On Exploiting Transaction Concurrency To Speed Up Blockchains

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Abstract—Consensus protocols are currently the bottlenecks that prevent blockchain systems from scaling. However, we argue that transaction execution is also important to the performance and security of blockchains. In other words, there are ample opportunities to speed up and further secure blockchains by reducing the cost of transaction execution.

Our goal is to understand how much we can speed up blockchains by exploiting transaction concurrency available in blockchain workloads. To this end, we first analyze historical data of seven major public blockchains, namely Bitcoin, Bitcoin Cash, Litecoin, Dogecoin, Ethereum, Ethereum Classic, and Zilliqa. We consider two metrics for concurrency, namely the single-transaction conflict rate per block, and the group conflict rate per block. We find that there is more concurrency in UTXO-based blockchains than in account-based ones, although the amount of concurrency in the former is lower than expected. Another interesting finding is that some blockchains with larger blocks have more concurrency than blockchains with smaller blocks. Next, we propose an analytical model for estimating the transaction execution speed-up given an amount of concurrency. Using results from our empirical analysis, the model estimates that 6× speed-ups in Ethereum can be achieved if all available concurrency is exploited.

I. INTRODUCTION

Consensus protocols are currently the fundamental obstacles that prevent blockchain systems from scaling. There is a large gap between the cost of consensus and the cost of other blockchain layers, in particular the execution and data model layer [8]. Most recent works that seek to improve blockchain performance focus on scaling the consensus layer, either by designing new protocols [9], [20], by leveraging sharding [5], [12], or by weakening security guarantees [1]. Despite these efforts, state-of-the-art blockchains with novel consensus protocols can only achieve a few thousands of transactions per second in throughput, which is far below what a typical distributed database can do [8], [10]. We argue that it is time to look at other layers of the blockchain for opportunities to increase performance.

We posit that the execution layer, where blockchain transactions are executed, offers ample opportunities to improve both the performance and security of blockchains. There are three reasons for that. First, many modern blockchains employ sharding, which splits the network into small committees that run consensus protocols independently from the other committees. Within a small committee, the gap between the cost of consensus and transaction execution shrinks significantly [5]. In other words, reducing the cost of the transaction layer can lead to significant performance gains at each committee, which in turn improves blockchain performance as a whole. Second, some private blockchains such as Hyperledger Fabric [1] abandon classic consensus protocols for other designs that require a trusted third party service, such as the ordering service discussed in [1]. By sacrificing security, these blockchains shift their bottlenecks away from consensus to other parts of the systems, one of which being the execution layer [15], [19]. Third, the cost of executing transactions negatively affects blockchains’ incentive mechanisms, as captured by the Verifier’s Dilemma [13]. As a consequence, making transaction execution faster strengthens the incentive mechanisms, which in turn strengthens the overall security.

We ask the following question: how much can we speed up blockchains by speeding up the execution layer? Although a large number of techniques from databases can be employed to speed up transaction execution, we focus on a single technique: exploiting concurrency to execute multiple transactions in parallel. The fact that existing blockchains execute transactions in batches (i.e., one batch per block), but within each batch execute transactions only sequentially, means there could be a large amount of untapped concurrency.

In this work, we take first steps at answering the above question. We have two goals. The first goal is to understand the amount of concurrency available in existing blockchains. To this end, we conduct an extensive empirical analysis of seven public blockchains, namely Bitcoin, Bitcoin Cash, Litecoin, Dogecoin, Ethereum, Ethereum Classic, and Zilliqa. We choose public blockchains over their private (or permissioned) alternatives because of their wide adoption and data availability. The selected blockchains cover a large design space, including state-of-the-art sharding-based systems. We measure concurrency using the conflict rate per block: a lower rate means higher concurrency. We compare the seven blockchains against two variants of this metric: the single-transaction conflict rate, and the group conflict rate. Our analysis differs significantly from recent work that evaluates concurrency in Ethereum [17] in that our approach is much more lightweight and can extract more concurrency, and that our analysis covers a more comprehensive dataset that includes more than one blockchain.

Our second goal is to understand how much execution speed-up can be achieved by exploiting the available concurrency. To this end, we propose an analytical model for the computation of the potential speed-up from the conflict rates per block. An accurate model is not trivial, because it must take into account variables other than conflict rate, for instance the number of cores per machine, scheduling policies, and synchronization overhead.
In summary, we make three important contributions.
1) We present an extensive data-driven analysis of the amount of concurrency in seven public blockchains. Our methodology is more lightweight and able to capture more concurrency from more comprehensive datasets and systems than existing works.
2) We discuss important findings from the analysis, including:
   - There are more concurrency in UTXO-based blockchains than in account-based ones. For example, the rate of single-transaction conflicts in Bitcoin is around 13% whereas in Ethereum it is close to 80%. Although the difference may seem unsurprising because of the nature of the two data models, a more interesting observation is that the amount of concurrency in UTXO-based blockchains is lower than expected. One extreme example is the Bitcoin block 358624[1] in which 3217 out of the total 3264 transactions are dependent on each other (i.e., there is no concurrency between them and they must be executed sequentially).
   - In every blockchain, the group conflict rate is lower than the single-transaction conflict rate. Although this is true by definition, the difference is considerable. For example, in Ethereum the former is around 20% whereas the latter is closer to 60% on average. The implication is that there is much more concurrency to be exploited when transactions are considered in groups as opposed to individually.
   - Blockchains with more transactions per block often have a lower group conflict rate. For example, on average Ethereum has an order of magnitude more transactions per block than Ethereum Classic, but its group conflict rate is much lower than that of the latter, namely 20% compared to 70%. The implication is that blockchains with a higher load potentially have more concurrency, or that blockchains with more users have both a higher network load and more concurrency.
3) We present a model that enables the extrapolation of transaction execution speed-ups. Applying the model to the seven blockchains under consideration, we show potential performance gains of up to $6 \times$.

The next section presents the relevant background on blockchains and discusses our motivation for speeding up the execution layer. Section III details the methodology of our empirical analysis, including the metrics and data collection process. Section IV discusses our findings. Section V describes the speed-up model. Section VI discusses the related work, before Section VII concludes the paper.

II. BACKGROUND & MOTIVATION

A. Blockchain Systems

A blockchain system (or blockchain) is a network of nodes that maintain a replicated, tamper-evident log data structure called a ledger. The nodes do not necessarily trust each other. The ledger is a sequence of blocks linked together via cryptographic hash pointers. Each block contains multiple transactions that modify some global state. A blockchain can be examined in four layers: data model layer, consensus layer, execution layer, and application layer[8]. The first concerns the storage and nature of the transactions. The second includes protocols that enable nodes to agree on the ledger. The third concerns how transactions are executed, and the fourth includes user applications. We refer readers to[7],[8] for a comprehensive discussion of the design space and to[10] for an overview of the potential security pitfalls.

Consensus: Consensus protocols are necessary for the security of blockchains because they allow decentralized, mutually distrustful nodes to agree on the same ledger. Public blockchains, in which any node can participate, often use variants of Proof-of-Work (PoW) protocols[14] which are computationally intensive. Private (or permissioned) blockchains employ more computationally efficient, classic distributed consensus protocols such as PBFT[4]. However, these protocols are communication-heavy and do not scale well to large networks[5].

Data model: The data model determines the nature of the transactions included in the block, and the operations that can be performed. Most blockchains employ one of the following two models: UTXO-based and account-based.

In the UTXO-based model, a transaction takes outputs of other transactions as inputs and creates its own transaction outputs (or TXOs). Each TXO contains a value. Outputs of one transaction can be taken as input of, or spent by, another transaction. A special type of transaction, called coinbase, has no input TXOs and produces one output TXO. Nodes keep track of unspent TXOs (or UTXOs). A transaction is valid if the total value of the output TXOs matches that of the input TXOs[2] and if the input TXOs are in the current UTXO set.

In the account-based model, a transaction makes modifications to some accounts’ states. For example, a payment transaction updates the state representing the balance in both the sender’s and the receiver’s account. Executing a transaction in this model involves the invocation of some computation logics, or smart contracts, that modify the global state. Together with smart contracts, this model enables blockchain applications that are more complex and interesting than cryptocurrencies.

Smart contract: A smart contract encodes computation over the blockchain states. The contract is identified by an address, and is triggered by sending a transaction to that address. Smart contracts in different blockchains differ in terms of contract expressiveness, and in terms of execution runtime. In particular, some blockchains such as Ethereum support Turing-complete contracts, which allows user to define arbitrary computation, whereas others such as Libra[2] support only a limited set of contracts. Furthermore, some blockchains use specific virtual machines (e.g., the Ethereum Virtual Machine or EVM) to execute the contract, whereas others rely on

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1 Hash: 0000000000000000000000000000000000000000000000000000000000000000
2 Minus some transaction fees.
general-purposed containers (e.g. Docker). Given a block, existing client software applications execute its transactions sequentially, that is, one transaction at a time and in the order in which they appear in the block.

Most blockchains that support smart contracts (particularly Ethereum) allow functions in smart contracts to initiate further calls to other contracts. These interactions do not appear as transactions in the blocks, but can still cause write conflicts. In the rest of this paper, we will refer to these interactions as internal transactions. In particular, we define as an internal transaction any interaction between contracts that generates a so-called trace in the geth client (which was used to create the Google BigQuery dataset that we use later), and which is not a regular or coinbase transaction.

### B. Public Blockchain Systems

We briefly describe the seven public blockchains that we examine in this paper. These systems cover a large design space, including state-of-the-art sharding-based blockchains. Table 1 summarizes their characteristics.

| Blockchain       | Data model | Consensus | Smart contracts | Data source |
|------------------|------------|-----------|----------------|-------------|
| Bitcoin          | UTXO       | PoW       | No             | BigQuery    |
| Bitcoin Cash     | UTXO       | PoW       | No             | BigQuery    |
| Litecoin         | UTXO       | PoW       | No             | BigQuery    |
| Dogecoin         | UTXO       | PoW       | No             | BigQuery    |
| Ethereum         | Account    | PoW       | Yes            | BigQuery    |
| Ethereum Classic | Account    | PoW+Sharding | Yes           | —           |
| Zilliqa          | Account    | PoW+Sharding | Yes           | —           |

**TABLE 1: Comparison of seven public blockchains.** The “data source column” indicates whether the blockchain data is available at sources other than the blockchain client.

We discuss three reasons why it is beneficial to make the execution layer more efficient. First, as shown in [5], for small networks, the cost of transaction execution is comparable to, if not greater than, the cost of consensus. In particular, for a 7-node private blockchain, the average execution time per block is 250ms while the average consensus time is 20ms. For a 31-node network, the average cost for execution and consensus are similar at around 250ms. In other words, the execution layer has a large contribution to the overall cost, therefore making it efficient will lead to significant performance gains. It might be countered that this observation does not hold in practice because blockchain networks are large. However, we note that most modern blockchains use sharding to break up the network into much smaller committees (or sub-networks), which means that within each sub-network the cost of the execution layer remains significant.

**Dogecoin:** Dogecoin is designed as a light-hearted cryptocurrency blockchain based on the now-defunct Luckycoin, which itself is a spin-off of Litecoin. Dogecoin has a higher block frequency than Litecoin, but is otherwise similar to Bitcoin and Litecoin. It has been online since December 2013.

**Ethereum:** Ethereum is the first blockchain platform that supports Turing-complete smart contracts. It uses a memory-hard variant of PoW and an account-based data model. Smart contracts are identified via an address, in the same way as a regular account. Ethereum miners and other validating nodes execute the transactions in the blocks in the Ethereum Virtual Machine (EVM). Each operation in the EVM incurs a cost called gas that is proportional to its computational cost. The gas system prevents denial-of-service or bugs caused by infinite loops and overly costly operations. Ethereum has been online since July 2015.

**Ethereum Classic:** Ethereum Classic is a fork of Ethereum that occurred in July 2016 following a dispute over governance after the attack on the DAO contract [3]. Ethereum Classic is currently still highly similar to Ethereum.

**Zilliqa:** Zilliqa [21] is one of the first blockchains that use sharding to increase throughputs. In particular, it employs network sharding which assigns nodes to small committees such that each committee maintains the complete global state. Zilliqa adopts the account-based data model and supports Turing-complete smart contracts. Its scalability comes from the fact that transactions are processed independently at different committees that are selected based on the senders’ addresses. The system uses a combination of PoW and classic consensus protocols. In particular, nodes run PoW to determine their committees, and a variant of PBFT [4] to ensure security at local committees. A major limitation of Zilliqa is that it does not support cross-shard transactions — ones that touch multiple committees. In addition, it needs to wait for state synchronization between committees before transactions are confirmed. Recent blockchains have addressed these limitations [5], [12], but we consider Zilliqa in this work because it is the only sharding-based public blockchain that is running live and that has a considerable amount of traffic.

### C. Why Improve the Execution Layer?

We discuss three reasons why it is beneficial to make the execution layer more efficient. First, as shown in [5], for small networks, the cost of transaction execution is comparable to, if not greater than, the cost of consensus. In particular, for a 7-node private blockchain, the average execution time per block is 250ms while the average consensus time is 20ms. For a 31-node network, the average cost for execution and consensus are similar at around 250ms. In other words, the execution layer has a large contribution to the overall cost, therefore making it efficient will lead to significant performance gains. It might be countered that this observation does not hold in practice because blockchain networks are large. However, we note that most modern blockchains use sharding to break up the network into much smaller committees (or sub-networks), which means that within each sub-network the cost of the execution layer remains significant.
Second, some blockchains sacrifice the security of the consensus protocols for performance, by abandoning PoW and other classic Byzantine fault-tolerant protocols. For example, Hyperledger Fabric employs a Kafka cluster, which does not tolerate Byzantine failures, to achieve transaction order. As shown in [13], such designs can shift the bottleneck away from consensus. For example, in Hyperledger Fabric, the bottleneck is the endorsing phase which executes (simulates) transactions before sending them to Kafka. Since the execution layer becomes a likely bottleneck in these blockchains, reducing its cost leads to significant performance gains.

Finally, the cost of transaction execution negatively affects the security of public blockchains, as captured by the Verifier’s Dilemma [13]. In particular, a rational node has considerable incentive to skip the transaction execution, and to spend all of its resources on consensus (for instance, to mine new blocks). But without a large number of nodes executing the same transactions, the overall security becomes lower because invalid and malicious transactions can slip through and get recorded in the ledger. In other words, reducing the cost of transaction execution helps to strengthen security, because rational nodes have less incentive to skip transaction execution.

III. METHODOLOGY

In this section we present the methodology behind our empirical study of the seven blockchain platforms. We begin in Section III-A with a discussion of the metrics that we seek to compute. We discuss our data sources in Section III-B and the queries for obtaining the metrics of interest from the online datasets in Section III-C.

A. Concurrency Metrics

We quantify concurrency per block via conflict rates: the lower the conflict rate, the higher the amount of concurrency. In the following, we first define conflicts in a model called the transaction dependency graph. We then derive two metrics for concurrency, namely single-transaction concurrency, and group concurrency.

1) Transaction Dependency Graph (TDG): Each block is modelled as a graph $(N, E)$ where $N$ denotes the set of nodes and $E$ the set of edges. The nature of nodes and edges depends on the data model.

- UTXO-based models: each node is a transaction in the block. An edge exists from $a$ to $b$, i.e., $(a, b) \in E$, if a TXO is created in node $a$ and spent in node $b$.
- Account-based models: each node is an address that is referenced by a transaction in the block. An edge exists from $a$ to $b$ if there is a (possibly internal) transaction in which $a$ is the sender and $b$ is the receiver.

For both data models, we ignore the coinbase transactions for simplicity. Any two edges in TDG that share an endpoint are said to be connected. A path is a sequence of connected edges. Two nodes $a, b \in N$ are said to be connected if a path exists such that $a$ is the first endpoint and $b$ the final endpoint. A set of nodes $C \subseteq N$ forms a a connected component of size $|C|$ if all pairs of nodes in $C$ are connected, yet no single other node in $N \setminus C$ exists that is connected to any node in $N$.

2) Transaction conflict: In the UTXO-based model, we say that a transaction $t \in N$ conflicts with another transaction $u \in N$ if $t$ and $u$ are part of the same connected component. In the account-based model, we say that a transaction $(a, b)$ conflicts with another transaction $(c, d)$ if their endpoints are part of the same connected component. We say that a transaction is conflicted if it conflicts with any other transaction.

3) Concurrency metrics: The following two metrics capture the amount of concurrency in a block.

- Single-transaction conflict rate. We define the single-transaction conflict rate as the ratio between the number of conflicted transactions and the total number of transactions within the block.
- Group conflict rate. Let the LCC size be the size of the largest connected component (LCC) in a block. We define the group conflict rate as the relative LCC size, that is, the ratio between the LCC size and the total number of transactions in the block.

When we display the evolution of these metrics for the historical datasets, we will always weight these metrics by the block size (or gas cost). The reason is that larger blocks contribute more to the blockchain’s total execution cost than smaller ones.

4) Examples: Figure 1 shows two examples of TDGs for account-based models, namely for Ethereum blocks 1000007 and 1000124. The first block (Figure 1a) contains 5 transactions and one coinbase transaction. The number above a transaction indicates its index in the block’s transaction list. In this block, transactions 3 and 4 are conflicting because their endpoints are part of the same connected component. According to etherscan.io, the 0x2a6... address that causes the conflict belongs to the DwarfPool mining pool. If we ignore the coinbase transaction, the block of Figure 1a has 5 transactions and 4 connected components, namely 3 of size 1 and 1 of size 2. Two of its transactions are conflicted, so its single-transaction conflict rate is 40%, and the group conflict rate is also 40%.

The second block (Figure 1b) contains 15 regular transactions, one coinbase transaction, and 18 internal transactions. Transactions 1-9 all send funds to the same address, which according to etherscan.io is owned by the Poloniex cryptocurrency exchange. Transactions 10-12 were sent to a smart contract (which is unverified but which received 73,369 transactions between January and March 2016). This contract in turn makes one call to another unverified contract, which then contacts the contract at 0x276..., which is a verified contract called ElcoinDb associated with the “ElCoin” ERC20 token. Transactions 13 and 14 are sent by the same address, which belongs to DwarfPool. The block contains 5 connected components. Furthermore, 14 out of its 16 transactions are conflicted, so its single-transaction conflict rate is 87.5%, but the group conflict rate is lower at 56.25%.
5) Discussion: We remark that our definition of conflicting transactions is different to that in [17]. In particular, the latter defines conflict as accessing the same storage location, which means that two transactions sent to the same address may not be considered conflicted if they invoke different methods and access different states. Additionally, it is not entirely clear from the discussion of their algorithm whether, during a situation where several transactions access the same memory location, the first transaction that does so is also considered as conflicting, or if only the later ones are placed in the conflicting transaction ‘bin’. Finally, the analysis in [17] does not consider pure payment transactions, which leads to fewer transactions per block. Because of these, single-transaction conflict rates reported in [17] are lower than in ours, indicating higher concurrency. However, as shown in Section IV by using group conflict instead of single-transaction conflict we are able to extract more concurrency.

B. Data Collection

We collect real data from seven public blockchains. Most of the datasets are available on Google BigQuery[^1][^2], which also supports large-scale query processing. We leverage this service for six out of the seven blockchains[^3]. Most of these datasets follow a similar format. The datasets for UTXO-based systems follow the schema of the Bitcoin dataset, and Ethereum Classic follows the schema of the original Ethereum dataset. They are queried using SQL and user-defined functions (UDFs) written in JavaScript, as described in the following section.

Zilliqa is not included in Google BigQuery public datasets, thus we implemented a lightweight client for downloading the data from Zilliqa’s mainnet. The client is written in Python and uses Zilliqa’s Python SDK for querying the blockchain. It works in two phases. In the first phase, it downloads all transaction hashes using `GetTransactionsForTxBlock` method. In the second phase, it downloads details for every transaction obtained from the first phase, using the `GetTransaction` method. Although the SDK throughputs are low (namely about 4 request per second), the collection of the entire Zilliqa blockchain is fast because there are only 360K blocks and 2.2M transactions.

C. SQL Queries

Since the six Google BigQuery datasets follow only two schemas, it is sufficient to construct two queries to process the data. Most of the computationally expensive parts are done using Javascript UDFs. An example query for the UTXO-based systems is shown in Figure 2. For each block, the query creates two equally-sized arrays, `inputs_merged.txs` and `inputs_merged.spent_txs`. The `ith` element in the former array is the hash of the transaction that creates the `ith` input TXO, and the `ith` element in the latter is the hash of the transaction that spends the `ith` input TXO. The TDG is then constructed as follows: since each transaction is a node, every pair in the two arrays defines an edge.

The `process_graph` computes the metrics of interest. Its main job is to first create the TDG, and then to determine the connected components using breadth-first search. We use three associative arrays as helpers. The first is `nbMap`, which maps each transaction to its neighbors in the graph, i.e., those nodes with which it shares an edge. The second is `inBlockMap` which tracks the block the transaction appears in. The third is `visitedMap` which tracks whether a transaction has been visited during breadth-first search. The core of the algorithm is shown in Figure 3. The result, `ccs`, is an array of arrays, where each element of the main array contains all the hashes of a connected component. Once the algorithm has finished, the number of unconflicted transactions equals the number of elements of `ccs` with length 1, and the LCC can be obtained by finding the element of `ccs` with the largest size.

The query for Ethereum is similar, and is only different in terms of how the nodes and edges are defined, and requires one

[^1]: https://cloud.google.com/bigquery/
[^2]: https://cloud.google.com/blog/products/data-analytics/introducing-six-new-cryptocurrencies-in-bigquery-public-datasets-and-how-to-analyze-them
In this section we present the main findings from the empirical analysis of seven blockchain datasets. In Section IV-A we compare the concurrency in UTXO-based versus account-based blockchains. In Section IV-B we examine the differences between the two main concurrency metrics, namely the single-transaction and group conflict rates. Finally, in Section IV-C we discuss the relationship between concurrency and average block sizes.

We use the SQL queries in the previous section to compute the two metrics for every block in the history of the seven blockchains. The figures are generated by dividing these histograms into fixed-size buckets for which we compute weighted averages. The number of buckets ranges from 20 to 200. To improve the accuracy of our results, we weight each block either by the number of transactions or by its gas consumption. In particular, if there is a high variance between the blocks in terms of the number of transactions or the amount of gas, then the blocks having more transactions or consuming more should be weighted more heavily, because they have a greater impact on the total execution time.

### IV. Empirical Analysis

A. UTXO-Based vs. Account-Based Models

We begin our comparison of the two data models with a detailed comparison of the two main cryptocurrency blockchains: Bitcoin and Ethereum. The results for Ethereum are shown in Figure 4. Figure 4a shows that the per-block average number of regular transactions is around 100 per block, and 300 if we include internal transactions. The sharp peaks in the number of internal transactions in the second half of 2017 are probably due to denial-of-service attacks that exploited EVM instructions that were underpriced [3].

The single-transaction conflict rates shown in Figure 4b are weighted by transaction count (thick line) and gas (thin line), respectively. We observe that the transaction-weighted conflict ratio is high, starting around 80% in 2016 and 2017 before decreasing to around 60%. By contrast, the gas-weighted conflict ratio is roughly 60% since Ethereum’s early days. One possible reason for this difference is that certain transactions with a very high gas cost (particularly contract creations) are less likely to be conflicting, since it is unusual for a single user to create more than one contract per block due to the high cost of doing so. Figure 4c shows the group conflict rate, which had a period of decrease until early 2018, and has been stable around 20% since then.

Figure 5 shows the same graphs for Bitcoin, in which the conflict rates are weighted by the number of transactions. We observe that the average number of transactions per block is currently over 2000, which is greater than for Ethereum. The average number of input TXOs per block is around 4000. However, the single-transaction conflict rate for Bitcoin is currently much lower than for Ethereum, namely roughly 15% compared to 60%. The group conflict rate is even lower, namely around 1%. This is to be expected: unlike accounts, which can send or receive transactions many times, TXOs can only be created or spent once. The only source of conflict in the UTXO-based model is when a TXO is created and spent within the same block. In fact, the frequency with which this occurs is surprisingly high, and may be due to mining pools, centralized cryptocurrency exchanges, or because of higher-level protocols being executed on top of Bitcoin via its scripting language. An example of a long sequence of Bitcoin transactions creating and spending each other’s TXOs is shown in Figure 6. This example is from the Bitcoin block 500,000. We observe that such sequences on average only form a relatively small part of the block.

Figure 7 compares the conflict rates for all seven blockchains, with the UTXO-based and the account-based ones grouped separately. The same patterns can be observed, namely that all conflict rates are considerably lower for the
Fig. 4: Ethereum: evolution over time of the transaction load and the conflict rates.

(a) Number of regular/total transactions per block
(b) Single-transaction conflict rate (weighted)
(c) Group conflict rate (weighted)

Fig. 5: Bitcoin: evolution over time of the transaction load and the conflict rates.

(a) Number of transactions/traces per block
(b) Single-transaction conflict rate (weighted)
(c) Group conflict rate (weighted)

Fig. 6: Example of a transaction sequence in Bitcoin that occurs in the block $B$ at height 500,000. Rectangles indicate transactions, and contain the first four hexadecimal digits of its hash. Solid rectangles occur within $B$, and dashed rectangle in other blocks. Circles indicate TXOs (the values are displayed in bitcoins up to five decimals of accuracy). Dotted lines connect transactions to their output TXOs, and a solid line indicates that a TXO was used as an input TXO for another transaction. The sequence start with the transaction $1836b68048373543a5e3557c5b192a92e07f7c5f3588ffceff332bba4e6214f$, which occurs in the block at height 499975. It has two outputs, of which the one with value $1.84052715$ in spent in a transaction in $B$. This transaction again has two outputs, of which one is again spent in one of $B$'s transactions. This pattern continues, resulting in a sequence of 18 transactions within $B$. The transactions within this sequence must be executed sequentially.
UTXO-based blockchains than for the account-based ones. However, we note that the account-based blockchains tend to support a wider and more computationally expensive functionality (i.e., smart contracts) than the UTXO-based ones (which mostly support cryptocurrencies with very limited scripting support). As the consequence, the higher concurrency on the latter may not translate to higher speed-ups in absolute terms than the former. Finally, we attribute the high conflict rates in Zilliqa to its workload characteristics, since the sharding design does not introduce any properties that may explain such a high rate.

B. Transaction vs. Group Concurrency

Another conclusion that can be drawn from Figure 7 is that the group conflict rate is significantly lower than the single-transaction conflict rate. This is to be expected: after all, unless all transactions are mutually independent, then all transactions in the largest connected component are necessarily conflicted, so the single-transaction conflict must always be at least as high as the group conflict rate. However, the difference is large, for example the single-transaction conflict rate for Ethereum is around 60% and the group conflict rate is around 20%. This suggests that techniques that exploit group concurrency have much more speed-up potential than ones that only focus on individual transactions.

C. Small vs. Big Blocks

We examine whether the average number of transactions has an impact on the conflict rates. In particular, we focus on the difference between Ethereum and Ethereum Classic. A fine-grained comparison of the two is shown in Figure 8. As we can see, Ethereum Classic has an order of magnitude fewer transactions than Ethereum since early 2018. However, both the single-transaction and group conflict rates are higher in Ethereum Classic than in Ethereum, in the latter case considerably so. This may be surprising, especially for the single-transaction case: if the size of the user base is similar, then a higher number of transactions per block means that the probability that two transactions conflict is higher. However, since this does not appear to be the case, this must mean that the user base for Ethereum Classic is relatively smaller than Ethereum’s.

V. Execution Speed-Up Model

In this section we discuss how the two concurrency metrics – the single-transaction and group conflict rates – can be used to predict the potential speed-ups of transaction execution in a block. Two transactions cannot be executed concurrently if they access the same memory, which in UTXO-based models means that they access the same elements of the UTXO set, and in account-based models that they access the same account and/or state variables. We note that the TDG contains all necessary information about the potential conflicts: if two transactions are not part of the same connected component, then at no point do they (or internal transactions resulting from them) conflict. This informs the two approaches below that approximate execution speed-ups in a model where transactions in a block have the same execution time. We begin in Section V-A by describing the technique based on [17], and highlight that our contributions are the closed-form expressions for the speed-up potentials. In Section V-B we describe a technique based on group concurrency. Finally, we present an empirical evaluation of the potential speed-ups based on historical datasets for Ethereum in Section V-C.

A. Single-Transaction Concurrency

[17] proposes a speculative execution technique that works in two phases. In the first phase, all transactions are executed concurrently, and all transactions that are found to conflict with other transactions are moved to a sequential ‘bin’. In the second phase, the transactions in the bin are executed sequentially. This is done without any a priori knowledge of
which transactions cause a conflict, meaning that the conflicting transactions are executed twice. We derive the following model that captures this technique.

Let \( T \) be the execution time of a given block if all of its transaction were to be executed sequentially. We can assume without loss of generality that the execution of a single transaction takes one time unit (after all, this is just a scale factor). Let \( x \) be the total number of transactions in the block, so that \( T = x \). Let \( c \) be the conflict rate of a block, and \( n \) the number of cores. During the first \( \lfloor x/n \rfloor \) time units of the concurrent phase, all cores are busy, and \( \lfloor x/n \rfloor \cdot n \) transactions can be executed during this phase. The remaining transactions take a single additional time unit. Hence, the execution time of the first phase takes \( (\lfloor x/n \rfloor + 1) \) time units in total. In the second phase, \( cx \) transactions need to be executed sequentially, which takes \( cx \) time units. The total execution time of this protocol, denoted by \( T' \) is therefore given by

\[
T' = \lfloor x/n \rfloor + 1 + cx.
\]

To compare the old and new execution times, we define the speed-up \( R \) in the same way as \[17\], i.e., as the ratio of the old execution time to the next execution time, or \( T/T' \). For the method described above, the speed-up equals

\[
R = \frac{x}{\lfloor x/n \rfloor + 1 + cx} = \frac{1}{(\lfloor x/n \rfloor + 1)/x + c}.
\]  

(1)

If we have perfect prior information about which transactions are going to conflict or not, then we do not need to execute the conflicted transactions twice, leading to even greater potential speed-ups. We assume that obtaining such knowledge requires a numerical pre-processing step that requires \( K \) time units. We then only have to process \((1 - c)x\) transaction during the first phase. The execution time of this scheme is given by

\[
T' = K + \lfloor (1 - c)x/n \rfloor + 1 + cx.
\]

and a speed-up of

\[
R = \frac{1}{(K + \lfloor (1 - c)x/n \rfloor + 1)/x + c}.
\]

This leads to large improvements when the conflict ratio is high and when the duration of the pre-processing is small compared to the total execution time. However, in \[17\] (Section 5.5) perfect knowledge of the conflicting transactions was not found to have a considerable impact in practice. We note that a further mild improvement is still possible in this case if \( \lfloor x/n \rfloor < x/n \), because not all cores will then be busy during the final time unit of the concurrent phase, which means that the sequential phase can be started (and completed) one time unit earlier.

As an example, we consider the two Ethereum blocks of Figure 1. Recall that the conflict rate for the two blocks are
40% and 87.5%, respectively. If the completely speculative approach is applied to the block of Figure 1a then the five transactions would first be executed concurrently, which can be done in 1 time unit if \( n \geq 5 \). However, the last two transactions would need to be rolled back and executed sequentially, which would take 2 time units. Hence, the new execution time is given by 3 time units, and because the old execution time is 5 time units, the speed-up equals 5/3 or roughly 1.67. Perfect information about the conflicting transaction only leads to an improvement in the first phase if \( n < 5 \), and incurs the additional cost of the preprocessing step. For the block of Figure 1b nearly all transactions must be executed twice, and the speed-up is minimal: with 16 or more cores, the first phase takes 1 time unit, but the sequential phase takes 14 time units. This leads to a speed-up of 16/15 or roughly 1.07. If between 8 and 15 cores are used, then the first phase takes 2 units, and the speed-up is therefore equal to 0. If fewer than 8 cores are used, then the speed-up becomes smaller than 1, which means that performance becomes worse.

### B. Group Concurrency

As discussed previously, we can improve on the performance of a fully speculative concurrency technique if we can perfectly predict which transactions are conflicted. As discussed in Section III-C one way to determine the set of conflicted transactions in a block is to construct the TDG and use breadth-first search to determine the connected components – the conflicted transactions are then those which share a connected component with at least one other transaction. However, instead of executing the full set of conflicted transactions sequentially, there is still concurrency between the sets of conflicted transactions that can be exploited. For example, in the block of Figure 1b transactions 1-14 are conflicted, but the set of transactions 1-9 do not conflict with the set of transactions 10-12, etc. This insight informs our approximations based on the group conflict rate as given via the relative LCC size, as the size of largest connect component is the largest number of transactions that need to be executed sequentially.

In a system with \( n \rightarrow \infty \), each connected component can be assigned to a single core. The maximum completion time is then \( L \) time units, where \( L \) denotes the absolute LCC size. Because the old execution time equals \( x \) time units and the new execution time equals \( L \) time units, the speed-up equals \( 1/L \), where \( L = L/x \) is the group conflict rate. If \( n \) is finite, then it is impossible to complete execution in fewer than \( x/n \) time units, because this corresponds to the situation where all cores are busy during the entire execution process. The speed-up in this case is precisely equal to \( n \). However, since it is still not possible to speed up beyond \( 1/L \), the maximum potential speed-up is bounded from above by

\[
R = \min(n, 1/L) .
\]

To establish a lower bound instead of an upper bound, more information about the complete structure of the connected components is known. Determining the optimal schedule to execute the different connected components on a small number of cores is equivalent to the multiprocessor scheduling problem, which is known to be NP-hard [11]. In the following, we will assume that, for a sufficiently large number of cores, \( \min(n, 1/L) \) forms a reasonable approximation of the speedup and leave the evaluation of this in practice to future work. Also note that a computational step is presumably necessary in this setting, which means that the true speedup is only

\[
\min \left( \frac{x}{x/n + K}, \frac{x}{x/l + K} \right),
\]

but the difference is negligible if \( K \) is small compared to the product of the number of transactions and the execution time per transaction.

### C. Potential Speed-Up

The approximate speed-ups for Ethereum over its history are shown in Figure 10 for different numbers of cores. To construct this graph, we combined (1) with the data of Figure 4b. It can be seen in Figure 10a that the speed-ups predicted by the single-transaction conflict rate are modest, between \( 1 \times \) and \( 2 \times \) depending on the number of cores. In some cases,
the speedup was even lower than 1×, which means worse performance than fully sequential execution. Figure 10b on the other hand, shows the predictions made using the group conflict rate, which combined with Figure 4c. It can be seen that the speedup in this case is much higher, up to 6× with 8 cores and 8× with 64 cores. We note that to be able to exploit group concurrency to its full potential, knowledge of the TDG is needed. However, the TDG uses information about internal transactions that is not available a priori. Nevertheless, an approximate TDG can be constructed by only using information about the regular transactions. Quantifying the effectiveness of such an approach is left to future work.

VI. RELATED WORK

Our work is not the first to look at concurrency in blockchains. [13] shows that there is inter-block concurrency in Ethereum that arises when a contract communicates with the external world, for example, to wait for an input form outside the blockchain. However, its goal is to demonstrate safety violations caused by concurrency, whereas our goal is to exploit concurrency for performance. [6] proposes a speculative execution scheme for transactions within the same block. It relies on software transaction memory to detect conflicts and perform execution rollbacks. This work is orthogonal to ours: in the paper, some concurrency is simulated in a block to validate the proposed technique, whereas our work sheds light on how much concurrency there are in existing blockchains.

The work that is most related to ours is [17]. It also examines potential speed-ups from exploiting concurrency. It proposes a two-phase technique to do so. First, it executes the transactions speculatively and detects conflicts at the storage layer. Next, any conflicting transactions are re-executed sequentially. Our goal is only to quantify concurrency, not the actual execution of transactions, therefore our approach is more lightweight and lets us analyze more blockchains and more complete data. We are also able to extract more concurrency than what reported in [17], due to group concurrency which is not visible at the storage layer.

In the permissioned setting, [19] examines concurrency in Hyperledger Fabric, which uses a trusted ordering service instead of a Byzantine fault-tolerant consensus protocol. However, Hyperledger Fabric’s execution is tightly coupled to the ordering service, and it is distinctively different to that of the seven blockchains we consider. By default, transaction execution in Hyperledger Fabric is concurrent and speculative. While our goal is to examine how much untapped concurrency there is, [19] is concerned with a concurrency control mechanism that limits transaction aborts.

VII. CONCLUSIONS & DISCUSSION

We have presented our analysis of how much concurrency is available in existing blockchains. We have considered two concurrency metrics: the single-transaction conflict rate, and the group conflict rate. We have examined historical data from seven public blockchains, and discussed several findings. One finding is that there is more concurrency in UTXO-based blockchains than in account-based ones, although the amount of concurrency in the former is lower than expected. Another is that some blockchains with larger blocks have more concurrency than blockchains with small blocks. Finally, we have proposed an analytical model for estimating execution speed-up given an amount of concurrency. The model estimates up to 6× speed-ups in Ethereum using 8 cores.

Our work provides insights into a largely unexplored avenue for increasing blockchain performance. However, it has several limitations that we plan to address in future work. One major limitation is that we have not designed and implemented an execution engine that can exploit the available concurrency. The main challenge is to minimize overhead in building the TDG and in scheduling concurrent execution. Another limitation is that we only focused on inter-transaction concurrency at block level, which leaves other sources of concurrency such as intra-transaction, inter-block and inter-blockchain unexplored. Exploiting multiple sources is likely to bring more performance gains.

REFERENCES

[1] Hyperledger Fabric. https://www.hyperledger.org/projects/fabric
[2] The Libra blockchain. https://github.com/libra/libra
[3] N. Atzei, M. Bartoletti, and T. Cimoli. A survey of attacks on Ethereum smart contracts (SoK). In International Conference on Principles of Security and Trust, pages 164–186. Springer, 2017.
[4] M. Castro, B. Liskov, et al. Practical Byzantine fault tolerance. In OSDI, 1999.
[5] H. Dang, T. T. A. Dinh, D. Loghin, E.-C. Chang, Q. Lin, and B. C. Ooi. Towards scaling blockchains via sharding. In SIGMOD, 2019.
[6] T. Dickerson, P. Gazzillo, M. Herlihy, and E. Koskinen. Adding concurrency to smart contracts. In Proceedings of the ACM Symposium on Principles of Distributed Computing, pages 303–312. ACM, 2017.
[7] T. T. A. Dinh, R. Liu, M. Zhang, G. Chen, and B. C. Ooi. Untangling blockchain: A data processing view of blockchain systems. TKDE, 2018.
[8] T. T. A. Dinh, J. Wang, G. Chen, R. Liu, B. C. Ooi, and K.-L. Tan. BLOCKBENCH: A framework for analyzing private blockchains. In SIGMOD, 2017.
[9] Y. Gilad, R. Hemo, S. Micali, G. Vlachos, and N. Zeldovich. Algorand: Scaling Byzantine agreements for cryptocurrencies. In SOSP, 2017.
[10] I. Homoliak, S. Venugopalan, Q. Hum, D. Reijserbergen, R. Schumi, and P. Szulachowski. The security reference architecture for blockchains: Towards a standardized model for studying vulnerabilities, threats, and defenses. arXiv preprint arXiv:1910.09775, 2019.
[11] F. Kasahara and S. Narita. Practical multiprocessor scheduling algorithms for efficient parallel processing. IEEE Transactions on Computers, (11):1023–1029, 1984.
[12] E. Kokoris-Kogias, P. Jovanovic, L. Gasser, N. Gailly, E. Syta, and B. Ford. OmniLedger: A secure, scale-out, decentralized ledger via sharding. In S&P, 2018.
[13] L. Luu, J. Teutsch, R. Kulkarni, and P. Saxena. Demystifying incentives in the consensus computer. In CCS, 2015.
[14] S. Nakamoto. Bitcoin: A peer-to-peer electronic cash system, 2008.
[15] M. Q. Nguyen, D. Loghin, and T. T. A. Dinh. Understanding the scalability of Hyperledger Fabric. In BCDL VLDB, 2019.
[16] P. Ruan, G. Chen, and T. T. A. Dinh. Q. Lin, D. Loghin, B. C. Ooi, and M. Zhang. Blockchains and distributed databases: a twin study. https://arxiv.org/pdf/1910.01310.pdf, 2019.
[17] V. Saraph and M. Herlihy. An empirical study of speculative concurrency in Ethereum smart contracts. arXiv preprint arXiv:1901.01376, 2019.
[18] I. Sergey and A. Hobor. A concurrent perspective on smart contracts. In Financial Cryptography and Data Security, 2017.
[19] A. Sharma, F. M. Schuhknecht, D. Agrawal, and J. Dittrich. Blurring the lines between blockchains and database systems: the case of Hyperledger Fabric. In SIGMOD, 2019.
[20] M. Yin, D. Malkhi, M. K. Reiter, G. G. Gueta, and I. Abraham. HotStuff: BFT consensus in the lens of blockchain. In PODC, 2019.
[21] Zilliqa. The Zilliqa technical whitepaper. https://docs.zilliqa.com/whitepaper.pdf