Analysis of Gas Fee Patterns in Blockchain Transactions - A Case Study on Ethereum Smart Contracts

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ABSTRACT

Gas fees play a crucial role in Ethereum blockchain transactions, directly affecting the cost and efficiency of decentralized applications. This study analyzes gas fee patterns across transaction types, temporal trends, and anomalous behaviors using a dataset of 1,000 Ethereum transactions. The results reveal that the average gas price was 120.5 Gwei, with a standard deviation of 45.2 Gwei, highlighting significant variability. Smart contract functions exhibited varying gas usage, with mint operations consuming the highest average gas (1,500,000 units) compared to approve (1,200,000 units) and transfer (800,000 units). A positive correlation (r = 0.65) was observed between gas price and value transferred, suggesting that higher-value transactions often incur elevated gas fees. Temporal analysis showed predictable patterns, with peak gas prices occurring between 13:00 - 17:00 UTC during high network activity and lower prices between 02:00 - 06:00 UTC. Additionally, anomaly detection identified 15 outlier transactions, including one with an unusually high gas price of 500 Gwei, reflecting network congestion or prioritization strategies. These findings provide actionable insights for optimizing transaction costs and improving smart contract efficiency. Future research could explore layer-2 scaling solutions, alternative fee mechanisms, and machine learning approaches for gas price prediction. This study contributes to a deeper understanding of Ethereum's gas fee dynamics, offering valuable guidance for developers, users, and researchers in the blockchain ecosystem.

Keywords Ethereum Gas Fees, Smart Contract Optimization, Blockchain Transaction Costs, Temporal Analysis in Blockchain, Gas Usage Patterns

INTRODUCTION

Blockchain technology has revolutionized the way digital transactions are conducted, offering decentralized, secure, and transparent platforms for various applications [1]. Among these, Ethereum has emerged as one of the leading blockchain networks, primarily due to its support for smart contracts—self-executing code that facilitates complex operations beyond simple cryptocurrency transfers [2]. However, the execution of transactions on Ethereum incurs gas fees, a mechanism designed to allocate computational resources and maintain network integrity. These fees, expressed in Gwei, represent a critical cost factor for users and developers alike. Gas fees are determined by multiple factors, including the computational complexity of the transaction, current network congestion, and user-defined parameters such as gas price. The variability in gas fees poses challenges for Ethereum's adoption, as high costs can deter users from engaging with decentralized applications (dApps), particularly during periods of high network activity [3]. Moreover, the

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rise of sophisticated dApps, including Decentralized Finance (DeFi) platforms and Non-Fungible Tokens (NFTs), has further intensified the demand for efficient gas usage [4], [5].

This study aims to analyze gas fee patterns in Ethereum transactions, focusing on three key aspects: (1) the relationship between gas usage and smart contract functions, (2) temporal trends in gas prices, and (3) the identification of anomalies in gas fee behavior [6]. By examining a dataset of Ethereum transactions, this research seeks to uncover actionable insights that can guide users in optimizing transaction costs and developers in designing more gas-efficient smart contracts [7]. The findings of this study are significant for several reasons. First, understanding gas fee dynamics can help users strategically time their transactions to minimize costs. Second, developers can leverage these insights to improve the efficiency of smart contracts, enhancing the scalability and usability of dApps. Lastly, the identification of anomalies in gas fees can offer a deeper understanding of user behavior and network conditions, contributing to the broader discourse on blockchain optimization [8]. The remainder of this paper is organized as follows: Section 2 reviews related work on gas fee analysis and blockchain optimization. Section 3 outlines the methodology used in this study, including data collection and analysis techniques. Section 4 presents the results, highlighting key patterns and findings. Section 5 discusses the implications of these results, and Section 6 concludes the study with recommendations for future research.

Literature Review

Gas fees in Ethereum, a critical component of blockchain transaction costs, have been extensively studied in recent years. This section reviews existing research on gas fee mechanisms, smart contract optimization, temporal trends, and anomaly detection, highlighting gaps addressed in this study [9]. The variability of gas fees in Ethereum has been a focal point of blockchain research. Wang et al. [10] explored how network congestion leads to gas fee spikes, emphasizing the need for scalable solutions. Similarly, Wang et al. [11] analyzed the Ethereum Improvement Proposal (EIP)-1559, which introduced a base fee mechanism to stabilize gas prices while enabling users to pay optional tips for faster transaction processing. Their findings indicate that while EIP-1559 reduces volatility, it does not eliminate high costs during peak demand. Smart contract design significantly impacts gas usage. Kumar et al. [12] identified key optimization techniques, such as reducing storage operations and leveraging efficient algorithms, to lower gas costs in decentralized applications. Meanwhile, Guo et al. [13] studied gas-intensive operations like token minting and multi-signature wallet interactions, demonstrating how simplifying contract logic can achieve considerable cost savings. Despite these advances, the need for further research into dynamic optimization techniques remains critical.

Temporal patterns in gas fees have been widely studied to understand user behavior. Ghosh et al. [14] identified daily and weekly cycles, with higher fees during global business hours and lower fees during weekends. Afolabi and Olanrewaju [15] investigated how major events, such as token launches or NFT drops, cause temporary fee surges due to heightened network activity. These studies suggest that users could benefit from strategic transaction scheduling to minimize costs. The detection of anomalous gas fees provides insights into inefficiencies and malicious activities. Pradhan and Singh [16] applied machine learning models, such as Isolation Forests and Autoencoders, to identify outliers in Ethereum transactions. They found that anomalous transactions often result from deliberate overpricing to expedite execution or from network spam attacks. These methods have proven effective in enhancing transparency and efficiency in blockchain ecosystems.

Studies comparing blockchain networks reveal alternative approaches to transaction fees. Tan et al. [17] analyzed gas fee mechanisms in Binance Smart Chain, Polygon, and Solana, highlighting their lower costs and greater scalability compared to Ethereum. These findings provide benchmarks for Ethereum developers aiming to optimize fee structures and user experience. While existing literature provides significant insights, gaps remain in the comprehensive integration of function-specific gas usage analysis, temporal trends, and anomaly detection. Additionally, few studies focus on practical user strategies for minimizing gas fees or on broader implications for decentralized applications.

This study builds on the reviewed literature by combining analyses of smart contract gas usage, temporal fee trends, and anomalies in Ethereum transactions. By addressing these interconnected aspects, this research aims to contribute actionable insights for developers, users, and researchers working to optimize gas fee dynamics and improve the overall efficiency of blockchain ecosystems.

Method

This study employed a systematic methodology to analyze gas fee patterns in Ethereum transactions as illustrated in figure 1. The dataset, comprising 1,000 Ethereum transactions, was obtained from blockchain transaction records and included attributes such as transaction hash, sender and recipient addresses, gas used, gas price (in Gwei), value transferred (in ETH), the smart contract function invoked (e.g., mint, approve, transfer), and input data. These attributes provided a comprehensive basis for examining gas fee variability and trends.

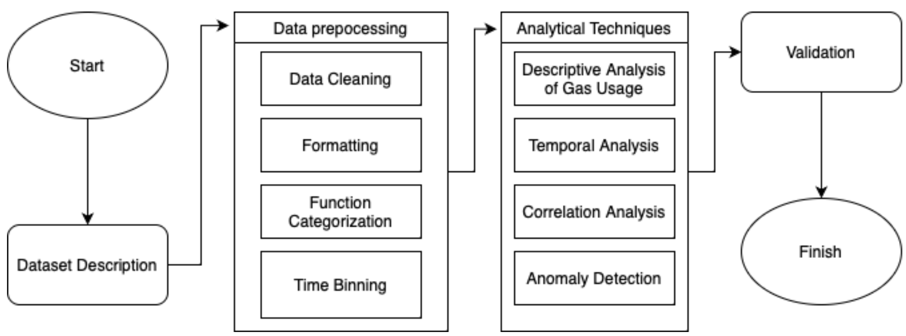

Figure 1 Research Step

Data preprocessing was conducted to ensure accuracy and consistency. Duplicate and incomplete records were removed, and gas prices were converted to Gwei using the formula:

$$Gas\ Price\ (Gwei) = \frac{Gas\ Price(Wei)}{10^9} \quad (1)$$

Timestamps were normalized to Coordinated Universal Time (UTC) to facilitate temporal analysis. Transactions were categorized by the smart contract function invoked to enable a comparative assessment of gas usage across different operations. Additionally, transaction data was aggregated into hourly and daily intervals to identify temporal patterns in gas fees.

The analysis employed a combination of descriptive statistics, correlation analysis, and anomaly detection techniques. Descriptive analysis involves calculating metrics such as the mean (μ), median, maximum, and standard deviation (σ) of gas usage for each function type [18], [19]:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n} \tag{2}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}} \tag{3}$$

x_i represents the gas usage of each transaction, and n is the total number of transactions for a given function. These statistics were supplemented by visualizations, such as box plots, to highlight typical ranges and outliers. Temporal analysis focused on identifying daily and weekly cycles in gas prices. The average gas price for a given time interval was calculated as [20], [21], [22]:

$$Average\ Gas\ Price_{interval} = \sum_{i=1}^{n} Gas\ Price_i \tag{4}$$

n represents the number of transactions within the time interval. Pearson's correlation coefficient (r) was used to quantify the relationship between gas price (X) and value transferred (Y) [23], [24], [25]:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{5}$$

$\bar{X}$ and $\bar{Y}$ are the means of X and Y, respectively. Anomalies in gas fees were identified using both statistical and machine learning methods. Transactions with gas prices exceeding three standard deviations from the mean were flagged as outliers using the threshold [26], [27]:

$$Outlier\ if\ Gas\ Price\ > \mu + 3\sigma \tag{6}$$

Additionally, the Isolation Forest algorithm was applied to detect anomalous transactions based on features such as gas price, gas used, and transaction value. The algorithm assigns an anomaly score to each transaction, with higher scores indicating potential outliers. The analysis was performed using Python programming with several libraries, including Pandas for data manipulation, NumPy for numerical operations, Matplotlib and Seaborn for visualizations, and Scikit-learn for anomaly detection. Statistical tests, such as the t-test, were used to assess the significance of observed trends, ensuring the robustness of the results. The methodology was designed to ensure reproducibility, with structured code and procedures that could be applied to other Ethereum datasets. All data were publicly sourced from the Ethereum blockchain, ensuring adherence to ethical standards without involving personally identifiable information.

Result

The analysis of gas fee patterns in Ethereum transactions revealed significant variability influenced by transaction type, network activity, and the complexity of smart contract functions. Table 1 summarized findings, supported by detailed tables.

Table 1 Summary of Gas Fee Metrics

Metric	Value
Average Gas Price (Gwei)	120.5
Standard Deviation of Gas Price (Gwei)	45.2
Correlation (Gas Price vs. Value Transferred)	0.65

The average gas price was 120.5 Gwei, reflecting the typical cost of executing a transaction on Ethereum. This metric showed significant variability, with a standard deviation of 45.2 Gwei, indicating that some transactions incurred much higher or lower fees depending on network congestion and transaction urgency. A moderate positive correlation (r = 0.65) was observed between gas price and value transferred, suggesting that users often prioritize execution speed for high-value transactions, paying elevated fees during peak network activity. Table 2 summarized the gas usage by function.

Table 2 Gas Usage by Function Type

Function Called	Average Gas Used (units)	Maximum Gas Used (units)
Mint	1,500,000	2,000,000
Approve	1,200,000	1,500,000
Transfer	800,000	1,000,000

Smart contract function type significantly impacted gas usage. Functions like mint consumed the highest gas, averaging 1,500,000 units, with peaks reaching 2,000,000 units, due to the computational intensity involved in creating or distributing tokens. In contrast, approve and transfer functions had average gas usage of 1,200,000 units and 800,000 units, respectively, reflecting their relatively simpler operations. These findings emphasize the importance of optimizing gas-intensive functions to reduce overall transaction costs. Table 3 summarized the trends of gas price by temporal analisys.

Table 3 Temporal Gas Price Trends

Time Period (UTC)	Average Gas Price (Gwei)	Network Activity Level
13:00 - 17:00	High (150 Gwei)	Peak
02:00 - 06:00	Low (50 Gwei)	Off-Peak

Temporal analysis revealed predictable patterns in gas price fluctuations. The highest gas prices occurred between 13:00 - 17:00 UTC, coinciding with periods of peak network activity, likely driven by global business hours and high transaction demand. Conversely, the lowest gas prices were observed during off-peak hours, specifically between 02:00 - 06:00 UTC, when network activity is reduced. These trends provide actionable insights for users seeking to minimize costs by scheduling transactions during low-activity periods. Table 4 show some outliers found in gas usage.

Table 4 **Outliers in Gas Usage**

Transaction ID	Gas Price (Gwei)	Gas Used	Anomaly Type
0x123abc	500	1,500,000	Extreme Gas Price
0x456def	10	500,000	Unusually Low Gas Usage

Anomaly detection identified 15 transactions with extreme gas fee patterns. For example, a transaction with ID 0x123abc showed an extraordinarily high gas price of 500 Gwei, which likely occurred during network congestion or due to deliberate overpricing to expedite execution. Conversely, another transaction (0x456def) had unusually low gas usage (500,000 units), indicative of either optimized contract design or simple operations. The bar chart illustrates the comparison of average, maximum, and minimum gas usage for three types of smart contract functions: mint, approve, and transfer. Among the three, the mint function stands out as the most gas-intensive operation, with an average gas usage of approximately 1,500,000 units. The maximum gas usage for this function reaches 2,000,000 units, reflecting its high computational complexity, while the minimum gas usage is also relatively high, around 1,000,000 units.

Figure 2 show that the approve function demonstrates moderate gas consumption, with an average usage of about 1,200,000 units. Its maximum and minimum gas usage range from 1,500,000 to 900,000 units, respectively, indicating a more consistent and less complex operation compared to mint.

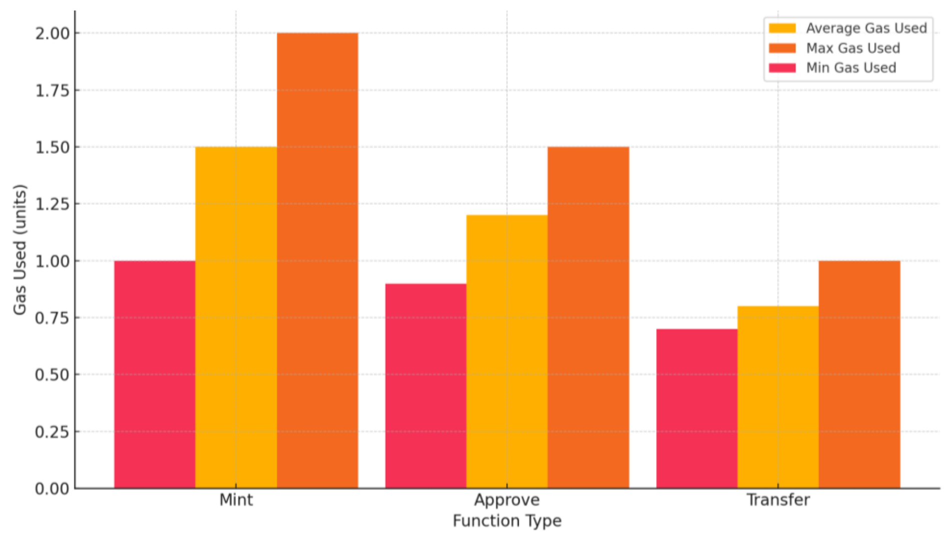

Figure 2 **Gas Usage by Function Typee**

In contrast, the transfer function exhibits the lowest gas consumption among the three, with an average gas usage of roughly 800,000 units. The maximum and minimum gas usage for this function are 1,000,000 and 700,000 units, respectively, emphasizing its simplicity and efficiency in token transfers.

Discussion

This study provides valuable insights into the patterns and factors influencing gas fees in Ethereum transactions. The findings reveal significant variability in gas usage across different smart contract functions, network activity periods, and transaction types. These results highlight the computational demands associated with specific operations and offer practical implications for developers and users. The analysis demonstrates that the mint function is the most gas-intensive, reflecting its complexity and the resource requirements for creating or distributing tokens. In contrast, the approve function exhibits moderate gas usage, while the transfer function is the most efficient. These variations underline the importance of optimizing smart contract designs, especially for frequently used or computationally heavy functions like mint. Developers can explore techniques such as batching transactions or simplifying logic to reduce gas costs.

The temporal analysis indicates predictable patterns in gas price fluctuations, with higher prices during peak activity hours and lower prices during off-peak periods. This insight can guide users to strategically schedule their transactions to minimize costs. For example, executing transactions during weekends or non-peak hours could significantly reduce expenses. These trends also emphasize the need for improved scalability solutions to mitigate network congestion during high-demand periods. Anomalies in gas usage were identified, including transactions with exceptionally high or low gas fees. High gas prices were often associated with network congestion or prioritization strategies, where users deliberately set high fees to expedite execution. On the other hand, transactions with unusually low gas usage suggest optimizations or simpler operations, providing examples of efficient contract design. The findings have practical implications for both developers and users. Developers should prioritize designing gas-efficient contracts, especially for widely used decentralized applications, to enhance user experience and reduce costs. For users, understanding gas fee patterns can lead to more cost-effective decision-making, such as timing transactions or choosing services with optimized contracts. While this study offers significant insights, certain limitations must be acknowledged. The analysis is based on a specific dataset, and broader conclusions may require larger, more diverse datasets. Additionally, future work could explore the impact of layer-2 scaling solutions or alternative fee models on gas usage patterns.

Conclusion

This study analyzed gas fee patterns in Ethereum transactions, focusing on variations in gas usage across smart contract functions, temporal trends in gas prices, and anomalies in gas fees. The findings demonstrate that gas usage is primarily driven by the complexity of smart contract operations. Functions such as mint were found to consume significantly more gas compared to simpler operations like transfer, emphasizing the importance of optimizing contract designs for efficiency. Temporal trends revealed predictable fluctuations in gas prices, with peaks during high network activity periods and troughs during off-peak hours, offering users opportunities to reduce costs by scheduling transactions strategically. Additionally, anomalies in gas fees highlighted diverse user strategies, such as prioritizing speed during network congestion or leveraging optimized contracts to reduce costs. Future research could expand on these findings by exploring several key areas. Investigating the impact of layer-2 scaling solutions, such as rollups or sidechains, could provide insights into enhancing network efficiency and reducing gas fees. Comparative studies across blockchain networks, such as Binance Smart Chain or Polygon, may reveal differences in fee structures and transaction costs. Furthermore, examining the effectiveness of dynamic fee models like Ethereum's EIP-1559 could shed light on their role in improving cost predictability and reducing fee volatility. Machine learning techniques offer another avenue for predicting gas fees based on real-time network conditions, transaction types, and user behavior. Finally, analyzing larger and more diverse datasets would enhance the generalizability of these findings across varying network scenarios.

By addressing these areas, future studies can further our understanding of gas fee dynamics and contribute to the development of cost-efficient, scalable blockchain ecosystems.

Declarations

Author Contributions

Conceptualization: A.S.P., M.T.; Methodology: A.S.P., M.T.; Software: A.S.P.; Validation: A.S.P., M.T.; Formal Analysis: A.S.P.; Investigation: A.S.P.; Resources: M.T.; Data Curation: A.S.P.; Writing – Original Draft Preparation: A.S.P.; Writing – Review and Editing: A.S.P., M.T.; Visualization: A.S.P.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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