An Analytical Study of Large Blocks on Ethereum

***Abstract*—Ethereum's application layer data, especially the analysis of large blocks, holds critical insights into its network dynamics and future developments. In this study, we systematically analyze various components of this data, including blocks, transactions, gas prices, and address interactions. This study places a significant emphasis on systematically analyzing Ethereum blocks of size 500KB and above, a crucial element considering the impending Ethereum Improvement Proposals (EIPs) like EIP4844. EIP4844 proposes the introduction of a new type of data, known as "blob data" specifically designed to be used in rollups, which are off-chain aggregation of transactions within a single on-chain transaction. Our analysis includes blocks, transactions, gas prices, and address interactions, with a special focus on the characteristics and implications of large block sizes. We observe notable trends such as block fullness, transaction count fluctuations, and gas price variations. Importantly, our findings reveal that a substantial number of Ethereum blocks exceed the expected size of 1.875MB, reaching up to 2MB. This is particularly relevant in the context of EIP4844, as many of these large blocks might be related to rollup data, which is a cornerstone of Ethereum's scalability strategy. We also discovered a moderate negative correlation between block sizes and number of transactions contained in them. Similarly, average daily gas prices tend to decrease with an increase in block sizes. These insights are invaluable for the blockchain community, offering guidance to developers and users for optimizing transaction strategies and managing costs in anticipation of future network changes. Our study not only contributes to a deeper understanding of Ethereum's current state but also provides a foundational analysis for assessing the impact of rollups and other scalability solutions on Ethereum's evolving ecosystem.**

***Index Terms*—Ethereum, Blocks, EIP4844, Rollup Data, Data Analysis, Scalability**

I. Introduction

Blockchain technology has emerged as one of the most transformative innovations of the 21st century. Among the various blockchain platforms available, Ethereum stands out as a pioneer in introducing smart contracts and decentralized applications (DApps), thus facilitating a more intricate set of interactions beyond mere transactions [1, 2]. While its contributions to the decentralized world are well recognized, it is imperative to delve deeper into the mechanics and behaviors of its network to further harness its potential.

In blockchain research, understanding the intricacies of network dynamics is crucial [3] for several reasons. Firstly, it allows stakeholders to predict and mitigate potential congestion scenarios, which can hamper the throughput and efficiency of the network. Secondly, by analyzing user behavior, researchers and developers can gain insights into usage patterns, thereby allowing them to refine and optimize the blockchain's design. Also, from a user perspective, understanding the nuances of transaction costs and their relation to network activities can lead to informed decisions regarding transaction initiation, gas price determination and other scalability factors.

As Ethereum continues to grow, scaling the network to accommodate increasing transaction volumes and reduce costs remains a paramount challenge. A key component of Ethereum's scaling strategy is the implementation of rollups: off-chain aggregation of transactions that are settled on-chain, effectively increasing throughput while maintaining security [4]. Central to this approach is the concept of 'blob data', a term introduced in the context of proto-danksharding [5], which is a step towards more extensive sharding mechanisms planned for Ethereum. Blob data, as proposed in EIP4844 [5], aims to facilitate rollups by providing a more cost-effective way to store large amounts of data on-chain without overburdening the network. This innovation is crucial as it lays the foundation for future scalability solutions, and it directly influences the characteristics and utilization of large blocks within the Ethereum blockchain. Therefore, our exploration into these sizable blocks not only reflects current network dynamics but also provides insights into how Ethereum's scalability developments, especially EIP4844, will reshape transaction patterns and network efficiency in the near future.

In this paper, we set out to realize these by analyzing blocks of size 500KB and above. We aim to decipher the patterns that emerge, especially those pertaining to block fullness trends and the interplay between transactions and block sizes. Furthermore, our study provides empirical evidence for the surprising phenomenon of Ethereum blocks surpassing the average block size of 100KB. We further reveal the inverse correlation between block sizes and both the number of transactions in the block and the gas prices. These findings not only add to the academic discourse surrounding blockchain dynamics but also offer tangible takeaways for developers and users in the Ethereum ecosystem.

The rest of the paper is organized as follows: Section II presents a related work on the analysis and relevance of Ethereum blockchain data. Section III describes our methodology and dataset. Section IV delves into the core findings and analysis. Finally, Section V concludes the paper with key takeaways and potential future research directions.

II. Related work

A. Background: Rollup Data

Rollups have emerged as a pivotal innovation in the Ethereum blockchain, offering a scalable solution to its growing transaction demands [4]. Fundamentally, rollups involve bundling or 'rolling up' a large number of transactions off-chain and then submitting them to the Ethereum network as a single transaction. This technique significantly reduces the on-chain footprint by handling the computation and state storage off-chain while ensuring data availability and security on-chain. There are two primary types of rollups: Optimistic Rollups and Zero-Knowledge (ZK) Rollups. Optimistic Rollups assume transactions are valid by default and only run a computation in the event of a dispute, making them efficient but with a longer finality time [6]. ZK Rollups, on the other hand, use cryptographic proofs to validate all transactions off-chain before posting them to the blockchain, offering faster finality at the cost of more complex technology [6]. Both types play a crucial role in enhancing Ethereum's scalability and throughput, addressing the limitations inherent in its original design.

The relevance of rollups in the context of large Ethereum blocks becomes apparent when considering their data storage requirements. As rollups process and store transaction data off-chain, they periodically post batches of this data to the Ethereum mainnet for validation and finality. These batches can be substantial in size, often contributing to the formation of larger blocks on the Ethereum blockchain. This is particularly noteworthy in light of the upcoming Ethereum Improvement Proposals (EIPs), such as EIP4844, which introduces the concept of 'blob data' to further optimize rollup efficiency [5]. Blob data aims to provide a more cost-effective means of storing large chunks of rollup data on the Ethereum network, reducing gas costs and enhancing throughput. As such, analyzing large blocks in the Ethereum network, many of which are increasingly composed of rollup data, becomes essential. This analysis not only offers insights into current network efficiency and scalability but also serves as a forerunner for understanding how future innovations, like EIP4844, will impact Ethereum's architectural evolution and user behavior.

B. Prior Study

Understanding the dynamics of blockchain networks is crucial for various stakeholders, including developers, users, and researchers. Network dynamics encompass various aspects, including network congestion, transaction costs, and user behavior. Previous studies have largely concentrated on the macro-level performance and security metrics of Ethereum. These encompass aspects such as its consensus mechanism [7, 8], resource analysis [9], smart contract analysis [10], and overall scalability concerns [11]. However, a detailed examination of the application layer data, particularly the relationship between block sizes, transactions, and gas prices, remains relatively underexplored. Such an analysis can shed light on some of the inherent behaviors and patterns that might not be immediately discernible from a high-level overview.

For example, Kuzlu et al. [12] provided a comprehensive assessment of Ethereum's throughput, latency, and overall system scalability, identifying bottlenecks that could be potential areas of optimization. Busse, Eberhardt, and Tai [13] took a different approach by concentrating on the Ethereum Virtual Machine (EVM) performance, revealing how contract execution affects network performance. However, neither of these works delved deep into application layer data, leaving room for our focused analysis of block sizes and transaction dynamics.

Zheng et al. [14] collected and processed on-chain data from Ethereum and conducted basic statistics and exploration for each of the well-processed datasets. While this work is similar to ours, Zheng et al. [14] did not analyze large block sizes, transactions and cost correlations. It is important to analyze large block sizes as it can help us better understand network dynamics such as transaction throughput, gas limits, fee considerations, and other economic consequences. The main contribution of this study is to reveal network dynamics and the impact of large block sizes, transaction volume and the associated fees on the Ethereum network. We achieve this by focusing on blocks of size 500KB and above, analyzing the patterns that emerge, and providing empirical evidence on Ethereum blocks surpassing the average size of 100 KB. To the best of our knowledge, this work is the first to investigate and report the negative correlation between block sizes vs number of transactions and block sizes vs gas prices.

III. Methodology

In our deep dive into Ethereum's big block data to reveal meaningful patterns, we adopted a systematic approach that ensured both the completeness and accuracy of our analysis. This section presents our methodology, detailing every step from data retrieval to comprehensive analysis. The methodology was structured as follows:

A. Data Retrieval and Preprocessing

Given that blockchain data is transparent and publicly accessible, the primary challenge lies in tapping into the application layer data. While the data may be public, the large volume of data on Ethereum makes this task not so trivial and demands a more sophisticated extraction technique.

1) Tool utilization: To tackle the challenge, we used Sys-A *[redacted for double-blind review]*, a state-of-the-art blockchain data indexing tool that draws data from a trusted beacon node. Recognizing the limitations of Sys-A in accessing intricate application layer details such as transactions, receipts, and gas prices, we augmented the tool by developing additional features tailored to our specific needs.

2) Target data collection: Our focus was particularly directed towards Ethereum blocks with sizes $\geq$ 500KB. 8,140 blocks within slot 5,901,000 to 7,224,000 (Mar-01-2023 to Sep-01-2023) and containing 1,216,205 transactions were analyzed. Furthermore, to aid in time series analyses like the interblock arrival time, consecutive blocks within the slot range were also carefully collected. Table I presents an overview of Ethereum blocks used in the analysis reported in this paper. The dataset encompasses a total of 8,140 such blocks. Within these blocks, 1,216,205 transactions were initiated by 559,919 unique sender addresses and directed towards 295,657 unique receiver addresses. On average, each block in this dataset contains approximately 149.41 transactions. The average time between the arrival of these blocks stands at 12.15 seconds. Furthermore, the mean size of these blocks is found to be

0.68MB, with an average gas price for transactions within these blocks pegged at 41.19 Gwei.

TABLE I
STATISTICS OF DATASET OF BLOCKS (SIZE $\geq$ 500KB)

Statistics	Values
No. of Blocks	8,140
No. of Transactions	1,216,205
No. of Sender Addresses	559,919
No. of Receiver Addresses	295,657
Mean Transactions per Block	149.41
Mean Block Arrival Time	12.15 seconds
Mean Block Size	0.68MB
Mean Gas Price	41.19 Gwei

3) Data preprocessing: We employed various data preprocessing techniques to ensure high-quality data. For example, we removed all orphaned blocks from our analysis. For our categorical analyses, especially those involving block sizes, we categorized the continuous block size data into predefined bins. This process was not just a simple range allocation but was done based on data distribution to ensure each bin had substantial data points. Thus, we created seven bins of block sizes: *0.5-0.75MB, 0.75-1MB, 1-1.25MB, 1.25-1.5MB, 1.5-1.75MB, 1.75-2MB, 2MB+*.

B. Detailed Analysis

Our investigation spanned several dimensions of the application layer data. Below, we present each aspect of the application layer data investigated and the methods used.

1) Block analysis: The essence of Ethereum's functionality lies at the heart of its blocks. Our in-depth block analysis was pivotal to understanding various network dynamics. To quantify the number of transactions packed into individual blocks, we counted the number of individual transactions it contained. This helped in observing how frequently blocks approached their transaction capacity. Histograms and time-series plots were utilized to visualize the distribution and trends of transaction volume across blocks.

To categorize blocks based on their sizes, allowing for a segmented analysis, blocks were sorted into predefined bins based on their sizes, such as *0.5-0.75MB and 0.75MB-1MB*. This segmentation facilitated a comparative analysis of different block size ranges. Bar charts were used to visualize the proportion of blocks falling into each size category. Similarly, after categorizing blocks into size bins, we aggregated the total number of transactions within each bin. This helped deduce which block size ranges were most populated with transactions. Bar chart was employed to juxtapose transaction volumes across size bins.

We assess the monetary value being transferred within each block by summing up the values of all transactions within a block as the total ether (or value) transferred. This offered insights into blocks that were significant in monetary terms, not just transaction counts. Scatter plots were employed to correlate block sizes with the value transferred, highlighting blocks that were dense both in terms of transaction numbers and monetary value.

To explore the relationship between block sizes and various metrics like the number of transactions, gas prices, and total value transferred, we conducted a correlation analysis. Using statistical measures like Pearson's or correlation coefficient, we quantified the relationships between block sizes and other variables. This revealed patterns like whether larger blocks typically had more transactions or if they were associated with higher/lower gas prices. Because some bins had more blocks than others, we used a weighted Pearson's correlation analysis. Correlation matrices and scatter plots with fitted regression lines were used to visually represent these relationships. To validate how frequently Ethereum blocks approach their maximum capacity, we compared the gas used in a block to its maximum limit of 30 million. We calculated a "fullness" percentage for each block. Time-series plots showcased the trends in block fullness over time.

2) Address analysis: Addresses, representing accounts or contracts within the Ethereum network, play a central role in understanding network interactions and behaviors. Our analysis of addresses sought to uncover the key players, their transactional behaviors, and the interplay between them. First, we identified the addresses that were transferring the most value, not just in terms of transaction count. This was done by aggregating the total value (in Ether) transferred from and to each address; we ranked addresses based on this aggregated value. We visualized this using bar charts. Also, we categorized addresses based on their transactional activity level. Addresses were grouped into predefined bins based on their transaction volumes, such as '0-50 transactions', '50-100 transactions', and so on. This helped in revealing the spread of activity levels across all addresses.

To visualize and analyze the interaction patterns between top addresses, we constructed a graph where nodes represented addresses and edges represented transactions between them. This was particularly insightful for understanding the flow of value or information between dominant network entities. Network graphs, color-coded or sized based on transaction volume, provided a visual representation of address interactions. Graph analytics tools provided metrics like node centrality to gauge the importance of specific addresses.

3) Gas Analysis: Gas in Ethereum not only serves as a mechanism to reward miners but also as a protective measure against network spam and inefficient code execution. Analyzing gas usage, gas prices, and their interplay with other blockchain parameters can offer valuable insights into network health, user behavior, and potential congestion points. To track the fluctuations in gas prices over the analysis period, We plotted gas prices against block timestamps. This also helped to identify trends and potential spikes in gas costs.

Further, we investigated if higher block fullness correlates with higher gas prices. For each block, the fullness percentage was calculated and then correlated with the average gas price of transactions within that block. Scatter plots were used to correlate block fullness with gas prices. Also, to understand if

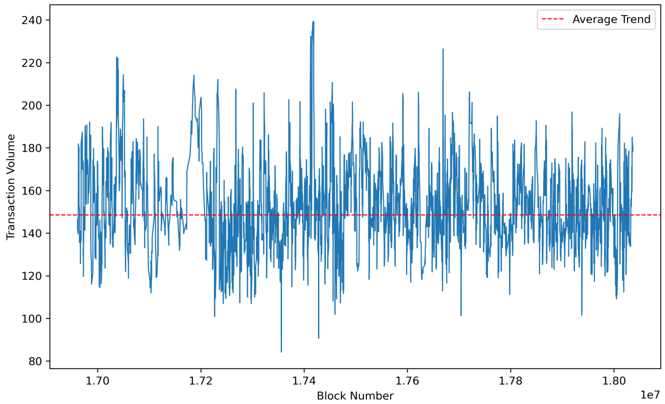

Fig. 1. Number of transactions per block

larger blocks (in terms of data) typically come with higher or lower gas prices, we calculated the average gas price for transactions within each block and correlated it with the block's size.

4) Time Series Analysis: Time series analysis is essential for understanding temporal patterns, forecasting future values, and uncovering underlying structures in sequential data. In the context of Ethereum and its application layer data, time series analysis can provide vital insights into how various metrics evolve over time. One of the key time series analyses in this paper is the interblock arrival time analysis. The objective of this analysis is to determine the time intervals between consecutive blocks and identify any anomalies or patterns. First, we calculate the time difference between the timestamps of consecutive blocks. Next, we analyzed the distribution of these time intervals for any patterns or outliers. Time-series plots were used to visualize interblock arrival times. Other time series analyses include the analysis of gas prices over time, where we visualize gas price evolution over the duration of our dataset.

IV. Results and Evaluation

In this section, we present the results of our analysis of block sizes of 500KB and above on the Ethereum blockchain.

A. Block analysis

Figure 1 displays a time-series plot of the transaction volume per block on the Ethereum blockchain. The transaction volume exhibits significant variability, with spikes that suggest periods of intense activity where blocks are filled with a high number of transactions. Despite these fluctuations, the plot reveals a relatively stable average trend, indicated by the dashed red line, which appears to hover around the 140-160 transaction range.

The bar chart shown in Figure 2 illustrates the distribution of Ethereum block sizes categorized into size bins. The majority of blocks are in the smallest size category, 0.5MB to 0.75MB, and there is a clear decrease in the frequency of blocks as the size categories increase. Very few blocks are larger than 1.5MB, with those over 2MB being particularly rare. This

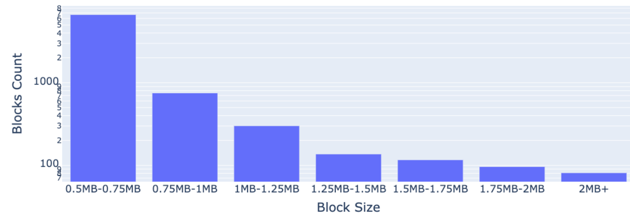

Fig. 2. Distribution of block across size bins

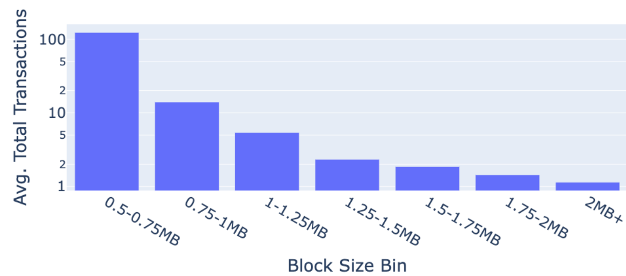

Fig. 3. Distribution of transactions across block size bins

suggests that while smaller blocks are common, the occurrence of blocks nearing or exceeding the 2MB size is comparatively infrequent. The logarithmic scale on the y-axis indicates an exponential decrease in block count with increasing block size, highlighting the skewed distribution towards smaller block sizes within the analyzed dataset. Similarly, in figure 3, as the block size increases, the total number of transactions within each bin generally decreases, which correlates with the trend of fewer blocks being present in larger-size bins. This informed our decision to use a weighted Pearson correlation when comparing the frequency of blocks in each size bin.

The box plot in Figure 4 shows the total ether transferred within blocks of varying sizes. Most blocks, regardless of size, transfer a relatively low value of ether, with the majority of data points clustering near the bottom of the chart. However, there are several notable outliers, especially in the 0.5-0.75MB and 0.75-1MB size bins, which show significantly higher values transferred, indicated by data points that lie far above the general cluster. These outliers suggest that there are blocks that, while not the largest in size, are carrying transactions of high monetary value. The distribution is such that no clear trend correlates the block size with the value transferred, showing that larger blocks do not necessarily contain higher-value transactions.

The scatter plot in Figure 5 displays a trend suggesting a negative correlation between the size of Ethereum blocks and the number of transactions they contain. As block sizes increase, there is a notable decrease in the concentration of data points representing a high number of transactions, particularly noticeable in blocks larger than 1 MB. This trend is accentuated by the weak negative Pearson correlation coefficient of -0.11, which becomes more pronounced when

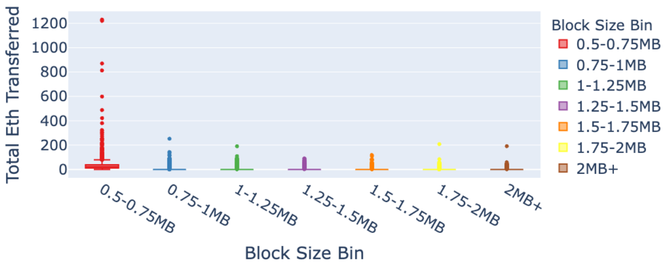

Fig. 4. Total Ether transferred in each block

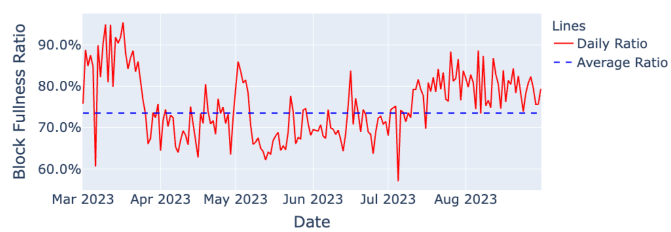

Fig. 6. Block fullness ratio measured as the gas used compared to the limit of 30 million

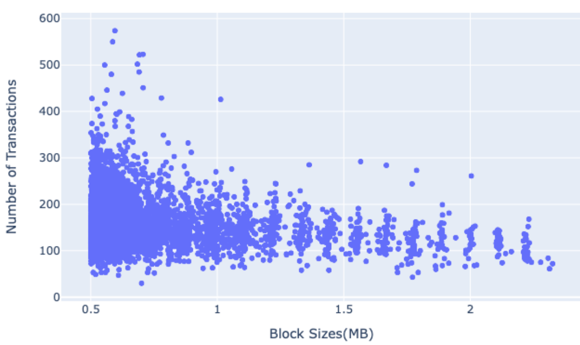

Fig. 5. Correlation between block sizes and number of transactions they contain

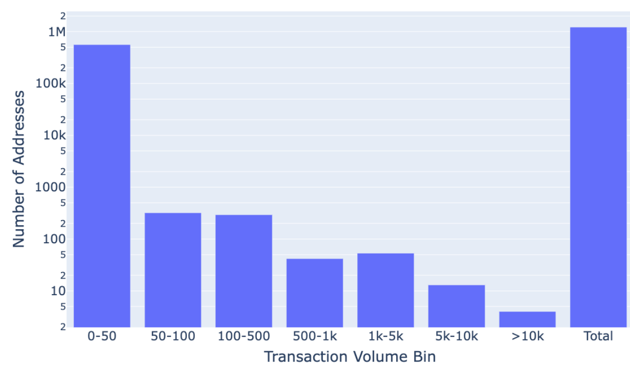

Fig. 7. Distribution of addresses based on number of transactions initiated

considering the weighted correlation of -0.46, accounting for the uneven distribution of blocks across size bins. In line with previous work, we regard a Pearson correlation score of $\geq |0.4|$ as moderate [15]. The sparse data points in the upper range of block sizes with relatively few transactions moderately suggest that larger block sizes do not correspond to a proportionally higher number of transactions. This could indicate a predominance of complex transactions that require more block space, thus inversely affecting the transaction count within larger blocks.

The time-series plot in Figure 6 illustrates that the block fullness on the Ethereum network exhibits considerable variation over time, with the daily block fullness ratio typically oscillating between 60% and 90%. The average block fullness hovers around 70%, as depicted by the dashed line, indicating that large blocks consume a lot of gas but are not consistently at full capacity. These observations suggest that while the network experiences periods of high utilization, there remains some headroom before the blocks reach their gas limit, offering scope for processing additional transactions.

B. Address analysis

Figure 7 categorizes Ethereum addresses in the observed data based on the number of transactions they have participated in, with each bar representing a range of transaction counts. The vast majority of addresses engage in a relatively low number of transactions (0-50), which indicates that infrequent transactions are typical for most users or contracts on the Ethereum network for blocks with sizes greater or equal to 500KB. As the transaction count ranges increase, there is a notable decrease in the number of addresses that engage in that level of activity, with very few addresses reaching transaction counts above 10,000. The "Total" bar indicates the aggregate number of all addresses, reinforcing that high transaction counts are rare and most network participants are involved in fewer transactions. This suggests that while there may be some highly active addresses, the network is largely composed of addresses with limited transactional activity.

Also, figure 8 displays the transaction volumes for the top 10 Ethereum addresses, with Binance leading by a significant margin, followed closely by an unnamed address, and with the rest showing progressively lower volumes of transactions. Notably, there are some named entities like zkSync Era: Validator, dYdX: L2 On-Chain Operator, Crypto.com, and MEXC: Mexc.com among the addresses, along with others that are unnamed, which suggests a mix of exchanges, smart contract operations, and possibly individual high-volume traders or holders. Figure 9 breaks down the transaction volumes of the top 10 Ethereum addresses by block size bins ranging from "0.5-0.75MB" to "2MB+". Binance and Unnamed Address 1 are the most active, with a diverse range of transaction block sizes, including some portions in the "2MB+" category.

Figure 10 depicts a network graph where each node represents an address, and the connections between them represent

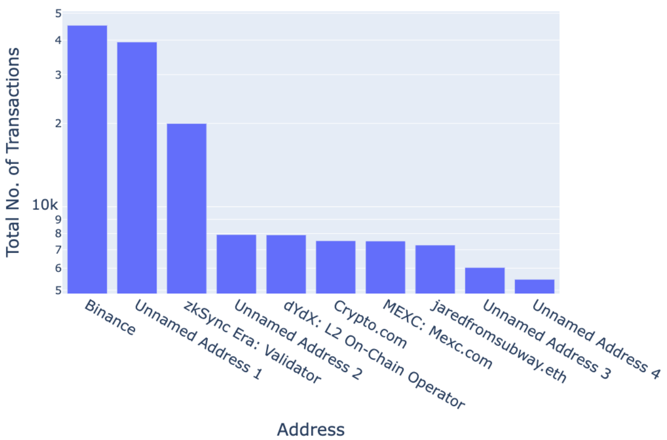

Fig. 8. Transactions count by addresses

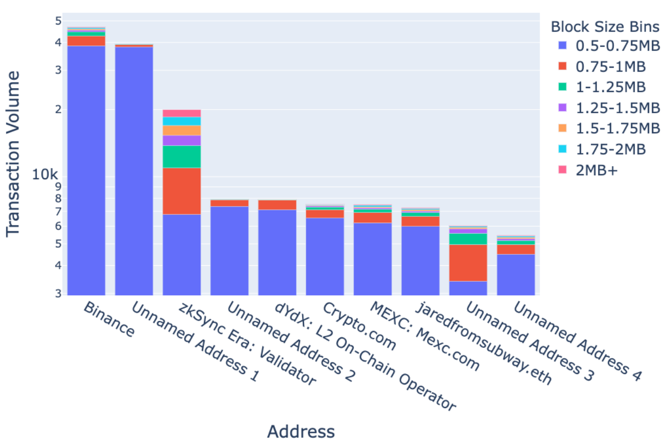

Fig. 9. Transactions count distributed into block size bins

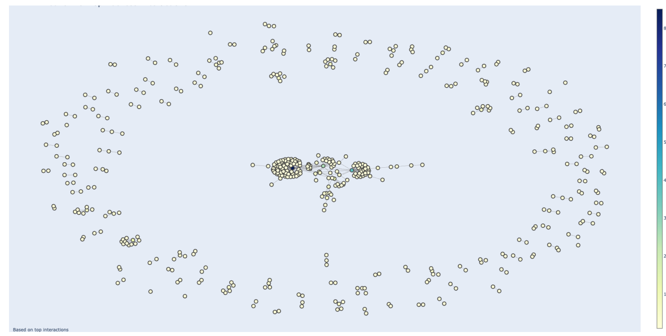

Fig. 10. Network interaction patterns between addresses

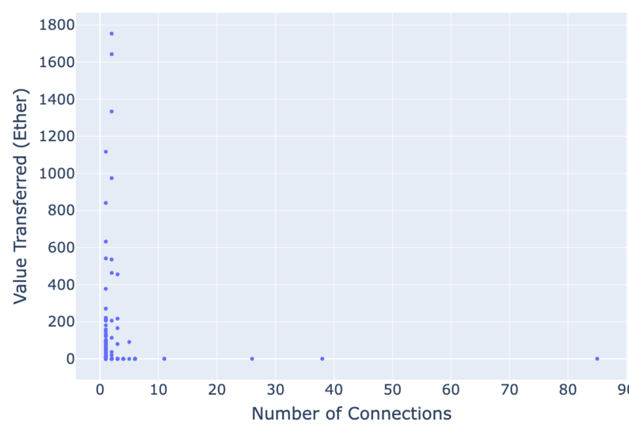

Fig. 11. Network interaction vs value transferred

transactions. The graph shows a central cluster of highly interconnected nodes, indicating a core group of addresses with frequent interactions, which could be interpreted as the main transaction hubs. The color coding of nodes from light yellow to dark blue suggests a gradient of node connections, with the darker nodes having more connections, signifying their higher activity within the network. For example, Tether: USDT Stablecoin has a dark dot to the left in the middle and has 65 connections. Following closely is Binance on the right in the middle with 35 connections. Most of the nodes are less connected and scattered around the graph's periphery, highlighting that most of the addresses have fewer interactions. Overall, the graph visualizes the disparity in connectivity among addresses, with a small number of highly connected nodes and many sparsely connected ones.

In terms of value (Ether) being transferred, Figure 11 indicates that addresses with fewer connections tend to transfer more amounts of value, with the majority at the lower end of value transferred, while addresses with a higher number of connections also show a wide range in the value they transfer, including some of the highest values on the graph.

C. Gas analysis

Figure 13 shows a distribution of data points that represents the relationship between block fullness and average gas prices, measured in Gwei, for Ethereum transactions in the blocks of size $\geq 500KB$ with actual gas prices shown in figure 12. The spread of data points indicates a weak correlation, as evidenced by the Pearson correlation coefficient of -0.29. A weighted Pearson correlation coefficient gave a score of -0.42, suggesting a moderate inverse relationship where increased block fullness moderately corresponds to lower average gas prices. Similarly, a moderately negative correlation exists between block sizes and total gas price charged within the block, as shown in Figure 14. A weighted Pearson correlation score of -0.42 was obtained in this case.

D. Time series analysis

Figure 15 shows the interblock arrival time for the blocks proposed in the same period as the $\geq 500KB$ sized blocks. Here, we notice most blocks arrive within the standard 12-second period for slots. In a few cases, we noticed a variation, and this could be attributed to scenarios of missed blocks and reorg activities.

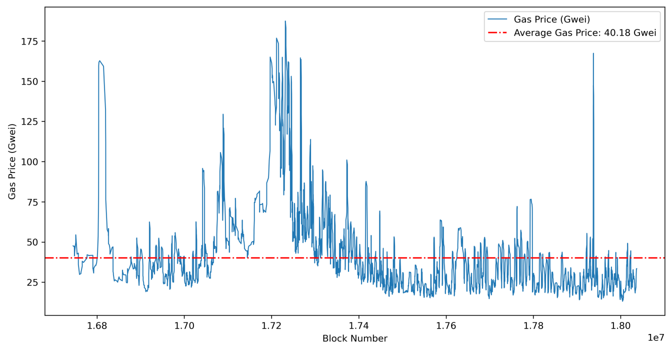

Fig. 12. Gas prices by blocks

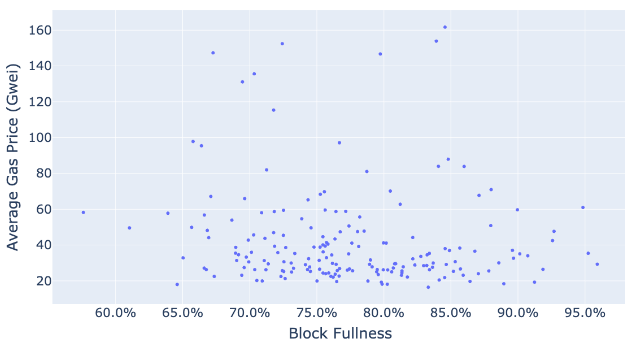

Fig. 13. Correlation between block fullness and gas prices

The time series plot in Figure 16 depicts the trend of gas prices in the period the blocks of sizes $\geq 500KB$ were mined, with lines representing the mean, median, minimum, and maximum gas prices. The graph shows frequent spikes in the maximum gas price, which far exceed the mean and median, indicating periods of extreme gas price volatility, while the median and mean prices remain relatively stable over time. These spikes could suggest occasional network congestion or increased competition for transaction processing, while the general stability of the mean and median indicates a relatively consistent average gas price over the observed period. In Figure 17, unlike the macro analysis in Figure 16,

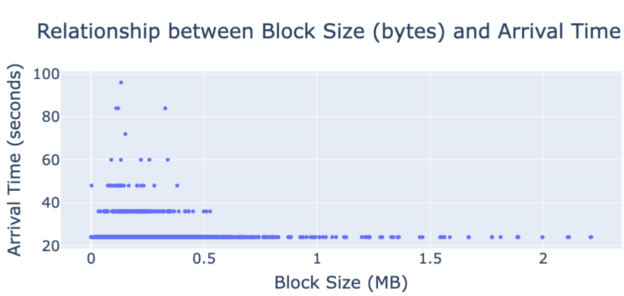

Fig. 14. Correlation between block sizes and total gas price charged within that block

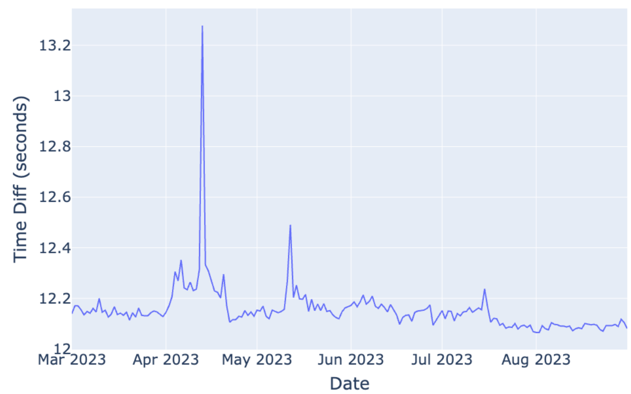

Fig. 15. Interblock arrival time

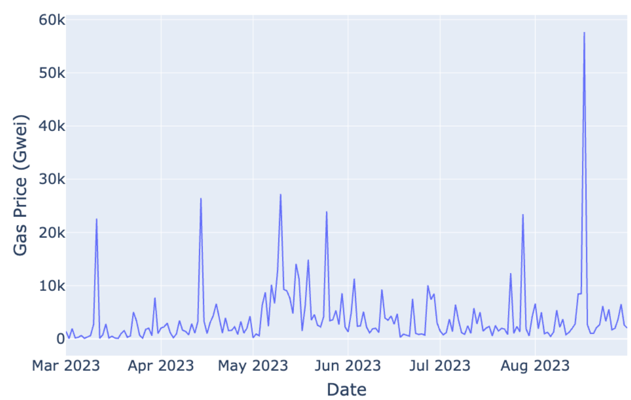

Fig. 16. Macro analysis of gas price variation over time

the mean and median values in this micro analysis appear more closely aligned and exhibit similar trends, with periodic peaks and troughs suggesting a pattern or cycle in price changes. The minimum gas price remains fairly consistent and low compared to the mean and median, indicating that while average prices fluctuate, there are always times when the gas price drops to a lower, more stable level.

V. Discussion

This paper provides a comprehensive analysis of Ethereum's application layer data, focusing on blocks of size 500KB and above. The findings reveal interesting patterns and correlations, such as the moderate negative correlation between block sizes and the number of transactions they contain and the decrease in average daily gas prices with an increase in block sizes. These insights are crucial for understanding Ethereum's network dynamics, including user behavior, network traffic, and transaction cost implications.

The observed trend of larger Ethereum blocks containing fewer transactions suggests the potential prevalence of complex transactions requiring more block space. Additionally, the

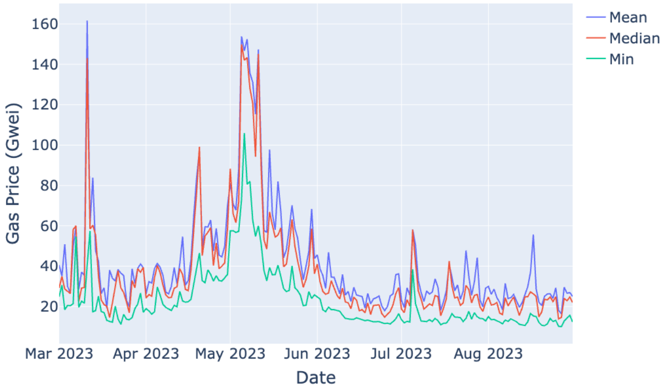

Fig. 17. Micro analysis of gas price variation over time

findings in this paper that a substantial number of Ethereum blocks exceed the expected 1.8 MB size limit, highlight the need for ongoing monitoring and potential adaptations in the network's infrastructure.

One limitation of this study is its focus on Ethereum blocks of size 500KB and above, which may not fully represent the entire spectrum of block sizes and their associated dynamics. Additionally, the study relies on historical data, which may not fully capture the rapidly evolving nature of blockchain technology and user behaviors. The use of specific tools and methodologies may also limit the generalizability of the findings to other blockchain platforms or different Ethereum network conditions.

VI. Conclusion and Future Work

This paper offers valuable insights into the application layer data of the Ethereum blockchain, particularly in relation to large block sizes, transaction volumes, and gas prices. We highlighted the complex interplay between various network elements and their impact on the overall functionality and efficiency of the Ethereum network. The findings provide a foundation for further research and development in optimizing blockchain technology, particularly in addressing scalability and efficiency challenges.

Future research could expand the scope to include a wider range of block sizes, offering a more comprehensive view of the Ethereum network's behavior. Investigating the implications of these findings for other blockchain platforms could also yield valuable insights. Additionally, real-time data analysis could be employed to keep pace with the rapidly evolving nature of blockchain networks. Further exploration into the relationship between transaction complexity, gas prices, and block sizes could provide deeper insights into network efficiency and optimization opportunities. Finally, the development of predictive models based on these findings could aid in forecasting network behaviors and inform strategic planning for Ethereum's continued evolution.

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