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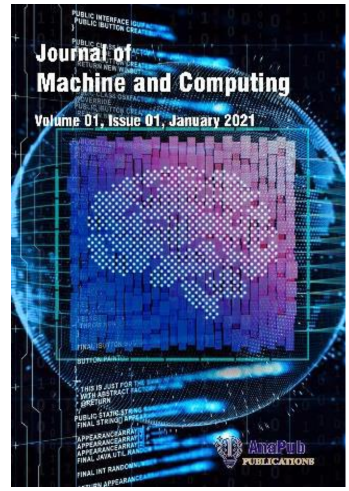

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Operating Cash Flow Ranking Using Data Envelopment Analysis with Network Security-Driven Blockchain Model

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Abstract

Accurate evaluation of innovative financial performance, primarily Operating Cash Flow (OCF), is crucial for informed decision-making. While Data Envelopment Analysis (DEA) is commonly used for efficiency evaluation, it challenges computational inefficiencies, data integrity problems, and a lack of transparency. This study proposes a DEA + Blockchain Technology that integrates DEA + BT to ensure data integrity, Tamper Detection (TD), and transparency through decentralized validation and cryptographic methods. Evaluated on the Securities and Exchange Commission (SEC)-Financial Statement Data Set and the Kaggle Financial Data Set, the DEA + BT achieves higher transaction Network Throughput (NT) (up to 1253 TPS), lower End-to-End Delay (EED) (as low as 120 *ms*), and superior technical efficiency accuracy (95.2%). This work proved enhanced security effectiveness with a 99.9% Consensus Rate (CR) and TD rates. Compared to traditional methods, the model provides higher ranking consistency (Spearman's correlation of 0.864 and 0.857). This DEA-BT proposes a robust, secure, and transparent method for enterprise OCF ranking, addressing key limitations of DEA and advancing financial performance evaluation methodologies.

Keywords: Network Security, Blockchain Technology, Operating Cash Flow, Data Envelopment Analysis, Tampering Detection.

1. Introduction

In recent years, analyzing and evaluating enterprise financial performance have become critical for stakeholders, including investors, management, and regulatory bodies [1-3]. One of the key metrics in assessing financial health is Operating Cash Flow (OCF), which reflects a company's ability to generate cash from its core business activities [4]. The ranked list of OCF performance is vital to determining financial decisions, finding Money invested, and developing approaches [5]. Computational analysis failure, security risks, and opaqueness are problems with traditional methods.

The technique that can be implemented to evaluate the impact of Decision-Making Units (DMUs) is referred to as Data Envelopment Analysis (DEA), a non-parametric method of analysis [6]. Because it depends on the ratio of weighted inputs to balanced results, it can be applied to algorithms that are used for measuring financial results [7]. The examination of company performance is performed in this approach. The computational speed of the DEA, on the other hand, presents problems, especially when it comes to maintaining large data sets. For developing properly informed choices regarding finances, it is necessary to have results that are both accurate and easily accessible [8]. New hybrid approaches that combine DEA with contemporary innovations are currently being studied by researchers. Several instances of these hybrid methods include DEA + BT and centralized security systems. In order to guarantee data integrity, transparency, and availability through Consensus Mechanisms (CM) and security using digital encryption, these techniques are being used to enhance the confidence and openness of the outcomes of the Drug Enforcement Administration (DEA). When BT and DEA are combined, it is feasible to ensure the validation and storage of efficiency rankings, which results in accurate findings [9-10].

The study recommends a process that combines DEA and BT, with the security of network functions serving as the primary motivation for the approach. The technique aims to improve the efficiency, security, and integrity of business OCF rankings. By applying this model, data integrity is improved, transactions are accelerated, EED is reduced, and the decentralized validation and encryption methods implemented by DEA + BT provide protection [11].

The contributions of this work are threefold.

a) This research work combines DEA + BT distributed network technology to improve OCF ranking accuracy.

b) This study also uses CM and TD detection to verify the DEA's findings.

c) This model is compared to traditional DEA, DEA with centralized security, and Stochastic Frontier Analysis (SFA) with BT using real-world financial datasets, such as the SEC Financial Statement Data Set and Kaggle Financial Data, which comprise over 4,400 public sector companies.

The proposed DEA + BT outperforms existing methods in terms of transaction speed, EED, security effectiveness, and technical efficiency accuracy. It also achieves higher Spearman correlation, improved data integrity, and optimized resource efficiency, indicating its probability for robust and transparent enterprise performance evaluation.

The following is the summary for the rest of the paper. The recommended system, describing the proposed DEA + BT, is provided in Section 2. Datasets, BT setup, and DEA configuration are provided in Section 3, which includes the experimental setup. The analysis of the performance and results of the experiments is addressed in Section 4. Finally, the work is concluded, and future research directions are presented in Section 5.

2. Methodology

2.1 Overview of the Proposed DEA + BT Model

The proposed DEA + BT to improve transparency, data integrity, and security in enterprise OCF ranking (Figure 1). Traditional methods are criticized for data manipulation, lack of verifiability, and insecure storage [12]. By combining DEA's efficiency analysis capabilities with BT's decentralized ledger system, the proposed model enhances the reliability and trustworthiness of the OCF ranking process.

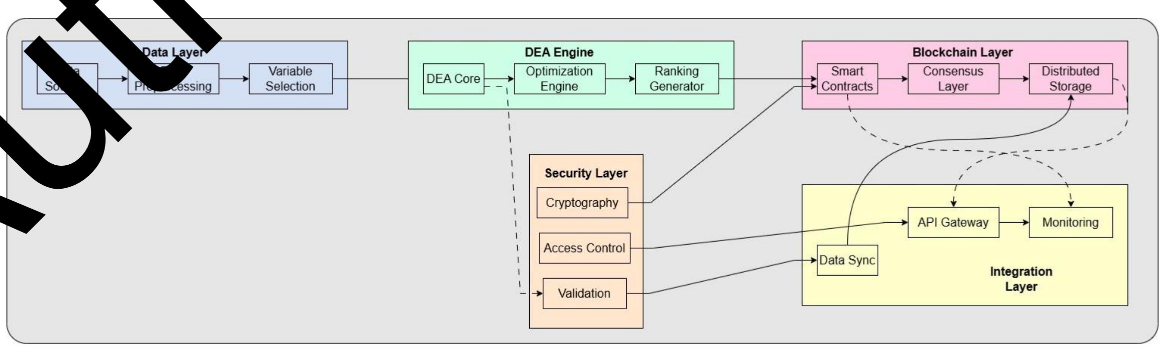

Figure 1: The proposed DEA + BT Model

The DMU uses the DEA to evaluate the efficiency of multiple enterprises. The DEA employs a linear programming method to consider multiple inputs and outputs, including operating expenses, capital costs, and working capital. The efficiency score is determined by solving an optimization problem that maximizes the weighted sum of outputs to the weighted sum of inputs [13].

This score is denoted as E_j for the j-th enterprise, is expressed as Eq. (1).

$$E_j = \max\left(\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}\right), \quad (1)$$

Subject to the constraint that the efficiency score of any other enterprise $'k'$, represented by $'E_k'$, does not exceed 1, *i.e.*, Eq. (2).

$$\frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1,\ \forall k = 1,2,\dots,n. \quad (2)$$

Where,

- x_{ij}→ The i-th input for enterprise
- j, y_{rj}→ The r-th output for enterprise
- j, while u_r and v_i d→ The weights assigned to outputs and inputs.

The enterprises are ranked based on their efficiency scores, with higher scores indicating superior performance in OCF efficiency.

The DEA phase generates efficiency scores and rankings, which are securely recorded on a blockchain (BT) using a decentralized, tamper-proof ledger: cryptographic hashing and CM-secure BT data. Input-output data, information called metadata, and the performance scores generated by DEA are all included with every BT transaction. As a safety measure during testing, the BT prevents users from updating those findings provided all in the network accept [14].

Asymmetric encryption and SHA-256 hashing are two examples of the cryptographic methods implemented by the model's BT module to secure data and prevent tampering. To prevent illegal activity and data tampering, consensus methods such as Practical Byzantine Fault Tolerance (PBFT) and Proof of Work (PoW) validate and verify DEA results [15].

The DEA + BT integration is reduced by systematic data flow. The DEA module determines efficiency scores from Business financial data and presents them into transactions for validation. Smart contracts in the BT automate DEA result verification, reducing human error and improving system efficiency [16]. This improves system efficiency. The proposed model improves business OCF ranking with DEA + BT security and transparency. It ensures accurate, verifiable, and unmanipulated economic tests, thereby enhancing the credibility of the ranking process and providing users with a reliable tool for informed decision-making [17].

2.2. DEA for OCF Ranking

The proposed model evaluates companies by OCF performance using the DEA, a non-parametric linear programming method. This method, which can manage multiple inputs and outputs without a practical relationship, is appropriate for financial efficiency evaluations in businesses with distinct scenarios and resource constraints [18].

i. **Input-Output Model for Ranking Enterprises:** The OCF ranking ranks each organization as a DMU based on inputs (Resources) and outputs (Financial Gains). Table 1 provides typical OCF efficiency inputs and outputs. The DEA measures an enterprise's input-to-output efficiency to others in the dataset. Each business's efficiency score indicates how effectively it maximizes outputs while minimizing inputs.

Table 1: Parameters of Inputs and Outputs

Class	Variable	Description
Inputs	OPEX	Operating Expenses
	CAPEX	Capital Expenditure
	Working Capital	Working Capital Management
Outputs	Cash Inflow	Net Operating Cash Inflow
	Growth	Revenue Growth
	Profitability	Profitability Ratio

i. **Mathematical Formulation of DEA:** The competence score of an enterprise, signified as E. For the j-th enterprise (DMU $'j'$), it is computed by solving an optimization problem. The DEA employed here is the input-oriented Charnes, Cooper, and Rhodes (CCR), which assumes Constant Returns-to-Scale (CRS) [19]. The efficiency score is defined as the ratio of the weighted sum of outputs to the weighted sum of inputs, Eq. (3) and Eq. (4).

$$E_j = \text{Max}\left(\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}\right), \tag{3}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \le 1,\ \forall k = 1,2,\dots,n \tag{4}$$

Where:

- y_{rj}→ The r-th output for enterprise $'j'$.
- x_{ij}→The i-th input for enterprise $'j'$.
- u_r→ The weight assigned to output $'r'$.
- v_i→ The weight assigned to input $'i'$.
- s→ The number of outputs.
- m→ The number of inputs.
- n→ The number of enterprises (DMU).

The weights u_r, v_i are determined through the optimization process to maximize the efficiency score for each enterprise. The constraint ensures that the efficiency score of any other enterprise $'k'$ does not exceed 1, maintaining the relative efficiency evaluation [20].

ii. **Dual Formulation for Computational Efficiency:** The above fractional program can be converted into a linear programming problem (Dual Form) to facilitate computation. The input-oriented CCR dual model for DMU j is assumed by Eq. (5).

$$\text{Min}\,\theta_j \tag{5}$$

Subject to, Eq. (6)

$$\begin{gathered} \sum_{k=1}^{n} \lambda_k x_{ik} \leq \theta_j x_{ij},\ i = 1,2,\dots,m \\ \sum_{k=1}^{n} \lambda_k y_{rk} \geq y_{rj},\ r = 1,2,\dots,s \\ \lambda_k \geq 0,\ \forall k = 1,2,\dots,n \end{gathered} \tag{6}$$

Where:

- θ_j→ The efficiency score of DMU $'j'$.
- λ_k→ The weights of the peer enterprises that form the reference set for DMU $'j'$.

An enterprise is considered efficient if $\theta_j = 1$ and inefficient if $\theta_j < 1$. Efficient enterprises operate on the DEA efficiency frontier, while inefficient enterprises lie below this frontier and can improve their efficiency by optimizing their input-output combinations.

iii. **Efficiency Scores and Ranking:** Once the DEA is solved for each enterprise, the resulting efficiency scores are used to rank them. Enterprises with higher efficiency scores are ranked higher, reflecting their superior ability to generate OCS relative to their resource expenditure. For example, an efficiency score of 1 indicates that an enterprise is operating efficiently, whereas a score of 0.85 proposes that the enterprise is operating at 85% efficiency and has room for improvement.

The DEA results provide valuable insights for financial analysts, enterprise managers, and investors by identifying which enterprises perform efficiently and which require strategic interventions to enhance their OCF performance. This ranking process forms the basis for secure recording and verification in the subsequent BT phase of the proposed framework, ensuring that efficiency evaluations are transparent, immutable, and resistant to manipulation.

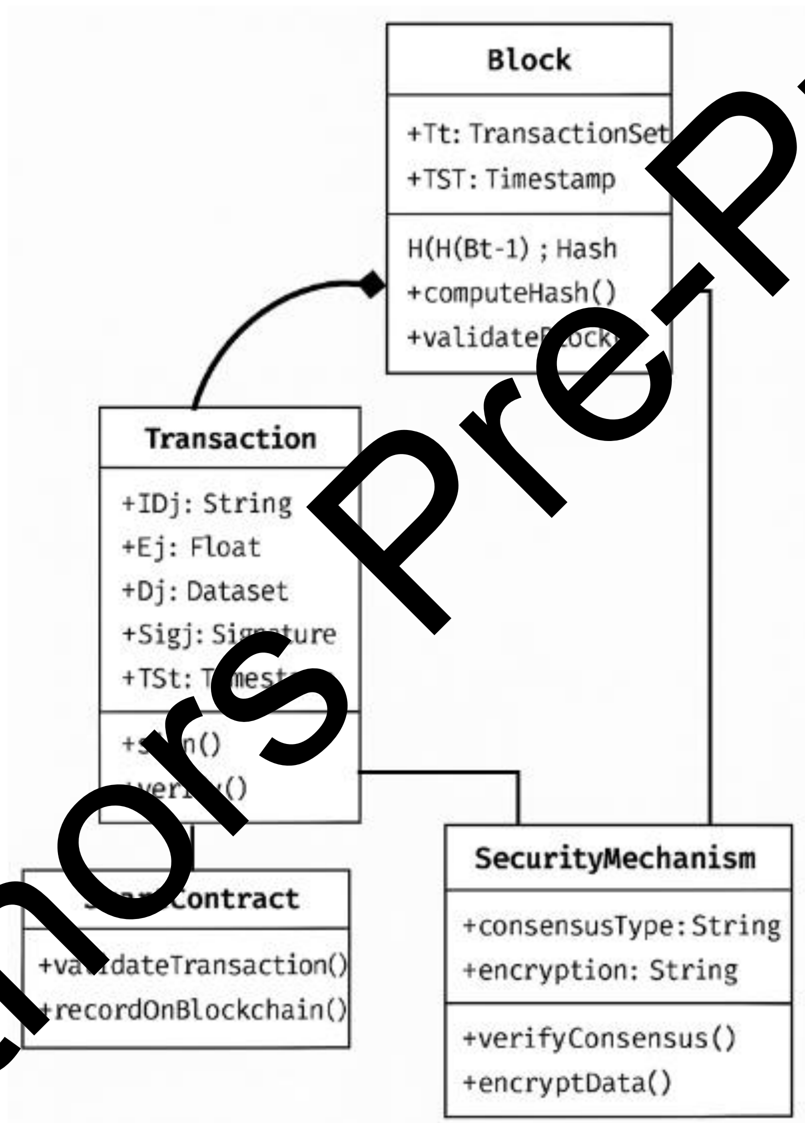

Figure 2: BT class diagram

2.3 BT Design

The proposed BT (Figure 2) ensures the security, integrity, and transparency of DEA-generated OCF rankings by leveraging a decentralized and robust network security model. The model is designed around a network of nodes as $N = \{n_1, n_2, \dots, n_p\}$, where each node $'n_i'$ maintains a complete copy of the BT ledger. Distributed design enhances resilience by ensuring multiple redundant data copies across the network, with each node validating transactions and maintaining consensus, thereby reducing the risks associated with centralized storage systems.

A block B_t In the BT, it is defined as Eq. (7).

$$B_t = \{H(B_{t-1}), T_t, \mathrm{TS}_t\} \tag{7}$$

Where:

- $H(B_{t-1})$→ The cryptographic hash of the previous block B_{t-1} ensures immutability and continuity in the BT.
- T_t→ The set of transactions recorded in the current block.
- TS_t→ The timestamp when the block was created.

Each transaction T_t^j records the DEA results for an enterprise $'j'$ and can be expressed as Eq. (8).

$$T_t^j = \{\mathrm{ID}_j, E_j, D_j, \mathrm{Sig}_j, \mathrm{TS}_t\} \tag{8}$$

Where:

- ID_j→ The unique identifier for enterprise $'j'$.
- E_j→ The DEA efficiency score for enterprise $'j'$, computed as Eq. (9).

$$E_j = \max\left(\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}\right), \tag{9}$$

Subject to Eq. (10).

$$\frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1,\ \forall k = 1,2,\ldots,n \tag{10}$$

Where:

- D_j→ The dataset used for the DEA computation for enterprise 'j' includes both input and output data.
- Sig_j→ The digital signature is generated by the enterprise's private key to guarantee its authenticity.
- TS_t→ The timestamp of the transaction.

The BT uses a cryptographic hash function H (*e.g.,* SHA-256) to secure the contents of each block. The hash of a block $'B_t'$ is computed as Eq. (11)

$$H(B_t) = \mathrm{SHA}-256(H(B_{t-1}) \| T_t \| \mathrm{TS}_t), \tag{11}$$

Where,

- ‖→ Concatenation.

This hash serves as the block's unique identifier, ensuring that any data modification results in a different hash, thereby preserving data integrity. PoW, or Practical Byzantine Fault Tolerance (PBFT), is implemented as a consensus mechanism to add only valid blocks to the BT in the proposed framework. In PoW, nodes solve a computational puzzle by finding a nonce $Nonce_t$ such that Eq. (12).

$$H(B_t \parallel Noncet) < \text{Target} \tag{12}$$

Where,

- The Target is a predefined difficulty threshold.

PBFT utilizes voting rounds to achieve consensus, making it energy-efficient and suitable for efficient financial validation. Smart Contracts (SC) improve BT automation and security. SC = Eq. (13).

$$SC\colon \left\{ \text{If valid } \left(T_t^j\right) \text{ then record } T_t^j \text{ on BT } \right\} \tag{13}$$

To reduce human intrusion and error risk, the SC automates DEA result validation to meet predefined measures before recording on the BT. Data transmission is secured by asymmetric encryption using Public Key Infrastructure (PKI) from BT. Each enterprise uses a private key K_j^{Priv} to sign the transaction, and other network users use the corresponding public key K_j^{Pub} to verify it, Eq. (14).

$$\text{Sig}_j = \text{Sign}\left(K_j^{\text{priv}}, T_t^j\right), \text{Verify}\left(K_j^{\text{pub}}, T_t^j, \text{Sig}_j\right) \tag{14}$$

This mechanism ensures that only authorized entities can submit DEA results, and any tampering with the transaction will render the signature invalid. Transport Layer Security (TLS) secures data interception, firewalls, IDS, and DDoS to prevent malicious attacks on the BT. DEA-based OCF rankings are secure, transparent, and tamper-proof due to decentralization and a permanent state.

2.4. Integration Mechanism

The DEA + BT idea secures and provides business OCF rankings. Data integrity, transparency, and tamper-proofing are ensured. DEA efficiency scores are verified by BT nodes and securely recorded on the BT. BT results cannot be altered due to its decentralized and immutable nature. The business name, efficiency result, input-output data, timestamps, and digital signature for authenticity are in DEA transactions. A transaction for enterprise j can be represented as Eq. (15).

$$T_j = \{\mathrm{ID}_j, E_j, \{x_{ij}, y_{rj}\}, \mathrm{TS}_j, \mathrm{Sig}_j\}. \tag{15}$$

Where,

- ID_j → The unique identifier for enterprise j.
- E_j → The DEA efficiency score for enterprise j.
- x_{ij} → The set of inputs, such as operating costs
- y_{rj} → The outputs, such as net cash inflow or revenue growth.
- TS_j → The timestamp indicates when the transaction was created.
- Sig_j →The digital signature, ensuring authenticity, computed as Eq. (16).

$$\mathrm{Sig}_j = \mathrm{Sign}\left(K_j^{\mathrm{priv}}, T_j\right). \tag{16}$$

The signature is generated using the enterprise's private key K_j^{priv} and can be verified using the corresponding public key K_j^{pub} with the verification function, Eq. (17).

$$\mathrm{Verify}\left(K_j^{\mathrm{pub}}, T_j, \mathrm{Sig}_j\right) \tag{17}$$

The BT broadcasts a transaction, which is verified by nodes through digital signatures and data integrity. If successful, the transaction is considered valid and grouped with other verified transactions to form a block, referred to as 'B_t'. Each block contains a set of transactions, timestamps, and previous block hash, as shown in Eq. 18.

$$B_t = \{H(B_{t-1}), T_t, \mathrm{TS}_t\} \tag{18}$$

Where,

- $H(B_{t-1})$ → The cryptographic hash of the previous block is used to link the new block to the BT.

The hash for the current block is generated using the SHA-256 hashing function, Eq. (19).

$$H(B_t) = \mathrm{SHA} - 256(H(B_{t-1}) \| T_t \| \mathrm{TS}_t) \tag{19}$$

To ensure the validity of new blocks, the BT deploys a consensus mechanism, such as PoW or Practical Byzantine Fault Tolerance (PBFT). In PoW, nodes solve a computational challenge by finding a nonce Nonce_t that satisfies the condition, Eq. (20).

$$H(B_t \, \| \, \mathrm{Nonce}_t) < \mathrm{Target}. \tag{20}$$

PBFT involves consensus-building by voting, validating blocks if the majority agrees, adding them to BT, and updating ledger copies among nodes. Each node in the BT decentralized system maintains a similar record of DEA results, ensuring tamper-proof results. Data exchanged between the DEA module and BT nodes is encrypted using TLS. This integration mechanism provides a robust, secure, and transparent enterprise OCF ranking solution that ensures confidential, secure, and interception-free data transmission, boosting financial evaluation trust and accountability.

3. Experimental Setup

3.1 Enterprise Data

The research study utilizes the SEC Financial Statement Data Sets and Kaggle Financial Data, comprising more than 4,400 publicly held companies, to rank businesses based on OCF using DEA. The SEC Financial Statement Data Sets provide statistics derived from US corporate financial reports encoded in eXtensible Business Reporting Language (XBRL). For ease of comparison, they have been reduced and include core financial statement footnotes. Applications up until the last business day of the previous financial year are included in quarterly datasets. Informational fields for businesses are included in the Standard Industrial Classification (SIC) framework. Financial data, including sales, profits, and employee counts, for over 4,400 publicly listed companies can be attained on Kaggle. For industry analysis, economic investigation, and developing business strategies, this data provides operational and financial insights. After maintaining and normalizing the datasets, they are aligned with financial periods to ensure data consistency and quality. To ensure that the DEA and OCF rankings accurately reflect the business's true financial results, these steps are essential.

3.2 BT Network Configuration

Enterprise OCF rankings data are stored and verified securely using the proposed model's BT, which ensures data integrity, transparency, and security against tampering. Identifying key factors, selecting suitable elements, and implementing security measures are all essential steps in the setup procedure to ensure the system's reliability. Only authorized users can validate transactions and maintain the transaction register on the BT, as it is a network that requires permission. It's suitable for trust- and confidentiality-sensitive applications related to finances. Ten to twenty nodes make up the network. Some nodes, known as "full nodes," are responsible for maintaining the entire blockchain and participating in the validation process. Other nodes, referred to as "light nodes," store a subset of the blockchain and rely on full nodes for verification.

The BT uses PBFT for consensus, which is ideal for permissioned BT due to its low End-to-End Delay (EED) and high Network Throughput (NT). It can process up to 1,000 Transactions Per Second (TPS). Nodes vote on transaction validity, ensuring only legitimate transactions are added, reducing malicious activities, and improving network reliability.

The BT uses an immutable chain model with each block containing transaction data, a timestamp, and a cryptographic hash. It uses SHA-256 for data integrity and generates unique hashes for each block. Transactions are secured using Public Key Infrastructure (PKI), with digital signatures ensuring the authenticity of data. Enterprises sign transactions with their private keys, and network nodes verify these signatures using public keys. The BT utilizes Hyperledger Fabric for permissioned blockchain development, offering features such as smart contracts (SC), identity management, and secure communication. SC, written in Go or JavaScript, automates verification and recording of DEA results, ensuring only verified DEA efficiency scores and rankings are recorded on the BT. The network configuration features a 1 MB block size for multiple DEA transactions and a 10-second block time, optimizing transaction speed and validation efficiency. TLS encrypts data transmission, while firewalls and IDS protect the network from unauthorized access and potential cyber-attacks. The network utilizes tools such as Prometheus and Grafana to monitor node performance, transaction rates, and system health. Regular updates ensure security and efficiency. This BT network configuration offers a transparent platform for storing and validating DEA-generated OCF rankings, enhancing the integrity of enterprise financial evaluations.

Table 2: BT Configuration Parameters

Parameter	Description	Value / Range
Consensus Mechanism	The protocol used to achieve agreement on the BT.	PBFT, PoW
Block Size	The maximum size of data that a block can hold.	1 MB
Block Time	The time interval for creating new blocks.	10 Seconds
Transaction Throughput	The number of transactions the network can process per second.	1,000 TPS

Number of Nodes	The total number of nodes in the BT network.	10 to 20 nodes
Cryptographic Hashing	The algorithm is used to generate unique hashes for blocks.	SHA-256
Digital Signature Algorithm	The method used for signing and verifying transactions.	ECDSA (Elliptic Curve Digital Signature Algorithm)
Network Type	The type of BT deployment.	Permissioned
Smart Contract Language	The programming language used to write SC.	Go, JavaScript
Ledger Database	The database is used to store the BT state.	LevelDB, CouchDB
Encryption Protocol	The protocol is used for secure communication between nodes.	TLS
Block Validation Time	The time taken by nodes to validate a block.	2 to 5 seconds
Fault Tolerance	The proportion of faulty nodes the network can handle.	Up to 33% (for PBFT)
Monitoring Tools	Tools used to monitor network health and performance.	Prometheus, Grafana

4. Results and Analysis

4.1 DEA Effectiveness

The experimental results prove the superior performance of the proposed DEA + BT in terms of Technical Efficiency Accuracy (TEA) (Figure 3) and Ranking Consistency (RC) (Fig. 4) across two comprehensive datasets. Analysis of the TEA reveals that the proposed model achieves significantly higher accuracy rates of 94.7% and 95.2% for the SEC and Kaggle datasets, respectively, compared to the traditional DEA, which generates accuracy rates of 85.3% and 84.9%. This represents an average improvement of approximately 10% over conventional methods.

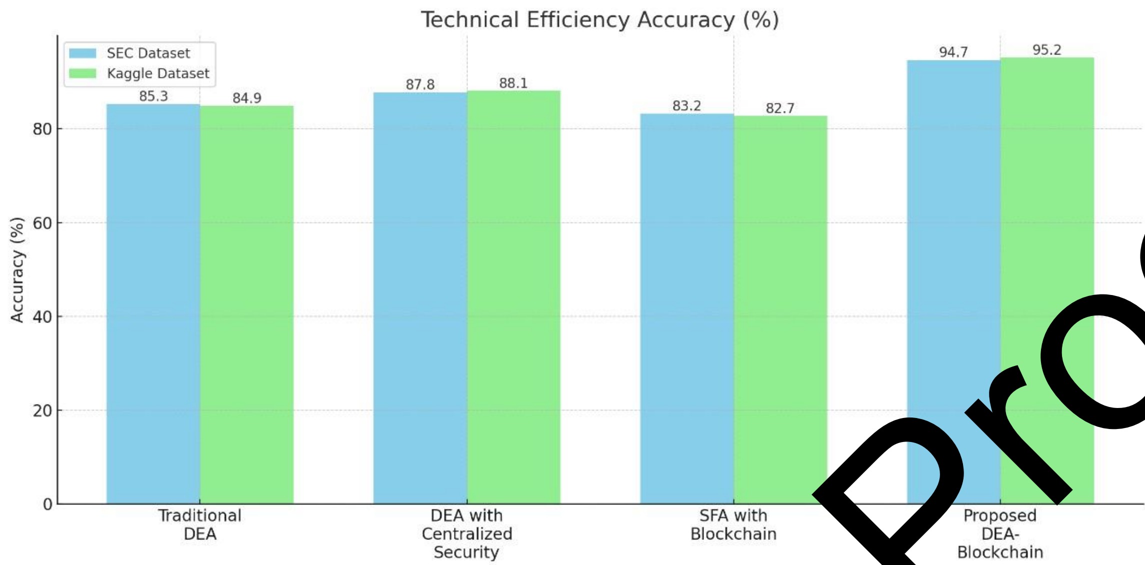

Figure 3: Analysis of TEA

Figure 4: Analysis of RC (Spearman's Correlation)

The DEA with the Centralized Security Model (CSM) shows moderate improvement over the traditional method, achieving accuracy rates of 87.8% and 88.1%, indicating that enhanced security measures contribute to improved accuracy. However, the SFA with BT proves slightly lower accuracy (83.2% and 82.7%), signifying that the stochastic approach, despite BT integration, may not be as practical for OCF ranking as the proposed deterministic DEA.

In terms of RC, measured using Spearman's Correlation coefficient, the proposed model exhibits superior performance with correlation values of 0.864 and 0.857 for the respective datasets. This represents a significant improvement over the traditional DEA

(0.751 and 0.748) and the CSM (0.783 and 0.775). The higher correlation coefficients indicate more substantial rank agreement and a more reliable assessment of enterprise performance. Notably, the SFA with BT shows the lowest ranking consistency (0.728 and 0.715), further supporting the superiority of the DEA for this application.

The proposed hypothesis is robust because the results remain similar across both datasets; however, they display distinct features and encompass different periods. Results from an extensive range of financial contexts, including the SEC and Kaggle, indicate that the proposed approach is robust and reliable. Additionally, there is minimal variation in metrics across datasets, demonstrating that the model's efficacy is not dependent on the specific datasets used. According to the research, the recommendation for DEA + BT enhances consistency, accuracy, and efficiency in ratings by making the ranking process more secure and transparent. This is because a more reliable basis for enterprise OCF ranking developed when DEA's analytical skills and BT's secure data handling were combined.

4.2. BT Performance

The proposed DEA + BT is compared against alternative models, including Traditional DEA, DEA with CSM, and Stochastic Frontier Analysis with BT, using SEC + Kaggle financial data from over 4,400 public companies. Results show significant improvements in transaction PT, FRD reduction, and security effectiveness.

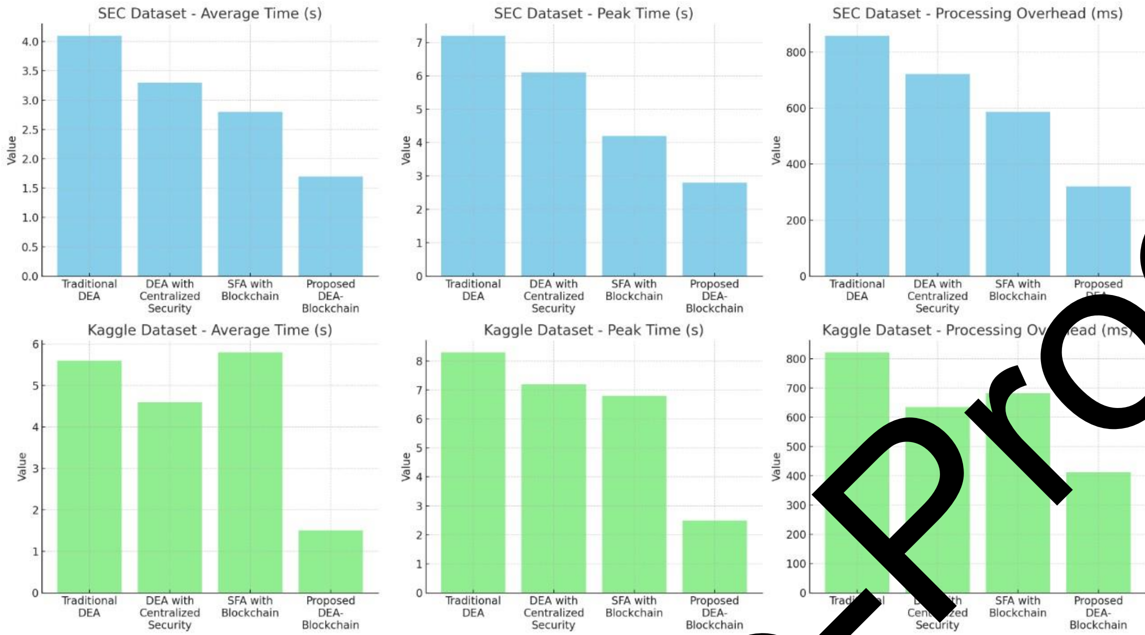

Figure 5: Transaction Speed (TPS-Transactions Per Second)

Figure 5 shows TPS and EED for each model across datasets, with Traditional DEA achieving an average TPS of 954 for SEC and 92[illegible] for Kaggle. However, the EED for Traditional DEA is relatively high, with values of 252 *ms* for the SEC and 260 *ms* for Kaggle. These results indicate that while Traditional DEA can handle a moderate volume of transactions, its higher EED limits real-time processing efficiency.

The DEA with CSM shows slight improvements, with an average TPS of 980 for the SEC and 967 for the Kaggle and peak TPS values of 1212 and 1150. EED is reduced to 208 and 218 *ms*. This improvement can be attributed to the enhanced security mechanisms, though the centralized nature still poses a bottleneck for scalability and real-time performance.

The SFA with BT performs better than the previous models, achieving an average TPS of 1050 for the SEC and 1020 for the Kaggle, with peak TPS reaching 1300 and 1251, respectively. EED is significantly reduced to 187 and 190 *ms*. The integration of BT helps decentralize the security processes, improving NT and reducing EED by ensuring faster consensus and validation times.

The Proposed DEA + BT outperforms all other models, achieving the highest average TPS of 1253 for the SEC and 1207 for the Kaggle. The peak TPS values reach 1500 and 1450. The EED is the lowest among all models, recorded at 120 *ms* for the SEC and 125 *ms* for the Kaggle. These improvements stem from the decentralized nature of BT, optimized CM, and the efficiency of the DEA in processing financial data. The reduced EED ensures real-time validation and recording of DEA results, making the system highly efficient for large-scale enterprise evaluations.

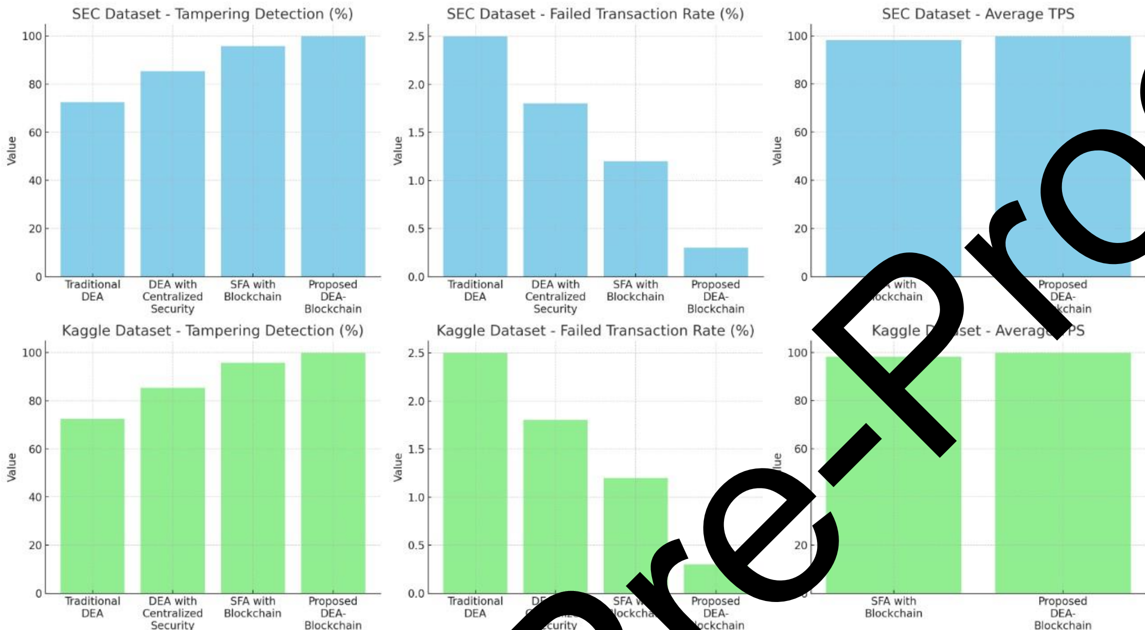

Figure 6: Security Effectiveness

Figure 6 highlights the security effectiveness of each model, focusing on metrics such as Consensus Rate (CR), Tampering Detection (TD), and Failed Transaction Rate (FTR). The Traditional DEA lacks a consensus mechanism and achieves a TD rate of only 72.5% for the SEC and 71.8% for the Kaggle. The FTR is relatively high at 2.5% and 2.8%, reflecting data integrity and security vulnerabilities.

The DEA with CSM demonstrations improved TD rates to 85.3% for the SEC and 84.1% for Kaggle, with lower FTRs of 1.8% and 2.0%. However, the absence of a decentralized consensus mechanism still poses risks, as the centralized system remains susceptible to single points of failure. The SFA with BT demonstrates a significant leap in security, achieving a consensus rate of 98.5% for the SEC and 98.2% for the Kaggle. TD rates improve to 95.8% and 92.9%, with FTR dropping to 1.2% and 1.4%, respectively. BT integration enhances data integrity by ensuring that all transactions are verified and recorded transparently.

The proposed DEA + BT achieves near-perfect security performance. The SEC and Kaggle have a high CR of 99.9% and 99.9% for TD. This performance is attributed to a decentralized validation process, robust cryptographic methods, and the immutability of the BT ledger. The low FTR indicates high reliability in recording and verifying DEA results.

4.3 Integration Efficiency

The proposed DEA + BT's integration efficiency is assessed by comparing System Response Times (SRT) and data integrity metrics with other models, including Traditional DEA, DEA with CSM, and SFA with BT, using two datasets: the SEC Financial Statement Data Set and Kaggle Financial Data, showing significant improvements in SRT, processing overhead, and data integrity.

Figure 7: Analysis of SRT

Figure 7 displays the SRT for each model across two datasets. Traditional DEA has the highest SRT (4.1 *Sec*) and peak time (7.2 *Sec*) for the SEC, while Kaggle has an average SRT (5.6 *Sec*) and peak time (8.3 *Sec*). Both models have high processing overheads (858 and 822 *ms*). These results indicate inefficiencies in handling large datasets, resulting in slower processing and higher EED.

The DEA with CSM shows moderate improvements over the Traditional DEA. The average SRT for the SEC is 3.3 *Sec*, with a peak time of 6.1 *Sec*. For the Kaggle, the average response time is 4.6 *Sec*, with a peak time of 7.2 *Sec*. Due to improved security measures, the processing overhead is reduced to 721 and 635 *ms*. However, the centralized architecture still introduces bottlenecks, affecting scalability and real-time performance.

The SFA with BT performs better, achieving an average SRT of 2.8 *Sec* and a peak time of 4.2 *Sec* for the SEC. The Kaggle shows an average SRT of 5.8 *Sec* and a peak time of 6.8 *Sec*. Processing overhead is reduced to 586 and 683 *ms*. The integration of BT enhances processing efficiency by decentralizing validation, though the stochastic nature of SFA introduces variability in processing times.

The Proposed DEA + BT achieves the best performance among all models. For the SEC, the average response time is just 1.7 *Sec*, with a peak time of 2.8 *Sec* and a processing overhead of 320 *ms*. The Kaggle shows an average SRT of 1.5 *Sec*, a peak time of 2.[illegible] *Sec*, and a processing overhead of 412 *ms*. These results reflect the efficiency of the decentralized BT combined with the streamlined DEA computations. The lower SRT and reduced processing overhead enable faster data validation and recording, making the system highly efficient for large-scale enterprise evaluations.

Figure 8: Data Integrity

Figure 8 evaluates data integrity using three key metrics: Verification Rate (VR), Data Consistency (DC), and Error Detection Rate (EDR). The Traditional DEA shows the weakest performance, with VRs of 77.8% for the SEC and 74.8% for Kaggle. DC is 81.2% and 81.9%, respectively, while EDR is relatively low at 69.4% and 77.5%. These figures highlight the vulnerabilities of traditional systems in maintaining data integrity.

The DEA with CSM improves upon Traditional DEA, achieving VR of 81.2% for the SEC and 83.7% for the Kaggle. DC is enhanced to 89.6% and 87.9%, while EDR increases to 83.6% and 85.8%. The centralized security measures help detect errors more effectively, though the lack of decentralization poses risks of single points of failure.

The SFA with BT demonstrates further improvements, with VR of 8[illegible].9% for the SEC and 93.9% for the Kaggle. DC reaches 91.2% and 90.6%, while EDR rises to 89.6% and 93.2%. The BT integration enhances the integrity and consistency of the data by ensuring that all transactions are validated and recorded transparently.

The Proposed DEA + BT achieves the highest data integrity metrics. The VR is 96.3% for the SEC and 97.8% for the Kaggle. DC reaches 9[illegible].7% and 96.9%, while error detection rates are 98.6% and 98.9%. These results demonstrate the robustness of the decentralized validation process, the cryptographic security, and the immutability of the BT ledger. The high VR ensures that all recorded data is accurate and verifiable, while the low error rates indicate minimal discrepancies during data processing.

4.4. Resource Efficiency

The resource efficiency of the proposed DEA + BT is evaluated by comparing its computational overhead (Figure 9) and storage optimization (Figure 10) with those of other models: Traditional DEA, DEA with CSM, and SFA with BT. The analysis utilizes the SEC Financial Statement Data Set and Kaggle Financial Data, which includes over 4,400 public companies. The results prove how the proposed DEA + BT efficiently utilizes computing resources and optimizes storage requirements.

Figure 9: Computational Overhead

The Traditional DEA shows the lowest CPU and Memory Usage (MU), with 47.3% CPU usage and 1.4 GB of memory for the SEC and 42.8% CPU usage and 1.1 GB for Kaggle. However, despite low Resource Consumption (RC), the Execution Times (ET) of 3.5 and 2.8 Sec. highlight inefficiencies due to the lack of integrated security and decentralized validation.

The DEA with CSM increases CPU and MU slightly, with CPU usage at 53.6% and MU of 1.6 GB for the SEC. ET increased to 4.2 and 4.0 seconds on Kaggle. The added security processes generate higher RC and slower ET than Traditional DEA.

The SFA with BT increases CPU usage to 58.5% and MU to 1.8 GB for the SEC, with ET of 4.1 *Sec*. For the Kaggle, CPU usage reaches 56.2%, and MU is 1.7 GB, with ET of 4.5 *Sec*. While BT integration improves security, the stochastic nature of SFA contributes to higher RC and slightly longer ET.

The Proposed DEA + BT shows the highest CPU and MU due to BT's decentralized processing and cryptographic operations. For the SEC, CPU usage is 63.4%, and MU is 2.1 GB, with the fastest ET of 3.2 *Sec*. For the Kaggle, CPU usage is 61.8%, MU is 2.0 GB, and ET is 4.1 *Sec*. The efficiency gains from BT's optimized CM offset the increased RC, resulting in faster ET despite higher RC.

Figure 10: Storage Optimization

The Traditional DEA has the most minor storage requirements, with 2.5 GB for the SEC and 2.2 GB for the Kaggle. However, it proposes no compression and shows a high Data Redundancy Rate (DRR) of 25.5% and 24.8%. This redundancy indicates inefficiencies in data storage.

The DEA with CSM increases storage size to 3.2 GB and 2.9 GB, with a compression ratio of 1.2:1 and a reduced DRR of 22.3% and 21.5%. The added security layers contribute to higher storage needs but slightly improve data redundancy.

The SFA with BT requires significantly more storage, with 4.8 GB for the SEC and 4.5 GB for the Kaggle. The compression ratio improves to 1.5:1, and DRR is reduced to 15.8% and 15.2%. BT's distributed ledger and cryptographic validation increase MU demand but enhance data integrity.

The Proposed DEA + BT has the highest storage requirements, with 5.2 GB for the SEC and 4.9 GB for the Kaggle. However, it achieves the best compression ratio of 2:1 and the lowest DRR of 12.4% and 11.8%. This improvement is attributed to BT's efficient storage mechanisms, including transaction compression, deduplication, and decentralized validation, which optimize storage without compromising data integrity.

5. Conclusion and Future Work

The objective of the present study was to develop a novel network to enhance the openness, security, and accuracy of business OCF rankings by combining DEA and BT, driven by network security. There are three dimensions in which conventional DEA models are lacking: computational efficiency, data integrity, and operational transparency. The use of BT in the model ensures decentralized validation, the implementation of cryptographic security, and the storage of permanent records. The proposed model achieved better results than standard DEA, DEA with CSM, and SFA with BT when evaluated on the SEC Financial Statement Data Set and the Kaggle Financial Data, which encompassed over 4,400 public companies. It secured the system with a 99.9% CR and TD, reduced EED to 120 *ms* and boosted transaction speed to 1253 TPS. Better technical efficiency accuracy (up to 95.2% of the time) and higher RC (Spearman's value of 0.864) were additionally verified by the model. To solve some of the problems with the previous methods of doing enterprise OCF ranking, this integration provides an improved approach that is secure, transparent, and robust.

It can be achieved that future work will be focused on improving scalability, optimizing the operational efficiency of BT, and applying Deep Learning (DL) in order to improve the accuracy of ranking further.

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