Cost Optimization of Blockchain-enabled Supply Chain System

by

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Optimisation des coûts du système de chaîne d'approvisionnement basé sur la blockchain

Hossein HAVAEJI

RÉSUMÉ

Le système de chaîne d'approvisionnement basé sur la technologie Blockchain (SCS compatible BT) promet de fournir des transactions fiables, des opérations mieux gérées et une traçabilité. SCS activé par BT est le système utilisant BT pour améliorer la transparence, la sécurité, la durabilité et l'intégrité des processus de SC. De plus, une chaîne d'approvisionnement pharmaceutique (PSC) est un système de processus, d'opérations et d'organisations de distribution de médicaments. La BT compatible PSC peut permettre au système de partager des informations médicales entre les systèmes, de suivre les médicaments, de surveiller la PSC de manière sûre et transparente, de réduire les retards et les erreurs humaines et d'améliorer la stabilité, la sûreté et la sécurité du système.

Cette thèse vise à concevoir un modèle de coût mathématique pour SCS compatible BT, qui pourrait aider certaines entreprises qui évaluent les coûts de BT en tant que base de données principale dans leur système SC. Le deuxième objectif est de minimiser les coûts du modèle SCS compatible BT conçu grâce à des algorithmes de calcul évolutif (EC) (CS/ACO/GA) en tant que techniques d'optimisation. Nous avons donc identifié les éléments de coût du SCS activé par BT sur la base de l'examen de la littérature connexe. Le troisième objectif de la thèse est d'estimer les coûts du modèle PSC basé sur BT, de sélectionner des algorithmes d'apprentissage supervisé évolutif avec des erreurs de prédiction minimales, d'attribuer des poids appropriés à tous les composants du modèle de coût et de déterminer les composants de coût du modèle PSC basé sur BT. Cette étude fournit un nouveau modèle de coût mathématique PSC, qui inclut BT, qui peut améliorer la sécurité, les performances et la transparence du partage d'informations médicales dans un système de santé. Le quatrième objectif de cette thèse est de déterminer le ou les algorithmes d'apprentissage supervisé évolutif les plus fiables avec un minimum d'erreurs de prédiction, d'estimer les coûts du modèle PSC basé sur BT en cas de

demande incertaine, de déterminer les composantes de coût du modèle multifonctionnel et révéler l'importance de chaque élément de coût.

Pour générer des données brutes pour le modèle SCS compatible BT, les auteurs ont révisé le modèle de recherche opérationnelle et le modèle de gestion des stocks et ont appliqué le logiciel Python pour la génération de données. Le logiciel Python nous aide également à générer des données brutes pour le modèle de coût PSC basé sur BT et le modèle de coût PSC multifonctionnel compatible BT en cas de demande incertaine. Pour atteindre ces objectifs, nous avons combiné quatre algorithmes d'apprentissage supervisé (KNN, DT, SVM et NB) avec deux algorithmes EC pour le modèle de coût PSC basé sur BT et le modèle de coût PSC multifonctionnel compatible BT sous une demande incertaine. Nous avons appliqué les algorithmes ACO et FA pour le modèle de coût PSC basé sur BT et les algorithmes PSO et HS pour le modèle de coût PSC multifonctionnel compatible BT en cas de demande incertaine. Les auteurs ont également utilisé l'approche de pondération des caractéristiques pour attribuer des pondérations appropriées à tous les composants du modèle de coût, révélant ainsi leur importance. Quatre mesures de performance ont été utilisées pour évaluer le modèle de coût, et le Score de classement total (Total Ranking Score-TRS) a été utilisé pour déterminer les algorithmes prédictifs les plus fiables.

En comparant les algorithmes CS/ACO/GA, les meilleures solutions pour le modèle de coût SCS compatible BT sont CS et ACO avec le TRS le plus élevé (noté par MSE, RMSE et ROC), suivi par GA debout dans la deuxième étape. Nos résultats montrent que les algorithmes ACO-NB et FA-NB fonctionnent mieux que les six autres algorithmes pour estimer les coûts du modèle de coût PSC basé sur BT avec des erreurs plus faibles, tandis que ACO-DT et FA-DT affichent les pires performances. Les résultats indiquent également que la pénurie, la conservation et les coûts des médicaments périmés influencent plus fortement le modèle de coût que les autres composantes de coût. Les résultats indiquent également que les algorithmes HS-NB et PSO-NB surpassent les six autres algorithmes dans l'estimation des coûts du modèle PSC multifonctionnel compatible BT en cas de demande incertaine avec des erreurs moindres.

Les résultats montrent également que le coût des matières premières a une plus grande influence sur le modèle multifonctionnel que les autres composants.

Mots-clés: Chaîne d'approvisionnement pharmaceutique compatible avec la chaîne de blocs, Système de chaîne d'approvisionnement compatible avec la chaîne de blocs, Algorithmes d'apprentissage supervisé, Algorithmes de calcul évolutif, Technologie de la chaîne de blocs, Demande incertaine

COST OPTIMIZATION OF BLOCKCHAIN-ENABLED SUPPLY CHAIN SYSTEM

Hossein HAVAEJI

ABSTRACT

Blockchain Technology-enabled Supply Chain System (BT-enabled SCS) promises to provide trustworthy transactions, better-managed operations, and traceability. BT-enabled SCS is the system using BT to improve the transparency, security, and process integrity of SC. Moreover, a Pharmaceutical Supply Chain (PSC) is a system of drug delivery processes, operations, and organisations. BT-enabled PSC may enable the system to share medical information between systems, track drugs, monitor PSC safely and transparently, reduce delays and human errors, and improve the system's stability, safety, and security.

This thesis aims to design a mathematical cost model for BT-enabled SCS, which may assist some companies that evaluate the costs of BT as the main database in their SC system. The second purpose is to minimize the costs of the designed BT-enabled SCS model through Evolutionary Computation (EC) algorithms (CS/ACO/GA) as optimization techniques. We, therefore, identified the cost components of BT-enabled SCS based on the related literature review. The third objective of the thesis is to estimate the costs of the BT-based PSC model, select Evolutionary Supervised Learning algorithms with minimum prediction errors, assign appropriate weights to all cost model components, and determine the cost components of the BT-based PSC model. This study provides a new PSC mathematical cost model, which includes BT, that can improve the safety, performance, and transparency of medical information sharing in a healthcare system. The fourth purpose of this thesis is to determine the most reliable Evolutionary Supervised Learning algorithm(s) with minimum prediction errors, estimate the costs of the BT-based PSC model under uncertain demand, determine the cost components of the multi-function model, and reveal the importance of each cost component.

To generate raw data for the BT-enabled SCS model, the authors revised the Operations Research model and Inventory Management model and applied Python software for data generation. Python software also helps us generate raw data for the BT-based PSC cost model and the multi-function BT-enabled PSC cost model under uncertain demand. To reach these goals, we combined four Supervised Learning algorithms (KNN, DT, SVM, and NB) with two EC algorithms for the BT-based PSC cost model and the multi-function BT-enabled PSC cost model under uncertain demand. We applied ACO and FA algorithms for the BT-based PSC cost model and PSO and HS algorithms for the multi-function BT-enabled PSC cost model under uncertain demand. The authors also used the Feature Weighting approach to assign appropriate weights to all cost model components, revealing their importance. Four performance metrics were used to evaluate the cost model, and the Total Ranking Score (TRS) was used to determine the most reliable predictive algorithms.

Comparing CS/ACO/GA algorithms, the best solutions for the BT-enabled SCS cost model are CS and ACO with the higher TRS (scored by MSE, RMSE, and ROC), followed by GA standing in the second step. Our findings show that the ACO-NB and FA-NB algorithms perform better than the other six algorithms in estimating the costs of the BT-based PSC cost model with lower errors, whereas ACO-DT and FA-DT show the worst performance. The findings also indicate that the shortage, holding, and expired medication costs more strongly influence the cost model than other cost components. The results also indicate that the HS-NB and PSO-NB algorithms outperform the other six algorithms in estimating the costs of the multi-function BT-enabled PSC model under uncertain demand with lower errors. The findings also illustrate that the Raw Materials cost has a stronger influence on the multi-function model than other components.

Keywords: Blockchain-enabled Pharmaceutical Supply Chain, Blockchain-enabled Supply Chain System, Supervised Learning algorithms, Evolutionary Computation algorithms, Blockchain Technology, Uncertain Demand

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LIST OF ABREVIATIONS

SCS	Supply Chain System
BT	Blockchain Technology
PSC	Pharmaceutical Supply Chain
EC	Evolutionary Computation
CS	Cuckoo Search
GA	Genetic Algorithm
ACO	Ant Colony Optimization
FA	Firefly Algorithm
HS	Harmony Search
PSO	Particle Swarm Optimization
SL	Supervised Learning
KNN	K-Nearest-Neighbors
DT	Decision Tree
SVM	Support Vector Machine
NB	Naive Bayes
TRS	Total Ranking Score
MSE	Mean Square Error
RMS	Root Mean Square Error
AUC	Area Under the ROC Curve
ROC	Receiver Operating Characteristic
ANFIS	Adaptive Network-based Fuzzy Inference System
NARX	Nonlinear AutoRegressive eXogenous
MATLAB	Matrix Laboratory
FW	Feature Weighting
MAE	Mean Absolute Error
BT-enabled SCS	Blockchain Technology-enabled Supply Chain System
BT-enabled PSC	Blockchain Technology-enabled Pharmaceutical Supply Chain

INTRODUCTION

0.1 Overview

Cost control is essential in identifying and reducing production expenses to increase business profits. Blockchain Technology-enabled Supply Chain System (BT-enabled SCS) promises to provide trustworthy transactions, better-managed operations, and traceability. However, similar to other emerging technologies, the costs of BT-enabled SCS deployment are still largely undefined. BT-enabled SCS is the system using BT to improve SC's transparency, security, and process integrity. Azzi et al. (2019) consider that centralized SC systems expose SC to corruption, fraud, and tampering. Blockchain has been introduced in SC areas to make the chain more economical, reducing the system's total costs. Implementing blockchain could improve efficiency in logistics and SCs since the technology accelerates the transfer of data streams between parties (Wang et al., 2019).

BT-enabled SC reduces the workload and ensures traceability while increasing efficiency, reducing cost, and securing more confidence that the products are genuine and of high quality (Helo & Hao, 2019). Helo and Hao believe it is interesting to note that blockchain is well-suited to address the challenges of SCs. Therefore, adopting BT, with its immutability, transparency, and trustworthiness features, is vital to providing more visibility and security in the SC (Helo & Hao, 2019). The SCS is an accepted approach to increase profit margins, protect the pharmaceutical industry against introduced pressures, and overcome obstacles to obtaining high efficiency while considering the limited available resources. Conversely, Pharmaceutical Supply (PSC) is a system of processes, operations, and organizations involved in drug discovery, development, and production. PSC processes ensure medication quality and favorable final patient outcomes (Chircu et al., 2014). As a system of processes, operations, and organizations, PSC plays a significant role in delivering the proper medication to the right customers (patients) at the right time and in the right conditions. In the current SCS, pharmacies, and manufacturers need help tracking their products and clear system visibility. Recalls are costly and complicated in the SCS, making follow-up with patients difficult for companies.

Therefore, the current SCS in the pharmaceutical industry appears outdated and may not provide visibility and control for manufacturers and regulatory authority over drug distribution (Haq & Esuka, 2018). In particular, it cannot withstand 21st-century cyber-security threats (Haq & Esuka, 2018). In addition, the multi-function Blockchain Technology-enabled Pharmaceutical Supply Chain (BT-enabled PSC) may positively affect medication quality, ultimate patient outcomes, tracking medical records/sources, the distribution of drugs, stability of information, and information safety. PSC performs reasonably in society's health care and manages a considerable part of health care expenditures. As mentioned, in SCS, information is not shared between systems, and manufacturers need help tracking their products. The stability and safety of medical records, medical devices, and supplies are among the highest standards in the pharmaceutical industry, and BT can monitor PSC safely and transparently. Blockchain applications can detect serious errors, including potentially deadly ones, in the medical industry (Haleem et al., 2021). According to Haleem et al., BT can enhance the efficiency, security, and openness of the exchange of medical data inside the healthcare sector. BT enables a distinctive data storage pattern at the greatest degree of security, assisting in avoiding data tampering in the healthcare industry (Haleem et al., 2021). Health records must be kept secure and private for several reasons. BT helps to prevent particular dangers and decentralize data protection in the healthcare industry.

Blockchain is a lengthy chain of confirmed "blocks" connected to one another (Haleem et al., 2021). After all, the name of records is Blockchain. BT offers many accountabilities because every transaction is recorded and examined in public. Once entered, nobody can change it (Haleem et al., 2021). Therefore, BT-enabled PSC can improve the safety and security of the system and reduce delays and human errors significantly. Generally, access to medical records is difficult because they are distributed in many different healthcare centers. BT significantly impacts the healthcare industry and has increased remarkably in the healthcare domain. BT shifts a healthcare network from a centralized manner into a decentralized one and preserves and exchanges patient information through hospitals, diagnostic laboratories, pharmacy firms, and physicians. One of the advantages of using BT in the PSC is to detect fake medicines with proper control oversupply and demand of the drugs. Another advantage of BT-enabled PSC is to improve the interoperability of patient health data between healthcare providers while keeping the privacy and security of their data. Using BT-enabled PSC has also enhanced the transparency and communications between healthcare organizations and patients—BT-enabled PSC preserves and exchanges patient information through hospitals, diagnostic laboratories, pharmacy firms, and physicians. The PSC also deals with demand uncertainty, in which the demand for each medicine is uncertain and changeable.

0.2 Research Objectives and Scope of Thesis

0.2.1 Objectives

The present research aims to design a mathematical cost model for a BT-enabled SCS. To access this object, we studied several research papers and publications (literature review) to identify the related cost components of BT-enabled SCS and create a cost model. The second objective of this research is to minimize the total costs of the designed mathematical model for the BT-enabled SCS through EC algorithms as optimization techniques. The Third objective of this study is to determine the cost components of the BT-based PSC model. Our fourth aim is to design the mathematical cost model for the BT-based PSC model. Then we aim to estimate the costs of the BT-based PSC model through four SL algorithms to select algorithms with the minimum prediction errors. Thus, this paper also aims to measure the importance of each cost component (feature) of the model, which is the degree of relevance of each feature to the model. The following research objective is to estimate the costs of the multi-function BT-enabled PSC model under demand uncertainty and determine SL algorithms with the minimum prediction errors and the cost components of the model. Determining the model's cost components is essential, which helps managers make proper decisions. The final objective of this research is to measure the importance of each cost component of the multi-function model, which is the relevance degree of each feature to the model.

0.2.2 Scope

The scope of the research study is as follows.

a) BT-enabled SCS cost model is a new mathematical model and formulation to develop the supply chain domain. Our first mathematical model contains two different cost components to cover the system's total costs: Supply Chain System (SCS) cost and Blockchain Technology (BT) Implementation cost. The SCS part of the cost model contains four main elements: Production Cost, Procurement Cost, Inventory Cost, and Delivery Cost. We then designed the mathematical part for the Blockchain Implementation cost with two components: Blockchain Transaction and Installation. Another scope of this thesis is to use Evolutionary Computation algorithms to optimize the related part of the cost model. We used three EC algorithms (CS, GA, and ACO) to find the minimum total cost for the BT-enabled SCS model.

b) The study also uses BT in the PSC domain and estimates the cost of BT-based PSC. A new PSC mathematical cost model entitled BT-based PSC includes Regular Purchases, Emergency Purchases, Shipping, Expired Medication, Holding, Shortage, BT Transaction, and BT Installation. BT can improve the safety, performance, and transparency of medical information sharing in a healthcare system. SL and EC are two approaches used in this research to predict and optimize the BT-based PSC cost model. We combine two approaches (EC and SL) for the evaluation of the BT-based PSC cost model: for EC (the ACO and FA algorithms are used) and for SL (the KNN, DT, SVM, and NB algorithms are used). Therefore, ACO and FA are used to improve the parameters of the KNN, DT, SVM, and NB algorithms and minimize the model prediction errors.

c) In the thesis, we added an uncertain demand factor to the BT-based PSC cost model and created the multi-function BT-enabled PSC cost model under uncertain demand. This multi-function cost model includes six components Raw Materials cost (Ordering cost, Holding cost for perfect raw materials, Holding cost for imperfect raw materials, Labor cost for order handling and receipt, and Transportation cost), Finished Products cost (Set-up cost, Holding cost, Production cost, Expected opportunity interest, and Expiry cost), Shortage-Surplus cost (Shortage cost and Surplus cost), Blockchain Installation cost (Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost), Blockchain Transaction cost (Gas cost and Storage cost), and Unsatisfied Demand. We combined four Supervised Learning algorithms (KNN, DT, SVM, and NB) with two EC algorithms (PSO and HS) for the multi-function BT-enabled PSC cost model under uncertain demand. HS and PSO optimize the parameters of the KNN, DT, SVM, and NB algorithms and minimize the model prediction errors.

0.3 Originality and Contributions

The use of BT-based PSC appears to be necessary for any pharmacy system. BT-based PSC helps the system improve the safety, performance, and transparency of medical information sharing and data transformation cost/time. BT-based PSC also improves the manufacturing process, distribution of the materials/drugs, and tracking of the materials/drugs sourced for manufacturing. BT in the PSC system can develop patient data cards for other medical practitioners' centers, especially hospitals, saving time and improving healthcare service. In this system, patients and healthcare centers can have different accessibility choices to the PSC data. Previous studies have reported the advantages and disadvantages of using BT in PSC; in contrast, the present study seeks to estimate the cost of a PSC system that uses BT and covers uncertain demand.

In contrast to several previous studies that have reported on the advantages and disadvantages of using BT in PSC, the present study seeks to estimate the costs of the BT-based PSC system. This BT-based PSC system uses BT as a new database, and in the rest of the research, the system will also cover uncertain demand. Other studies do not provide a cost mathematical model and related cost components for a PSC system based on the BT approach. On the other hand, the difference between this paper and others is to introduce a cost mathematical model for a BT-based PSC system and the cost components of the system. The cost factor is crucial to managers because the knowledge of cost helps them control all financial resources employed in the system's performance, manage the cash flow, identify the rate of return and profitability, and correctly decide whether the new system benefits their organization.

Moreover, Managers tend to control financial resources employed in the system's performance, decide whether the new system benefits their organization, monitor the business's financial health, reduce expenses, stay within the budget, and analyze the information to identify unnecessary costs and better business opportunities. Another significant contribution of this study is to provide a PSC system with BT and demand uncertainty. BT can improve the safety, performance, and transparency of medical information sharing in a healthcare system, minimize the data transformation cost and time, and maintain hospital financial statements. The multi-function BT-enabled PSC includes two objectives: system costs and uncertain demand. Demand uncertainty in PSC may affect product demand, product prices, raw material availability, regulatory changes, investment risk, unit manufacturing, and transportation costs. In addition, the unavailability and the dynamic and imprecise nature of the required data may cause uncertainty in PSC.

This study is necessary to introduce the cost components and the mathematical cost model of three different systems: BT-enabled SCS, BT-based PSC, and the multi-function BT-enabled PSC model under demand uncertainty. All these systems prefer using BT in the SC system instead of their current database systems. Several papers investigate various aspects of SC in an organization or the implementation of BT in a company/pharmacy/hospital. However, more research needs to be carried out to model the BT-enabled SCS cost problems from a mathematical point of view. Therefore, this research helps readers better understand the components and the mathematical model for the systems.

0.4 Research Approach

In the first publication, we applied Cuckoo Search (CS), Genetic Algorithm (GA), and Ant Colony Optimization (ACO) algorithms to optimize the main total cost model. We then used Python software to generate raw data for the nonlinear BT-based PSC cost model under the cost components of a hospital.

The research questions are answered in the following direction.

In the second and third articles, we first designed a mathematical BT-based PSC cost model and a multi-function BT-based PSC mathematical cost model (under uncertain demand) after determining the cost components of each model. In the following step, we applied Python software to generate raw data, which was used to evaluate our models. The third step is to apply four Supervised Learning (SL) algorithms (K-Nearest-Neighbors (KNN), Decision Tree (DT), Support Vector Machine (SVM), and Naive Bayes (NB)) combined with two EC algorithms for both models. We selected (Ant Colony Optimization (ACO) and Firefly Algorithm (FA) as EC algorithms for the BT-based PSC cost model and Harmony Search (HS) and Particle Swarm Optimization (PSO) for the multi-function BT-based PSC mathematical cost model. EC algorithms have optimized the hyperparameters of the SL algorithms and have minimized the prediction errors of the models. These algorithms were selected because they are well-known algorithms successfully applied to solve many engineering problems, facilitating the discussion of their behaviors in our new cost model. In the fourth step, we used four performance metrics to evaluate the mathematical BT-based PSC cost model and the multi-function BT-based PSC mathematical cost model under demand uncertainty. We finally utilized the Total Ranking Score (TRS), a score-based ranking system, to determine the most reliable predictive algorithms.

0.5 Structure of Thesis

The Outline of this thesis is as follows:

- The introduction provides an overview, problem statement and motivation, objectives, originality, and research approach.

- Chapter 1 reviews the literature on the PSC, BT-enabled PSC, SL optimized by EC, Uncertain Demand in PSC, Research Gaps, and Research Questions.

- Chapter 2 contains Research Methodology and Data Collection.

- Chapter 3 presents our first journal article on the research topic, in which we formulated Blockchain Transaction cost, Blockchain Installation cost, and SCS cost model. We tended to minimize the costs of the designed BT-enabled SCS model through EC algorithms (CS/ACO/GA) as optimization techniques.

- Chapter 4 presents our second journal article on the research topic, in which we estimated the costs of the BT-based PSC model through four SL algorithms to select algorithms with the minimum prediction errors. Two EC algorithms (ACO/FA) have optimized the hyperparameters of the SL algorithms and have minimized the prediction errors of the models.

- Chapter 5 presents our third journal article on the research topic, in which we estimated the costs of the multi-function BT-enabled PSC model under demand uncertainty through four SL algorithms to select algorithms with the minimum prediction errors.

We also applied two EC algorithms (PSO/HS) to optimize the SL algorithms' hyperparameters and minimize the models' prediction errors.

- Finally, we present the conclusions of the thesis.

CHAPTER 1

LITERATURE REVIEW

1.1 Introduction to PSC

SCS works in a total systems approach to manage the entire flow of information, materials, and services in satisfying customer demand (Li & Wang, 2007; Chase & Aquilano, 1998). Lambert, Cooper, and Pagh (1998) introduce a comprehensive explanation of SCS as "the integration of key business processes from end-user through original suppliers, which provides product, service, and information that add value for customers and other stakeholders" (Manzini et al., 2008). According to Haq and Esuka, the defects of the SCS are as follows: information is not shared between systems, manufacturers cannot track their products, drug regulatory authority has no visibility of the system, recalls are complicated and costly, and the healthcare system cannot follow up with patients. The SCS is required for any industry that moves materials and goods in any way; on the other hand, PSC is important for tracking the materials and goods sourced for manufacturing, the manufacturing process, and the distribution of the products (Kamel et al., 2018). The pharmaceutical industry is a system of processes, operations, and organizations involved in drug detection, development, and production (Goodarzian et al., 2020). PSC processes affect the quality of medication and patient outcomes (Chircu et al., 2014). As an accepted approach, the SCS protects the pharmaceutical industry against the introduced pressures, increases profit margins, and overcomes efficiency issues (Ahmadi et al., 2017). PSCs seek to ensure that the right people receive the proper medication at the right time and conditions (Salehi et al., 2020). These responsibilities of PSCs are complex and increase their vulnerability and probability of distribution (Salehi et al., 2020). Uthayakumar and Priyan define PSC as "the integration of all activities associated with the flow and transformation of drugs from raw materials to the end-user, as well as the associated information flows, through improved SC relationships to achieve a sustainable competitive advantage" (Uthayakumar et al., 2013). Haq and Muselemu Esuka (2018) consider that the

PSC system keeps patients' private data secret and uses the medical records publicly and anonymously. PSC is an approach with suitable quality that distributes drugs at the right time and place to reach the final customers (Goodarzian et al., 2020). The healthcare sector includes publicly traded companies supporting all facets of the healthcare sector (Haq & Esuka, 2018). Saberi et al. consider that many SC industries pay special attention to traceability as an urgent requirement and a fundamental differentiator (SC industries such as agri-food, pharmaceutical/medical products, and high-value goods). They believe BT is the proper response to whether the current SC information systems can support the necessary information for the timely origin of services and goods. As the technology accelerates the transfer of data streams between parties, Wang et al. (2019) explain that BT can also improve efficiency in SCS (Bedell, 2016). Wang et al. continue that BT can also improve inventory management and reduce waste and cost by reducing the time products spend in transit.

1.2 BT-enabled PSC

BT-enabled PSC improves the security and trust of the system, prevents any single person from modifying the data and transactions, and eliminates the biases found in traditional SCS (Haq & Muselemu Esuka, 2018). The current PCS of the pharmaceutical industry is outdated. Features such as immutability, integrity, and transparency ensure that the information used in the supply chain process is authentic and reliable (Mezquita, Podgorelec, González, & Corchado, 2022). It needs to provide visibility and control for manufacturers and drug distributions and withstand the current cyber-security threats (Haq & Esuka, 2018). Conversely, Haq and Esuka believe that sharing the patient's medical record with various participants on the network is possible without disclosing the patient's private data. As a cutting-edge technology, BT has been used in applications such as cryptocurrency, financial services, risk management, and public and social services (Hosseini et al., 2021). BT offers higher security in relation to keeping and managing information online and can prevent the leaking of confidential information and help to protect organizational intellectual property (Wang, Luo, Zhang, Tian, & Li, 2022). Blockchain (BCT) promises to change the way individuals and businesses exchange value and information online and is well placed to facilitate a new level of collaboration between players in international supply chains (Meng, 2022). BT in the pharmaceutical industry plays a significant role in safeguarding and optimizing the SC (Kumar et al., 2021). BT improves safety, displays information, achieves transparency, and is used for health record-keeping, clinical trials, and patient monitoring (Haleem et al., 2021). According to Zahiri et al. (Zahiri et al., 2018), BT maintains hospital financial statements and minimizes data transformation time and cost. Haleem et al. highlight that BT preserves and exchanges patient data through hospitals, Importantly, Haq and Esuka note that visibility and privacy are mostly contradictory, and to obtain one, the other is often lost. They clarify that BT can guarantee to verify the origin of publicly available data while keeping an entity's private data secret without compromising privacy. According to Haq and Esuka, the decentralized nature of BT allows patients, doctors, and healthcare providers to share data quickly and securely. Traceability plays a significant role in securing drugs and is the basis for reliance by the consumer on the PSC and its products (Hosseini et al., 2021). They continue that the traceability of BT enables the PSC to verify the background of a product and tracks the path of all the locations and the participants that handle it. According to Hosseini Bamakan et al., BT can also provide transparency to the PSC and consider the needs of the suppliers, producers, logistics, distributors, and customers in the PSC. They assert that all pharmaceuticals adhere to patient protection maintenance, and intelligent contracts facilitate this process if a system applies BT. Another advantage of BT is maintaining hospital financial statements and minimizing the data transformation time and cost (Haleem et al., 2021). Among all factors of BT-enabled PSC, the cost factor is significant for an organization. Therefore, the benefits of BT for enhancing management of the PSC include a) reducing or eliminating fraud and errors, b) reducing delays from paperwork, c) improving inventory management, d) identifying issues more rapidly, e) minimizing courier costs, and f) increasing consumer and partner trust (Clauson et al., 2018).

1.3 SL Optimized by EC

Supervised Learning (SL) algorithms can predict the costs of the system, and Evolutionary Computation (EC) is applied to optimize the hyperparameters of SL to build a model, exploring possible combinations of parameters. EC algorithms often offer a better trade-off between solution quality and computing time, particularly for complicated problems or large problem instances (Glover & Sörensen, 2015). Rather than searching for the global optimum solution, Evolutionary Computation (EC) techniques aim to find sufficiently "good" solutions efficiently exploiting the characteristics of the problem and provide an attractive alternative for large-scale applications (Garg, 2009). An intelligent optimization algorithm is applied to optimize the hyperparameters of the machine learning model or deep learning model to build a model (Hu et al., 2022). During evolutionary progress, the EC algorithm explores possible combinations of parameters (Zhang et al., 2016). The deep learning model has the issue that the training time is generally long, and the model's parameters are not optimal (Li et al., 2022). Therefore, Li et al. state that improving the deep learning model and optimizing the hyperparameters is significant. Li et al. also mention that the parameters of deep learning neural network models are usually set empirically, which makes finding the best predictive performance of the model take much time to test. The neural network model training usually faces some problems, such as local optimization or overfitting, and it is difficult to determine many network parameters, so intelligent optimization algorithm constantly improves the neural network model or optimize the parameters (Tian & Chen, 2021). For example, the improved Sparrow Search Algorithm used in the paper of Tian and Chen is to optimize the hyperparameters of Long Short-Term Memory. Shu et al. (2022) also apply Bayesian optimization to search the hyperparameter space of label propagation and spreading and use the default random Forest Algorithm (Shu et al., 2022). In addition, the swarm intelligence optimization algorithm can find the model's optimal parameters according to the dataset's characteristics (Li et al., 2022).

1.4 Uncertain Demand in PSC

Uncertainty in PSC may arise in product demand, price, clinical trials, raw material availability, regulatory changes, investment risk, unit manufacturing, and transportation costs. (Ahmadi, Mousazadeh, Ali Torabi, & Pishvaee, 2017). Ahmadi et al. continue that uncertainty may also arise because of the required data's unavailability and the dynamic and imprecise nature of the data necessary. PSC deals with uncertainty, which makes it different from other SCs; for example, the demand for each medicine is uncertain and can be influenced by seasonal changes (Franco & Alfonso-Lizarazo, 2020). Moreover, the costs and reimbursement values can be uncertain due to the regulatory conditions (Franco & Alfonso-Lizarazo, 2020). Ahmadi et al. (2017) classify uncertainty into two categories: (a) uncertainty in data (which is the most common uncertainty faced in SCs) and (b) flexibility in constraints and goals. There are typically two forms of uncertainty in data: (a) randomness, which originates from the random nature of the data, and (b) epistemic uncertainty, which is due to the unavailability or insufficiency of needed data, leading to imprecise data extracted from experts' subjective opinions (Ahmadi et al., 2017).

1.5 Research Gaps and Research Questions

1.5.1 Research Gaps

After reviewing the related SCS and PSC domain literature, we understand that SCS requires moving materials and goods. However, PSC also needs to track the materials and goods sourced for manufacturing, the manufacturing process, and the distribution of the products. PSCs aim to distribute the proper medication and reach the final customers at the right time and conditions. Previous studies say that BT enhances safety, displays information, achieves transparency, and is used for health record-keeping, clinical trials, and patient monitoring (Haleem et al., 2021). BT in the PSC can detect fake medicines with proper control over the supply and demand of the drugs and can enable pharmaceutical companies to control counterfeit and unregistered medicines (Kumar et al., 2021).

The first research gap left by many works in literature is determining the mathematical formulation of Blockchain Implementation cost. Other studies describe the reasons for the importance and benefits of using BT in SCS and PSC. However, there needs to be more studies on the cost model for BT in SCS, especially the Public BT. Therefore, we need to determine the cost components of Public BT and then design a mathematical model for SCS and BT-enabled PSC. There are several mathematical cost models with various components for SCS and PSC, but they do not include BT, and this is the gap research that we try to bridge in this thesis.

The second research gap is a lack of mathematical cost models for combining BT and SCS/PSC. That is why we need to design a mathematical cost model combined with BT. Doing so enables us to use SL and EC algorithms to predict the costs of the system. Therefore, we should determine the cost components of SCS, PSC, and BT to design BT-enabled SCS and BT-enabled PSC.

Although some authors cover the uncertain demand in their SCS mathematical models, we notice a need for PSC systems combined with BT containing the uncertain demand factor. PSC may have uncertain demand because of the required data's unavailability and the dynamic and imprecise nature of the data necessary. In PSC, the demand for each medicine is uncertain and can be influenced by seasonal changes. We consider this fact as the third research gap in the thesis.

1.5.1 Research Questions

To achieve the research objectives, we attempt to answer the following research questions:

Q1: What are the cost components of a hospital's BT-based PSC cost model, and what is its mathematical cost model?

Q2a: Which SL algorithms show better performance in minimizing the prediction errors of the BT-based PSC cost model?
Q2b: Which EC algorithms show better performance to optimize the hyperparameters of the SL algorithms and minimize the prediction errors of the BT-based PSC model?
Q3: What are the essential cost components of the BT-enabled PSC model?

Q4a: What are the components of the multi-function BT-enabled PSC model under uncertain demand?
Q4b: What is the mathematical cost model?

Q5a: Which SL algorithms perform better in minimizing the prediction errors of the multi-function BT-enabled PSC model (among the selected algorithms)?
Q5b: Which EC algorithms perform better to optimize the SL algorithms' hyperparameters and minimize the multi-function model's prediction errors?
Q6: What are the important cost components of the multi-function BT-enabled PSC model under uncertain demand?

This thesis responds to all the above research questions and investigates various aspects of the questions. This thesis also analyzes the designed mathematical models in two software, achieving the thesis goals.

CHAPTER 2

RESEARCH METHODOLOGY AND RESEARCH DESIGN

The BT-enabled SCS (Blockchain Technology -enabled Supply Chain System) model is newly designed in the first paper, as no specific case study introduces its parameters. BT can improve the safety, performance, and transparency of medical information sharing in a healthcare system. Our model contains two different cost components to cover the total costs of the system: SCS cost and Blockchain Implementation cost. To generate data for our model, we revised the Operation Research model for PSC (Pharmaceutical Supply Chain) and Inventory Management for a single pharmaceutical company and a single hospital published by Uthayakumar and Priyan (2013).

In our second and third papers, we designed the BT-based PSC cost model and the multi-function BT-enabled PSC cost model under uncertain demand. We first used Python software to generate raw data for model evaluation in the procedure. The research method selected in the second and third papers combines two Evolutionary Computation (EC) algorithms and four Supervised Learning (SL) algorithms to evaluate the BT-based PSC cost model. In the next step, four metrics were used to assess the cost models. To select the EC algorithms in the research, we studied several related articles because the performance of optimization algorithms significantly depends on the landscape of the problems and there is no single algorithm that outperforms others on problems with different fitness landscapes (Meidani, Mirjalili, & Barati Farimani, 2022). We applied EC algorithms to optimize the hyperparameters of SL algorithms. This results in enhancing SL algorithms and reducing prediction errors. There are two different strategies for parameter tuning in EC algorithms: the off-line parameter initialization (or meta-optimization; also called endogenous strategy parameters) and the online parameter tuning strategy (also called exogenous strategy parameters) (Talbi, 2009).

In off-line parameter initialization, the values of different parameters are fixed before the execution of the metaheuristic, whereas in the online approach, the parameters are controlled and updated dynamically or adaptively during the execution of the metaheuristic (Talbi, 2009). We used off-line strategy to tune the parameters of EC algorithms.

2.1 Design and evaluation of a cost model optimization for BT-enabled SCS

In the first publication, the total cost for BT-enabled SCS includes these two main components: SCS and Blockchain Implementation cost. There are four components in our formulation of the SCS cost: Production Cost, Procurement Cost, Inventory Cost, and Delivery Cost. We further subdivided the blockchain implementation cost into blockchain transaction cost, and installation cost to better represent the actual operating principles of the blockchain. Our model's parameters are those published by Uthayakumar and Priyan on PSC and inventory management strategies (Uthayakumar et al., 2013). We used three Evolutionary Computation (EC) algorithms (Cuckoo Search - CS, Genetic Algorithm - GA, and Ant Colony Optimization - ACO) to find the minimum total cost for our BT-enabled SCS model. The following metrics evaluate the performance of these algorithms: the Mean Square Error (MSE), Root Mean Square Error (RMSE), R2, and Area Under the ROC Curve (AUC-ROC or simply AUROC). Code written by MATLAB was used for the optimization procedure, and the maximum number of iterations was set to 2000 for all three algorithms. An effective hybrid of an ANN with a fuzzy inference system is the ANFIS model. FIS is the process of utilizing fuzzy logic to create a mapping from a given input to an output. A recurrent dynamic network with feedback links encompassing numerous network levels is the nonlinear autoregressive network with exogenous inputs (NARX). The linear ARX model (Autoregressive Exogenous Input), frequently employed in time-series modeling, is the foundation of the NARX model. The combination of an ANFIS (Adaptive Network-based Fuzzy Inference System) model and a NARX (Nonlinear AutoRegressive eXogenous) structure called the ANFIS–NARX method provides a robust system to create an accurate and transparent identification method, which is the combination of universal approximation capability, transparency of fuzzy inference system, and training ability of neural networks with an adaptive and predictive potential of NARX structure. We used a combination of

ANFIS- NARX with three EC algorithms called CS-ANFIS–NARX, GA-ANFIS–NARX, and ACO- ANFIS–NARX to compare the accuracy. After training ANFIS–NARX by EC algorithms, the Receiver Operating Characteristic
(ROC) curves are used to test the three algorithms' predictions. A score-based ranking system called Total Ranking Score (TRS) is finally used to determine the most reliable predictive algorithms. Each method received a score in TRS based on the calculated MSE, RMSE, and ROC values. Finally, the ranking position of each model was assigned based on the sum of all obtained score states. Each model receives a score based on this procedure's calculated MSE, RMSE, and ROC in both approaches and phases. Eventually, the ranking position of each model is allocated to the summation of all acquired score states. In TRS, the lowest MSE and RMSE receive the highest scores, and the highest ROC has the highest score (and vice versa).

2.2 PSC cost model enhancement and optimization using supervised learning techniques

The second article provides a new PSC mathematical cost model, which includes Regular Purchases, Emergency Purchases, Shipping, Expired Medication, Holding, Shortage, BT Transaction, and BT Installation. BT can improve the safety, performance, and transparency of medical information sharing in a healthcare system. We first used Python software to generate raw data for the nonlinear BT-based PSC cost model, including the cost components of a hospital. The widely known tool for generating random data in Python is its random module, and we applied randint() as an inbuilt function of the random module. This module returns a random integer value from the inclusive range between the two lower and higher limits (including both limits) provided as two parameters. In the data generation step, the following features, which are the model's components, were generated using a Python program: Regular Purchases, Emergency Purchases, Shipping, Expired Medication, Holding, Shortage, BT

Transaction, and BT Installation. The 5000 series of raw data generated for all eight BT-based PSC cost model components and the total cost were uploaded to https://data.mendeley.com/datasets/jxv5jrydnc . Other researchers can use these data sets as sample data.

The research method selected in the second paper is to combine two approaches (Evolutionary Computation - EC and Supervised Learning - SL) for the evaluation of the BT-based PSC cost model: for EC (the Ant Colony Optimization - ACO and Firefly Algorithm - FA algorithms are used) and for SL (the K-Nearest-Neighbors - KNN, Decision Tree - DT, Support Vector Machine - SVM, and Naive Bayes - NB algorithms are used). These algorithms are well-known and can be successfully applied to solve many engineering problems, facilitating the discussion of their behaviors in our new cost model. Here, ACO and FA are used to improve the parameters of the KNN, DT, SVM, and NB algorithms, as well as to minimize the model prediction errors. The parameters of SL algorithms are usually set empirically, and it takes much time to test and find the best predictive performance of the model. Therefore, the EC algorithms explore possible combinations of parameters, optimize hyperparameters of the SL algorithms, and reduce the prediction errors of the SL algorithms. Therefore, EC algorithms play a significant role in enhancing the performance of the selected SL algorithms. Thus, EC combined with four algorithms (KNN, DT, SVM, and NB) reduces prediction errors. The generated dataset has eight features (including Regular Purchases, Emergency Purchases, Shipping, Expired Medication, Holding, Shortage, BT Transaction, and BT Installation). It has the total cost as the label in the regression process (see https://data.mendeley.com/datasets/jxv5jrydnc). Although the dataset was generated using Python, implementing the algorithm illustrated in the flowchart in Figure 2.1 was carried out in MATLAB.

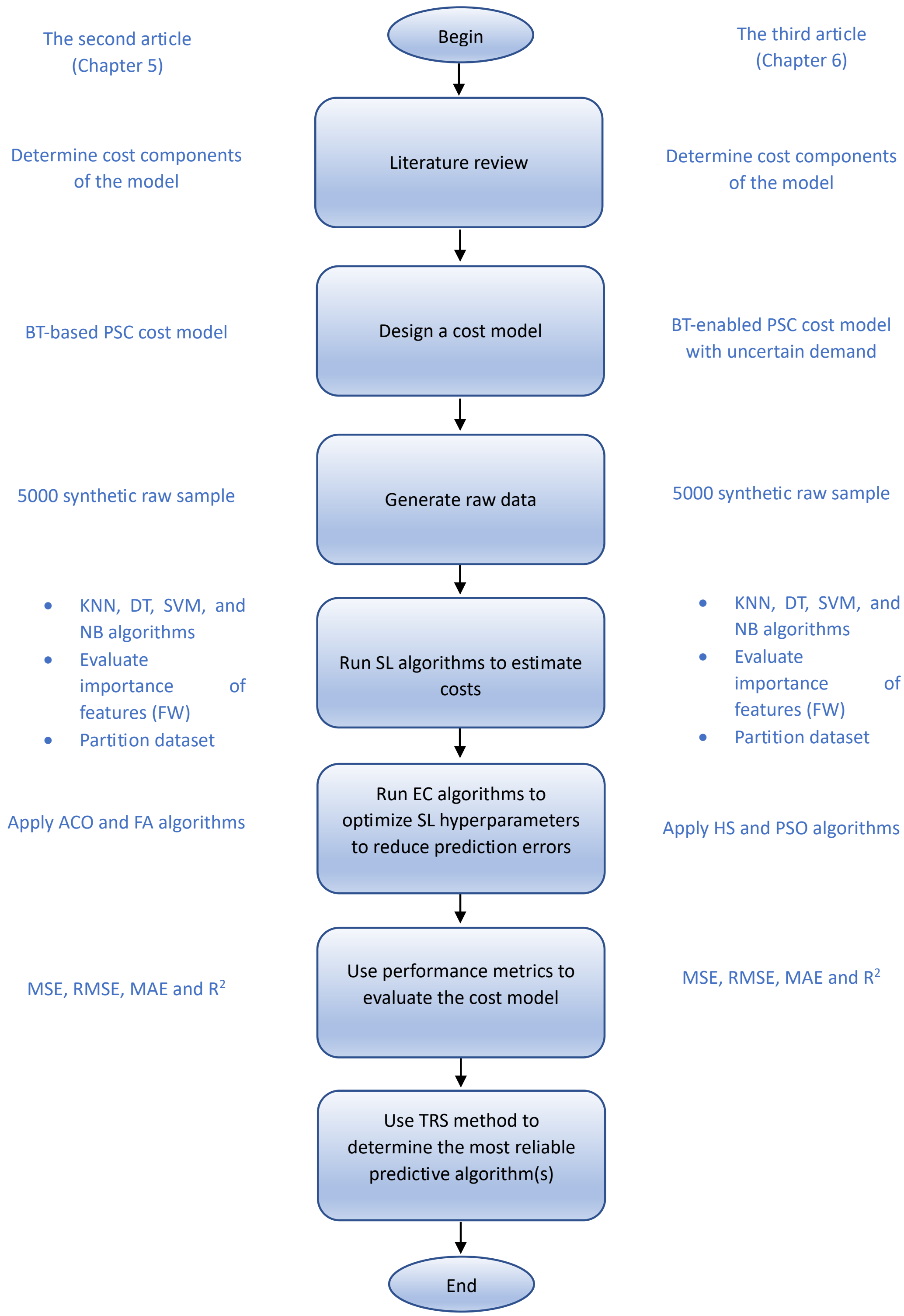

Figure 2.1 Methodology steps used in the second and third articles

Figure 2.1 illustrates the flowchart of the methodology for four SL algorithms and two EC algorithms. The flowchart starts with creating the population and initializing the parameters. In the next step, the Feature Weighting (FW) approach, one of the most efficient approaches, is applied to evaluate the importance of features, assign an appropriate weight to each feature, and estimate the degree of relevance of each feature to the model. The FW process is executed by multiplying the value of every instance of all the features and ordering features by their values (Al-Zoubi et al., 2021). FW is considered more efficacious than the Feature Selection process in several problems and cases because the features are very sensitive, so removing these features may negatively affect the classification performance (Al-Zoubi et al., 2021). Traditionally, all selected features are equally important when estimating the output. However, if some features have a higher weight than others, the results can be strongly influenced by them, affecting the overall algorithm's performance and accuracy. Then, the dataset was partitioned, with 70% of the dataset used for training and the remaining 30% for testing. Four different SL algorithms were used to find the optimal method to estimate the cost of the BT-based PSC cost model, including KNN, DT, SVM, and NB. In the next step, we applied two EC algorithms, ACO and FA, to improve the performance of the SL algorithms and optimize the hyperparameters of SL algorithms, reducing the prediction errors. Four metrics were used to evaluate the cost model, including Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean absolute error (MAE), and correlation coefficient (R2). Therefore, this approach produced the following results: eight FWs (one weight for each feature), MSE, RMES, MAE, and R2. Eventually, a score-based ranking system called Total Ranking Score (TRS) was used to determine the most reliable predictive algorithms. Each method received a score in TRS based on the calculated MSE, RMES, MAE, and R2 values. Finally, the ranking position of each model was assigned based on the sum of all obtained score states. The following section starts to model the casts of the BT-based PSC system based on the literature review and the methodology.

2.3 PSC cost model with uncertainties

This last part of our research introduces a multi-function BT-enabled PSC cost model. In the first step, Python software helps us generate raw data for our multi-function BT-enabled PSC model. To generate random data, we applied randint() as an inbuilt function of the random module among the widely known tool in Python. This module returns a random integer value from the inclusive range between the two lower and higher limits (including both limits), provided as two parameters. The generated dataset includes six features as the components of the model ($C_{raw\_materials}$, $C_{finished\_products}$, $C_{shortage\_surplus}$, $C_{BT\_Installation}$, $C_{BT\_Transaction}$, and $D_{i,uncertainty}$) and the total cost for objective 1 (C_{Total}) as the label in the regression process. Uncertainty in PSC may arise in product demand, price, clinical trials, raw material availability, regulatory changes, investment risk, unit manufacturing, and transportation costs. (Ahmadi, Mousazadeh, Ali Torabi, & Pishvaee, 2017). Ahmadi et al. continue that uncertainty may also arise because of the required data's unavailability and the dynamic and imprecise nature of the data necessary. We uploaded 5000 series of the generated raw data for all six components of the multi-function BT-enabled PSC model and the total cost to https://data.mendeley.com/datasets/sfc7hst95m. The research method selected in the third paper is to combine two approaches (EC and SL) for the evaluation of the multi-function BT-enabled PSC model: for EC (the Harmony Search - HS and Particle Swarm Optimization - PSO algorithms are used) and for SL (the KNN, DT, SVM, and NB algorithms are used). HS and PSO optimize the parameters of the KNN, DT, SVM, and NB algorithms and minimize the model prediction errors. EC combined with four algorithms (KNN, DT, SVM, and NB) reduces prediction errors. Therefore, EC algorithms play an important role in enhancing the performance of the selected SL algorithms. The right-hand side of Figure 2.1 presents the methodology's flowchart and algorithm's implementation in MATLAB. This flowchart includes these steps: creating the population using four SL algorithms (KNN, DT, SVM, and NB), using two EC algorithms (HS and PSO), using the Feature Weighting approach, using four performance metrics (MSE, RMES, MAE, and R2), and using Total Ranking Score. The flowchart starts with creating a new population and initializing the parameters. In the following step, we applied the Feature Weighting (FW) approach to evaluate the importance of features, assign an appropriate weight to each feature, and estimate the degree of relevance of each feature to the model. The FW process is executed by multiplying the value of every feature instance and ordering them by their values (Al-Zoubi et al., 2021). Usually, the selected features are equally important when estimating the output. On the other hand, some features with a higher weight than others can influence the results and affect the overall algorithm's performance and accuracy. Then, we split the dataset into two parts: 70% of the dataset for training and 30% for testing. Four different SL algorithms were used to find the optimal method to estimate the cost of the multi-function BT-enabled PSC model (KNN, DT, SVM, and NB). Then, we applied two EC algorithms (HS and PSO) to optimize the hyperparameters of the SL algorithms and improve the performance of the SL algorithms. We then used four performance metrics to evaluate the model, including Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean absolute error (MAE), and correlation coefficient (R2). Then, this approach produced the following results: five FWs (one weight for each feature) for objective 1 and four performance metrics for objectives 1 and 2. Eventually, we used a score-based ranking system called Total Ranking Score (TRS) to determine the most reliable predictive algorithms. Each method received a score in TRS based on the calculated MSE, RMES, MAE, R2, and five feature weight values in objectives 1 and 2. Finally, the ranking position of each model was assigned based on the sum of all obtained score states.

2.4 Conclusion

In the first article, we designed the cost mathematical model of the Blockchain Implementation and divided it into Blockchain Transaction and Installation costs. We used this in our mathematical models in the second and third articles. We also used a score-based ranking system called Total Ranking Score (TRS) in all three articles to determine the most reliable predictive algorithms. In all papers, Python software helps us generate raw data, and we applied randint() as an inbuilt function of the random module among the widely known tool in Python.

The only difference is that in the first paper, we revised the operations research model for PSC and Inventory Management for a single pharmaceutical company and a single hospital to generate data for the BT-enabled SCS model, meaning there are two different models. However, we used our main models to generate data through Python software in the second and third papers. Although the performance metrics in all our papers are the same (MSE, RMSE, and R2), we used MAE in the second and third papers and ROC in the first. EC algorithms were used in all three articles to explore possible combinations of parameters, optimize hyperparameters of the SL algorithms, and reduce the prediction errors of the SL algorithms. However, we selected different EC algorithms in each article. We also applied four SL algorithms (KNN, DT, SVM, and NB) to evaluate the cost prediction of the models in the second and third articles.

The mathematical formulation in the first research paper helps studies with the limitation of finding real data sets to generate raw data in healthcare fields. Comparing CS/ACO/GA algorithms, the best solutions for the BT-enabled SCS cost model are CS and ACO, with the higher Total Ranking Score (TRS) (scored by MSE, RMSE, and ROC), followed by GA standing in the second step. The more noteworthy finding is that all three algorithms have found the global minimum for the BT-enabled SCS cost model with acceptable accuracy obtained from ROC.

The findings of the second article show that the ACO-NB and FA-NB algorithms perform better than the other six algorithms in estimating the costs of the model with lower errors. In contrast, ACO-DT and FA-DT show the worst performance. The results also indicate that the Shortage, Holding, and Expired Medication costs influence the cost model more strongly than other cost components.

In the third research publication, findings indicate that the HS-NB and PSO-NB algorithms outperform the other six algorithms in estimating the costs of the multi-function model with fewer errors. The results also show that the Raw Materials cost substantially influences the model more than the other components. This study also introduces the components of the multi-function BT-enabled PSC model.

CHAPTER 3

COST OPTIMIZATION OF BLOCKCHAIN TECHNOLOGY-ENABLED SYPPLY CHAIN SYSTEM USING EVOLUTIONATY COMPUTATION APPROACHES: A HEALTHCARE CASE STUDY

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3.1 Abstract

This study aims to design a mathematical cost model for Blockchain Technology-enabled Supply Chain System (BT-enabled SCS), which may assist some companies that tend to evaluate the costs of BT as the main database in their SC system. We, therefore, identified the cost components of BT-enabled SCS based on the related literature review. The second purpose is to minimize the costs of the designed BT-enabled SCS model through Evolutionary Computation algorithms (CS/ACO/GA) as optimization techniques. To generate raw data for the model, the authors revised the Operations Research model and Inventory Management model as a mathematical formulation in Pharmaceutical Supply Chain. This mathematical formulation helps studies with the limitation of finding real data sets generate raw data in healthcare fields. Comparing CS/ACO/GA algorithms, the best solutions for the BT-enabled SCS cost model are CS and ACO with the higher Total Ranking Score (TRS) (scored by MSE, RMSE, and ROC), followed by GA standing in the second step.

The more noteworthy finding is that all three algorithms have been able to find the global minimum for the BT-enabled SCS cost model with acceptable accuracy obtained from ROC.

Keywords: BT-enabled SCS, Cuckoo Search, Genetic Algorithm, Ant Colony Optimization, Blockchain Technology

3.2 Introduction

Cost control is an important practice of identifying and reducing production expenses to increase business profits. Blockchain Technology-enabled Supply Chain System (BT-enabled SCS) promises to provide trustworthy transactions, better-managed operations, and traceability, but similar to other emerging technologies, the costs of BT-enabled SCS deployment are still largely undefined. BT-enabled SCS is the system using BT to improve the transparency, security, and process integrity of SC. Azzi et al. (2019) consider that centralized SC systems expose SC to corruption, fraud, and tampering. Blockchain has been introduced in SC areas to make the chain more economic, reducing the total costs of the system. Implementing blockchain could improve efficiency in logistics and SCs since the technology accelerates the transfer of data streams between parties (Wang, Singgih, Wang, & Rit, 2019). BT-enabled SC reduces the workload and ensures traceability, while increasing efficiency, reducing cost, and securing more confidence that the products are genuine and of high quality (Helo & Hao, 2019). Helo and Hao believe it is interesting to note that blockchain is well suited to address the challenges of SCs, and therefore it is vital to adopt BT, with its features of immutability, transparency, and trustworthiness, to provide more visibility and security in the SC (Helo & Hao, 2019). The necessity of carrying this study out is to introduce the cost components and the mathematical cost model of BT-enabled SCS to some companies that may prefer using BT in the SC system instead of their current database systems. Several papers investigate various aspects of SCS in an organization or the implementation of BT in a company; but limited research has been carried out into modeling the BT-enabled SCS cost problems from a mathematical point of view. Therefore, this research helps readers better understand the components and the mathematical model for this system.

The present study aims firstly to design a mathematical cost model for a BT-enabled SCS. To access this object, we studied several academic papers and books (literature review) to identify the related cost components of BT-enabled SCS and create a cost model. The second purpose of this research is to minimize the total costs of the designed mathematical model for the BT-enabled SCS through Evolutionary Computation (EC) algorithms as optimization techniques. To generate the raw data for the model, we revised and designed a mathematical formulation of the Operations Research (OR) model for Pharmaceutical Supply Chain (PSC) and Inventory Management model for a single pharmaceutical company and a single hospital. Using this formulation as a newly designed model, the authors simulated raw data for the BT-enabled SCS model as there is no real data for our BT-enabled SCS model. In the next step, we applied Cuckoo Search (CS), Genetic Algorithm (GA), and Ant Colony Optimization (ACO) algorithms to optimize the main total cost model. This research used a score-based ranking system called Total Ranking Score (TRS) to determine the most reliable predictive algorithms. Our research question is which EC algorithms (among three applied algorithms: ACO/GA/CS) are the best solution(s) for our designed mathematical cost model (BT-enabled SCS), minimizing this total cost model. The outline of this article is as follows: Section 2 reviews the literature on BT-enabled SCS, Private/Public/Hybrid Blockchain, and Evolutionary Computation (ACO/GA/CS). Section 3 contains the Proposed BT-enabled SCS model, and the next section shows Case Study: Healthcare System. The Research Results is in the following section and, finally, we draw a Conclusion and a recommendation for future studies in Section 6.

3.3 Literature Review

3.3.1 BT-enabled SCS

SCS works in a total systems approach to manage the entire flow of information, materials, and services in satisfying customer demand (Li & Wang, 2007; Chase & Aquilano, 1998). Lambert, Cooper, and Pagh (1998) introduce the comprehensive explanation of SCS as “the integration of key business processes from end-user through original suppliers, which provides product, service, and information that add value for customers and other stakeholders" (Manzini, Gamberi, Gebennini, & Regattieri, 2008). Therefore, SC is an organization's network that may have various formats extended from two to more levels, one to more suppliers, or one to more products (Li & Wang, 2007; Maxwell & Muckstadt, 1985). Li and Wang mention the network structure of SCS for a large-scale production or inventory system. BT performs and shares a distributed database of a public ledger of all transactions, records, or digital events among parties' participation (Crosby, Nachiappan, Pattanayak, Verma, & Kalyanaraman, 2016). The Internet is different from BT as the Internet moves information (not value) as well as copies of things (not original information) (Saberi, Kouhizadeh, Sarkis, & Shen, 2018). Crosby, et al. also notice BT may play a role as a new engine of growth in the digital economy because we increasingly use the Internet to conduct digital commerce and share our data and life events. To verify ownership of an asset and also trace the transaction history, they assert that BT can register assets to identify by one or more identifiers that are difficult to destroy or replicate. Saberi et al. consider that many SC industries pay special attention to traceability as it is an urgent requirement and a fundamental differentiator (SC industries such as the agri-food sector, pharmaceutical/medical products, and high-value goods). They believe BT is the proper response to this question that whether the current SC information systems can support the information being necessary for the timely origin of services and goods. This, according to them, results in improving SC transparency, and security. As the technology accelerates the transfer of data streams between parties, Wang et al. (2019) explain that BT can improve efficiency in SCS as well (Bedell, 2016). Wang et al. continue that BT also can improve inventory management, and ultimately reduce waste and cost by reducing the time products spend in the transit process. Therefore, the benefits of BT for enhancing management of the SC include a) reducing or eliminating fraud and errors, b) reducing delays from paperwork, c) improving inventory management, d) identifying issues more rapidly, e) minimizing courier costs, and f) increasing consumer and partner trust (Clauson, Breeden, Davidson, & Mackey, 2018).

3.3.2 Private/Public/Hybrid Blockchain

Saberi et al. (2018) assert blockchain design can be the network players and the rules to maintain the blockchain. A blockchain is essentially a distributed database of records, or a public ledger of all transactions or digital events that have been executed and shared among participating parties (Crosby, Nachiappan, Pattanayak, Verma, & Kalyanaraman, 2016). Each transaction in the public ledger, according to them, is verified by the consensus of a majority of the participants in the system. Once entered, information can never be erased (Crosby, Nachiappan, Pattanayak, Verma, & Kalyanaraman, 2016). There are three types of BT based on the technology application: open type (permissionless) or public; closed type (permissioned) or private or corporate; mixed-type or hybrid, an open–type blockchain that uses closed-type platform building technologies to achieve consensus (Mesengiser & Miloslavskaya, 2021).

In a private, unlike in an SC network with known entities working to produce and distribute products, the parties know each other and there is no anonymity (Saberi, Kouhizadeh, Sarkis, & Shen, 2018). To increase performance and improve scalability in private, the number of distributed nodes added blocks to the chain is small (Toufaily, Zalan, & Dhaou, 2121). Toufaily, Zalan, and Dhaou introduce a weakness of private/centralized blockchain that private more exposed to fraud risk because the administration and system design remain focused with one or few. Private blockchain may require different levels of access needs to be crafted for different roles of usage permission (Lai & Chuen, 2018). Lai and Chuen state that approval for access permission for participants is necessary meaning that private blockchain networks are for members only. Yang et al. (2020) mention that there is a very high transaction processing rate with very few authorized participants in a private blockchain. Therefore, to get the consensus for the network, a shorter time is used, and more transactions can be processed within a second (Yang, et al., 2020). Private blockchain, according to Yang et al., has very strong data privacy as all nodes should agree by consensus to change data in a private one.

On a public blockchain, companies can easily interact with each other like on the public Internet, as long as privacy, security, scalability, and all other technical challenges identified by interviewees are resolved network (Toufaily, Zalan, & Dhaou, 2121). Saberi et al. (2018) suggest that public blockchain uses cryptographic methods to let users enter the network and record their transactions, maintaining trust with many anonymous users. Without any providing forms of identification or asking for permission, public blockchain assumes joining or leaving from the blockchain network is possible for anyone from the public Internet (Lai & Chuen, 2018). On the other hand, Yang et al. (2020) highlight the entire node must agree on any change in public blockchain as it records the same information. Therefore, it takes more time to mine just one block to the blockchain because any change should be recorded in all succeeding blocks (Yang, et al., 2020).

A combination of public and private blockchain is known as Hybrid blockchain or Consortium blockchain which has a semi-decentralized and semiprivate structure and has a controlled user group but works across various organizations (Komalavalli, Saxena, & Laroiya, 2020). To verify the transaction processes, in the hybrid system, a named leader is assigned instead of a single entity, which is a significant difference of this system (Yang, et al., 2020). In other words, a hybrid network is a kind of federated blockchain constituted of the low-trust (public blockchain) and the single highly trusted entity model (private blockchain) (Yang, et al., 2020). The most obvious differences between public and private blockchain can be explained by the type of blockchain adopted – permissioned blockchain: the established organizations (the private and public sectors) and permissionless blockchain in start-ups (Toufaily, Zalan, & Dhaou, 2121) although they are both decentralized and shared among their users to record all peer-to-peer transactions (Yang, et al., 2020). Compared to a private or public blockchain, the speed of validation on a public blockchain is likely to be slow (Yang, et al., 2020). Yang et al. also assert in a public blockchain, each of the transactions is open for the public to verify. However, to verify and validate transactions, only the trusted parties can be presented in the network in a private blockchain, according to them. Controlling the users in uploading information, according to them, is another issue with a public blockchain. For instance, there is no way to change sensitive information uploaded into the system by anyone in the system (Yang, et al., 2020).

3.3.3 Evolutionary Computation: ACO/GA/CS

Evolutionary Computation (EC) algorithms are optimization methods and heuristic in nature (Glover & Sörensen, 2015). EC uses evolutionary principles for automated and parallel problem solving (Drugan, 2019; Jong, 2006). In Heuristic methods, trial and error are used to search for solutions, but it seems EC methods are at a higher level than heuristic methods using information and solutions selection to guide the search process (Yang X.-S., 2014). Three are the main goals for Modern Metaheuristic algorithms to carry out a global search: solving problems faster, solving large problems, and obtaining robust algorithms (Gandomi, Yang, & Alavi, 2013). These algorithms try to find near-optimal solutions as they are a state-of-the-art and efficient strategy (Telikani, Gandomi, & Shahbahrami, 2020) and to find a solution that is “good enough” in a computing time that is “small enough” (Glover & Sörensen, 2015). The obvious efficiency of EC algorithms is that they imitate the best features in nature, in which the fittest selection in biological systems evolves through natural selection over millions of years (Gandomi, Yang, & Alavi, 2013). There are various EC algorithms for optimization problems including Genetic Algorithms, Simulated Annealing, Ant Colony Optimization, Bat Algorithm, Particle Swarm Optimization, Harmony Search, Firefly Algorithm, Flower Pollination Algorithm, Cuckoo Search, and so forth (Yang X.-S., 2014).

3.3.3.1 Ant Colony Optimization (ACO)

The Ant Colony Optimization (ACO) algorithm came from the collective performance of real-life ant colonies (Nourelfath, Nahas, & Montreuil, 2007; Deneubourg & Pasteels, 1983). To solve optimization problems, Colorni, Dorigo, Maniezzo, and Trubian (1994) as well as Dorigo and Gambardella (1997) proposed the idea of employing a colony of simple cooperating agents. The simulation approach uses the described behavior of real ant colonies to solve these problems with artificial ants, searching the solution space, simulating real ants, and searching their environment (Nourelfath, Nahas, & Montreuil, 2007). The next step, according to Nourelfath et al., is to adapt ant colonies with the other combinatorial optimization problems such as the vehicle routing problem, telecommunication networks management, graph coloring, constraint satisfaction, and Hamiltonian graphs (Bullnheimer, Hartl, & Strauss, 1999).

3.3.3.2 Genetic Algorithm (GA)

GA algorithms, as a powerful tool, solve search and optimization problems based on natural selection principles, natural genetics, and evolution (Safaei, Rezayan, Zeaiean Firouzabadi, & Sadidi, 2021). GA algorithms, as part of Evolutionary optimization techniques, are largely used for engineering problems (Pourrajabian, Dehghan, & Rahgozar, 2021). They introduce three operators as the procedure of GAs: selection, crossover, and mutation. GA consists of five distinct parts; initialization, fitness assignment, selection, crossover, and mutation (Safaei, Rezayan, Zeaiean Firouzabadi, & Sadidi, 2021).

These are five steps to explain the GA process: (a) at each step, the GA process selects individuals from the current population to play the role of parents and produce the children for the next generation; (b) the selection process gives preference to the fittest individuals to let them pass the quality genes to the next generation; (c) a fitness function is used to evaluate the potential solutions and a fitter solution is the one with a better fitness value; (d) this fitness function can be identical to the objective function; (e) a new population of solutions is created using genetic operators (Fahimnia, Davarzani, & Eshragh, 2018). Pourrajabian, Dehghan, and Rahgozar consider that a mutation operator is employed to avoid algorithm converging to local optima, maintaining genetic diversity.

3.3.3.3 Cuckoo Search (CS)

Cuckoo Search (CS), as a population-based technique, simulates the parasitic and brooding behavior in some cuckoo species to solve effectively complex optimization problems (Song, Pan, & Chu, 2020). Although CS is a quite new nature-inspired EC optimization algorithm, engineering applications extensively use CS as it is highly efficient in solving complex nonlinear problems (Tsipianitis & Tsompanakis, 2020). CS algorithm has fewer key parameters than other similar algorithms and is easy to implement (Song, Pan, & Chu, 2020). Yang (2014) explains that this algorithm is enhanced by the behavior of the so-called Lévy flight of some birds (a kind of swarm intelligence algorithm), rather than by simple isotropic (standard) random walks. CS can explore the search space more efficiently than other algorithms using standard Gaussian processes as Lévy flights have infinite mean and variance (Yang X.-S. , 2014). A possible solution in the algorithm is a nest of a cuckoo, and the position of the nest is constantly updated by the combination of the algorithm with Lévy flight, finding a potentially better solution to be a new cuckoo's nest (Song, Pan, & Chu, 2020). According to Afshari, Dehkordi, and Akbari (2016), the main influence for the development of this algorithm is the interesting and different lifestyle as well as egg-laying of a cuckoo. This bird can clearly deceive other birds and make them participate in its own survival (Afshari, Dehkordi, & Akbari, 2016). These cuckoos dump some eggs in some nests of host birds: those eggs with more similarity to the host bird's eggs have a better chance of growing into a mature cuckoo, and the rest are identified and killed by the host bird (Bahmani, GhasemiNejad, Nazari Robati, & Amani Zarin, 2020).

3.4 Proposed BT-enabled SCS model

In this section, a mathematical model is proposed to minimize the cost of BT-enabled SCS. It needs to consider at least two different cost components to cover the total costs of the system. Therefore, the total cost for BT-enabled SCS (C_{Total}) includes these two main components: Supply Chain System cost (C_{SCS}) and Blockchain Implementation cost ($C_{Blockchain}$):

$$C_{Total} = C_{SCS} + C_{Blockchain} \quad (3.1)$$

3.4.1 Cost elements of SCS

Revising the economic model by Belmokaddem and Benatek (2012) as well as the model by Li (2014), there are four components in our formulation of the Supply Chain System cost (C_{SCS}). These components are Production Cost, Procurement Cost, Inventory Cost, and Delivery Cost. Figure 3.1 illustrates the structure of the SCS in a healthcare system, which is a revised Healthcare SC structure from Mustaffa and Potter's (2009) research.

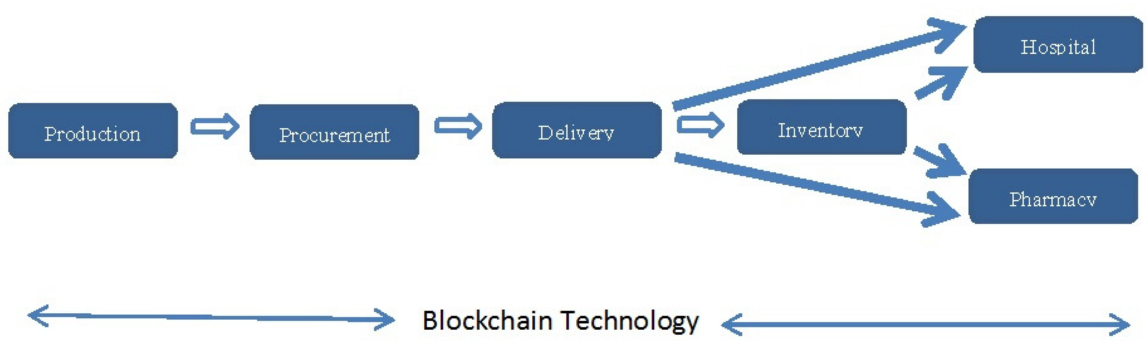

Figure 3.1 The SCS structure in a healthcare system

Therefore, the C_{SCS} can be expressed as follows:

$$C_{SCS} = \sum_{i \in N}[\, C_{i,Production}q_i + C_{i,Procurement}r_i + C_{i,Inventory}h_i + C_{i,Delivery}f_i] \quad (3.2)$$

Where $C_{i,Production}q_i$ represents the Production costs ($C_{i,Production}$ is the cost of producing one unit of product i; q_i is the order quantity for the i^{th} product), $C_{i,Procurement}r_i$ is the Procurement costs ($C_{i,Procurement}$ is the supply cost of one unit of i; r_i is the amount of raw material i that must supply per day), $C_{i,Inventory}h_i$ is the Inventory costs ($C_{i,Inventory}$ is the storage cost of product i; h_i is the stock level of product i), $C_{i,Delivery} f_i$ is the Delivery costs ($C_{i,Delivery}$ is the quantity of finished product i distributed per day; f_i is the distribution cost of one unit of i).

3.4.1.1 Cost elements of Blockchain Implementation

We then designed the mathematical part for the Blockchain Implementation cost ($C_{Blockchain}$) with two components including Blockchain Transaction cost ($C_{BT\_Transaction}$) and Blockchain Installation cost ($C_{BT\_Installation}$). Identifying the available blockchain platforms is the first step for selecting a blockchain platform to develop a business solution (Nanayakkara, Rodrigo, Perera, Weerasuriya, & Hijazi, 2121). Various blockchain platforms have been introduced to deploy smart contracts and provide enterprise solutions to issues in numerous industries (Nanayakkara, Rodrigo, Perera, Weerasuriya, & Hijazi, 2121). Depending on the system requirements of the blockchain application that is developed, a suitable blockchain platform should be selected (Nanayakkara, Rodrigo, Perera, Weerasuriya, & Hijazi, 2121). In this study, according to the advantages of the Public blockchain in section 1.2, the Public type of Blockchain platform is selected for the SCS as a hosting platform according to our literature section. To select a Blockchain platform, we assumed that the system decides to use the platforms available in the market instead of designing and developing a Blockchain platform.

$$C_{Blockchain} = C_{BT\_Transaction} + C_{BT\_Installation} \tag{3.3}$$

To measure the Blockchain Transaction cost ($C_{BT\ Transaction}$) within the network, it seems necessary to use an agreed method for transmitting value. There is a transaction fee for a blockchain participant who wants to execute a transaction (Longo, Nicoletti, Padovano, d'Atri, & Forte, 2019). To address this issue, Wood (2014) mentions Ethereum is a kind of currency called Ether (ETH) where there is a fee for all programmable computation in Ethereum. The most popular consensus protocol in the public blockchain is Proof-of-Work (PoW), such as in

Bitcoin and Ethereum (Wang, et al., 2021). Two parts determine the cost of the transaction: gasLimit and gasPrice. To calculate the cost of the Ethereum blockchain, Longo et al. state it is necessary to do this calculation based on the gas used by a transaction.

Wood introduces gasLimit as a scalar value equal to the maximum amount of gas that should be used in executing this transaction. Every BT transaction includes a specific amount of gas named gasLimit (purchased from the sender's account balance) in which any unused gas is refunded at the end of the transaction (at the same rate of purchase) to the sender's account (Wood, 2019). It seems necessary to evaluate gasPrice for every transaction in the Ethereum blockchain if a BT will be used in a real SC context (Longo, Nicoletti, Padovano, d'Atri, & Forte, 2019). Wood explains gasPrice (a scalar value) is the number of Wei to be paid for each unit of gas including all computation costs incurred as a result of the execution of this transaction. Longo et al. also point out the Ethereum blockchain's software defines and hard-codes the gasPrice for each operation (Wood, 2019). A given amount of gas is associated with a transaction after submitting a transaction (Longo, Nicoletti, Padovano, d'Atri, & Forte, 2019). Wood (2017) introduces this calculation used by the platform to pay miners: Transaction fee = Total gasUsed × gasPrice paid (Longo, Nicoletti, Padovano, d'Atri, & Forte, 2019; Jabbar & Dani, 2020).

$$\mathrm{E} \times g \times 365 + s \times \mathrm{C_s} \tag{3.4}$$

$\mathrm{E} \times g$ is the BT Transaction costs ($C_{BT\_Transaction}$) (E is the amount of Ether as gasUsed per day; g is the of gWei to be paid for gasUsed (per unit of gas/per day). Wei is the unit of ETH typically used to denominate gas prices. We used ETH Gas Station to calculate $\mathrm{E} \times g$ to incentivize computation within the network (ETH Gas Station, 2021; Jabbar & Dani, 2020) (See Figure 3.2). The authors assumed the amount 65000 as gasUsed and 26 and 333 gWei as gasPrice to calculate E × g cost through the ETH Gas Station website. Based on these ranges, the ETH Gas Station proposes the cost of \$3.36 to \$43.07 per day for E × g.

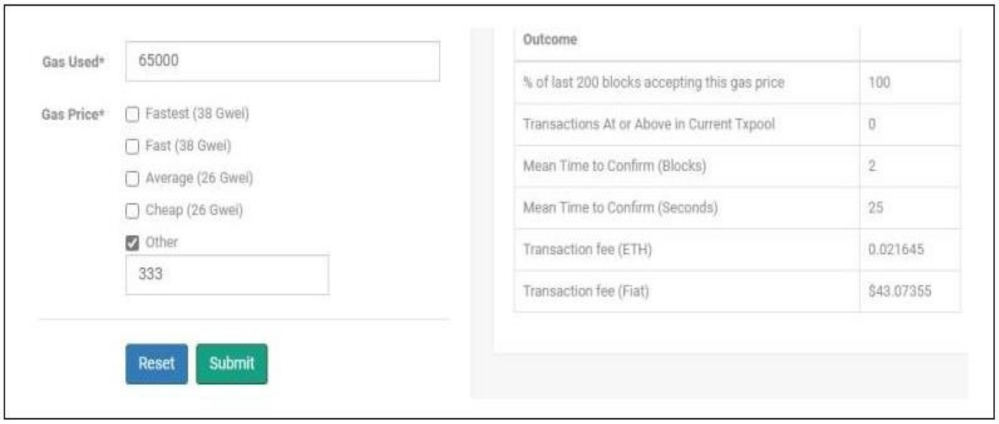

Figure 3.2 Transaction cost by ETH Gas Station

Longo et al. (2019) define two costs for BT transaction cost from a simple ether transaction to the execution of a smart contract's function: the gas (the cost of each operation performed on the blockchain) and the storage of data on the blockchain. $s \times C_s$ is the storage cost which is a secured cloud-based warehouse to store the actual data off-chain. As IBM Cloud came in with the lowest prices across 67 cloud computing scenarios to beat out Microsoft, Google, and AWS (Fork, 2020), we used this service for the storage cost part. IBM Cloud website proposes a price of \$0.1400 for Public outbound bandwidth (USD/GB) with the range of 0 and 50 TB (IBM, 2021). The authors, based on the IBM Cloud website, assumed \$1680 (USD/TB) per year (C_s) for Public outbound bandwidth service. s also represents the storage size to store the data ranging from 180 TB to 420 TB per year. Table 3.1 represents the parameters and constraints (come from variance sources and our imagination) for the BT Transaction costs.

Table 3.1 Parameters and constraints for the BT Transaction costs

Parameters	**Explanation**	**Constrains**
Wei	The unit of ETH typically used to denominate gas prices	---
E	The amount of Ether as gasUsed	$\$3.36 \leq E \times g \leq \$43.07$
g	Number of gWei to be paid for gasUsed per day	
s	The data storage size	180 TB/yr $\leq s \leq$ 420 TB/yr
C_s	Cost storage per year (USD/TB)	\$1680

The basic mathematical part of the Blockchain Installation cost ($C_{BT\_Installation}$) in our model comes from the recent research proposed by Gopalakrishnan, Hall, and Behdad (2021). $C_{BT\_Installation}$ is the cost of utilizing BT for SCS, and this cost needs to consider at least four different cost elements including a Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost.

$$c_{fixed} + (c_{Onboarding}\, U + c_{mc} + c_{mo}) \times \text{avg.}(q_i) \tag{3.5}$$

Where the initial Fixed cost (c_{fixed}) is associated with the utilization of Blockchain; the Onboarding cost (as a function of $c_{onboarding}$) is to train suppliers and clients into active users of a product or service; the Maintenance cost and Monitoring cost are based on the unit Maintenance (c_{mc}) and Monitoring (c_{mo}) cost; q_i expresses the order of products; U is the number of Blockchain users (different types of users) based on consensus protocol in the Blockchain platform. The Maintenance and Monitoring costs occur yearly and contribute to 15–25 percent of the project value (LeewayHertz, 2021b; Gopalakrishna-Remani, Brown, Shanker, & Hu, 2018). The third-party services are used for parts such as mobile apps, admin and web interfaces, and tracking services products (LeewayHertz, 2021b). Onboarding cost (such as onboarding and training) is any expenses and costs related to integrating new employees into a company to learn and train about BT. We also assumed that SCS uses the platforms available in the market. Table 3.2 illustrates the parameters and constraints (come from variance sources and our imagination) for the Blockchain Installation cost.

Table 3.2 Parameters and constraints for the Blockchain Installation cost

Parameters	Explanation	Constrains
c_{fixed}	The initial fixed cost per year	$860 \leq c_{fixed} \leq 1160$
$c_{onboarding}$	The Onboarding cost	$\$180 \leq c_{onboarding} \leq \$260$
c_{mc}	The unit Maintenance cost	$\$25 \leq c_{mc} + c_{mo} \leq \$45$
c_{mo}	The unit Monitoring cost	
U	The number of Blockchain users	4
M	Number of products controlled in the Supply Chain Decision variables	122
q_i	Order quantity for the i^{th} product ($i = 1, 2, 3, \ldots, M$)	50 $q_i \leq 100$ (integer)

3.4.2 Optimization Function of BT-enabled SCS

Updating the Eq. (3.2) by applying the Blockchain costs in Eq. (3.4) and Eq. (3.5), the objective function (3.6) is to minimize the nonlinear BT-enables SCS costs and can be expressed as follows:

$$C_{Total} = [C_{SCS}] + [C_{Blockchain}]$$

$$C_{Total} = [C_{Production} + C_{Procurement} + C_{Inventory} + C_{Delivery}] + [C_{BT\_Transaction} + C_{BT\_Installation}]$$

$$\min \begin{pmatrix} \sum_{i \in N} [\, C_{i,Production} q_i \; + \; C_{i,Procurement} r_i + C_{i,Inventory} h_i \\ + C_{i,Delivery} f_i + \; C_{i,BT\_Transaction} \; + \; C_{i,BT\_Installation}] \end{pmatrix} \tag{3.6}$$

3.5 Case Study: Healthcare System

3.5.1 Model of SC in Healthcare System

As the BT-enabled SCS model introduced in this study is newly designed, there is no specific case study matched with its parameters. To generate data for our model, we, therefore, revised the OR model for PSC and Inventory Management for a single pharmaceutical company and a single hospital published by Uthayakumar and Priyan (2013).

A wide range of methodologies that can help healthcare systems including hospitals and can significantly improve their operations is presented in OR (Uthayakumar & Priyan, 2013). We deeply selected some elements of Model 3.2, 3.3, and 3.7 from Uthayakumar and Priyan's research related to our BT-enabled SCS cost model. As mentioned before, our model contains two different cost components to cover the total costs of the system: Supply Chain System (SCS) cost and Blockchain Implementation cost. Applying simulation technique, this section tries to redesign models for the SCS part of our model (to simulate raw data) which contains four main elements: Production Cost, Procurement Cost, Inventory Cost, and Delivery Cost. Therefore, we present the mathematical formulation in healthcare facilities for each element (using some parts of models in Uthayakumar and Priyan's paper) to generate raw data, evaluating our BT-enabled SCS model, and find the best optimization approach in the result section. PSC can be defined as "the integration of all activities associated with the flow and transformation of drugs from raw materials through to the end-user, as well as the associated information flows, through improved SC relationships to achieve a sustainable competitive advantage" (Uthayakumar & Priyan, 2013; Mustaffa & Potter, 2009). The three main players of PSC are producers, purchasers, and pharmaceutical providers. After receiving the hospital orders of some products (with q_i size), the pharmaceutical company, in each production cycle, starts to produce the product i with the size of nq_i, and then send the order in n lots each of size q_i (i = 1, 2, 3, . . ., M) to the hospital.

The following model in Eq. (3.7) shows the elements of the Production Cost: the Set-up Cost for all finished products in the pharmaceutical company ($\frac{s_i\, d_i}{nq_{i_i}}$), the Production Cost for all finished products in the pharmaceutical company ($d_i\, p_{ci}\, (q_i)$), the Screening Cost for all raw materials in the pharmaceutical company ($\frac{sci\ qwi\ di}{nq_i}$), and the Revenue from imperfect raw materials in the pharmaceutical company ($\frac{s_{di}\ \text{avg.}(\beta_i)\ q_{wi}\ d_i}{nq_i}$).

$$\sum_{i=1}^{M}\left[\frac{s_i\, d_i}{nq_i} + d_i\, p_{ci}\,(q_i) + \frac{s_{ci}\, q_{wi}\, d_i}{nq_i} - \frac{s_{di}\,\text{avg.}(\beta_i)\, q_{wi}\, d_i}{nq_i}\right] \tag{3.7}$$

The following function, in Eq. (3.8), represents the Procurement Cost including the Cost Order for all M products in the hospital ($\frac{d_i}{q_i}\, a_i$), the Cost Order for all raw materials in the pharmaceutical company ($\frac{a_{wi}\, d_i}{nq_i}$), and the Labor Cost for order handling and receipt for all raw materials in the pharmaceutical company ($\frac{d_i\, q_{wi}\, v_{wi}}{nq_i}$).

$$\sum_{i=1}^{M}\left[\frac{d_i}{q_i}\, a_i + \frac{a_{wi}\, d_i}{nq_i} + \frac{d_i\, q_{wi}\, v_{wi}}{nq_i}\right] \tag{3.8}$$

The following cost function called Inventory Cost in Eq. (3.9) for a product i involves: the Holding Cost for all M products in the hospital ($\frac{h_{bi}\, q_i}{2}$), the Holding Cost for all finished products in the pharmaceutical company ($\frac{h_{vi}\, q_i}{2}[n(1 - \frac{d_i}{p_i}) - 1 + \frac{2d_i}{p_i}]$), the Holding Cost for perfect raw materials in the pharmaceutical company ($\frac{d_i\,(1-\text{avg.}(\beta_i))\, q_{wi}\, h_{wi}}{n\, q_i}$), the Holding Cost for imperfect raw materials in the pharmaceutical company ($\frac{h_{wi}\ \text{avg.}(\beta_i)\, q_{wi}\, q_{wi}\, d_i}{r_{si}\, n\, q_i}$), the Safety Stock Cost for all M products in the hospital ($(h_{bi} + p_{hi}\, \mathrm{I}_c)\, k_i\, \sigma_i \sqrt{\mathrm{L}}$), the Expiry Cost for all M products in the hospital ($d_i\,(z_i\, c_{di}\,(\mathrm{L}) + v_i)$), and the Expiry Cost for all finished products in the pharmaceutical company ($q_i\, d_{ci}\, c_{dci}\,[(\frac{d_i}{p_i} + (n-1)) - \frac{nd_i}{2p_i}]$).

$$\sum_{i=1}^{M}\Big[\frac{h_{bi}\, q_i}{2} + \frac{h_{vi}\, q_i}{2}[n(1 - \frac{d_i}{p_i}) - 1 + \frac{2d_i}{p_i}] + \frac{d_i\,(1-\text{avg.}(\beta_i))\, q_{wi}\, h_{wi}}{n\, q_i} + \frac{h_{wi}\ \text{avg.}(\beta_i)\, q_{wi}\, q_{wi}\, d_i}{r_{si}\, n\, q_i} + (h_{bi} + p_{hi}\, \mathrm{I}_c)\, k_i\, \sigma_i \sqrt{\mathrm{L}} + d_i\,(z_i\, c_{di}\,(\mathrm{L}) + v_i) + q_i\, d_{ci}\, c_{dci}\,[(\frac{d_i}{p_i} + (n-1)) - \frac{nd_i}{2p_i}]\Big] \tag{3.9}$$

The Delivery Cost function (Eq. (3.10)) for a product *i* has also these elements: the Transportation and Labor Cost for all *M* products in the hospital ($\frac{d_i}{q_i}$ F) and the Transportation Cost for all raw materials in the pharmaceutical company ($\frac{F_w d_i}{nq_i}$).

$$\sum_{i=1}^{M}[\frac{d_i}{q_i}\mathrm{F} + \frac{\mathrm{F}_w d_i}{nq_i}] \tag{3.10}$$

It is assumed that the hospital and the pharmaceutical company, in practice, pay a fixed transportation cost of F_w and F respectively. The parameters and constraints (come from sources and our imagination) for the Blockchain Installation cost are shown in Table 3.3.

Table 3.3 Parameters and constraints for the Blockchain Installation cost

Parameters	Explanation	Constrains
M	Number of products controlled in the Supply Chain Decision variables	35
q_i	Order quantity for the i^{th} product per year (i = 1, 2, 3, . . . , M)	$50 \leq q_i \leq 100$ (integer)
d_i	Average demand for the i^{th} product per year	$45 \leq d_i \leq 75$ (integer)
L	Lead time (days) for all products (days)	12
n	Total number of lots of M products delivered by the pharmaceutical company to the hospital per year	$50 \leq n \leq 100$ (integer)
z_i	Expiry rate for the i^{th} product at the hospital	$1.04\% \leq z_i \leq 4.21\%$
h_{bi}	Holding cost per year excluding interest charges for the i^{th} product	$45 \leq h_{bi} \leq 75$
a_i	Ordering cost per order for the i^{th} product	$65 \leq a_i \leq 85$
I_c	Interest charge paid per $ in stock to the bank for all products per year	$I_c = 0.03$
p_{hi}	Purchase price per unit for the i^{th} product	$5 \leq p_{hi} \leq 10$
k_i	The safety factor for a product i	$25 \leq k_i \leq 35$ (integer)
$\sigma_i\sqrt{L}$	where σ_i is the standard deviation for the demand per year for the i^{th} product	$1\% \leq \sigma_i \leq 100\%$
F	Fixed transportation cost for all products per delivery per year	4500
h_{vi}	Holding cost for the i^{th} finished product per year	$20 \leq h_{vi} \leq 40$
s_i	Set-up cost for the i^{th} finished product per year	$12 \leq s_i \leq 25$
p_i	Production rate for the i^{th} finished produce	$45 \leq d_i \leq p_i \leq 75$
p_{ci}	Production cost for a product i per year	$80 \leq p_{ci} \leq 120$
v_i	A labor cost for a product i per year	$145 \leq v_i \leq 195$
d_{ci}	Expiration rate for the i^{th} finished product	$1.2\% \leq d_{ci} \leq 9.21\%$
c_{dci}	Cost of expiry for the i^{th} finished product	$25 \leq c_{dci} \leq 55$
c_{di}(L)	Cost of expiry of a linear function of the lead time	$2.6 \leq c_{di}(L) \leq 5.3$
q_{wi}	Replenishment quantity for the i^{th} raw material for production	$20 \leq q_{wi} \leq 27$
a_{wi}	Ordering cost for the i^{th} raw material	$15 \leq a_{wi} \leq 25$
h_{wi}	Holding cost per year for the i^{th} raw material	$10 \leq h_{wi} \leq 15$
F_w	Fixed transportation cost for all raw materials per year	3500
v_{wi}	Labor cost for order handling and receipt for the i^{th} raw material per year	$16 \leq v_{wi} \leq 28$
β_i	Defect rate for the i^{th} raw material in an order lot, $\beta_i \in [0, 1]$, a random variable	$0 \leq \beta_i \leq 1$
s_{ci}	Screening cost per year for the i^{th} raw material	$8 \leq s_{ci} \leq 13$
s_{di}	Imperfect cost per year for the i^{th} raw material	$11 \leq s_{di} \leq 15$
r_{si}	Screening rate per year for the i^{th} raw material	$1.04\% \leq r_{si} \leq 7.2\%$
f_i	Storage space for the i^{th} product	$0.2 \leq f_i \leq 0.6$
W	Total space available for the M products (m^2)	750

3.5.2 Data generation

The authors used Python software to generate raw data for our main BT-enabled SCS model. Then, the following equations (formulas) were turned into a program in Python: $C_{BT\_Transaction}$ (4), $C_{BT\_Installation}$ (5), $C_{Production}$ (7), $C_{Procurement}$ (8), $C_{Inventory}$ (9), and $C_{Delivery}$ (10). Table 3.4 illustrates 100 series of simulated raw data for all six parts of the BT-enabled SCS model, as well as the total cost which is the added values of these parts.

Table 3.4 The simulated raw data

No.	$C_{Inventory}$	$C_{Production}$	$C_{Procurement}$	$C_{Delivery}$	$C_{BT\_Installation}$	$C_{BT\_Transaction}$	C_{Total}
1	34205632	16237091.8	2195	126074.7	626075.9	69665.5	51266734.8
2	30357880.1	15845852	2255.8	124662.2	516547	72833.7	46920030.9
3	29933928.7	15531782.3	2190	121330.2	393267.6	80529.6	46063028.4
4	32670868.7	14744994.3	2402.5	135365.9	608133.1	63095	48224859.4
5	28002373	14803589.5	2439.8	135819.9	494836.4	60739.1	43499797.7
6	30977577.9	16652002.2	2392.2	134673.6	443365.7	67517.2	48277528.9
7	31995018.8	14577183.9	2396.7	134074.1	392981.6	64410.6	47166065.7
8	30459533.7	15496064.7	2360.7	130421.2	358494	81618.7	46528493
9	34056545.	16311475	2309.6	128984.6	651725.2	61472	51212512
10	30625708.4	15581742.8	2360.9	132063.1	532966.4	79484.8	46954326.5
11	31719090.9	15874779.4	2261.3	125837.4	433030.8	74109.6	48229109.5
12	30662660.7	14874716.6	2377.5	133099.1	375081	67564.4	46115499.4
13	31667434.9	14608197.4	2509.6	141334.4	604832.5	58502.5	47082811.4

No.	$C_{Inventory}$	$C_{Production}$	$C_{Procurement}$	$C_{Delivery}$	$C_{BT\_Installation}$	$C_{BT\_Transaction}$	C_{Total}
14	30928928.9	14641305.6	2488.4	134759.1	348223.8	71313.9	46127019.8
15	27843036.9	16763910.4	2243.8	125604.9	671907	82445.9	45489148.9
16	28107666.6	15141932.4	2323.6	130532.1	499639.6	80121.3	43962215.6
17	31127976.4	14797422.1	2253.9	127416	476840.2	71717.2	46603625.8
18	26396159	16647587.5	2328.9	129259	654216.4	63852.6	43893403.5
19	29239131.8	16219659.8	2326.7	127447.6	572750.9	81698.2	46243015
20	32097476.7	15003667	2298.5	129400.2	627322.8	77526.2	47937691.5
21	27388614	15111947.7	2462.7	139478	707911.8	75526.5	43425940.5
22	25865617.3	14731218.5	2567.8	142081.8	474579.2	57752	41273816.7
23	28129379.5	15075683.3	2493.2	135721.1	670929.8	66633.7	44080840.7
24	30489457.9	16091938.2	2423.6	136101.7	690577.6	62644.2	47473143.2
25	26933370.1	13747712.9	2490.2	136637.8	645330.4	54824	41520365.3
26	28911628.1	15040243.1	2435.9	135176.7	474735.2	67537.3	44631756.3
27	25463762.2	15771536.8	2459.2	136056.9	586608	62841	42023264.1
28	32441669.1	15618856.5	2234.6	126544.9	478327.2	61344.1	48728976.3
29	33566323.1	15095432.1	2323.7	129341.9	316771.4	69333.2	49179525.4
30	33934607.1	16534362.4	2246.1	125258.2	387109.8	68895.3	51052478.9
31	28209557.1	14805188.1	2637.2	147349.7	479269.8	63357.8	43707359.7
32	29705452.8	14339504.7	2206.7	122619.2	558445.5	76121.4	44804350.3
33	36580291.6	16181546.1	2392.6	133699.5	660288.8	77088.9	53635307.4

No.	$C_{Inventory}$	$C_{Production}$	$C_{Procurement}$	$C_{Delivery}$	$C_{BT\_Installation}$	$C_{BT\_Transaction}$	C_{Total}
34	28112507.9	15358455.9	2460.4	138993	710751.4	61218.5	44384387.1
35	30621108.3	15102483.5	2484.4	139704	353043.2	55889.1	46274712.6
36	26250290.9	14342230.6	2495.9	137424.9	594539.8	69308.6	41396290.7
37	30451447	14811299.7	2486.4	136616.3	499045.9	67946.7	45968842
38	30102521.8	16119401.4	2213.7	122253.8	466893.3	79908.6	46893192.7
39	28212776.4	15072332.9	2367.4	134776.6	420176.5	72916	43915345.7
40	29756054	15209552.4	2268.4	128393.7	352996.8	63421.5	45512686.8
41	35511865.4	17023416.7	2220.3	123564.8	586474.6	84587	53332128.
42	32742466.6	15502586.7	2346.5	131198.5	698460.6	73913	49150971.9
43	28041675	15520558	2379.5	131017.8	686771.6	73667	44456068.8
44	27868224.9	14538944.1	2361.8	132353	473121.9	62478.4	43077484.1
45	25138267.1	14498531.8	2418.8	133340.5	429997.7	73025.2	40275581
46	33903273.2	14843685.1	2190.1	122936.1	657740.7	75601	49605426.4
47	32658182.7	16528934.5	2435.9	135122.7	455216.6	75259.4	49855151.8
48	29316115.2	14479719.4	2355.1	129284.7	330160	76900.3	44334534.7
49	29638526.6	15003849.6	2498.6	139762.5	448294.2	68760.5	45301692
50	39431225.1	15607043.6	2346.5	130057.5	541215.2	72307.5	55784195.4
51	31770224.5	15876658.5	2416	133934.1	704207.6	75721.5	48563162.3
52	30196007.2	14726152.6	2459.3	136025.2	462498	64719.3	45587861.6
53	30530882.3	14846816.7	2372.6	131849.1	323393.5	69171.6	45904485.8
54	31211679.7	15003477.7	2425.1	133985	529138.2	68095.1	46948800.9

No.	$C_{Inventory}$	$C_{Production}$	$C_{Procurement}$	$C_{Delivery}$	$C_{BT\_Installation}$	$C_{BT\_Transaction}$	C_{Total}
55	31269236.8	15863408.1	2296.8	127144.2	700439.8	63846.3	48026372.1
56	32604149.8	15641553.6	2324.7	128006.1	325478.6	67069.7	48768582.5
57	32234013.6	16102422.6	2365.3	128372.1	574306.4	80467.7	49121947.7
58	29129877.2	15961793.5	2422.6	134983.7	321547	73399.6	45624023.5
59	28221603.6	15457885.9	2376.6	132111.4	347047.6	77520.4	44238545.5
60	27212213.3	15724100.6	2439.3	135402	566283.1	72732.1	43713170.3
61	29870533.5	15971459.4	2256.8	128006.4	620724.3	66427.4	46659407.8
62	26672049.5	16131430.2	2385.6	133646.6	664295.8	81136.3	43684944
63	33021546.7	17175247.7	2233.3	124059.1	380208.2	84083	50787378
64	28750663.5	17275414.5	2251.3	127511.4	363001.8	71930.4	46590772.9
65	27844381.4	14302035.9	2684.4	145798.4	557882.4	53156.5	42905939
66	30480853.3	14425754	2413.9	133978.9	661035.4	74608	45778643.5
67	26493526.9	14552405.1	2432.6	134991.1	554266.2	71181.3	41808803.3
68	31404442.3	15193556.7	2171.2	122453	565541.4	72736.7	47360901.2
69	35103962	14753769	2491.3	138429.4	603369.5	61108.5	50663129.7
70	29964223	15373950.7	2363.5	131837.7	466420.8	78620.6	46017416.3
71	31702820.7	15606633.1	2386.4	132534.8	630582.3	58976.3	48133933.6
72	33677043.6	14660117.7	2309.2	128910.4	485745.3	76091.7	49030217.9
73	32997265.9	16121673.2	2379.8	129836.5	573036.2	63660.9	49887852.5
74	34291083.4	16491803.9	2301.4	128558.7	458485	68307.7	51440540.1
75	30380474.3	15636928.5	2334.8	131246.8	535224.2	74939.6	46761148.1

No.	$C_{Inventory}$	$C_{Production}$	$C_{Procurement}$	$C_{Delivery}$	$C_{BT\_Installation}$	$C_{BT\_Transaction}$	C_{Total}
76	28025073.9	16577959.8	2209.8	124666.6	641002.8	80443.3	45451356.2
77	34019579.6	15299169.4	2384.9	130724.3	534574.8	66855.1	50053288.1
78	30057766	15109794.1	2550.2	139937.9	529526.8	57744.9	45897319.9
79	26378002.7	15056295.6	2423.8	132090	448880.2	78585	42096277.2
80	32608045.9	15274089.5	2393.2	131587.9	669156	66599.4	48751871.8
81	32892334.8	14772104.2	2341.7	130339.3	699368.4	73155.8	48569644.2
82	28619045.2	14930728.6	2304.5	128353.1	398739	66638.8	44145809.1
83	34773199.3	15403756.1	2340.9	131420.1	569824.2	63052	50943592.7
84	32404360.5	14630619.5	2345.6	132779.6	351720.9	66038	47587864.1
85	32592666.7	15651688.3	2416.2	135802.4	667067.8	78175	49127816.5
86	35076072.9	16434465.6	2350	131117.7	497422	62368.1	52203796.3
87	34654944.2	15344798.7	2363.3	128813.5	569373.3	65059.6	50765352.6
88	31828350.6	15289168	2461.8	135044	620357	58050.3	47933431.8
89	35330852.7	15157112.2	2192.1	123594	526796.6	78525.9	51219073.5
90	27668419.9	15804944.6	2464.4	134198.8	359864.8	59100.5	44028992.9
91	30694869.4	14799528.6	2303	129747.7	400770.4	69272.1	46096491.4
92	25309801.9	14252068.8	2363.8	130939.6	410981.2	64948.3	40171103.4
93	31046568.6	16204955.4	2353.5	130186.5	586550.6	69458	48040072.5
94	29334682.1	15410773.8	2507	141074.3	622363.2	55116.5	45566516.8
95	25397027.8	16246241.5	2475.4	136051.2	546832.5	81396.5	42410024.8
96	31220403.8	15553609.4	2313.5	130399.1	342061.6	58052	47306839.5

No.	$C_{Inventory}$	$C_{Production}$	$C_{Procurement}$	$C_{Delivery}$	$C_{BT\_Installation}$	$C_{BT\_Transaction}$	C_{Total}
97	31589283.6	15509291	2349.1	130248.6	481801	80611.2	47793584.6
98	30067878.8	15531262.5	2251.3	125644	354213.2	61303.3	46142553.2
99	32174028.5	15879305.6	2184.2	123438.8	501891.6	78208.3	48759057
100	29001793.5	16148213	2283.9	129633.7	426225.2	64571.8	45772721.3

3.6 Results

In this section, we used three EC algorithms (CS, GA, and ACO) to find the minimum total cost for our BT-enabled SCS model, using the simulated data, as our case study in section 3.5. Therefore, to optimize the parameters of the model, Eq. (3.11), which is the revised version of Eq. (3.6), calculated total costs for all 100 series of simulated data (Table 3.4) through three mentioned EC algorithms coded in MATLAB. The objective function of EC algorithms is Eq. (3.11) which should be minimized:

$$\min \begin{pmatrix} \sum_{i \in N} [\, C_{i,Production}\mathrm{Q} + C_{i,Procurement}\mathrm{R} + C_{i,Inventory}\mathrm{H} + \\ C_{i,Delivery}\mathrm{F} + \mathrm{C}_{i,BT\_Transaction} + \mathrm{C}_{i,BT\_Installation}] \end{pmatrix} \tag{3.11}$$

$$0 \leq \ i \leq 100 \tag{3.12}$$

$$\mathrm{R} \leq \mathrm{F} \tag{3.13}$$

$$\mathrm{Q} \leq \mathrm{F} \tag{3.14}$$

$$\mathrm{F} + \mathrm{R} \leq \mathrm{H} \tag{3.15}$$

$$\mathrm{Q} + \mathrm{R} \leq \mathrm{H} \tag{3.16}$$

Where $C_{i,Production}$Q represents the Production costs in the pharmaceutical company ($C_{i,Production}$ is the cost of producing all products in the i^{th} series of data; Q is the order quantity of a hospital for each series of data); $C_{i,Procurement}$R is the Procurement costs ($C_{i,Procurement}$ is the cost order for all products in the hospital in the i^{th} series of data; R is the amount of all products in the hospital for each series of data); $C_{i,Inventory}$H is the Inventory costs in both hospital and pharmaceutical companies ($C_{i,Inventory}$ is the storage cost of all products in the i^{th} series of data; H is the stock level of each series of data); $C_{i,Delivery}$F is the Delivery costs to both hospital and pharmaceutical companies ($C_{i,Delivery}$ is the distribution cost to both hospital and pharmaceutical companies in the i^{th} series of data; F is the quantity of all finished products for each series of data); and BT cost ($C_{i,BT\_Transaction}$) and Blockchain Installation cost ($C_{i,BT\_Installation}$) are the costs for the i^{th} series of data. The authors, based on constraints, assumed the following parameters as constants with these values before running the selected algorithms: R = 30; F = 35; Q = 25; H = 75.

The performance of the applied algorithms is evaluated by some well-known accuracy criteria, namely the Mean Square Error (MSE), Root Mean Square Error (RMSE), R^2, and Area Under the ROC Curve (AUC-ROC or simply AUROC). The MSE was defined as the objective function to measure the performance error after each try. A code written by MATLAB was used for the optimization procedure, and the maximum number of iterations is set to 2000 for all three algorithms. The reason behind evaluating various criteria is that the problem with MSE and RMSE, not even getting deep into the details, stems from the fact that they are just based on an error assessment, while the models should be treated holistically based on their all capabilities (Razavi Termeh, Kornejady, Pourghasemi, & Keesstra, 2018). To compare the declining trend of the error, the convergence curves of training error of all three algorithms (CS, GA, and ACO) are presented in Figure 3.3. The convergence curve of both GA and ACO remained steady on the MSE of around 0.09 after iteration 1000. However, CS shows an MSE of around 0.075 after iteration 1000, which has the minimum training error and better results compared to the other algorithms even in the low number of iterations. The baseline, in this figure, also illustrates the minimum training error as an indicator for comparison.

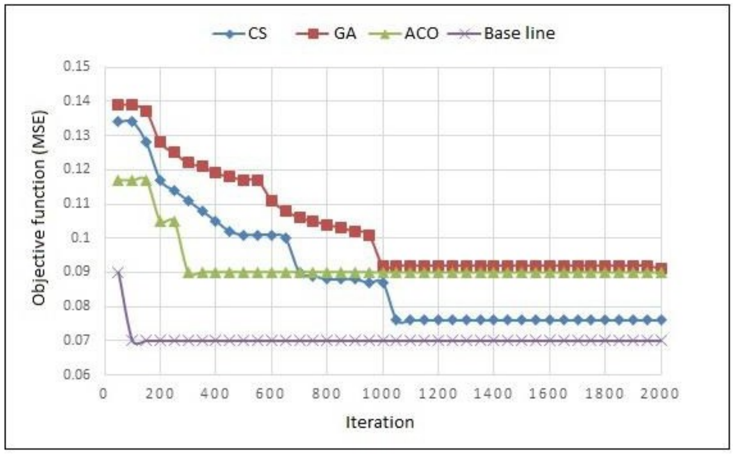

Figure 3.3 The convergence curves of training error for CS, GA, and ACO

Figure 3.4 illustrates the cost minimization results for all three algorithms. As depicted in this figure, there is a significant difference in the convergence rates between ACO and the rest functions. Algorithms CS and GA converge similarly, slightly cheaper than ACO. Now it is seen that ACO has not been able to find the global minimum in 2000 iterations, but CS has reached a global minimum at the 800^{th} iteration.

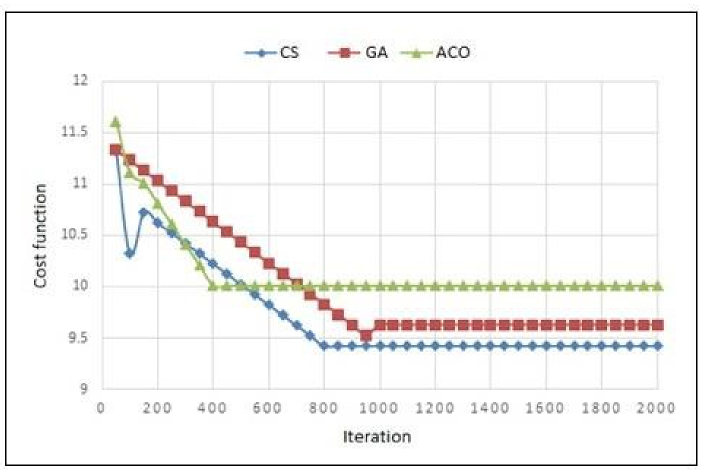

Figure 3.4 Comparison of convergence curves for the cost function of CS, GA, and ACO

Figure 3.5 shows the comparison of running time results (seconds) over 2000 iterations for CS, GA, and ACO algorithms. As it can be seen in the figure, CS has been converged with a high speed and in the lower number of iterations, less than 900, can attain a better solution compared to others. ACO and GA also take longer to find a solution.

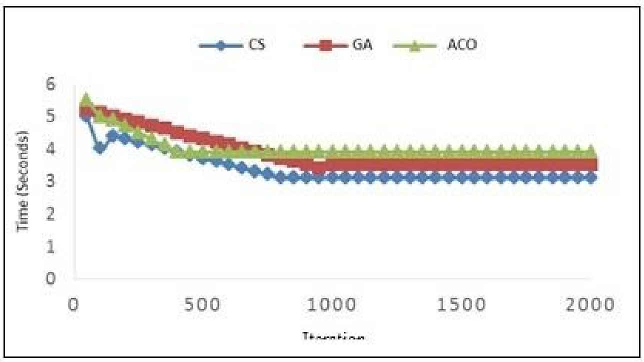

Figure 3.5 Running time comparison (seconds) of CS, GA, and ACO

The performance of the applied algorithms is evaluated by some criteria, namely MSE, RMSE, Error Mean, and Error St.D. in Figure 3.6. The simulated data were randomly examined via 70:30 partitioned data sets where a testing dataset was 70% for training the models and the remaining 30% was used for the validation purpose.

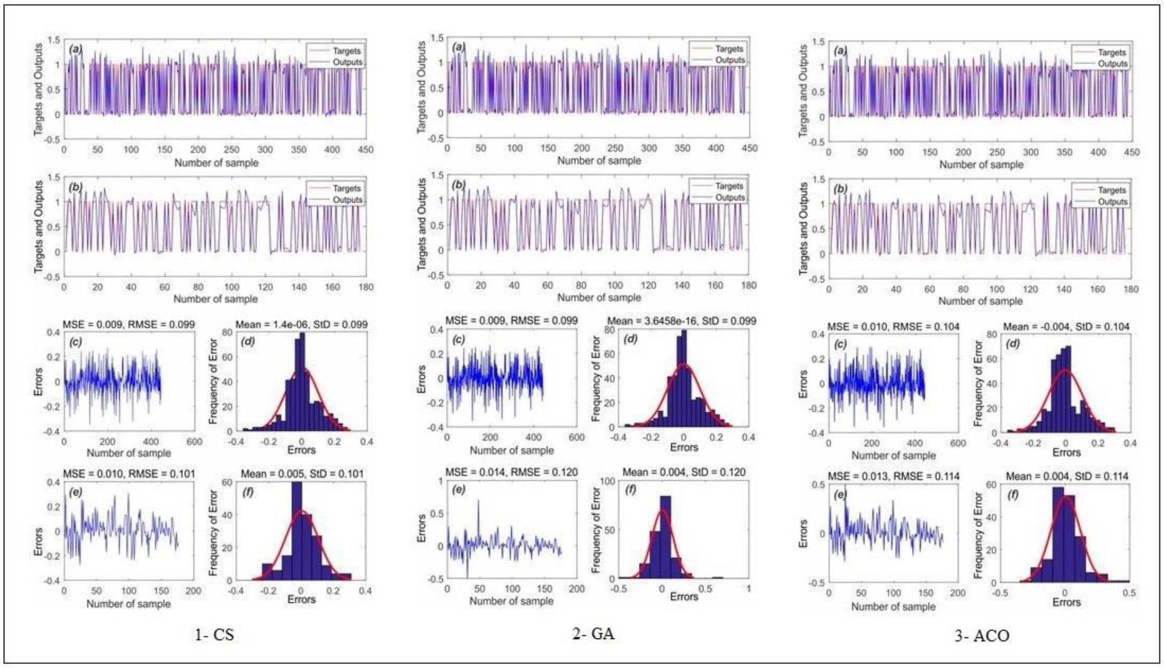

Figure 3.6 The results were obtained for 1- CS, (b) 2- GA, and 3- ACO in which (a, c, d) and (b, e, f) were allocated to training and testing phases respectively

The combination of an ANFIS model and a NARX structure called the ANFIS–NARX method provide a powerful system to create an accurate and transparent identification method, which is the combination of universal approximation capability, transparency of fuzzy inference system, and training ability of neural networks with an adaptive and predictive potential of NARX structure (Annabestani & Naghavi, 2014). They assert that the main reason for ANFIS–NARX selection is its interpretability, transparency, and readability as well as better estimation accuracy that are important characteristics playing a significant role in the performance of the system and its superiority. We, therefore, used a combination of ANFIS-NARX with three EC algorithms called CS-ANFIS–NARX, GA-ANFIS–NARX, and ACO-ANFIS–NARX to compare the accuracy. After training ANFIS–NARX by EC algorithms, the Receiver Operating Characteristic (ROC) curves for testing predictions of the three algorithms were plotted in Figure 3.7. To assess the performance of algorithms, the results are analyzed, and the prediction accuracy of the employed ensembles is evaluated by ROC. The ROC curve is a common method to determine the accuracy of a diagnostic test, and it is considered as a graphical representation of the trade-off between the false-negative (X-axis) and false positive (Y-axis) rates for every possible cut-off value (Razavi Termeh, Kornejady, Pourghasemi, & Keesstra, 2018). The Area Under the ROC Curve (AUC-ROC or simply AUROC) represents the prediction value of an algorithm (and the accuracy of the prediction) characterized by its ability to compare quantitatively between various ROC curves and estimate the true positive and negative events. This value summarizes the corresponding ROC curve into a single value between 0 and 1. According to these figures, all obtained ROCs in the testing phase show a high accuracy (>80%) for the EC-ANFIS-NARX. In detail, the highest accuracy, among three algorithms, for predicting (83.9 % accuracy) was obtained by the ACO-ANFIS-NARX, followed by the CS-ANFIS–NARX 83.3 %), and the GA-ANFIS-NARX (81.9 %). Part (d), as the Total Average for all algorithms, illustrates the accuracy which is higher than the accuracy of the three algorithms to produce the reasonable global minimum outputs for the BT-enabled SCS cost model. The parameter sets used in CS, GA, and ACO are also compared in Table 4.5.

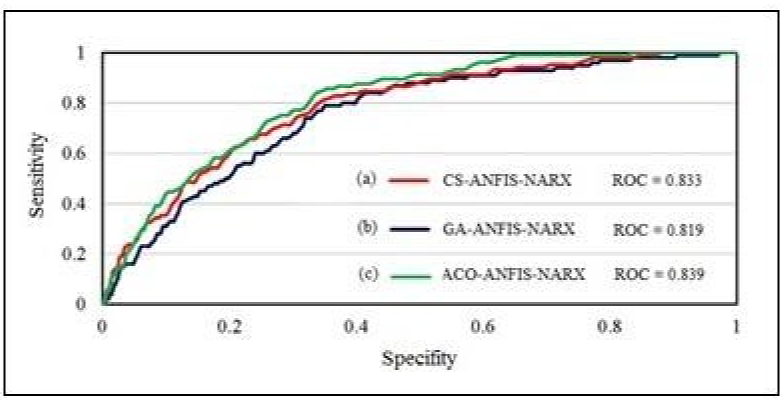

Figure 3.7 The ROC curves were plotted for the testing dataset and obtained from the ensembles of (a) CS-ANFIS-NARX, (b) GA-ANFIS-NARX, and (c) ACO-ANFIS-NAR

The results of the optimization for three algorithms are summarized in Table 3.5. There are two approaches to train and test the data set and then to evaluate the used model through

CS, GA, and ACO algorithms. In both Ensemble and Network approaches, the results illustrate the ranking score in both training and testing phases for ROC are similar, showing a good accuracy of the used model. ACO has the better accuracy (ROC) in both approaches and phases, and GA stands in the third level. Therefore, all three algorithms have an acceptable accuracy obtained from ROC to perform consistently in both approaches/phases and reach the global minimum for the BT-enabled SCS cost model. MSE in both approaches and phases indicates the minimum amount in CS except in the testing phase of the Network approach where it has the maximum amount. The table denotes that while the CS in both phases of the Ensemble approached reached the lowest RMSE, ACO kept decreasing the RMSE in Network approach in both phases. Having a look at MSEs and RMSEs values in the training phase indicates that CS is genuinely doing better than other approaches in learning the pattern. All obtained results from MSEs and RMSEs show a good capability of the used models for predicting the unseen costs. To determine the most reliable predictive algorithms, a score-based ranking system called Total Ranking Score (TRS) is finally used (Moayedi, Mehrabi, Bui, Pradhan, & Foong, 2020). In this procedure, each model receives a score based on the calculated MSE, RMSE, and ROC in both approaches and phases. Eventually, the ranking position of each model is allocated to the summation of all acquired scores states (Moayedi, Mehrabi, Bui, Pradhan, & Foong, 2020). In TRS, the lowest MSE and RMSE receive the highest scores and the highest ROC has the highest score (and vice versa). The overall results of this study show that both CS and ACO algorithms have performed better than the compared algorithm and achieved the first position in terms of all criteria with a TRS of 27, followed by GA with a TRS of 18.

Table 3.5 The developed ranking system based on MSE, RMSE, and ROC criteria

Algorithms		Ensemble medels						Network results						TRS	Rank
		Training phase			Testing phase			Training phase			Testing phase				
		MSE	RMSE	ROC	MSE	RMSE	ROC	MSE	RMSE	ROC	MSE	RMSE	ROC		
CS		0.086	0.294	0.833	0.08	0.284	0.833	0.075	0.275	0.835	0.069	0.277	0.830		
GA		0.088	0.297	0.818	0.081	0.285	0.819	0.077	0.278	0.819	0.065	0.276	0.818		
ACO		0.087	0.295	0.841	0.084	0.29	0.839	0.078	0.269	0.840	0.066	0.275	0.839		
Ranking score	CS	3	3	2	3	3	2	3	2	2	1	1	2	27	1
	GA	1	1	1	2	2	1	2	1	1	3	2	1	18	2
	ACO	2	2	3	1	1	3	1	3	3	2	3	3	27	1

3.7 Conclusion

This paper introduces the cost components of BT-enabled SCS including the Production costs (in the pharmaceutical company), Procurement costs, Inventory costs (in both hospital and pharmaceutical company), Delivery costs (to both hospital and pharmaceutical company), Blockchain Transaction cost (gasUsed and gasPrice), and Blockchain Installation cost (Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost). To evaluate the total costs of the system, these components are useful for companies and organizations that tend to use Public BT as the main database in their SC system. Another advantage of this paper is to model the mathematical formulation for the BT-enabled SCS based on the mentioned components. The simulated raw data for the main BT-enabled SCS model is another output for this research, which comes from the designed mathematical formulation in healthcare facilities (the OR model for PSC and Inventory Management for a single pharmaceutical company and a single hospital). This mathematical formulation helps other studies that have a limitation of finding real data generate raw data in a healthcare field for their research. According to Yang (2014), there are many optimization algorithms in the literature and no single algorithm is suitable for all problems.

This paper found out that both CS and ACO algorithms fulfill the BT-enabled SCS cost model with the higher TRS (including MES, RMSE, and ROC) than the GA. Compared with other metaheuristic algorithms, CS seems to be more generic and robust for some optimization problems (Gandomi, Yang, & Alavi, 2013). The results also show GA, based on TRS, stands in the second step for this case. While the ROC of ACO is higher than others, CS comes in the second level, followed by GA. The more interesting finding is that all three applied algorithms produce reasonable global minimum outputs for the BT-enabled SCS cost model. This means that our cost model can fulfill all three mentioned algorithms as the accuracy of the three algorithms to produce the reasonable global minimum outputs for the BT-enabled SCS cost model seems acceptable. According to reaching the reasonable global minimum outputs for the BT-enabled SCS cost model by the three algorithms, we also find out that the designed mathematical formulation in healthcare facilities is able to give us the reliable simulated dataset as it ends up with the high ROCs and low MESs/RMSEs in the main model.

The authors suggest examining this mathematical model with a private or hybrid BT system for future research. This results in changing some parts and components of the Blockchain Implementation cost (these components in our case are the Blockchain Transaction cost and the Blockchain Installation cost). In this regard, the future study will be able to compare the costs of this study with the new one to show which direction has the lowest cost. One remaining question is to examine this model using our simulated data with some other metaheuristics algorithms to identify and compare it with our three results of CS, ACO, and GA. Therefore, readership can understand which algorithm is more suitable for the mentioned model. Last but not least, it is needed to investigate the performance of the BT-enabled SCS cost model in real problems after proving in test cost functions.

CHAPTER 4

SUPERVISED LEARNING THROUGH EVOLUTIONARY COMPUTATION TUNNING: AN APPLICATION TO BLOCKCHAIN-BASED PHARMACEUTICAL SUPPLY CHAIN COST MODEL

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4.1 Abstract

Pharmaceutical Supply Chain (PSC) is a system of processes, operations, and organisations for drug delivery. This paper provides a new PSC mathematical cost model, including Blockchain Technology (BT), that can improve the safety, performance, and transparency of medical information sharing in a healthcare system. We aim to estimate costs of the BT-based PSC model, select algorithms with minimum prediction errors, and determine the cost components of the model. After data generation, we applied four Supervised Learning algorithms (K-Nearest Neighbour, Decision Tree, Support Vector Machine, and Naive Bayes) combined with two Evolutionary Computation algorithms (Ant Colony Optimization and Firefly Algorithm). We also used the Feature Weighting approach to assign appropriate weights to all cost model components, revealing their importance. Four performance metrics were used to evaluate the cost model, and the Total Ranking Score (TRS) was used to determine the most reliable predictive algorithms. Our findings show the ACO-NB and FA-NB algorithms perform better than the other six algorithms in estimating the costs of the model with lower errors, whereas ACO-DT and FA-DT show the worst performance. The findings also indicate that the Shortage

cost, Holding cost, and Expired Medication cost more strongly influence the cost model than other cost components.

Keywords: Blockchain-based Pharmaceutical Supply Chain; Supervised Learning algorithms; Evolutionary Computation algorithms; Blockchain Technology

4.2 Introduction

The Supply Chain System (SCS) is an accepted approach to increase profit margins, protect the pharmaceutical industry against introduced pressures, and overcome obstacles for obtaining high efficiency while taking the limited available resources into account (Ahmadi, Mousazadeh, Torabi, & Pishvaee, 2017). Conversely, the Pharmaceutical Supply Chain (PSC) is a system of processes, operations, and organisations involved in drug discovery, development, and production. PSC processes are crucial for ensuring medication quality and favourable final patient outcomes (Chircu, Sultanow, & Saraswat, 2014). As a system of processes, operations, and organisations, PSC plays a significant role in delivering the right medication to the right customers (patients) at the right time and in the right conditions. In the current SCS, pharmacies and manufacturers cannot track their products and have no clear system visibility. Recalls are costly and complicated in the SCS, making follow up with patients difficult for companies. Therefore, the current SCS in the pharmaceutical industry appears to be out-dated and may not provide visibility and control for manufacturers and regulatory authority over drug distribution (Haq & Esuka, 2018)**.** In particular, it cannot withstand 21st-century cyber-security threats (Haq & Esuka, 2018)**.** The use of Blockchain-based Pharmaceutical Supply Chain (BT-based PSC) appears to be necessary for any pharmacy system BT-based PSC helps the system improve the safety, performance, transparency of medical information sharing, and data transformation cost/time, as well as the manufacturing process, distribution of the materials/drugs, and tracking of the materials/drugs sourced for manufacturing. BT in PSC system can develop patient data cards for other medical practitioners' centres especially hospitals, leading to save of time and improve a healthcare service. In this system, patients and healthcare centers can have different accessibility choices to the PSC data. In addition, any block in BT contains the medical information with a hash connected to it to another block.

In contrast to several previous studies that have reported on the advantages and disadvantages of using BT in PSC, the present study seeks to address the cost problem of the BT-based PSC. Other studies do not provide a cost mathematical model and related cost components for PSC system based on the BT approach. On the other hand, the difference this paper and others is to introduces a cost mathematical model for BT-based PSC system and the cost components of the system. The cost factor is important to managers because the knowledge of cost helps them to control all financial resources employed in the performance of the system, control the cash flow, identify the rate of return and profitability, and correctly decide whether the new system benefits their organisation. Moreover, the knowledge of cost helps to monitor the business financial health, optimise the institution financial planning, reduce expenses, and stay within the budget, and analyse the information to identify unnecessary costs and better business opportunities. Another important contribution of this study is to provide a PSC system with BT. BT can improve the safety, performance, and transparency of medical information sharing in a healthcare system, minimise the data transformation cost and time, and maintain the financial statements in hospitals.

The purpose of this study is to estimate the costs of the BT-based PSC model in a hospital, select algorithms with the minimum prediction errors, and determine the cost components of the BT-based PSC model in a hospital. To understand the importance of the BT-based PSC cost model, determining the cost components of the model is essential. Thus, this paper also aims to measure the importance of each cost component (feature) of the model, which is the degree of relevance of each feature to the model. To achieve these objectives, this research attempts to respond to the following research questions: (i) What are the cost components of the BT-based PSC cost model in a hospital, and what is the mathematical cost model? (ii) Which algorithms show better performance in minimising the prediction errors of the BT-based PSC cost model? (iii) What are the important cost components of the model? The research questions are answered in the following direction. First, we designed a mathematical BT-based PSC cost model after determining the cost components. Then, following data generation, we applied four Supervised Learning (SL) algorithms (K-Nearest-Neighbors (KNN), Decision Tree (DT), Support Vector Machine (SVM), and Naive Bayes (NB)) combined with two Evolutionary Computation (EC) algorithms (Ant Colony Optimization (ACO) and Firefly Algorithm (FA) for a total of eight algorithms. These algorithms were selected because they are well-known algorithms that have been successfully applied to solve many engineering problems, facilitating the discussion of their behaviours in our new cost model. Finally, four performance metrics were used to evaluate the cost model, and the Total Ranking Score (TRS), which is a score-based ranking system, was used to determine the most reliable predictive algorithms.

The rest of the paper is organised as follows. First, we provide an overview of BT in PSC, EC, and SL in Section 2. Next, we discuss the methodology and data generation used to optimise the estimation of the BT-based PSC cost model in Section 3. Then, designing the mathematical cost model for BT-based PSC comes in section 4. All experiments and results are described in Section 5. Then, the results, limitations, and future research are discussed in Section 6 called Discussion. Finally, we briefly present the conclusions in Section 7.

4.3 Literature Review

This background tends to explain the related literature regarding PSC and its components for a hospital, BT drives PSC, Evolutionary Computation and Supervised Learning (ACO and FA; KNN, DT, NB, and SVM.

4.3.1 PSC and its components for a hospital

The SCS is required for any industry that moves materials and goods in any way; on the other hand, PSC is important for tracking the materials and goods sourced for manufacturing, for the manufacturing process, and for the distribution of the products (Kamel Boulos, Wilson, & Clauson, 2018). PSC processes affect the quality of medication and patient outcomes (Chircu, Sultanow, & Saraswat, 2014). As an accepted approach, the SCS protects the pharmaceutical industry against the introduced pressures, increases profit margins, and overcomes efficiency issues (Ahmadi, Mousazadeh, Torabi, & Pishvaee, 2017). PSCs seek to ensure that the right people receive the right medication at the right time and in the right conditions (Salehi, Salehi, Mirzayi, & Akhavizadegan, 2020). These responsibilities of PSCs are complex and increase their vulnerability and probability of distribution (Salehi, Salehi, Mirzayi, & Akhavizadegan, 2020). PSC can be defined as "the integration of all activities associated with the flow and transformation of drugs from raw materials through to the end user, as well as the associated information flows, through improved SC relationships to achieve a sustainable competitive advantage" (Uthayakumar & Priyan, 2013). The pharmaceutical industry is a system of processes, operations, and organisations involved in drug detection, development, and production (Goodarzian, Hosseini-Nasab, Muñuzuri, & Fakhrzad, 2020). They (Goodarzian, Hosseini-Nasab, Muñuzuri, & Fakhrzad, 2020) assert PSC is described as an approach with suitable quality that distributes drugs at the right time and place to reach the final customers**.** The healthcare sector includes publicly traded companies supporting all facets of the healthcare sector (Haq & Esuka, 2018). They (Haq & Esuka, 2018) state the healthcare sector consists of clinical, preventive, treatment, and therapeutic services providers, including doctors, nurses, hospitals, drugs, medical equipment suppliers, health insurance companies, and other private, government, and voluntary institutions such as residential, educational, dental, domestic health, medical, surgical, ambulatory, and medical and diagnostic laboratories. The PSC includes three significant players: producers, purchasers, and pharmaceutical providers (Uthayakumar & Priyan, 2013). They (Uthayakumar & Priyan, 2013) consider the producers are the pharmaceutical companies, medical surgical product companies, device manufacturers, capital equipment manufacturers, and information systems manufacturers. According to Uthayakumar and Priyan (Uthayakumar & Priyan, 2013), purchasers comprise the grouped purchasing organisations, the pharmaceutical wholesalers, the medical surgical distributors, independently contracted distributors, and the product representatives. They (Uthayakumar & Priyan, 2013) also explain that providers include hospitals and their systems, integrated delivery networks, and alternative site facilities. The BT-enabled PSC cost model in this article contains eight elements, namely (a) Regular Purchases Cost, (b) Emergency Purchases Cost, (c) Shipping Cost, (d) Expired Medication Cost, (f) Holding Cost, (g) Shortage Cost, (h) Blockchain Transaction Cost, (i) Blockchain Installation Cost.

4.3.2 BT drives PSC

The current PCS of the pharmaceutical industry appears to be outdated and does not provide visibility and control for manufacturers and drug distributions and cannot withstand the current cyber-security threats (Haq & Esuka, 2018)**.** BT is as cutting-edge technology that has been used in different applications such as cryptocurrency, financial services, risk management, and public and social services (Hosseini Bamakan, Ghasemzadeh Moghaddam, & Dehghan Manshadi, 2021). BT can be public, private, hybrid, or consortium. Each BT type has various advantages and disadvantages that influence its optimal applications. According to Haq and Esuka (Haq & Esuka, 2018), the defects of the SCS are as follows: information is not shared between systems, manufacturers cannot track their products, drug regulatory authority has no visibility of the system, recalls are complicated and costly, and the healthcare system cannot follow up with patients. Haq and Esuka (Haq & Esuka, 2018) also mention that the products in a PSC are verifiable without any information about the manufacturer's secret techniques.

Conversely, Haq and Esuka (Haq & Esuka, 2018) believe that it is possible to share the patient's medical record with various participants on the network without disclosing the patient's private data. Several players move a product throughout the PSC: (i) primary manufacturers, (ii) secondary manufacturers, (iii) distribution centers/wholesalers, and (iv) retailers (i.e., pharmacies)/hospitals (Zahiri, Jula, & Tavakkoli-Moghaddam, 2018). BT improves safety, displays information, achieves transparency, and is used for health record-keeping, clinical trials, and patient monitoring (Haleem, Javaid, Pratap Singh, Suman, & Rab, 2021). According to Zahiri et al. (Zahiri, Jula, & Tavakkoli-Moghaddam, 2018), BT maintains financial statements in the hospitals and minimises the time and cost of data transformation. Haleem et al. (Haleem, Javaid, Pratap Singh, Suman, & Rab, 2021) highlight that BT preserves and exchanges patient data through hospitals, diagnostic laboratories, pharmacy firms, and physicians in a healthcare system. BT in the PSC can detect fake medicines with proper control over the supply and demand of the drugs and can enable pharmaceutical companies to control fake and unregistered medicines (Kumar Badhotiya, Prakash Sharma, Prakash, Kalluri, & Singh, 2021). Kumar Badhotiya et al. (Kumar Badhotiya, Prakash Sharma, Prakash, Kalluri, & Singh, 2021) assert that fake and unregistered medicines with no medical recovery pose a significant threat to human life, causing many side effects leading to severe damage to health or even death. Therefore, BT's advantages improve the performance, security, and transparency of medical data sharing in the healthcare system (Haleem, Javaid, Pratap Singh, Suman, & Rab, 2021). Haleem et al. (Haleem, Javaid, Pratap Singh, Suman, & Rab, 2021) also state that BT gains insight and enhances the analysis of medical records in medical institutions. BT with PSC enables data integration, secure transactions, serialisation, and traceability (Hosseini Bamakan, Ghasemzadeh Moghaddam, & Dehghan Manshadi, 2021). Importantly, Haq and Esuka (Haq & Esuka, 2018) note that visibility and privacy are mostly contradictory, and to obtain one, the other is often lost. They (Haq & Esuka, 2018) clarify that BT can guarantee to verification of the origin of data that are made available publicly while keeping the private data of an entity secret without compromising privacy. According to these authors (Haq & Esuka, 2018), the decentralized nature of BT allows patients, doctors, and healthcare providers to share data quickly and securely. Hosseini Bamakan et al. (Hosseini Bamakan, Ghasemzadeh Moghaddam, & Dehghan Manshadi, 2021) also show that traceability plays a significant role in securing drugs and is the basis for reliance by the consumer on the PSC and its products. They (Hosseini Bamakan, Ghasemzadeh Moghaddam, & Dehghan Manshadi, 2021) continue that the traceability of BT enables the PSC to verify the background of a product and tracks the path of all the locations and the participants that handle it. According to Hosseini Bamakan et al. (Hosseini Bamakan, Ghasemzadeh Moghaddam, & Dehghan Manshadi, 2021), BT can also provide transparency to the PSC and considers the needs of the suppliers, producers, logistics, distributors, and customers in the PSC. They (Hosseini Bamakan, Ghasemzadeh Moghaddam, & Dehghan Manshadi, 2021) assert that all pharmaceutical adheres to patient protection maintenance, and intelligent contracts facilitate this process if a system applies BT. Among all factors of BT-enabled PSC, the cost factor is significant for an organization. Supervised Learning (SL) algorithms can predict the costs of the system and Evolutionary Computation is applied to optimize the hyperparameters of SL to build a model, exploring possible combinations of parameters.

4.3.3 Evolutionary Computation and Supervised Learning

The Evolutionary Computation (EC) algorithm is the main object of interest in evolutionary computation (Zhang, et al., 2022). The scientific community has demonstrated that metaheuristics are a viable and often superior alternative to the more traditional (exact) methods of mixed-integer optimisation such as branch and bound and dynamic programming (Glover & Sörensen, 2015). Metaheuristics often offer a better trade-off between solution quality and computing time, particularly for complicated problems or large problem instances (Glover & Sörensen, 2015). Using metaheuristic techniques reasonably good solutions are obtained without exploring the whole solution space (Yusta, 2009). Rather than searching for the global optimum solution, these techniques aim to find sufficiently “good” solutions efficiently exploiting the characteristics of the problem and provide an attractive alternative for large-scale applications (Garg, 2009). SL tries to predict the output feature's value based on the input features' values (Abd-Alsabour, 2015). They(Abd-Alsabour, 2015) also point out that SL learns the relationship between the target feature and the input features from the training data for which the target feature value is already known.

4.3.3.1 ACO and FA

Metaheuristics are powerful techniques for solving complex, real-world problems in many application domains (Rojas-Morales, Riff, & Neveu, 2021). The behaviour and performance of EC algorithms depend strongly on their ability to efficiently explore and exploit the search space (Rojas-Morales, Riff, & Neveu, 2021). They (Rojas-Morales, Riff, & Neveu, 2021) state that ACO is a well-known EC that was inspired by the collective performance of real-life ant colonies and has been used to solve many engineering problems. ACO algorithm employs a colony of simple cooperating agents and solves combinatorial optimisation problems (Nourelfath, Nahas, & Montreuil, 2007). FA is mainly inspired by the light connection between fireflies (Goodarzian, Hosseini-Nasab, Muñuzuri, & Fakhrzad, 2020). Goodarzian et al. (Goodarzian, Hosseini-Nasab, Muñuzuri, & Fakhrzad, 2020) explain that in swarm intelligence, the cooperation (and possibly the competition) of more straightforward and less intelligent members creates a higher degree of intelligence that certainly cannot be achievable by any of the components alone. Thus, according to Goodarzian et al. (Goodarzian, Hosseini-Nasab, Muñuzuri, & Fakhrzad, 2020), FA is inspired by the natural species behaviour to optimise nonlinear functions simultaneously using low-cost algorithms. Each member of the fireflies' group in FA moves to a point where their best personal experience has occurred (Mashhour, Houby, TawfikWassif, & IbrahimSalah, 2020).

4.3.3.2 KNN, DT, NB, and SVM

SL is defined as the use of labelled datasets to train algorithms that classify datasets or predict outcomes accurately (Zhang, et al., 2022). Zhang et al. (Zhang, et al., 2022) mention that SL adjusts the weights until the model is fitted appropriately after inputting the data into the model. According to Zhang et al. (Zhang, et al., 2022), the cross-validation process ensures that the model can avoid-overfitting and under-fitting. They present SL uses several methods, including Neural Networks, Naïve Bayes (NB), Linear Regression, Logistic Regression, Random Forest, Support Vector Machine (SVM).

The K-Nearest-Neighbors (KNN) is an SL algorithm used in classification and regression problems (Almomany, Ayyad, & Jarrah, 2022). They (Almomany, Ayyad, & Jarrah, 2022) highlight that KNN is applied in a variety of applications such as text categorisation, agriculture, medicine, finance, facial recognition, economic forecasting, and heart disease diagnosis. They (Almomany, Ayyad, & Jarrah, 2022) express that KNN calculates the distance between each unlabelled data point and all other points in the dataset to classify the unlabelled data. Then, KNN, according to these authors (Almomany, Ayyad, & Jarrah, 2022), assigns each unlabelled data point to the class of the most identically labelled data by finding patterns in the dataset.

A DT is an SL algorithm primarily used to analyse data and perform regression and classification problems (Singh Kushwah, et al., 2022). They (Singh Kushwah, et al., 2022) introduce that DT contains decision nodes (test the value of an attribute), edges (outcome of a test and connect with next node), and leaf node (predict the result), that are combined and comprise a complete structure of DT. In the DT, according to these authors (Singh Kushwah, et al., 2022), each dataset attribute is treated as a node, where a special and unique node is a root node. The process starts with a unique node and proceeds down the tree to satisfy the parameters and decision (Singh Kushwah, et al., 2022). They (Singh Kushwah, et al., 2022) believe this procedure is carried out until a terminal node is encountered.

An NB classifier is a simple probabilistic classifier that has been widely used due to its high efficiency, solid theoretical foundation, and good generalisation ability (Ren, et al., 2022). According to Ren, et al. (Ren, et al., 2022), NB assumes that the attribute variables are conditionally independent when class variables are given. To classify the given item, they state that NB determines the probability of each category appearing under the condition of the occurrence of this item and classifies the item that belongs to the category with the highest probability (Ren, et al., 2022).

An SVM is a binary classification model that has been widely used due to its global optimisation capability and good robustness in fields such as environment, medicine, and finance (Zhang, Shi, Yang, & Zhou, 2021). They (Zhang, Shi, Yang, & Zhou, 2021) explain the basic principle of SVM requires that the distance from the nearest sample point to the decision surface is the largest in solving a classification problem; that is, the minimum distance maximises the two classes of the sample points to separate the edges. A straight line in a two-dimensional space makes it the most suitable segmentation line in the middle of the two data classes, and SVM finds an optimal decision plane as the classification benchmark in the high-dimensional dataset (Zhang, Shi, Yang, & Zhou, 2021). The next section explains the methodology of the study and the procedure to generate data.

4.4 Methodology and Data Generation

In this section, we introduce the procedure of data generation as well as the methodology for the optimisation of the estimation of the BT-based PSC cost model in a hospital. We first used Python software to generate raw data for the nonlinear BT-based PSC cost model, including the cost components of a hospital. The widely known tool for the generation of random data in Python is its random module, and we applied randint() as an inbuilt function of the random module. This module returns a random integer value from the inclusive range between the two lower and higher limits (including both limits) provided as two parameters. In the data generation step, the following features, which are the components of the model, were generated using a Python program: $C_{p,Regular\_Purchases}$; $C_{p,Emergency\_Purchases}$; $C_{p,Shipping}$; $C_{p,Expired\_Medication}$; $C_{p,Holding}$; $C_{p,Shortage}$; $C_{p,BT\_Transaction}$; and $C_{p,BT\_Installation}$. 5000 series of the generated raw data for all eight components of the BT-based PSC cost model and the total cost were uploaded to https://data.mendeley.com/datasets/jxv5jrydnc. The research method selected in this paper is to combine two approaches (EC and SL) for the evaluation of the BT-based PSC cost model: for EC (the ACO and FA algorithms are used) and for SL (the KNN, DT, SVM, and NB algorithms are used). These algorithms are well-known and can be successfully applied to solve many engineering problems, facilitating the discussion of their behaviours in our new cost model. Here, ACO and FA are used to improve the parameters of the KNN, DT, SVM, and NB algorithms, as well as to minimise the model prediction errors. The parameters of SL algorithms are usually set empirically, and it takes much time to test and find the best predictive performance of the model. Therefore, the EC algorithm explores possible combinations of parameters, optimizes hyperparameters of the SL algorithms, and reduces the prediction errors of the SL algorithms. Therefore, EC algorithms play a significant role in enhancing the performance of the selected SL algorithms. Thus, EC combined with four algorithms (KNN, DT, SVM, and NB) is used to reduce prediction errors. The generated dataset has eight features (including $C_{p,Regular\_Purchases}$; $C_{p,Emergency\_Purchases}$; $C_{p,Shipping}$; $C_{p,Expired\_Medication}$; $C_{p,Holding}$; $C_{p,Shortage}$; $C_{p,BT\_Transaction}$; and $C_{p,BT\_Installation}$), and has the total cost (C_{Total}) as the label in the regression process (see https://data.mendeley.com/datasets/jxv5jrydnc). Although, the dataset was generated using Python, the implementation of the algorithm illustrated the flowchart presented in Figure 4.1 was carried out in MATLAB. Figure 4.1 illustrates the flowchart of the methodology for four SL algorithms and two EC algorithms. The flowchart starts with creating the population and initialising the parameters. In the next step, the Feature Weighting (FW) approach which is one of the most efficient approaches is applied to evaluate the importance of features, assign an appropriate weight to each feature, and estimate the degree of relevance of each feature to the model. The FW process is executed by multiplying the value of every instance of all the features and orders them by their values (Al-Zoubi, et al., 2021). FW is considered to be more efficacious than the Feature Selection process in several problems and cases because the features are very sensitive, so that removing these kinds of features may negatively affect the classification performance (Al-Zoubi, et al., 2021). Traditionally, all of the selected features are equally important when estimating the output, but if some features have a higher weight than others, the results can be influenced by them strongly, affecting the performance and the accuracy of the overall algorithm. Then, the dataset was participated with 70% of the dataset used for training while the remaining 30% were used for testing. Four different SL algorithms were used to find the optimal method to estimate the cost of the BT-based PSC cost model, including KNN, DT, SVM, and NB. In the next step, we applied two EC algorithms, ACO and FA, to improve the performance of the SL algorithms and optimize hyperparameters of SL algorithms, reducing the prediction errors. Four metrics were used to evaluate the cost model, including Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean absolute error (MAE), and correlation coefficient (R^2). Therefore, this approach produced the following results: eight FWs (one weight for each feature), MSE, RMES, MAE, and R^2. Eventually, a score-based ranking system called Total Ranking Score (TRS) was used to determine the most reliable predictive algorithms. In TRS, each method received a score based on the calculated MSE, RMES, MAE, and R^2 values. Finally, the ranking position of each model was assigned by the sum of all obtained score states. The following section starts to model the casts of BT-based PSC system based on the literature review and the methodology.

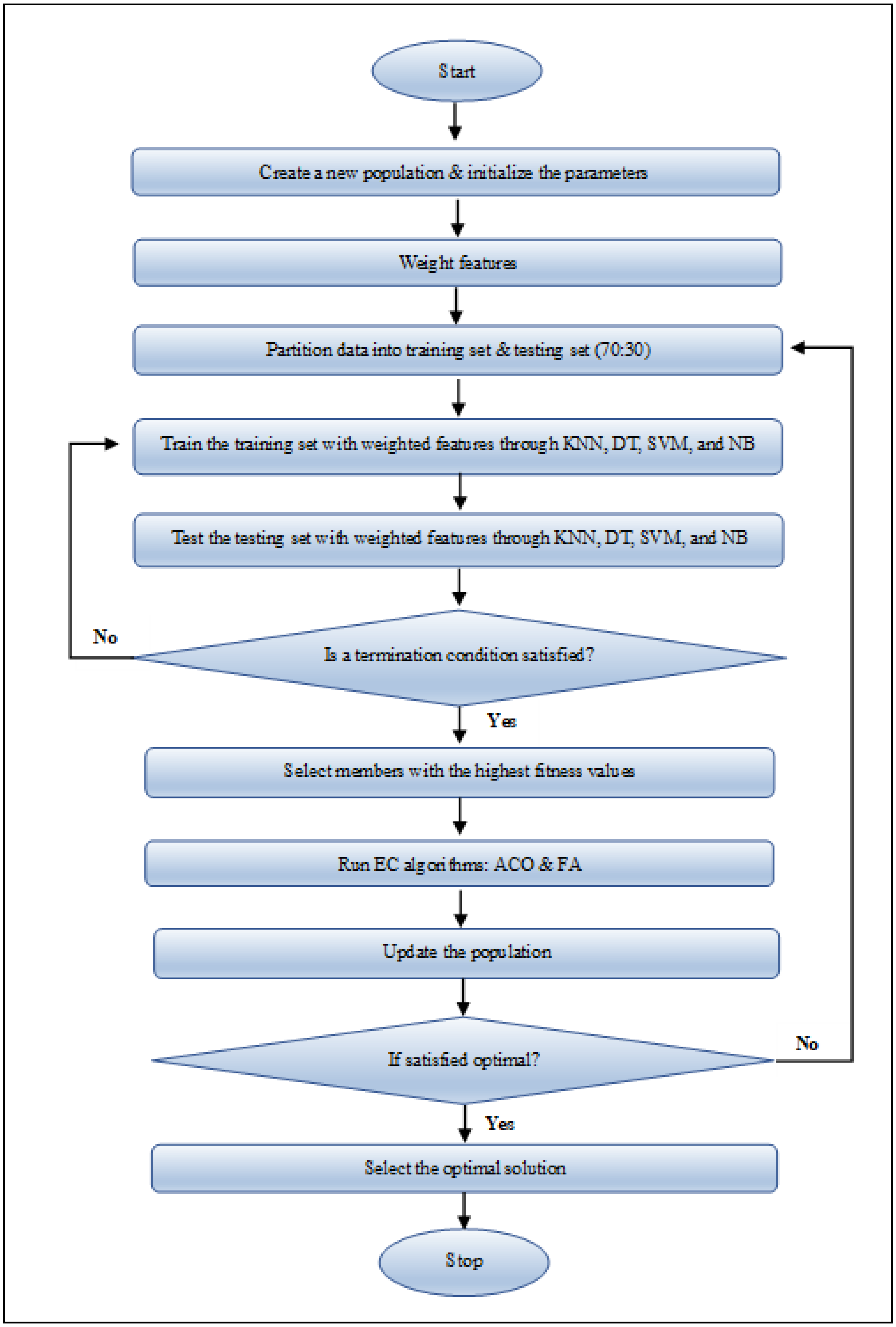

Figure 4.1 Flowchart of the methodology

4.5 Mathematical cost model for BT-based PSC

This section proposes the nonlinear BT-based PSC cost model in a hospital. The model focuses on the costs of a Pharmaceutical Supply Chain System (in a hospital) that used a public blockchain as a modern, trustable, traceable database. Inspired by recent articles by Weraikat, Kazemi Zanjani, and Lehoux (Weraikat, Kazemi Zanjani, & Lehoux, 2019), Franco and Alfonso-Lizarazo (Franco & Alfonso-Lizarazo, 2020), and Havaeji, Dao, and Wong (Havaeji, Dao, & Wong, 2022), we determine that the cost components of the BT-based PSC model are Regular Purchases Cost, Emergency Purchases Cost, Shipping Cost, Expired Medication Cost, Holding Cost, Shortage Cost, Blockchain Transaction Cost, and Blockchain Installation Cost. Based on these references and our knowledge, this research proposes a mathematical model and assumptions to estimate the costs of a PSC based on blockchain in a hospital. Eqs. (1) and (2) show the cost components of the mathematical model. The assumptions of the mathematical model in the approach are as follows.

A 1. The planning horizon is one year.

A 2. The drug expiration date is constant, and the producer ships drugs with a long-life cycle to the hospital to reduce the likelihood of expiration.

A 3. The hospital orders medicines in bulk packs (and not units).

A 4. At the beginning of the planning horizon, the age and the number of medications available in the hospital (including the initial stock) are zero.

A 5. Demand should be satisfied at all levels in a hospital. Emergency purchases are made if the hospital's pharmacy has a drug shortage. The price of emergency medicine is equal to or higher than its regular purchase price.

A 6. Medicines in the forms of both regular and emergency purchases are available.

A 7. The producer ships only fresh medications to the hospital to minimise the likelihood of expiration.

A 8. The cost of medicines is determined at the cycle time when a decision to purchase is made. This is because drug prices can change every period.

A 9. The medicines are used to satisfy the demand and/or are kept in the inventory after arrival.

Hospitals highly recommended to have a high level of technology and infrastructure that would facilitate the future implementation of a technological system supporting BT. As the main customers of medications, hospitals adopt conservative inventory control policies by keeping large quantities of drugs in stock (Weraikat, Kazemi Zanjani, & Lehoux, 2019). The demand of the hospital should be fulfilled by the producer over the planning horizon because of the criticality of medications (Weraikat, Kazemi Zanjani, & Lehoux, 2019). In addition, the producer communicates with the hospital to decide on a minimum amount of each medication that has to be available in the hospital stock at all times in the safety stock level (Weraikat, Kazemi Zanjani, & Lehoux, 2019). Medications move from the producer, through a transportation provider, to the hospital site to satisfy its demand in each period of the planning horizon (Weraikat, Kazemi Zanjani, & Lehoux, 2019). Leaving expired medications at customer zones and disposing them improperly generate a significant negative environmental footprint (Weraikat, Kazemi Zanjani, & Lehoux, 2019). Once the medicine arrives, it can be used to satisfy the demand and/or kept in inventory by using the age-based inventory constraints and the age of medicines to model the perishability (Franco & Alfonso-Lizarazo, 2020). After a number of cycles, some medicines are expired because of their age; therefore, if there is not enough quantity of medicines on inventory to satisfy the demand that is a random element too, an emergency purchase can be made to satisfy the demand, but the purchase will be made at a higher price (Franco & Alfonso-Lizarazo, 2020). Any medication that reaches the end of its shelf life is quarantined and then shipped to government safe disposal sites, while unexpired medications remain at the hospital to be used in a next period (Weraikat, Kazemi Zanjani, & Lehoux, 2019). The parameters, variables, and constraints used in the model are listed in Table 4.1.

Table 4.1 Parameters, variables, and constraints of the BT-based PSC cost model

Parameters	**Explanation**	**Constraints**
M	Number of medication types in the PSC variables (p= 1, 2, 3, …, M)	45
U	The number of Blockchain users	4
C_s	Cost storage per year (USD/TB) for Public outbound bandwidth service (IBM, IBM Cloud, 2022)	\$20×12 = 2400 \$/yr
G_u	The amount of Ether as gasUsed per day	$\$1.31 \leq G_u \times g \leq \$3.94$
g	Number of gWei to be paid for gasUsed per day	
i_p	Inventory level of medication type p	$25 \leq i_p \leq 140$ (integer)
q_p	Order quantity for the p^{th} medicine product per year	$10 \leq q_p \leq 100$ (integer)
s	The data storage size to store the data	2 TB/yr $\leq s \leq 5$ TB/yr
eq_p	Number of lots of medicine types p purchased in case of emergency	$1 \leq eq_p \leq 40$ (integer)
exq_p	Quantity of expired medication type p sent to the government disposal site	$1 \leq exq_p \leq 25$ (integer)
s_p	Shortage quantity of medication type p that is needed to be outsourced	$1 \leq s_p \leq 40$ (integer)
r_p	Regular cost of medicine type p (\$)	$15 \leq r_p \leq 250$ $r_p \leq e_p$
e_p	Emergency cost of medicine type p (\$)	$20 \leq e_p \leq 300$
t_p	Shipping cost of medication type p shipped to the hospital (\$)	$5 \leq t_p \leq 35$
ex_p	Costs obligated by governments for each unit of medication type p disposed at their sites (\$)	$5 \leq ex_p \leq 10$
tex_p	Shipping cost of expired medication type p sent to the government disposal site (\$)	$1 \leq tex_p \leq 15$
h_p	Holding cost of medication type p at the hospital site (\$)	$20 \leq h_p \leq 30$
π_p	Penalty that the producer pays to the hospital for each unit of shortage in the supply of medication type p (\$)	$10 \leq \pi_p \leq 20$
o_p	Cost of outsourced medication type p that the producer could not satisfy (\$)	$12 \leq o_p \leq 18$
c_{fixed}	The initial fixed cost per year	$580 \leq c_{fixed} \leq 680$
$c_{onboarding}$	The Onboarding cost	$\$20 \leq c_{onboarding} \leq \$28$
c_{mc}	The unit Maintenance cost; $c_{mc} + c_{mo}$ is 15%–25% of the project value	$\$15 \leq c_{mc} + c_{mo} \leq \$25$
c_{mo}	The unit Monitoring cost; $c_{mc} + c_{mo}$ is 15%–25% of the project value	

Eq. (4.1) and (4.2) describe the components of the model mathematically.

$$\textbf{Min TC} = \text{Min}\left(\sum_{p=1}^{M}\left[C_{p,Regular\_Purchases} + C_{p,Emergency\_Purchases} + C_{p,Shipping} + C_{p,Expired\_Medication} + C_{p,Holding} + C_{p,Shortage} + C_{p,BT\_Transaction} + C_{p,BT\_Installation}\right]\right) \tag{4.1}$$

$$\textbf{Min TC} = \text{Min} \sum_{p=1}^{M} [r_p \times q_p + e_p \times eq_p + (eq_p + q_p + s_p) \times t_p + (ex_p + tex_p) \times exq_p + h_p \times i_p + (\pi_p + o_p) \times s_p] + \text{G}_\text{u} \times g \times 365 + s \times \text{C}_\text{s} + c_{fixed} + (c_{onboarding} \times \text{U} + c_{mc} + c_{mo}) \times (eq_p + q_p + s_p) \tag{4.2}$$

Eq. (4.2) specifies the objective function that seeks to minimise the producer costs that involve the following elements.

$C_{p,Regular\_Purchases}$: Regular Purchases Cost is the cost of buying different types of medicines ($r_p \times q_p$).

(1) $C_{p,Emergency\_Purchases}$: Emergency Purchases Cost, at a higher price than its regular cost, can be made to satisfy the demand if there is not sufficient drugs in the inventory or if some medicines are expired because of their age ($e_p \times eq_p$).
(2) $C_{p,Shipping}$: Shipping Cost of medications from the producer site to the hospital site is (($eq_p + q_p + s_p$) $\times$ t_p). During shipping, it is necessary to keep some medications in certain conditions (such as temperature, light, or humidity). Therefore, the transportation cost varies with each medication type although the distance between the producer and the hospital is constant.
(3) $C_{p,Expired\_Medication}$: Expired Medication Cost involves the safe disposal fees for different types of expired medication at government sites and the cost of shipping from the hospital to the safe government disposal sites (($ex_p + tex_p$) $\times$ exq_p). Expired medications incur governmental penalties and environmental forfeits due to their negative impact on the environment.
(4) $C_{p,Holding}$: Holding Cost is the inventory cost of the different types of medications at the hospital site ($h_p \times i_p$).
(5) $C_{p,Shortage}$: Shortage Cost is the cost that producers pay to the hospital due to the shortage in the supply of different types of medications (unsatisfied demand) and due to the

outsourced medication cost satisfied by another pharmaceutical producer $((\pi_p + o_p) \times s_p)$.

(6) $C_{p,BT\_Transaction}$: BT Transaction Cost consists of gasCost (gasUsed × gasPrice) and Storage cost ($G_u \times g \times 365 + s \times C_s$) (Longo, Nicoletti, Padovano, d'Atri, & Forte, 2019; Jabbar & Dani, 2020; Wood, 2014; Havaeji, Dao, & Wong, 2022). $G_u \times g$ is the BT Transaction cost per day, and $s \times C_s$ is the storage cost per year, a secured cloud-based warehouse to store the actual data off-chain. IBM Cloud website was used to calculate the storage cost (IBM, IBM Cloud, 2022).

(7) $C_{p,BT\_Installation}$: BT Installation Cost includes Fixed cost (c_{fixed}), Onboarding cost ($c_{onboarding}$), Maintenance cost (c_{mc}), and Monitoring cost (c_{mo}) ($c_{fixed} + (c_{onboarding} \times U + c_{mc} + c_{mo}) \times (eq_p + q_p + s_p)$) (Takyar, 2021a; Havaeji, Dao, & Wong, 2022).

The most widely-used consensus protocol in the public blockchain is Proof-of-Work (PoW) (used in e.g. Bitcoin and Ethereum) (Wang, et al., 2021). The cost of the blockchain transaction consists of gasLimit and gasPrice. The gasLimit is the maximum amount of gas used to execute the transaction and is purchased from the sender's account balance. At the end of the transaction, any unused gas is refunded to the sender's account (Wood, 2014; Havaeji, Dao, & Wong, 2022). According to Wood (Wood, 2014), gasPrice (a scalar value) is the number of Wei to be paid for each unit of gas, and consists of all computation costs incurred as a result of the execution of this transaction. The ETH Gas Station is a suitable place to calculate Gu × g and incentivise computation within the network (Jabbar & Dani, 2020; ETH Gas Station, 2021) The gWei includes the cost of a transaction on the Ethereum Blockchain as well as the cost of the transaction validators and the network. To convert gWei to USD, we can use the ETH Gas Station website based on the current price of Ethereum (ETH Gas Station, 2022). In Table 4.1, to calculate $G_u \times g$ cost and convert gWei cost to USD through the ETH Gas Station website, the gasUsed (as the total gas used in transactions) is 21000 (a scalar value), and the range of the gasPrice is between 20 and 60 gWei. The range of $G_u \times g$ is between $1.31 and 3.94$. This transaction cost was calculated by ETH Gas Station website (ETH Gas Station, 2022).

The cost of Blockchain Installation consists of Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost (Gopalakrishna-Remani, Brown, Shanker, & Hu, 2018; Havaeji, Dao, & Wong, 2022). The Onboarding cost is the cost of training clients and suppliers to become active users of a service or product (training cost) and is the cost related to integrating new employees into a company to learn and train BT. The c_{mc} and c_{mo} costs are 15–25% of the project value per year (Gopalakrishna-Remani, Brown, Shanker, & Hu, 2018; Takyar, 2021a). After designing the mathematical model, it is necessary to evaluate it statically, coming to the next section.

4.6 Results

This section comprehensively presents all experiments and the obtained and shows the performance metrics of eight algorithms on the generated dataset, in addition to the weights of the cost features of the BT-based PSC cost model. The numerical examples examined in this research validate the proposed methodology and the cost model and demonstrate the performance of the proposed approach. We designed and executed the proposed method using MATLAB software to validate the BT-based PSC cost model. We used FA and ACO (EC algorithms) to improve the results of the KNN, DT, SVM, and NB SL algorithms. To reduce prediction errors and improve the SL results, this combination provides eight algorithms namely FA-KNN, FA-DT, FA-SVM, FA-NB, ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB. The MSE, RMSE, MAE, and R^2 performance metrics were used to evaluate the efficiency of the proposed algorithms. We also used the FW approach to estimate the influencing features for the generated dataset in the cost model. FW has an important role in analysis without changing the initial data content. The authors ran each algorithm (FA-KNN, FA-DT, FA-SVM, FA-NB, ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB) for 10 runs (totally eighty runs) with 1000 iterations. These experiments help us be more valid. This experiment assessed the ‘‘average’’ of the performance metrics and the ‘‘average’’ of the weight of the cost features to improve the reliability of all methods in eighty (4×10 + 4×10) runs. This average is used because the runs can have various outcomes, and the average can help us achieve stability and reliability in behavioural data. Each run was performed for at most 1000 iterations. Therefore, instead of comparing the predictions of the BT-based PSC cost model in each run, we compared the average of every 10 runs. This research finally used TRS to determine the most reliable predictive algorithms for the BT-based PSC cost model. Tables 4.2 to 4.9 present the related results.

4.6.1 FA combined with four SL

In this step, FA combined with four SL algorithms (FA-KNN, FA-DT, FA-SVM, and FA-NB) was run 40 times)each algorithm was executed 10 times) in 1000 iterations. Four performance metrics and the weights of eight cost features were evaluated for the BT-based PSC cost model in the 40 runs. Table 4.2 presents the eight weights of the cost features and the four performance metrics for four algorithms in 40 runs. The average values for each performance metric and each cost feature are presented in Table 4.2. Tables 4.8 and 4.9 are derived from Table 4.2.

Table 4.2 Feature weighting and performance evaluation for FA combined with four SL algorithms in 10 runs for each

	Run	Feature Weighting								Performance metrics			
		W_(Regular_Purchases)	W_(Emergency_Purchases)	W_(Shipping)	W_(Expired_Medication)	W_(Holding)	W_(Shortage)	W_(BT_Transaction)	W_(BT_Installation)	MSE	RMSE	MAE	R^2
FA_KNN	1	0.42761	0.70372	0.4019	0.77805	0.66441	0.54303	0.3898	0.75549	6410531.181	2531.9027	1911.4867	0.93669
	2	0.38097	0.40696	0.67108	0.07136	0.57776	0.96633	0.25649	0.71504	6543559.636	2558.0382	1844.5367	0.95009
	3	0.39918	0.22744	0.88195	1	0.45745	0.60981	0.28345	0.49667	7109497.639	2666.3641	1895.78	0.94165
	4	0.48472	0.70427	0.11742	0.56176	0.60325	0.55416	0.72756	0.70165	4820413.661	2195.544	1861.4267	0.94784
	5	0.44293	0.36279	1	1	0.27841	1	0.53327	0.66643	8836400.862	2972.6084	2380.51	0.95397
	6	0.57136	0.43084	0.086856	0.80261	0.38824	0.61953	0.7207	0.56945	3341730.069	1828.04	1563.43	0.96499
	7	0.29971	0.25515	0.25957	0.56899	0.69676	0.89902	0.37948	0.58159	7298087.42	2701.4973	2191.1033	0.93169
	8	0.51998	0.39227	0.11292	0.50207	0.30936	0.73901	0.25718	0.71075	4636038.367	2153.1462	1730.3067	0.95829
	9	0.38097	0.40696	0.67108	0.07136	0.57776	0.96633	0.25649	0.71504	6543559.636	2558.0382	1844.5367	0.95009
	10	0.39918	0.22744	0.88195	1	0.45745	0.60981	0.28345	0.49667	7109497.639	2666.3641	1895.78	0.94165
Average		**0.430661**	**0.411784**	**0.5084726**	**0.63562**	**0.501085**	**0.750703**	**0.408787**	**0.640878**	**6264931.611**	**2483.15432**	**1911.88968**	**0.947695**

	Run	Feature Weighting								Performance metrics			
		W_(Regular_Purchases)	W_(Emergency_Purchases)	W_(Shipping)	W_(Expired_Medication)	W_(Holding)	W_(Shortage)	W_(BT_Transaction)	W_(BT_Installation)	MSE	RMSE	MAE	R^2
FA_DT	1	0.47321	1	0	0.55029	0.077932	0.98129	0	0.76499	20931129.39	4575.0551	3459.9621	0.78428
	2	0.68103	0	0.22354	0	0.86119	0.38003	0.88603	0.64452	35006777.18	5916.6525	4540.5366	0.71695
	3	0.15466	0.5686	0.54932	0.7612	0.58896	0.79381	0	0.2224	15666495.59	3958.0924	3054.3802	0.69542
	4	0.69663	0.44451	0.60297	0.45421	0.66456	0.24065	0.2454	0	19723753.67	4441.1433	3129.7053	0.82664
	5	0.019254	0.20955	0.56631	0.74343	0.6613	0	0.05882	0.92978	30911374.48	5559.7999	4279.7594	0.70113
	6	0.88511	0.14417	0.80373	0	0.8651	0.45487	0.46228	0.6855	16236754.9	4029.4857	3445.5285	0.8264
	7	0.47321	1	0	0.55029	0.077932	0.98129	0	0.76499	20931129.39	4575.0551	3459.9621	0.78428
	Feature Weighting	Performance metrics	Run	Feature Weighting	Performance metrics	Run	Feature Weighting	Performance metrics	Run	Feature Weighting	Performance metrics	Run	Feature Weighting
	8	0.68103	0	0.22354	0	0.86119	0.38003	0.88603	0.64452	35006777.18	5916.6525	4540.5366	0.71695
	9	0.15466	0.5686	0.54932	0.7612	0.58896	0.79381	0	0.22248	15666495.59	3958.0924	3054.3802	0.69542
	10	0.69663	0.44451	0.60297	0.45421	0.66456	0.24065	0.2454	0	19723753.67	4441.1433	3129.7053	0.82664
Average		**0.4915424**	**0.437994**	**0.41217**	**0.427483**	**0.5911684**	**0.524643**	**0.278396**	**0.487918**	**22980444.11**	**4737.11722**	**3609.44563**	**0.757411**
	Run	Feature Weighting								Performance metrics			
		W_(Regular_Purchases)	W_(Emergency_Purchases)	W_(Shipping)	W_(Expired_Medication)	W_(Holding)	W_(Shortage)	W_(BT_Transaction)	W_(BT_Installation)	MSE	RMSE	MAE	R^2
FA_SVM	1	0.23175	0.2259	0.53019	0.00011658	0.98963	0.99971	0.37348	0.32717	173343.7829	416.3457	333.2585	0.99958
	2	0.49827	0.1213	0.044341	0.37469	0.078956	0.076338	0.84056	0.025916	123519.554	351.4535	295.5338	0.99944
	3	0.23175	0.2259	0.53019	0.00011658	0.98963	0.99971	0.37348	0.32717	173343.7829	416.3457	333.2585	0.99958
	4	0.49827	0.1213	0.044341	0.37469	0.078956	0.076338	0.84056	0.025916	123519.554	351.4535	295.5338	0.99944
	5	0.11145	0.18245	0.80071	0.91571	0.3337	0.27808	0.999	0.1206	187904.5992	433.4796	345.0264	0.99973
	6	0.062505	0.13831	0.17654	0.83871	0.55852	0.43634	0.21079	0.072986	133984.4159	366.0388	304.2886	1
	7	0.12535	0.10758	0.88876	0.99971	0.28039	0.38197	0.99797	0.11452	217426.4673	466.2901	349.1649	0.99967
	8	0.069619	0.11732	0.22129	0.89167	0.5806	0.5368	0.59439	0.075245	170350.8234	412.7358	348.6053	0.9999
	9	0.070616	0.15011	0.19064	0.95425	0.4204	0.92513	0.22981	0.082785	119067.7801	345.062	276.8873	0.99995
	10	0.038819	0.37321	0.098169	0.3057	0.17506	0.19189	0.30862	0.044591	167675.474	409.482	356.8005	0.99984
Average		**0.1938399**	**0.176338**	**0.3525171**	**0.565536316**	**0.4485842**	**0.4902306**	**0.576866**	**0.1216899**	**159013.6234**	**396.86867**	**323.83576**	**0.999713**
	Run	Feature Weighting								Performance metrics			
		W_(Regular_Purchases)	W_(Emergency_Purchases)	W_(Shipping)	W_(Expired_Medication)	W_(Holding)	W_(Shortage)	W_(BT_Transaction)	W_(BT_Installation)	MSE	RMSE	MAE	R^2
FA_NB	1	0.032531	0.041745	0.08032	0.9808	0.10975	0.18195	1	0.031338	0.02788	0.16697	0.1257	1
	2	0.010457	0.015939	0.033751	0.99143	0.056218	0.05816	0.96678	0.011013	0.016316	0.12773	0.10697	1
	3	0.060931	0.084856	0.18278	0.91442	0.59413	0.3198	0.30078	0.063357	0.01369	0.117	0.096242	1
	4	0.060931	0.084856	0.18278	0.91442	0.59413	0.3198	0.30078	0.063357	0.01369	0.117	0.096242	1
	5	0.029986	0.052286	0.086725	0.99994	0.14185	0.24168	0.31756	0.033475	0.019494	0.13962	0.11491	1

Run	W_(Regular_Purchases)	W_(Emergency_Purchases)	W_(Shipping)	W_(Expired_Medication)	W_(Holding)	W_(Shortage)	W_(BT_Transaction)	W_(BT_Installation)	MSE	RMSE	MAE	R^2
			0.038483			0.077546			0.035156		0.13605	
									0.02788			
			0.033751		0.056218				0.016316		0.10697	
									0.01369		0.096242	
									0.02788			
Average	**0.0346459**	**0.0481632**	**0.098201**	**0.966838**	**0.3088716**	**0.1940796**	**0.637718**	**0.035402**	**0.0211992**	**0.143449**	**0.1130726**	**1**

Table 4.3 compares the average of four performance evaluation metrics for each method. In Table 4.3, FA-DT has the weakest result in terms of all performance metrics (Ave-MSE = 22980444.11, Ave-RMSE = 5916.65, Ave-MAE = 3609.44), and R^2 = 0.75, while FA-NB demonstrates robust behaviour with the best average R^2 of 1 and a minimum Ave-MSE = 0.021, Ave-RMSE = 0.143, Ave-MAE = 0.113 among the four methods. Although the averages R^2 values for all methods are acceptable (ranging from 0.757 to 1), the average MSE, RMSE, and MAE values for FA-KNN, FA-DT, and FA-SVM are the worst (ranging from 323.83 to 22980444.11). Therefore, the above-mentioned metrics indicate that the FA-NB algorithm has better performance for the BT-based PSC cost model than the other proposed algorithms.

Table 4.3 Performance metrics evaluation for FA combined with four SL algorithms

	Performance metrics			
Methods	**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**
FA_KNN	6264931.611	2483.15432	1911.88968	0.930856
FA_DT	**22980444.11**	**5916.6525**	**3609.44563**	**0.757411**
FA_SVM	159013.6234	396.86867	323.83576	0.999713
FA_NB	**0.0211992**	**0.143449**	**0.1130726**	**1**

We also focused on the average of the weights of each cost feature through the FW approach for the FA-KNN, FA-DT, FA-SVM, and FA-NB algorithms, as shown in Table 4.4. Among these four methods, FA-NB provides the highest average weight for the Expired Medication cost feature (0.966), and the lowest average weight for the Regular Purchases cost feature (0.034). The second-highest average weight is allocated to the BT Installation cost feature through the FA-KNN algorithm (0.849), followed by the Holding cost feature through the FA-DT algorithm (0.591). BT Installation cost feature also has the second-lowest average weight with FA-SVM (0.121). In addition, the BT Transaction cost fluctuates because it has the average weight of 0.576 and 0.278 for FA-SVM and FA-DT, respectively.

Table 4.4 FW criteria for FA combined with four SL algorithms

Feature weighting		
Methods	**Max_Ave_Weighting**	**Min_ Ave_Weighting**
FA_KNN	W_(BT_Installation) = 0.84988	W_(Expired_Medication) = 0.34659
FA_DT	W_(Holding) = 0.5911684	W_(BT_Transaction) = 0.278396
FA_SVM	W_(BT_Transaction) = 0.576866	W_(BT_Installation) = 0.1216899
FA_NB	**W_(Expired_Medication) = 0.966838**	**W_(Regular_Purchases) = 0.0346459**

4.6.2 ACO combined with four SL algorithms

In the second step, ACO combined with four SL algorithms (ACO -KNN, ACO -DT, ACO -SVM, and ACO -NB) was executed 40 times (each algorithm ran 10 times). Then, the four performance metrics and the weights of the eight cost features were evaluated for the BT-based PSC cost model in the 40 runs. Table 4.5 illustrates eight weightings of cost features and performance metrics for four algorithms in 10 runs for each algorithm. Table 4.5 are presented the average values of the performance metrics and the average values of the weights of the cost features. Tables 4.11 and 4.12 are also derived from the data presented in Table 4.5.

Table 4.5 FW and performance evaluation for ACO combined with four SL algorithms in 10 runs for each

	Run	Feature Weighting								Performance metrics			
		W_(Regular_Purchases)	W_(Emergency_Purchases)	W_(Shipping)	W_(Expired_Medication)	W_(Holding)	W_(Shortage)	W_(BT_Transaction)	W_(BT_Installation)	MSE	RMSE	MAE	R^2
ACO_KNN	1	0.35695	0.92549	0.89039	1	0.009856	0.18912	0.47227	0.99903	5543172.364	2354.3943	1949.4633	0.92596
	2	1	0.76434	0.43676	0	0.88697	1	0.34671	1	4695227.88	2166.8475	1864.3933	0.95763
	3	0.92009	0.62512	0.8734	1	0.76675	0	0.86776	0.84005	4692998.943	2166.3331	1818.2033	0.93246
	4	0.70324	0.64935	0.47864	0.021711	0.59772	0.26598	0.36632	0.45778	6719708.626	2592.2401	2065.3833	0.89936
	5	1	0.66795	0	0.15666	0.72265	1	0.55566	0.50375	6928149.833	2632.1379	2027.5067	0.94752
	6	0.48851	0.97333	0.65892	0	0.30371	1	0.41044	1	6221307.472	2494.2549	2142.3833	0.92888
	7	0.45446	0.51932	0.49337	0.38196	0.93485	1	0.34229	0.98086	4565317.918	2136.6605	1844.1267	0.94594
	8	0.36326	0.34374	1	0.47294	0.91225	0.4744	0.20598	0.99651	4394372.317	2096.2758	1794.3933	0.92742
	9	0.52039	0.70382	0.077738	0	0.69597	0	0.92397	1	10706939.15	3272.146	2655.27	0.90856
	10	0.40842	0.36388	0.21883	0.43267	0.95833	1	0.61236	0.72077	5833434.956	2415.2505	2088.6967	0.93483
Average		**0.621532**	**0.653634**	**0.5128048**	**0.3465941**	**0.6789056**	**0.59295**	**0.510376**	**0.849875**	**6030062.946**	**2432.65406**	**2024.98199**	**0.930856**
	Run	Feature Weighting								Performance metrics			
		W_(Regular_Purchases)	W_(Emergency_Purchases)	W_(Shipping)	W_(Expired_Medication)	W_(Holding)	W_(Shortage)	W_(BT_Transaction)	W_(BT_Installation)	MSE	RMSE	MAE	R^2
ACO_DT	1	0.36831	0.65313	0	0	0	1	0.48975	0	27725280.24	5265.4801	3918.345	0.8088
	2	0.78548	1	0	0.35183	0	0	0.96679	0.78077	17268337.62	4155.5189	3358.6605	0.73903
	3	0.39139	0.30496	0	1	0	0	0	0.078329	20862939.19	4567.5967	3543.8508	0.78735
	4	1	0.70817	0	1	0.61945	0.15374	0.36463	0.38276	14114845.23	3756.9729	3134.379	0.79848
	5	0.78077	0	0	0.39765	0	0	0	1	22127369.33	4703.9738	3421.1334	0.77706
	Run	Feature Weighting	Performance metrics	ACO_KNN	Run	Feature Weighting	Performance metrics	ACO_KNN	Run	Feature Weighting	Performance metrics	ACO_KNN	Run
	6	0.11978	0.46586	1	0.43738	0	1	0.86613	0	15853729.5	3981.6742	2765.302	0.83271
	7	0.41597	1	0	0	0	1	0	1	13566853.1	3683.3209	2900.3703	0.82056
	8	0.72963	0.5107	0	0	0.44327	0	0.58999	1	18853360.55	4342.0457	3218.8045	0.80982
	9	0.35453	0	0.50304	0.26006	0.29699	0	0	0.10223	19129278.4	4373.7031	3173.7969	0.83869
	10	0.35628	0.37771	0	0.89254	0	0.44445	0	0.27212	23472850.57	4844.8788	3620.1248	0.8251
Average		**0.530214**	**0.502053**	**0.150304**	**0.433946**	**0.135971**	**0.359819**	**0.327729**	**0.4616209**	**19297484.37**	**4367.51651**	**3305.47672**	**0.80376**
	Run	Feature Weighting								Performance metrics			
		W_(Regular_Purchases)	W_(Emergency_Purchases)	W_(Shipping)	W_(Expired_Medication)	W_(Holding)	W_(Shortage)	W_(BT_Transaction)	W_(BT_Installation)	MSE	RMSE	MAE	R^2
ACO_SVM	1	0.13205	0.17919	0.47213	0.99797	0.41098	0.53424	0.94092	0.16085	214988.4336	463.6685	372.7033	0.99976
	2	0.98237	0.26347	0.97017	0.0054287	0.65009	0.99563	0.69419	0.52966	118716.9279	344.5532	291.8931	0.99858
	3	0.36341	0.07529	0.44152	0.94205	1	0.13531	0.35334	0.84212	85394.6138	292.2236	239.0761	0.99908

	Run	Feature Weighting	Performance metrics	Run	Feature Weighting	Performance metrics	Run	Feature Weighting	Performance metrics	Run	Feature Weighting	Performance metrics	Run
	4	0.31839	0.21878	0.80193	0	0.88418	0.86379	0.34368	0.59425	178499.0214	422.4914	337.9536	0.99957
	5	0.22478	0.99994	0.90923	0.99996	0.68076	0.62322	0.28197	0.23503	79662.2247	282.245	220.6187	0.99944
	6	0.1891	0.181	0.81952	1	1	0.62985	0.99913	0.17333	282360.1537	531.3757	415.7638	0.99926
	7	0.15083	0.32986	0.40481	0.99984	0.96917	0.93384	0.98662	0.21624	170985.299	413.5037	343.692	0.9999
	8	0.97605	0.20016	0.47514	0.9965	0.98931	0.85258	0.99817	0.18793	168623.3192	410.6377	350.2368	0.99905
	9	0.31839	0.21878	0.80193	0	0.88418	0.86379	0.34368	0.59425	178499.0214	422.4914	337.9536	0.99957
	10	0.22478	0.99994	0.90923	0.99996	0.68076	0.62322	0.28197	0.23503	79662.2247	282.245	220.6187	0.99944
Average		**0.388015**	**0.366641**	**0.700561**	**0.69417087**	**0.814943**	**0.705547**	**0.622367**	**0.376869**	**155739.1239**	**386.54352**	**313.05097**	**0.999365**
	Run	**Feature Weighting**								**Performance metrics**			
		W_(Regular_Purchases)	**W_(Emergency_Purchases)**	**W_(Shipping)**	**W_(Expired_Medication)**	**W_(Holding)**	**W_(Shortage)**	**W_(BT_Transaction)**	**W_(BT_Installation)**	**MSE**	**RMSE**	**MAE**	**R^2**
	1	0.066266	0.083497	0.16188	1	0.22171	0.36769	0.99974	0.064689	0.028975	0.17022	0.12833	1
	2	0.051676	0.076568	0.15739	1	0.39803	0.25806	1	0.055018	0.016852	0.12981	0.10561	1
	3	0.036712	0.055901	0.083755	0.99983	1	0.18925	0.19181	0.041779	0.01459	0.12079	0.092924	1
	4	0.052031	0.0655	0.11217	0.99977	0.32118	0.20282	0.99953	0.047636	0.020784	0.14417	0.12146	1
ACO_NB	5	0.066266	0.083497	0.16188	1	0.22171	0.36769	0.99974	0.064689	0.028975	0.17022	0.12833	1
	6	0.051676	0.076568	0.15739	1	0.39803	0.25806	1	0.055018	0.016852	0.12981	0.10561	1
	7	0.036712	0.055901	0.083755	0.99983	1	0.18925	0.19181	0.041779	0.01459	0.12079	0.092924	1
	8	0.052031	0.0655	0.11217	0.99977	0.32118	0.20282	0.99953	0.047636	0.020784	0.14417	0.12146	1
	9	0.05725	0.07226	0.1489	1	1	0.44111	0.52877	0.058602	0.032984	0.18161	0.1356	1
	10	0.045911	0.080262	0.13201	0.99984	0.23087	0.33649	1	0.053764	0.012642	0.11244	0.098423	1
Average		**0.0516531**	**0.0715454**	**0.13113**	**0.999904**	**0.511271**	**0.281324**	**0.791093**	**0.053061**	**0.0208028**	**0.142403**	**0.1130671**	**1**

Table 4.6 presents the averages values of the performance metrics considered in the evaluation of the proposed ACO combined with four SL algorithms. In Table 4.6, ACO-DT has the weakest result in terms of all performance metrics (Ave-MSE = 19297484.37, Ave-RMSE = 4367.51, Ave-MAE = 3305.47, and R^2 = 0.80), while ACO-NB does better with an average R^2 of 1 and a minimum of Ave-MSE = 0.020, Ave-RMSE = 0.142, Ave-MAE = 0.113 among the four methods. Although the average R^2 values are acceptable for all methods (ranging from 0.803 to 1), the averages MSE, RMSE, and MAE values for ACO-KNN, ACO-DT, and ACO-SVM are the worst (ranging from 313.05 to 19297484.37). Therefore, we consider the ACO-NB results to be more reliable than the results obtained

by other proposed methods and shown in this table.

Table 4.6 Performance metrics evaluation for ACO combined with four SL algorithms

	Feature weighting			
Methods	**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**
ACO_KNN	6030062.946	2432.65406	2024.98199	0.930856
ACO_DT	**19297484.37**	**4367.51651**	**3305.47672**	**0.80376**
ACO_SVM	155739.1239	386.54352	313.05097	0.999365
ACO_NB	**0.0208028**	**0.142403**	**0.1130671**	**1**

We also investigated the average weights of each cost feature through the FW approach in the ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB algorithms (see Table 4.7). Among all four methods, the maximum average weight of 0.999 is allocated to the Expired Medication cost feature, and the minimum average weight 0.051 obtained for the Regular Purchases cost feature, both for the ACO-NB algorithm. For the ACO-KNN algorithm, the second maximum average weight is obtained for the BT Installation cost feature (0.849), followed by the Holding cost feature (0.814) obtained by ACO-SVM (see Table 4.7). Accordingly, the ACO-SVM algorithm gives the second lowest average weight of 0.135 for the Holding cost feature. In addition, a variation in the average weight of the Expired Medication cost feature is observed, which is obtained as 0.346 and 0.999 by ACO-KNN and ACO-NB, respectively. Similarly, the Holding cost feature weight varies, with 0.135 and 0.814 obtained by ACO-DT and ACO-SVM, respectively.

Table 4.7 FW criteria for ACO combined with four SL algorithms

	Feature weighting	
Methods	**Max_ Ave_Weighting**	**Min_ Ave_Weighting**
ACO_KNN	W_(BT_Installation) = 0.849875	W_(Expired_Medication) = 0.3465941
ACO_DT	W_(Regular_Purchases) = 0.530214	W_(Holding) = 0.135971
ACO_SVM	W_(Holding) = 0.814943	W_(Emergency_Purchases) = 0.366641
ACO_NB	**W_(Expired_Medication) = 0.999904**	**W_(Regular_Purchases) = 0.0516531**

4.6.3 Determining reliable algorithms for BT-based PSC cost model

Table 4.8 summarises the TRS of eight algorithms based on the obtained Ave-MSE, Ave-RMSE, Ave-MAE, and Ave-R^2 values. In TRS, the lowest Ave-MSE, Ave-RMSE, and Ave-MAE receive the highest scores, and the highest Ave-R^2 obtains the highest score (and vice versa). Overall, the ACO-NB algorithm outperforms the other compared algorithms and achieved the first position among all algorithms (TRS of 32), followed by FA-NB with TRS of 29, ACO-SVM with TRS of 24, and FA-SVM with TRS of 22. FA-DT and ACO-DT achieve the worst scores of 6 (rank 8^{th}) and 10 (rank 7^{th}), respectively.

Table 4.8 Ranking of eight selected algorithms based on TRS scores through performance metrics

		Performance metrics					
Methods		**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**	**TRS**	**Rank**
FA_KNN		6264931.611	2483.15432	1911.88968	0.930856		
FA_DT		**22980444.11**	**5916.6525**	**3609.44563**	**0.757411**		
FA_SVM		159013.6234	396.86867	323.83576	0.999713		
FA_NB		**0.0211992**	**0.143449**	**0.1130726**	**1**		
ACO_KNN		6030062.946	2432.65406	2024.98199	0.930856		
ACO_DT		**19297484.37**	**4367.51651**	**3305.47672**	**0.80376**		
ACO_SVM		155739.1239	386.54352	313.05097	0.999365		
ACO_NB		**0.0208028**	**0.142403**	**0.1130671**	**1**		
Total Ranking Score	**FA_KNN**	3	3	4	5	15	6
	FA_DT	**1**	**1**	**1**	**3**	**6**	**8**
	FA_SVM	5	5	5	7	22	4
	FA_NB	**7**	**7**	**7**	**8**	**29**	**2**
	ACO_KNN	4	4	3	5	16	5
	ACO_DT	**2**	**2**	**2**	**4**	**10**	**7**
	ACO_SVM	6	6	6	6	24	3
	ACO_NB	**8**	**8**	**8**	**8**	**32**	**1**

Table 4.9 shows the ranking of the average weights of eight costs features, namely Regular-Purchases, Emergency-Purchases, Shipping, Expired-Medication, Holding, Shortage, BT-Transaction, and BT-Installation for the FA-KNN, FA-DT, FA-SVM, FA-NB, ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB algorithms. This table assigns an appropriate weight to

each cost feature to show their importance. The average weight with higher TRS receives a higher priority in the TRS process (and vice versa). Overall, Shortage cost obtains the best TRS of 46 for the average weight, followed by Holding cost with TRS of 45, and Expired-Medication cost with TRS of 43. The minimum TRS for the average weight is allocated to Emergency-Purchases cost (TRS = 28), followed by both Regular-Purchases cost and Shipping cost, which have the same rank of 5th with TRS = 30.

Table 4.9 FW Ranking based on TRS scores for eight selected algorithms

		Methods									
Ave_FW		**FA_KNN**	**FA_DT**	**FA_SVM**	**FA_NB**	**ACO_KNN**	**ACO_DT**	**ACO_SVM**	**ACO_NB**	**TRS**	**Rank**
W_(Regular_Purchases)		0.430661	0.4915424	0.1938399	0.0346459	0.621532	0.530214	0.388015	0.0516531		
W_(Emergency_Purchases)		0.411784	0.437994	0.176338	0.0481632	0.653634	0.502053	0.366641	0.0715454		
W_(Shipping)		0.5084726	0.41217	0.3525171	0.098201	0.5128048	0.150304	0.700561	0.13113		
W_(Expired_Medication)		0.63562	0.427483	0.56553631	0.966838	0.3465941	0.433946	0.69417087	0.999904		
W_(Holding)		0.501085	0.5911684	0.4485842	0.3088716	0.6789056	0.135971	0.814943	0.511271		
W_(Shortage)		0.750703	0.524643	0.4902306	0.1940796	0.59295	0.359819	0.705547	0.281324		
W_(BT_Transaction)		0.408787	0.278396	0.576866	0.637718	0.510376	0.327729	0.622367	0.791093		
W_(BT_Installation)		0.640878	0.487918	0.1216899	0.035402	0.849875	0.4616209	0.376869	0.053061		
Total Ranking	**W_(Regular_Purchases)**	**3**	**6**	**3**	**1**	**5**	**8**	**3**	**1**	**30**	**5**
	W_(Emergency_Purchases)	**2**	**4**	**2**	**3**	**6**	**7**	**1**	**3**	**28**	**6**
	W_(Shipping)	**5**	**2**	**4**	**4**	**3**	**2**	**6**	**4**	**30**	**5**
	W_(Expired_Medication)	6	3	7	8	1	5	5	8	43	3
	W_(Holding)	**4**	**8**	**5**	**6**	**7**	**1**	**8**	**6**	**45**	**2**
	W_(Shortage)	**8**	**7**	**6**	**5**	**4**	**4**	**7**	**5**	**46**	**1**
	W_(BT_Transaction)	1	1	8	7	2	3	4	7	33	4
	W_(BT_Installation)	7	5	1	2	8	6	2	2	33	4

4.7 Discussion

This section discusses the results for the proposed eight algorithms, that minimise the prediction errors of the BT-based PSC cost model. The proposed algorithms aim to answer the three research questions mentioned in the introduction. As stated in Section 3, there are eight components in the BT-based PSC cost model: Regular Purchases cost, Emergency Purchases cost, Shipping cost, Expired Medication cost, Holding cost, Shortage cost, BT Transaction cost, and BT Installation cost. This provides the answer to our first research question.

Regarding second research question, among the eight examined algorithms, we select some algorithms that demonstrate better performance in minimising the prediction errors of the BT-based PSC cost model. Figure 4.2 is derived from the data presented in Table 4.8 and shows the TRS for all eight studied algorithms (FA-KNN, FA-DT, FA-SVM, FA-NB, ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB). Four performance metrics (MSE, RMSE, MAE, and R^2) evaluate the algorithm efficiency. The overall results of this study show that both ACO-NB (first position) and FA-NB (second position) algorithms outperform the other compared algorithms. This means that NB combined with either FA of ACO is considered to be the most effective in performing the regression. EC algorithms (FA and ACO) also play a significant role in optimizing the hyperparameters of the selected SL algorithms. Moreover, the SVM algorithm, combined with FA and ACO, shows the second position with respect to TRS. The DT algorithm, combined with FA and ACO, cannot predict the costs of the BT-based PSC model well. Thus, we have determined the most reliable predictive algorithms for our cost model using TRS and four performance metrics.

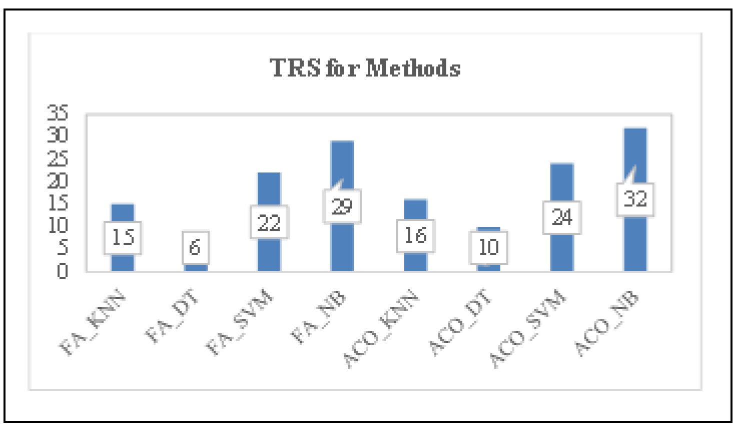

Figure 4.2 TRS of all algorithms

The third research question is to determine the significant cost components of the model. The FW approach measures the importance of the features and assigns an appropriate weight to each feature. Figure 4.3 is derived from Table 4.9 and shows the TRS for the weights of all cost components (features) of the BT-based PSC model. These weights estimate the degree of relevance that each feature has for extracting the cost prediction. The Shortage cost, Holding cost, and Expired Medication cost strongly influence the cost model. The remaining five cost features have relatively the same position based on the weighs (Regular Purchases cost, Emergency Purchases cost, Shipping cost, BT Transaction cost, and BT Installation cost).

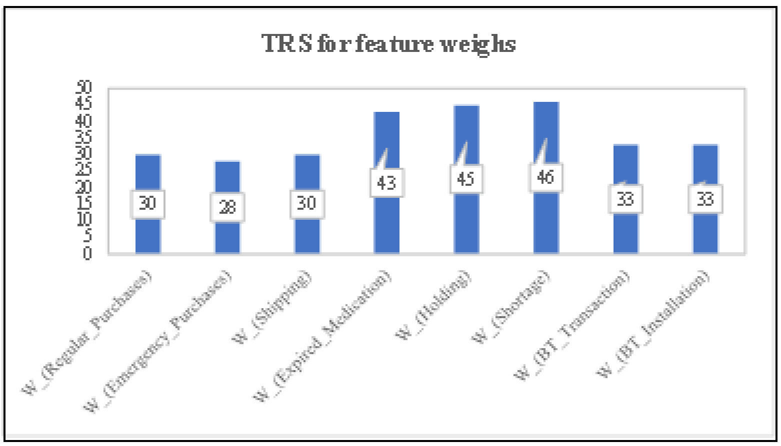

Figure 4.3 TRS for feature weighs

Compared to previous work that modelled the costs of PSC, this study developed a new mathematical cost model called BT-based PSC that includes BT Transaction cost and BT Installation cost. Researchers in other fields can also use BT cost formulation (BT Transaction cost and BT Installation cost) in their mathematical model to estimate the SC costs integrated with BT. The practical significance of the study lies in providing the most reliable predictive algorithms for the BT-based PSC cost model, the cost components of the model, the degree of relevance of each component to the cost model, and the components of BT in the SC model. However, similar to the other studies, this research is subject to two limitations. The first significant limitation is the inaccessibility of real data because the use of BT in PSC is a new area of research. Therefore, the eight algorithms studied in this work applied generated data to validate the proposed BT-based PSC cost model. The use of generated data rather than real data may influence the outcomes and conclusions of the research. The second limitation is related to the model design. To design the cost model, we first selected some parts of the mathematical model inspired by other papers and then added BT costs. This means that the study may not cover some cost components of a real case, hindering the comparison of the results of this research with the results of other studies.

Finally, future research may extend the BT-based PSC cost model to a multi-objective model, for example including the uncertainty demand in PSCs. Another promising direction is to use other EC algorithms to enhance the performance of the SL algorithms or to test different SL algorithms to predict costs. The use of Feature Selection (instead of FW) is another direction that should be investigated to compare the optimisation process of this model. The last potential future research direction is to determine the cost components of the private BT and formulate the private BT instead of the public BT used in the current study.

4.8 Conclusion

The BT-based PSC enables traceability and transparency of the drugs' movement and stakeholders in the supply chain and can affect medication quality and final patient outcomes. This paper presents a mathematical cost model for a BT-based PSC system to estimate the costs of the model. This study is important because it provides a PSC system with BT (BT Transaction cost and BT Installation cost) that can improve the safety, performance, and transparency of medical information sharing in a healthcare system.

One of the main contributions of this research is to formulate this cost problem and apply a combination of EC (ACO and FA) and SL (KNN, DT, SVM, and NB) algorithms and use four performance metrics (MSE, RMSE, MAE, and R^2) to evaluate the efficiency of the proposed algorithms. This combination of EC and SL algorithms provides eight algorithms (as the regression producer), reducing prediction errors and improving the SL results. Overall, the ACO-NB and FA-NB algorithms outperform the other six algorithms in estimating the costs of the model with lower errors. ACO-DT and FA-DT show the worst performance for this comparison, showing that the DT algorithm is not an appropriate predictive approach for the current cost model.

The findings also show that the Shortage cost, Holding cost, and Expired Medication cost strongly influence the cost model more than the other cost components that have almost the same effect on the model (Regular-Purchases cost, Emergency-Purchases cost, Shipping cost, BT-Transaction cost, and BT-Installation cost). This selection of components is derived from the allocation of an appropriate weight to each cost feature to show their importance through the FW approach. Therefore, the statistical outcomes on the generated dataset show that some of the proposed algorithms can obtain satisfactory results and assign appropriate feature weights. In the real world, managers in the field of healthcare services can use this model practically to control financial resources, stay within the budget, analyse information, and identify unnecessary costs, particularly if they decide to use BT in the system. The important contribution of this research is to provide a PSC system with BT. Selected SL algorithms can also help managers estimate costs with the minimum prediction errors and correctly decide whether the new system benefits their organization. As the cost factor is important to managers, this study also determines and measures the importance of each cost component of the BT-based PSC model.

Data Availability:

The data that support the findings of this study are openly available in https://data.mendeley.com/datasets/jxv5jrydnc. This sentence was stated in the section 3 of the manuscript to show data availability: “5000 series of the generated raw data for all eight components of the BT-based PSC cost model and the total cost were uploaded to https://data.mendeley.com/datasets/jxv5jrydnc.”

CHAPTER 5

BLOCKCHAIN-ENABLED PHARMACEUTICAL SUPPLY CHAIN UNDER UNCERTAIN DEMAND: COST PREDICTION THROUGH EVOLUTIONARY SUPERVISED LEARNING TUNING

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5.1 Abstract

Blockchain Technology-enabled Pharmaceutical Supply Chain (BT-enabled PSC) may allow medical information to be shared between systems, make it possible to track drugs, monitor PSCs safely and transparently, reduce delays and human errors, and improve the stability, safety, and security of a medical information exchange system. This paper provides a new multi-function PSC mathematical cost model, including PSC costs, BT costs, and uncertain demand fluctuations. The purpose of this study is to find the most appropriate algorithm(s) with minimum prediction errors to estimate the costs of the BT-based PSC model. This paper also aims to determine the cost components of the multi-function model and the importance of each cost component. To reach these goals, we combined four Supervised Learning algorithms (KNN, DT, SVM, and NB) with two Evolutionary Computation algorithms (PSO and HS) after data generation. We also applied the Feature Weighting approach to reveal the importance of each cost component of the multi-function model. Next, four performance metrics evaluated the multi-function model, and the Total Ranking Score (TRS) determined the most reliable predictive algorithms. Our findings indicate that the HS-NB and PSO-NB algorithms outperform the other six

algorithms in estimating the costs of the multi-function model with fewer errors. The results also show that the Raw Materials cost has a stronger influence on the model than the other components. This study also introduces the components of the multi-function BT-enabled PSC model.

Keywords: Blockchain Technology-enabled Pharmaceutical Supply Chain; Uncertain Demand; Supervised Learning algorithms; Evolutionary Computation algorithms; Blockchain Technology

5.2 Introduction

The multi-function Blockchain Technology-enabled Pharmaceutical Supply Chain (BT-enabled PSC) may positively affect medication quality, ultimate patient outcomes, the tracking of medical records/sources, the distribution of drugs, stability of information, and information safety. The PSC performs reasonably well in Canada's healthcare system and manages a considerable part of healthcare expenditures. However, in a Supply Chain System (SCS), information is not shared between systems, and manufacturers have difficulty tracking their products. The regulations for the stability and safety of medical records, medical devices, and supplies are among the highest standards in the pharmaceutical industry, and Blockchain Technology (BT) can monitor PSC safely and transparently. Therefore, BT-enabled PSC can improve the safety and security of the system and significantly reduce delays and human errors. Generally, access to medical records is difficult because they are distributed in many different healthcare centers. Already, BT significantly impacts the healthcare industry, and its use has increased remarkably in the healthcare domain. BT shifts a centralized healthcare network into a decentralized one and preserves and exchanges patient information among hospitals, diagnostic laboratories, pharmaceutical firms, and physicians. One of the important advantages of using BT in the PSC is to detect fake medicines with appropriate control over the supply and demand of drugs. Another advantage of BT-enabled PSC is to improve the interoperability of patient health data between healthcare providers while maintaining the privacy and security of their data. Using BT-enabled PSC has also enhanced the transparency and communications between healthcare organisations and patients. The PSC also deals with demand uncertainty, in which the demand for each medicine is uncertain and changeable.

Previous studies have reported the advantages and disadvantages of using BT in PSC; in contrast, the present study seeks to estimate the cost of a PSC system that uses BT and manages uncertain demand. Managers control the financial resources employed in a system's performance, decide whether a new system benefits their organisation, monitor the business's financial health, seek to reduce expenses, and stay within their budget, and analyse information to identify unnecessary costs and better business opportunities. Another significant contribution of this study is to provide a PSC system with BT that considers the demand uncertainty. BT in a PSC could improve safety, performance, and medical information transparency while reducing the data transformation cost and time. The multi-function BT-enabled PSC has two objectives: to manage system costs and deal with uncertain demand. Demand uncertainty in a PSC may affect product demand, product prices, raw material availability, regulatory changes, investment risk, unit manufacturing, costs of transportation, etc.

This study aims to estimate the costs of the multi-function BT-enabled PSC model, including demand uncertainty, and determine SL algorithms with the least prediction errors and the lowest-cost model components. Determining the model's cost components is essential, which helps managers make the most appropriate decisions. Another purpose of this research is to measure the importance of each cost component of the multi-function model or the relevance degree of each feature to the model. This study seeks to answer the following research questions: (*i*) What are the components of a multi-function BT-enabled PSC model, including uncertain demand? What is the mathematical model? (*ii*) Which algorithms perform better in minimising the prediction errors of the multi-function BT-enabled PSC model among eight algorithms? (*iii*) What are the most important cost components of a multi-function model? The procedure to determine the responses to these questions is as follows. First, we designed a multi-function BT-based PSC mathematical cost model after determining the cost components and paying particular attention to demand uncertainty as the second objective. After data generation, we applied four Supervised Learning (SL) algorithms: K-Nearest-Neighbors (KNN), Decision Tree (DT), Support Vector Machine (SVM), and Naive Bayes (NB), combined with two Evolutionary Computation (EC) algorithms: Harmony Search (HS) and Particle Swarm Optimization (PSO), for a total of eight algorithms. The EC algorithms were applied to optimize the hyperparameters of the SL algorithms and improve the multi-function model. We selected these well-known algorithms because they have been successfully applied to solve engineering problems, and they can facilitate the discussion of their behaviors in our new cost multi-function model. Finally, we used four performance metrics to evaluate our multi-function model and utilized the Total Ranking Score (TRS), a score-based ranking system, to determine the most reliable predictive algorithms.

The rest of the paper is organised as follows. First, we provide an overview of the theoretical background for BT-enabled PSC, SL optimized by EC, and uncertain demand in Section 2. Next, we discuss the methodology and data generation in Section 3 and the design of the mathematical model for the multi-function BT-enabled PSC model in section 4. Section 5 presents the experiments and their results. The results, limitations, and future research are discussed in section 6, and then we briefly explain the conclusions in Section 7.

5.3 Theoretical Background

5.3.1 Introduction to PSC (Pharmaceutical Supply Chain)

PSC management is essential for tracking materials sourced for manufacturing and distributing pharmaceuticals, while SCS is necessary for any industry moving materials and goods (Kamel Boulos, Wilson, & Clauson, 2018). PSC is a considerable part of healthcare expenditures and plays an essential role in healthcare (Jafar Heydari & Rabbani, 2020), and the PSC process significantly influences ultimate patient outcomes and medication quality (Chircu, Sultanow, & Saraswat, 2014). Uthayakumar and Priyan define PSC as ‘‘the integration of all activities associated with the flow and transformation of drugs from raw materials to the end-user, as well as the associated information flows, through improved SC relationships to achieve a sustainable competitive advantage'' (Uthayakumar & Priyan, 2013). Haq and Muselemu Esuka (2018) stress that PSC systems protect patient data privacy. Finally, several stakeholders participate in the movement of a product in the PSC system. They are (I) Primary manufacturers, (ii) Secondary manufacturers, (iii) Distribution centers/wholesalers, and (iv) Retailers (i.e., pharmacies/hospitals), each with their specifications, obligations, and priorities (Zahiri, Jula, & Tavakkoli-Moghaddam, 2018).

5.3.2 Introduction to BT (Blockchain Technology)

BT is a cutting-edge technology with various applications such as cryptocurrency, financial services, risk management, and public and social services (Hosseini Bamakan, Ghasemzadeh Moghaddam, & Dehghan Manshadi, 2021). Hosseini Bamakan et al. (2021) introduce three categories of BT: public, private, and consortium, according to the type of access for their users. In public BT, all data and transactions are recorded in a chain of blocks, and normally, medical organisations do not participate in networks that anyone can access and join because clinical institutes deal with highly classified and sensitive data (Mamun, 2022). BT is currently being explored for the following areas in healthcare**:** securing patient and provider identities, managing supply chains in pharmaceuticals and medical devices, medical fraud detection, public health surveillance, and sharing public health data to help public health workers respond faster to a crisis (Kamel Boulos, Wilson, & Clauson, 2018)**.** Decentralization is the main aspect of BT, as all information is stored permanently and securely without requiring a centralized authority to monitor the transactions (Mansur Hussien, Md Yasin, Izura Udzir, Hafez Ninggal, & Salman, 2021).

5.3.3 Key Features and Benefits of BT in PSC

BT can improve healthcare data sharing and storage systems thanks to its decentralization, immutability, transparency, and traceability features (Abu-elezz, Hassan, Nazeemudeen, Househ, & Abd-alrazaq, 2020). PSC has four main elements, the suppliers, the pharmacy, the hospital, and the patients. The suppliers manufacture or distribute the medicines; a pharmacy orders medicines from the suppliers, keeps the medicines safe, manages the inventory, and distributes the medicines to the hospital; a hospital provides medicines to patients and places orders from the pharmacy; and the patients require treatment and medicines (Franco & Alfonso-Lizarazo, 2020). The key features of BT ensure the traceability of medical products by providing a transparent, decentralized tracking system (Mansur Hussien, Md Yasin, Izura Udzir, Hafez Ninggal, & Salman, 2021). Mansur Hussien et al. state that the immutability and timestamps of BT transactions allow the accurate tracking of products and ensure that the information inside a block cannot be altered. Mansur Hussien et al. also found that the data transparency feature in BT can detect the full path of counterfeit medication**.** The key BT attributes that allow it to meet the requirements of many applications in the healthcare industry are decentralisation, transparency, security and privacy, and scalability and storage capacity. Decentralisation prevents a single point of security failures, as BT distributes medical data across the network rather than from a single central point. BT uses transactions and multilateral relationships that have been made more accurate, stable, and efficient by using smart contracts, and BT's transparency allows different healthcare providers to access patients' medical data, thereby overcoming the lack of transparency in the healthcare industry. BT can allow patients to have secure access to their medical history records and professionals involved in their treatment (Hosseini Bamakan, Ghasemzadeh Moghaddam, & Dehghan Manshadi, 2021). Security and privacy are especially crucial as the volume of medical data continues to grow, requiring creative processing and storage methods. BT's methods serve to safeguard healthcare storage and data transfer. Scalability and storage capacity are directly linked to confidentiality and scalability issues (Mansur Hussien, Md Yasin, Izura Udzir, Hafez Ninggal, & Salman, 2021).

5.3.4 Enabling BT in PSC

BT in the pharmaceutical industry plays a significant role in safeguarding and optimizing the SC (Kumar Badhotiya, Prakash Sharma, Prakash, Kalluri, & Singh, 2021). The current pharmaceutical SCS does not provide visibility and control for manufacturers or regulatory authority over drug distribution; therefore, it is outdated and cannot withstand 21st-century cyber-security threats (Haq & Muselemu Esuka, 2018). Haq and Muselemu Esuka note that a BT-enabled PSC will verify the products without any information about the manufacturer's secret techniques; however, patients' medical records will be accessible to certified network participants – without revealing any patient's private data (Haq & Muselemu Esuka, 2018). BT-enabled PSC improves the security and trust of the system, prevents any single person from modifying the data and transactions, and eliminates the biases found in traditional SCSs (Haq & Muselemu Esuka, 2018). BT can maintain the PSC's monitoring system, track medication responsibilities, store individual patient information, and analyze the effects of a particular procedure (Haleem, Javaid, Pratap Singh, Suman, & Rab, 2021). Another advantage of BT is maintaining hospital financial statements and minimizing the data transformation time and cost (Haleem, Javaid, Pratap Singh, Suman, & Rab, 2021). Kumar Badhotiya et al. (2021) believe that the concept of BT in the PSC can be utilized to detect fake medicines with proper control oversupply and demand of the drugs, allowing pharmaceutical companies to unmask fake and unregistered medicines (Kumar Badhotiya, Prakash Sharma, Prakash, Kalluri, & Singh, 2021).

5.3.5 Uncertain Demand in PSC

Uncertainty in a PSC may arise in product demand, price, clinical trials, raw material availability, regulatory changes, investment risk, unit manufacturing, transportation costs, etc. (Ahmadi, Mousazadeh, Ali Torabi, & Pishvaee, 2017). Ahmadi et al. observe that uncertainty may also arise because of the required data's unavailability and the dynamic and imprecise nature of this data. PSCs deal with uncertainty, which makes them different from other SCs; for example, the demand for each medicine is uncertain and can be influenced by seasonal changes (Franco & Alfonso-Lizarazo, 2020). Moreover, Ahmadi et al. (2017) classify uncertainty into two categories: (a) uncertainty in data (which is the most common uncertainty faced in SCs) and (b) flexibility in constraints and goals. There are typically two forms of uncertainty in data: (a) randomness, which originates from the random nature of the data, and (b) epistemic uncertainty, which is due to the unavailability or insufficiency of required data, leading to imprecise data being extracted from the experts' subjective opinions (Ahmadi, Mousazadeh, Ali Torabi, & Pishvaee, 2017).

5.3.6 SL Optimized by EC

An intelligent optimization algorithm is applied to optimize the hyperparameters of the machine learning or deep learning model to build a modified model (Hu, et al., 2022). During the evolutionary progress, the EC algorithm explores possible combinations of parameters (Zhang, Deb, Lee, Yang, & Shah, 2016). The deep learning model generally has a long training time, and its parameters are not optimal (Li, et al., 2022). Therefore, Li et al. state that improving the deep learning model and optimizing the hyperparameters would make a notable difference. Li et al. also mention that the parameters of deep learning neural network models are usually set empirically, which means that finding the best predictive performance of the model takes a considerable amount of time. Neural network model training usually faces some problems, such as local optimization or overfitting, and it is difficult to determine many network parameters. An intelligent optimization algorithm that constantly improves the neural network model or optimizes the parameters is an important addition (Tian & Chen, 2021). For example, the improved Sparrow Search Algorithm used in t Tian and Chen optimizes the hyperparameters of the Long Short-Term Memory model. Shu et al. (2022) apply Bayesian optimization to search the hyperparameter space of label propagation and spreading using the default random Forest Algorithm (Shu, Xia, Tu, Williams, & Menzies, 2022). Another approach is to use the swarm intelligence optimization algorithm to find a model's optimal parameters according to the dataset's characteristics (Li, et al., 2022).

5.4 Methodology and Data Generation

This section introduces the procedure of data generation and the methodology that evaluates, optimizes, and estimates the cost of the multi-function BT-enabled PSC model. In the first step, Python software helps us generate raw data for our multi-function BT-enabled PSC model. We applied randint() as an inbuilt function of the random module, one of the most well-known tools for generating random data in Python. This module returns a random integer value from the inclusive range between the two lower and higher limits (including both limits), provided as two parameters. The generated dataset includes six features as the components of the model ($C_{raw\_materials}$, $C_{finished\_products}$, $C_{shortage\_surplus}$, $C_{BT\_Installation}$, $C_{BT\_Transaction}$, and $D_{i,uncertainty}$) and the total cost for objective 1 (C_{Total}) as the label in the regression process. We uploaded 5000 series of the generated raw data for all six components of the multi-function BT-enabled PSC model and the total cost to https://data.mendeley.com/datasets/sfc7hst95m. The research method selected in this paper combines two approaches (EC and SL) to evaluate the multi-function BT-enabled PSC model. The HS and PSO algorithms are used for the EC approach, and the KNN, DT, SVM, and NB algorithms are used for SL. The HS and PSO algorithms optimize the parameters of the KNN, DT, SVM, and NB algorithms and minimize the model prediction errors. EC combined with four algorithms (KNN, DT, SVM, and NB) reduces prediction errors and thus plays an important role in enhancing the performance of the selected SL algorithms. Figure 5.1 presents the flowchart of the methodology and the implementation of the algorithm performed in MATLAB. This flowchart includes the following steps: creating the population using four SL algorithms (KNN, DT, SVM, and NB) combined with two EC algorithms (HS and PSO), incorporating the Feature Weighting approach and using four performance metrics (MSE, RMES, MAE, and R^2), and each method (SL combined with EC algorithms) received a score with a Total Ranking Score technique. The flowchart starts with creating a new population and initializing the parameters. Next, we apply the Feature Weighting (FW) approach to evaluate the importance of features, assign an appropriate weight to each feature, and estimate the degree of relevance of each feature to the model. The FW process is executed by multiplying the value of every feature instance and ordering them by their values (Al-Zoubi, et al., 2021). Usually, the selected features are equally important when estimating the output. However, some features with a higher weight can influence the results and affect the performance and the accuracy of the overall algorithm. We then split the dataset into two parts: 70% of the dataset for training and 30% for testing. Four different SL algorithms are used to find the optimal method to estimate the cost of the multi-function BT-enabled PSC model (KNN, DT, SVM, and NB). Two EC algorithms (HS and PSO) are then utilized to optimize the hyperparameters of the SL algorithms and improve the performance of the SL algorithms. Next, we use four performance metrics to evaluate the model, The Mean Square Error (MSE), the Root Mean Square Error (RMSE), the Mean absolute error (MAE), and the correlation coefficient (R^2). This approach produced the following results: five FWs (one weight for each feature) for objective 1 and four performance metrics for objectives 1 and 2. We used a score-based ranking system called the Total Ranking Score (TRS) to determine the most reliable predictive algorithms. Each method received a score in the TRS based on the calculated MSE, RMES, MAE, R^2, and five feature weight values in objectives 1 and 2. Finally, the ranking position of each method was assigned based on the sum of all the scores.

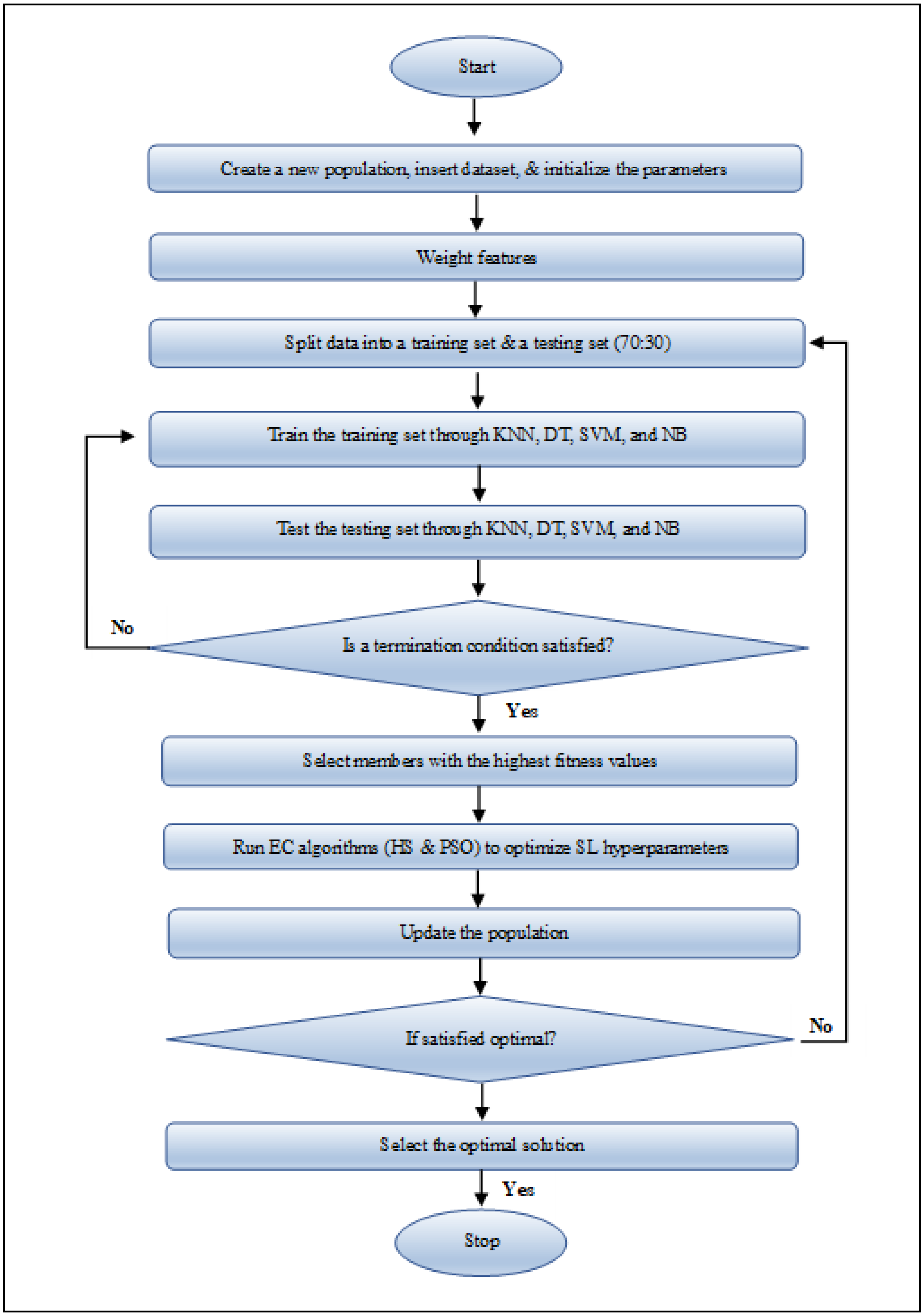

Figure 5.1 Flowchart of the methodology

Figure 5.1 Flowchart of the methodology, including creating the population, using four SL algorithms (KNN, DT, SVM, and NB), two EC algorithms (PSO and HS), the Feature Weighting approach, four performance metrics (MSE, RMES, MAE, and R^2), and the Total Ranking Score.

5.5 Proposed Optimization Multi-Function BT-enabled PSC Model

This section defines the nonlinear BT-enabled PSC cost model with two objectives. The proposed model is a nonlinear multi-function approach to evaluate Pharmaceutical Supply Chains with their uncertainties in demand parameters. The model is designed to estimate the total costs of BT-enabled PSCs, including considering the unmet demand in the pharmaceutical system. The mathematical model with two objectives includes the Raw Materials cost, Finished Products cost, Shortage-Surplus cost, Blockchain Installation cost, Blockchain Transaction cost, and the Unsatisfied Demand of product families. Eq. (5.1) expresses the multi-function BT-enabled PSC model.

$$\mathbf{Obj_1} = [C_{PCS}] + [C_{Blockchain}]$$

$$\mathbf{Obj_1} = [C_{raw\_materials} + C_{finished\_products} + C_{shortage\_surplus}] + [C_{BT\_Installation} + C_{BT\_Transaction}]$$

$$\mathbf{Min\ Obj_1} = \text{Min} \left(\sum_{i=1}^{M} [\, C_{i,raw\_materials} + C_{i,finished\_products} + C_{i,shortage\_surplus} + C_{i,BT\_Installation} + C_{i,BT\_Transaction}]\right)$$

$$\mathbf{Min\ Obj_2} = \text{Min (Max} \sum_{i=1}^{M} [D_{i,uncertainty}] \tag{5.1}$$

Table 5.1 lists the parameters and constraints for the BT-enabled PSC cost model in the pharmaceutical system, including the parts of the mathematical model.

Table 5.1 Parameters and constraints for all parts of the BT-enabled PSC cost model

Parameters	**Explanation**	**Constrains**
M	Number of products controlled in the PSC variables	35
q_i	Order quantity for the i^{th} product per year (i = 1, 2, 3, . . . , M)	$50 \le q_i \le 100$ (integer)
d_i	The average demand for the i^{th} product per year	$45 \le d_i \le 115$ (integer)
n	Total number of lots of M products delivered by the pharmaceutical system to the client per year	$50 \le n \le 100$ (integer)
I_v	The interest rate for calculating the opportunity interest loss for the pharmaceutical system due to delayed payment per year	$I_v = 0.02$
T_c	Common trade credit period for all products offered by the pharmaceutical system in years	0.1
h_{vi}	Holding cost for the i^{th} finished product per year	$20 \le h_{vi} \le 40$
s_i	Set-up cost for the i^{th} finished product per year	$12 \le s_i \le 25$
p_i	The production rate for the i^{th} finished product	$45 \le p_i \le 115$ (integer)
bi	The purchase price per unit for the i^{th} product	$80 \le bi \le 150$
p_{ci}	Production cost for a product i per year	$25 \le p_{ci} \le 50$
d_{ci}	Expiration rate for the i^{th} finished product	$6\% \le d_{ci} \le 15\%$
c_{dci}	Cost of expiry for the i^{th} finished product	$25 \le c_{dci} \le 55$
q_{wi}	Replenishment quantity for the i^{th} raw material for the production	$20 \le q_{wi} \le 27$
a_{wi}	Ordering cost for the i^{th} raw material	$15 \le a_{wi} \le 25$
h_{wi}	Holding cost per year for the i^{th} raw material	$10 \le h_{wi} \le 15$
F_w	Fixed transportation cost for all raw materials per year	3500
v_{wi}	Labor cost for order handling and receipt for the i^{th} raw material per year	$16 \le v_{wi} \le 28$
β_i	Defect rate for the i^{th} raw material in an order lot, $\beta_i \in [0, 1]$, a random variable	$0 \le \beta_i \le 1$
r_{si}	Screening rate per year for the i^{th} raw material	$1.04\% \le r_{si} \le 7.2\%$
$costSi$	Shortage cost of unit product type i	$10 \le costSi \le 20$
$costSUi$	Surplus cost of unit product type i	$15 \le costSUi \le 25$
$z^1{}_i$	Surplus amount of product i	$0 \le z^1{}_i \le 70$ (integer) $z^1{}_i \ge p_i - d_i$
$z^2{}_i$	Shortage amount of product i	$0 \le z^2{}_i \le 70$ / (integer) $z^2{}_i \le d_i - p_i$
τ_i	Comparative importance of product i	$1 \le \tau_i \le 5$ (integer)
gWei	The cost paid to the transaction validators and the network (Wei is the unit of ETH)	---
G_u	The amount of Ether as gasUsed per day	$\$3.86 \le G_u \times$
g_p	Number of gWei to be paid for gasUsed per day	$g_p \le \$41.66$

Parameters	Explanation	Constrains
s	The data storage size to store the data	51 TB/yr $\leq s \leq$ 99 TB/yr
C_s	Cost storage per year (USD/TB) for Public outbound bandwidth service (IBM, IBM Cloud, 2022)	\$110×12 = 1320 \$/yr
c_{fixed}	The initial fixed cost per year	860 $\leq c_{fixed} \leq$ 1160
$c_{onboarding}$	The Onboarding cost	\$180 $\leq c_{onboarding} \leq$ \$260
c_{mc}	The unit Maintenance cost; $c_{mc} + c_{mo}$ is 15%–25% of the project value	\$230 $\leq c_{mc} + c_{mo} \leq$ \$550
c_{mo}	The unit Monitoring cost; $c_{mc} + c_{mo}$ is 15%–25% of the project value	
U	The number of Blockchain users	4
d_i - p_i	The demand uncertainty	≥ 0

A list of the assumptions is provided below, along with additional notations and assumptions as required (Uthayakumar & Priyan, 2013).

1. The PSC comprises a single pharmaceutical system with multiple (M) pharmaceutical products. For the i^{th} product, the pharmaceutical system produces nq_i units at a finite production rate of p_i per unit time in one production cycle.
2. For the i^{th} raw material, all orders are delivered to the pharmaceutical system in one shipment by an external supplier. In other words, the quantity of the i^{th} raw material required for production in each production cycle is instantaneous.
3. All expired pharmaceutical products held in inventory by the pharmaceutical system are a constant fraction of the accumulated inventory.
4. The pharmaceutical system offers a certain trade credit period (permissible payment delay) for all products to cooperate with clients (like a hospital or a pharmacy) in an integrated strategy. Thus, the customers do not have to pay immediately on receipt of products.
5. The credit period T_c is less than the reorder interval for each product, meaning the credit period cannot be longer than when another order is placed. This agrees with the usual practice in health care industries.

6. Products are all packed, and the number of products is an integer.
7. It is assumed the model uses the available Public Blockchain platform in the market as a hosting platform.
8. Node hosting space (cloud storage) is used to store data, and the number of nodes is the number of copies of data. We assigned one node in this research (A Blockchain node's primary job is to confirm the legality of each subsequent batch of network transactions, known as blocks).
9. Unsatisfied demand is positive; otherwise, it is zero.

5.5.1 Cost Elements of a PSC

5.5.1.1 Raw Materials Cost Elements

The following function, Eq. (5.2), represents the Raw Materials cost in the pharmaceutical system, including the Ordering cost, Holding cost for perfect raw materials, Holding cost for imperfect raw materials, Labor cost for order handling and receipts, and Transportation cost. Eq. (5.2) shows the Cost Order ($\frac{a_{wi}\, d_i}{nq_i}$), the Holding cost for perfect raw materials ($\frac{d_i\,(1-\beta_i)\, q_{wi}\, h_{wi}}{n\, q_i}$), the Holding cost for imperfect raw materials ($\frac{h_{wi}\ \beta_i\, q_{wi}\, q_{wi}\, d_i}{r_{si}\, n\, q_i}$), the Labor cost for order handling and receipt ($\frac{d_i\, q_{wi}\, v_{wi}}{nq_i}$), and the Transportation cost ($\frac{F_w\, d_i}{nq_i}$) (Uthayakumar & Priyan, 2013; Havaeji, Dao, & Wong, 2022). It is assumed that each quantity q_{wi} contains defective raw materials at a rate of β_i, which is a random variable.

$$\sum_{i=1}^{M}\left[\frac{a_{wi}\, d_i}{nq_i} + \frac{d_i\,(1-\beta_i)q_{wi}\, h_{wi}}{n\, q_i} + \frac{h_{wi}\,\beta_i\ q_{wi}\, q_{wi}\, d_i}{r_{si}\, n\, q_i} + \frac{d_i\, q_{wi}\, v_{wi}}{nq_i} + \frac{F_w\, d_i}{nq_i}\right] \tag{5.2}$$

5.5.1.2 Finished Products Cost Elements

Finished Product i for the pharmaceutical system, which equals the sum of the Set-up cost, Holding cost, Production cost, Expected opportunity interest, and Expiry cost. Eq. (5.3) shows the cost elements of the Finished Products in the pharmaceutical system: the Set-up cost ($\frac{s_i\, d_i}{nq_i}$), the Holding cost ($\frac{h_{vi}\, q_i}{2}[n(1 - \frac{d_i}{p_i}) - 1 + \frac{2d_i}{p_i}]$), the Production cost ($d_i\, p_{ci}\, q_i$), the Expected opportunity interest loss per unit time for the product i is $I_v b_i T_c d_i$, and the Expiry cost ($q_i\, d_{ci}\, c_{dci}\,[(\frac{d_i}{p_i} + (n - 1)) - \frac{nd_i}{2p_i}]$) (Uthayakumar & Priyan, 2013; Havaeji, Dao, & Wong, 2022).

$$\sum_{i=1}^{M}[\frac{s_i\, d_i}{nq_i} + \frac{h_{vi}\, q_i}{2}[n(1 - \frac{d_i}{p_i}) - 1 + \frac{2d_i}{p_i}] + d_i\, p_{ci}\, q_i + I_v b_i T_c d_i + q_i\, d_{ci}\, c_{dci}\,[(\frac{d_i}{p_i} + (n - 1)) - \frac{nd_i}{2p_i}]] \tag{5.3}$$

5.5.1.3 Shortage-Surplus Cost Elements

It should be noted that medicine and drug shortages are serious issues in any society, a worldwide problem that governments face because of demand uncertainty and other factors (Roshan, Tavakkoli-Moghaddam, & Rahimi, 2019). Eq. (5.4) expresses the shortage-surplus cost equation, including Shortage and Surplus costs.

$$\sum_{i=1}^{M}[\, z^1{}_i \times costSU_i + z^2{}_i \times \tau_i \times costS_i] \tag{6.4}$$

In Table 1, $z^1{}_i \geq p_i - d_i$ and $z^2{}_i \leq d_i - p_i$ represent a lower bound for the surplus and an upper bound for the shortage of a product, respectively.

5.5.2 Blockchain Implementation Cost Elements

According to Havaeji, Dao, and Wong (2022), Blockchain Implementation cost ($C_{Blockchain}$) consists of two components, Blockchain Transaction cost ($C_{BT\_Transaction}$) and Blockchain Installation cost ($C_{BT\_Installation}$) (Eq. (5.5)). As an alternative for designing and developing a Blockchain platform, it is assumed the model uses the available public Blockchain platform in the market as a hosting platform.

$$C_{Blockchain} = C_{BT\_Transaction} + C_{BT\_Installation} \tag{5.5}$$

Havaeji, Dao, and Wong (2022) introduced the $C_{BT\_ Transaction}$ calculation to pay miners in Eq. (5.6): Total Transaction cost = Gas cost (gasUsed × gasPrice) + Storage cost (Longo, Nicoletti, Padovano, d'Atri, & Forte, 2019; Jabbar & Dani, 2020; Wood, 2020).

$$\mathrm{G_u} \times g_p \times 365 + s \times \mathrm{C_s} \tag{5.6}$$

$\mathrm{G_u} \times g_p$ is the Gas cost per day, and $s \times \mathrm{C_s}$ is the storage cost per year, with a secured cloud-based warehouse storing the actual data off-chain. The IBM Cloud website calculates the storage cost portion (IBM, IBM Cloud, 2022). Table 5.1 also presents the parameters and constraints for the BT Transaction costs.

Wood (2020) mentions Ethereum as a fee for all programmable computation and a kind of currency called Ether (ETH). Proof-of-Work (PoW), like Bitcoin and Ethereum, is the most popular consensus protocol in a public blockchain system (Wang, et al., 2021). There are two parts to the cost of a typical transaction: gasLimit and gasPrice. Longo et al. (2019) state that this calculation must be performed based on the gas used by a transaction to calculate the cost of the Ethereum blockchain. The gasLimit (purchased from the sender's account balance) is the maximum amount of gas that should be used to execute any transaction; any unused gas at the end of a transaction is refunded (at the same rate of purchase) to the sender's account (Wood, 2020; Havaeji, Dao, & Wong, 2022). Wood clarifies that the number of W_{ei} units to be paid for each unit of gas is the gasPrice (a scalar value), which consists of all computation costs incurred as a result of the execution of that transaction. After submitting a transaction, a given amount of gas is associated with that transaction (Longo, Nicoletti, Padovano, d'Atri, & Forte, 2019).

ETH Gas Station calculates $G_u \times g_p$ and incentivizes computation within the network (Jabbar & Dani, 2020; ETH Gas Station, 2022). The gW_{ei} is the cost paid to the transaction validators (or the network) for conducting a transaction on the Ethereum Blockchain. The most important aspect is how gW_{ei} is converted to USD based on the current price of Ethereum by using the ETH Gas Station website (ETH Gas Station, 2022). The gasUsed (a scalar value) is the total gas used in transactions. The amount 65000 as the amount of gasUsed and the range of 19 gW_{ei} to 205 gWei as the gasPrice were selected to calculate the $G_u \times g_p$ cost and convert the gW_{ei} cost to USD via the ETH Gas Station website (Figure 5.2).

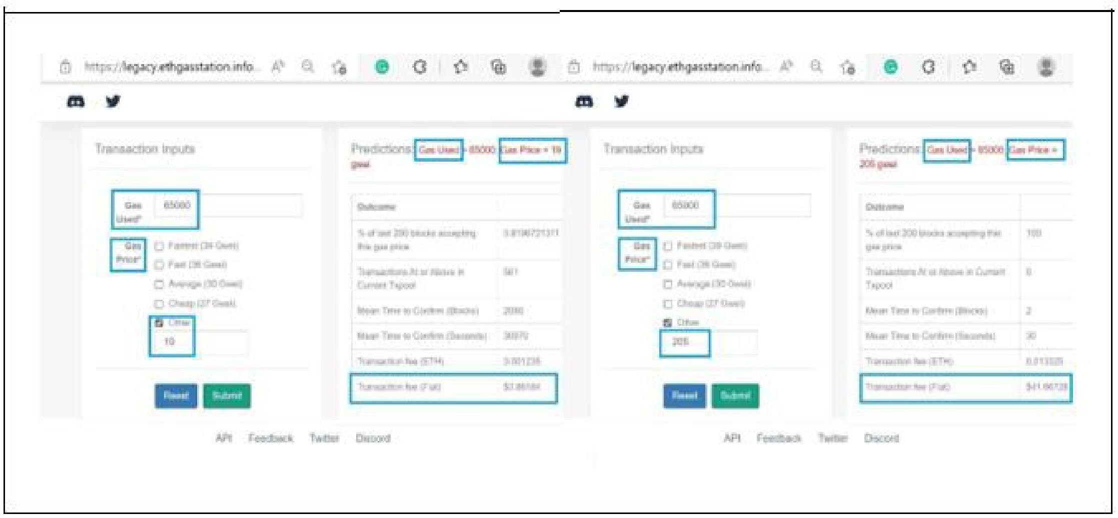

Figure 5.2 Transaction cost by ETH Gas Station

The Blockchain Installation cost ($C_{BT\_Installation}$), or the cost of utilizing BT for PSC, has four cost elements (Eq. (5.7)), including a Fixed cost (c_{fixed}), Onboarding cost ($c_{onboarding}$), Maintenance cost (c_{mc}), and Monitoring cost (c_{mo}) (Gopalakrishnan, Hall, & Behdad, 2021; Havaeji, Dao, & Wong, 2022).

$$\sum_{i=1}^{M}[c_{fixed} + (c_{onboarding} \times U + c_{mc} + c_{mo}) \times q_i] \quad (6.7)$$

The Onboarding cost (such as onboarding and training) is the cost involved in training suppliers and clients into active users of a product or service and includes any expenses and costs related to integrating new employees into a system to learn about and be trained in BT. The c_{mc} and c_{mo} costs occur yearly and contribute to 15–25 percent of a project's value (Takyar, 2021a; Gopalakrishnan, Hall, & Behdad, 2021). Other parameters, including the parameters and constraints for the Blockchain Installation cost, are also shown in Table 1.

5.5.3 Uncertain Demand elements

The PSC deals with uncertainty, given that the demand for each product of medicine is uncertain and can be influenced by various factors, such as seasonal changes. Uncertain demand occurs when the amount of demand exceeds the available stock. For instance, if a drug price is too low, the demand for that product will be increased, and customers will purchase it from suppliers that can accommodate their demand. This process leads to drug shortages, and so producers should raise their prices and output until supply equals demand and equilibrium is reached. The uncertainty imposes many challenges for modeling and determining optimal solutions. Our model represents the demand uncertainty as shown in Eq. (5.8), with the input parameters considered under uncertainty (Mousazadeh, Torabi, & Zahiri, 2015; Zahiri, Jula, & Tavakkoli-Moghaddam, 2018; Roshan, Tavakkoli-Moghaddam, & Rahimi, 2019; Ahmadi, Mousazadeh, Ali Torabi, & Pishvaee, 2017).

$$\text{Min Obj}_2 = \text{Min}\left(\text{Max}\sum_{i=1}^{M}[\tau_i[d_i - p_i]]\right) \quad (6.8)$$

The second objective function in Eq. (5.1) (Obj_2) seeks to minimize the maximum unsatisfied demand of product families, which implies an upper bound for the total unsatisfied demand. Since the unit unfulfilled demand of a low-priority product family is not as important as that of a high-priority product family, this objective is empowered by incorporating the importance parameters π_p to take a balanced attitude towards different product families. To better explain Eq. (5.1), $D_{i,uncertainty}$ is equal to $\tau_i[d_i - p_i]$ and should be positive; otherwise, it is zero ($D_{i,uncertainty} \geq 0$).

5.5.4 Optimization Multi-Function for BT-enabled PSC

The integrated expected total cost for the multi-function BT-enabled PSC model for products in a pharmaceutical system can be expressed in Eq. (5.9) as the sum of the expected total costs of the following components: Raw Materials cost (Ordering cost, Holding cost for perfect raw materials, Holding cost for imperfect raw materials, Labor cost for order handling and receipt, and Transportation cost) (Eq. (5.2)), Finished Products cost (Set-up cost, Holding cost, Production cost, Expected opportunity interest, and Expiry cost) (Eq. (5.3)), Shortage-Surplus cost (Shortage cost and Surplus cost) (Eq. (5.4)), Blockchain Installation cost (Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost (Eq. (5.7)), and Blockchain Transaction cost (Gas cost and Storage cost) (Eq. (5.6)). The second objective is the Unsatisfied Demand, given by Eq. (5.8).

$$\textbf{Min Obj}_\mathbf{1} = \sum_{i=1}^{M}\Big[\frac{a_{wi}\, d_i}{nq_i} + \frac{d_i\,(1-\beta_i)q_{wi}\,h_{wi}}{n\,q_i} + \frac{h_{wi}\ \beta_i\, q_{wi}\, q_{wi}\, d_i}{r_{si}\, n\, q_i} + \frac{d_i\, q_{wi}\, v_{wi}}{nq_i} + \frac{\mathrm{F}_w\, d_i}{nq_i} +$$
$$\frac{s_i\, d_i}{nq_i} + \frac{h_{vi}\, q_i}{2}\Big[n\Big(1 - \frac{d_i}{p_i}\Big) - 1 + \frac{2d_i}{p_i}\Big] + d_i\, p_{ci}\, q_i + \mathrm{I}_v b_i \mathrm{T}_c d_i +$$
$$q_i\, d_{ci}\, c_{dci}\Big[\Big(\frac{d_i}{p_i} + (n-1)\Big) - \frac{nd_i}{2p_i}\Big] + z^1{}_i \times costSU_i + z^2{}_i \times \tau_i \times costS_i +$$
$$c_{fixed} + (c_{onboarding} \times \mathrm{U} + c_{mc} + c_{mo}) \times q_i\Big] + \mathrm{G_u} \times g_p \times 365 + s \times \mathrm{C_s}$$

$$\textbf{Min Obj}_\mathbf{2} = \mathrm{Min}\ \Big(\mathrm{Max} \sum_{i=1}^{M}[\tau_i[d_i - p_i]]\Big) \tag{6.9}$$

5.6 Results

In this section, the numerical examples examined in this study validate the proposed multi-function BT-enabled PSC model. The model is designed to minimize the total costs of BT-enabled PSC, or objective 1, and the unmet demand in the pharmaceutical company, objective 2. This section presents the obtained results, the performance metrics of eight algorithms on the generated datasets in objectives 1 and 2, and the weights of the cost features of objective 1. The numerical dataset examined here validates the multi-function model and demonstrates the performance of the proposed methodology. We used HS and PSO (EC algorithms) to improve the results and to optimize the hyperparameters of the KNN, DT, SVM, and NB SL algorithms. This combination provides eight algorithms to reduce prediction errors: HS-KNN, HS-DT, HS-SVM, HS-NB, PSO-KNN, PSO-DT, PSO-SVM, and PSO-NB. To evaluate the efficiency of the proposed algorithms, four performance metrics were used: the MSE, RMSE, MAE, and R^2. In objective 1, we also used the FW approach to estimate the influencing features for the generated dataset. There was no need to use FW for objective 2 because it only has one component. FW plays an important role in analysis without changing the initial data content. After data generation, we designed the model, executed the proposed methodology, and used MATLAB software to validate the multi-function BT-enabled PSC model. We assessed the ‘‘average’’ of the four performance metrics in objectives 1 and 2 and the ‘‘average’’ of the weight of the cost features in objective 1 to improve the reliability of all methods in eighty runs (4×10 + 4×10). We calculated the averages to analyse the results because the runs have various outcomes, and the average can help us achieve stability and reliability in behavioral data. Each run was performed for at most 1000 iterations. Therefore, we compared the average of every 10 runs instead of comparing the predictions of the multi-function BT-enabled PSC model in each run. Lastly, we used the TRS method to determine the most reliable predictive algorithms for the multi-function BT-enabled PSC model. All these results are presented in Tables 5.2 to 5.9.

5.6.1 HS combined with four SLs

The multi-function BT-enabled PSC model has two objectives measured by four performance metrics and incorporates the weights of five cost features. Through MATLAB, HS combined with four SL algorithms (HS-KNN, HS-DT, HS-SVM, and HS-NB) was run 40 times) each algorithm was executed 10 times) in 1000 iterations.

Table 5.2 presents the four performance metrics for four algorithms in objectives 1 and 2, the five weights of the cost features in objective 1, the average values for each performance metric, and the average values for each cost feature in 40 runs. Tables 5.3 and 5.4 are derived from Table 5.2.

Table 5.2 Objectives 1 and 2 evaluated by feature weighting and performance metrics for HS combined with four SL algorithms in 10 runs for each

		Objective 1									Objective 2			
		Feature weighting					Performance metrics				Performance metrics			
	Run	W_(Raw_Materials)	W_(Finished_Products)	W_(Shortage_Surplus)	W_(BT_Installation)	W_(BT_Transaction)	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
HS_KNN	1	0.31	1	0.83	1	1	447578659.37	21156.05	15225.04	0.99	24710.22	157.19	122.09	0.006
	2	0.321	0.978	0.911	0.874	0.568	12216876173.60	110529.97	83903.98	0.991	24508.02	156.55	120.55	0.003
	3	0.493	0	0.797	0	0.253	2584577237772.87	1607662.04	1428615.72	0.033	23231.68	152.41	117.72	0.006
	4	0.855	0	0.239	0	0.067	2559565339629.15	1599864.16	1316755.65	0.082	8411.63	91.71	59.56	0.132
	5	0.513	0.332	0.087	0.358	0.892	24544114160.46	156665.61	112810.15	0.983	4820.3	69.42	39.76	0.474
	6	0.068	0.974	1	1	0.938	592467081.45	24340.64	16459.35	0.999	3021.13	54.96	34.6	0.554
	7	0.0989	0.994	1	1	1	558779878.15	23638.52	16243.51	0.999	13822.96	117.57	88.13	0.195
	8	**1**	0.934	0.695	0.848	**1**	517518033.07	22749.0227	16312.7089	0.999	23441.02	153.10	117.82	0.004
	9	**1**	0.940	0.685	0.915	**1**	18935746767.50	137607.21	101185.10	0.986	13012.55	114.07	85.42	0.205
	10	0	0.548	0.479	0.584	0.672	414695195.67	20364.0663	15134.7278	0.999	7351.13	85.73	59	0.0302
Average		0.46	0.67	0.67	0.65	0.73	520237035335.13	283604.18	227843.03	0.86	14633.06	115.27	84.47	0.16

		Objective 1									Objective 2			
		Feature weighting					Performance metrics				Performance metrics			
	Run	W_(Raw_Materials)	W_(Finished_Products)	W_(Shortage_Surplus)	W_(BT_Installation)	W_(BT_Transaction)	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
HS_DT	1	0.194	0.257	0.838	0.271	0.248	487814443.56	22086.52	16297.92	0.999	22777.09	150.92	114.31	0.010
	2	0	0.898	0	1	0	2499618098.92	49996.18	35512.63	0.998	19404.58	139.30	106.21	0.004
	3	0	0.866	0	0.691	0	2008075275.94	44811.55	32162.61	0.998	19118.08	138.26	105.64	0.004
	4	0	1	0	0.572	0	2222526522.60	47143.67	34027.37	.998	18782.17	137.04	106.68	0.010
	5	0.878	0.299	0.714	1	0	2124057520.85	46087.49	33848.02	0.998	10892.02	104.36	77.62	0.313
	6	0	0.154	0	1	0	2407898995.12	49070.34	35782.17	0.998	19876.76	140.98	106.38	0.002
	7	0	0.406	0	0.896	0	2268558510.16	47629.38	34306.15	0.998	19171.03	138.45	105.52	0.006
	8	0.356	0.012	0.957	1	0	2121641968.13	46061.28	34345.41	0.998	9716.27	98.57	73.83	0.341
	9	1	0.108	1	0.500	0	2425609238.87	49250.47	35790.56	0.998	10676.44	103.32	77.43	0.304
	10	0.166	0.044	0.392	0.784	0	2760284205.16	52538.40	36269.32	0.998	10342.51	101.69	74.97	0.324
Average		0.26	0.40	0.39	0.77	0.02	2132608477.93	45467.53	32834.22	1.00	16075.70	125.29	94.86	0.13

		Objective 1									Objective 2			
		Feature weighting					Performance metrics				Performance metrics			
	Run	W_(Raw_Materials)	W_(Finished_Products)	W_(Shortage_Surplus)	W_(BT_Installation)	W_(BT_Transaction)	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
HS_SVM	1	0.231	0.981	0.642	0.076	0.744	8216337569.52	90644.01	78810.96	0.999	1343.01	36.64	27.23	0.713
	2	0.679	0	0.020	0.003	0.153	6757738172.25	82205.46	70810.95	0.997	2076.14	45.56	33.16	0.588
	3	0.126	0.504	0.799	0.198	0.0431	4785591120.97	69177.96	63238.64	0.999	2076.14	45.56	33.16	0.588
	4	0.001	0.599	0.818	0.208	0.115	5539994619.11	74431.14	63613.45	0.999	1764.26	42.00	33.29	0.727
	5	0.993	0.287	1	0.243	0.174	6618206320.17	81352.35	64946.07	0.995	2887.11	53.73	45.25	0.579
	6	0.689	0.725	0.533	0.104	0.126	6964170744.91	83451.60	72470.90	0.999	1764.26	42.00	33.29	0.727
	7	0.064	0.172	1	0.027	0.68	6600773868.49	81245.14	68273.45	0.999	8108.04	90.04	73.82	0.346
	8	0.750	0.016	0.035	0.007	0.534	6002777653.01	77477.59	68913.88	0.999	2155.18	46.42	37.33	0.814
	9	0.460	0.031	0.787	0.031	0.432	4877903687.16	69841.99	57241.79	0.996	5128.06	71.61	53.09	0.535
	10	0.679	0	0.020	0.003	0.153	6757738172.25	82205.46	70810.95	0.997	2934.60	54.17	36.95	0.773
Average		0.47	0.33	0.57	0.09	0.32	6312123192.78	79203.27	67913.10	1.00	3023.68	52.77	40.66	0.64

		Objective 1									Objective 2			
		Feature weighting					Performance metrics				Performance metrics			
	Run	W_(Raw_Materials)	W_(Finished_Products)	W_(Shortage_Surplus)	W_(BT_Installation)	W_(BT_Transaction)	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
HS_NB	1	0.968	0.001	0.987	0	0.047	757.59	27.52	20.52	1	2618.22	51.16	34.57	0.809
	2	0.576	0.008	0.966	0.001	0.403	115.42	10.74	9.53	1	1713.43	41.39	34.15	0.634
	3	1	0.002	0.982	0	0.146	193.52	13.91	11.66	1	2256.35	47.50	36.31	0.551
	4	0.986	0.001	0.905	0	0.169	197.89	14.06	11.57	1	2141.78	46.27	31.92	0.655
	5	0.761	0.002	0.650	0	0.039	164.36	12.82	10.43	1	1959.94	44.27	33.18	0.649
	6	0.871	0.003	0.924	0	0.955	162.34	12.74	10.87	1	2918.73	54.02	44.42	0.584
	7	0.926	0.006	0.920	0.001	0.728	185.71	13.62	11.60	1	4111.33	64.11	47.80	0.402
	8	0.950	0.003	0.527	0	0.080	217.95	14.76	12.86	1	2566.81	50.66	41.41	0.447
	9	0.990	0.002	0.355	0	0.034	130.74	11.43	8.04	1	2451.95	49.51	37.18	0.704
	10	0.576	0.008	0.966	0.001	0.403	115.42	10.74	9.53	1	1323.14	36.37	29.23	0.694
Average		0.86	0.00	0.82	0.00	0.30	224.09	14.23	11.66	1.00	2406.17	48.53	37.02	0.61

Table 5.3 summarizes and compares the average of four performance evaluation metrics for each method in objectives 1 and 2. In Table 5.3, HS-NB demonstrates robust behaviour in both objectives, with a minimum average of MSE, RMSE, and MAE and the best average R^2 of 1 for objective 1 among the four methods. Objective 2 is realized well in both HS-SVM and HS-NB, with R^2 values of 0.64 and 0.61, respectively. The weakest results in all performance metrics are for HS-KNN in objective 1 and HS-DT in objective 2. Table 5.3 shows that the HS-NB algorithm performs better at realizing objectives 1 and 2 for the multi-function BT-enabled PSC model than the other proposed algorithms.

Table 5.3 Objectives 1 and 2 evaluated by performance metrics for HS combined with four SL algorithms

	Objective 1				Objective 2			
	Performance metrics				Performance metrics			
Methods	**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**	**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**
HS_KNN	520237035335.13	283604.18	227843.03	0.86	14633.06	115.27	84.47	0.16
HS_DT	2132608477.93	45467.53	32834.22	1.00	16075.70	125.29	94.86	0.13
HS_SVM	6312123192.78	79203.27	67913.10	1.00	3023.68	52.77	40.66	**0.64**
HS_NB	**224.09**	**14.23**	**11.66**	**1.00**	**2406.17**	**48.53**	**37.02**	0.61

In Table 5.4, we focus on the average of the weights of each cost feature through the FW approach for the HS-KNN, HS-DT, HS-SVM, and HS-NB algorithms in objective 1. Objective 2 has just one element, and the FW approach does not work. Among these four methods, HS-NB provides the highest average weight for the Raw Materials cost feature (0.86) and the lowest average weight for Finished Products and BT Installation (0.00). The second-highest average weight is allocated to the BT Installation cost feature through the HS-DT algorithm (0.77), followed by the BT Transaction cost feature through the HS-KNN algorithm (0.73). The BT Transaction cost feature has the second-lowest average weight with HS-DT (0.02). In addition, some features like the BT Transaction cost and BT Installation fluctuate because the algorithms have different behavior.

Table 5.4 FW criteria for HS combined with four SL algorithms in objective 1

	Feature weighting	
Methods	**Max_Ave_Weighting**	**Min_ Ave_Weighting**
HS_KNN	W_(BT_Transaction) = 0.73	W_(Raw_Materials) = 0.46
HS_DT	W_(BT_Installation) = 0.77	W_(BT_Transaction) = 0.02
HS_SVM	W_(Shortage_Surplus) = 0.57	W_(BT_Installation) = 0.09
HS_NB	W_(Raw_Materials) = 0.86	W_(Finished_Products) & W_(BT_Installation) = 0.00

5.6.2 PSO combined with four SL algorithms

In the next step, a PSO combined with four SL algorithms (PSO -KNN, PSO -DT, PSO -SVM, and PSO -NB) was executed 40 times (each algorithm ran 10 times) (see Table 5.5).

NB results to be more reliable than the results obtained used the four performance metrics for the four algorithms in objectives 1 and 2, and the weights of the five cost features in objective 1 to evaluate the multi-function BT-enabled PSC model in these 40 runs (10 runs for each algorithm). In addition, Table 5.5 shows the average values of the performance metrics and the average values of the weights of the cost features. Tables 5.6 and 5.7 are derived from the data presented in Table 5.5.

Table 5.5 Objectives 1 and 2 evaluated by feature weighting and performance metrics for PSO combined with four SL algorithms in 10 runs for each

		Objective 1									Objective 2			
		Feature weighting					Performance metrics				Performance metrics			
	Run	W_(Raw_Materials)	W_(Finished_Products)	W_(Shortage_Surplus)	W_(BT_Installation)	W_(BT_Transaction)	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
PSO_KNN	1	0	0.825	0	1	1	549741219.89	23446.5609	16634.91	0.999	23806.25	154.29	117.60	0.011
	2	0.533	0.744	0.322	0.817	0.884	491607040.75	22172.21	15688.57	0.999	22455.19	149.85	114.24	0.009
	3	0.767	0.007	0.102	0.018	0.786	61527504303.02	248047.38	185904.62	0.959	19758.51	140.56	106.62	0.042
	4	0.676	0.049	0.794	0.045	0	525110440.86	22915.28	17221.68	0.999	23954.87	154.77	118.47	0.009
	5	0.516	0.560	0.111	0.907	0.281	550748692.11	23468.03	17092.62	0.999	24544.10	156.66	122.29	0.079
	6	1	1	0.617	1	0.627	454654767.36	21322.63	15340.97	0.999	24004.42	154.93	118.78	0.006
	7	1	0.186	0	0.080	0.942	10745095521.78	103658.55	79592.31	0.987	12554.8	112.04	79.13	0.103
	8	0	0.554	1	0.702	0.470	431096960.34	20762.87	15099.64	0.999	6669	81.66	59.33	0.226
	9	1	1	0.543	1	0.616	454972132.96	21330.07	15345.73	0.999	24561.92	156.72	122.34	0.007
	10	0.886	0.047	1	0.152	0	742284495.02	27244.89	20085.31	0.999	20796.63	144.21	109.21	0.020
Average		0.64	0.50	0.45	0.57	0.56	7647281557.41	53436.85	39800.64	0.99	20310.57	140.57	106.80	0.04

	Run	Feature weighting					Performance metrics				Performance metrics			
		W_(Raw_Materials)	W_(Finished_Products)	W_(Shortage_Surplus)	W_(BT_Installation)	W_(BT_Transaction)	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
PSO_DT	1	0.074	0.453	0.252	0.142	0	2124057520.85	46087.49	33848.02	0.998	10892.02	104.36	77.62	0.313
	2	0.333	0.322	0.811	0.069	0.406	66808063437.00	258472.55	196228.98	0.952	10643.44	103.16	77.68	0.337
		Run	**Feature weighting**	**Performance metrics**	**Performance metrics**	**Run**	**Feature weighting**	**Performance metrics**	**Performance metrics**	**Run**	**Feature weighting**	**Performance metrics**	**Performance metrics**	**Run**
	3	0.232	0.304	0.073	0.088	0	2222537815.15	47143.79	34199.82	0.998	9340.04	96.64	72.67	0.351
	4	0.917	0.778	0.670	0.210	0	68611472474.87	261937.91	202530.73	0.953	2361.72	48.59	29.84	0.694
	5	0.225	1	0.277	1	0	2464171102.89	49640.41	35610.29	0.998	3199.95	56.56	34.61	0.409
	6	0	0.145	0.627	0.285	0	50446994254.48	224604.08	166066.93	0.957	2678.00	51.74	35.21	0.654
	7	0	1	0.169	0.315	0	68200434557.48	261152.12	201638.36	0.925	2920.60	54.04	40.28	0.552
	8	0.602	0.248	0.020	0.947	0.061	65259550220.65	255459.48	194744.85	0.946	3266.07	57.14	41.86	0.537
	9	0.789	0.134	0.134	0.751	0	2331651357.13	48287.17	35532.25	0.998	10094.09	100.46	74.92	0.313
	10	0.428	0.428	0.208	0.011	0.948	2353131810.38	48509.09	35571.26	0.998	10475.52	102.35	76.50	0.325
Average		0.36	0.48	0.32	0.38	0.14	33082206455.09	150129.41	113597.15	0.97	6587.15	77.50	56.12	0.45
		Objective 1									**Objective 2**			
	Run	Feature weighting					Performance metrics				Performance metrics			
		W_(Raw_Materials)	W_(Finished_Products)	W_(Shortage_Surplus)	W_(BT_Installation)	W_(BT_Transaction)	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
PSO_SVM	1	0.834	0.994	0.999	0.340	0.535	6481651810.93	80508.70	72188.64	0.999	293747.64	541.98	437.60	0.136
	2	1	0.527	0.283	0.184	0.966	5547584998.00	74482.11	69169.55	0.999	3507.26	59.22	48.12	0.745
	3	0.935	1	0.481	0.347	1	3605444643.76	60045.35	55331.24	0.999	3373.98	58.08	48.39	0.572
	4	0.916	1	0.680	0.351	1	4514645983.04	67191.11	61008.17	0.999	3715.10	60.95	51.35	0.354
	5	0.783	0.832	0.080	0.181	0.862	5844285150.30	76447.92	68615.39	0.999	1644.43	40.55	31.86	0.699
	6	0.530	0.340	1	0.134	0	5986270734.82	77370.99	66270.24	0.999	3927.42	62.66	52.17	0.651
	7	0.490	0.305	0.999	0.106	1	4348863443.90	65945.91	57060.60	0.999	2011.16	44.84	34.05	0.650
	8	0.679	0.107	0.392	0.037	0.313	4509807347.28	67155.09	58613.10	0.999	3655.66	60.46	47.21	0.504
	9	1	0.281	0.282	0.108	0.617	6022445081.15	77604.41	66322.34	0.999	1170745.01	1082.00	919.48	0.0669
	10	0.895	0.624	0.413	0.245	0.753	4374513944.83	66140.10	57651.87	0.999	1149307.12	1072.05	753.85	0.174
Average		0.81	0.60	0.56	0.20	0.70	5123551313.80	71289.17	63223.11	1.00	263563.48	308.28	242.41	0.46

		Objective 1									Objective 2			
		Feature weighting					Performance metrics				Performance metrics			
	Run	W_(Raw_Materials)	W_(Finished_Products)	W_(Shortage_Surplus)	W_(BT_Installation)	W_(BT_Transaction)	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
PSO_NB	1	0.019	0.091	0.883	0.244	0.335	27165.54	164.81	139.53	1	4374.03	66.13	54.98	0.438
	2	1	0.004	1	0.001	1	241.74	15.54	13.24	1	2335.18	48.32	40.55	0.60
	3	1	0.029	0.995	0	0.999	158.73	12.59	10.48	1	1622.74	40.28	33.03	0.679
	4	0.336	0.472	1	0.377	0.582	385352.01	620.76	517.70	1	4244.30	65.14	55.06	0.255
	Feature weighting	Performance metrics	Performance metrics	Run	Feature weighting	Performance metrics	Performance metrics	Run	Feature weighting	Performance metrics	Performance metrics	Run	Feature weighting	Performance metrics
	5	1	0.529	0.990	0.965	1	653210.23	808.21	583.32	1	9377.69	96.83	69.14	0.243
	6	1	0.005	1	0.001	0.085	80.76	8.98	7.00	1	1874.46	43.29	36.17	0.560
	7	0.992	0.464	0.989	0.026	0.650	754.26	27.46	22.41	1	3180.67	56.39	52.21	0.116
	8	0.558	0	0.942	0	1	147.15	12.13	9.87	1	2392.15	48.90	35.94	0.554
	9	0.992	0.001	0.984	0	0.157	277.38	16.65	13.96	1	1929.62	43.92	34.37	0.638
	10	0.750	0.015	0.999	0	0.656	264.05	16.24	13.20	1	5488.47	74.08	59.06	0.310
Average		0.76	0.16	0.98	0.16	0.65	106765.19	170.34	133.07	1.00	3681.93	58.33	47.05	0.44

Table 5.6, derived from Table 5.5, presents the average values of four performance metrics considered in evaluating the proposed PSO combined with four SL algorithms in objectives 1 and 2. In this table, PSO-NB performs better than the others, with an average R^2 of 1 and a minimum of Ave-MSE = 106765.19, Ave-RMSE = 170.34, and Ave-MAE = 133.07 in objective 1. On the other hand, PSO-DT has the weakest result in all performance metrics in objective 1. In objective 2, PSO-NB also behaves well with all performance metrics among the four methods. Therefore, we consider the PSO-NB results more reliable than the results obtained by other proposed methods in both objectives.

Table 5.6 Objectives 1 and 2 evaluated by performance metrics for PSO combined with four SL algorithms

	Objective 1				Objective 2			
	Performance metrics				Performance metrics			
Methods	**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**	**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**
PSO_KNN	7647281557.41	53436.85	39800.64	0.99	20310.57	140.57	106.80	0.04
PSO_DT	33082206455.09	150129.41	113597.15	0.97	6587.15	77.50	56.12	0.45
PSO_SVM	5123551313.80	71289.17	63223.11	**1.00**	263563.48	308.28	242.41	0.46
PSO_NB	**106765.19**	**170.34**	**133.07**	**1.00**	**3681.93**	**58.33**	**47.05**	**0.44**

Table 5.7 illustrates the average weights of five cost features through the FW approach in the PSO-KNN, PSO-DT, PSO-SVM, and PSO-NB algorithms in objective 1. Objective 2 has only one element, which is why the FW approach does not work. PSO-NB provides the minimum and maximum average weights among all cost features. The maximum average weight of 0.98 is allocated to the Shortage Surplus cost feature, and the minimum average weight of 0.16 is obtained for the Finished Products and BT Installation cost features, both for the PSO-NB algorithm. The second maximum average weight for the Finished Products cost feature (0.48) was obtained with the PSO-DT algorithm. A variation in the average weight of some features in this table is observed, such as Shortage Surplus with 0.98 and 0.45 by PSO-NB and PSO-KNN, respectively. The reason for this variation is explained by the algorithms' varying behavior.

Table 5.7 FW criteria for PSO combined with four SL algorithms in objective 1

	Feature weighting	
Methods	**Max_ Ave_Weighting**	**Min_ Ave_Weighting**
PSO_KNN	W_(Raw_Materials) = 0.64	W_(Shortage_Surplus) = 0.45
PSO_DT	W_(Finished_Products) = 0.48	W_(BT_Transaction) = 0.14
PSO_SVM	W_(Raw_Materials) = 0.81	W_(BT_Installation) = 0.20
PSO_NB	W_(Shortage_Surplus) = 0.98	W_(Finished_Products) & W_(BT_Installation) = 0.16

5.6.3 Determining reliable algorithms for multi-function BT-enabled PSC

Table 5.8 presents the TRS of eight algorithms based on the Ave-MSE, Ave-RMSE, Ave-MAE, and Ave-R^2 values obtained in objectives 1 and 2. To calculate the TRS, we assigned the highest scores to the lowest Ave-MSE, Ave-RMSE, and Ave-MAE and the highest score to the highest Ave-R^2 (and vice versa). Overall, the HS-NB algorithm outperformed the other algorithms with a TRS of 63, followed by PSO-NB with a TRS of 51, HS-SVM with a TRS of 47, and HS-DT with a TRS of 37. HS-KNN and PSO-KNN achieved the worst TRS scores of 23 (rank 8th) and 27 (rank 7th), respectively.

Table 5.8 Ranking of eight selected algorithms based on their TRS scores through performance metrics in objectives 1 and 2

		Objective 1				Objective 2					
		Performance metrics				Performance metrics				TRS	Rank
Method		**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**	**Ave_MSE**	**Ave_RMSE**	**Ave_MAE**	**Ave_R^2**		
HS_KNN		520237035335.13	283604.18	227843.03	0.86	14633.06	115.27	84.47	0.16		
HS_DT		2132608477.93	45467.53	32834.22	1.00	16075.70	125.29	94.86	0.13		
HS_SVM		6312123192.78	79203.27	67913.10	1.00	3023.68	52.77	40.66	0.64		
HS_NB		224.09	14.23	11.66	1.00	2406.17	48.53	37.02	0.61		
PSO_KNN		7647281557.41	53436.85	39800.64	0.99	20310.57	140.57	106.80	0.04		
PSO_DT		33082206455.09	150129.41	113597.15	0.97	6587.15	77.50	56.12	0.45		
PSO_SVM		5123551313.80	71289.17	63223.11	1.00	263563.48	308.28	242.41	0.46		
PSO_NB		106765.19	170.34	133.07	1.00	3681.93	58.33	47.05	0.44		
Total Ranking Score	**HS_KNN**	1	1	1	5	4	4	4	3	23.00	8
	HS_DT	**6**	**6**	**6**	**8**	**3**	**3**	**3**	**2**	37.00	**4**
	HS_SVM	4	3	3	8	7	7	7	8	47.00	3
	HS_NB	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**7**	63.00	**1**
	PSO_KNN	3	5	5	7	2	2	2	1	27.00	7
	PSO_DT	**2**	**2**	**2**	**6**	**5**	**5**	**5**	**5**	32.00	**5**
	PSO_SVM	5	4	4	8	1	1	1	6	30.00	6
	PSO_NB	**7**	**7**	**7**	**8**	**6**	**6**	**6**	**4**	51.00	**2**

Table 5.9 presents the ranking of the average weights of the five cost features in objective 1: Raw Materials, Finished Products, Shortage Surplus, BT Installation, and BT Transaction for the HS-KNN, HS-DT, HS-SVM, HS-NB, PSO-KNN, PSO-DT, PSO-SVM, and PSO-NB algorithms. This table assigns an appropriate average weight and a TRS to each cost feature to show their importance. The average weight with a higher TRS receives a higher priority in the TRS process (and vice versa). Overall, the Raw Materials cost in objective 1 obtains the best TRS,30, for the average weight, followed by the Shortage Surplus cost with a TRS of 26, and the Finished Products cost with a TRS of 25. The minimum TRS for the average weight is allocated to BT Installation and BT Transaction cost features, which have the same rank of 4th with TRS = 22.

Table 5.9 FW Ranking based on TRS scores for five selected algorithms in objective 1

Objective 1											
Methods										TRS	Rank
Ave_FW		**HS_KNN**	**HS_DT**	**HS_SVM**	**HS_NB**	**PSO_KNN**	**PSO_DT**	**PSO_SVM**	**PSO_NB**		
W_(Raw_Materials)		0.46	0.26	0.47	0.86	0.64	0.36	0.81	0.76		
W_(Finished_Products)		0.67	0.40	0.33	0.00	0.50	0.48	0.60	0.16		
W_(Shortage_Surplus)		0.67	0.39	0.57	0.82	0.45	0.32	0.56	0.98		
W_(BT_Installation)		0.65	0.77	0.09	0.00	0.57	0.38	0.20	0.16		
W_(BT_Transaction)		0.73	0.02	0.32	0.30	0.56	0.14	0.70	0.65		
Total Ranking Score	**W_(Raw_Materials)**	2	**2**	**4**	**5**	**5**	**3**	**5**	**4**	30	**1**
	W_(Finished_Products)	4	4	3	2	2	5	3	2	25	3
	W_(Shortage_Surplus)	4	3	5	4	1	2	2	5	26	2
	W_(BT_Installation)	**3**	**5**	**1**	**2**	**4**	**4**	**1**	**2**	**22**	**4**
	W_(BT_Transaction)	**5**	**1**	**2**	**3**	**3**	**1**	**4**	**3**	**22**	**4**

5.7 Discussion

This section discusses the results of the proposed eight algorithms that minimise the prediction errors of the multi-function BT-enabled PSC model. In this section, respond to the three research questions mentioned in the introduction and discuss the results. As mentioned before, the multi-function BT-enabled PSC model has six components: Raw Materials cost, Finished Products cost, Shortage-Surplus cost, Blockchain Installation cost, Blockchain Transaction cost, and Unsatisfied Demand of product families. Our model has two objectives. The first includes Raw Materials cost (Ordering cost, Holding cost for perfect raw materials, Holding cost for imperfect raw materials, Labor cost for order handling and receipt, and Transportation cost), Finished Products cost (Set-up cost, Holding cost, Production cost, Expected opportunity interest, and Expiry cost), Shortage-Surplus cost (Shortage cost and Surplus cost), Blockchain Installation cost (Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost, and Blockchain Transaction cost (Gas cost and Storage cost). The second objective covers the Unsatisfied Demand. This explanation provides the answer to our first research question. Regarding the second research question, we selected some algorithms (among the eight examined here) that showed better performance in minimising the prediction errors of the multi-function BT-enabled PSC model. Figure 5.3 is derived from the data presented in Table 5.8 and shows the TRS for all eight studied algorithms (HS-KNN, HS-DT, HS-SVM, HS-NB, PSO-KNN, PSO-DT, PSO-SVM, and PSO-NB). Four performance metrics (MSE, RMSE, MAE, and R^2) evaluate the efficiency of the eight algorithms. The overall results of this study show that both HS-NB (first position) and PSO-NB (second position) algorithms outperformed the other compared algorithms in minimising the model's prediction errors. This means that NB, combined with either HS of PSO, is considered the most effective in performing the regression. EC algorithms (HS and PSO) also play a significant role in optimizing the hyperparameters of the eight SL algorithms. Moreover, according to the performance metrics' values and the TRS scores, the SVM, DT, and KNN algorithms, combined with HS and PSO, cannot adequately predict the costs of the multi-function BT-enabled PSC model. Thus, we have determined that the NB algorithm, combined with HS and PSO, is the most reliable predictive algorithm for our multi-function model using TRS and four performance metrics, responding to the second question.

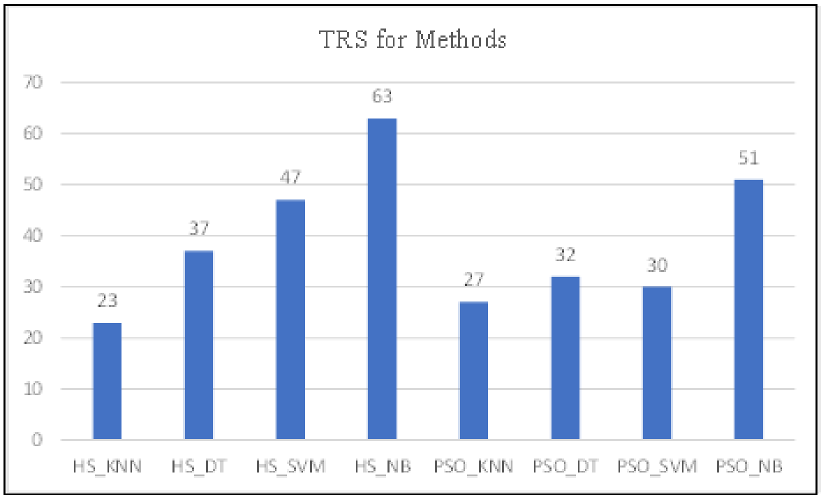

Figure 5.3 TRS of all algorithms in objectives 1 and 2

The third research question is to determine the significant components of the model. The only component of objective 2 in the model is the Unsatisfied Demand of product families. On the other hand, objective 1 includes five cost components, and the FW approach measures the importance of the cost features and assigns an appropriate weight to each feature. Figure 5.4 is derived from Table 5.9 and shows the TRS for the weights of all the cost components (features) of the multi-function BT-enabled PSC model in objective 1. These weights estimate the degree of relevance that each feature has for extracting the cost prediction. The results show the Raw Materials cost strongly influences the cost model. The remaining four cost features in objective 1 have relatively the same weight (Shortage-Surplus cost, Finished Products cost, Blockchain Installation cost, and Blockchain Transaction cost).

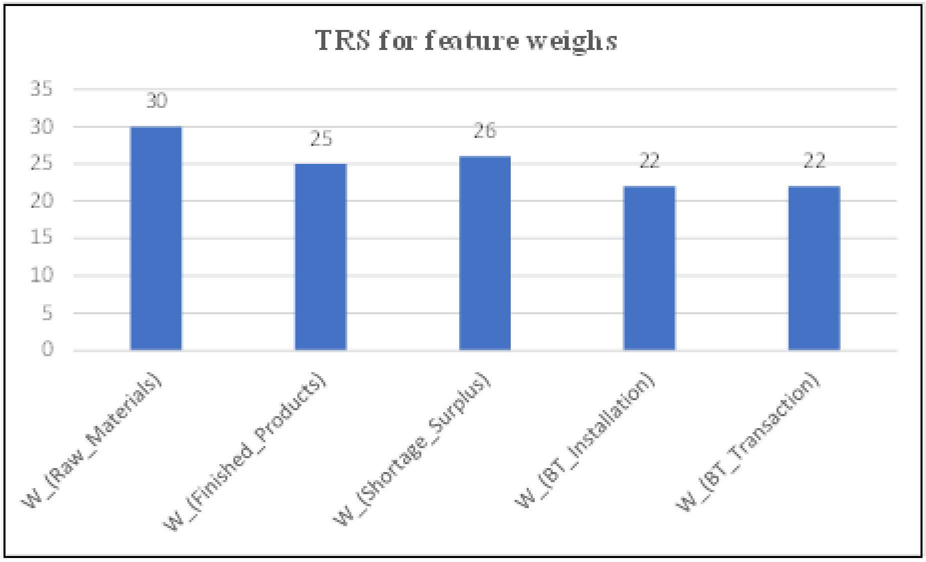

Figure 5.4 TRS for feature weighs in objective 1

Compared to previous work that modeled the costs of PSC, this study developed a new mathematical model called the multi-function BT-enabled PSC model that includes BT Transaction cost and BT Installation cost. Researchers in other fields can also use BT cost formulation (BT Transaction cost and BT Installation cost) in their mathematical models to estimate the SC costs integrated with BT. Another significant contribution of this study is to provide a BT-enabled PSC system with uncertain demand, which occurs when the demand exceeds the available stock. The study's practical significance is that it provides the most reliable predictive algorithms for the multi-function BT-enabled PSC model, the cost components of the model, the degree of relevance of each model component, and the components of BT in the PSC model.

Similar to other studies, there are some limitations in this research. As the use of BT in PSC is a new area of research, our first limitation is the inaccessibility of real data. Therefore, we generated raw data to validate the proposed multi-function BT-enabled PSC model. Using generated data rather than real data may influence the outcomes and conclusions of the research. The second limitation relates to the model's components, as this study may not cover some of the cost components of a real case.

Finally, future research could extend the BT-enabled PSC model to a multi-function BT-enabled Pharmaceutical Cold Supply Chain model. Pharmaceutical Cold Supply Chain utilizes advanced technology to control the temperature inside cargo containers and storage units. Another proposal for upcoming research involves using other EC algorithms to enhance the performance of the SL algorithms or to test different SL algorithms to predict costs. Finally, future research may determine the cost components of private BT and thereby formulate private BT instead of the public BT used in the current study.

5.8 Conclusion

The BT-enabled PSC provides traceability and transparency for the movement of drugs and stakeholders in the supply chain and can affect medication quality and final patient outcomes. This paper presents a mathematical multi-function model for a BT-based PSC system to estimate the costs of the model.

This study is important because it provides a PSC system with BT costs (BT Transaction cost and BT Installation cost) that can improve the safety, performance, and transparency of medical information sharing in a healthcare system. The research also provides six components of the multi-function model: Raw Materials cost (Ordering cost, Holding cost for perfect raw materials, Holding cost for imperfect raw materials, Labor cost for order handling and receipt, and Transportation cost), Finished Products cost (Set-up cost, Holding cost, Production cost, Expected opportunity interest, and Expiry cost), Shortage-Surplus cost (Shortage cost and Surplus cost), Blockchain Installation cost (Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost), Blockchain Transaction cost (Gas cost and Storage cost), and Unsatisfied Demand. The combination of two EC algorithms and four SL algorithms provides eight algorithms to reduce prediction errors, optimize the hyperparameters of the SL algorithms, and improve the multi-function model.

The findings reveal that the HS-NB and PSO-NB algorithms outperform the other six algorithms in estimating the costs of the multi-function model with lower errors. This means that the NB algorithm can estimate the costs of the BT-enabled PSC system better than the KNN, DT, and SVM algorithms. The other six algorithms perform similarly for this comparison, except HS-SVM, which acts better, showing that these algorithms are not an appropriate predictive approach for the current cost model.

The results also show that the Raw Materials cost strongly influences the cost model, more so than the remaining four cost features: Shortage-Surplus cost, Finished Products cost, Blockchain Installation cost, and Blockchain Transaction cost. Therefore, the statistical outcomes on the generated dataset show that the NB algorithm can obtain satisfactory results and assign appropriate feature weights.

These findings can help healthcare service managers make the right decisions, control financial resources, stay within the budget, analyze information, and identify unnecessary costs, particularly if they decide to use BT in the system. Another contribution of this research is to provide a PSC system with BT, which contains demand uncertainty. Managers can use the selected SL algorithms to estimate costs with the minimum prediction errors and then decide whether the new system benefits their organisation. Using this approach will also allow managers to know how to determine and measure each cost component of the multi-function BT-enabled PSC model to make the best decision before installing the new system.

Data Availability:

The data supporting this study's findings are openly available at https://data.mendeley.com/datasets/sfc7hst95m.

This sentence was stated in the manuscript to show data availability.

“We uploaded 5000 series of the generated raw data for all six components of the multi-function BT-enabled PSC model and the total cost to https://data.mendeley.com/datasets/sfc7hst95m.”

CONCLUSION

The BT-based PSC enables traceability and transparency of the drugs' movement and stakeholders in the Supply Chain and can affect medication quality and final patient outcomes. The important contribution of this thesis is to provide a PSC and SCS system with BT cost (BT Transaction cost and BT Installation cost) that can improve the safety, performance, and transparency of medical information sharing in a healthcare system.

According to Yang (2014), there are many optimization algorithms in the literature, and no single algorithm is suitable for all problems. Selected Evolutionary Supervised Learning algorithms in this research can help managers estimate costs with the minimum prediction errors and correctly decide whether the new system benefits their organization. As the cost factor is crucial to managers, this research also determines and measures the importance of each cost component of the BT-enabled SCS, BT-based PSC, and BT-enabled PSC under the Uncertain Demand models. The thesis also presents a mathematical model for the BT-enabled SCS, BT-based PSC, and BT-enabled PSC under the Uncertain Demand models to estimate the costs of the model. These mathematical formulations help other studies that are limited in finding real data generate raw data in a healthcare field for their research. The determination of the cost components of the model is also useful for companies and organizations that tend to use Public BT as the main database in their SC system to evaluate the system's total costs.

Chapter 3, which presents the first article, introduces the cost components of BT-enabled SCS, including the Production costs (in the pharmaceutical company), Procurement costs, Inventory costs (in both hospital and pharmaceutical company), Delivery costs (to both hospital and pharmaceutical company), Blockchain Transaction cost (gasUsed and gasPrice), and Blockchain Installation cost (Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost). Another advantage of the first article is to model the mathematical formulation for the BT-enabled SCS based on the mentioned components. The simulated raw data for the main BT-enabled SCS model is another output for this research, which comes from the designed mathematical formulation in healthcare facilities (the OR model for PSC and Inventory Management for a single pharmaceutical company and a single hospital). This paper found that CS and ACO algorithms fulfill the BT-enabled SCS cost model with a higher TRS (including MES, RMSE, and ROC) than the GA. Compared with other metaheuristic algorithms, CS seems to be more generic and robust for some optimization problems (Gandomi et al., 2013). The results also show that GA, based on TRS, stands in the second step for this case. While the ROC of ACO is higher than others, CS comes in the second level, followed by GA.

Interestingly, all three applied algorithms produce reasonable global minimum outputs for the BT-enabled SCS cost model. This means that our cost model can fulfill all three mentioned algorithms as the accuracy of the three algorithms to produce the reasonable global minimum outputs for the BT-enabled SCS cost model seems acceptable. According to reaching the sensible global minimum results for the BT-enabled SCS cost model by the three algorithms, we also find out that the designed mathematical formulation in healthcare facilities can give us the reliable simulated dataset as it ends up with the high ROCs and low MESs/RMSEs in the main model.

Chapter 4, which presents the second article, provides a mathematical cost model for a BT-based PSC system to estimate the costs of the model. This study is important because it allows for a PSC system with BT (BT Transaction cost and BT Installation cost) that can improve the safety, performance, and transparency of medical information sharing in a healthcare system. One of the main contributions of this research is to formulate this cost problem and apply a combination of EC (ACO and FA) and SL (KNN, DT, SVM, and NB) algorithms and use four performance metrics (MSE, RMSE, MAE, and R2) to evaluate the efficiency of the proposed algorithms. This combination of EC and SL algorithms provides eight algorithms (as the regression producer), reducing prediction errors and improving the SL results. Overall, the ACO-NB and FA-NB algorithms outperform the other six algorithms in estimating the costs of the model with lower errors. ACO-DT and

FA-DT show the worst performance for this comparison, showing that the DT algorithm is not an appropriate predictive approach for the current cost model. The findings also show that the Shortage cost, Holding cost, and Expired Medication cost strongly influence the cost model more than the other cost components that have almost the same effect on the model (Regular-Purchases cost, Emergency-Purchases cost, Shipping cost, BT-Transaction cost, and BT-Installation cost). This selection of components is derived from allocating an appropriate weight to each cost feature to show their importance through the FW approach. Therefore, the statistical outcomes on the generated dataset show that some of the proposed algorithms can obtain satisfactory results and assign appropriate feature weights. In the real world, managers in the field of healthcare services can use this model practically to control financial resources, stay within the budget, analyze information, and identify unnecessary costs, particularly if they decide to use BT in the system.

Chapter 5, which presents the third article, introduces six components of the multi-function BT-enabled PSC under Uncertain Demand model: Raw Materials cost (Ordering cost, Holding cost for perfect raw materials, Holding cost for imperfect raw materials, Labor cost for order handling and receipt, and Transportation cost), Finished Products cost (Set-up cost, Holding cost, Production cost, Expected opportunity interest, and Expiry cost), Shortage-Surplus cost (Shortage cost and Surplus cost), Blockchain Installation cost (Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost), Blockchain Transaction cost (Gas cost and Storage cost), and Unsatisfied Demand. The combination of two EC algorithms and four SL algorithms provides eight algorithms to reduce prediction errors, optimize the hyperparameters of the SL algorithms, and improve the multi-function model. Findings show that the HS-NB and PSO-NB algorithms outperform the other six algorithms in estimating the costs of the multi-function model with lower errors. This means that the NB algorithm can estimate the costs of the BT-enabled PSC system better than KNN, DT, and SVM algorithms. Therefore, we can conclude that NB is the proper algorithm among NB, KNN, DT, and SVM algorithms. The other six algorithms perform similarly for this comparison, except HS-

SVM, which acts better, showing that these algorithms are not an appropriate predictive approach for the current cost model. The findings also show that the Raw Materials cost strongly influences the cost model more than the remaining four cost features: Shortage-Surplus cost, Finished Products cost, Blockchain Installation cost, and Blockchain Transaction cost. Therefore, the statistical outcomes on the generated dataset show that the NB algorithm can obtain satisfactory results and assign appropriate feature weights. These findings can help healthcare service managers make the right decisions, control financial resources, stay within the budget, analyze information, and identify unnecessary costs, particularly if they decide to use BT in the system. Another contribution of this research is to provide a PSC system with BT, which is the BT-enabled PSC under the Uncertain Demand model.

Research Limitations and Future Research

Compared to previous work that modeled the costs of PSC and SCS, this study developed three new mathematical cost models (Eq. (4.6) on page 45, Eq. (5.1) on page 81, and Eq. (6.1) on page 110), including BT transaction cost and BT installation cost. Researchers in other fields can also use BT cost formulation (BT transaction cost and BT installation cost) in their mathematical models to estimate the SC costs integrated with BT. However, similarly to the other studies, this thesis is subject to two limitations. The first significant limitation is the inaccessibility of real data because the use of BT in the PSC is a new area of research. Therefore, the Evolutionary Supervised Learning algorithms studied in this work applied the generated data to validate the proposed BT-based PSC cost model. The use of generated data, rather than real data, may influence the outcomes and conclusions of the research. The second limitation is related to the model design. We selected parts of the mathematical model inspired by other papers to design the cost model and then added BT costs. This means that the study may not cover some cost components of a real case, hindering the comparison of a real case, hindering the comparison of this research's results with those of other studies.

Finally, future research may extend the BT-enabled PSC under the Uncertain Demand model to a multi-function BT-enabled Pharmaceutical Cold Supply Chain model. Pharmaceutical Cold Supply Chain utilizes advanced technology to control the temperature of cargo containers and storage units. Another proposal for upcoming research involves using other EC algorithms to enhance the performance of the SL algorithms or to test different SL algorithms to predict costs. Finally, future research can determine the cost components of the private BT or hybrid BT system and formulate them instead of the public BT used in the current study.

ANNEX I

OPTIMIZING A TRANSPORTATION SYSTEM USING METAHEURISTICS APPROACHES (EGD/GA/ACO): A FOREST VEHICLE ROUTING CASE STUDY

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Abstract

The large-scale optimization problem requires some optimization techniques, and the Metaheuristics approach is highly useful for solving difficult optimization problems in practice. The purpose of the research is to optimize the transportation system with the help of this approach. We selected forest vehicle routing data as the case study to minimize the total cost and the distance of the forest transportation system. MATLAB software helps us find the best solution for this case by applying three algorithms of Metaheuristics: Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Extended Great Deluge (EGD). The results show that GA, compared to ACO and EGD, provides the best solution for the cost and the length of our case study. EGD is the second preferred approach, and ACO offers the last solution.

Keywords: Metaheuristics Approach; Transportation System; Optimization Techniques

I.1 Introduction

In recent years, a large number of studies have been carried out on the development of heuristics and Metaheuristics. The large-scale optimization problem needs some optimization techniques to search the problem space profoundly and to optimize the problem efficiently and effectively (Devika, Jafarian, & Nourbakhsh, 2014). Metaheuristics solve difficult optimization problems in practice.
The first problem is related to the total costs of the forest transportation system by a significant wooden company that distributes wood products from the depot of the company to its customers in different cities. The second problem refers to the total distance of this forest transportation system. In the study, we aim to minimize the total cost and the total length of

this transportation system and then compare the cost and the length of this case to find the best solution.

I.2 Research Methods

To achieve our objectives, we reviewed literature by reading academic articles and books to learn about Metaheuristics techniques and select the right Metaheuristics algorithms for the case study. Therefore, the authors applied three algorithms (GA, ACO, and EGD) to minimize the total cost and the total length of the forest transportation system. Matlab software was used to find the best solutions for these algorithms. Validating the obtained results to compare the results with the previous studies came two important to make to the last step. The Metaheuristic techniques prepare reasonably good solutions without exploring the space of the whole solution (Yusta, 2009). Metaheuristics often can offer a better trade-off between the solution quality and computing time, especially for complicated or large-scale problems (Glover & Sörensen, 2015). Moreover, they assert two important ways to make Metaheuristics more flexible than other methods. First, Metaheuristics algorithms can fulfill the needs of most real-life optimization problems regarding the quality of the expected solution and allows computing time, which are different in problems and situations (Glover & Sörensen, 2015). Secondly, there are no demands on the formulation of the optimization problem in Metaheuristics (for instance, requiring limitations or objective functions to be stated as linear functions of the decision variables), according to them. However, they highlight that his flexibility comes at the cost of requiring significant problem-specific adaptation to attain good performance.

The most usage of Metaheuristic strategy applied to the variable selection problem is the Genetic Algorithm (GA) (Yusta, 2009). GA is a population-based Metaheuristics and is an evolutionary computation technique replicating the mechanism of biological evolution and the process of natural selection (Fahimnia, Davarzani, & Eshragh, 2018). They continue GAs follow Charles Darwin 's principles, based on which the fittest individuals have the highest chance of survival. According to these authors, the algorithm works with a potential solutions population represented by chromosomes, and each chromosome (solution) carries encoded information represented by genes. The Extended Great Deluge (EGD) algorithm is a local search procedure introduced by Dueck (1993). The idea of this algorithm comes from the analogy that an individual climbs a hill and tries to move in any direction to find a way up to keep his feet dry as the water level rises during a great deluge (Badawi & Alsmadi, 2013). Colorni, Dorigo, Maniezzo, and Trubian (1994), as well as Dorigo and Gambardella (1997a), proposed the idea of Ant Colony Optimization (ACO) to solve combinatorial optimization problems. The ant algorithm was inspired by the collective performance of real life of colonies (Nourelfath, Nahas, & Montreuil, 2007). ACO shows very good results in an applied area. The ant colony uses other combinatorial optimization problems such as the problem of the vehicle routing, telecommunication networks management, graph coloring, constraint satisfaction, and Hamiltonian graphs (Nourelfath, Nahas, & Montreuil, 2007).

I.3 Mathematical Model and Case Study

The heuristic solutions quality differs and depends on the methods used (Yusta, 2009). Metaheuristics techniques have proved to be superior methodologies in various optimization problems (Yusta, 2009). The success of methods (such as GA, SA, TS, SS, AS, and so forth) depends on some factors such as their ability to consider specific constraints rising in practical applications, their ease of implementation, and the quality of the solutions they produce (Taillard, Gambardella, Gendreau, & Potvin, 2001). This research refers to a real-life location routing problem encountered by a major wooden company distributing wood products from the company's depot to its customers located in various cities. The data of 50 costumers comes from Marinakis and Marinaki's (2007) article (Table-A I-1). According to the literature review, we decided to use three algorithms to solve the factory's localization problem, the dimensioning problem, and the forest products vehicle problem: GA, ACO, and EGD.

Table-A I-1 Costumers' Demand (Marinakis & Marinaki, 2007)

Customer	Location		Demand (m3)	Start time	Finish time
1	50	-290	29.379	0	40
2	-120	-250	3.711	0	40
3	-90	-250	23.664	0	40
4	-145	-320	4.79	0	40
5	-100	-390	4.517	0	40
6	-80	-390	2.018	0	40
7	-82	-337	1.57	0	40
8	-40	-332	5.317	0	40
9	-46	-324.5	13.403	0	40
10	-42	-286	3.725	0	40
11	-63	-200.5	6.676	0	40
12	-112.5	-199	6.78	0	40
13	-38	-242	4.3	0	40
14	9	-251	2.065	0	40
15	40	-230	5.335	0	40
16	-159	-108	3.797	0	40
17	-211	-126	0.856	0	40
18	-142	-163	5.631	0	40
19	-121	-242	1.496	0	40
20	-124	-213	24.741	0	40
21	-61	-6	3.464	0	40
22	-79	-11	3.691	0	40
23	-51	14	1.293	0	40
24	-117	18	7.899	0	40
25	-126	-8	2.255	0	40
26	-88	-28	2.664	0	40
27	-95	-9	1.504	0	40
28	-112	-54	0.859	0	40
29	3	-3	8.319	0	40
30	38	-29	1.299	0	40

Customer	Location		Demand (m3)	Start time	Finish time
31	-35	-41	1.715	0	40
32	-5	39	1.535	0	40
33	46	48	6.198	0	40
34	91	52	18.079	0	40
35	187	47	2.008	0	40
36	225	19	1.692	0	40
37	-40.5	-97.5	44.018	0	40
38	-90	-100	6.067	0	40
39	-83	-118	0.539	0	40
40	0.5	-117	2.432	0	40
41	-180	468	1.978	0	40
42	-106	126	7.446	0	40
43	-269	81	11.174	0	40
44	34.5	237.5	43.413	0	40
45	149.5	45	0.744	0	40
46	-195	-198	2.103	0	40
47	-200	-207	1.829	0	40
48	-52	-231	0.676	0	40
49	5	-446	3.978	0	40
50	109.5	38	3.116	0	40

The other important information which used in MATLAB software for three different algorithms (GA, ACO, and EGD) is as follows:
Population size: 50
Number of generations: 50
Crossover probability: 0.8
Mutation probability: 0.25
Three different threshold values e1: 1%, 3% and 5%
Size of the Restricted Candidate List: 20
The location: Kilometer
The central depot of all costumers is started to serve in the location: (0, 0)
The central depot is open: 0hr to 40hr.
The fleet is: homogeneous.
The average speed of vehicles: 65 Km/h
The cost of transport: 2.8$
The vehicles used have a load capacity Q: 50 cubic meters.

Total number of vehicles: 9

The total cost of transport is a mathematical model shown in equation (A I.1). This model is adapted from Bagayoko, Dao, and Ateme-Nguema (2013).

$$\text{The Min } C_t = MC_f + \sum_{i=1}^{L+1} \sum_{j=1}^{L+1} \sum_{k=1}^{m} Cijk\ Dij\ Xijk + (C_{vt} + C_{dt}) \sum_{i=1}^{L+1} \sum_{j=1}^{L+1} \sum_{k=1}^{m} Xijk(Tij + Wjk + Sj) \tag{A I.1}$$

The elements of this function are as follows:

MCf = the total vehicles fixed cost

C_f = the unit vehicle fixed cost, covering loading and unloading

$\sum_{i=1}^{L+1} \sum_{j=1}^{L+1} \sum_{k=1}^{m} Cijk\ Dij\ Xijk$ = the total distance cost summation

C_{ijk} = the unit cost of transport per kilometer of vehicle k from i to j

D_{ij} = the distance between two locations i and j

X_{ijk} = vehicle k go from i to j

$(C_{vt} + C_{dt}) \sum_{i=1}^{L+1} \sum_{j=1}^{L+1} \sum_{k=1}^{m} Xijk(Tij + Wjk + Sj)$ = the total vehicles route time cost and total drivers work time cost summations

C_{vt} = the unit vehicle route time cost

C_{dt} = the unit driver work time cost

W_{jk} = the vehicle k waiting time at customer j

S_j = the customer j service time

The equation (A I.2) shows the time spends from i to j.

$T_{ij} = D_{ij} / V \qquad i \in [1, L+1]\ ;\ j \in [1, L+1] \qquad$ (A I.2)

$W_{ik} = \max(T^s_i - T_{ik}\ .\ 0) \qquad i \in [1, L+1]\ ;\ k \in [1, m] \qquad$ (A I.3)

The definitions of elements are:

T_{ij} = vehicle k arrival time to customer i

W_{ik} = vehicle k waiting time at customer i

S_i = customer i service time

There are nine constraints restrictions:

The vehicle k total load cannot exceed the maximum vehicle load Q:

$\sum_{j=2}^{L+1} Q_j\, Y_{kj} \leq Q \qquad k \in [1, m] \qquad$ (A I.4)

Every customer is served only by one vehicle:

$\sum_{k=1}^{m} Y_{kj} = 1 \qquad j \in [1, L+1] \qquad$ (A I.5)

$j \in [1, L+1]\ ;\ k \in [1, m] \qquad$ (A I.6)

The variable X_{ijk} is binary:

$$X_{ijk} = \begin{cases} 1, \text{ the vehicle k goes from i to j} \\ 0, \text{ otherwise} \end{cases} \tag{A I.8}$$

The bond between vehicle k arrival times to customers i and j:

$$Xijk = (T_{ik} + W_{ik} + S_i + T_{ij}) = T_{jk} \qquad I, j \in [1, L+1] \text{ ; } k \in [1, m] \tag{A I.9}$$

The service at customer j must be completed before T_k, the end of the vehicle k time:

$$\sum_{i=1}^{L+1} \sum_{j=1}^{L+1} Xijk(Tij + Wjk + Sj) \leq T_k \qquad k \in [1, m] \tag{A I.10}$$

No customer can be served before his time of beginning:

$$T_j \geq T^s_j \qquad j \in [1, L+1] \tag{A I.11}$$

No customer can be served after his time of the end:

$$T_j \leq T^e_j \qquad j \in [1, L+1] \tag{A I.12}$$

The distance between two locations x_i and x_j is calculated with equation (A I.13).

$$D_{ij} = \sqrt{(Xi - Xj)^2 + (Yi - Yj)^2} \qquad i, j \in [1, L+1] \tag{A I.13}$$

We used the cost calculation data of Bagayoko, Dao, and Ateme-Nguema (2013) in which the unit vehicle fixed cost is c_f = 160$, the unit vehicle route time cost is c_{vt} = 120$, the unit driver work time cost is c_{dt} = 18$ and all service times are $s_j = 0$.

I.4 Results

People, in real-world applications, are more interested in finding good solutions in a reasonable amount of time instead of being obsessed with optimal solutions (Yusta, 2009). As mentioned before, this study refers to the problem of real-life location routing. A major wooden company distributes wood products from the company's depot to its customers located in various cities. The data comes from the study of Marinakis and Marinaki (2007). Three algorithms (GA, ACO, and EGD) were selected to solve the cost and the length problems of the forest transportation system. We used the Matlab software to find the best solutions for these algorithms. The results of each algorithm are illustrated in different following sections.

I.4.1 Results obtained by Genetic Algorithm

The most popular genetic operators are (a) crossover operator generating new solutions by combining some of the existing solutions and (b) mutation operator maintaining diversity in the population by making small changes on genes of individual solutions (Fahimnia, Davarzani, & Eshragh, 2018). For our case study, the result obtained by the GA shows the best cost is 19901.1417$ and the total distance is 1093.46 (km). This came from the MATLAB software in 1540.7213 seconds. Figure-A I-1 shows the best cost of the GA forest vehicle routing convergence graphic. Figure-A I-2 illustrates the GA forest vehicle routing optimization graphic in which the vehicles' routes have different colors. There are nine vehicles and 50 costumers. The central depot is also shown with a blue dot in the center. In this figure, each vehicle passed the specific route to some costumers; each vehicle route is shown by one color. Therefore, there are nine different colors that show nine vehicle routes. Table-A I-2 shows the GA route for each vehicle, the length of each route, and the capacity used by each vehicle. The maximum capacity of each vehicle is 50 m3, the number of costumers is 50, and the number of vehicles is 9.

Table-A I-2 Results for GA

No. of truck	**GA Route**	**Length (km)**	**Capacity used by each vehicle (m^3)**
1	[22, 43 ,17 ,46 ,47 ,2 ,12]	147.82	30.144
2	[29, 36, 35, 50, 34, 33, 32]	78.77	40.947
3	[31, 20, 7, 49, 9, 10]	150.38	49.132
4	[23, 41, 44]	166.11	46.684
5	[38, 19, 4, 5, 6, 48, 40, 30]	137.71	23.295
6	[45, 15, 1, 8, 14]	147.39	42.84
7	[13, 3, 28, 25, 24, 26, 21]	110.90	45.105
8	[39, 11, 18, 16, 27, 42]	121.87	25.593
9	[37]	32.48	44.018
	Total Distance: 1093.46		

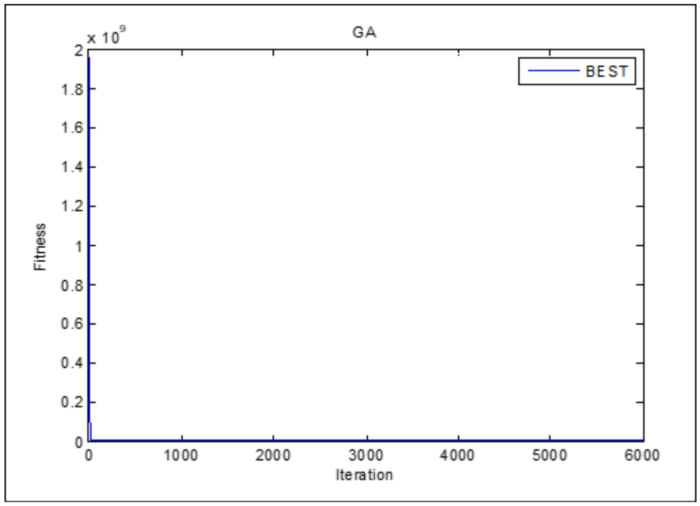

Figure-A I-1 Cost of GA forest vehicle routing convergence graphic

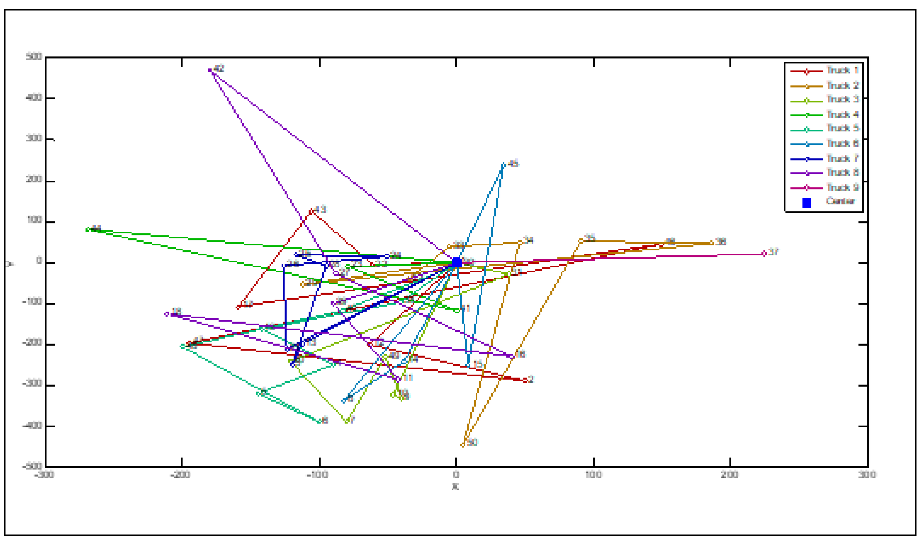

Figure-A I-2 GA forest vehicle routing optimization graphic

I.4.2 Results obtained by Ant Colony Optimization

ACO algorithms are population-based optimization approaches that have been applied with success in order to solve various combinatorial optimization problems, such as the traveling salesman problem (Nourelfath, Nahas, & Montreuil, 2007). We also used this algorithm for our case study to solve the problem by the Matlab software. In 1889.60 seconds, the software shows the best cost of 42345519.77 \$ and the total distance of 1679.81 (km) for this case.

Figure-A I-3 and Figure-A I-4 show the cost of the ACO forest vehicle routing convergence graphic, and the ACO forest vehicle routing optimization graphic respectively. Figure-A I-4 shows various routes passed by nine vehicles; the specific route of each vehicle allocates one color. The central depot is blue in the figure. Table-A I-3 illustrates the routes of nine vehicles, the length of each route, and the capacity used by each vehicle (m3). There are nine vehicles, 50 costumers, and the maximum vehicle capacity of 50 m3 for each.

Table-A I-3 Results for ACO

No. of vehicle	**ACO Route**	**Length (km)**	**Capacity used by each vehicle (m^3)**
1	[9, 1]	111.38	42.782
2	[19, 3, 49, 36]	193.93	30.83
3	[20, 10, 5, 4, 18, 13, 48]	169.3	48.38
4	[33,44]	76.35	49.611
5	[30, 38, 37]	53.74	51.384
6	[2, 6, 11, 12, 15, 17, 24, 27, 28, 32, 35]	288.11	42.297
7	[29, 47, 25]	97.01	12.403
8	[43, 46, 34, 42, 45, 7, 16]	355.13	44.913
9	[26, 31, 8, 14, 21, 22, 23, 39, 40, 41]	334.86	25.158
	Total Distance: 1679.81		

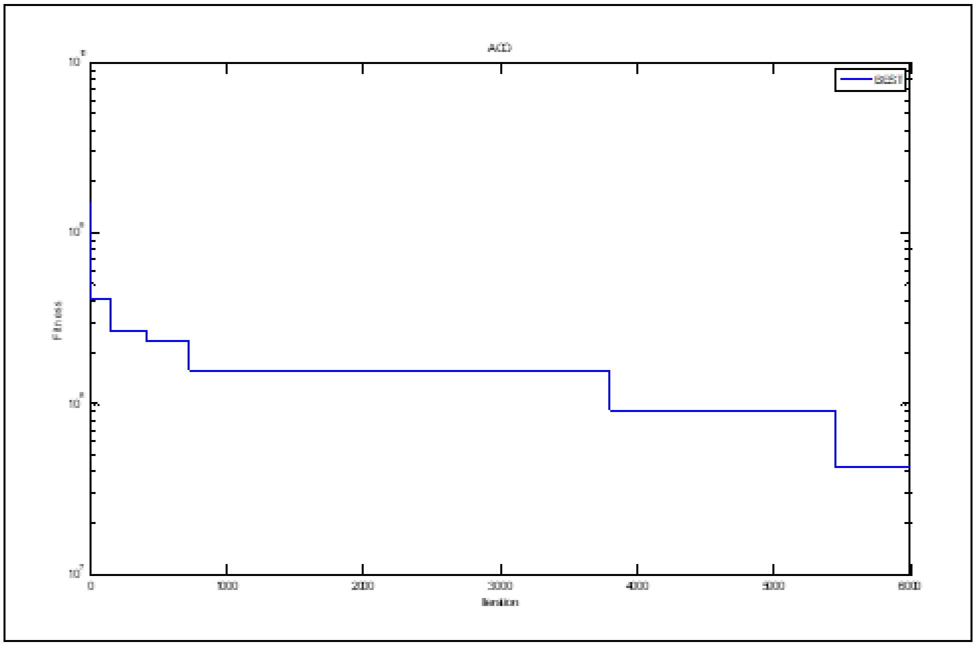

Figure-A I-3 Cost of ACO forest vehicle routing convergence graphic

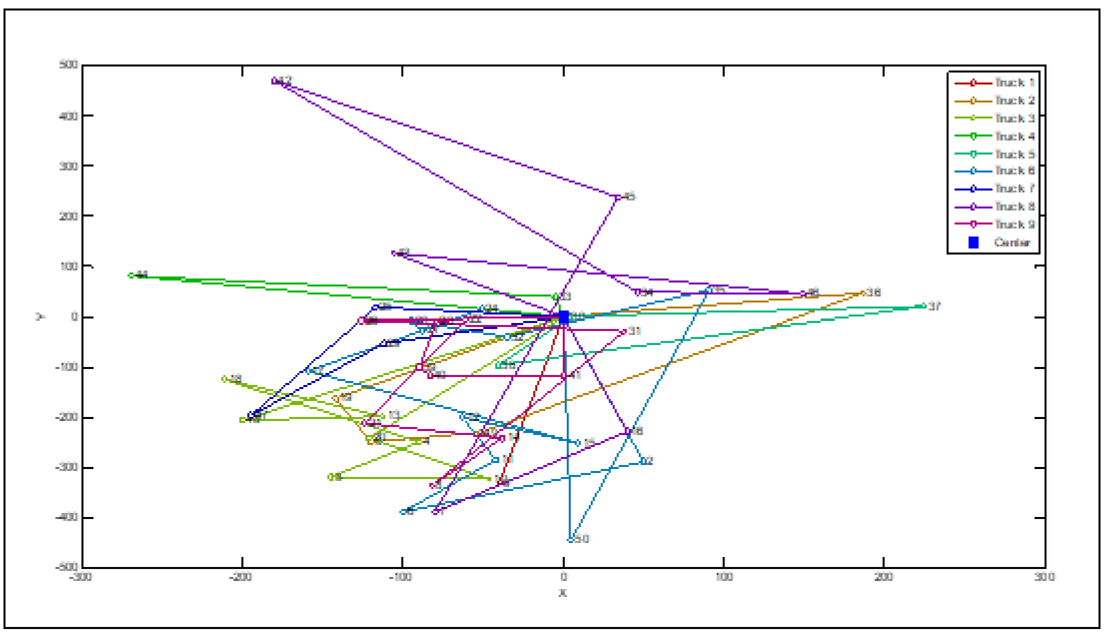

Figure-A I-4 ACO forest vehicle routing optimization graphic

I.4.3 Results obtained by Extended Great Deluge

Using a mathematical model in the Extended Great Deluge (EGD) algorithm seems useful as we aim to minimize the total transport cost as well as the total distance that each vehicle should pass. The EGD method converges in 6000 iterations, with the best distance of 4383.3053 (km), the best cost of 48930.6899 $, and 3110.01 seconds. Figure-A I-5 shows the EGD forest vehicle routing cost convergence graphic. It illustrates that the best cost converges into approximately 50000 $ after 6000 iterations. Figure-A I-6 shows the EGD forest vehicle routing optimization graphic. In this figure, each color clarifies the route of each vehicle that passes own direction to different cost customers blue point in the center is the central depot. Table-A I-4 illustrates each vehicle that passes the route to some customers (EGD Rout), the length of each route, and the vehicle capacity. In this case, there are nine vehicles with a maximum capacity of 50 m3.

Table-A I-4 Results for EGD

No. of truck	EGD Route	Length (km)	Capacity used by each vehicle (m^3)
1	[30,50,34,45,35,36]	538.46	26.938
2	[31,38,18,12,3]	584.24	43.857
3	[32,41,44]	1057.49	46.926
4	[39,2,4,6,49,1]	1009.63	44.415
5	[33,42,43]	687.35	24.818
6	[21,27,28,16,17,46,47,19,20]	702.53	40.649
7	[10,9,8,7,5,15,40]	884.95	36.299
8	[29,23,22,26,24,25]	325.77	26.121
9	[37,11,48,13,14]	560.24	57.735
	Total Distance:	6350.66	

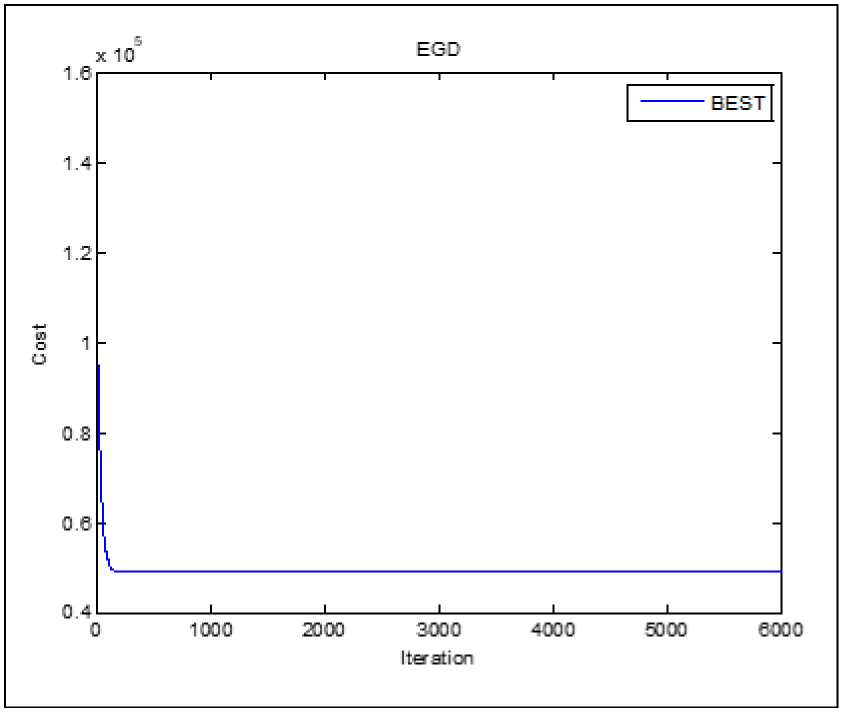

Figure-A I-5 Cost of EGD forest vehicle routing convergence graphic

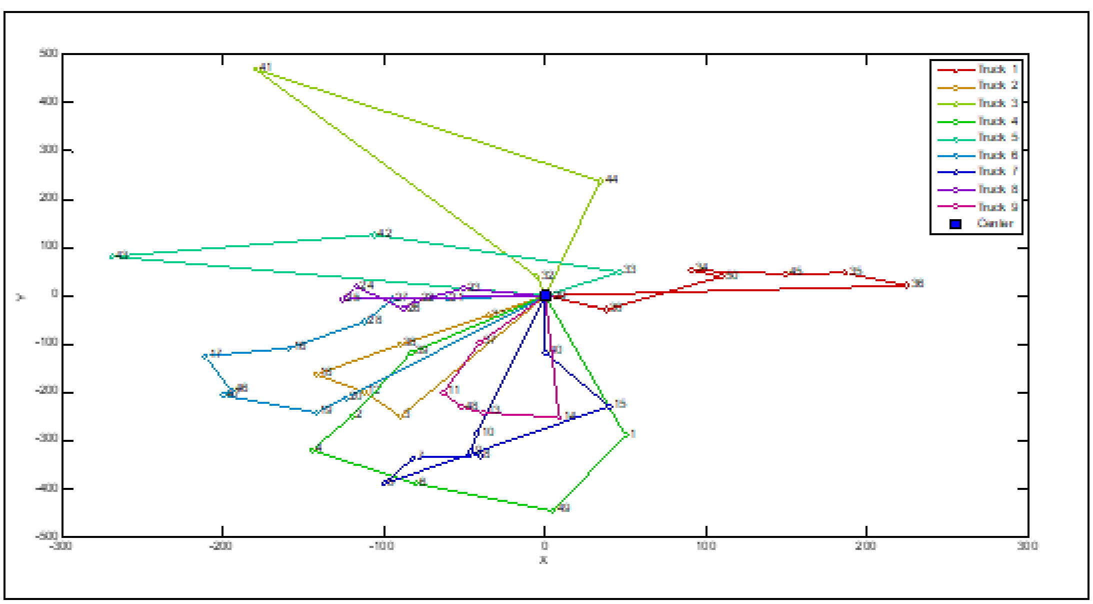

Figure-A I-6 EGD forest vehicle routing optimization graph

I.5 Discussion: Comparison of GA, ACO, and EGD results

Table-A I-5 clearly shows that in comparing three algorithms, GA proposes the best cost of 19901.1417 $, the minimum distance (1093.46 km), and the computation time (1540.7213 sec). On the other hand, EGD took the computation time with 3110.01 (sec), the best cost of 48930.6899 $, and the total distance of 6350.66 (km), and stands in the second position. ACO is the one that proposes the highest cost of these three algorithms.

Table-A I-5 Compares the best solutions obtained by GA, ACO, and EGD

	GA		ACO		EGD	
No. of truck	**GA Route**	**GA Length (km)**	**ACO Route**	**ACO Length (km)**	**EGD Route**	**EGD Length (km)**
1	[22, 43,17,46,47 ,2 12]	147.82	[9, 1]	111.38	[30,50,34,45,35,36]	538.46
2	[29, 36, 35, 50, 34, 33, 32]	78.77	[19, 3, 49, 36]	193.93	[31,38,18,12,3]	584.24
3	[31, 20, 7, 49, 9, 10]	150.38	[20, 10, 5, 4, 18, 13, 48]	169.3	[32,41,44]	1057.49
4	[23, 41, 44]	166.11	[33,44]	76.35	[39,2,4,6,49,1]	1009.63
5	[38, 19, 4, 5, 6, 48, 40, 30]	137.71	[30, 38, 37]	53.74	[33,42,43]	687.35
6	[45, 15, 1, 8, 14]	147.39	[2, 6, 11, 12, 15, 17, 24, 27, 28, 32, 35]	288.11	[21,27,28,16,17,46,47,19,20]	702.53
7	[13, 3, 28, 25, 24, 26, 21]	110.90	[29, 47, 25]	97.01	[10,9,8,7,5,15,40]	884.95
8	[39, 11, 18, 16, 27, 42]	121.87	[43, 46, 34, 42, 45, 7, 16]	355.13	[29,23,22,26,24,25]	325.77
9	[37]	32.48	[26, 31, 8, 14, 21, 22, 23, 39, 40, 41]	334.86	[37,11,48,13,14]	560.24
	1093.46		1679.81		6350.66	
Total Distance	1540.7213		1889.60		3110.01	
Best Cost	19901.1417		42345519.77		48930.6899	

Looking carefully at figures-A I-1, A I-3, and A I-5, we find out the cost of the forest vehicle routing for GA, ACO, and EGD converge into the best cost in different iterations: GA after around 100 iterations (see Figure-A I-7); ACO after around 6000 iterations (see Figure-A I-8); and EGD after around 200 iterations (see Figure-A I-9). Therefore, we run the MATLAB for these new iterations and compare them in Figures-A I-7, A I-8, and A I-9.

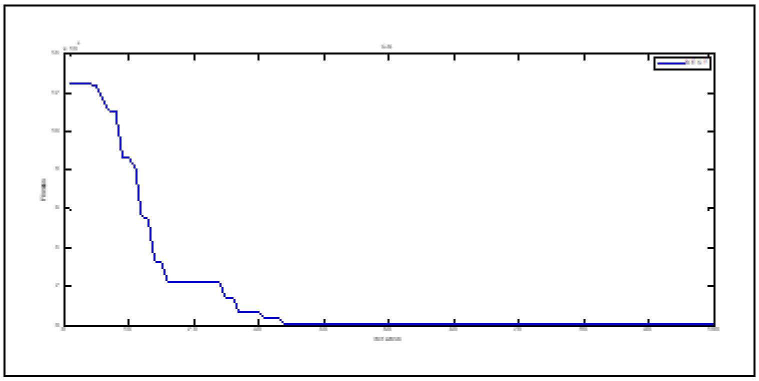

Figure-A I-7 Cost of GA forest vehicle routing convergence graphic after 100 iterations

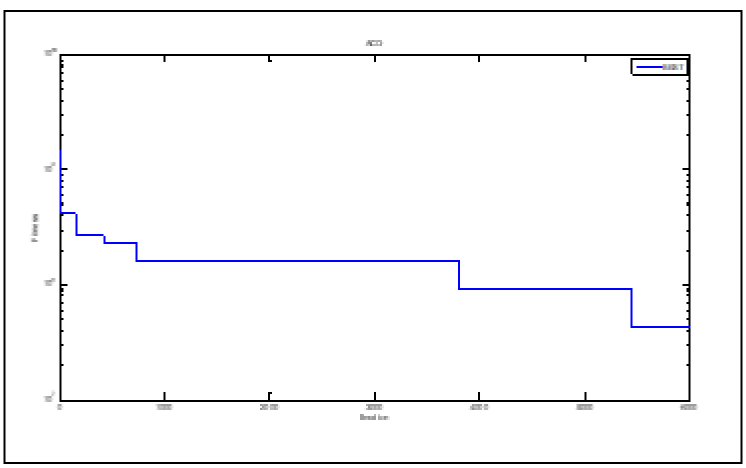

Figure-A I-8 Cost of ACO forest vehicle routing convergence graphic after 6000 iterations

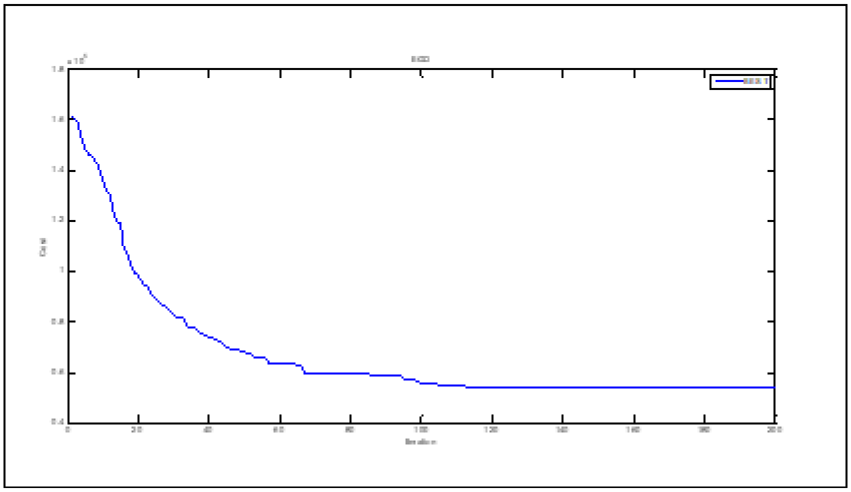

Figure-A I-9 Cost of EGD forest vehicle routing convergence graphic after 200 iterations

I.6 Conclusion

Transportation cost is a noticeable issue for each company to reduce cost and distance. This study uses the Metaheuristics approach to solve this problem for the transportation system in Forest Vehicle Routing adopted by Marinakis and Marinaki (2007). We applied three algorithms of Metaheuristics for this case study: Genetic Algorithm, Ant Colony Optimization, and Extended Great Deluge. The authors then compare the best cost, the total distance, and the computation time for these three algorithms. The results show that the best solution for all three items (cost, distance, and computation time) is for the GA. EGD stands in the second step for this case, and ACO comes in the following. In the study of Bagayoko, Dao, and Ateme-Nguema (2013), Tabu Search and EGD were applied for the same case (with some small differences), and the results of the total cost and the total length for these two algorithms are higher than GA. Therefore, GA is the preferred algorithm in this case study.

APPENDIX
BASIC DESIGN OF EC ALGORITHMS

I.1 Formulation of Optimization Problem

In the development of an optimization problem, maybe the most important and the crucial thing is to produce the optimization model of the physical problem, and it requires a very good understanding of the physical process itself together with some expertise (Eren, B. Küçükdemiral , & Üstoğlu, 2017). The modeling and building of an optimization problem require the following steps:

- Data collection,
- Problem definition and formulation,
- Model development,
- Model validation and evaluation of performance, and
- Model application and interpretation.

Between these steps, the data collection is the most time-consuming step, but it is the fundamental basis of the model-building process. The availability and accuracy of data can have considerable effect on the accuracy of the model and on the ability to evaluate the model. Problem definition and formulation step involves the identification of the decision variables, formulation of the model objective(s), and the formulation of the model constraints. In this step, one must identify the important elements that the problem consists of. Then, the determination of the number of independent variables, the number of equations required to describe the system, and the number of unknown parameters are performed. After this, one needs to evaluate the structure and complexity of the model and finally in the last step, the accuracy of the model is selected. Model development includes the mathematical description, parameter estimation, and software development. Note that the model development phase is an iterative process, and it may require returning back to the model definition and formulation phase several times. During the model validation and evaluation of the performance, one checks the performance of the model as a whole. The performance of the model is to be evaluated using standard performance measures such as root mean squared error or some other metrics. A sensitivity analysis should also be performed in this step to test the model inputs and parameters. This phase also is an iterative process and may require returning to the model definition and formulation phase. Finally, model application and interpretation include the use of the model in the particular area of the solution and the translation of the results into operating instructions issued in understandable form to the individuals who will administer the recommended system (Eren, B. Küçükdemiral , & Üstoğlu, 2017). Optimization algorithms developed based on nature-inspired ideas deal with selecting the best alternative based on the given objective function (Shehab , 2020). To elaborate, each optimization algorithm can be categorized into three classes: evolutionary algorithms (EAs), swarm-based algorithms, and trajectory-based algorithms (Figure I-1) (Shehab , 2020).

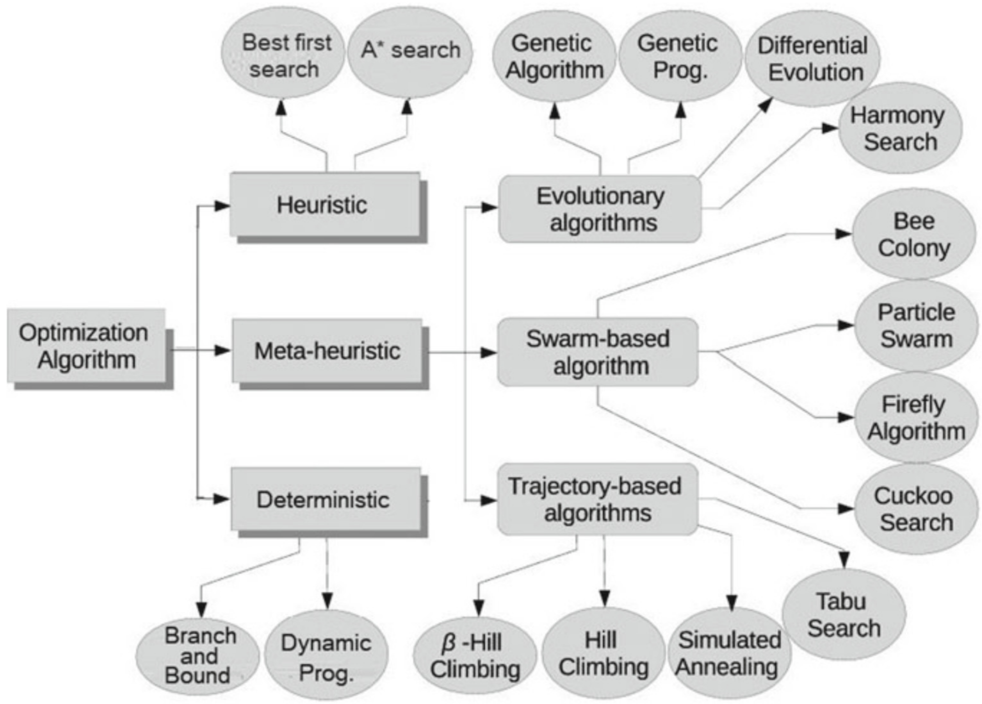

Figure I-1 Optimization algorithms (Shehab , 2020)

I.2 Basic Design of Ant Colony Optimization Algorithm (ACO)

On colony and is mainly inspired by the activities of real army ant in nature. It is belonged to the random searching algorithm. This algorithm was first proposed by M. Dorigo, an Italian researcher, who makes full use of the similarity between the paths of ant colony searching for food and the famous Travelling Salesman Problem (TSP), to solve the TSP by artificially simulated the process of ant searching for food, namely finding the shortest path from ant-colony to food sources through exchange of information and mutual cooperation. This algorithm is called "Artificial Ant Colony Algorithm" to distinguish the real ant group system (Pei, Wang, & Zhang, 2012).

The general theory of the ant system: Pre-initialize the taboo table of each ant and the pheromone intensity on all sides. Each ant needs to choose the next destination based on the restriction of the taboo table according to some special probability rules until it creates a legal path. Compute the length of path generated by each ant. The length of path means the sum of the length of each path. Update the pheromone on all sides. Firstly, each side will evaporate the pheromone, and then access to the pheromone released by ants according to the length of path generated by each ant. Record the recent shortest path, after all ants have completed the updating process to the pheromone. At the same time, Initialize the added value of pheromone and the taboo table, then go to Step 2. Do the cycle continuously until the end of the algorithm. For example: The solution cannot get further improvement or has been reached a predetermined number of cycles (Pei, Wang, & Zhang, 2012).

Figure I-2 depicts the general flowchart of ACO technique which is summarized below. Advantages and disadvantages of ACO show similarity with PSO technique, so that the position of the ants is defined on coordinate planes and this technique is also suitable for the problem with parameters lower than three (Eren, B. Küçükdemiral , & Üstoğlu, 2017).

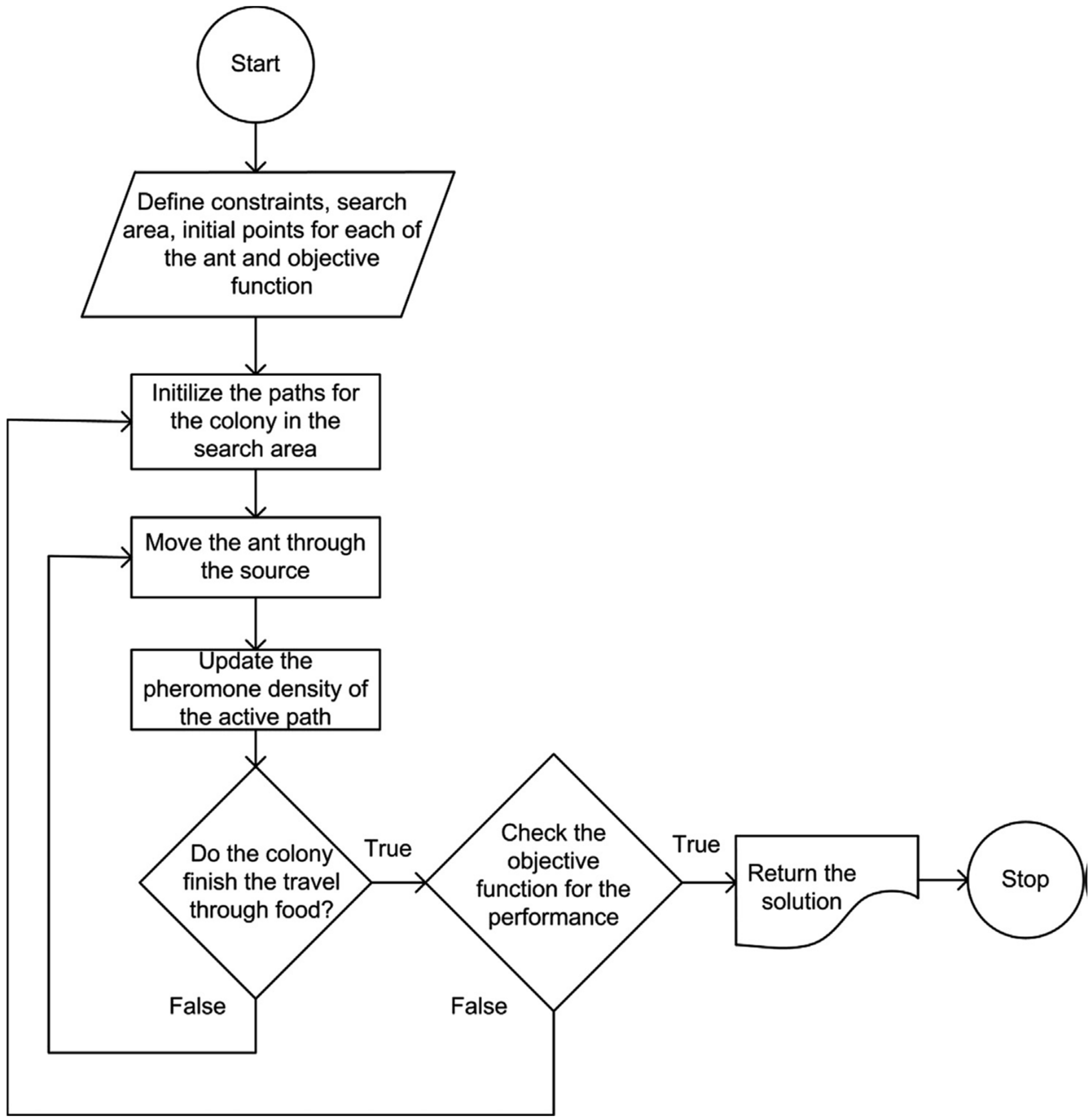

Figure I-2 Flowchart of ACO technique (Eren, B. Küçükdemiral , & Üstoğlu, 2017)

I.3 Basic Design of Particle Swarm Optimization Algorithm (PSO)

Particle swarm optimization (PSO) technique is proposed by Eberhart and Kennedy inspired by the swarming act of the bird, fish, and insect groups as searching for food. Every individual in the group is called "particle", and this technique generally simulates the social behavior of the animal groups focusing on position changing of the particles. As reaching the goal, positioning patterns of the particles and whole group enable to define an algorithm based on swarming methodology. For example, let us consider a flock of birds attempting to find source of food. When one gets closer position to the source than the rest, chirps loudly and the others go toward to that bird. In this attempt of keeping up the closest one, all the group adjust their velocities depending on their own position. And this process depending on the variation of position and velocity happens iteratively until any of the members reaches the food source in the searching area (Eren, B. Küçükdemiral , & Üstoğlu, 2017).

As seen in Figure I-3, PSO algorithm starts with defining the constraints of the problem and related parameters. Then, the fitness function is evaluated for each of the particles to measure the optimality of the current results. In this way, the process is iterated until satisfying the termination criterion. Termination criteria of the algorithm can be imposed as achieving the minimum distance between the current position and target or reaching the minimum number of iterations. Besides that, alternative stopping criteria can be added for the case of no-target is found in the limit of the predetermined iterations. For discussion of the pros and cons of the PSO technique, first, it should be mentioned that PSO algorithm proposes two version of solutions which are global and local. Local version of the solution comprises a limited space which is called "working space" and focuses on the optimal solution. From this point of view, this version is slower than the global one and more reliable for converging the optimal solution. Besides, global version of the algorithm focuses on outer space to find the solution space which includes the optimal solution. So that, this version of the technique is faster than the local one, but convergence rate is less reliable than the local one (Eren, B. Küçükdemiral , & Üstoğlu, 2017).

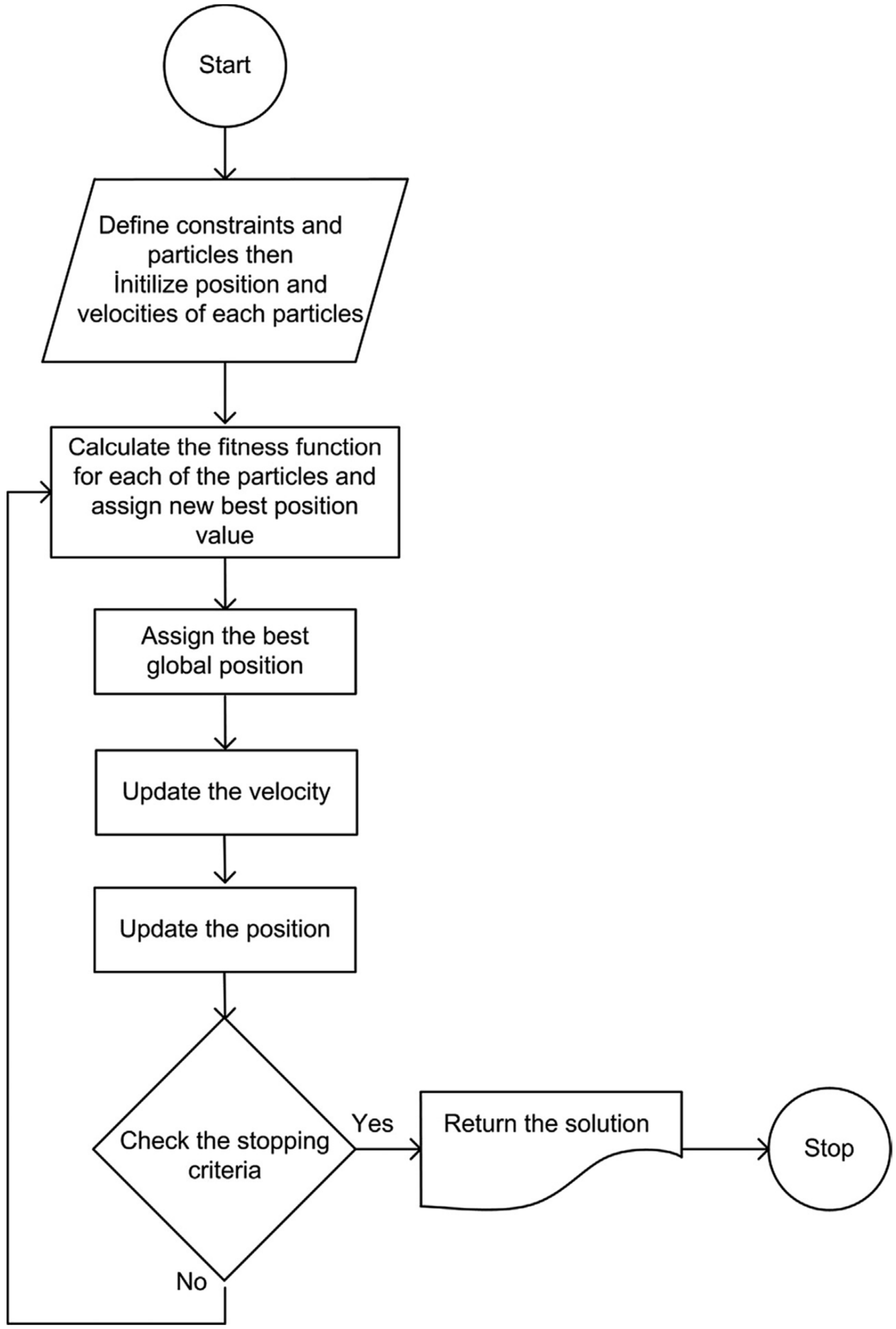

Figure I-3 Flowchart of PSO technique (Eren, B. Küçükdemiral , & Üstoğlu, 2017)

I.4 Basic Design of Firefly Algorithm (FA)

Firefly algorithm is classified as swarm intelligent, metaheuristic and nature-inspired, and it is developed by Yang in 2008 by animating the characteristic behaviors of fireflies. In fact, the population of fireflies show characteristic luminary flashing activities to function as attracting the partners, communication, and risk warning for predators. As inspiring from those activities, Yang formulated this method under the assumptions of all fireflies are unisexual such that all fireflies has attracting potential for each other, and the attractiveness is directly proportionate to the brightness level of individuals. Hence, the brighter fireflies attract to the less brighter ones to move toward to them, besides that in the case of no fireflies brighter than a certain firefly then it moves randomly (Eren, B. Küçükdemiral , & Üstoğlu, 2017).

In the formulation of firefly algorithm, the objective function is associated with flashing light characteristics of the firefly population. Considering the physical principle of the light intensity, it is inversely quadratic proportional to the square of the area, so that this principle enables to define fitting function for the distance between any two fireflies. For the optimization of fitting function, the individuals are forced to systematic or random moves in the population. In this way, it is ensured that all the fireflies move toward to more attractive ones which have brighter flashing until the population converge to brightest one. Within this procedure, firefly algorithm is executed by three parameters which are attractiveness, randomization, and absorption. Attractiveness parameter is based on light intensity between two fireflies and defined with exponential functions. When this parameter is set to zero, then it happens to the random walk corresponding to the randomization parameter which is determined by Gaussian distribution principle as generating the number from the [0,1] interval. On the other hand, absorption parameters affect to the value of attractiveness parameters as changing from zero to infinity. And, for the case of converging to the infinity, the move of fireflies appears as random walk (Eren, B. Küçükdemiral , & Üstoğlu, 2017). The procedure of the firefly optimization technique is briefly rendered in Figure I-4.

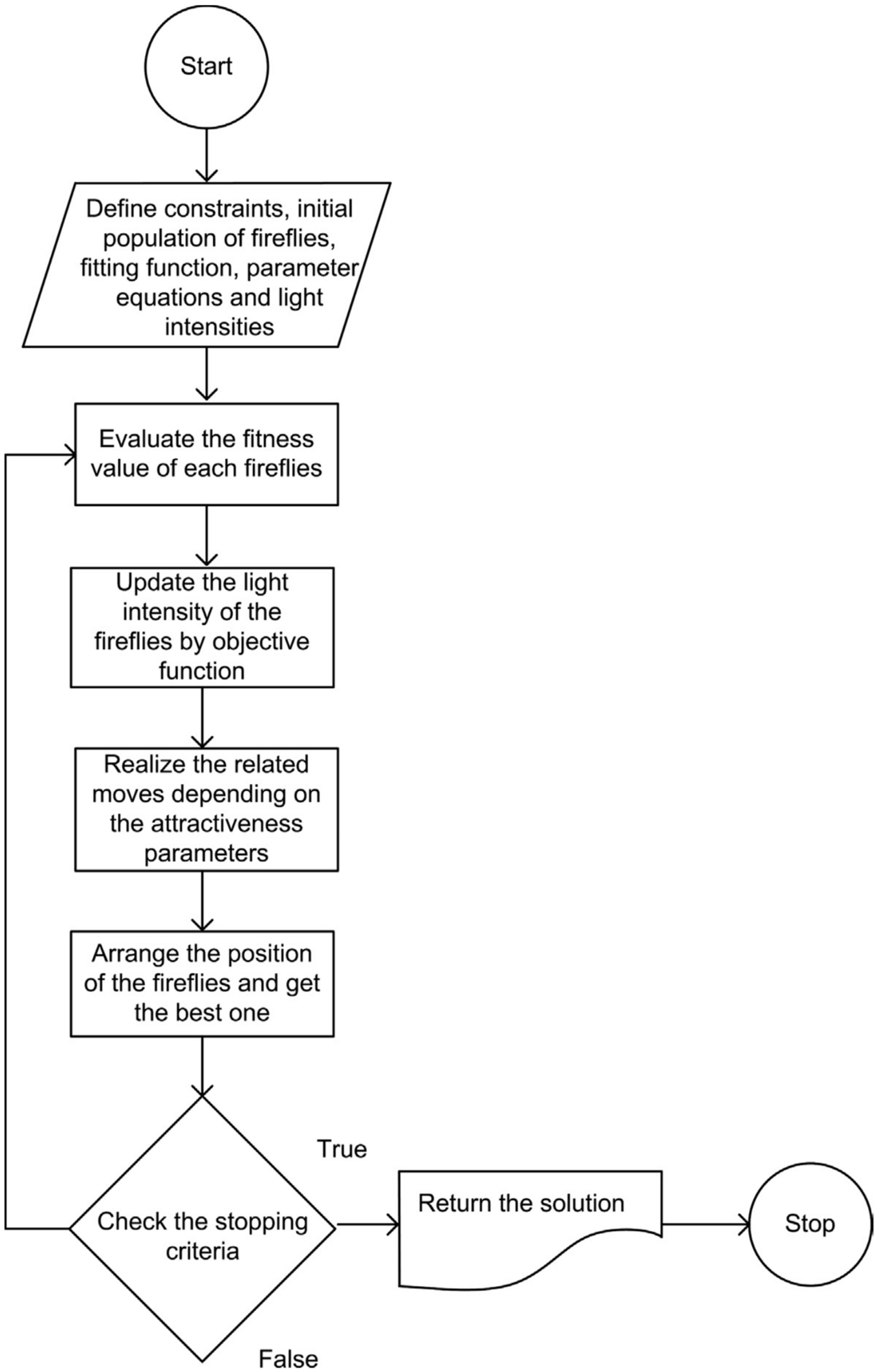

Figure I-4 Flowchart of Firefly Algorithm technique (Eren, B. Küçükdemiral , & Üstoğlu, 2017)

I.5 Basic Design of Cuckoo Search Algorithm (CS)

The basic CS procedure is established by Yang and Deb in 2009, the founders of CS. Figure I-5 shows a flowchart of the CSA. Similar to other swarm-based algorithms, the CS starts with an initial population of n host nests. These initial host nests will be randomly attracted by the cuckoos with eggs and also by random Lévy flights to lay the eggs. Thereafter, nest quality will be evaluated and compared with another random host nest. In case the host nest is better, it will replace the old host nests. This new solution has the egg laid by a cuckoo. If the host bird discovers the egg, the host either throws out the egg, or abandons it and builds a new nest. This step is done by replacing the abundant solutions with the new random solutions. Yang and Deb used a certain and simple representation for the implementation, with each egg representing a solution. As the cuckoo lays only one egg, it also represents one solution. The purpose is to increase the diversity of new, and probably better, cuckoos (new solutions) and replace them instead with the worst solutions. By contrast, the CSA can be more complicated by using multiple eggs in each nest to represent a set of solutions (Shehab , 2020).

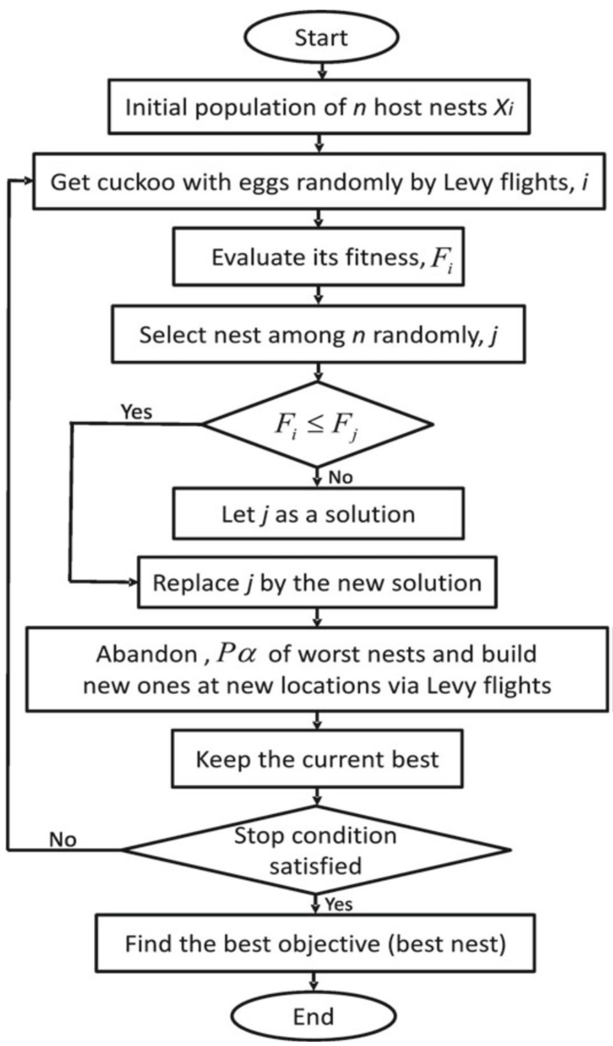

Figure I-5 Flowchart of Cuckoo Search Algorithm (Shehab , 2020)

I.6 Basic Design of Harmony Search Algorithm (HS)

Harmony search is a novel meta-heuristic algorithm, which has been conceptualized using the musical process of searching for a perfect state of harmony. This meta-heuristic is based on the analogy with music improvisation process where music players improvise the pitches of their instruments to obtain a better harmony. In the optimization context, each musician is replaced with a decision variable, and the possible notes in the musical instruments correspond to the possible values for the decision variables. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques. Musical performances seek to find pleasing harmony (a perfect state) as determined by an aesthetic standard, just as the optimization process seeks to find a global solution (a perfect state) as determined by an objective function (Merzougui, Hasseine, & Laiadi, 2012). Figure I-6 shows the optimization procedure of the HS algorithm, which consists of the following steps:

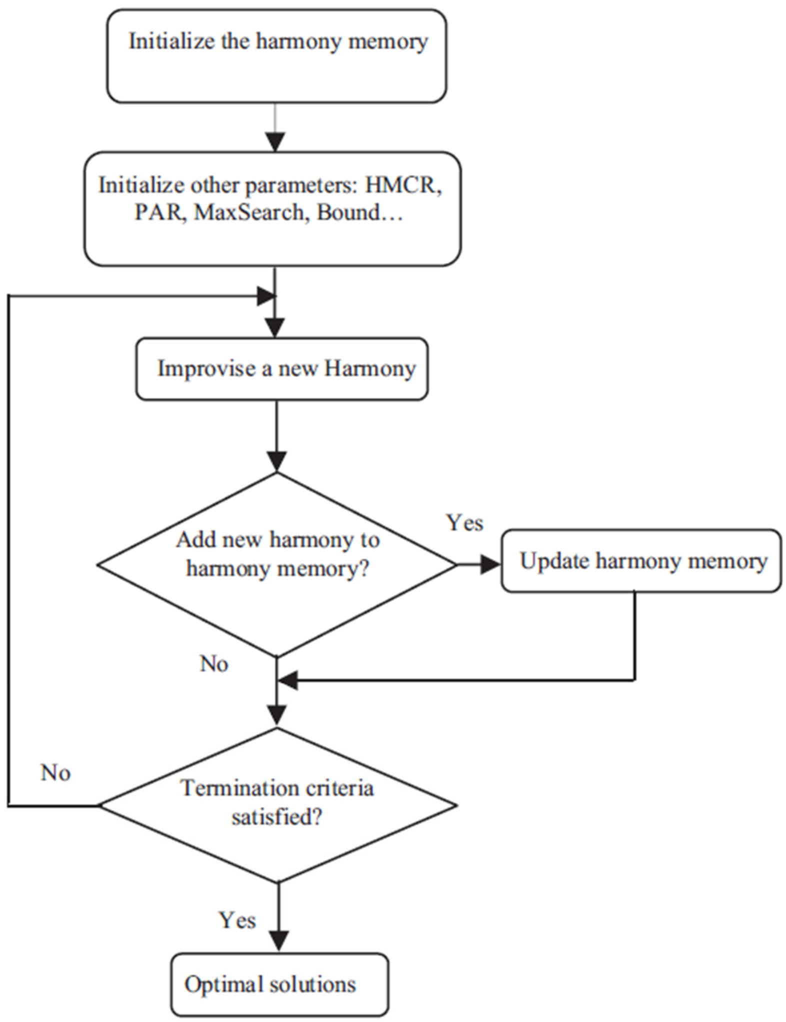

Figure I-6 Flowchart of Harmony Search algorithm (Merzougui, Hasseine, & Laiadi, 2012)

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