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**Article** · October 2020

DOI: 10.1093/comnet/cnaa042



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*IMA Journal of Complex Networks* (2021) Page 1 of 25
doi:10.1093/comnet/xxx000

# On the Transaction Dynamics of the Ethereum-based Cryptocurrency

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[Received on 7 January 2021]

Distributed blockchain-based consensus platforms have witnessed steady growth in recent years. In special, cryptocurrency is one of the main applications of the blockchain technology. Despite the recent interest in blockchain, we still lack in-depth analysis of systems that use such a technology. In fact, most of the existing works focus on Bitcoin. Moreover, blockchain-based cryptocurrency systems are highly dynamic. Their internal mechanisms and consensus algorithms evolve over time. Users also change their interests in a given platform, which in turn, reflect their behavior. In this paper, we model the Ethereum-based cryptocurrency transaction network, a more recent blockchain platform that is gaining a significant share in the cryptocurrency market. We model the transactions of Ethereum as a complex system, representing this complex system as a time-varying graph. Our model and the analysis we conduct rely on a 3-years dataset of Ethereum-based cryptocurrency transactions, comprising more than 38 million users (i.e., unique wallet addresses) and almost 300 million transactions. We analyze the evolution of users and transactions over time. Our study also highlights the centralization tendency of the transaction network on both user and time aspects. Finally, we also analyze the formation of communities and the evolution of connected components considering the dynamics of the Ethereum-based cryptocurrency transaction network.

*Keywords*: Blockchain, Ethereum, Cryptocurrency, Transaction Network, Network Science, Time-Varying Graph, Multi-Aspect Graph

## 1. Introduction

Distributed blockchain-based consensus platforms have witnessed a steady growth in recent years [1, 13, 20, 25]. In this context, cryptocurrency is one of the main applications of this technology, whereas Bitcoin [14] is the first, and most notable, blockchain-based platform. Since Bitcoin's ascension and despite its notority, many other blockchain-based platforms emerged. Bitcoin still leads the rank of blockchain-based cryptocurrency platforms. However, it is losing his domain over the market. For example, Ethereum [3]—a more recent blockchain-based consensus platform—is gaining a significant market share in the cryptocurrency scenario. Ethereum made its debut in 2015 and appeared as a key player in the blockchain-based cryptocurrency context by the end of 2017 and the beginning of 2018. It has disrupted the blockchain technology by introducing the concept of smart contracts. Smart contracts are self-executable programs with predefined rules. Lately, Ethereum is the second most used cryptocurrency platform and leads the smart contracts market. Indeed, a recent study [18] has considered ether, the Ethereum-based cryptocurrency, more efficient than Bitcoin (in terms of the efficient market hypothesis).

Despite the recent—and growing—interest in blockchain, we still lack in-depth analysis of real systems that use this technology as a building block. Most of the existing works focus on Bitcoin and, only very recent works address specific features of new platforms, like Ethereum. Moreover, blockchain-based cryptocurrency systems are highly dynamic. Their internal mechanisms and consensus algorithms evolve. Users also change their interests in a given platform, which in turn, reflects their behavior.

In this paper, we model the monetary transactions of Ethereum as a complex system, representing the Ethereum-based cryptocurrency transaction network as a time-varying and multi-layer graph (i.e., a multidimensional network represented by a MultiAspect graph (MAG) [21, 22]). This modeling allows us to understand the dynamic behavior of Ethereum-based cryptocurrency users, their preferences, profiles, and how the transaction network has evolved since its very beginning. When analyzing the time-varying behavior of a complex system, one can thus trace a sequence of transactions on the Ethereum-based cryptocurrency system, link distinct periods, given specific transactions or contracts, and determine specific important periods of the network.

Our modeling and analysis rely on a 3-years dataset of Ethereum-based cryptocurrency transaction network, comprising more than 38 million users (i.e., unique wallet addresses) and almost 300 million total transactions, in which over 185 million transactions correspond to effective fund transfers between wallet addresses. We evidence the evolution of users and transactions over time. Our study also highlights the centralization tendency of the transaction network on both user and time aspects. We depict the communities formation considering the multi-aspect transactions network of Ethereum. For example, the time perspective shows changes in the network behavior, in special, during specific events and periods. We also present the utilization preferences of the transaction network and its cryptocurrency users. Finally, by analyzing the Ethereum-based cryptocurrency network as a multi-aspect transactions network, we can define the node importance using typical metrics from network analytics, such as degree centrality.

The remainder of this article is organized as follows: First, in Section 2, we present the related work, where we discuss previous works that characterize blockchain-based applications and architectures. In Section 3, we briefly describe the Ethereum platform. The model used to represent the Ethereum-based cryptocurrency transaction network is introduced in Section 4. The Ethereum cryptocurrency data that we capture and the Ethereum modeling are also discussed in Section 4. In Section 5, we present the data characterization, while we analyze the Ethereum-based cryptocurrency transaction network in Section 6. Finally, in Section 7, we conclude the paper and present future work.

## 2. Related Work

Most of the related work that addresses blockchain so far focuses on Bitcoin. Moreover, these works often study security issues related to blockchain technology. For example, Eyal and Sirer [7] analyze the security level of Bitcoin transactions. Authors analytically evaluate the Bitcoin protocol and the incentive policies for miners. Meiklejohn et al. [12] characterize the Bitcoin network in terms of users' anonymity and the risks anonymity causes. Ron and Shamir [17] propose a model to determine the costs to ensure users anonymity in Bitcoin through users' address exchange. Additionally, a few works intend to predict whether a Bitcoin transaction will be confirmed or not. For example, Ricci et al. [16] propose a framework encompassing machine learning and a queueing theory model to early identify which transactions are likely to be confirmed and characterize the confirmation time of confirmed transactions.

The increasing popularity of Ethereum has also attracted the attention of researchers. Researchers seek to understand the dynamics of users and transactions in this new blockchain-based platform. Again, as occurred to Bitcoin, several studies focus on the security and performance aspects of Ethereum. For example, Li et al. [11] conduct a systematic study on the security threats to the Ethereum blockchain.

Only very recent studies have proposed a graph-based analysis of Ethereum contracts. In this sense, Chen et al. [5] characterize contracts in Ethereum, taking into consideration the characteristics of users, the financial flow, and the relationship among them (user to users; a user to a smart contract; and smart contract to smart contract) using multi-flow graph analysis. Kiffer et al. [9] also model Ethereum contracts as a graph. In their work, the authors study the main characteristics of user contracts, the relationship between contracts, the contract lifetime, and smart contracts code reuse. Both works answer how smart contracts are really used and reveal their main characteristics.

A few works study the users (i.e., nodes addresses) in the Ethereum ecosystem. For example, Payette et al. [15] group Ethereum users using automatic machine learning algorithms. Authors consider the transaction history and, among other features, they arrange users according to the amount of ether they exchange, the number of transactions in a given time. Somin et al. [19] also evaluate the Ethereum ecosystem as a social network. In this case, wallet addresses are vertices and monetary transactions link two wallets. Authors rebuild the Ethereum graph to evaluate the ERC20 protocol (*Ethereum Request for Comment* 20)[1] properties. They reveal, for example, the probability distribution function that Ethereum tokens follow a power-law distribution. More recently, some works study the relation of Ethereum features and its performance. Chan et al. [4], for instance, analyze the gas fee in Ethereum and identify denial of service (DoS) attacks. The authors propose a new mechanism to charge users (i.e., gas cost). Authors are also able to detect accounts controlled by attackers and to prevent DoS attacks.

To the best of our knowledge, this is the first work that considers the temporal aspect while characterizing the Ethereum-based cryptocurrency transaction network. In this paper, we consider the monetary transactions on the Ethereum platform and we model these transactions as a complex system, representing this system as a time-varying and multilayer graph. Our study allows one to understand the dynamics of the Ethereum-based cryptocurrency transaction network, observing how the system evolves. Finally, we also analyze the formation of communities and the evolution of connected components considering the dynamics of the Ethereum-based cryptocurrency transaction network.

## 3. A Brief Ethereum Background

In general, Ethereum works like most blockchain-based platforms. It is a platform with many features similar to Bitcoin since it is based on transactions and it uses blockchain as its structure. For example, in a transaction, ordinary users exchange value (money) between them. Several transactions are grouped and validated by special users, also known as miners. These groups of transactions, known as blocks, are linearly chained in a blockchain. The Ethereum blockchain is defined as a single shared state transactional machine paradigm [3]. Thus, Ethereum is a general implementation of this paradigm [24]. Ethereum is the first blockchain-based platform that implements a complete distributed consensus Turing machine through the smart contract technology [24]. The Ethereum platform is comprised of decentralized virtual machines, known as Ethereum Virtual Machines (EVM), which execute smart contracts.

[1] `https://github.com/ethereum/eips/issues/20`

A smart contract is identified by an address and is triggered when its address is referenced as a destination by a transaction. Once triggered, the smart contract runs automatically on each EVM network node [6].

There are special state objects in Ethereum, namely "accounts". State transitions mean a direct transfer of values between accounts [3]. There are two types of accounts: externally owned accounts (EOA), controlled by users' private keys; and the *contract accounts*, controlled by their contract codes. Contracts are addresses defined at the time of their creation. These are capable of performing various operations besides ether transfer between accounts. Accounts can belong to two types of users: miners and traders (i.e., ordinary users). A mining user aims at the financial gain from the block mining process. Mining users receive a fee due to their computational work on a block. However, this value is only transferred after the block is inserted into the blockchain. Ordinary users, on the other hand, use the Ethereum platform mostly to perform contracts or to transfer values between accounts. However, ordinary users and miners may interchange their roles.

As shown in Figure 1, transactions, once performed, go through several steps to be validated. These steps involve verifying the digital signature of users; verifying the nonce (integer corresponding to the total transactions performed by the sender) of the transaction; verifying the *gas limit* that should not be smaller than the intrinsic *gas*, which is the amount of gas required to execute the transaction; and, verifying the sender's account balance that must have at least the transaction cost [24]. More in-depth, *gas*, in Ethereum, is a metric used to determine the maximum computational work that will be spent to validate a transaction. The amount of *gas* and the *gas price*—which is the ether value for each unit of *gas*—represents the maximum amount of ether a user intends to spend on mining her/his transaction. If the declared *gas* is insufficient, the transaction is not mined. Figure 2 presents the steps that define the state of a transaction as successful or failed. These transactions (created by EOAs) are inserted into the blockchain. Other transactions, informally called internal transactions, have no records.

Once a transaction has been validated, it is available to be inserted into a block by a miner. This process is similar to what occurs in Bitcoin, where transactions are mined before they are inserted into the blockchain. However, Ethereum has some differences when compared with Bitcoin. For example, Ethereum rewards miners that do not successfully mined the transaction. Nowadays, Ethereum still uses the well-known proof-of-work (PoW) adopted by Bitcoin. However, the Ethereum 2.0 is due to implement a protocol shift from PoW, to Proof of Stake (PoS). At a glance, in a PoS, instead of miners, transaction validators, known as validators lock up (or stake) their crypto as collateral for the right to verify transactions.

## 4. Network Modeling

Graphs are largely used to represent networks in the literature. A graph representing a network may have one or more values associated with each edge. These values can represent distances, costs, reliability, or other relevant parameters. Traditionally, a graph $G = (V, E)$ is defined by the set $V$ of vertices and $E$ of edges. Static graphs do not allow the representation of time-related network behavior. In contrast, Time-Varying Graphs (TVGs) provide a representation for the dynamics of complex networks. In the literature, dynamic networks are also known as temporal or time-dependent networks [8, 10]. In a TVG, nodes and edges of the graph may vary with time [23].

In this work, we use a MultiAspect Graph (MAG) [22] to represent different graph structures, including a TVG with rich detail. A MAG is defined as $H = (A, E)$, where $E$ is a set of edges and $A$ is a finite

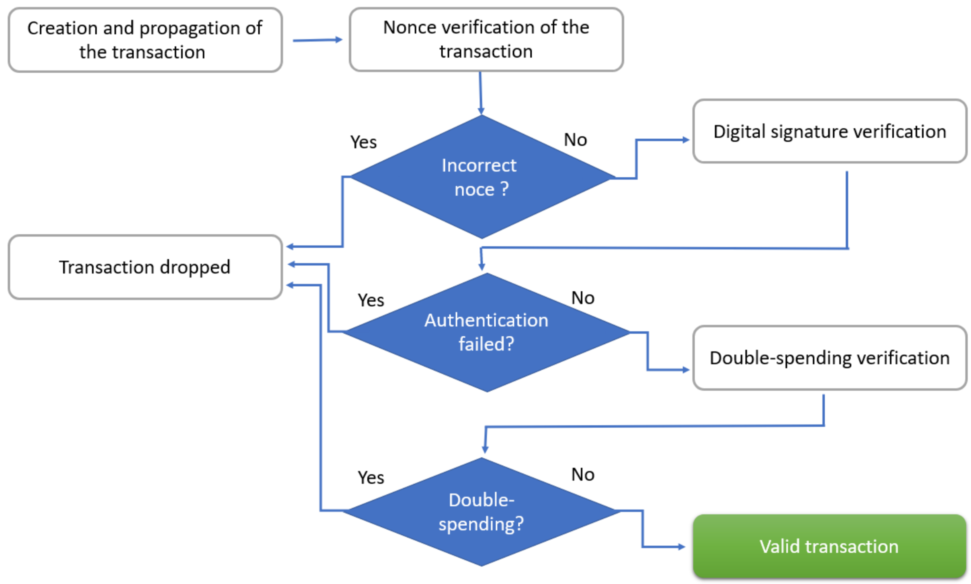



FIG. 1. Transaction verification process flowchart.

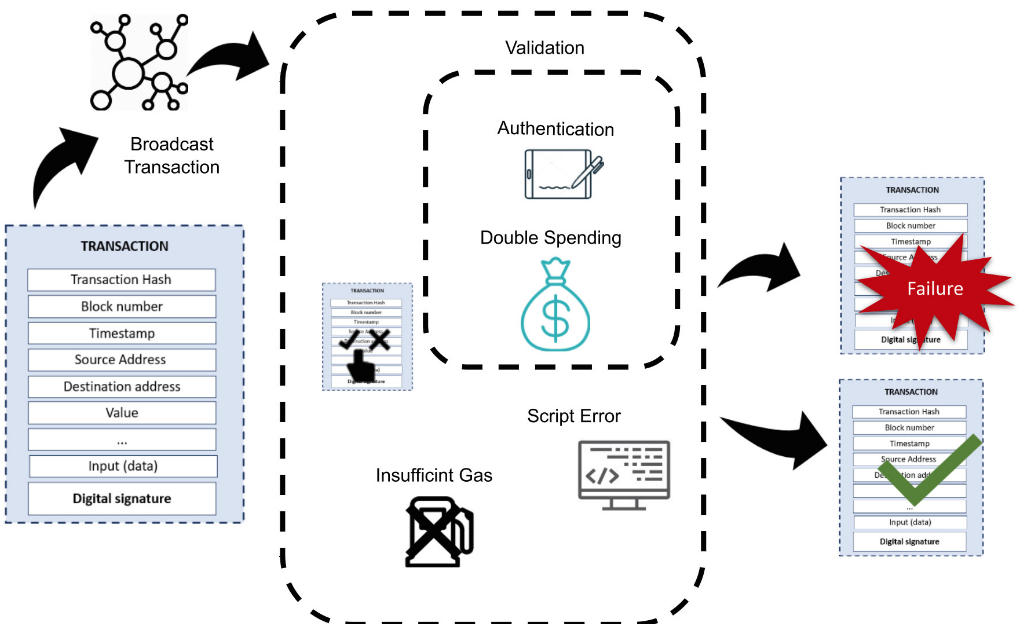



FIG. 2. States of a transaction in Ethereum.

list of sets, each of them is called an *aspect*. Each aspect $\sigma \in A$ is a finite set, and the number of aspects $p = |A|$ is called the order of $H$. Each edge $e \in E$ is a tuple with $2 \times p$ elements. All edges are constructed so that they are of the form $(a_1, \ldots, a_p, b_1, \ldots, b_p)$, where $a_1, b_1$ are elements of the first aspect of $H$, $a_2, b_2$ are elements of the second aspect of $H$, and so on, until $a_p, b_p$ which are elements of the $p$-th aspect of $H$. The most important property of MAGs is that they generalize classic graphs. This means that Time-Varying Graphs or Multi-layer Graphs can be represented by MAGs in a way that is isomorphic to a classic graph. Therefore, all of the known graph theory applies directly to these representations, and TVGs and Multi-layer networks can be treated as a classic graph, greatly simplifying the work with such networks. The complete theory behind MAGs can be found at [21, 22].

In the following, we show how we model Ethereum-based crytocurrency transaction data as a MAG (Section 4.1). Then, we present the Ethereum data crawling methodology and the data we use in this work (Section 4.2).

### 4.1 *Ethereum-based Crypotocurrency Transaction Network as a MAG*

We define the Ethereum transactions network as $ETH = (A, E, w)$, where $A$ is a list with two sets of aspects, $E$ is the finite set of edges, and $w$ corresponds to the weighted function of an edge. The list $A$ has two aspects, one for the set of addresses, and another aspect for the set of timestamps. The weights $w$ represent the value, in ether, of the transactions. Spacial edges represent transactions between accounts (addresses) and temporal edges connect the accounts through time.

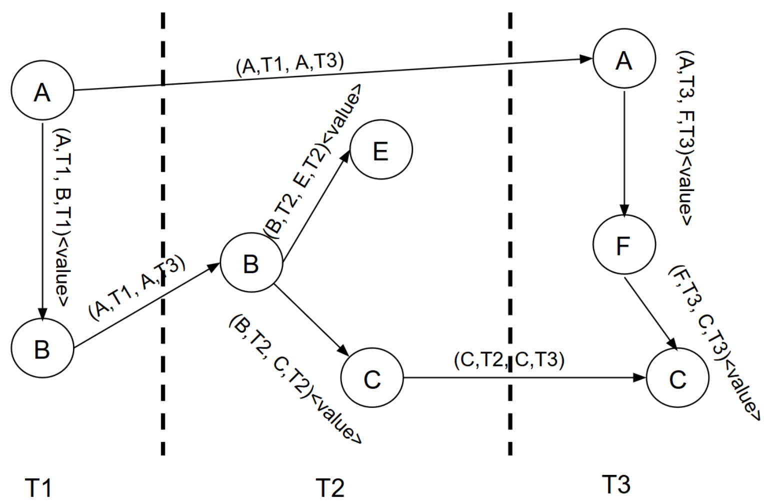



FIG. 3. Illustration of an Ethereum-based cryptocurrency transaction network represented as a MAG.

Figure 3 shows an example of how we model Ethereum using MAG. According to this figure, the edge between the addresses $A$ and $B$ denotes a transaction from $A$ to $B$. Moreover, also note a temporal edge between the node (address) $A$ from the timestamp T1 to T3. In this case, we can infer that the address $A$ performed one or more transactions in both instants of times.

### 4.2 *Data Crawling Method and Data Summary*

In this work, we model the transactions of the Ethereum network as a complex system. In Ethereum, there are two types of transactions: the internal and the external transactions [24]. Users with an account in the network perform external transactions, and these transactions are later registered in the blockchain. An internal transaction is a contract result. An internal transaction does not have a digital signature and a record in the blockchain. This type of transaction occurs due to a contract call or due to the transaction creation by another contract.

We can collect Ethereum data using a well-known client, instrumenting it, and getting all Ethereum blockchain; or through the use of existing APIs. In this work, we decided to use the etherscan.io API.[2] We have sampled the etherscan.io platform during the period between 12-Dec-2015 and 28-Aug-2018. During this period, we have observed 299,234,030 external transactions and 38,313,204 addresses. These addresses are wallets (*External Property Accounts* - EOA) as well as contracts addresses.

For each address, we have collected the current account balance, the total of records, TAGs (name or information about an account), the mined blocks, and the account type. This data is optional and it is available only to the account owner. Transactions we collect have the block number, the user from (origin of the transaction), the user to (destination of the transaction), gas, gas price, hash, timestamp, nonce, value, and input. The field *value* corresponds to the ether value transferred between accounts. We do not collect special transaction fields, as the miner's fees and reward. We have discharged all data inconsistencies and imprecision, e.g., we first removed 10,560 repeated transactions.

To model and to characterize the money transactions of the Ethereum network, we generate a subset of data, removing the contracts. We have noted several transactions where the destination address was not informed. By default, a transaction without a defined destination (with or without values) refers to a new contract. Moreover, contracts usually present a null ether value. In this work, we focus on the external transactions of funds transfer; in other words, transactions with effective transfer of ether. The null-value transactions that represent 38% of the dataset were discarded. These null-value transactions, usually, involve operations with contracts, such as token transfer or contract creation. Despite the considerable number of contracts, Ethereum is mainly used as a cryptocurrency application.

We have then focused on analyzing the emergence and consolidation of the transaction network of the Ethereum-based cryptocurrency during its first three years of existence (2015-2018), which already constitutes a significant amount of data with almost 300 million transactions for more than 38 million addresses. This period is very interesting to be analyzed, since it covers the launch of the platform and its cryptocurrency, its huge usage growth, and conquest of a significant market share in the competitive cryptocurrency scenario.

## 5. Ethereum Network Characterization

In this section, we characterize the Ethereum network dataset we collected. First, we present the overall Ethereum transaction characteristics (Section 5.1). Then, we present a perspective of its users (Section 5.2). Finally, we characterize the Ethereum transaction volume and the amount of ether exchanged during the evaluated period (Section 5.3).

[2] `https://etherscan.io/`

### 5.1 *Overall Ethereum Network Characteristics*

Table 1 summarizes the data we have collected to conduct our analyses. Overall, we have collected almost 300 million transactions from 2015 to 2018. About 114 million of these transactions (38%) present null values, meaning that these transactions refer to contracts. On the other hand, we can assure that over 185 million transactions have transferred funds between Ethereum cryptocurrency users. Null-value (zero ether) transactions usually are operations such as token transfer, trades, contract calls, and so on. It is possible to identify the transaction type by looking at the input of the transaction. The input carries information, such as method id, the destination address, and the value. The method id identifies the transaction type, e.g., the value “0xa9059cbb” corresponds to a token transfer. According to our analyses, token transfers correspond to 52.67% of null-value transactions, whereas contract creation corresponds to less than 2% of these transactions. Also note that, according to Table 1, the number of transactions increases over the years. This behavior occurs especially because of the increasing popularity of Ethereum over the years. Moreover, we also note that the main use of Ethereum does not change: since its beginning, users tend to use it as a cryptocurrency.

Table 1. Ethereum total number of transactions and total number of null-value transactions.

| Year | Transactions | Null-value Transactions | Percentage |
|---|---|---|---|
| 2015 | 266,853 | 60,029 | 22.50% |
| 2016 | 13,662,805 | 1,506,201 | 11.02% |
| 2017 | 103,003,372 | 33,573,437 | 32.59% |
| 2018 | 182,301,000 | 78,788,814 | 43.22% |
| **Total** | **299,234,030** | **113,928,481** | **38.07%** |

Table 2 shows the Ethereum average and maximum block size (in number of transactions per block) and the transaction rate (in number of transactions per second), during the period from 2015 to 2018. Recall that we have disregarded all null size blocks. The block size increases over the years, as well as the Ethereum’s transaction rate. As long as Ethereum has gained popularity, more users performed more transactions. As a consequence, miners were able to join more transactions in the same block to be validated. Moreover, more miners were attracted to the network, which helped to increase the network capacity in processing transactions.

Table 2. Ethereum blocks size (average/maximum) and transaction rate (average/maximum).

| Year | Average block size | Maximum block size | Average transaction/s | Maximum transaction/s |
|---|---|---|---|---|
| 2015 | 3 | 151 | 2 | 151 |
| 2016 | 8 | 228 | 4 | 228 |
| 2017 | 43 | 381 | 40 | 381 |
| 2018 | 74 | 381 | 124 | 488 |

### 5.2 *Ethereum Number of Users*

One can also assess the Ethereum popularity (or network activity) by observing the evolution of its number of users. In this work, we consider a fine-grained user identification, using the network transaction address as a unique user. In this sense, we study the evolution of active addresses, the evolution of new addresses, and the evolution of new contracts in the Ethereum network.

As one could expect, an active address is an address that performs a transaction (e.g., a contract or a fund transfer). Addresses used only as a transaction output are not considered active. Further, when an address triggers a contract for its first time, we consider it as a new contract address.

Table 3 summarizes the evolution of active addresses, new addresses, and new contracts in the Ethereum cryptocurrency network from 2015 to 2018. The most significant growth of the Ethereum cryptocurrency network occurred between 2016 and 2017. In this period, we observe a growth of almost 14 million new unique addresses in the network. During this same period, Ethereum has achieved its highest utilization level, with more than 11.8 million transactions. In the first 8 months of 2018, the number of transactions has already achieved 10.8 million of transactions. During the first two years of Ethereum existence (i.e., 2015 to 2017), the number of new addresses was larger than the number of active addresses. This shows that users created a large number of new addresses to receive funds or activate contracts. More recently, in 2018, the number of active addresses surpasses the number of new addresses.

Table 3. Evolution of new addresses in the Ethereum network.

| Year | New active addresses | New addresses | New contract addresses |
|---|---|---|---|
| 2015 | 4,111 | 6,357 | 905 |
| 2016 | 557,468 | 645,103 | 100,387 |
| 2017 | 12,392,938 | 14,605,840 | 906,171 |
| 2018 | 23,228,573 | 23,055,904 | 909,054 |

Figure 4 presents the evolution of active addresses and the daily creation of new addresses in the period from 2015 to 2018. In this figure, we note a sharp growth at the beginning of 2018. This growth in activity corroborates the validation rate increase, as shown in Table 2. After this growth trend, we note a fall in the activity of the network as well as in the creation of new addresses, associated with a generalized fall of the cryptocurrencies market in this period.

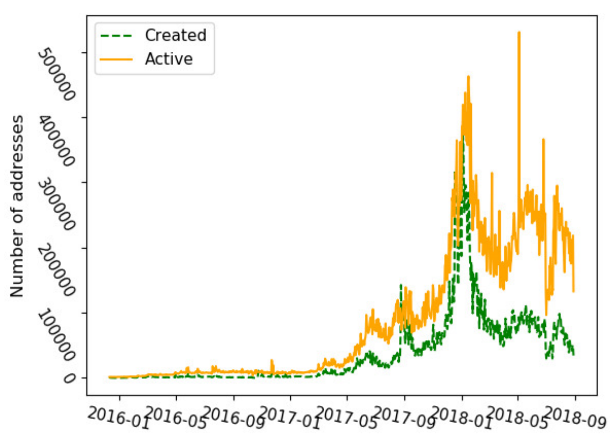



FIG. 4. The temporal perspective of the active and created addresses.

We also evaluate the lifetime of active Ethereum addresses during the period from 2015 to 2018. We consider as a lifetime, the period between the address creation, i.e., from its first to its last transaction.

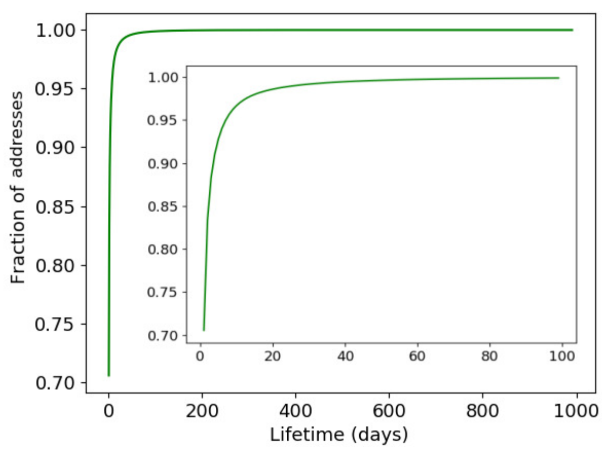



FIG. 5. CDF of the lifetime of addresses.

When an address performs only one transaction, we consider it has a one day lifetime. According to Figure 5, most addresses present a very low lifetime. In fact, about 70% of all addresses have a lifetime of a day or less, while less than 1% remain active over a year.

## 5.3 *Volume of Ethereum transactions*

Table 4 shows the mean and maximum number of Ethereum transactions, per day, during the analyzed period. As we previously stated, the number of transactions increases over the years. This increasing trend occurs most significantly in the last two years of the period. In some cases, during 2018, Ethereum has experienced more than one million transactions in a single day.

Table 4. Number of Ethereum transactions (average/maximum).

| Period | Average transactions per day | Maximum transactions per day |
|---|---|---|
| 2015 | 9,266 | 20,799 |
| 2016 | 38,802 | 59,091 |
| 2017 | 179,976 | 859,506 |
| 2018 | 379,888 | 1,146,897 |

Figure 6 depicts the number of transactions per day, from 2015 to 2018. Note that, until the first month of 2018, the number of daily transactions presents an exponential growth. However, for the same reasons that explain the change in the increasing trend of the number of new addresses, the number of transactions also stopped raising.

Figure 7 shows the daily amount of ether exchanged (in millions). The number of transactions grows from the beginning of 2017 to the beginning of 2018, in which we have observed a dramatic fall in the value of most of the cryptocurrencies and, as a consequence, the Ethereum network reflected it by exchanging a lower amount of ether.

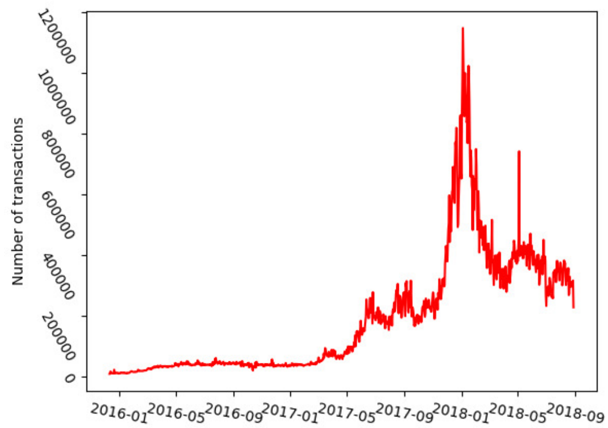



FIG. 6. The temporal perspective of the number of transactions.

Table 5. Amount of transacted ether per year

| Period | Transacted ether | Number of Transactions | Ether/transactions |
|---|---|---|---|
| 2015 (1 month) | 655,749.35 | 206,824 | 0.31 |
| 2016 (12 months) | 66,277,280.09 | 12,156,604 | 0.18 |
| 2017 (12 months) | 435,347,801.10 | 69.429.935 | 0.15 |
| 2018 (8 months) | 83,235,507.55 | 103,512,186 | 1.24 |

Table 6 shows the dynamic behavior of Ethereum users, in terms of the number of transactions and terms of the amount of ether transferred per transaction. Despite the overall growing tendency of the Ethereum network, its users tend to transfer a low amount of ether. Moreover, a given address is used only a very few times. More precisely, 97% of the addresses present this profile of low value and low transfer rate. Only a very small percentage of addresses (0,00305848%) transfer a very high amount of Ether within a transaction, in the order of thousand ethers.[3] These transactions may indicate the use of Ethereum by special users, such as traders.

Table 6. Classification of addresses (nodes) per transactions versus values.

| Transactions \ Value | Low[1; 100] | Average ]100; 1,000] | High ]1,000; 10,000] | Very high ]10,000] |
|---|---|---|---|---|
| Very low [1; 100] | 97.68% | 2.05% | 0.017% | 0.0013% |
| Low ]100; 1,000] | 0.23% | 0.0047% | 4.8e-05% | 3.49e-06% |
| Average ]1,000; 10,000] | 0.012% | 0.00031% | 3.49e-06% | 0% |
| High average ]10,000; 100,000] | 0.0012% | 2.095e-05% | 0% | 0% |
| High ]100,000; 1M] | 0.00027% | 6.98e-06% | 0% | 3.5% |
| Very high ]1M | 3.14e-05% | 3.49e-06% | 0% | 0% |

[3] 1 ether = 117.72 US dollars in 01/24//2019 - https://coinmarketcap.com/pt-br/currencies/ethereum/).

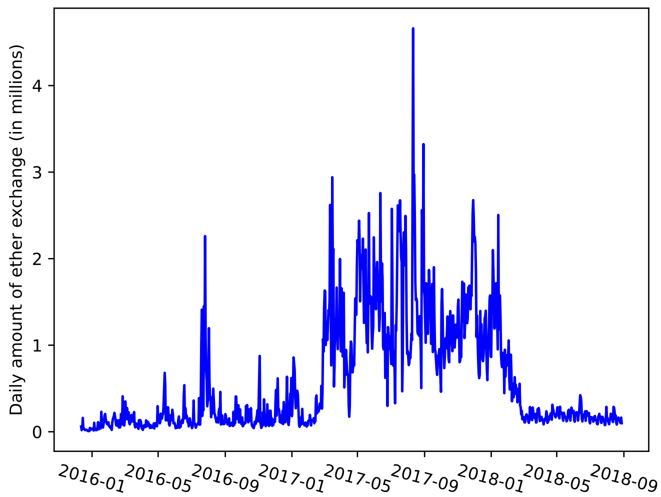



FIG. 7. Daily amount of ether exchange in the Ethereum Network.

## 6. The Dynamics of the Ethereum-Based Cryptocurrency Transaction Network

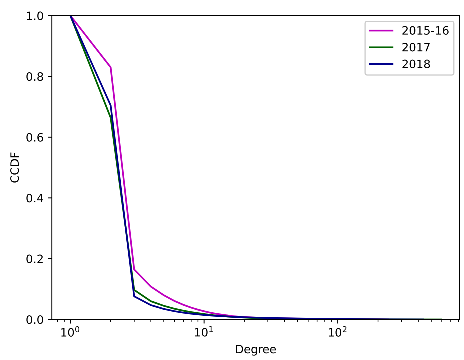
In this section, we analyze the dynamics of the Ethereum-based cryptocurrency transaction network. We first evaluate the connectivity dynamics of this network, modeled as a TVG (Section 6.1). We characterize the typical temporal node behavior and we present a ranking of the most important nodes of the Ethereum-based cryptocurrency transaction network. We also analyze the network disregarding the time aspect (Section 6.2). In other words, we consider a traditional static view of the network, where we aggregate all events in a single snapshot. This time aggregation causes a biased view of the Ethereum-based transaction network. Then, we characterize the transaction network weighted by the transaction value (Section 6.3). In this sense, the TVG vertex considers the amount of ether exchanged between nodes. Finally, we evaluate community generation and the evolution of the connected components in the Ethereum-based cryptocurrency transaction network (Section 6.4).

### 6.1 *Connectivity Dynamics of the Ethereum-based Cryptocurrency Transaction Network*

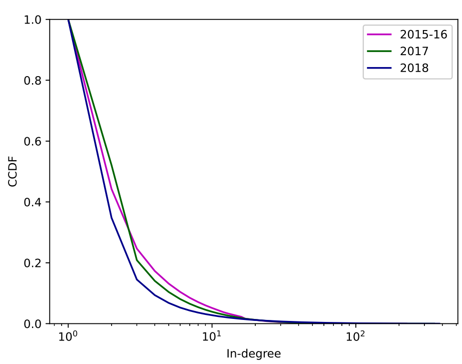
We model the Ethereum-based cryptocurrency transaction network as a TVG, as described in Section 4, and evaluate the connectivity dynamics of the studied network. In this analysis, we disregard the value of the transactions and each composite vertex in the MAG used to represent this dynamic network has an Ethereum address and a timestamp. Therefore, this analysis reflects the temporal dynamics of the volume of Ethereum transactions.

Figures 8(a), 8(b), and 8(c) present the distribution of the total degree, in-degree, and out-degree of the nodes in the Ethereum-based cryptocurrency transaction network, respectively. The degree highlights the node connectivity and can also show some interesting network properties, as the existence of specific node profiles accordingly to the connectivity or the presence of source (only out-degree) and sink (only in-degree) nodes in the network.

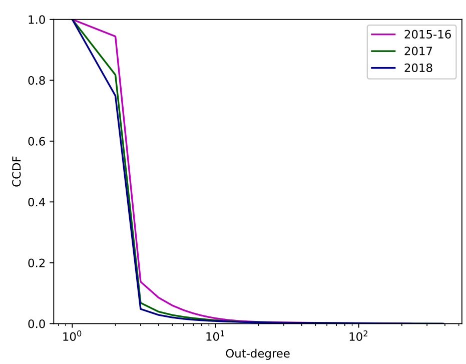
Note that, the distribution of the total degree, in-degree, and out-degree are quite similar at each time period. As we can observe in Figures 8(a), 8(b), and 8(c), most of network nodes present low degree values (for all kinds of degree values: total, in and out). In fact, more than 90% of all composite nodes present no more then a couple of transactions. In other words, almost all nodes perform, in a specific time instant, no more than a few transactions. This behavior is similar for all periods we have analyzed (i.e., 2015-2016, 2017, and 2018). Moreover, for all the analyzed periods, we observe a heavy tail, where very few nodes present a very high degree. These nodes, also known as hubs, may present more than 600 transactions in a single time period. Note that hubs achieve higher degrees during 2017 and 2018 when compared with the earlier periods. However, hubs still represent the very small portion of the network. In sum, most of the existing nodes present very few transactions and are connected to a limited number of hubs in the transaction network. These hubs may act as Ethereum nodes with particular roles, such as miners and coin traders.




(a) Total degree




(b) In-degree




(c) Out-degree

FIG. 8. Total Degree, In-degree, and Out-degree distribution for the Ethereum-based cryptocurrency network.

Tables 7, 8, and 9 present the top 10 nodes concerning the total degree for the 2015-2016, 2017, and 2018 periods, respectively. In sum, we present information about the composite nodes, such as their addresses, their total degrees, and the time instant corresponding to the composite node. Moreover, we present the metadata of the Ethereum address, as its TAG (a string which describes it) and type. For a matter of simplification, we refer to an Ethereum address using its final five characters only.

According to Table 7, the Ethereum address *be3b5* belongs to all top 10 composite nodes. In other words, this Ethereum address performed a high number of transactions, in distinct time instants. In some cases, during the same day, this node performed a high number of transactions (e.g. 2016-06-21 during the day and night periods). According to our investigations, this address belongs to a miner, tagged as *Nanopool*. This miner is one of the few nodes that remain active since the early periods of the Ethereum network, until the current date.

Table 7. Top 10 of composite vertices in 2015-2016 – MAG.

| Composite vertice | | Degree | TAG | Type |
|---|---|---|---|---|
| Address | Time instant | | | |
| be3b5 | 2016-05-16 | 238 | Nanopool | Miner |
| be3b5 | 2016-06-17 | 235 | Nanopool | Miner |
| be3b5 | 2016-06-21 | 234 | Nanopool | Miner |
| be3b5 | 2016-06-20 | 232 | Nanopool | Miner |
| be3b5 | 2016-06-21 | 232 | Nanopool | Miner |
| be3b5 | 2016-06-04 | 232 | Nanopool | Miner |
| be3b5 | 2016-06-24 | 232 | Nanopool | Miner |
| be3b5 | 2016-06-29 | 232 | Nanopool | Miner |
| be3b5 | 2016-06-17 | 232 | Nanopool | Miner |
| be3b5 | 2016-06-21 | 231 | Nanopool | Miner |

During 2017, as shown in Table 8, we only observe two Ethereum addresses among the top 10 total degree composite nodes. The address *29c4c*, tagged as SparkPool, is a miner address. However, the address *d2dcb* has not been publicly tagged and it seems to be a common account. We have further investigated the actions of this address and we have verified a regular use of smart contracts as well as a positive balance of ether during the total analyzed period.

Table 8. Top 10 of composite vertices in 2017 – MAG.

| Composite vertex | | Degree | TAG | Type |
|---|---|---|---|---|
| Address | Time instant | | | |
| d2dcb | 2017-10-31 | 592 | Anonymous | Common account |
| 29c4c | 2017-12-28 | 383 | SparkPool | Miner |
| 29c4c | 2017-12-23 | 382 | SparkPool | Miner |
| 29c4c | 2017-12-23 | 382 | SparkPool | Miner |
| 29c4c | 2017-12-31 | 381 | SparkPool | Miner |
| 29c4c | 2017-12-28 | 381 | SparkPool | Miner |
| 29c4c | 2017-12-13 | 381 | SparkPool | Miner |
| 29c4c | 2017-12-19 | 381 | SparkPool | Miner |
| 29c4c | 2017-12-21 | 381 | SparkPool | Miner |
| 29c4c | 2017-12-31 | 381 | SparkPool | Miner |

During 2018, we note a larger number of addresses among the top 10 total degree composite nodes. As shown in Table 9, we observe four distinct Ethereum addresses. The *29c4c* address, which was one of the top 10 of 2017, prevails as one of the addresses among the 2018 top 10 composite nodes. One of the addresses that appear among the top 10 composite nodes of 2018, the *3a830*, tagged as F2Pool2, is a miner. One may expect miners to be typically important active nodes that exchange ether among a high number of addresses. However, the other addresses (i.e., *6d317* and *1680b*) are not special, at a first glance. We have then investigated these addresses and, during the moments pointed out by the composite nodes, they have made a high interaction with the main address of a well-known ether exchange. For example, the composite node, with the address *6d317*, presents its highest degree in a moment where it performs a considerable number of transactions with the *ShapeShift* exchange, a well-known ether exchange. Transactions with ether exchanges are more clear to the address *1680b*, which is also highly related to the *ShapeShift* exchange. In this sense, we may conclude that both addresses may be associated with a single user that has a high amount of ether, spread among several addresses. At the end of an activity, these users concatenate the total volume of ether into a single account, usually managed by an exchange.

Table 9. Top 10 of composite vertices in 2018 – MAG.

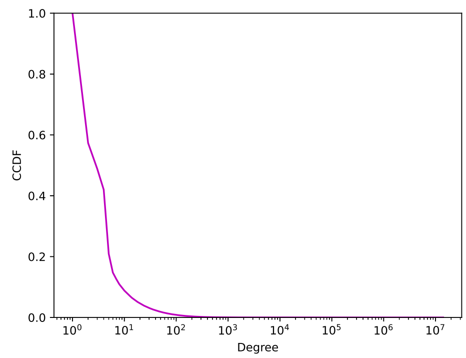
| Composite vertex | | Degree | TAG | Type |
|---|---|---|---|---|
| Address | Time instant | | | |
| 3a830 | 2018-06-06 | 436 | F2Pool_2 | Miner |
| 6d317 | 2018-04-17 | 391 | Anonymous | Common account |
| 29c4c | 2018-01-10 | 386 | SparkPool | Miner |
| 29c4c | 2018-01-10 | 385 | SparkPool | Miner |
| 1680b | 2018-04-13 | 383 | Anonymous | Common account |
| 29c4c | 2018-02-07 | 383 | SparkPool | Miner |
| 29c4c | 2018-04-18 | 383 | SparkPool | Miner |
| 6d317 | 2018-04-17 | 383 | Anonymous | Common account |
| 29c4c | 2018-01-27 | 383 | SparkPool | Miner |
| 6d317 | 2018-04-18 | 383 | Anonymous | Common account |

### 6.2 *Connectivity Dynamics of the Aggregated Transaction Network*

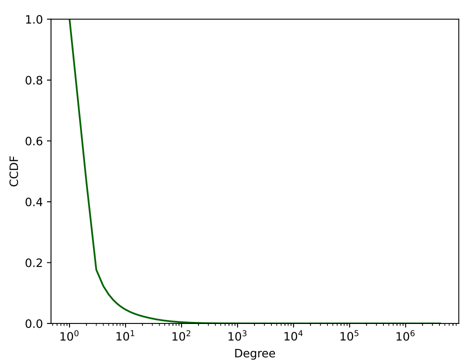
We may suppress the time aspect of the Ethereum-based cryptocurrency transaction network by sub-determining the previous TVG we have used to model that network in Section 6.1. In this sense, we have an aggregated view of the network, covering the totality of the evaluated period. The sub-determined network also shows that a small portion of the network (i.e., a relative small number of Ethereum addresses) performs a larger number of transactions. According to our evaluations, about 90% of the network presents an out-degree smaller than 7 and only 1% of the network performs more than 2.5 million transactions.

In this sense, Figures 9(a), 9(b), and 9(c) present the distribution of the total degree, in-degree, and out-degree of the nodes in the sub-determined Ethereum-based cryptocurrency transaction network, respectively. In this case, as the network suppresses the time aspect, nodes only present an Ethereum address. Again, as occurred to the TVG in Section 6.1, the degree distributions (total, in, and out-degrees) present a heavy tail. However, differently from the degree distributions presented in Figures 8(a), 8(b), and 8(c), in the sub-determined network, the maximum degree achieves considerably higher values, i.e., up to $10^7$. The sub-determined network shows that, from 2015 to 2018, approximately 22% of all the network addresses have performed no transactions. These addresses likely belong to miners, which only receive fees by special transactions or are old accounts, abandoned by their users. On the other hand, more than 76% of the network addressees exchange ether with other addresses, acting as transmitters and receivers during all the aggregated period. A negligible fraction of nodes (0.5%) only acts as a transmitter of ethers during the evaluated period.

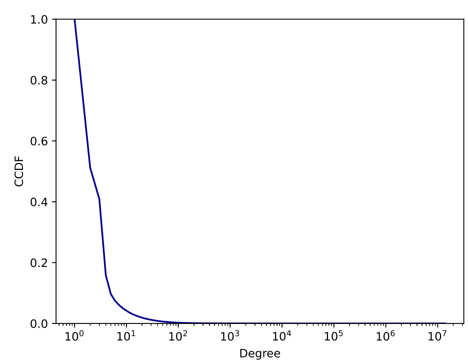
Table 10 presents the top 10 total degree nodes of the sub-determined network. Again, the most important a node is, according to its position in the ranking, the higher is its transaction volume. Therefore, a high degree indicates a network hub, during the evaluated period. First, we highlight a significant difference between the top 10 ranking nodes in Table 10, when compared with the top 10 rank presented




(a) Total degree




(b) In-degree




(c) Out-degree

FIG. 9. Total degree, in-degree, and out-degree distribution for the sub-determined Ethereum-based cryptocurrency network.

in the previous subsection (Table 7). As expected, aggregating all years in the studied period into a single network view presents a biased perspective of the network and does not allow one to capture its dynamic and evolution. We observe a considerable number of exchanges and miners (or miner pools) between the top 10 total degree ranking nodes. In fact, we observe six miners. Two of these miners also appear in a given period of the TVG as a top-ranked node. For example, Nanopool, which is one of the oldest addresses of the Ethereum network, is a top-ranked node during a given period of the 2015-2016 dataset.

Finally, note that the top-ranked node in the sub-determined network, the address *98ec8*, tagged as Ethermine, is not an important node to the TVG (Section˜6.1). Indeed, this particular address is not top-ranked for none of the evaluated periods, presented in Table 7. Despite the not so high degree of Ethermine in a specific period, the aggregation of its transactions for all the evaluated period (i.e, 2015-2018) turns this node into a top-ranked one. In other words, a high (likely burst) rate of transactions may give a node a top-ranked position in the TVG. On the other hand, a continuous transaction rate may give a node a top-ranked position in the aggregated view of the transaction network. That is the reason we found a larger number of miners between the top-ranked nodes in the aggregated network, since miners tend to remain online for longer periods, continuously performing transactions in the network.

Table 10. Top 10 degree sub-determined MAG with self-loops.

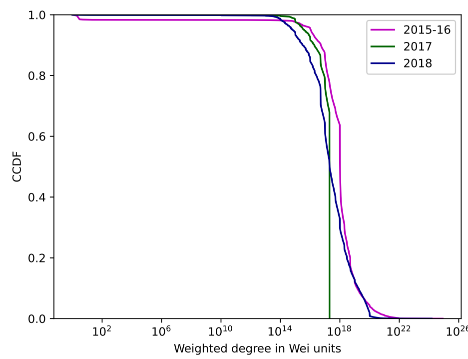
| Addresses | *Degree* | *In-degree* | *Out-degree* |
|---|---|---|---|
| 98ec8 | 16,349,202 | 1,161,326 | 15,187,876 |
| be3b5 | 9,979,871 | 544,561 | 9,435,310 |
| 6f0be | 6,239,806 | 4,512,990 | 1,726,816 |
| 3a830 | 6,152,962 | 105,872 | 6,047,090 |
| 98226 | 5,790,877 | 1,070,849 | 4,720,028 |
| 29c4c | 3,968,719 | 27,574 | 3,941,145 |
| 02d88 | 3,759,768 | 1,691,056 | 2,068,712 |
| fbb98 | 3,347,255 | 702,352 | 2,644,903 |
| ba413 | 2,482,677 | 2,028,278 | 454,399 |
| a0347 | 2,203,176 | 378,056 | 1,825,120 |

### 6.3 *Ethereum-based Cryptocurrency Transaction Network Weighted by the Transaction Value*

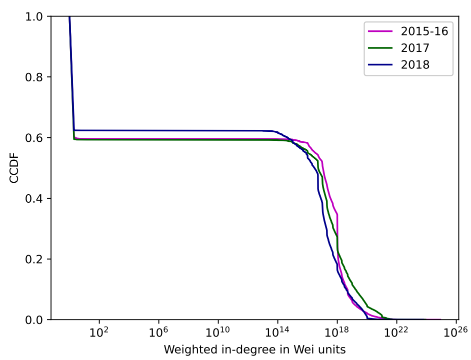
In this section, we consider the amount of ether in each transaction to evaluate the connectivity dynamics of the Ethereum-based cryptocurrency transaction network. In weighing the transaction network by the transaction value in ether,[4] we show the changes in the distribution of node importance (as a measure of the amount of ether each node deals with). In this case, the weighted degree of each node considers not only the number of edges (transactions) incident to that node but also the weights (transaction values) of the transactions of that node.

Figures 10(a), 10(b), and 10(c) present the distribution of the weighted total degree, in-degree, and out-degree of the nodes in the Ethereum-based cryptocurrency transaction network, respectively. For all the analyzed periods, we observe a similar behavior and, then we summarize our discussion in the following. As previously observed, the major part of the network nodes performs very few transactions in a given moment. Again, we also observe a few addresses accounting for almost all transactions of the network, which may indicate the presence of hubs (of traders) even when weighting the network links (transactions) by their ether values. Despite these particular similarities between both unweighted and weighted networks, the degree rank presents important differences between these networks.

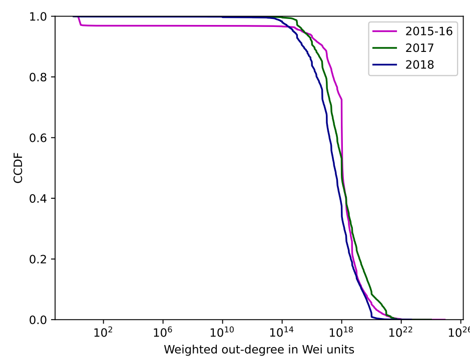
[4]Results in this section are actually expressed in Wei, where 1 Ether = $10^{18}$ Wei.




(a) Total degree




(b) In-degree




(c) Out-degree

FIG. 10. Weighted degree, weighted in-degree, and weighted out-degree distribution for the Ethereum-based cryptocurrency transaction network.

Tables 11, 12, and 13 show the ranking of the top 10 nodes by the weighted degree. In other words, we summarize the previous figures (Figures 10(a), 10(b), and 10(c)) showing the top-10 most important nodes for each period (i.e., 2015-2016, 2017, and 2018, respectively). As we have already discussed, there is a small number of addresses that correspond to exchanges in the network. However, these few nodes trade a large amount of ether. The rank highlights six exchanges within the top 10 nodes. Investigating these addresses, we observe two contracts in the ranking, as shown in Table 11. Finally, we highlight the presence of an anonymous account in the top 10 rank, which was not present in the rank shown in Section 6.2. We have further investigated the address *15bdd*, one of the contract addresses in the top-ranked nodes. An address performed this contract right after its first appearance in the Ethereum transaction network in 2016. In this case, it is the address *02d88* that belongs to an ether exchange (Poloniex_1). This ether exchange has two addresses composing the top 10 composite vertices for the 2015-2016 period (Table 11). A significant ether amount is exchanged by the distinct addresses of Poloniex, with meaningful participation in the top 10 ranking.

Table 11. Top 10 composite vertices - MAG 2015-2016.

| Composite vertices | | Weighted Degree in Wei | TAG | Type |
|---|---|---|---|---|
| Address | Time instant | | | |
| c8a3d | 2016-07-20 | 8,335,689.66 | Anonymous | Common account |
| 1caea | 2016-07-20 | 8,335,689.66 | ReplaySafeSplit | Contract |
| 02d88 | 2016-02-27 | 1,400,000 | Poloniex_1 | Exchange |
| 79268 | 2016-02-27 | 1,400,000 | Poloniex_3 | Exchange |
| a63d2 | 2016-03-02 | 1,391,762.09 | Kraken_1 | Exchange |
| 198bd | 2016-03-02 | 1,379,750.27 | TheAccumulator | Common account |
| 79268 | 2016-08-02 | 1,100,000 | Poloniex_3 | Exchange |
| 15bdd | 2016-08-02 | 1,100,000 | – | Contract |
| 79268 | 2016-05-12 | 1,000,000 | Poloniex_3 | Exchange |
| 02d88 | 2016-05-12 | 1,000,000 | Poloniex_1 | Exchange |

During 2017, we observe a decrease in the maximum amount of exchanged ether in this period. This decrease occurs probably due to the rise in the ether price (in US$) along the same period. However, according to our study, ether exchanges persist with a fundamental role in the network. Exchanges still appear among the five highest weighted degrees in the period. We execute the same address investigation made in Section 6.1. During this investigation, we identified a connection between the address *8d128* and a financial company (EO.FINANCE) that operates with cryptocurrencies. Continuing the investigation, we detected interactions with the ether exchange Polinex_1 and the address *8d128*. The address *8d128* tends to use smart contracts. Several times the Poloniex_2's contract was called by this address. The 200M_Trader address also has a strong relationship with some ether exchanges, in special with Bittrex_1, Poloniex_1, and Kraken_4.

Table 12. Top 10 composite vertices – MAG 2017.

| Composite vertices | | Weighted Degree in Wei | TAG | Type |
|---|---|---|---|---|
| Address | Time instant | | | |
| fe30f | 2017-05-01 | 1,000,000 | Bitfinex_1 | Exchange |
| c18ef | 2017-02-27 | 850,062.25 | Poloniex_2 | Contract |
| 8d128 | 2017-02-27 | 850,000 | EO.FINANCE[5] | Common account |
| 68318 | 2017-02-27 | 850,000 | Anonymous | Common account |
| 68318 | 2017-02-27 | 849,999.90 | Anonymous | Common account |
| 51919 | 2017-02-27 | 700,000 | Kraken_3 | Exchange |
| ffdc0 | 2017-02-27 | 700,000 | Kraken_4 | Exchange |
| 51919 | 2017-01-20 | 600,000 | Kraken_3 | Exchange |
| ffdc0 | 2017-01-20 | 600,000 | Kraken_4 | Exchange |
| a5184 | 2017-11-21 | 588,153.48 | 200M_Trader | Common account |

During 2018, we observe a larger number of ether exchanges within the top 10 ranking, as shown in Table 13. Moreover, the amount of ether transferred among the accounts grows during the 2018 period when compared with 2017. The addresses associated with ether exchanges dominate ranking positions, reinforcing their fundamental roles in the dynamics of the transaction network. The interesting fact is that the exchanges Polinex and Bitfinex are responsible for the highest amount of transferred ether for both the 2017 and 2018 datasets. These addresses connect a diverse set of other addresses and perform distinct actions (transactions and contracts). In particular, the address *79268*, associated with Polienx_3 (inactive since February 2018) that deals with smart contracts of different ether exchanges. The Bitfinex address, on the other hand, has predominant support to the ether exchange operation. For example, this address has transferred more than 600 thousand ethers among Ethereum accounts. Differently from the network majority, the anonymous account *6e2a8*, active since 2017, performs transactions with high average transaction value. Finally, regardless of the ether price (in US$), we observe a high amount of ether transfer among these exchanges, for all the analyzed period (2015-2018).

Table 13. Top 10 composite vertices – MAG 2018.

| Composite vertices | | Weighted Degree in Wei | TAG | Type |
|---|---|---|---|---|
| Address | Time instant | | | |
| 79268 | 2018-02-22 | 1,508,750.00 | Poloniex_3 | Exchange |
| 50cfa | 2018-03-13 | 610,001.69 | Bitfinex_4 | Exchange |
| 6e2a8 | 2018-03-13 | 610,000.00 | Anonymous | Common account |
| 8f44e | 2018-07-31 | 600,000.00 | Bitfinex_5 | Exchange |
| 50cfa | 2018-07-31 | 600,000.00 | Bitfinex_4 | Exchange |
| f5770 | 2018-03-28 | 595,000.00 | Anonymous | Common account |
| 11e82 | 2018-03-28 | 595,000.00 | Anonymous | Common account |
| 50cfa | 2018-07-31 | 594,457.71 | Bitfinex_4 | Exchange |
| 8f44e | 2018-07-31 | 594,453.80 | Bitfinex_5 | Exchange |
| 50cfa | 2018-04-23 | 475,000.04 | Bitfinex_4 | Exchange |

Overall, we observe significant differences between the top 10 rank for unweighted and weighted degrees during the analyzed period. First, we have noted that the miners were the most connected addresses. However, when we analyze the amount of ether transferred (weighted degree), the ether exchanges assume this role. This represents significant changes in the top 10 ranks over time, reflecting the typical behavior of nodes. In Section 6.1, the most important connectivity-level is in the hands of a few miners in the first years, as the Tables 7 and 8 show. This changes in 2018 (Table 9). However, in the current section, we note just the opposite. During the first years, i.e., 2015-2016 and 2017, there are four to five known actors (owner accounts) on the weighted degree top 10 rank. Nevertheless, in the last year, only two ether exchanges find a place in the top 10 rank.

### 6.4 *Communities and Connected Components*

In the previous sections, we have observed that the Ethereum-based cryptocurrency transaction network is composed of a majority of low-connectivity nodes. However, at the same time, there are some highly connected hubs. This small portion of the network, usually, consists of exchanges that also concentrate a large volume of transferred ether. In this section, we analyze how the nodes in the Ethereum-based cryptocurrency transaction network group with each other, either by forming communities in the main (giant) connected component or by forming separated components. Since, in a high abstraction level, the main actors of the Ethereum-based cryptocurrency transaction network are actually human beings behind wallet addresses, groups in this network may reveal a community structure (or separated components), reflecting preferences and behaviors of the Ethereum cryptocurrency users.

We first analyze the clustering coefficient of the Ethereum transaction network and study how dense the groups of the network are. For this analysis, we express the network as a directed graph (instead of a directed multi-graph) and aggregate the amount of ether on parallel edges. We then analyze the attachment preference of the nodes, realizing that the preferential attachment mode of this network is degree-based.

Table 14 presents the average clustering coefficient, the clustering coefficient to the total degree correlation, and the clustering coefficient to total weighted degree correlation. From this table, we observe that the network has a very low clustering coefficient, showing a low interaction level among its composite vertices. It follows that on average the nodes interact quite sparsely, corroborating the low transaction rate shown previously at the end of Section 5.2. Further, Table 14 shows that the clustering coefficient to the total degree correlation is close to zero, while the clustering coefficient to total weighted degree correlation is always negative. This negative correlation implies that high-degree nodes weakly connect to low-degree nodes. On the other hand, the weighted degree shows a positive correlation. To better understand this behavior, further analysis is required.

Table 14. Connection preferences of the transaction network with MAG.

| Period | Clustering Coefficient (Average) | Degree correlation | Weighted degree correlation |
|---|---|---|---|
| 2015 - 2016 | $1.62 \times 10^{-5}$ | -0.078 | 0.348 |
| 2017 | $4,058 \times 10^{-5}$ | -0.028272 | 0.440 |
| 2018 | $2,401 \times 10^{-06}$ | -0.04904 | 0.285 |

We analyze aspects of community formation by segmenting the Ethereum-based cryptocurrency transaction network using the well-known Louvain method [2] for community detection. Due to computational constraints, we have only analyzed the communities on the more recent Ethereum data (i.e., the last three months of our 2018 dataset). Communities, in this case, capture aspects of time. In this sense, communities are distributed in time and may present a temporal interaction among their nodes. The Figure 11 shows the distribution of the size of communities for this time period. The majority of the communities are composed of up to two vertices; in other words, there is a low interaction between the vertices per instant of time. The frequency of node activity is low, and a small portion of the nodes is more active to the point of making several connections per instant of time. Due to the low-level connectivity, there are few connections among the vertices, influencing the community formation. Moreover, as the number of components grows, the number of communities decrease.

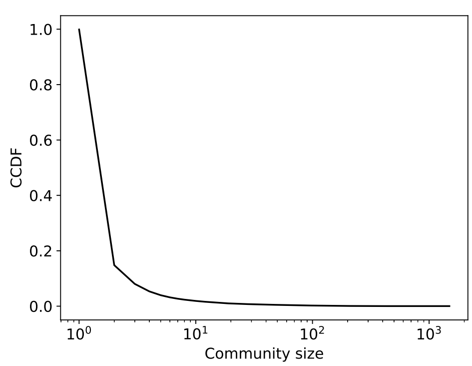



FIG. 11. Distribution of the size of communities (three last months of the 2018 dataset).

Figures 12(a), 12(b), and 12(d) present the distribution of the size of the communities for the sub-determined Ethereum transaction MAG for the analyzed periods. Despite the smaller networks when sub-determined, the computational cost is still high and then we have split the 2017 and 2018 periods into two networks in each period. As shown in Figure 12(a), which details the sub-determined MAG between 2015 and 2016, the network presents a low-level of interaction and small communities. In this case, 8.44% of the network formed by communities with only two vertices. The majority of communities is made of hundreds of nodes, whereas a very small number of communities includes thousands of vertices. However, we note some very big communities. The largest one presents 17.79% of the network vertices. Although a significant fraction of vertices composes communities, it still represents a small portion of the network. We even perceive that most of the users make transactions with a reduced number of addresses creating small groups.

We realize that the highly active period of the transaction network benefits the most significant interaction occurrence among the addresses in the sub-determined network. The substantial increase of communities, especially in 2018.1, contributes to this understanding. The largest communities also appear in this period, indicating that a significant number of nodes make transactions with each other, keeping some relationship. Observing the results of this work, we perceive that the interaction and activity contribute to community formation. Besides that, the role of ether exchanges, that increased in 2018, is probably responsible for part of the cooperation among the network addresses. Based on this factor and the negative degree-correlation (previously presented in Table 14), the ether exchanges largely contribute to the inter-connectivity of the Ethereum-based cryptocurrency transaction network.

Finally, Figure 15 shows the time evolution of the weakly connected components in the Ethereum-based cryptocurrency transaction network. We observe that the number of weakly connected components increases a lot with the usage of the network over the years. Nevertheless, the fraction of nodes in the giant (weakly connected) component remains stable, dominating over 99% of the nodes. Considering the mean and the median of the number of nodes per component over the analyzed period, we observe that the mean number of nodes per component decreases, in particular with sharp decrease from 2017 to 2018 (associated with a sharp increase in the number of components), but the median number of nodes per component remains quite small. This attests the high positive skew of the distribution of nodes per weakly connected components over all the analyzed period (2015-2018).

Table 15. Evolution of weakly connected components in the Ethereum-based cryptocurrency transaction network.

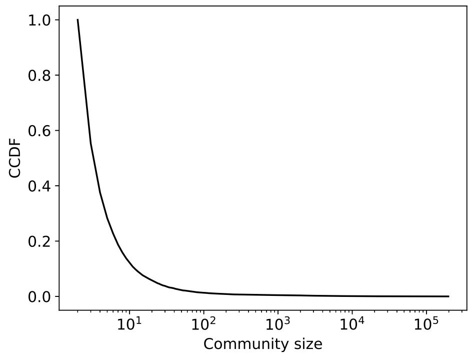
| Period | Number of weakly connected components | Fraction of nodes in the giant component | Mean number of nodes per component | Median number of nodes per component |
|---|---|---|---|---|
| 2015 - 2016 | 243 | 0.9986 | 2,622 | 2 |
| 2017 | 5,688 | 0.9989 | 2,538 | 2 |
| 2018 | 61,578 | 0.9939 | 411 | 2 |

## 7. Conclusion

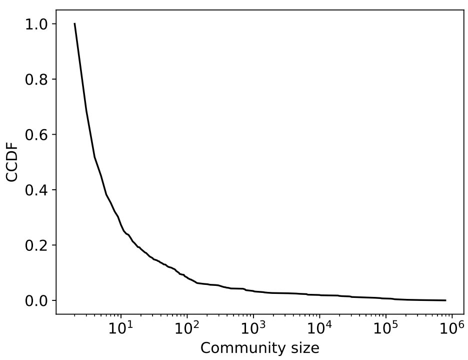
In this work, we present the modeling and temporal analysis of the Ethereum-based cryptocurrency transaction network. Although Ethereum is a platform capable of offering functionalities beyond those found on a simple cryptocurrency, we realize that its main use is as a cryptocurrency. Therefore, we focus our analysis on ether, the Ethereum-based cryptocurrency.

We represent ether's transaction network using a time-varying graph. This approach allows the representation of transactions and time in a single mathematical object, enabling an integrated analysis of both transactions and time aspects. Using this theoretical framework we are able to study the network evolution and user behavior in a time frame ranging from the creation of Ethereum (2015) until 2018. In some analyses, we can choose to consider the whole network or to create an aggregated view of the network capable of offering a time independent analysis.

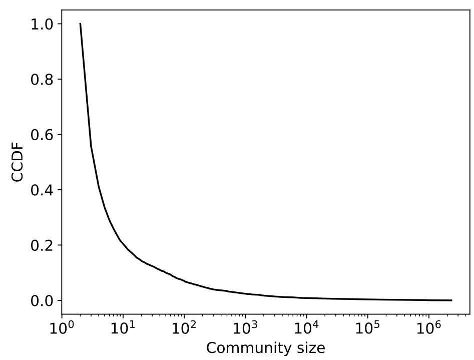
In the structural analysis, we show that the transaction network is composed of few high-degree nodes and many low-degree nodes. The high-degree nodes are, in general, associated with exchanges and miners. These hubs are usually connected to many lower degree nodes. In particular, miner nodes present the characteristic behavior of having a particularly high out-degree as compared with other kinds of nodes. We remark that, in general, the communities detected in the network also have few high-degree



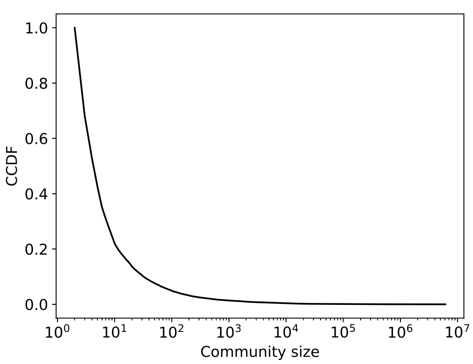

(a) Communities distribution on 2015-2016



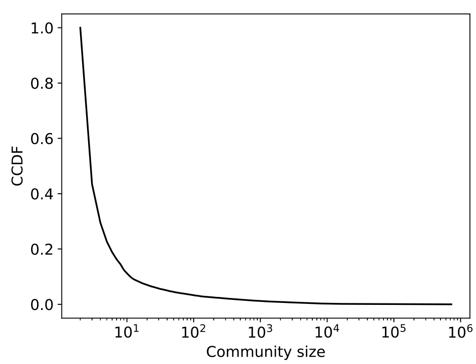

(b) Communities distribution on 2017.1




(c) Communities distribution on 2017.2




(d) Communities distribution on 2018.1




(e) Communities distribution on 2018.2

FIG. 12. Distribution of the community sizes on the sub-determined Ethereum-based cryptocurrency transaction network.

nodes and a majority of low-degree nodes.

The results we obtained are promising and encourage us to expand the analysis as a future work. It would be interesting to explore specific behaviors of the network, such as ether flow characteristics and node centralities beyond simple node degree.

### Acknowledgment

This work was partially funded by CAPES, CNPq, FAPESP, and FAPERJ. Authors also acknowledge the INCT in Data Science – INCT-CiD.

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