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HASHRATE DYNAMICS: EXPLORING ITS RELATIONSHIP WITH BITCOIN'S NETWORK METRICS

ДИНАМІКА ХЕШРЕЙТУ: ВИВЧЕННЯ ВЗАЄМОЗВ'ЯЗКУ З МЕТРИКАМИ МЕРЕЖІ BITCOIN

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This study delves into the dynamics of Bitcoin's hashrate and its correlation with network metrics, aiming to illuminate the underlying factors shaping Bitcoin's ecosystem. Employing a multi-metric analysis, the research examines Bitcoin price, public interest, and total daily transactions alongside hashrate data. Findings reveal nuanced relationships between these variables, with traditional metrics like hashrate showing inconsistent correlations with public interest over long-term trends. However, short-term analyses unveil potential predictive capabilities, especially when integrating additional factors like Bitcoin price and daily transactions. A novel metric, termed the 'popularity coefficient, is introduced, derived from averaging daily values of price, interest, and transactions, offering a more holistic understanding of Bitcoin's popularity dynamics. The practical implications of this research lie in enhancing our ability to predict short-term fluctuations in Bitcoin's network dynamics, thereby informing decision-making processes within the cryptocurrency ecosystem.

Keywords: economy, crypto, cryptocurrencies, BTC, hashrate, multi-metric analysis.

Це дослідження розглядає динаміку хешрейту Bitcoin та його взаємозв'язок з метриками мережі, спрямоване на висвітлення основних чинників, які формують екосистему Bitcoin. Застосовуючи багатометричний аналіз, дослідження вивчає ціну Bitcoin, громадський інтерес та загальну кількість щоденних транзакцій разом із даними про хешрейт. Виявлені висновки розкривають відтінені взаємозв'язки між цими змінними, де традиційні метрики, такі як хешрейт, показують нестійкі кореляції з громадським інтересом протягом тривалих тенденцій. Проте аналізи короткострокових періодів розкривають потенційні прогностичні можливості, особливо коли враховуються додаткові фактори, такі як ціна Bitcoin та щоденні транзакції. Вводиться новий показник, що називається «коефіцієнт популярності», який випливає з усереднення щоденних значень ціни, інтересу та транзакцій, що дозволяє отримати більш повне уявлення про динаміку популярності Bitcoin. Практичні наслідки цього дослідження полягають в покращенні можливостей прогнозування короткострокових коливань в мережевій динаміці Bitcoin, тим самим сприяючи процесам прийняття рішень у криптовалютній екосистемі. Це дослідження надає важливі висновки для інвесторів, дослідників та учасників ринку криптовалют, допомагаючи їм краще розуміти фундаментальні чинники, що впливають на Bitcoin. Враховуючи динаміку ціни, інтересу громадськості та транзакцій, разом з хешрейтом, стає можливим не лише аналізувати минулі тенденції, але й робити кращі прогнози для майбутнього. Крім того, введення «коефіцієнта популярності» відкриває нові можливості для оцінки загальної придатності Bitcoin та сприяє розвитку більш точних моделей аналізу ринку криптовалют. Це дослідження стає важливим кроком у напрямку глибшого розуміння криптовалютних ринків та сприяє розвитку більш точних стратегій інвестування.

Ключові слова: економіка, крипто, криптовалюти, BTC, хешрейт, мультиметрична аналітика.

Formulation of the problem in general. Given a historical dataset of cryptocurrency price movements and relevant market data, the objective is to research how hashrate depends on popularity and cryptocurrency price. Given the dynamic nature of the cryptocurrency market, particularly with respect to mining, the relationship between hashrate, price, and popularity is of significant interest. The problem at hand involves understanding and quantifying how the hashrate of a cryptocurrency network is influenced by both its price and its popularity. Specifically, we seek to explore how changes in price and popularity metrics affect the overall hashrate of the network. To formulate this problem, we need to consider the following components: Hashrate: The total computational power dedicated to mining a cryptocurrency network. This is a fundamental metric that reflects the security and efficiency of the network. Price: The market value of the cryptocurrency. Price fluctuations are common in the volatile cryptocurrency market and can influence various aspects of the network, including mining activity. Popularity: The level of interest and adoption of the cryptocurrency among users, investors, and miners. Popularity can be measured by metrics such as trading volume, social media mentions, number of active wallets, or mining pool participation.

Analysis of recent research and publications. There is not a large number of published works devoted to the study of crypto currency and mathematical models. Hayes, Adam S, Stoll, Kristoufek, Kjærland, Schar and Berentsen. That's why this topic has to be researched in detail.

Unresolved parts of the common problem. While correlations between cryptocurrency price, popularity, and hashrate have been observed, the direction of causality remains unclear. It's unclear whether changes in price and popularity drive changes in hashrate, or if it's the other way around. Resolving this aspect is crucial for accurately understanding the dynamics of cryptocurrency markets and mining activity. Existing research often assumes linear relationships between price, popularity, and hashrate. However, the relationships may be non-linear or exhibit time delays and asymmetries. Further investigation is needed to uncover potential non-linearities and better capture the complexities of these relationships. External Factors and Confounding Variables: Cryptocurrency markets are influenced by a myriad of external factors, such as regulatory changes, technological advancements, macro-economic trends, and geopolitical events. Understanding how these external factors interact with price, popularity, and hashrate dynamics is essential for a comprehensive analysis but remains largely unresolved.

Behavioral Dynamics: The behavior of market participants, including miners, investors, and developers, plays a significant role in shaping cryptocurrency ecosystems. However, the psychological and behavioral aspects driving their decisions are not fully understood. Exploring the behavioral dynamics underlying mining activity and market sentiment could provide valuable insights into the relationship between price, popularity, and hashrate.

The purpose of the article. This article highlights mathematical approaches for hashrate dependency on bitcoin price analysis. This article shows the results of current research.

Presenting main material. In Hayes paper [1], makes several key assumptions to estimate the primary factors influencing the price of Bitcoin. Here is a more detailed explanation of these assumptions and the framework he builds:

– <u>Computational Power and Bitcoin Value</u>: Hayes posits that there is a positive correlation between the computational power employed by the Bitcoin network and the value of Bitcoin. The more computational power that is dedicated to mining Bitcoin, the more secure and valuable the network becomes. This is because higher computational power implies a more robust and tamper-resistant network, which enhances the trust and perceived value of Bitcoin.

– <u>Rational Miners</u>: The second assumption is that all miners operate rationally, seeking to maximize their profits. Rational miners will only participate in mining if it is profitable for them to do so. This means that if a cryptocurrency has no demand or market value, rational miners will not waste resources mining it, and they will redirect their computational power to more profitable ventures. Essentially, this assumption links the demand for Bitcoin directly to the efforts of miners; if there is no demand, there will be no mining activity.

– <u>Network Difficulty as a Proxy for Mining Power</u>: The third assumption is that the network difficulty can be used as an indicator of the aggregate mining power of the network. Within the Bitcoin protocol, the difficulty of mining adjusts periodically to ensure that blocks are mined at a consistent rate, regardless of the total computational power of the network. If more miners join the network and the total computational power increases, the difficulty will increase accordingly, and vice versa. This mechanism ensures the stability and predictability of the Bitcoin network.

Building on these assumptions, Hayes constructs a framework to illustrate the relationship between the computational power employed by a miner and their expected profitability, given the current conditions of the network. When a miner evaluates their baseline profitability, they start by calculating the expected number of bitcoins they can produce each day. This calculation involves several factors, including the miner's share of the total network hash rate, the current network difficulty, and the Bitcoin block reward.

The expected number of bitcoins produced per day by a miner can be expressed with the formula:

$$\frac{BTC}{day} = \left(\frac{\beta\rho \cdot sec_{hr}}{\delta \cdot 2^{32}}\right) \cdot hr_{day},$$

where β is block reward (bitcoin per block), δ is the difficulty (expressed in units of Giga-Hash/block), ρ is the hashing power employed by a miner expressed in Giga-Hash/second, sec_{hr} is the number of seconds in an hour, hr_{day} is a number of hours in a day and $1/2^{32}$ is a normalized probability of a

single hash "solving" a block and is an attribute of the mining algorithm.

This formula allows miners to estimate their potential earnings based on their contribution to the total network hash rate and the current state of the network. By comparing this expected revenue with their operational costs (e.g., electricity, hardware depreciation), miners can decide whether it is profitable to continue mining or if they should redirect their resources elsewhere. These three constants can be fit into a single parameter θ, so the formula takes the following view:

$$\frac{BTC}{day} = \left(\frac{\beta\rho}{\delta}\right)\theta, \theta = hr_{day} \cdot sec_{hr} / 2^{32}.$$

The daily cost of mining can be expressed as follows,

$$E_{day} = \left(\frac{\rho}{100 GH/s}\right)\left(\frac{\$}{kWh} \cdot EEF \cdot hr_{day}\right),$$

where Eday is the cost per day for a producer, $/kWh is the price of a kilowatt-hour, and EEF is the energy consumption efficiency of the miner's hardware. Given the assumption of perfect competition so that the marginal cost of production and the marginal profit are equal, the equilibrium price takes the following form:

$$P = \frac{E_{day}}{BTC/day} = \frac{\frac{\$}{kWh} \cdot EEF \cdot hr_{day} \cdot \delta}{\beta \cdot 1000 GH/s \cdot \theta},$$

where we set ρ = 1000 GH/s as in Hayes [1]. The CPM offers a simple but effective framework for estimating the cost of production price. However, it simplifies the mining expenses by dismissing several other important factors, such as the capital and the operational expenses of the running mining operation. Another important drawback of this model emerges around the times of the bitcoin halving events, when the reward in bitcoins for finding new blocks is cut in half: unlike real-world miners, this model does not anticipate this change and therefore it produces unreliable results (this issue will be discussed later in this paper). Interestingly Hayes found that the CPM Granger-causes the market price but not the other way around [2].

It is important to note that the Cryptocurrency Pricing Model (CPM) proposed by Hayes [1; 2] requires certain inputs that are not easily observable or reliably approximated. One such input is the electricity cost, which Hayes assumes to be a constant USD 0.135 per kWh – an average global rate at the time of his publications. However, this assumption does not reflect the diverse reality faced by miners. For example, some miners benefit from free energy through subsidies or covert use, as discussed in Stoll. [3].

Another critical input is the parameter for mining equipment's energy efficiency. While it is possible to identify the most efficient mining equipment available at any given time, determining the distribution of this equipment among miners is challenging. The actual average energy efficiency of the network is unknown. Additionally, there are specialized ASIC models, like the GMO miners (gmominer.z.com/en), which have limited market presence but can significantly impact overall energy efficiency. This variability in equipment and its distribution complicates the accurate assessment of the network's total energy efficiency.

Given that the CPM heavily relies on accurate data for electricity costs and energy efficiency, fixing these parameters accurately is crucial yet difficult. Inaccurate assumptions can lead to misleading results, making it essential for researchers and practitioners to approach these parameters with caution and consider the potential variability and uncertainties involved.

Kristoufek [4] was one of the first researchers to emphasize that the factors influencing the price of Bitcoin tend to change over time due to its "dynamic nature and rapid price fluctuations." This concept was later expanded upon by Kjærland , who examined the impact of various major commodities and indices, different metrics from the Bitcoin network, and Google Trends data on Bitcoin price dynamics [5].

Kjærland converted daily data into weekly averages to mitigate potential autocorrelation issues [5]. They also addressed outliers and structural breaks within the dataset. The data was divided into three distinct periods for analysis. They utilized Autoregressive Distributed Lag (ARDL) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models for their estimations. Contrary to Hayes' findings [1,2], Kjærland [5] discovered that the Bitcoin network's hashrate did not significantly impact the market price of Bitcoin. The only exception was during Bitcoin's exponential growth in 2017, suggesting that the Bitcoin price likely influences the hashrate rather than the other way around.

Moreover, their findings indicated that the Efficient Market Hypothesis (EMH) does not hold for Bitcoin. They observed that Bitcoin prices could be explained by their own historical values, indicating that investors are influenced by the momentum effect. This effect suggests that rising prices attract more investors, driven by the potential for quick profits, consistent with the "Greater Fool theory" reviewed by Santoni [6] and the "Momentum theory" discussed in detail by Jegadeesh and Titman [7; 8].

Kjærland also demonstrated that Google Trends data has a positive and significant impact on Bitcoin prices, aligning with previous studies [5]. The S&P 500 index was found to have a positive impact on Bitcoin prices as well, which the researchers interpreted as a sign of overall investor optimism and a willingness to invest in various assets. In contrast, gold and oil prices were found to be insignificant, and the VIX index (a measure of market volatility) was also largely insignificant except for one period.

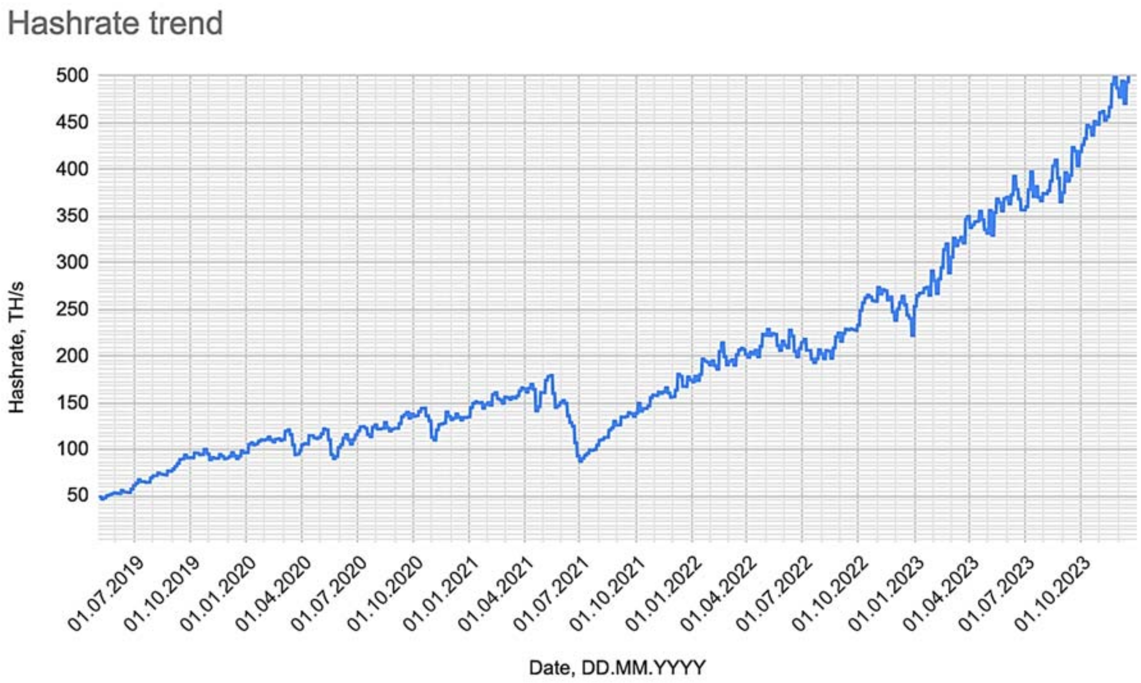
These findings highlight the complex and evolving nature of the factors that drive Bitcoin prices. They underscore the importance of considering a wide range of variables, including market sentiment and investor behavior, in understanding Bitcoin's price dynamics.

With this information, let's apply it to trend analysis. To validate the correctness of chosen methods, let's analyze already known data, in our case it's the bitcoin hashrate trend during 5 years (Graph 1).

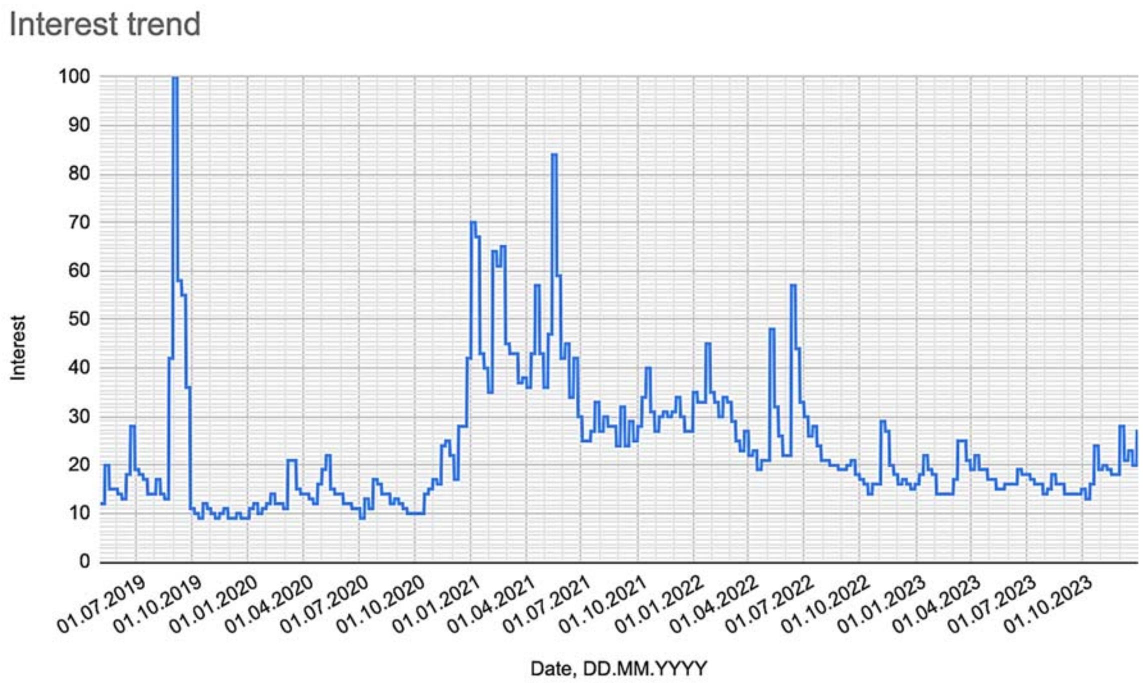
Google Trends data tracking global interest in 'Bitcoin' over the last five years was chosen for this analysis and visualized in Graph 2.

For accurate and objective analysis, both the hashrate trend data (graph 1) and interest data (graph 2) were normalized and presented together on graph 3.

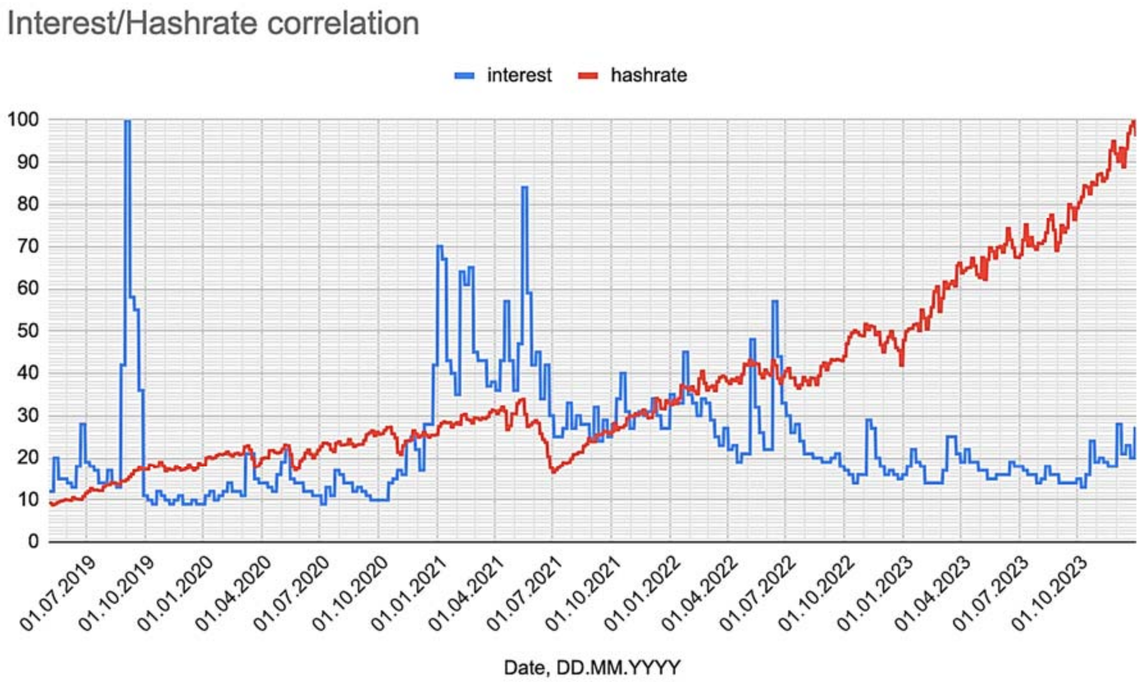
At first glance, graph 3 appears to show no correlation between hashrate and public interest in cryptocurrencies, especially when considering long-term trends. However, upon closer



Graph 1. BTC Hashrate trend for 5 years



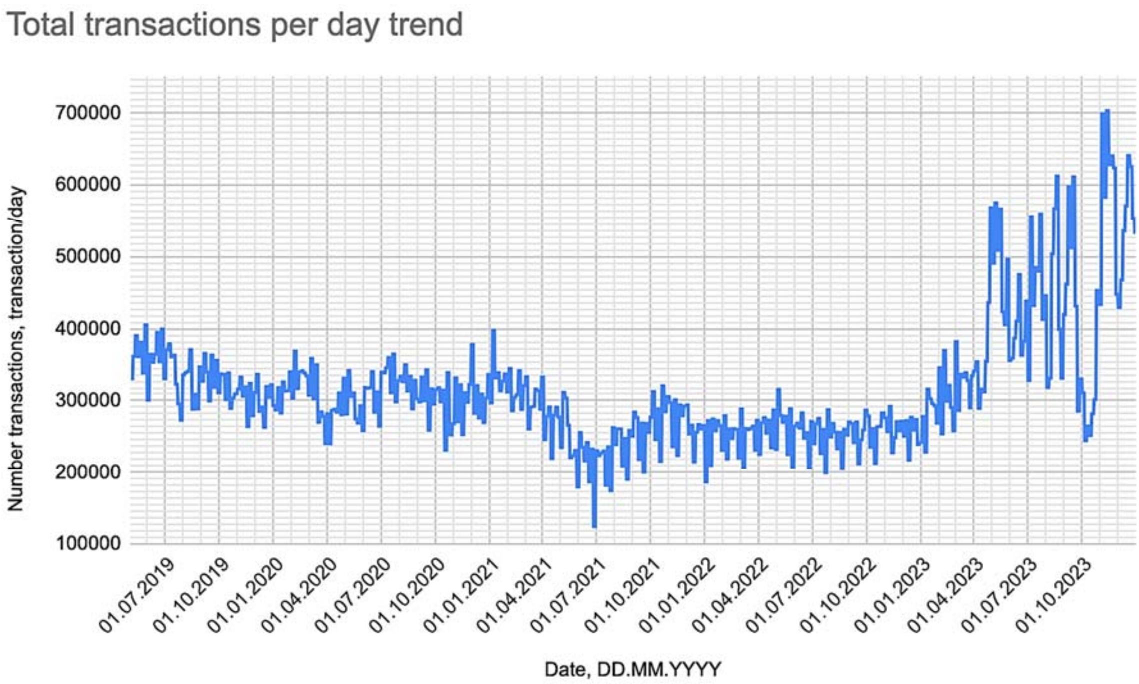
Graph 2. BTC Interest trend for 5 years (according Google Trend results)



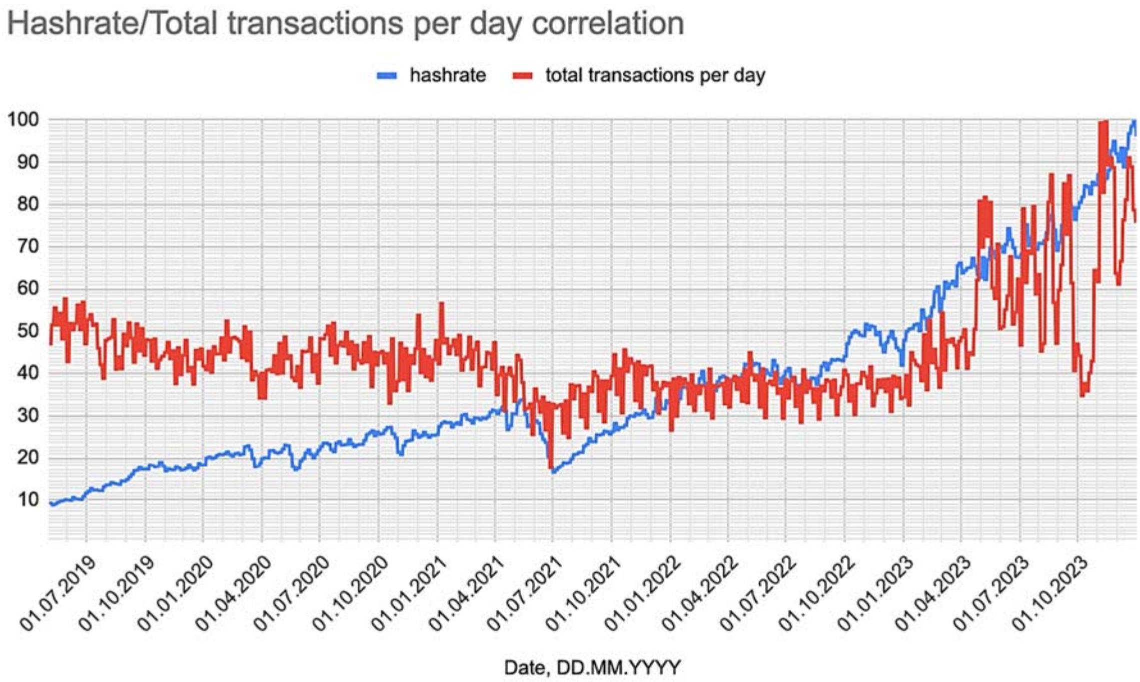
Graph 3. Normalized BTC interest and BTC hashrate trends for 5 years

examination of short-term data, some correlation becomes evident. However, it remains uncertain whether public interest in Bitcoin, as measured by Google searches for 'Bitcoin,' fully represents its popularity. Further research is required to obtain a more comprehensive understanding, necessitating the incorporation of additional data into the analysis. To enhance the accuracy of this study, we will also consider the total number of daily transactions on the blockchain network (graph 4).

The results of incorporating this additional data to hashrate trend by normalizing data are displayed in graph 5.



Graph 4. Total daily transactions in BTC network for 5 years

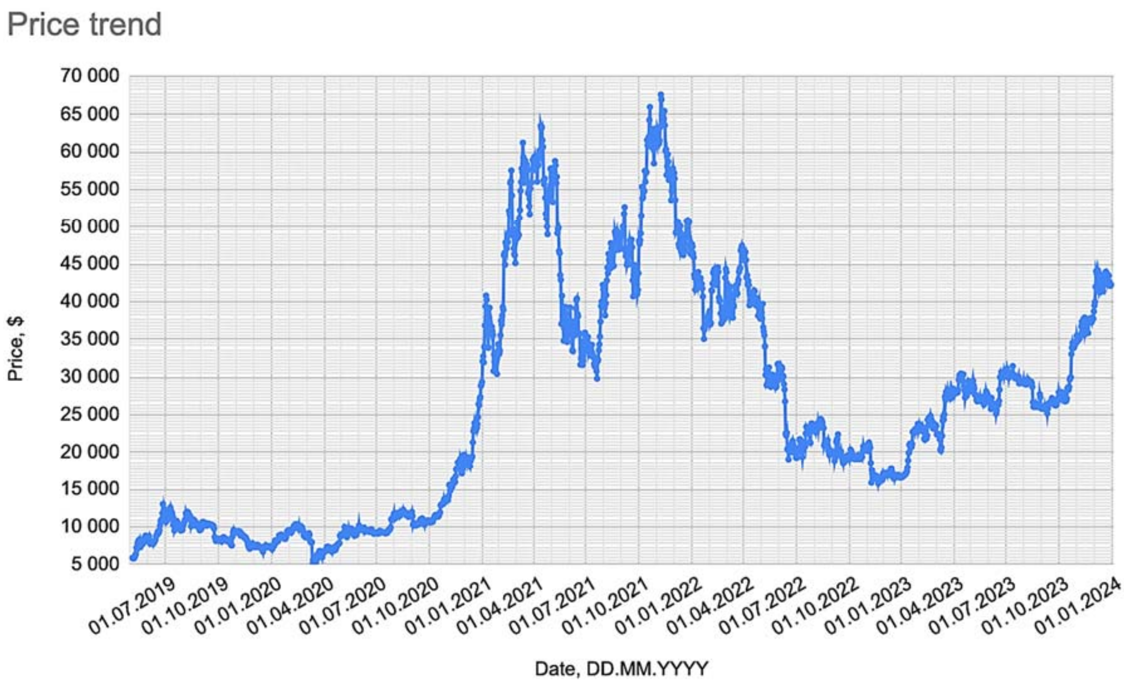


Graph 5. Normalized BTC hashrates and total daily transactions in bitcoin network trends for 5 years

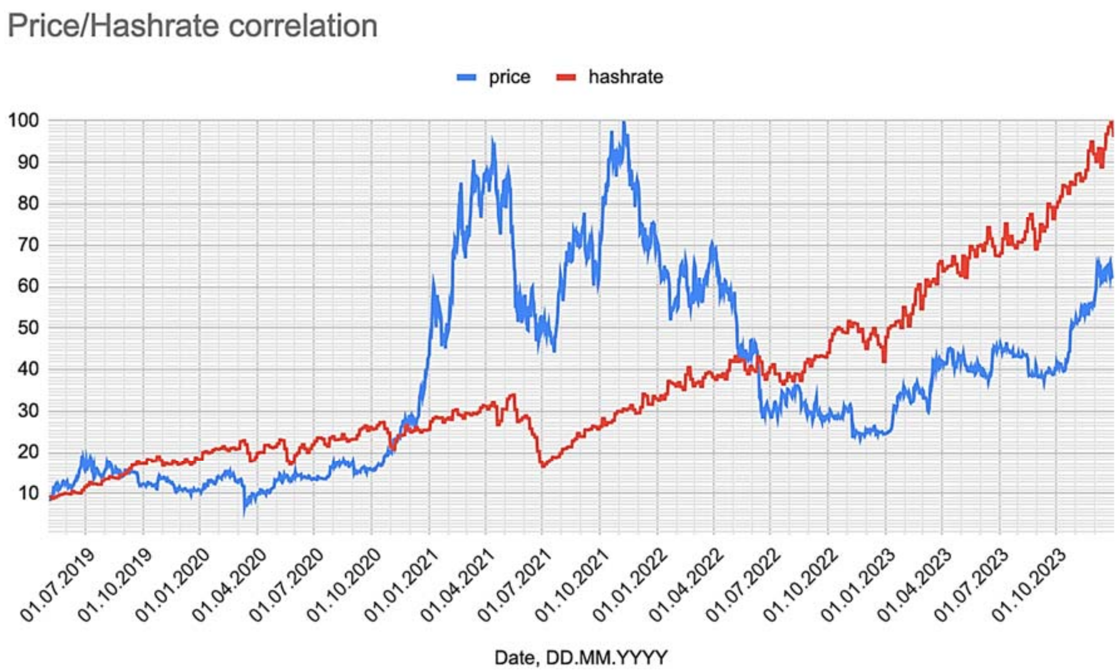
Graph 5 seems to show no correlation between hashrate and public interest in cryptocurrencies, particularly over long-term trends. However, a closer examination of short-term data reveals some fluctuations. To further expand this research, we propose incorporating Bitcoin price data into the analysis. By examining the relationship between Bitcoin price, hashrate, public interest (as measured by Google searches for 'Bitcoin'), and daily blockchain transactions, we aim to achieve a more comprehensive understanding of the factors influencing Bitcoin's popularity and network activity. This additional data will help to identify any correlations or trends that may not be apparent when considering each factor in isolation. Price trend for 5 years is shown on graph 6. And results of incorporating pricing data to hashrate trend by normalizing data are displayed in graph 7.

After incorporating Bitcoin price data into the analysis (graph7), the results mirror those observed with hashrate and public interest data. In the long term, there appears to be no significant correlation between Bitcoin price and the other variables. However, a closer examination of shorter time frames reveals some correlations, suggesting that Bitcoin price may have a more immediate relationship with public interest and network activity.

For the final result, we aim to calculate the average daily values for Bitcoin price, public interest, and total daily transactions. These values will be combined to create a 'popularity coefficient' which will provide a comprehensive metric for assessing Bitcoin's overall popularity.



Graph 6. BTC price trend for 5 years

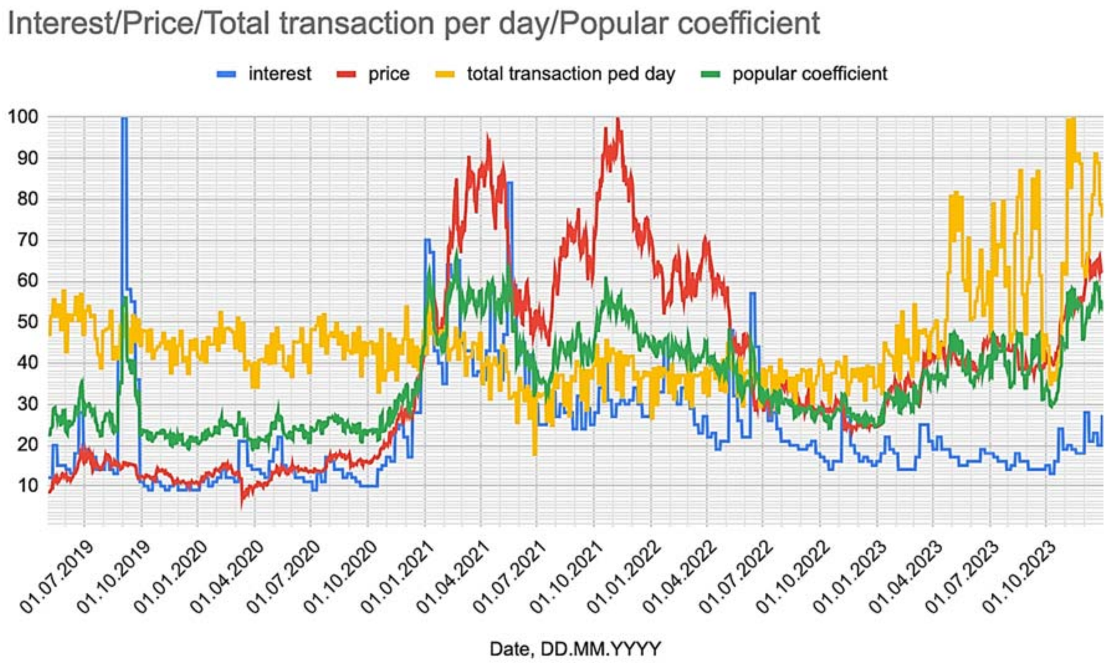


Graph 7. Normalized BTC hashrates and bitcoin price trends for 5 years

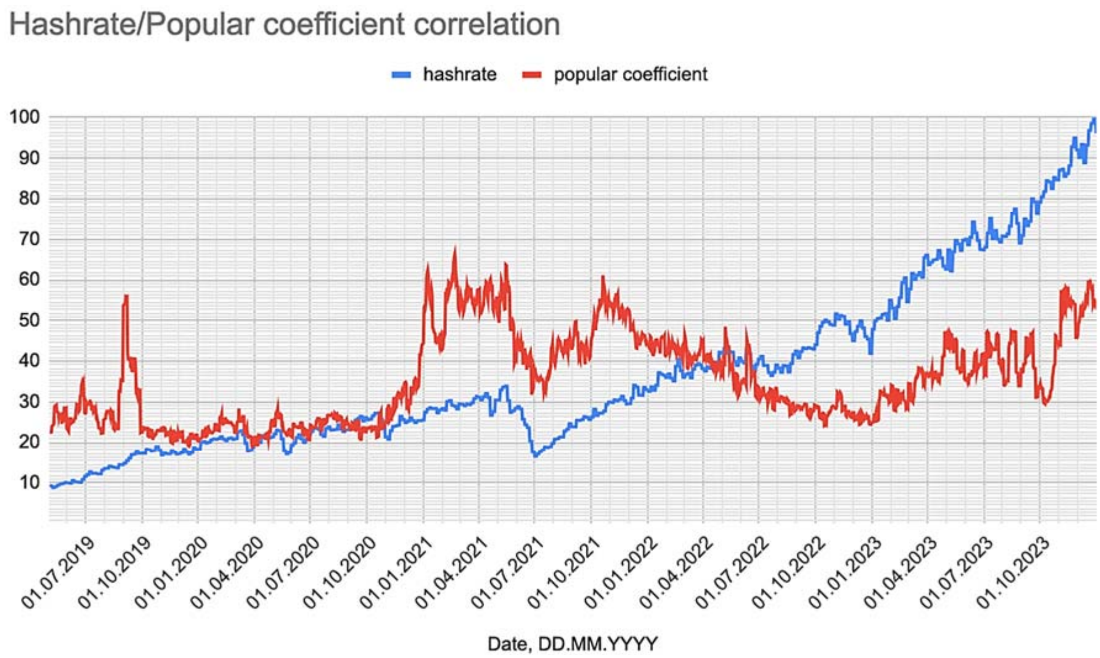
$$P_{day} = \frac{Price_{day} + Tt_{day} + I_{day}}{3},$$

where P_{day} – popularity coefficient, $Price_{day}$ – price, Tt_{day} – total transaction, I_{day} – interest. In this study, the representation of the 'popularity coefficient' is visually depicted on the graph 8 alongside Bitcoin price, public interest, and total daily transactions. This graphical representation allows for a clear visualization of the relationship between these factors and provides insight into Bitcoin's overall popularity dynamics.

In the final analysis, we compare the hashrate with the 'popularity coefficient' to create a more comprehensive and representative graph. By juxtaposing these two key metrics, we aim to gain deeper insights into the interplay between the technical aspects of Bitcoin's network and its broader popularity dynamics (graph 9).



Graph 8. Popularity coefficient visualization in comparison with the elements of formation of this coefficient for 5 years



Graph 9. Popularity coefficient and normalized bitcoin hashrate for 5 years

We observe that the 'popularity coefficient' offers results closely aligned with real-world conditions, potentially serving as a predictive indicator for short-term fluctuations. This suggests its utility as a factor for enhancing short-term predictive models of Bitcoin's network dynamics, complementing traditional metrics like hashrate.

Conclusions. Our research underscores the complexity of understanding Bitcoin's popularity and network dynamics. We found that traditional metrics like hashrate do not consistently correlate with public interest over long-term trends. However, incorporating additional factors such as Bitcoin price and daily transactions can provide valuable insights, especially in predicting short-term fluctuations.

The introduction of the 'popularity coefficient,' derived from averaging daily values of price, interest, and transactions, emerged as a promising tool for gauging Bitcoin's overall popularity. This metric not only closely reflects real-world conditions but also demonstrates potential for enhancing short-term predictive models for Bitcoin's network dynamics.

Overall, our findings highlight the importance of considering multiple factors when analyzing Bitcoin's ecosystem. By integrating diverse data sources and innovative metrics like the 'popularity coefficient,' we can gain a more nuanced understanding of Bitcoin's evolving dynamics and improve our ability to predict its future trends.

In summary, while there is a general trend for the Bitcoin hashrate to increase over time due to technological advancements and increasing adoption, it is not completely independent of external factors such as Bitcoin's price, electricity costs, regulatory environment, and market sentiment. These factors can cause fluctuations in the hashrate over shorter periods.

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