product of the logistic regression model, arbitrary constant and binary variable, will compute the binary results for the authenticity variables for the ith product from jth supplier at tth period in real-time.

4 Numerical illustrations

Firstly, a detailed description based on the mathematical model is presented in Sect. 3. The proposed work imparts real-time ML-based solutions for drugs and equipment resilient SC in the procurement problems. In Appendix "A", detailed datasets are available related to minor's red and green signal strength in percentage for the computation of standard authenticity factor inside the mathematical model. It is a very complex task to compute the work associated with data in Kilobyte, the number of blocks authenticates, lot size, block size, and cost of all these items. Therefore, the ML concept is introduced to find a real-time model which will make the drugs and equipment SC model resilient. The authors have randomly developed this dataset to make the whole dataset homogeneous and transform the storage information in Kilobyte/Megabyte into numbers. A part of Appendix "D" represents the datasets that belong to the homogeneous details of BCT. BCT is integrated with SC through ML to optimise the overall cost for realistic procurement problems to reduce stiffness and disruption in the SC and make it robust, resilient SC. Five datasets that have been considered here are of variation in periods. Significant variation in the dataset helps verify the flexibility, sustainability, and robustness of the MINLP model developed through the BCT integrated with the procurement problem. Datasets are randomly generated for the verification of the model. Here, the number of blocks computed by assuming the same storage size, data transfer rate, and delay time in transfer rate are considered equal for all the processes in the procurement model for resilient SC.

Five different instances for demonstrating the real-time procurement problem are as follows: the first two instances are low-level datasets (3product-3supplier-2period i.g. 3P-3S-2T), the second instance is 3P-3S-4T. The third and fourth instances represent the moderate level of datasets, in which the third dataset is 3P-3S-5T, and the fourth is 3P-3S-7T. The last and highest level of the dataset is restricted to 3P-3S-11T only. The variation in periods is considered in the illustration, while the variation in products and suppliers (drugs and equipment) is prohibited. Variation in parameters of BCT is deemed to be w.r.t periods, suppliers, and products. The uniform capacity of the trucks is considered throughout the model with the utilisation of their full capacity. The individual supplier carries only a known and fixed quantity of individual products. In all the instances, under the multiple suppliers, periods, and the products, the capacities of the manufacturing plant and its supplier, order cost, purchasing cost, transportation cost, demands, and variation in products are randomly generated. The individual product carries different purchasing costs, and the unit purchasing cost offered by the supplier varies across all products and periods. The firm incurs the ordering cost, which can fluctuate over time, the nature of the products, and demands in the open market. These variations are prone to any disastrous event. In these cases, the supplier capacities can fluctuate and may fall, but the corresponding prices can fluctuate simultaneously and rise at a very high rate. The transportation cost may or may not fluctuate for an individual spare part based on the supply of material by suppliers over the planning horizon and are accountable for fluctuation in any disaster situation. Therefore, variations in the costs, demands, and supplies are considered, and they vary due to disruption in the flow over the entire planning horizon. The inventory cost is fixed over the variation in time and may differ w.r.t the nature of the products. Detailed analysis of results is explained in Sect. 5, named as result and discussion.

5 Results and discussion

The standard authenticity factor has been computed based on the randomly generated dataset. The significance test for the developed logistic regression-based authenticity factor has been verified through the ML. Herein ML, Python language is used to create the logistic regression model based on the probabilistic datasets as depicted in Appendix "A". After that G-test and Walt test are performed to verify model significance and significance of individual variables for logistic regression model. This standard logistic model is further deployed in the objective function for the cost computation of the number of blocks produced individually in every sub-process pertaining to procurement. Constraints 15, 16,17, and 18 are developed for computing the authenticity variable value as the binary result for the BCT based mathematical procurement model. In this research work, BCT integrated procurement model run over the LINGO 19.0 (LINGO Code for MINLP based ML model is depicted in Appendix "B" & LINGO Code for MILP model without ML is depicted in Appendix "C") software for the computation of optimised total integrated cost and MINLP model is validated and solved through the five different datasets (low (three, four), moderate (five, seven), and high(eleven) periods) for supplier selection in procurement problem, depicted in Appendix "D".

If the period increases beyond five, the optimal solution is not obtained within feasible polynomial-time due to the non-linearity, hardness, and complexity in the MINLP model. Disaster events, generally, impact the SC directly, irrespective to the period. Integration of digital technology with the supply chain to eradicate the disruption in the flow of goods and speedily recover from the disruption invasion on the supply chain. Whenever any geographical zone faces natural calamities or man-made disaster (riots/war zone), it's supply chain is completely disrupted due to damage to the internet line, life losses, hard copy and soft copy records, and ample time consumption in investigation and tracing. Sometimes corrupt persons intentionally damage the system or network. In this scenario, BCT-integrated SC recovers the data rapidly and makes the flow of goods smoother and helpful in tracing the location of

Table 3 CPU details for ML-based mathematical model

S. No	Dataset	Iterations	CPU time consumed (s)	Objective value	Solution nature for MINLP model
1	3P-3S-2T	4,466,828	469.07	314,221	Local
2	3P-3S-4T	52,338,003	41,215.24	1,180,789	Local
3	3P-3S-5T	890,305,272	513,321.54	935,458	Feasible#
4	3P-3S-7T	603,190,019	489,982.22	1,279,439	Feasible#
5	3P-3S-11T	582,819,999	486,571.10	2,070,467	Feasible#

#Lingo 19.0 has been interrupted randomly after 130 h.

Table 4 CPU details for Mathematical model without ML(WML)

S. No	Dataset	Iterations	CPU time consumed (s)	Objective value	Solution nature for MILP model
1	3P-3S-2T	2043	0.29	325,728	Global
2	3P-3S-4T	7500	0.89	1,186,885	Global
3	3P-3S-5T	66,029	12.66	988,842	Global
4	3P-3S-7T	202,156	41.45	1,348,582	Global
5	3P-3S-11T	9,551,877	2513.10	2,098,651	Global

goods including computing the loss due to the damages in floods, earthquakes, etc. Therefore, the role of BCT is significant for the current resilient SC model in drugs and equipment and give solution for the realistic problem.

Details about CPU timing to solve the ML and WML models for all instances, including other essential details given in Tables 3 and 4. From the CPU results, it is concluded that as the dataset volume increases w.r.t. periods, the problem becomes more complex and goes under exponential time. To test the authenticity of BCT based mathematical model, the authors have used computer whose hardware details are as follows: (1) Windows 10 Enterprise (2) CPU: AMD Ryzen 5 PRO 5650U with Radeon Graphics 2.30 GHz, (3) System type: 64-bit operating system, × 64-based processor (4) Installed RAM: 16.00 GB (15.3 GB usable) to run the randomly generated five different datasets over the (5) LINGO 19.0 software. In addition, for the development of ML based MINLP model, Python language (Python software version 3.9.1 (64 bit)) is used.

5.1 Illustration of small dataset 3P-3S-2T

Lingo 19.0 solves the model for 3P-3S-2T dataset after executing the code and gives the objective value for the first dataset is 325,728 for without ML-based (WML-based) model. This objective value has been compared with 314,221 from the ML-based model. This subsection splits into two parts (1) ML-based mathematical model and (2) WML-based mathematical model. Lot size procurement from suppliers for each period is depicted in Table 5 for the solu-

Table 5 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-2T dataset through ML

t	i	Items	j = 1	j = 2	j = 3	D	N^{λ}	λ
3P-3S-2T								
t = 1	**i = 1**	$\boldsymbol{x}$	265			265	0	0
		N^{α}	4		**2**			
		N^{Ψ}	3					
		N^{β}	7	**1**	**3**			
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	$\boldsymbol{x}$	175			175	**1**	**0**
		N^{α}	4	**3**				
		N^{Ψ}	3	**2**				
		N^{β}	7	**5**				
		α, Ψ, β	1	**0**				
	i = 3	$\boldsymbol{x}$	290			290	0	0
		N^{α}	4	**1**	**1**			
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β	1	**0**	**0**			
t = 2	**i = 1**	$\boldsymbol{x}$		425		425	0	0
		N^{α}	**1**	4	**1**			
		N^{Ψ}	**1**	3	**1**			
		N^{β}	**2**	13	**1**			
		α, Ψ, β	**0**	1	**0**			
	i = 2	$\boldsymbol{x}$	79		233	312	0	0
		N^{α}	1		3			
		N^{Ψ}	3	**2**	3			
		N^{β}	7	**1**	7			
		α, Ψ, β	1	**0**	1			
	i = 3	$\boldsymbol{x}$			180	180	0	0
		N^{α}			4			
		N^{Ψ}			3			
		N^{β}			7			
		α, Ψ, β			**0**			

α, Ψ, β = Standard authenticity variable for $\forall, i, j, t$.
λ = Standard authenticity variable for $\forall, i, t$..

tions obtained after implementing the ML concept. Table 5 illustrates the detailed solution for 3P-3S-2T (smallest dataset) without ML.

5.1.1 Detailed explanation for ML-based model

In Table 5 for the small dataset (3P-3S-2T), supplier j = 1 is selected from the pool for the period t = 1, and the complete pool of the suppliers j = 1, 2, 3 is selected for the t = 2 period. For period t = 1, the lot sizes procured from suppliers j = 1 are: $x_{111} = 265$, $x_{211}=$ 175, $x_{311}=$ 290. Neither supplier j = 2 nor supplier j = 3 have been selected from the pool for the procurement of lot size for period t = 1. Number of blocks produced during period t = 1 are as follows: $\boldsymbol{N}^{\boldsymbol{\alpha}}_{211}= 4$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{311}=4$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{211}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{311}=3$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{211}=7$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{311}=7$. For period t = 1, the number of gross blocks including fake blocks is 60 but ML only develops only 28 in real-time for period t = 1. ML reluctant to develop blocks for $x_{111} = 265$. Few other fake blocks ($\boldsymbol{N}^{\boldsymbol{\alpha}}_{131}=2$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{221}=3$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{321}=1$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{331}=1$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{221}=2$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{121}=1$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{131}=3$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{221}=5$) also have not been produced due to ML and developed constraints 15,16,17, and 18. One fake block ($\boldsymbol{N}^{\boldsymbol{\lambda}}_{21}=1$) is also not produced for the inventory process in period t = 1.

For the period t = 2 the lot-sizes are being procured from supplier j = 1: $x_{212}=$ 79 and from j = 2: $x_{122} = 425$, from j = 3: $x_{232} = 233$, $x_{332} = 180$. The following number of blocks have been produced during procurement at period t = 2: $\boldsymbol{N}^{\boldsymbol{\alpha}}_{122}=4$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{212}=1$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{232}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{122}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{212}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{232}=3$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{122}=13$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{212}=7$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{232}=7$. Here for period t = 2, there are no blocks produced for inventory. The number of gross blocks including fake blocks is 68 but ML only develops only 44 in real-time for t = 2 period. ML reluctant to produced blocks for $x_{332} =$ 180. Twenty four other fake blocks ($\boldsymbol{N}^{\boldsymbol{\alpha}}_{112}=1$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{132}=1$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{332}=4$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{112}=1$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{132}=1$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{222}=2$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{332}=4$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{112}=2$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{132}=1$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{222}=1$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{332}=7$) also have not been produced due to ML. Herein Table 5, red colour quoted cell shows that blocks has not been produced due to the ML based value assign to the standard authenticity variable is equal to zero in real-time. These fake blocks can be produced but ML based constraints 15,16,17 and 18 have not only reluctant to produced, strongly rejected them but also save cost, carbon and makes SC resilient.

5.1.2 Detailed explanation for WML-based model

In Table 6 for the same lowest volume dataset (2P-2S-2T), for period t = 1 the lot sizes of all respective supplier of plant are j = 1: $x_{111}=$ 265, $x_{211}=$ 175, $x_{311} = 290$. Only supplier j = 1 is selected from the pool of suppliers for the procurement of lot size for period t = 1. The number of blocks produced during period t = 1 are as follows: $\boldsymbol{N}^{\boldsymbol{\alpha}}_{111}=4$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{211}=4$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{311}=4$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{111}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{211}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{311}=3$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{111}=7$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{211}=7$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{311}=7$. For period t = 1, the total number of blocks produced is 42. For the inventory process, there are no blocks produced due to the presence of zero inventory. For the period t = 2 the lot-sizes are being procured from supplier j = 1: $x_{212} = 79$ and from j = 2: $x_{122} = 425$, from j = 3: $x_{232} = 233$, x_{332} = 180. The following number of blocks have been produced while procurement for period t = 2: $\boldsymbol{N}^{\boldsymbol{\alpha}}_{122}=4$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{212}=1$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{232}=3$, $\boldsymbol{N}^{\boldsymbol{\alpha}}_{332}=4$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{122}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{212}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{232}=3$, $\boldsymbol{N}^{\boldsymbol{\Psi}}_{332}=3$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{122}=13$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{212}=7$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{232}=7$, $\boldsymbol{N}^{\boldsymbol{\beta}}_{332}=7$. Here for period t = 2, there is no block produced for inventory. Total number of blocks produced is 58. In absence of ML, the model has developed 100% blocks required for the sub-processes without verifying their necessity.

5.2 Illustration of three datasets: 3P-3S-4T, 3P-3S-5T, 3P-3S-7T, 3P-3S-11T

Finally, complete details about the dataset 3P-3S-4T, 3P-3S-5T, 3P-3S-7T, 3P-3S-11T are shown in Appendix "D". This second dataset (3P-3S-4T) is also a low-level data type but higher in volume than the first 3P-3S-2T dataset. For other medium level datasets (3P-3S-5T

Table 6 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-2T dataset without ML

t	i	Items	j = 1	j = 2	j = 3	D	N^{λ}	λ
3P-3S-2T								
t = 1	**i = 1**	x	265			265	0	1
		N^{α}	4					
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β	1					
	i = 2	x	175			175	0	1
		N^{α}	4					
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β	1					
	i = 3	x	290			290	0	1
		N^{α}	4					
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β	1					
t = 2	**i = 1**	x		425		425	0	1
		N^{α}		4				
		N^{Ψ}		3				
		N^{β}		13				
		α, Ψ, β		1				
	i = 2	x	79		233	312	0	1
		N^{α}	1		3			
		N^{Ψ}	3		3			
		N^{β}	7		7			
		α, Ψ, β	1		1			
	i = 3	x			180	180	0	1
		N^{α}			4			
		N^{Ψ}			3			
		N^{β}			7			
		α, Ψ, β			1			

$\alpha, \Psi, \beta =$ Standard authenticity variable for $\forall, i, j, t..$

$\lambda =$ Standard authenticity variable for $\forall, i, t..$

& 3P-3S-7T) and high-level datasets (3P-3S-11T), the same computation steps are followed for both ML-based and WML-based Mathematical models. Code for both mathematical models is executed on Lingo 19.0. Similar to the previous instance (3P-3S-2T), the lot-size distribution policy is the same amongst all suppliers for the four-periods, five-periods, seven-periods, eleven-periods and solutions are obtained in terms of blocks produced for all i, j, t and objective values w.r.t. to instances for both models. Detailed solutions for 3P-3S-4T, 3P-3S-5T, 3P-3S-7T, 3P-3S-11T datasets are reported in Appendix "G" from tables 36 to 43.

5.3 Discussion

After obtaining the result from all instances, Table 7 represents the cost comparison between the ML-based mathematical model and without ML for all instances. Table 8 shows the detailed comparison of blocks produced for both ML-based mathematical models and WML-based models. In Table 8, it is depicted that count of real-time blocks produced and in Table 7, the cost associated with these blocks in BCT for ML-based mathematical model will never be higher than the count of blocks produced and costs for WML-based model.

Furthermore, Table 9 shows the details about actual blocks produced and fake blocks. Herein, forge blocks have been clubbed with a few other actual blocks, which are denied producing through ML based constraints. The information available in these actual blocks are

Table 7 Cost analysis between ML-based Mathematical model Vs. WML model

S. No	Dataset	Objective value based on ML	Objective value without ML
1	3P-3S-2T	314,221	325,728
2	3P-3S-4T	1,180,789	1,186,885
3	3P-3S-5T	935,458	988,842
4	3P-3S-7T	1,279,439	1,348,582
5	3P-3S-11T	2,070,467	2,098,651

Table 8 Blocks mining analysis between ML-based Mathematical Model Vs. WML-based model

S. No	Dataset	Blocks mining through ML	Blocks mining Without ML
1	3P-3S-2T	72	100
2	3P-3S-4T	247	261
3	3P-3S-5T	13	314
4	3P-3S-7T	81	422
5	3P-3S-11T	97	645

Table 9 Block produce analysis for all instances within ML-based model

S. No	Dataset	Produced blocks	Blocks not produced due to ML
1	3P-3S-2T	72	57
2	3P-3S-4T	247	23
3	3P-3S-5T	13	376
4	3P-3S-7T	81	454
5	3P-3S-11T	97	761

already available in records in previously mined blocks which are verified during solving the complex puzzle for the authentication of the transaction pertaining to current sub-processes.

6 Conclusion, implication and future direction

The specific model assumptions have been disclosed earlier in Sect. 3 while explaining the mathematical model. The authors have not considered carbon emission cost under various constraints, even under carbon cap and trade policy for the carriers used by the supplier (fixed and variable emission), for the order placing and the holding process.

6.1 Conclusion

The standard authenticity factor model for all procurement processes in the model has been computed through ML. Here, Datasets have been randomly generated, and the variation in employees (miners) strength has also been considered for getting red and green signals. Dataset for developing the authenticity factor model has been restricted to a hundred only including impact of biasing in red or green signal. Python language has been used for computing the standard authenticity factor. To make the model more realistic in real-time, goons and greedy miners' influence over the strength of honest miners has been accounted for in the standard authenticity factor model. Equal signals of both red and green sent by miners are neither feasible nor considered for the computation of the model through ML. The significance level is limited to five per cent only in the model for verifying the significance of the standard authenticity factor model and its independent variables.

This ML-based BCT integrated SC approach transforms the traditional SC into resilient digital SC. The infancy BCT will keep the complete SC information on the chain. Therefore hacking, and burglary will not be possible which resulting the SC will become more robust and resilient. The same datasets have been used to keep the significant value of binary decision variables in objective function from the standard authenticity factor model. This factor is deployed individually and separately in the mathematical model for all purchasing, ordering, transportation, and inventory sub-processes.

The objective value of the ML-based model for the first dataset (3P-3S-2T) is 314,221, for the second dataset (3P-3S-4T) is 1,180,789, for the third dataset (3P-3S-5T) is 935,458, for the fourth dataset (3P-3S-7T) is 1,279,439, and finally for the last and fifth dataset (3P-3S-11T) is 2,070,467. Here, the corresponding objective values for the WML-based is higher than the ML-based mathematical model, and the comparison can be seen in Fig. 2. Figure 2 depicts the variation in costs w.r.t. datasets for ML and WML-based mathematical models.

The total number of blocks is directly influenced and dependent on the ML-based authenticity factor model in real-time. Figures 3 and 4 let us know that a countable massive number of blocks are produced if the ML-based authenticity factor model is not deployed in the procurement model. ML is essential to eradicate the fake and unessential blocks produced in the model, which is necessary to significant drop down the number of blocks by a large percentage w.r.t. the cost involved in producing blocks for the ML based digital procurement problems in drug and equipment SC.

Figure 2 shows the cost comparison amongst the five illustrations w.r.t. the variation in periods. The cost comparison of the proposed WML based MILP model where authenticity factor variable is one for all i, j, t (Appendix "E") and ML based MINLP model where the authenticity factor value (Appendix "F") is depended upon the real-time information, shown

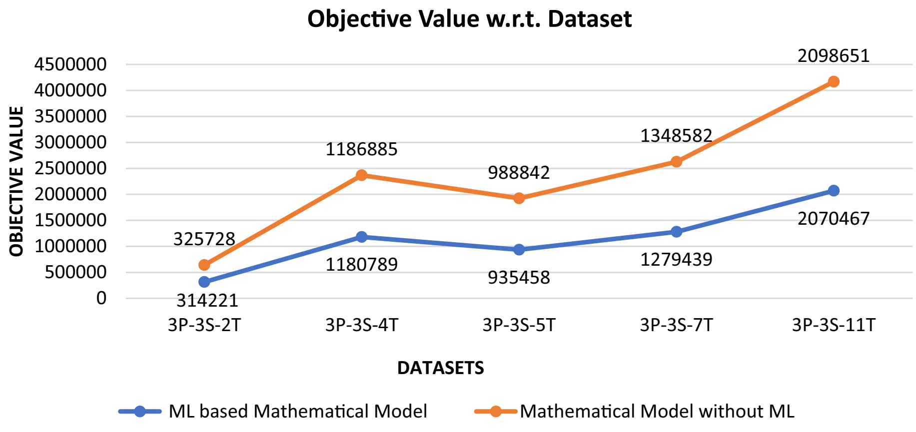

Fig. 2 Comparison between the objective values Vs. Blocks produced w.r.t. period

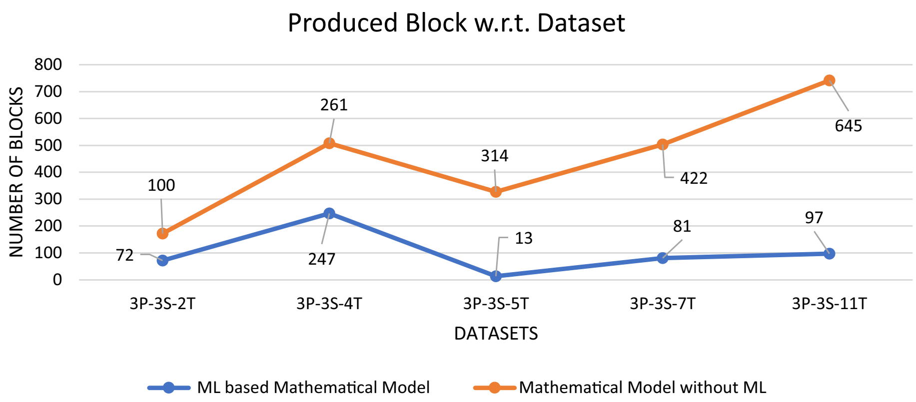

Fig. 3 Blocks production analysis between ML-based and mathematical models without ML for various instances

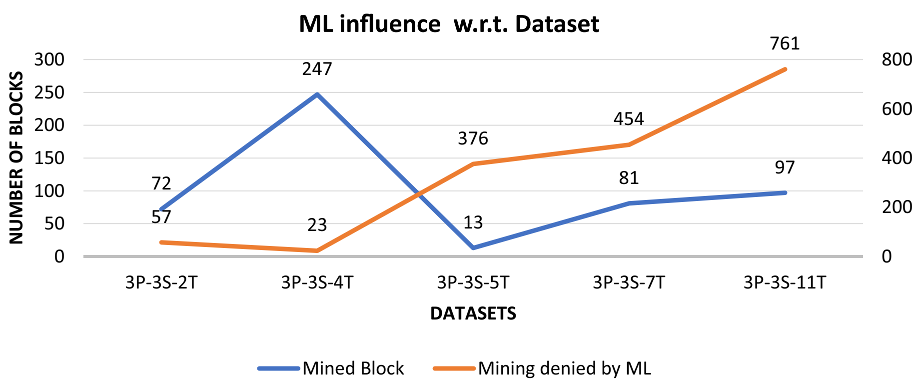

Fig. 4 ML significance on Blocks mining behaviour w.r.t dataset for procurement model

in Fig. 2. The significant role of ML is clear represents in Fig. 2. Figures 2, 3, and 4 show how ML is essential for cost savings and avoiding the production of non-essential blocks, while BCT plays a vital role in security, transparency, and immutability. This ML-based mathematical model saves carbon costs and make SC more sustainable and resilient in the long run for drugs and equipment. This mathematical model presents the transparent, secured lot-for-lot ordering policy with optimal results with minimum cost for all the illustrations.

The behaviour in the time consumption to solve the MINLP w.r.t. variation in datasets is drastically rising from polynomial to exponential. It is concluded from the results that the problem is complex and tangled for the massive dataset to solve in polynomial time; therefore, the model solution is restricted to 130–150 h for 7T and 11T period datasets illustration. The solution obtained shows that the total cost is lower for the ML-based model and significantly achieve long time goal, customer satisfaction, transparency and security in the end. But once the industry starts to integrate their traditional system with BCT, they will achieve higher profit in the long run than the conventional methods due to resilience in SC.

6.2 Implications

In the proposed paper, the ML-based mathematical model for resilient SC using BCT has developed a positive ideology for researchers and practitioners. This model considers procurement and BCT costs associated with all four sub-processes for supplier selection. This positive approach will encourage stakeholders to integrate their traditional SC system with BCT. ML approach is constructive for getting real-time procurement cost estimation based on the available industrial data. This real-time data will also reduce overall costs and improve quality and transparency. This proposed model is beneficial for investigating any fraud without wasting time. This research will also encourage the government body to establish the ML-based integrated approach of BCT and SC to make their system more transparent and cost-effective and reduce the time response during the investigation against fraud, burglary in revenue and quality. Most software companies invest their money and technology in developing cryptocurrency. Still, this positive step of our research will motivate the software industry and encourage them to create an ML-based integrated BCT platform for the existing SC to transform into digital and resilient at a reasonably minimal cost. In the long run, this integrated digital approach will save paper, improve security, motivate people to learn and implement technology in their existing traditional business for drugs and equipment SC and trace real-time information anywhere and anytime without stress. Suppose within the time amidst COVID-19, Governments of these developing countries could have deployed BCT to distribute and manage drugs. In that scenario, they could save themselves from the scam in medicines and equipment mismanagement and protect lives due to fake medications, lack of tracing, ripple effects, shortages and disruption in the SC of drugs and equipment.

6.3 Future directions

ML is restricted to the authenticity factor only in this paper, but it is not the end for the future. Furthermore, an integrated approach of the qualitative and quantitative model may be incorporated to achieve the optimised cost of BC integrated SC. Individual datasets might be used for calculating the authenticity factor through machine learning for the sub-processes in procurement problems. Some other IT technology, e.g., cloud computing, ERP, Industry 5.0, 6G, etc., can be integrated into SC to make the best cost comparison. Other dimensions of the inventory model, i.e., shortage and penalty for late service, may be incorporated. Variation in carriers load capacity and trade policy is restricted in the model but may be accounted for future work. Moreover, this research is restricted to a heuristic mathematical model, but the future project may incorporate this approach. International border policy, fluctuation in taxes and inter border policy can be consolidated for developing the taxes and policies-based procurement model in future. LINGO 19.0 software has been used for optimisation purposes, but the results obtained from CPLEX and other software may be compared in the future.

Appendix A: Data collection for machine learning

See Table 10.

Table 10 Data for authenticity factor

S. No	Total strength	Green signal %	Green signal	RED signal	Value
1	64	11	7	57	0
2	168	6	10	158	0
3	101	49	49	52	0
4	157	21	33	124	0
5	68	37	25	43	0
6	112	46	52	60	0
7	56	81	45	11	1
8	180	64	115	65	1
9	202	68	137	65	1
10	235	98	230	5	1
11	182	49	89	93	0
12	97	46	45	52	0
13	76	18	14	62	0
14	50	42	21	29	0
15	174	21	37	137	0
16	205	5	10	195	0
17	41	22	9	32	0
18	95	69	66	29	1
19	155	13	20	135	0
20	78	50	39	39	0
21	224	30	67	157	0
22	177	12	21	156	0
23	60	77	46	14	1
24	157	67	105	52	1
25	224	67	150	74	1
26	150	34	51	99	0
27	59	24	14	45	0
28	90	96	86	4	1

Table 10 (continued)

S. No	Total strength	Green signal %	Green signal	RED signal	Value
29	25	7	2	23	0
30	166	5	8	158	0
31	40	59	24	16	1
32	**98**	**55**	**54**	**44**	**0**
33	118	9	11	107	0
34	108	83	90	18	1
35	45	65	29	16	1
36	56	57	32	24	1
37	112	6	7	105	0
38	172	99	170	2	1
39	152	11	17	135	0
40	146	57	83	63	1
41	155	70	109	46	1
42	25	8	2	23	0
43	117	97	113	4	1
44	27	22	6	21	0
45	150	74	111	39	1
46	211	98	207	4	1
47	107	81	87	20	1
48	83	41	34	49	0
49	25	52	13	12	1
50	141	38	54	87	0
51	106	5	5	101	0
52	183	96	176	7	1
53	95	23	22	73	0
54	166	52	86	80	1
55	**210**	**43**	**90**	**120**	**1**
56	189	75	142	47	1
57	59	73	43	16	1
58	126	57	72	54	1
59	205	50	103	102	1
60	222	91	202	20	1
61	157	86	135	22	1
62	63	21	13	50	0
63	230	54	124	106	1
64	63	29	18	45	0
65	241	49	118	123	0
66	221	95	210	11	1
67	86	62	53	33	1
68	**101**	**58**	**59**	**42**	**0**

Table 10 (continued)

S. No	Total strength	Green signal %	Green signal	RED signal	Value
69	53	14	7	46	0
70	121	32	39	82	0
71	169	9	15	154	0
72	66	12	8	58	0
73	241	87	210	31	1
74	102	37	38	64	0
75	93	64	60	33	1
76	25	57	14	11	1
77	218	66	144	74	1
78	65	67	44	21	1
79	224	83	186	38	1
80	85	70	60	25	1
81	201	81	163	38	1
82	199	95	189	10	1
83	43	93	40	3	1
84	164	44	72	92	0
85	60	78	47	13	1
86	**53**	**48**	**25**	**28**	**1**
87	175	51	89	86	1
88	224	43	96	128	0
89	115	29	33	82	0
90	94	22	21	73	0
91	86	84	72	14	1
92	233	73	170	63	1
93	226	9	20	206	0
94	164	26	43	121	0
95	70	30	21	49	0
96	196	8	16	180	0
97	83	94	78	5	1
98	76	52	40	36	1
99	39	83	32	7	1
100	182	56	102	80	1

Bold represents the malpractice, biasing, and the influence of a few goons or greedy miners on honest miners and negligence in the mining process when a new block is mined

Appendix B: Lingo coding for ML-based MINLP model

```
MODEL:

TITLE OPTIMISATION OF Procurement COST FOR SUSTAINABLE SUPPLY CHAIN UNDER THE
UMBERRALA OF BC TECHNOLOGY;

SETS:
PERIODS/1..4/;
TIME/1..4/;
PRODUCTS/1..3/:Pro_Vol;
SUPPLIERS/1..3/;
PRO_SUP_PER(PRODUCTS,SUPPLIERS,PERIODS):
PBC,NPB,PC,X,OBC,NOB,OC,Y,TBC,NTB,TC,NOT,SC,P,O,L,A;
PRO_PER(PRODUCTS,PERIODS):HBC,NHB,W,HC,INV,D,PLC,H,B;
PRO_TIME(PRODUCTS,TIME):DEM;
ENDSETS

MIN =
@SUM(PRO_SUP_PER(I,J,T):PBC(I,J,T)*NPB(I,J,T)*P(I,J,T))+
@SUM(PRO_SUP_PER(I,J,T):PC(I,J,T)*X(I,J,T)) +
@SUM(PRO_SUP_PER(I,J,T):OBC(I,J,T)*NOB(I,J,T)*O(I,J,T)) +
@SUM(PRO_SUP_PER(I,J,T):OC(I,J,T)*Y(I,J,T)) +
@SUM(PRO_SUP_PER(I,J,T):TBC(I,J,T)*NTB(I,J,T)*L(I,J,T)) +
@SUM(PRO_SUP_PER(I,J,T):TC(I,J,T)*D(I,T)*NOT(I,J,T)) +
@SUM(PRO_PER(I,T):HBC(I,T)*NHB(I,T)*H(I,T)) +
@SUM(PRO_PER(I,T):HC(I,T)*INV(I,T));
@FOR(PRO_PER(I,T)|T#EQ#0:Inv(I,T)=0);
@FOR(PRO_PER(I,T)|T#EQ#1:@SUM(SUPPLIERS(J):X(I,J,T))=D(I,T)+Inv(I,T));
@FOR(PRO_PER(I,T)|T#GT#1:Inv(I,T-1) + @SUM(SUPPLIERS(J):X(I,J,T))
=D(I,T)+Inv(I,T));
@FOR(PRO_SUP_PER(I,J,T):X(I,J,T)<= SC(I,J,T));
@FOR(PRO_PER(I,T): INV(I,T) + @SUM(SUPPLIERS(J):X(I,J,T)) <= PLC(I,T));
@FOR(PRO_SUP_PER(I,J,T):@SUM(TIME(K)|K#GE#T:DEM(I,K))*Y(I,J,T)- X(I,J,T)>=0)
;
@FOR(PRO_SUP_PER(I,J,T):NOT(I,J,T) >= Pro_Vol(I)/Truck_Vol * X(I,J,T));
@FOR(PRO_SUP_PER(I,J,T):NPB(I,J,T) >= N1* R1/BS *TD1* X(I,J,T)/D(I,T));
@FOR(PRO_SUP_PER(I,J,T): NOB(I,J,T) >= N2* R2/BS *TD2* Y(I,J,T));
@FOR(PRO_SUP_PER(I,J,T): NTB(I,J,T) >= N3* R3/BS *TD3* NOT(I,J,T));
@FOR(PRO_SUP_PER(I,J,T):NHB(I,T) >= N4* R4/BS *TD4* W(I,T));

@FOR(PRO_PER(I,T):
    INV(I,T)>= 0-1000*(1-W(I,T));
    INV(I,T)<= 0+1000*W(I,T);
);

@FOR(PRO_SUP_PER(I,J,T):
             1-A(I,J,T)*Y(I,J,T)<=1000*(1-P(I,J,T));
             A(I,J,T)* Y(I,J,T)-1<=1000*P(I,J,T);
);

@FOR(PRO_SUP_PER(I,J,T):
         1-A(I,J,T)*Y(I,J,T)<=1000*(1-O(I,J,T));
         A(I,J,T)* Y(I,J,T)-1<=1000*O(I,J,T);
);
@FOR(PRO_SUP_PER(I,J,T):
            1-A(I,J,T)*Y(I,J,T)<=1000*(1-L(I,J,T));
             A(I,J,T)*Y(I,J,T)-1<=1000*L(I,J,T);
);

@FOR(PRO_PER(I,T):
   1-B(I,T)*W(I,T)<=1000*(1-H(I,T));
    B(I,T)*W(I,T)-1<=1000*H(I,T);
);

@FOR(PRO_SUP_PER(I,J,T):@GIN(X));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NOT));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NPB));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NOB));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NTB));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NHB));
@FOR(PRO_SUP_PER(I,J,T):@BIN(Y));
@FOR(PRO_PER(I,T):@BIN(W));

@FOR(PRO_SUP_PER(I,J,T):@BIN(P));
@FOR(PRO_SUP_PER(I,J,T):@BIN(O));
@FOR(PRO_SUP_PER(I,J,T):@BIN(L));
@FOR(PRO_PER(I,T):@BIN(H));

DATA:


END DATA
END
```

Appendix C: Lingo coding for WML-based MILP model

```
SETS:
PERIODS/1..7/;
TIME/1..7/;
PRODUCTS/1..3/:Pro_Vol;
SUPPLIERS/1..3/;
PRO_SUP_PER(PRODUCTS,SUPPLIERS,PERIODS):
PBC,NPB,PC,X,OBC,NOB,OC,Y,TBC,NTB,TC,NOT,SC,P,O,L,A;
PRO_PER(PRODUCTS,PERIODS):HBC,NHB,W,HC,INV,D,PLC,H,B;
PRO_TIME(PRODUCTS,TIME):DEM;
ENDSETS

MIN =
@SUM(PRO_SUP_PER(I,J,T):PBC(I,J,T)*NPB(I,J,T)*P)+
@SUM(PRO_SUP_PER(I,J,T):PC(I,J,T)*X(I,J,T)) +
@SUM(PRO_SUP_PER(I,J,T):OBC(I,J,T)*NOB(I,J,T)*O) +
@SUM(PRO_SUP_PER(I,J,T):OC(I,J,T)*Y(I,J,T)) +
@SUM(PRO_SUP_PER(I,J,T):TBC(I,J,T)*NTB(I,J,T)*L) +
@SUM(PRO_SUP_PER(I,J,T):TC(I,J,T)*D(I,T)*NOT(I,J,T)) +
@SUM(PRO_PER(I,T):HBC(I,T)*NHB(I,T)*H) +
@SUM(PRO_PER(I,T):HC(I,T)*INV(I,T));

 ! Subjective to Constraints;

@FOR(PRO_PER(I,T)|T#EQ#0:Inv(I,T)=0);
@FOR(PRO_PER(I,T)|T#EQ#1:@SUM(SUPPLIERS(J):X(I,J,T))=D(I,T)+Inv(I,T));
@FOR(PRO_PER(I,T)|T#GT#1:Inv(I,T-1) + @SUM(SUPPLIERS(J):X(I,J,T))
=D(I,T)+Inv(I,T));
@FOR(PRO_SUP_PER(I,J,T):X(I,J,T)<= SC(I,J,T));
@FOR(PRO_PER(I,T): INV(I,T) + @SUM(SUPPLIERS(J):X(I,J,T)) <= PLC(I,T));
@FOR(PRO_SUP_PER(I,J,T):@SUM(TIME(K)|K#GE#T:DEM(I,K))*Y(I,J,T)- X(I,J,T)>=0)
;
@FOR(PRO_SUP_PER(I,J,T):NOT(I,J,T) >= Pro_Vol(I)/Truck_Vol * X(I,J,T));
@FOR(PRO_SUP_PER(I,J,T):NPB(I,J,T) >= N1* R1/BS *TD1* X(I,J,T)/D(I,T));
@FOR(PRO_SUP_PER(I,J,T): NOB(I,J,T) >= N2* R2/BS *TD2* Y(I,J,T));
@FOR(PRO_SUP_PER(I,J,T): NTB(I,J,T) >= N3* R3/BS *TD3* NOT(I,J,T));
@FOR(PRO_SUP_PER(I,J,T):NHB(I,T) >= N4* R4/BS *TD4* W(I,T));

@FOR(PRO_PER(I,T):
    INV(I,T)>= 0-1000*(1-W(I,T));
    INV(I,T)<= 0+1000*W(I,T););
@FOR(PRO_SUP_PER(I,J,T):@GIN(X));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NOT));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NPB));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NOB));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NTB));
@FOR(PRO_SUP_PER(I,J,T):@GIN(NHB));
@FOR(PRO_SUP_PER(I,J,T):@BIN(Y));
@FOR(PRO_PER(I,T):@BIN(W));

DATA:
END DATA
```

Appendix D: Dataset common for WML-based and ML-based mathematical model

Datasets: 3Product-3Supplier-2Time period (3P-3S-2T)

See Tables 11, 12, and 13.

Table 11 Cost & Supplier Capacity for 3P-3S-2T

	i	j = 1		j = 2		j = 3	
		t = 1	t = 2	t = 1	t = 2	t = 1	t = 2
$€^{\alpha}$	**1**	80	85	90	75	90	88
	2	100	85	110	89	90	78
	3	90	80	100	56	58	57
$€^{\Psi}$	**1**	200	250	280	190	210	220
	2	190	150	180	180	150	170
	3	200	150	210	190	180	160
$€^{\beta}$	**1**	58	78	68	62	58	59
	2	50	60	90	70	77	75
	3	65	70	85	86	88	82
SC	**1**	265	195	250	480	550	390
	2	198	287	312	256	123	287
	3	555	350	129	451	146	188
$£^{\alpha}$	**1**	574	585	497	517	481	430
	2	418	570	371	406	351	430
	3	429	489	374	399	450	406
$£^{\Psi}$	**1**	296	258	319	323	356	294
	2	386	322	320	322	386	364
	3	374	374	331	370	400	399
$£^{\beta}$	**1**	416	411	481	367	369	452
	2	375	414	486	385	437	430
	3	380	499	366	440	350	370

Table 12 Additional details for all i, j, t for 3P-3S-2T

	α	ψ	β	λ
Data flow rate	16	12	12	14
Delay time	360	300	480	120
No. of IoT devices	6	8	11	3
Truck_Vol = 3500				
B_S = 10,240				

Table 13 Cost & other details 3P-3S-2T for WML model

	i	t = 1	t = 2
€$^{\lambda}$	1	2	2
	2	2	2
	3	2	2
£$^{\lambda}$	1	178	170
	2	188	175
	3	190	185
Demand	1	265	425
	2	175	312
	3	290	180
PLC	1	280	450
	2	200	320
	3	300	190
Product volume	1	10	
	2	15	
	3	10	

Datasets: 3Product-3Supplier-4Time period (3P-3S-4T)

See Tables 14, 15, and 16.

Table 14 Cost & other details 3P-3S-4T

	i	t = 1	t = 2	t = 3	t = 4
€$^{\lambda}$	1	2	2	2	2
	2	2	2	2	2
	3	2	2	2	2
£$^{\lambda}$	1	178	170	180	175
	2	188	175	190	178
	3	190	185	188	182
Demand	1	265	425	550	700
	2	175	312	480	600
	3	290	180	390	450
PLC	1	280	450	600	810
	2	200	320	550	700
	3	300	190	450	590
Product volume	1	10			
	2	15			
	3	10			
Truck_Vol = 3500					
B_S = 10,240					

Table 15 Cost & supplier capacity for 3P-3S-4T

	i	j = 1				j = 2				j = 3			
		t = 1	t = 2	t = 3	t = 4	t = 1	t = 2	t = 3	t = 4	t = 1	t = 2	t = 3	t = 4
€$^{\alpha}$	1	80	85	90	75	90	88	80	84	78	70	77	95
	2	100	85	110	89	90	78	99	80	95	85	105	94
	3	90	80	100	56	58	57	70	65	85	95	60	88
€$^{\Psi}$	1	200	250	280	190	210	220	225	195	205	185	250	285
	2	190	150	180	180	150	170	165	175	185	195	200	160
	3	200	150	210	190	180	160	170	220	195	185	175	205
€$^{\beta}$	1	58	78	68	62	58	59	60	70	75	65	66	72
	2	50	60	90	70	77	75	80	85	81	84	75	65
	3	65	70	85	86	88	82	75	68	78	84	80	69
SC	1	265	195	250	480	550	390	250	410	150	320	310	333
	2	198	287	312	256	123	287	155	296	245	256	310	185
	3	555	350	129	451	146	188	169	197	247	312	651	250
£$^{\alpha}$	1	574	585	497	517	481	430	450	530	490	510	525	475
	2	418	570	371	406	351	430	400	550	502	485	470	465
	3	429	489	374	399	450	406	420	425	435	439	445	400
£$^{\Psi}$	1	296	258	319	323	356	294	275	310	290	300	295	305
	2	386	322	320	322	386	364	370	360	365	355	378	368
	3	374	374	331	370	400	399	380	386	376	396	388	392
£$^{\beta}$	1	416	411	481	367	369	452	444	432	396	426	388	408
	2	375	414	486	385	437	430	400	390	410	465	445	475
	3	380	499	366	440	350	370	480	470	450	455	390	410

Table 16 Additional details for all i, j, t for 3P-3S-4T

	α	ψ	β	λ
Data flow rate	16	12	12	14
Delay time	360	300	480	120
No. of IoT devices	6	8	11	3
Truck_Vol = 2500				
B_S = 10,240				

Datasets: 3Product-3Supplier-5Time period (3P-3S-5T)

See Tables 17, 18, and 19.

Table 17 Cost & supplier selection for 3P-3S-5T

	I	j = 1					j = 2					j = 3				
		t = 1	t = 2	t = 3	t = 4	t = 5	t = 1	t = 2	t = 3	t = 4	t = 5	t = 1	t = 2	t = 3	t = 4	t = 5
€$^{\alpha}$	1	80	85	90	75	90	88	88	92	79	92	96	87	68	75	96
	2	100	85	110	89	90	78	90	68	77	90	80	80	88	90	80
	3	90	80	100	56	58	57	85	65	75	90	90	90	90	60	75
€$^{\Psi}$	1	200	250	280	190	210	220	240	180	220	100	90	210	153	164	198
	2	190	150	180	180	150	170	190	180	240	90	200	180	150	210	190
	3	200	150	210	190	180	160	220	200	180	120	180	210	110	210	170
€$^{\beta}$	1	58	78	68	62	58	59	50	87	69	78	87	95	68	87	65
	2	50	60	90	70	77	75	120	100	98	110	85	98	96	86	106
	3	65	70	85	86	88	82	80	140	77	100	85	99	92	130	90
SC	1	265	195	250	480	550	390	300	250	158	310	159	198	254	305	288
	2	198	287	312	256	123	287	99	210	256	300	286	196	193	190	205
	3	555	350	129	451	146	188	203	199	187	252	190	290	150	170	92
£$^{\alpha}$	1	331	371	357	353	385	331	354	388	377	327	343	346	331	391	393
	2	388	374	352	390	362	339	392	386	392	342	345	376	373	398	382
	3	356	392	332	400	365	347	385	362	331	393	331	371	348	384	400
£$^{\Psi}$	1	270	271	257	265	297	300	295	298	250	290	280	264	299	295	300
	2	262	266	286	280	274	283	255	271	299	281	281	287	270	259	267
	3	258	263	299	271	276	292	265	296	272	251	285	276	283	299	278
£$^{\beta}$	1	464	487	492	476	475	457	453	477	500	475	455	487	485	453	455
	2	494	478	484	468	451	456	496	493	495	496	490	453	466	487	498
	3	486	490	488	459	500	499	489	452	478	467	493	494	476	451	454

Table 18 Cost & other details for 3P-3S-5T

	i	t = 1	t = 2	t = 3	t = 4	t = 5
$€^{\lambda}$	1	1	1	1	1	1
	2	2	2	2	2	2
	3	1	1	1	1	1
$£^{\lambda}$	1	136	140	148	150	145
	2	142	155	160	131	130
	3	166	178	170	168	165
Demand	1	265	425	295	190	320
	2	175	312	265	320	290
	3	290	180	215	255	145
PLC	1	300	450	350	250	350
	2	200	350	300	390	340
	3	330	290	260	280	200
Product volume	1	10				
	2	15				
	3	15				

Table 19 Additional details for all i, j, t for 3P-3S-5T

	α	ψ	β	λ
Data flow rate	16	12	12	14
Delay time	360	300	480	120
No. of IoT devices	6	8	11	3

Datasets: 3Product-3Supplier-7Time period (3P-3S-7T)

See Tables 20, 21 and 22.

Table 20 Cost & supplier capacity for 3P-3S-7T

	i	j = 1							j = 2							j = 3						
		t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7
€$^{\alpha}$	1	80	85	90	75	90	88	88	92	79	92	96	87	68	75	96	100	80	85	99	84	95
	2	100	85	110	89	90	78	90	68	77	90	80	80	88	90	80	105	110	90	91	88	91
	3	90	80	100	56	58	57	85	65	75	90	90	90	90	60	75	90	88	86	69	78	92
€$^{\Psi}$	1	200	250	280	190	210	220	240	180	220	100	90	210	153	164	198	250	200	210	120	190	160
	2	190	150	180	180	150	170	190	180	240	90	200	180	150	210	190	170	190	150	180	190	210
	3	200	150	210	190	180	160	220	200	180	120	180	210	110	210	170	200	210	240	210	180	160
€$^{\beta}$	1	58	78	68	62	58	59	50	87	69	78	87	95	68	87	65	95	87	88	89	86	84
	2	50	60	90	70	77	75	120	100	98	110	85	98	96	86	106	110	120	120	90	95	80
	3	65	70	85	86	88	82	80	140	77	100	85	99	92	130	90	90	98	85	75	95	85
SC	1	265	195	250	480	550	390	300	250	158	310	159	198	254	305	288	453	354	258	350	212	226
	2	198	287	312	256	123	287	99	210	256	300	286	196	193	190	205	190	260	190	165	190	220
	3	555	350	129	451	146	188	203	199	187	252	190	290	150	170	92	274	309	180	210	190	265
£$^{\alpha}$	1	331	371	357	353	385	331	354	388	377	327	343	346	331	391	393	377	399	344	390	365	335
	2	388	374	352	390	362	339	392	386	392	342	345	376	373	398	382	381	397	363	350	358	348
	3	356	392	332	400	365	347	385	362	331	393	331	371	348	384	400	360	394	356	344	338	359
£$^{\Psi}$	1	270	271	257	265	297	300	295	298	250	290	280	264	299	295	300	252	276	251	284	251	291
	2	262	266	286	280	274	283	255	271	299	281	281	287	270	259	267	273	254	281	277	263	268
	3	258	263	299	271	276	292	265	296	272	251	285	276	283	299	278	264	287	250	264	267	289
£$^{\beta}$	1	464	487	492	476	475	457	453	477	500	475	455	487	485	453	455	469	485	462	487	458	466
	2	494	478	484	468	451	456	496	493	495	496	490	453	466	487	498	461	471	467	457	478	459
	3	486	490	488	459	500	499	489	452	478	467	493	494	476	451	454	468	490	487	492	480	467

Table 21 Cost & other details for 3P-3S-7T

	i	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7
$€^{\lambda}$	1	1	1	1	1	1	1	1
	2	2	2	2	2	2	2	2
	3	1	1	1	1	1	1	1
$£^{\lambda}$	1	136	140	148	150	145	193	190
	2	142	155	160	131	130	170	168
	3	166	178	170	168	165	197	156
Demand	1	265	425	295	190	320	350	240
	2	175	312	265	320	290	285	150
	3	290	180	215	255	145	290	145
PLC	1	300	450	350	250	350	400	350
	2	200	350	300	390	340	355	224
	3	330	290	260	280	200	390	195
Product Volume	1	10						
	2	15						
	3	15						

Table 22 Additional details for all i, j, t for 3P-3S-7T

	α	ψ	β	λ
Data flow rate	16	12	12	14
Delay Time	360	300	480	120
No. of IoT devices	6	8	11	3
Truck_Vol = 2500				
B_S = 10,240				

Datasets: 3Product-3Supplier-11Time period (3P-3S-11T)

See Tables 23 and 24.

Table 23 Additional details for all i, j, t for 3P-3S-11T

	α	ψ	β	λ
Data flow rate	16	12	12	14
Delay time	360	300	480	120
No. of IoT devices	6	8	11	3
Truck_Vol = 2500				
B_S = 10,240				

Table 24 Cost & other details for 3P-3S-11T

	i	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10	t = 11
€$^{\lambda}$	1	1	1	1	1	1	1	1	1	1	1	1
	2	3	3	3	3	3	3	3	3	3	3	3
	3	2	2	2	2	2	2	2	2	2	2	2
£$^{\lambda}$	1	136	140	148	150	188	193	190	197	156	166	145
	2	142	155	160	131	160	170	168	175	163	144	130
	3	166	178	170	168	140	155	165	170	142	149	165
Demand	1	265	425	295	190	350	240	150	290	145	320	425
	2	175	312	265	320	285	150	140	165	110	290	325
	3	290	180	215	255	300	296	399	178	156	145	295
PLC	1	300	450	350	250	400	310	260	355	200	350	500
	2	200	350	300	390	370	280	270	220	210	340	395
	3	330	290	260	280	350	396	450	230	190	200	365
Product volume	1	10										
	2	15										
	3	15										

Appendix E: Only for WML-based mathematical model for all datasets

See Table 25.

Table 25 Authenticity variable value for all i, j, t

Procurement processes	Authenticity factor value
Purchasing process	1
Order process	1
Transportation process	1
Holding process	1

Appendix F: Dataset for ML-based model

Datasets: 3Product-3Supplier-2Time period (3P-3S-2T)

See Tables 26 and 27.

Table 26 Authenticity factor value for purchasing, ordering and transportation process for 3P-3S-2T dataset

I	j = 1		j = 2		j = 3	
	t = 1	t = 2	t = 1	t = 2	t = 1	t = 2
1	0.649955	1.6659841	1.1669474	1.220427	1.666169	1.109982
2	1.531575	1.3158848	0.6480281	1.429456	1.270128	1.641207
3	1.666242	1.6261438	1.4598217	1.663358	0.664907	0.665164

Table 27 Authenticity factor value for holding process for 3P-3S-2T dataset

i	t = 1	t = 2
1	1.049955	1.6659841
2	0.531575	1.3158848
3	1.666242	1.6261438

Datasets: 3Product-3Supplier-4Time period (3P-3S-4T)

See Tables 28 and 29.

Table 28 Authenticity factor value for holding process for 3P-3S-4T dataset

Product	t = 1	t = 2	t = 3	t = 4
1	1.049955	1.6659841	1.1669474	1.220427
2	1.531575	1.3158848	1.6480281	1.429456
3	1.666242	1.6261438	1.4598217	1.663358

Datasets: 3Product-3Supplier-5Time period (3P-3S-5T)

See Tables 30 and 31.

Table 29 Authenticity factor value for purchasing, ordering and transportation process for 3P-3S-4T dataset

i	j = 1				j = 2				j = 3			
	t = 1	t = 2	t = 3	t = 4	t = 1	t = 2	t = 3	t = 4	t = 1	t = 2	t = 3	t = 4
1	0.049955	1.6659841	1.1669474	1.220427	0.666169	1.109982	1.611582	1.4867895	1.3576461	1.6659841	1.6530367	1.650726
2	1.531575	1.3158848	1.6480281	1.429456	1.270128	1.641207	1.3158848	1.109982	1.6550148	1.3954604	1.1669474	1.6567076
3	1.666242	1.6261438	1.4598217	1.663358	1.664907	1.665164	1.5106171	1.549936	1.6448795	1.5920276	1.4598217	1.6613583

Table 30 Authenticity factor value for purchasing, ordering and transportation process for 3P-3S-5T dataset

i	j = 1					j = 2					j = 3				
	t = 1	t = 2	t = 3	t = 4	t = 5	t = 1	t = 2	t = 3	t = 4	t = 5	t = 1	t = 2	t = 3	t = 4	t = 5
1	1.665984	0.6659841	1.1669474	1.220427	0.666169	0.109982	1.611582	0.4867895	0.3576461	0.6659841	0.6530367	0.650726	0.109982	0.6194043	0.6657306
2	1.531575	0.3158848	0.6480281	0.429456	1.270128	1.641207	0.3158848	1.109982	0.6550148	0.3954604	0.1669474	0.6567076	1.5799169	0.6025163	1.109982
3	0.666242	0.6261438	0.4598217	0.663358	0.664907	0.665164	0.5106171	0.6448795	0.6448795	0.5920276	0.4598217	0.6613583	1.220427	0.660453	0.6660838

Table 31 Authenticity factor value for holding process for 3P-3S-5T dataset

i	t = 1	t = 2	t = 3	t = 4	t = 5
1	0.049955	1.6659841	1.1669474	0.220427	1.666169
2	1.531575	1.3158848	1.6480281	0.429456	1.270128
3	1.666242	0.6261438	1.4598217	1.663358	1.664907

Datasets: 3Product-3Supplier-7Time period (3P-3S-7T)

See Tables 32 and 33

Table 32 Authenticity factor value for holding process for 3P-3S-7T dataset

I	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7
1	0.049955	1.6659841	0.1669474	1.220427	1.666169	0.109982	0.611582
2	1.531575	0.3158848	0.6480281	1.429456	0.270128	0.641207	0.3158848
3	0.666242	1.6261438	0.4598217	1.663358	0.664907	0.665164	0.5106171

Datasets: 3Product-3Supplier-11Time period (3P-3S-11T)

See Tables 34 and 35

Table 33 Authenticity factor value for purchasing, ordering and transportation process for 3P-3S-7T dataset

	j = 1							j = 2						
i	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7
1	0.749955	0.6659841	1.1669474	1.220427	0.666169	0.109982	0.611582	0.4867895	1.3576461	1.6659841	0.6530367	0.650726	0.109982	0.6194043
2	0.531575	1.3158848	0.6480281	0.429456	0.270128	0.641207	0.3158848	0.109982	0.6550148	0.3954604	1.1669474	0.6567076	0.5799169	0.6025163
3	1.666242	1.6261438	0.4598217	0.663358	0.664907	1.665164	0.5106171	0.549936	0.6448795	0.5920276	0.4598217	0.6613583	0.220427	0.660453

	j = 3						
i	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7
1	1.6657306	0.3158848	0.6646056	0.1669474	0.220427	0.662132	1.5659655
2	0.109982	0.4598217	0.1669474	1.6655705	0.665383	0.2701282	1.4598217
3	0.6660838	0.6642533	0.5315752	0.3158848	0.109982	0.6593941	0.2701282;

Table 34 Authenticity factor value for holding process for 3P-3S-11T dataset

Product	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10	t = 11
1	0.049955	1.6659841	0.1669474	0.220427	0.666169	0.109982	0.611582	0.4867895	0.3576461	0.6659841	0.6530367
2	0.531575	0.3158848	0.6480281	0.429456	0.270128	1.641207	0.3158848	0.109982	0.6550148	0.3954604	1.1669474
3	0.666242	0.6261438	1.4598217	0.663358	0.664907	0.665164	0.5106171	0.549936	1.6448795	0.5920276	0.4598217

Table 35 Authenticity factor value for purchasing, ordering and transportation process for 3P-3S-11T dataset

i	j = 1										
	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10	t = 11
1	0.049955	1.6659841	0.1669474	1.220427	0.666169	0.109982	1.611582	1.4867895	0.3576461	0.6659841	0.6530367
2	1.531575	0.3158848	0.6480281	0.429456	1.270128	0.641207	0.3158848	1.109982	0.6550148	0.3954604	0.1669474
3	0.666242	0.6261438	0.4598217	1.663358	0.664907	0.665164	0.5106171	0.549936	0.6448795	0.5920276	0.4598217
i	j = 2										
	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10	t = 11
1	0.650726	0.709982	1.6194043	0.6657306	0.3158848	0.6646056	0.1669474	0.220427	0.662132	0.5659655	1.6530367
2	0.6567076	0.5799169	1.6025163	1.109982	0.4598217	0.1669474	0.6655705	0.665383	0.2701282	0.4598217	0.1669474
3	0.6613583	0.220427	0.660453	0.6660838	1.6642533	1.5315752	0.3158848	0.109982	0.6593941	0.2701282	0.4598217
i	j = 3										
	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10	t = 11
1	0.650726	0.220427	0.666169	0.109982	0.6194043	0.220427	0.662132	0.600562	0.5315752	0.0499546	0.6659841
2	0.6567076	1.4294559	0.2701282	0.5799169	0.6025163	0.665383	1.2701282	0.173279	1.6567076	0.5315752	0.3158848
3	0.6613583	0.6633582	0.6649065	0.220427	0.660453	0.109982	0.6593941	0.6593941	0.923026	0.6662417	0.626143

Appendix G: Detailed solutions for 3P-3S-4T, 3P-3S-5T, 3P-3S-7T, 3P-3S-11T datasets

See Tables 36, 37, 38, 39, 40, 41, 42 and 43.

Table 36 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-4T dataset through ML

3P-3S-4T								
T	i	Items	j = 1	j = 2	j = 3	D	N^{λ}	λ
t = 1	**i = 1**	$\boldsymbol{x}$	265			265	0	0
		N^{α}	4	**1**				
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β	**0**	**0**				
	i = 2	$\boldsymbol{x}$	175			175	0	0
		N^{α}	4					
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β						
	i = 3	$\boldsymbol{x}$	290			290	0	0
		N^{α}	4					
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β	1					
t = 2	**i = 1**	$\boldsymbol{x}$		105	320	425	0	0
		N^{α}		1	3			
		N^{Ψ}		3	3			
		N^{β}		7	7			
		α, Ψ, β		1	1			
	i = 2	$\boldsymbol{x}$	79	233		312	0	0
		N^{α}	1	3				
		N^{Ψ}	3	3				
		N^{β}	7	7				
		α, Ψ, β	1	1				
	i = 3	$\boldsymbol{x}$		180		180	**1**	**0**
		N^{α}		4				
		N^{Ψ}	**3**	3				
		N^{β}		7				
		α, Ψ, β	**0**	1				
t = 3	**i = 1**	$\boldsymbol{x}$		240	310	550	**1**	**0**
		N^{α}		2	2			
		N^{Ψ}		3	3			

Table 36 (continued)

3P-3S-4T								
T	i	Items	j = 1	j = 2	j = 3	D	N^{λ}	λ
		N^{β}		7	7			
		α, Ψ, β		1	1			
	i = 2	$\boldsymbol{x}$	196		284	480	0	0
		N^{α}	2		2			
		N^{Ψ}	3		3			
		N^{β}	7	**2**	13			
		α, Ψ, β	1	**0**	1			
	i = 3	$\boldsymbol{x}$			390	390	0	0
		N^{α}			4			
		N^{Ψ}			3			
		N^{β}		1	13			
		α, Ψ, β		**0**	1			
t = 4	**i = 1**	$\boldsymbol{x}$	350	350		700	0	0
		N^{α}	2	2				
		N^{Ψ}	3	3				
		N^{β}	7	7				
		α, Ψ, β	1	1				
	i = 2	$\boldsymbol{x}$	233	233	134	600	0	0
		N^{α}	2	2	1			
		N^{Ψ}	3	3	3			
		N^{β}	7	7	7			
		α, Ψ, β	1	1	1			
	i = 3	$\boldsymbol{x}$	350	100		450	0	0
		N^{α}	3	1				
		N^{Ψ}	3	3				
		N^{β}	7	7				
		α, Ψ, β	1	1				

$\alpha, \Psi, \beta =$ Standard authenticity variable for $\forall, i, j, t$..
$\lambda =$ Standard authenticity variable for $\forall, i, t$..

Table 37 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-4T dataset without ML

3P-3S-4T								
T	i	Items	j = 1	j = 2	j = 3	D	N^{λ}	λ
t = 1	**i = 1**	$\boldsymbol{x}$	265			265	0	1
		N^{α}	4					
		N^{Ψ}	3					

Table 37 (continued)

3P-3S-4T								
T	i	Items	j = 1	j = 2	j = 3	D	N^{λ}	λ
		N^{β}	7					
		α, Ψ, β	1					
	i = 2	$\boldsymbol{x}$	175			175	0	1
		N^{α}	4					
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β	1					
	i = 3	$\boldsymbol{x}$	290			290	0	1
		N^{α}	4					
		N^{Ψ}	3					
		N^{β}	7					
		α, Ψ, β	1					
t = 2	**i = 1**	$\boldsymbol{x}$		105	320	425	0	1
		N^{α}		1	3			
		N^{Ψ}		3	3			
		N^{β}		7	7			
		α, Ψ, β		1	1			
	i = 2	$\boldsymbol{x}$	79	233		312	0	1
		N^{α}	1	3				
		N^{Ψ}	3	3				
		N^{β}	7	7				
		α, Ψ, β	1	1				
	i = 3	$\boldsymbol{x}$		180		180	0	1
		N^{α}		4				
		N^{Ψ}		3				
		N^{β}		7				
		α, Ψ, β		1				
t = 3	**i = 1**	$\boldsymbol{x}$		240	310	550	0	1
		N^{α}		2	2			
		N^{Ψ}		3	3			
		N^{β}		7	7			
		α, Ψ, β		1	1			
	i = 2	$\boldsymbol{x}$	196		284	480	0	1
		N^{α}	2		2			
		N^{Ψ}	3		3			
		N^{β}	7		13			
		α, Ψ, β	1		1			
	i = 3	$\boldsymbol{x}$			390	390	0	1
		N^{α}			4			

Table 37 (continued)

3P-3S-4T								
T	i	Items	j = 1	j = 2	j = 3	D	N^{λ}	λ
		N^{Ψ}			3			
		N^{β}			13			
		α, Ψ, β			1			
t = 4	**i = 1**	$\boldsymbol{x}$	350	350		700	0	1
		N^{α}	2	2				
		N^{Ψ}	3	3				
		N^{β}	7	7				
		α, Ψ, β	1	1				
	i = 2	$\boldsymbol{x}$	233	233	134	600	0	1
		N^{α}	2	2	1			
		N^{Ψ}	3	3	3			
		N^{β}	7	7	7			
		α, Ψ, β	1	1	1			
	i = 3	$\boldsymbol{x}$	350	100		450	0	1
		N^{α}	3	1				
		N^{Ψ}	3	3				
		N^{β}	7	7				
		α, Ψ, β	1	1				

$\alpha, \Psi, \beta =$ Standard authenticity variable for $\forall, i, j, t$..
$\lambda =$ Standard authenticity variable for $\forall, i, t$..

Table 38 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-5T dataset through ML

3P-3S-4T								
t	I	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 1	**i = 1**	x		265		265	0/1	0
		N_{ijt}^{α}	1	4	1			
		N_{ijt}^{Ψ}	1	3				
		N_{ijt}^{β}	2	13				
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x			175	175		
		N_{ijt}^{α}	1		4			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}	2		13			
		α, Ψ, β	**0**		**0**			

Table 38 (continued)

3P-3S-4T								
t	I	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
	i = 3	x	124	166		290		
		N_{ijt}^{α}	2	3	1			
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	13				
		α, Ψ, β	**0**	**0**	**0**			
t = 2	**i = 1**	x		227	198	425	0/1	1
		N_{ijt}^{α}		2	2			
		N_{ijt}^{Ψ}	3	3	3			
		N_{ijt}^{β}	6	7	7			
		α, Ψ, β	**0**	**1**	**0**			
	i = 2	x	146		166	312		
		N_{ijt}^{α}	2	1	2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x	166		63	180	49/1	0
		N_{ijt}^{α}	5	1	2			
		N_{ijt}^{Ψ}	**3**	1	3			
		N_{ijt}^{β}	7	2	7			
		α, Ψ, β	**0**	**0**	**0**			
t = 3	**i = 1**	x		45	250	295		
		N_{ijt}^{α}	1	1	3			
		N_{ijt}^{Ψ}	1	3	3			
		N_{ijt}^{β}	3	7	7			
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x	265			265	0/1	1
		N_{ijt}^{α}	4	1	1			
		N_{ijt}^{Ψ}	3		1			
		N_{ijt}^{β}	13	**3**	2			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x		166		215		
		N_{ijt}^{α}		3				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		7				

Table 38 (continued)

3P-3S-4T

t	I	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		α, Ψ, β		**0**				
t = 4	**i = 1**	x			220	190	30/1	0
		N_{ijt}^{α}		1	4			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			7			
		α, Ψ, β		**0**	**0**			
	i = 2	x	154	166		320	0/1	0
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3	3			
		N_{ijt}^{β}	7	7	6			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x		89	166	255		
		N_{ijt}^{α}		2	3			
		N_{ijt}^{Ψ}	2	3	3			
		N_{ijt}^{β}	6	7	7			
		α, Ψ, β	**0**	**0**	**0**			
t = 5	**i = 1**	x	290			320		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13		1			
		α, Ψ, β	**0**		**0**			
	i = 2	x		290		290		
		N_{ijt}^{α}		4				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		13				
		α, Ψ, β		**0**				
	i = 3	x	145			145		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7	1	1			
		α, Ψ, β	**0**	**0**	**0**			

$\alpha, \Psi, \beta =$ Standard authenticity variable for $\forall, i, j, t$..
$\lambda =$ Standard authenticity variable for $\forall, i, t$..

Table 39 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-5T dataset without ML

3P-3S-5T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 1	**i = 1**	x	265			265		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	1					
	i = 2	x	20	155		175		
		N_{ijt}^{α}	1	3				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	1	1				
	i = 3	x	310			290	20/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	1					
t = 2	**i = 1**	x	195	230		425		
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	1	1				
	i = 2	x	146		166	312		
		N_{ijt}^{α}	2		2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	1		1			
	i = 3	x	225			180	65/1	1
		N_{ijt}^{α}	5					
		N_{ijt}^{Ψ}	**3**					
		N_{ijt}^{β}	13					
		α, Ψ, β	1					

Table 39 (continued)

3P-3S-5T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 3	**i = 1**	x	57		250	295	12/1	1
		N_{ijt}^{α}	1		3			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	1		1			
	i = 2	x		157	108	265		
		N_{ijt}^{α}		2	2			
		N_{ijt}^{Ψ}		3	3			
		N_{ijt}^{β}		**7**	7			
		α, Ψ, β		1	1			
	i = 3	x			150	215		
		N_{ijt}^{α}			3			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			7			
		α, Ψ, β			1			
t = 4	**i = 1**	x	214			190	36/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	1					
	i = 2	x	166		155	320	1/1	1
		N_{ijt}^{α}	2		2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	1		1			
	i = 3	x	255			255		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	1					
t = 5	**i = 1**	x	284			320		

Table 39 (continued)

3P-3S-5T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		N_{ijt}^{α}	3					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	1					
	i = 2	x	123		166	290		
		N_{ijt}^{α}	2		2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	1		1			
	i = 3	x	145			145		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	1					

$\alpha, \Psi, \beta =$ Standard authenticity variable for $\forall, i, j, t$..
$\lambda =$ Standard authenticity variable for $\forall, i, t$..

Table 40 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-7T dataset through ML

3P-3S-7T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 1	**i = 1**	x	250	32		265	17/1	0
		N_{ijt}^{α}	4	4				
		N_{ijt}^{Ψ}	3	3	1			
		N_{ijt}^{β}	7	7	1			
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x	179			175	4/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3	1				
		N_{ijt}^{β}	13					
		α, Ψ, β	**0**	**0**				

Table 40 (continued)

3P-3S-7T

t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
	i = 3	x	290			290	0/1	0
		N_{ijt}^{α}	4	1				
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**	**0**				
t = 2	**i = 1**	x	195		220	425	7/1	1
		N_{ijt}^{α}	2		2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	**0**		**0**			
	i = 2	x	163	166		312	21/1	0
		N_{ijt}^{α}	2	2	1			
		N_{ijt}^{Ψ}	3	3	1			
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**0**	**0**			
	i = 3	x		160	20	180	0/1	0
		N_{ijt}^{α}	1	3	1			
		N_{ijt}^{Ψ}	1	3	3			
		N_{ijt}^{β}	2	7	7			
		α, Ψ, β	**0**	**0**	**0**			
t = 3	**i = 1**	x	69		250	295	31/1	0
		N_{ijt}^{α}	1		3			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	**1**		**0**			
	i = 2	x	272			265	28/1	0
		N_{ijt}^{α}	4	1	1			
		N_{ijt}^{Ψ}	3	1				
		N_{ijt}^{β}	13	**4**				
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x	58		166	215	9/1	0
		N_{ijt}^{α}	1		3			
		N_{ijt}^{Ψ}	3	1	3			
		N_{ijt}^{β}	7		7			

Table 40 (continued)

3P-3S-7T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		α, Ψ, β	**0**	**0**	**0**			
t = 4	**i = 1**	x		159		190		
		N_{ijt}^{α}	2	3	1			
		N_{ijt}^{Ψ}	0	3	1			
		N_{ijt}^{β}	2	7	2			
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x	166	166		320	40/1	1
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**0**	**1**				
	i = 3	x	151	112		255	17/1	1
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3	1			
		N_{ijt}^{β}	7	7	3			
		α, Ψ, β	**0**	**0**	**0**			
t = 5	**i = 1**	x	320			320		
		N_{ijt}^{α}	4	1	1			
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x	85		165	290	0/1	0
		N_{ijt}^{α}	1	2	2			
		N_{ijt}^{Ψ}	3	3	3			
		N_{ijt}^{β}	7	5	7			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x	128			145		
		N_{ijt}^{α}	3	1	4			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		6			
		α, Ψ, β	**0**	**0**	**0**			

Table 40 (continued)

3P-3S-7T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 6	**i = 1**	x	375			350	25/1	0
		N_{ijt}^{α}	4	3	1			
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	13	6				
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x	166	119		285	0/1	0
		N_{ijt}^{α}	2	2	1			
		N_{ijt}^{Ψ}	3	3	2			
		N_{ijt}^{β}	7	7	3			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x	166	124		290	0/1	0
		N_{ijt}^{α}	2	2	1			
		N_{ijt}^{Ψ}	3	3	3			
		N_{ijt}^{β}	7	7	4			
		α, Ψ, β	**1**	**0**	**0**			
t = 7	**i = 1**	x			215	240	0/1	0
		N_{ijt}^{α}	4		4			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	**0**		**1**			
	i = 2	x		150		150	0/1	0
		N_{ijt}^{α}		4				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		7				
		α, Ψ, β		**0**				
	i = 3	x	145			145	0/1	0
		N_{ijt}^{α}	4	1	1			
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**0**	**0**	**0**			

α, Ψ, β = Standard authenticity variable for $\forall, i, j, t$..
λ = Standard authenticity variable for $\forall, i, t$..

Table 41 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-7T dataset without ML

3P-3S-7T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 1	**i = 1**	x	235		47	265	17/1	1
		N_{ijt}^{α}	3		1			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	**1**		**1**			
	i = 2	x	175			175		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
	i = 3	x	306			290	16/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
t = 2	**i = 1**	x		158	250	425		
		N_{ijt}^{α}		2	2			
		N_{ijt}^{Ψ}		3	3			
		N_{ijt}^{β}		7	7			
		α, Ψ, β		**1**	**1**			
	i = 2	x	165	166		312	19/1	1
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 3	x	213			180	49/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					

Table 41 (continued)

3P-3S-7T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 3	**i = 1**	x	250	57		295	12/1	1
		N_{ijt}^{α}	3	1				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 2	x	246			265		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
	i = 3	x			166	215		
		N_{ijt}^{α}			3			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			7			
		α, Ψ, β			**1**			
t = 4	**i = 1**	x	214			190	36/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
	i = 2	x	166	166		320	12/1	1
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 3	x	267			255	12/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
t = 5	**i = 1**	x	284			320		
		N_{ijt}^{α}	3					

Table 41 (continued)

3P-3S-7T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
	i = 2	x	123		155	290		
		N_{ijt}^{α}	2		2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	**1**		**1**			
	i = 3	x			166	145	33/1	1
		N_{ijt}^{α}			4			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			7			
		α, Ψ, β			**0**			
t = 6	**i = 1**	x	100	250		350		
		N_{ijt}^{α}	1	3				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 2	x	285			285		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
	i = 3	x	166		157	290	66/1	1
		N_{ijt}^{α}	2		2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	**1**		**0**			
t = 7	**i = 1**	x	240			240		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					

Table 41 (continued)

3P-3S-7T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
	i = 2	x			150	150		
		N_{ijt}^{α}			4			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			7			
		α, Ψ, β			**1**			
	i = 3	x	79			145		
		N_{ijt}^{α}	2					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					

α, Ψ, β = Standard authenticity variable for $\forall, i, j, t$..
λ = Standard authenticity variable for $\forall, i, t$..

Table 42 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-4T dataset through ML

3P-3S-11T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 1	**i = 1**	x	235	30		265	0/1	0
		N_{ijt}^{α}	3	1	1			
		N_{ijt}^{Ψ}	3	3	1			
		N_{ijt}^{β}	7	7	2			
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x			187	175	12/1	0
		N_{ijt}^{α}	2	2	4			
		N_{ijt}^{Ψ}	2		3			
		N_{ijt}^{β}	4	3	13			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x	310			290	20/1	0
		N_{ijt}^{α}	4	1	1			
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**0**	**0**	**0**			

Table 42 (continued)

3P-3S-11T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 2	**i = 1**	x	175	250		425		
		N_{ijt}^{α}	2	2	1			
		N_{ijt}^{Ψ}	3	3	3			
		N_{ijt}^{β}	7	7	4			
		α, Ψ, β	**1**	**0**	**0**			
	i = 2	x	166	158		312	24/1	0
		N_{ijt}^{α}	4	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**0**	**0**				
	i = 3	x	166			180	6/1	0
		N_{ijt}^{α}	4	1	1			
		N_{ijt}^{Ψ}	3		1			
		N_{ijt}^{β}	7		3			
		α, Ψ, β	**0**	**0**	**0**			
t = 3	**i = 1**	x		305		295	10/1	0
		N_{ijt}^{α}	3	4				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	13				
		α, Ψ, β	**0**	**1**				
	i = 2	x		157	113	265	29/1	0
		N_{ijt}^{α}	1	2	2			
		N_{ijt}^{Ψ}	1	3	3			
		N_{ijt}^{β}	1	**7**	7			
		α, Ψ, β	**0**	**1**	**0**			
	i = 3	x			209	215		
		N_{ijt}^{α}	1	1	4			
		N_{ijt}^{Ψ}		1	3			
		N_{ijt}^{β}		2	13			
		α, Ψ, β	**0**	**0**	**0**			
t = 4	**i = 1**	x	215			190	35/1	0
		N_{ijt}^{α}	4		1			

Table 42 (continued)

3P-3S-11T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**		**0**			
	i = 2	x	166		125	320	0/1	0
		N_{ijt}^{α}	2		2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7	1	7			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x			255	255	0/1	0
		N_{ijt}^{α}	2	1	4			
		N_{ijt}^{Ψ}	2		3			
		N_{ijt}^{β}	6		13			
		α, Ψ, β	**0**	**0**	**0**			
t = 5	**i = 1**	x	357			350	42/1	0
		N_{ijt}^{α}	4	1	1			
		N_{ijt}^{Ψ}	3	1				
		N_{ijt}^{β}	13	2				
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x	123	166		285	4/1	0
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7	1			
		α, Ψ, β	**1**	**0**	**0**			
	i = 3	x	146	161		300	7/1	0
		N_{ijt}^{α}	2	2	3			
		N_{ijt}^{Ψ}	3	3	1			
		N_{ijt}^{β}	7	7	2			
		α, Ψ, β	**0**	**1**	**0**			
t = 6	**i = 1**	x			198	240	0/1	0
		N_{ijt}^{α}	3	1	3			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	6	1	7			
		α, Ψ, β	**0**	**0**	**0**			

Table 42 (continued)

3P-3S-11T

t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
	i = 2	x	133	13		150		
		N_{ijt}^{α}	3	1				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**0**	**0**				
	i = 3	x	166		166	296	43/1	0
		N_{ijt}^{α}	2	2	2			
		N_{ijt}^{Ψ}	3	2	3			
		N_{ijt}^{β}	7	5	7			
		α, Ψ, β	**0**	**0**	**0**			
t = 7	**i = 1**	x		204	1	150	55/1	0
		N_{ijt}^{α}		5	1			
		N_{ijt}^{Ψ}		3	3			
		N_{ijt}^{β}		7	7			
		α, Ψ, β		**0**	**0**			
	i = 2	x		159		140	19/1	0
		N_{ijt}^{α}	1	4	2			
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		7	4			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x		166	210	399	20/1	0
		N_{ijt}^{α}	2	2	2			
		N_{ijt}^{Ψ}	2	3	3			
		N_{ijt}^{β}	6	7	13			
		α, Ψ, β	**0**	**0**	**0**			
t = 8	**i = 1**	x		236		290	1/1	0
		N_{ijt}^{α}	1	3	1			
		N_{ijt}^{Ψ}	1	3				
		N_{ijt}^{β}	1	7				
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x			146	165	0/1	0
		N_{ijt}^{α}			3			
		N_{ijt}^{Ψ}	**3**		3			
		N_{ijt}^{β}			7			

Table 42 (continued)

3P-3S-11T

t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		α, Ψ, β	**1**		**0**			
	i = 3	x		158		178	0/1	0
		N_{ijt}^{α}		3				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		7				
		α, Ψ, β		**0**				
t = 9	**i = 1**	x		172		145	28/1	0
		N_{ijt}^{α}	3	5	1			
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	6	7				
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x	160			110	50/1	0
		N_{ijt}^{α}	5					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**0**					
	i = 3	x	156			156	0/1	0
		N_{ijt}^{α}	4	1	1			
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**0**	**0**	**0**			
t = 10	**i = 1**	x			321	320	29/1	0
		N_{ijt}^{α}	3	1	4			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	6		13			
		α, Ψ, β	**0**	**0**	**0**			
	i = 2	x	85		166	290	11/1	0
		N_{ijt}^{α}	1	2	2			
		N_{ijt}^{Ψ}	3	2	3			
		N_{ijt}^{β}	7	6	7			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x		145		145		
		N_{ijt}^{α}	1	4				
		N_{ijt}^{Ψ}		3				

Table 42 (continued)

3P-3S-11T								
t	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		N_{ijt}^{β}		7				
		α, Ψ, β	**0**	**0**				
t = 11	**i = 1**	x	154	242		425	0/1	0
		N_{ijt}^{α}	2	2	1			
		N_{ijt}^{Ψ}	3	3	2			
		N_{ijt}^{β}	7	7	5			
		α, Ψ, β	**0**	**1**	**0**			
	i = 2	x		148	166	325		
		N_{ijt}^{α}	3	2	2			
		N_{ijt}^{Ψ}		3	3			
		N_{ijt}^{β}	6	7	7			
		α, Ψ, β	**0**	**0**	**0**			
	i = 3	x		166	129	295	0/1	0
		N_{ijt}^{α}	1	2	2			
		N_{ijt}^{Ψ}	1	3	3			
		N_{ijt}^{β}	3	7	7			
		α, Ψ, β	**0**	**0**	**0**			

$\alpha, \Psi, \beta =$ Standard authenticity variable for $\forall, i, j, t$..
$\lambda =$ Standard authenticity variable for $\forall, i, t$..

Table 43 Optimally supplier selection and produced blocks for order allocation for the 3P-3S-4T dataset without ML

3P-3S-11T								
T	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
t = 1	**i = 1**	x	265			265		
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
	i = 2	x	179			175	4/1	1
		N_{ijt}^{α}	4					

Table 43 (continued)

3P-3S-11T								
T	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
	i = 3	x	308			290	18/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
t = 2	**i = 1**	x	175	250		425		
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 2	x	166		163	312	21/1	1
		N_{ijt}^{α}	2		2			
		N_{ijt}^{Ψ}	3		3			
		N_{ijt}^{β}	7		7			
		α, Ψ, β	**1**		**1**			
	i = 3	x	226			180	64/1	1
		N_{ijt}^{α}	5					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
t = 3	**i = 1**	x	45	250		295		
		N_{ijt}^{α}	1	3				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 2	x		166	78	265		
		N_{ijt}^{α}		3	1			
		N_{ijt}^{Ψ}		3	3			
		N_{ijt}^{β}		**7**	7			
		α, Ψ, β		**1**	**1**			
	i = 3	x		166		215	15/1	1

Table 43 (continued)

3P-3S-11T								
T	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		N_{ijt}^{α}		3				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		7				
		α, Ψ, β		**1**				
t = 4	**i = 1**	x	220			190	30/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
	i = 2	x	166	166		320	12/1	1
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 3	x	260			255	20/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
t = 5	**i = 1**	x	352			350	32/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					
		α, Ψ, β	**1**					
	i = 2	x	123	164		285	14/1	1
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 3	x	146	166		300	32/1	1
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				

Table 43 (continued)

3P-3S-11T

T	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		α, Ψ, β	**1**	**1**				
t = 6	**i = 1**	x	250			240	42/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
	i = 2	x	166			150	30/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
	i = 3	x	166	164		296	66/1	1
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
t = 7	**i = 1**	x	177			150	69/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
	i = 2	x			165	140	55/1	1
		N_{ijt}^{α}			4			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			7			
		α, Ψ, β			**1**			
	i = 3	x		333		399		
		N_{ijt}^{α}		3				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		13				
		α, Ψ, β		**1**				
t = 8	**i = 1**	x	250			290	29/1	1

Table 43 (continued)

3P-3S-11T								
T	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		N_{ijt}^{α}	3					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
	i = 2	x	165			165	55/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
	i = 3	x		204		178	26/1	1
		N_{ijt}^{α}		4				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		13				
		α, Ψ, β		**1**				
t = 9	**i = 1**	x	158			145	42/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
	i = 2	x			130	110	75/1	1
		N_{ijt}^{α}			4			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			7			
		α, Ψ, β			**1**			
	i = 3	x	160			156	30/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	7					
		α, Ψ, β	**1**					
t = 10	**i = 1**	x	310			320	32/1	1
		N_{ijt}^{α}	4					
		N_{ijt}^{Ψ}	3					
		N_{ijt}^{β}	13					

Table 43 (continued)

3P-3S-11T								
T	i	Items	j = 1	j = 2	j = 3	**D**	Inv/N_{it}^{λ}	λ
		α, Ψ, β	**1**					
	i = 2	x		220		290	5/1	1
		N_{ijt}^{α}		3				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		13				
		α, Ψ, β		**1**				
	i = 3	x		157		145	42/1	1
		N_{ijt}^{α}		4				
		N_{ijt}^{Ψ}		3				
		N_{ijt}^{β}		7				
		α, Ψ, β		**1**				
t = 11	**i = 1**	x	151	242		425		
		N_{ijt}^{α}	2	2				
		N_{ijt}^{Ψ}	3	3				
		N_{ijt}^{β}	7	7				
		α, Ψ, β	**1**	**1**				
	i = 2	x			320	325		
		N_{ijt}^{α}			4			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			13			
		α, Ψ, β			**1**			
	i = 3	x			253	295		
		N_{ijt}^{α}			3			
		N_{ijt}^{Ψ}			3			
		N_{ijt}^{β}			13			
		α, Ψ, β			**1**			

Appendix H: ML dataset & results

See Figs. 5 and 6

```
In [1]: import numpy as np
        import pulp as p
        import pandas as pd
        import scipy
        import matplotlib.pyplot as plt
        from sklearn import linear_model
        from sklearn.metrics import mean_squared_error
        from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import classification_report, confusion_matrix
        df =pd.read_excel(r'C:\Users\esha\Desktop\yadavji.xlsx')

In [3]: df

Out[3]:
```

	serialnumber	total strength	percnt	green	red	value
0	1	64	11	7	57	0
1	2	168	6	10	158	0
2	3	101	49	49	52	0
3	4	157	21	33	124	0
4	5	68	37	25	43	0
...	...	...	...	...	...	...
95	96	196	8	16	180	0
96	97	83	94	78	5	1
97	98	76	52	40	36	1
98	99	39	83	32	7	1
99	100	182	56	102	80	1

100 rows × 6 columns

```
In [5]: x=  df[["green","red"]]
        y= df[["value"]]

In [6]: import statsmodels.api as sm

In [7]: x1= sm.add_constant (x)
```

Fig. 5 Formation of ML model

```
In [5]: x=  df[["green","red"]]
        y= df[["value"]]

In [6]: import statsmodels.api as sm

In [7]: x1= sm.add_constant (x)

In [8]: logit_model= sm.Logit (y, x1)

In [9]: result= logit_model.fit()

        Optimization terminated successfully.
                 Current function value: 0.217678
                 Iterations 9

In [10]: print(result.summary2())

                              Results: Logit
        =================================================================
        Model:              Logit            Pseudo R-squared: 0.686
        Dependent Variable: value            AIC:              49.5356
        Date:               2020-10-22 15:54 BIC:              57.3511
        No. Observations:   100              Log-Likelihood:   -21.768
        Df Model:           2                LL-Null:          -69.235
        Df Residuals:       97               LLR p-value:      2.4288e-21
        Converged:          1.0000           Scale:            1.0000
        No. Iterations:     9.0000
        -------------------------------------------------------------------
                   Coef.    Std.Err.      z      P>|z|    [0.025   0.975]
        -------------------------------------------------------------------
        const     0.7641     0.7036    1.0860   0.2775   -0.6149   2.1432
        green     0.0751     0.0193    3.8815   0.0001    0.0372   0.1130
        red      -0.0829     0.0206   -4.0278   0.0001   -0.1233  -0.0426
        =================================================================
```

Fig. 6 Significance testsss

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