Hajiaghapour-Moghimi, Mehran; Heydari Tafreshi, Omidreza; Hajipour, Ehsan; Vakilian, Mehdi; Lehtonen, Matti

# Investigating the Cryptocurrency Mining Loads' High Penetration Impact on Electric Power Grid

*Published in:*
IEEE Access

*DOI:*
10.1109/ACCESS.2024.3482098

Published: 01/01/2024

*Document Version*
Publisher's PDF, also known as Version of record

IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 30 September 2024, accepted 13 October 2024, date of publication 16 October 2024, date of current version 29 October 2024.

*Digital Object Identifier 10.1109/ACCESS.2024.3482098*

RESEARCH ARTICLE

# Investigating the Cryptocurrency Mining Loads' High Penetration Impact on Electric Power Grid

**MEHRAN HAJIAGHAPOUR-MOGHIMI[1], OMIDREZA HEYDARI TAFRESHI[1], EHSAN HAJIPOUR[1], (Member, IEEE), MEHDI VAKILIAN[1], (Senior Member, IEEE), AND MATTI LEHTONEN[2]**

[1]Department of Electrical Engineering, Sharif University of Technology, Tehran 11365-11155, Iran
[2]Department of Electrical Engineering and Automation, Aalto University, 00076 Espoo, Finland

Corresponding author: Matti Lehtonen (matti.lehtonen@aalto.fi)

**ABSTRACT** Cryptocurrency has become a pivotal player in global financial transactions due to its decentralized mining process, which eliminates the need for intermediaries. However, the operation of cryptocurrency mining devices (CMDs) requires significant electrical power, leading to an increase in network-connected cryptocurrency mining loads (CMLs) that pose challenges for power grid operators. This paper evaluates the integration of CMLs into power grids, focusing on distribution network performance. A technology-accepted model for assessing cryptocurrency mining performance is presented, along with an analysis of the impacts of high CML penetration on power grid planning and operation. Findings reveal that high CML penetration can complicate load forecasting, congest transmission lines, and increase the coincident peak load in distribution networks. A case study of Iran's power network indicates that CMLs account for approximately 2.8% of the nation's electricity consumption. Furthermore, if 5% of residential customers in Tehran install CMDs, the average coincident peak demand for this group rises by 26.81%. Additionally, the average power factor of a sample CMD is about 0.99, while total current distortion and third harmonic current exceed permissible limits, indicating potential power quality issues. This study highlights the challenges posed by CMLs and proposes strategies for their sustainable integration into power grids.

**INDEX TERMS** Bitcoin, cryptocurrency mining, distribution network, electricity rate, power quality.

## I. INTRODUCTION

Blockchain technology, initially popularized by cryptocurrencies, has rapidly gained recognition for its potential to revolutionize various industries due to its decentralized, secure, and transparent nature. Beyond cryptocurrency, blockchain technology has found applications in numerous fields, demonstrating its versatility and transformative potential. For instance, in the energy sector, blockchain is being integrated with smart grids to enhance security, decentralization, and efficiency in managing renewable energy sources [1]. In electronic voting systems, blockchain offers robust solutions to prevent fraud and ensure democratic integrity by leveraging its secure and transparent nature, with ongoing advancements aiming to reduce energy consumption associated with traditional proof-of-work mechanisms [2]. Furthermore, in the realm of the Internet of Things (IoT), blockchain addresses significant challenges such as data security, privacy, and interoperability, facilitating secure and efficient data exchange and decentralized decision-making [3].

Cryptocurrencies, such as Bitcoin (BTC) and Ethereum (ETH), utilize blockchain technology to operate independently of central banking systems, offering benefits such as reduced transaction costs, faster transfer rates which needs lower time duration, and enhanced privacy. The adoption of cryptocurrencies is driven by their ability to provide financial autonomy and security, enabling direct peer-to-peer transactions that bypass traditional financial institutions and eliminates intermediary oversight entities [4]. Cryptocurrency mining, which is the process of generating new digital currencies and verifying transactions, demands significant computational power.

The associate editor coordinating the review of this manuscript and approving it for publication was Elizete Maria Lourenco.

Cryptocurrency networks are designed to be complex for enhanced security, employing intricate algorithms that require powerful hardware to solve mathematical problems. These algorithms are so complex that only computers with high processing power, like application-specific integrated circuits (ASIC) miners, can execute them [5]. However, this high processing power results in significant electricity consumption of cryptocurrency mining operation. In addition to the direct power consumption by the cryptocurrency mining devices (CMDs), considerable energy is required for cooling systems to dissipate the heat generated and maintain optimal operating temperatures [5].

In 2023, it was estimated that the BTC network, holding more than 80 percent of the market share of cryptocurrencies, consumed approximately 0.7 percent of the world's total electricity consumption [6]. To put this into perspective, the energy consumed by the BTC network alone was estimated to be about 173 TWh per year, which even exceeded the overall electricity usage of Poland in one year [7]. Additionally, the power demand required by the BTC network in 2023 was estimated to be around 19.7 GW, equivalent to the size of the power system of a country like Colombia, which has a capacity of 19.4 GW [6].

People place their CMDs at the disposal of the cryptocurrency network and, depending on their CMD's processing power and capacity, receive rewards in the form of cryptocurrencies [8]. The profitability of cryptocurrency mining has led to the emergence of a new category of loads on the power grid known as cryptocurrency mining loads (CMLs), resulting in their increased penetration into the network [5]. In addition to the significant energy consumption characterizing CMLs, their widespread integration into both power and cryptocurrency networks poses numerous challenges as well. Therefore, it is imperative to thoroughly examine various dimensions surrounding the rapid expansion of these loads. This involves conducting comprehensive analyses across diverse domains, including economics, security, electrical, and data-related aspects, among others [9]. Of particular significance is the electrical aspect, given the substantial energy consumption associated with CMLs, which may present challenges for the planning and operation of different parts of the power grid [10]. Understanding and addressing these challenges are critical for planners and operators of the power grid to ensure the sustainable integration of CMLs into power networks.

This paper investigates the high penetration of cryptocurrency loads in power grids, with a specific focus on the planning and operation of the distribution sector. The employed approach involves several key components to provide a comprehensive understanding of this penetration. Firstly, a technology accepted model, specifically tailored for cryptocurrency mining, is introduced by delineating the influential parameter, and the electricity purchase rate that has a great impact on its adoption. Based on using this foundation, a set of criteria is employed for the integration of these loads into different countries' power networks. Furthermore, an estimation method is proposed to quantify the energy consumption associated with these loads. Subsequently, an analysis of the impact of penetration of CMLs on the planning of generation, transmission, and distribution systems of the power grid is conducted, employing real-world data from a case study related to Iran power grid to furnish some empirical insights to its impacts and to validate the findings. By synthesizing these diverse perspectives, the paper aims to provide valuable insights into the challenges and opportunities posed by the integration of cryptocurrency loads into the distribution grids. This can help policymakers and strategic planners in the energy sector to make proper decisions.

### A. LITERATURE REVIEW

The penetration of CMLs and their intense energy consumption can introduce new challenges and opportunities for power systems, as examined in the literature. Previous research on the high penetration of CMLs in power systems has explored various aspects of these loads, including energy consumption [11], [12], [13], [14], [15], economic factors [16], [17], environmental effects [18], [19], [20], [21], [22], and the feasibility of renewable energy integration in cryptocurrency mining operations [23], [24], [25], [26], [27], [28]. Generally, research in this field can be divided into two main areas: examining the challenges posed by CML penetration in power systems and providing solutions to address these challenges. Despite the numerous studies on energy consumption and environmental impacts of CMLs, the effects of high CML penetration on the planning and operation of electric power grids have not been thoroughly addressed in the literature. Only a limited number of references focus on studying the adverse impacts of these loads on power systems.

Reference [29] highlights that CMLs have caused significant strain on energy grids, resulting in frequent blackouts and power shortages in countries like Kazakhstan and Venezuela. They discuss how the rapid increase in mining activities has worsened these impacts on their power system, revealing the vulnerability of weak energy grids to the high electricity demands of mining operations. The authors in [30] examine the multifaceted impacts of CMLs on electricity grids, emphasizing three main effects: increased average electricity prices, heightened carbon emissions, and reduced grid reliability. They note that the constant and significant demand from CMLs flattens the overall electricity demand curve, leading to lower price variance despite higher average costs. Additionally, the extra demand of miners can strain the grid, especially in regions without robust demand response programs or those prone to severe weather, thus affecting grid reliability.

Reference [18] uses high-resolution data to assess the effects of expanding CMLs on the large-scale Texas power grid, focusing on grid stability, electricity markets, and prices. The study shows that CMLs could disrupt markets, and the impact on electricity markets varies significantly depending on location. In [12], a detailed study examines energy consumption and power quality (PQ) in cryptocurrency mining facilities in Texas. The analysis includes energy usage, voltage, current, power, and current harmonics, based on data from both grid-connected and islanded facilities. The authors in [31] investigate the impact of CMLs on PQ in low-voltage networks, finding that while an optimized mining rig has a smaller effect on PQ compared to a personal computer cluster, it demands significantly higher and nearly constant power.

Reference [10] explores the influence of CMLs on the premature aging of distribution transformers, using real-world data to highlight potential risks and financial implications for distribution utilities if small-scale miners are not regulated. References [32] and [33] present a data-driven approach to predict CML-tripping events, focusing on the low-voltage ride-through (LVRT) problem and using diverse fault scenarios generated through electromagnetic transient program (EMTP) software for training data.

To address the challenges posed by CML penetration in the electricity grid, several studies explore the feasibility of integrating renewable energy into cryptocurrency mining operations [23], [24]. Additionally, [34] presents energy efficiency programs aimed at encouraging customers to use high-efficiency CMDs. These programs include informational, regulatory, and financial policy instruments designed to reduce CML energy consumption. Furthermore, the authors in [5] propose a practical electricity pricing strategy to mitigate the adverse impacts of CMLs on power system operations, addressing concerns arising from the high penetration of these loads. However, to the best of our knowledge, existing literature predominantly views CMLs as energy-hungry loads, often neglecting their impact on various parts of the power grid, particularly regarding power system planning and operation.

This paper addresses this gap by providing a comprehensive analysis of the impacts of high CML penetration on the planning and operation of generation, transmission, and distribution systems within a power grid, using real-world data and case studies from Iran to develop empirical insights into the challenges caused by CML penetration. Table 1 illustrates the contribution of the proposed approach versus the data from selected reviewed literature investigating the impact of CMLs on power systems.

### B. CHALLENGES IN PREVIOUS STUDIES

In reviewing the literature on the integration of CMLs into power grids, several key challenges have been identified:

- Load Forecasting Uncertainty: The unpredictable nature of CML power consumption complicates accurate grid load forecasting and power generation capacity planning.
- Transmission Line Congestion: High CML penetration can cause congestion in transmission lines, reducing power transmission capability.
- Distribution Network Strain: A surge in CMLs, especially in residential areas, significantly increases distribution network peak loads, potentially leading to outages.
- PQ Concerns: CMLs can introduce harmonic distortions and electrical noise, impacting equipment performance and grid stability.
- Economic and Operational Costs: High and continuous electricity consumption by CMLs raises operational costs and may require infrastructure upgrades.

### C. MOTIVATIONS FOR THE PRESENT WORK

In the following, the motivations for performing this study are presented.

- Rapid Adoption of Cryptocurrencies: The widespread acceptance and utilization of cryptocurrencies like BTC are driven by their decentralized nature, reduced transaction costs, faster transfer times, and enhanced privacy.
- Significant Energy Consumption: Cryptocurrency mining requires substantial computational power, leading to high electricity consumption for both the mining

**TABLE 1. Comparison of studies investigating the impact of CMLs on power systems.**

| Ref. | Country | Study | Dataset | Outcome |
|---|---|---|---|---|
| [12] | USA | Power quality analysis of BTC mining facilities | Measured data from BTC mining facilities and laboratory data | Analyzed power quality; discussed; presented voltage ride-through test results; tabulated data on commercial and laboratory mining facilities |
| [18] | USA | Impact of CMLs on power grids | Real-world data from Texas | Provided insights into grid stability, electricity market disruptions, and variable electricity prices |
| [29] | Kazakhstan | Energy grid strain due to cryptocurrency mining | National energy consumption | Highlighted frequent blackouts and power shortages caused by increased mining activities |
| [30] | China | Effects of mining on power reliability | National energy consumption | Identified significant strain on energy grids and challenges in maintaining power reliability |
| [31] | Serbia | Effects of cryptocurrency mining rig on distribution network | Measured data from mining rig and PC cluster | Compared power quality impacts; found mining rig had less harmonic impact but higher constant power demand |
| This paper | Iran | CML penetration in power distribution networks | Real-world data from Iran | Offered empirical insights into the challenges and impacts of high CML penetration in planning and operation of power systems |

equipment and the cooling systems necessary to maintain optimal operating temperatures.

- Challenges for Power Grids: The profitability of mining operations has resulted in increased activity in regions with lower energy prices, causing a surge in power consumption that poses significant challenges for local power grids, including potential strain and stability issues.
- Impact on Power Network Planning and Operation: The introduction of CMLs creates a new category of loads on the power grid. While existing research primarily addresses energy consumption, it often overlooks the broader impacts on the planning and operation of power systems, especially within the distribution network.

### D. MAIN CONTRIBUTIONS

The main contribution of this paper is to investigates the high penetration of CMLs in power grids, specifically focusing on the planning and operation of the distribution network, and other contribution can be summarized as follow:

- Technology-Accepted Model: Introduces a tailored model for cryptocurrency mining, focusing on critical factors such as electricity rates that affect mining adoption.
- Integration Criteria: Establishes criteria for integrating CMLs into power networks, taking into account regional differences to ensure effective integration.
- Energy Consumption Estimation: Proposes a method for quantifying the energy consumption of CMLs, providing a clearer picture of their demand on power systems.
- Impact Analysis: Conducts a thorough analysis of how CMLs affect the planning and operation of power systems, supported by real-world data from the Iranian power grid case study.
- Guidance for Policymakers: Offers valuable insights to assist policymakers and planners in making informed decisions about the sustainable integration of CMLs into power grids.

### E. PAPER ORGANIZATION

The rest of the paper is organized as follows. Section II introduces how CMLs penetrate into the power grid. Section III is devoted to the energy consumption of CMLs. Section IV deals with the analysis of the high penetration of CMLs on the power grid, focusing on generation and transmission expansion planning. Section V discusses the impact of CMLs on the power distribution network. Section VI presents the results of PQ analysis of CMLs. Finally, the concluding remarks are presented in Section VII.

## II. PENETRATION OF CMLS INTO THE POWER GRID

### A. TECHNOLOGY ACCEPTED MODEL FOR CRYPTOCURRENCY MINING

In this section, some questions are raised in order to explore the possible serious threats to the power networks in case of CMLs penetration; such as: which networks planners and which networks operators should examine the effects of penetration of CMLs as a serious threat to their network. Addressing this concern requires, first, identifying the factors that attract individuals and organizations to cryptocurrency mining technology and then evaluating the impact of these mining loads on the power grid. To achieve this, the Technology Acceptance Model (TAM) is employed, which emphasizes two primary factors influencing the acceptance and adoption of a new technology like cryptocurrency mining: perceived usefulness and perceived ease of use [35].

Fig. 1 also presents various internal and external variables that influence cryptocurrency mining adoption, including regulatory and legal frameworks, market trends, technological innovations, and socio-economic factors [36]. Perceived usefulness refers to the extent to which users believe cryptocurrency mining will enhance their performance or profitability. Several factors shape this perception. First, the profitability potential of cryptocurrency mining is a key driver, as individuals and businesses are attracted by the ability to generate significant profits through mining rewards, often in the form of cryptocurrencies. This positions mining as an appealing investment opportunity, particularly when cryptocurrencies are in high demand or prices are rising. Furthermore, cryptocurrency mining technology offers an efficiency advantage over traditional business models [37].

Mining operations, when optimized, can process blockchain transactions quickly and cost-effectively, resulting in higher returns on investment. This efficiency, combined

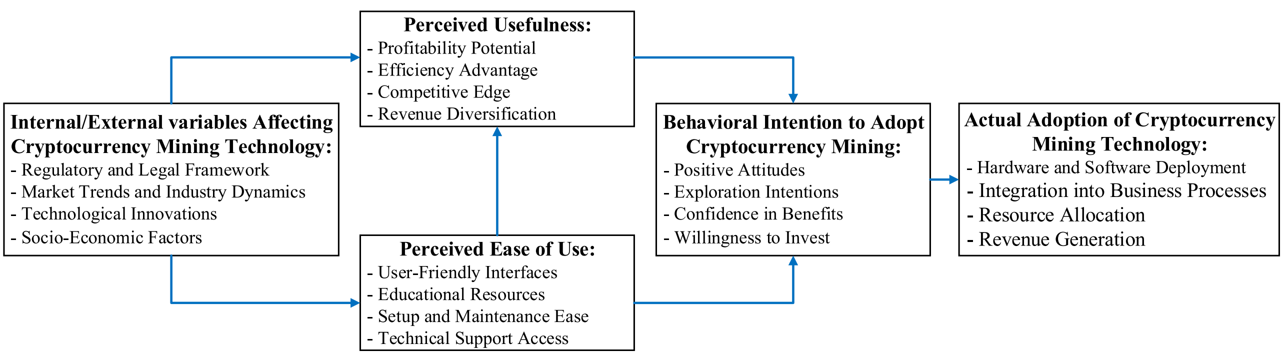



FIGURE 1. Technology accepted model for cryptocurrency mining.

with the decentralized nature of blockchain, makes mining an attractive venture for those seeking to maximize financial gains with relatively low operational costs. Another important aspect of perceived usefulness is the competitive edge provided by engaging in cryptocurrency mining. As the blockchain and cryptocurrency ecosystem continues to evolve, early adopters or those with access to advanced mining technologies can position themselves as leaders in this growing industry. This potential for gaining a competitive advantage drives interest and investment in mining, as individuals and companies strive to establish themselves as key players in the blockchain space [38]. Additionally, cryptocurrency mining presents opportunities for revenue diversification. Miners are able to generate income through multiple streams, such as transaction fees and rewards from solving complex computational problems, further enhancing the perceived attractiveness of this technology as a strategic investment [39].

Perceived ease of use, another critical factor in TAM, reflects how effortless users expect cryptocurrency mining technology to be. Several elements contribute to this perception. User-friendly interfaces provided by modern mining platforms have significantly lowered the barriers to entry, allowing even those with limited technical expertise to participate in mining activities. The availability of educational resources also plays a crucial role, as these resources empower individuals by providing the knowledge and skills necessary to navigate the technical aspects of cryptocurrency mining. This ease of access encourages broader adoption, as users feel more confident in their ability to successfully engage with the technology. Moreover, the simplicity of setting up and maintaining mining operations enhances perceived ease of use [40].

Over time, advancements in hardware and software have streamlined the process of initiating cryptocurrency mining, making it easier for users to acquire, install, and manage the necessary equipment. This ease of setup reduces the technical complexity that often deters new users. Additionally, access to reliable technical support further facilitates adoption by ensuring that users can resolve issues quickly and continue mining operations without significant downtime. These factors together make the technology more accessible to a wider audience, thus increasing its appeal [40].

Behavioral intention to adopt cryptocurrency mining technology is influenced by users' attitudes toward the benefits and risks of mining. Positive attitudes toward mining are shaped by the perceived profitability and efficiency advantages previously mentioned. Many users are motivated by the opportunity to explore new financial and technological opportunities. The desire to engage with an emerging technology that promises significant rewards often drives exploration intentions, pushing individuals and businesses to experiment with cryptocurrency mining. Confidence in the benefits of mining also plays a pivotal role in this behavioral intention. Users who strongly believe in the long-term profitability and sustainability of mining activities are more likely to invest in the necessary resources to engage in it. This confidence fosters a willingness to invest in cryptocurrency mining hardware, software, and electricity despite the inherent risks and uncertainties associated with the volatile nature of digital currencies [41].

Actual adoption of cryptocurrency mining technology involves concrete steps taken by users to implement mining operations. This adoption is marked by the deployment of both hardware and software necessary for mining. Users invest in specialized devices, such as application-specific integrated circuits (ASICs), and software that allow them to participate in mining activities efficiently. Integration of mining operations into broader business processes is another indicator of adoption [42]. For some users, cryptocurrency mining becomes a strategic part of their business model, contributing to diversified income streams. In these cases, resource allocation becomes critical, as users dedicate financial, technical, and human resources to ensure the sustainability and profitability of their mining operations. Moreover, actual adoption is closely tied to revenue generation. For most users, the ultimate goal of cryptocurrency mining is to generate profits, either through the creation of new cryptocurrency tokens or by processing blockchain transactions [42].

The revenue generated from mining validates the adoption decision and reinforces continued investment in the technology. As more users recognize the potential profitability of mining, they are likely to increase their involvement, further integrating cryptocurrency mining into their economic activities. A critical factor in this entire model is the cost of electricity, which directly affects the profitability of cryptocurrency mining operations [23]. Electricity is one of the largest expenses for miners, and the price of electricity in a given region determines the economic viability of mining activities. This factor plays a significant role in shaping users' behavioral intention to adopt mining technology, as regions with lower electricity costs are more attractive for mining operations. The relationship between electricity prices and mining profitability is discussed in further detail in the following subsection, where the economic implications of cryptocurrency mining on power grids are explored [5].

### B. CRYPTOCURRENCY MINING AND ELECTRICITY RATE

The penetration of CMLs in a power system refers to the amount of energy consumed by cryptocurrency mining operations within the larger energy ecosystem of a particular geographic area. As cryptocurrency mining becomes more popular, it can put a strain on the power system and potentially impact the overall energy demand and cost. The high penetration of these loads can be influenced by various factors, including the size of the mining operations, the energy efficiency of the mining equipment, the type of energy source used to power the mining loads, and the overall stability and reliability of the power system [24].

Proper planning and coordination between mining operators and power system managers are crucial to ensure that the integration of CMLs into a power system is sustainable and does not have negative impacts on the energy ecosystem. Calculating the power consumption of CMLs around the world can be challenging due to the decentralized nature of mining operations and the lack of centralized data on energy usage. However, estimates can be made by looking at the energy consumption of specific cryptocurrencies and the geographic distribution of mining operations.

**TABLE 2.** Characteristics of Bitmain Antminer S19 Pro as a CMD.

| Parameter | Value |
|---|---|
| Power consumption (kW) | 3.25 |
| Hash rate (THash) | 110 |
| Energy efficiency (GHash/J) | 33.846 |

The geographic distribution of cryptocurrency mining is heavily influenced by the cost of electricity [43]. This is because cryptocurrency mining requires a significant amount of energy to power CMDs used to solve complex mathematical problems and verify transactions on the blockchain. In order to determine the effects of electricity price on the miner profit function, the break-even point where the cost is equal to the obtained revenue can be calculated as follows [5]:

$$MEP(t) = \frac{3600 \times BR_{BTC}(t) \times HR_{CMD} \times BP_{BTC}(t)}{2^{32} \times Diff_{BTC}(t) \times P_{CMD}} \quad (1)$$

where, $MEP$ is the marginal electricity price (in cents/kWh), $BR_{BTC}$ is the BTC block reward (in BTC/block), $HR_{CMD}$ is the hash power or hash rate of a CMD (in THash/s), $Diff_{BTC}$ is the difficulty level of the BTC network (in THash/block), $BP_{BTC}$ is the is the instantaneous market price of one BTC (in \$), and $P_{CMD}$ is the power consumption of a CMD (in kW). The ratio of hash rate of a CMD to its power consumption is defined as energy efficiency of this mining device as follows [34]:

$$EE_{CMD} = \frac{HR_{CMD}}{P_{CMD}} \quad (2)$$

where $EE_{CMD}$ represents the energy efficiency of a CMD (in THash/J or GHash/J), indicating its ability to perform computational task (in THash/s) while consuming a specific amount of electricity (one Joule) [34]. Therefore, a higher value denotes higher efficiency, meaning that the CMD can perform more computational execution for each unit of electricity consumed, and vice-versa. By substituting (2) into (1), the following equation is formed to calculate the marginal electricity price for BTC mining:

$$MEP(t) = \frac{3600 \times BR_{BTC}(t) \times BP_{BTC}(t)}{2^{32} \times Diff_{BTC}(t)} \times EE_{CMD} \quad (3)$$

The proposed marginal electricity price model incorporates all key factors influencing the profitability of cryptocurrency mining, including cryptocurrency network characteristics

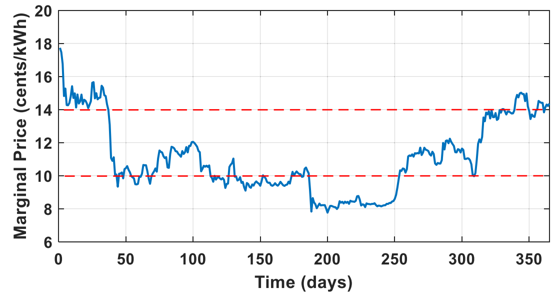



**FIGURE 2.** Marginal electricity price for BTC mining from January to December 2023 considering Bitmain AntminerS19 Pro as a CMD [44].

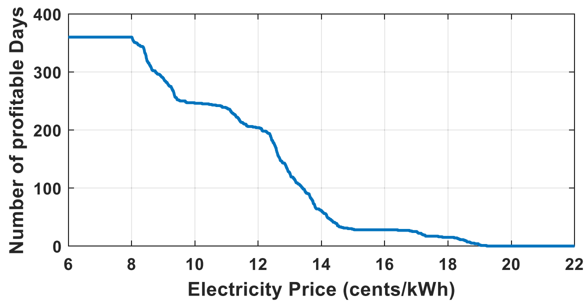



**FIGURE 3.** Number of profitable days for BTC mining in different Countries based on their electricity price [40].

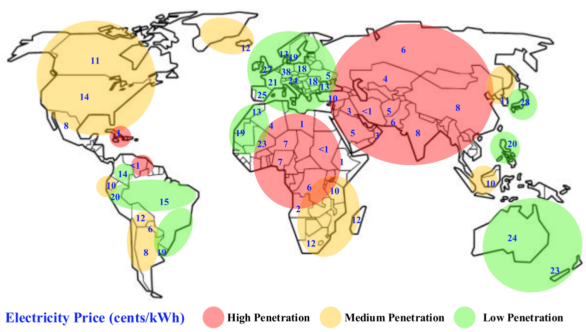



**FIGURE 4.** Average electricity price in different countries for residential customer and the level of CMLs penetration in 2023 [40].

(such as price and mining difficulty), electricity costs, mining device efficiency, and broader economic conditions. By accounting for these variables, the estimates provide a realistic reflection of market conditions for cryptocurrency mining, making the model a robust tool for assessing the feasibility of mining activities across different countries. Since electricity costs are a critical factor in determining the economic lifespan of mining hardware, the proposed marginal electricity price was compared against actual electricity prices to estimate the penetration levels of CMLs in various regions. This comparison highlights the model's effectiveness in capturing the economic realities of cryptocurrency mining.

According to (3), for calculating and estimating the marginal electricity price for BTC mining profitability,

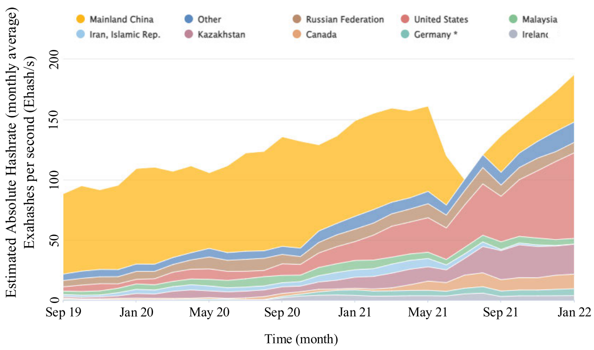



**FIGURE 5. Evolution of countries' share of the global hashrate for BTC mining [6].**

hourly data from the BTC network (difficulty, block reward, and BTC price) and the energy efficiency of CMDs utilized for BTC mining are required. In this paper, the difficulty level and block reward of the BTC network, and the BTC price are obtained from [44], as the most trusted source for data on the BTC blockchain, over one year, from January to December 2023. Additionally, to estimate the average energy efficiency of CMDs used in the BTC network, data provided by the Cambridge Centre for Alternative Finance (CCAF) is utilized [6]. CCAF, located at the University of Cambridge presents a tool known as Cambridge Blockchain Network Sustainability Index (CBNSI) to explore the scale and implications of the BTC network's electricity consumption. It features many important related parameters, for example: an index providing a daily estimate of the total electricity load and electricity consumption, a mining map tracking the geographic distribution of BTC mining facilities over time, comparisons putting the electricity footprint into a broader perspective, and the average energy efficiency of CMDs connected to the BTC network [6].

Based on [6], the average energy efficiency of CMDs connected to the BTC network at the beginning of 2024 is estimated to be 33.85 GHash/J. On the one hand, reference [45] provides comprehensive specifications for all CMDs produced by various manufacturers for BTC mining. By comparing the data presented in this reference for the energy efficiency of different CMDs with the average energy efficiency of CMDs connected to the BTC network in 2024 estimated by reference [6], it can be inferred that the Bitmain Antminer 19 Pro represents a typical CMD whose energy efficiency aligns closely with the estimated average energy efficiency of all CMDs connected to the BTC network. Therefore, it is suitable for inclusion in this study in 2024. Table 2 presents the characteristics of this CMD [45].

Fig. 2 illustrates the marginal electricity price of BTC mining from January to December 2023 considering Bitmain Antminer S19 Pro as a CMD. As depicted in this figure, in countries where the electricity price is approximately less than 8 cents/kWh, BTC mining remained profitable throughout the year, allowing cryptocurrency miners to keep their CMDs running continuously. For a better understanding, Fig.3 depicts the number of profitable days for BTC mining during the specified period. As depicted in Fig. 3, the penetration of CMLs is rapidly increasing in countries with low electricity prices. Based on Figs. 2 and 3, three electricity price ranges can be distinguished in the world: countries with electricity prices less than 10 cents/kWh, between 10 and 14 cents/kWh, and more than 14 cents/kWh, to be used for cryptocurrency mining profitability and penetration analysis. Taking into account these electricity price ranges and the electricity prices in various countries, Fig. 4 provides an estimation of the level of CMLs penetration in different countries. As illustrated in Fig. 4, countries in Asia, such as China, Russia, Iran, Malaysia, and Kazakhstan, where electricity prices are lower than 10 cents/kWh, are highly susceptible to significant penetration of CMLs on their power grids. This classification aligns well with the information published in [6], as shown in Fig. 5, which categorizes different countries based on the distribution of BTC network hash rate. Therefore, power network planners and operators in these countries must consider the impact of high penetration of CMLs on the power grid performance. Consequently, this paper delves into examining the consequences of the high penetration of these loads in the power grid.

## III. ENERGY CONSUMPTION OF CMLS

Cryptocurrencies are reshaping the global economy, with increasing use in international trade. They enable decentralized, peer-to-peer transactions that bypass traditional financial intermediaries, reducing costs related to foreign exchange, banking fees, and transfers [46]. This is especially useful for businesses in regions with high transaction costs or underdeveloped banking systems. They offer faster cross-border payments, completing transactions in minutes, and provide a hedge against currency fluctuations through stable coins, minimizing financial risks in volatile economies [47]. Cryptocurrencies also help businesses in countries facing sanctions or restrictions participate in global trade. By leveraging blockchain technology, they offer secure, transparent transaction records, reducing fraud. As adoption grows, cryptocurrencies are reshaping global trade and challenging traditional financial systems [48]. Understanding their impact requires scrutiny of various dimensions, notably energy consumption. Security and transactions in cryptocurrency networks rely on CMDs, whose devices consume significant electrical energy. The complexity of cryptocurrency network, especially BTC's, necessitates high computational power and, consequently, substantial electricity consumption. This section examines BTC network electricity usage, globally and in Iran.

### *A. COMPARING THE POWER CONSUMPTION OF A CMD AGAINST A TYPICAL RESIDENTIAL CONSUMER IN IRAN*

The power consumption a CMD significantly influences both the electricity expenses of this CMD and, hence, its profitability. This section aims to compare the power consumption of a sample CMD with that of a typical residential consumer of the Tehran Electricity Distribution Company in Iran. We designate the Bitmain Antminer S19 pro as our representative CMD, boasting a power consumption of 3.25 kW, as outlined in Table 2. Assuming that this CMD is employed and operated by a residential consumer in Tehran, where the average electricity tariff stands at approximately 0.6 cents/kWh, the utilization of the Antminer S19 Pro is deemed financially advantageous, thus its continuous connection to the power grid is highly expected. Subsequently, a residential electricity consumer in Tehran, energized through a single-phase 32 A. residential tariff (by Tehran Power Distribution Company) is scrutinized in this study. The contracted demand for this connection amounts to 4.6 kW [49]. The electrical engineer planner in this company base on [5] calculates the coincidence peak load of the residential customers through (4):

$$D_c^n = n \times P_{demand} \times CF \tag{4}$$

where $n$ represents the number of customers, $P_{demand}$ stands for the contracted demand, and $CF$ denotes the coincidence factor of single-phase residential customers. It should be noted that in this electricity company, the coincidence factor of residential customers is assumed to be 0.17. The simultaneous peak demands of three household subscribers in this group is calculated as follows.

$$D_c^3 = 3 \times 6.4 \times 0.17 = 3.26 \tag{5}$$

The electrical planners and operators at this power distribution company consider these three customers to have a consumption capacity of 3.26 kW. Comparing this with the power consumption of a Bitmain Antminer S19 Pro as a sample CMD reveals that the latter exceeds the simultaneous peak load of the three residential customers. Consequently, as cryptocurrency networks expand and more CMDs connect to the electricity grid, challenges arise due to both the high power consumption and the unique electricity usage patterns of these devices, a topic to be further explored in this paper.

### B. PREDICTING THE POWER DEMAND OF BTC NETWORK WORLDWIDE

While electricity demand forecasting has been extensively researched, the unique characteristics of the BTC network require a different approach. Traditional electricity demand models typically focus on factors such as population growth, weather, and economic activity [50]. However, cryptocurrency mining is influenced primarily by the characteristics of CMDs and BTC network both of which are directly measurable and publicly available. Among cryptocurrencies, the BTC network is highly transparent. In fact, all statistics and information related to it are publicly available, and the electricity consumption of CMLs worldwide can be calculated using the following equation:

$$P_{mining}^{BTC} = n_{miner} \times P_{CMD} \tag{6}$$

In (6), it is assumed that all CMDs connected to the BTC network are of the same type. Therefore, in this equation, $P_{mining}^{BTC}$ is the electricity consumption of the BTC network, $n_{miner}$ is the total number of CMDs connected to the BTC network, and $P_{CMD}$ is the power consumption of a CMD. The total number of CMDs can be evaluated as follows [23]:

$$n_{miner} = \frac{Diff_{BTC} \times 2^{32}}{\Delta t \times HR_{CMD}} \tag{7}$$

where $\Delta t$ is the time taken to mine a block (which is 10 minutes for BTC network). By substituting (7) into (6), the following equation is formed to estimate the total power demand of BTC mining:

$$P_{mining}^{BTC} = \frac{Diff_{BTC} \times 2^{32}}{\Delta t \times EE_{CMD}} \tag{8}$$

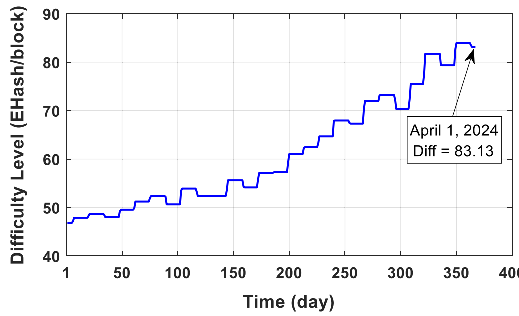



**FIGURE 6. Difficulty level of BTC network in EHash/block from April 2023 to April 2024.**

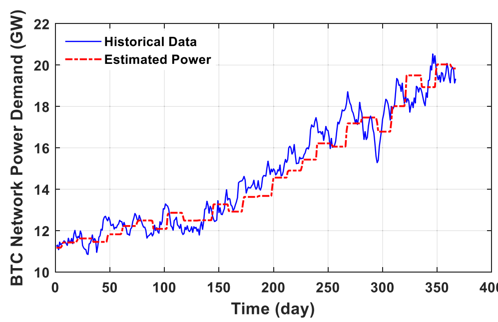



**FIGURE 7. Comparison between historical data of BTC network power demand and the estimated demand presented in this work.**

The deterministic model developed in this study is specifically designed to estimate the power consumption of the BTC network. Unlike traditional electricity demand forecasting models, which often involve complex machine learning techniques or statistical approaches [51], [52], [53], [54], this model utilizes publicly available data such as BTC network difficulty, block time, and the specifications of widely-used CMD. These factors are directly related to the energy consumption of cryptocurrency mining operations, allowing for a more targeted and efficient estimation process. The model's simplicity is intentional, as it reflects the well-understood relationships between network difficulty, CMD efficiency, and power consumption in BTC mining. Given the deterministic nature of these parameters, the model can generate accurate predictions without the need for complex training datasets. This approach is particularly effective in capturing the unique, rapidly changing characteristics of the BTC network, which are not easily addressed by general electricity forecasting models.

The data utilized in this model includes BTC network difficulty statistics and the specifications of commonly used CMD. Network difficulty data was sourced from publicly accessible BTC network monitoring platforms, covering the period from April 2023 to April 2024, as shown in Fig. 6. The specifications of the Bitmain Antminer S19 Pro, including its power consumption of 3.25 kW, were used to represent typical CMDs in use globally. This device accounts for a significant portion of BTC mining capacity due to its widespread adoption. These data sources are crucial for ensuring the accuracy of the model, as they are directly tied to the cryptocurrency mining process. Since network difficulty and CMD specifications are transparent and reliable, the model avoids the complexities of traditional machine learning-based approaches and instead relies on mathematical calculations to estimate power consumption.

As shown in Fig. 6, the BTC network's difficulty level on April 1st was estimated at 83.13 EHash/block. Using (8), the BTC network's power consumption on that date is estimated at 19.83 GWs, compared to 19.47 kilowatts as estimated by [6]. This underscores the accuracy of our proposed method. Fig. 7 further validates our approach and (8) presented in this study displaying the network's power consumption from April 2023 to April 2024 alongside historical data from [6].

To evaluate the model's accuracy, two common prediction error metrics were calculated: Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The MAPE for the model's predictions was approximately 3.9%, indicating that the estimated power demand closely aligns with the historical data. The RMSE was calculated as 0.75 GW, demonstrating that the model's prediction errors remain low throughout the study period. These metrics validate the model's ability to predict the power consumption of the BTC network with a high degree of accuracy, as also shown in Fig. 7. The low MAPE and RMSE values reflect the reliability and precision of the estimates produced by the model.

### *C. ESTIMATING THE POWER DEMAND OF CMLS IN IRAN*

Cryptocurrency mining, including BTC mining, has witnessed a notable surge in energy consumption in Iran, primarily due to several key factors. One significant reason is the availability of subsidized electricity rates in the country, which have attracted miners seeking to capitalize on lower operational costs. Additionally, Iran benefits from an abundance of natural gas resources, which can be utilized to generate electricity at relatively low costs, further incentivizing cryptocurrency mining activities [34]. Moreover, economic sanctions imposed on Iran have led to restrictions on international trade and financial transactions, prompting some individuals and businesses to turn to cryptocurrency mining as a means of circumventing these barriers and accessing global markets [55]. As a result, the combination of subsidized electricity, abundant energy resources, and economic incentives has fuelled the rapid expansion of cryptocurrency mining efforts in Iran, contributing to the significant increase in electrical energy consumption associated with this industry.

In order to estimate the power consumption of CMLs in Iran, we can use the information provided in [6] regarding the share of different countries in the total hash rate of the BTC network. Based on the data from [6], Iran, with an approximate share of about 4% in cryptocurrency mining is ranked sixth globally in BTC mining. This level of participation is due to the assumption of having the average energy efficiency of CMDs for BTC mining devices used in Iran. On the other hand, reference [34] has scientifically and practically examined the energy efficiency of CMDs used in Iran, considering their profitability. The studies in this reference demonstrate that in countries with low electricity rates, the utilization of less efficient CMDs renders cryptocurrency mining more profitable. Consequently, miners are not encouraged to adopt state-of-the-art technology involving CMDs with high energy efficiency. Therefore, the power demand of CMLs in these regions must consider not only the hash rate but also the energy efficiency of CMDs used. Consequently, the power demand of CMLs in Iran can be estimated as follows:

$$P_{Iran}^{BTC} = P_{mining}^{BTC} \times \frac{HR_{BTC}^{Iran}}{HR_{BTC}^{Total}} \times \frac{EE_{CMD}^{Average}}{EE_{CMD}^{Iran}} \tag{9}$$

**TABLE 3. Estimated BTC power demand in Iran from 2019 to 2024.**

| Year | Total BTC power demand (GW) [6] | Iran's share of the total BTC network hash rate (%) [6] | Average energy efficiency of CMDs (GHash/J) [6] | Average energy efficiency of CMDs installed in Iran (GHash/J) [34] | Historical data of BTC power in Iran (MW) [57]-[60] | Estimated power of BTC network in Iran (MW) |
|---|---|---|---|---|---|---|
| 2019 | 4.95 | 1.50 | 6.69 | 1.30 | 300 | 382.10 |
| 2020 | 6.23 | 1.96 | 11.35 | 1.96 | 750 | 707.39 |
| 2021 | 7.26 | 3.40 | 16.06 | 3.88 | 1050 | 1021.47 |
| 2022 | 10.16 | 3.26 | 15.73 | 5.84 | 813 | 891.89 |
| 2023 | 10.91 | 4.22 | 21.83 | 7.93 | 1200 | 1267.37 |
| 2024 | 14.18 | 3.98 | 29.94 | 9.00 | 2000 | 2057.32 |

where $P_{Iran}^{BTC}$ is the estimated power demand of CMLs in Iran. $HR_{BTC}^{Total}$ and $HR_{BTC}^{Iran}$ are the total hash rate of the BTC network worldwide and in Iran, respectively. Finally, $EE_{CMD}^{Average}$ and $EE_{CMD}^{Iran}$ are the average of energy efficiency of CMDs connected to the BTC network and the average of that used in Iran, respectively. Reference [34] has estimated that the average energy efficiency of CMDs installed in Iran is equal to 9 GHash/J. Taking this value into account, along with Iran's 4% share of the total BTC network hash rate, the estimated power demand of the BTC network in Iran is approximately 2.1 GW in April 2024. However, According to unofficial statistics, it is estimated that at least 2 GW of CMLs are currently connected to the Iranian distribution networks [56]. This estimate indicates that approximately 2.8% of Iran's total electricity consumption is allocated to CMLs [34].

In Table 3, the estimated power demand of the BTC network in Iran is further detailed, providing year-over-year data for Iran's share of the total BTC network hash rate, energy efficiency comparisons, and the corresponding power estimates [57], [58], [59], [60]. The table highlights how Iran's mining efficiency lags behind global standards, yet the mining operations remain profitable due to low energy costs, which is reflected in the increasing power demand over time. Fig. 8 also demonstrates the comparison between historical data on the power consumption of the BTC network in Iran and the power demand estimated by the model from 2019 to 2024. As illustrated, the model's estimates align closely with the historical data, particularly in recent years.

To further validate the model, accuracy metrics were calculated. Similar to the global BTC power demand estimation, MAPE and RMSE were calculated for Iran's power demand. The MAPE was found to be 8.9%, and the RMSE was 62.5 MW. These metrics indicate that the model produces reliable estimates.

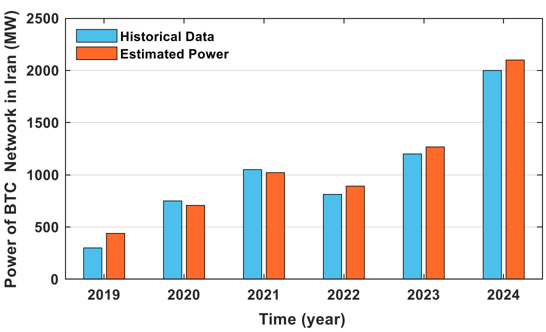



**FIGURE 8.** Comparison between historical and estimated BTC network power demand in Iran from 2019 to 2024.

## IV. ANALYSIS OF CML PENETRATION IN POWER NETWORK

Given the rising prominence of cryptocurrencies in the global economy, especially in regions with low electricity costs, their integration into the power grid is rapidly increasing. Hence, it is crucial to examine various aspects of this industry's rapid growth, including economic factors, cybersecurity concerns, and energy consumption patterns. The electrical aspect is particularly noteworthy due to the significant energy usage associated with cryptocurrencies. Cryptocurrencies, like other technologies, have specific energy consumption patterns that are increasingly influencing the power grid. CMLs, as energy-intensive loads connected to the grid, require careful consideration of their impact, both in terms of challenges and opportunities. Therefore, this section aims to explore the implications of cryptocurrency adoption across different sections of energy power network planning. Prior to this exploration, the following subsection will analyse two prevailing scenarios regarding the integration of CMLs into the power grid.

Although many references present modeling parts regarding the power grid, such as power flow in distribution networks, to study the impact of loads on power grids [61], [62], a number of others do not include detailed modeling parts in the presence of CMLs [12], [63], [64]. Similarly, this paper focuses on the characteristics of CMLs and does not include detailed modeling of the power distribution network, such as power flow analyses. Future research should address this gap by incorporating comprehensive power flow models to fully understand the impacts of CMLs on power systems. For further insights, readers are directed to works such as those by Azmi et al. [61], which discusses the applications and challenges of active electric distribution networks, and Zhou et al. [62], which addresses dynamic reconfiguration in unbalanced distribution networks. These studies offer valuable frameworks and methodologies that can be applied to future investigations into the impacts of CMLs on power systems.


(a) (b)

**FIGURE 9.** BTC mining in Iran through a) micro-miners and b) cryptocurrency mining farms [65].

### A. TWO SCENARIOS OF CMLS PENETRATION INTO THE POWER GRID

In countries with low electricity prices, the cryptocurrency industry is highly lucrative, attracting many individuals to engage in cryptocurrency mining. Users typically pursue income in two scenarios [23]:

- Mining cryptocurrencies with a large number of CMDs, known as cryptocurrency mining farm;
- Mining cryptocurrencies with a limited number of CMDs, known as micro-miner.

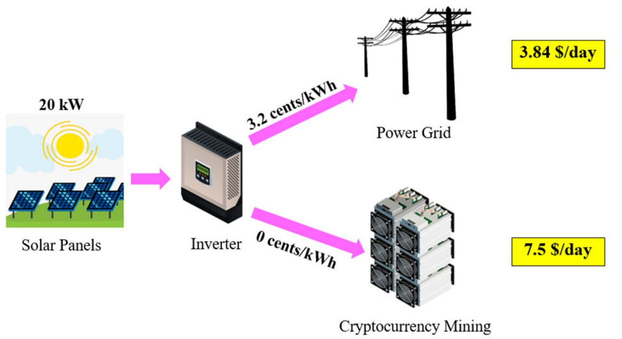



**FIGURE 10.** **Two proposed scenarios for utilizing the generated power of a solar power plant.**

In the first scenario, customers set up mining farms by acquiring a large number of CMDs to maximize profitability. These operations, known for their significant energy consumption and noise, are often located in warehouses away from residential areas. They may directly connect to the power transmission network for electricity supply [34]. In the second approach, customers install a few CMDs in their homes, connecting them to household electricity. Unlike mining farms, these individual setups may not be immediately noticeable to distribution system operators, despite increasing residential energy consumption and altering their consumption patterns [5]. Fig. 9 depicts an overview of both scenarios for BTC mining in Iran [65].

This paper primarily examines the penetration of cryptocurrencies through the second method, focusing on mining with a limited number of devices rather than large-scale operations. Specifically, it explores how micro-miners integrate into the power distribution network. The heavy penetration of cryptocurrency mining operations in power networks not only leads to a massive surge in electricity consumption and greenhouse gas emissions, but also profoundly impacts the planning and operation of various sectors within the power network, including generation, transmission, and distribution. In this paper, the potential consequences of this penetration are briefly outlined in two main areas: power generation and transmission systems. Subsequently, a more detailed examination is conducted, with a focus on the distribution power network.

### B. IMPACT OF CMLS ON POWER GENERATION EXPANSION PLANNING

The primary prerequisite for production planning across different time horizons is the estimation and prediction of future power network loads. Effective load prediction involves studying past load trends, understanding influential factors, and selecting the most suitable prediction method and model to approximate the required load for various time periods with acceptable accuracy. Despite the inherent randomness of load behavior and the emergence of new technologies like cryptocurrency mining, load prediction errors should remain within acceptable limits to avoid production shortages and equipment damage. In the electricity market, accurate load prediction is crucial for maximizing profits, minimizing penalties, and ensuring network security and reliability. Interactive market players, including power plants, regional electricity companies, and large industries, focus on improving load prediction accuracy to meet these objectives [66]. Ignoring consumption changes in specific areas and new industry trends, such as cryptocurrency mining, can lead to significant challenges in development planning and network operation.

In Iran, the share of cryptocurrency mining in the electricity network's peak load was approximately 2.8% in 2023. Awareness of consumption changes, especially in regions affected by emerging industries, is vital for effective electricity market management and infrastructure planning. Failure to account for these changes can jeopardize the stability and sustainability of the electricity network in the long term. In many power systems worldwide, there has been a shift from traditional to modern structures. This restructuring leads to decentralized decision-making by market players, influenced by various market behaviors. This impacts development planning, as private investors drive investment in the generation sector, aiming to maximize profits while considering uncertainties like future electricity prices and return on investment. In regions with low energy costs, the highly profitable cryptocurrency industry offers short-term capital returns, tempting investors to mine cryptocurrencies rather than contribute their electricity to the grid. This can threaten overall generation in production planning.

Continuing with an example, we emphasize the significance of this concern by providing a practical example in Iran. In 2023, the Ministry of Energy announced the renewable energy feed-in tariff for solar power plants with capacities below 20 kilowatts as 3.2 cents/kWh [67]. Consider a solar power plant with a capacity of 20 kW. Two scenarios are considered for the owner of this power plant in a day, as depicted in Fig. 10. In the first scenario, the solar power plant owner sells electricity to the national grid at a guaranteed price. Assuming 6 hours of daily sunlight exposure and maximum capacity operation, the plant generates 120 kWh per day, yielding $3.84 in revenue. In the second scenario, the owner opts for BTC mining, using the electricity generated. Using the power plant capacity, they can mine BTC using six Bitmain Antminer S19 Pro devices, yielding approximately $7.5 daily. This redirection of electricity to BTC mining increases the daily income by nearly 95%. However, in a fluctuating energy market, this trend may lead to decreased grid production and associated challenges. The example underscores the potential shift of energy producers towards cryptocurrency mining due to the uncertain energy market, raising concerns about grid reliability and production levels.

While using renewable energy sources, such as solar and wind power, for cryptocurrency mining may reduce the injection of renewable energy into the main grid, it significantly decreases the dependence of CMLs on the grid, thereby reducing their overall impact on grid stability. This trade-off can be effectively managed through the integration of electrical energy storage systems (EESSs) and demand response (DR) programs. By storing excess renewable energy and adjusting CMLs based on grid conditions, the variability of renewable energy generation can be balanced, ensuring a stable energy supply for both the cryptocurrency mining operations and the grid. Proper management of cryptocurrency mining loads alongside renewable resources offers a solution that mitigates the negative effects on the grid while promoting the use of clean energy.

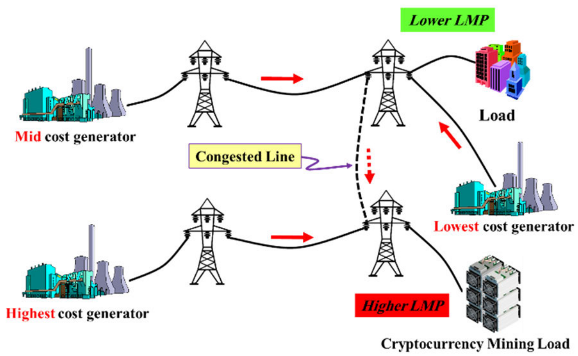



**FIGURE 11.** Graphic illustration of the impact of high penetration of CMLs on transmission line congestion.

### C. IMPACT OF CMLS ON TRANSMISSION EXPANSION PLANNING

This subsection addresses potential challenges that may arise when CMLs penetrate the power transmission sector, primarily focusing on the impact of cryptocurrency mining farms. The initial step in power system planning is load forecasting. Given the uncertainties associated with load prediction, particularly with the rising presence of CMLs, it's crucial to anticipate and address these challenges in transmission network expansion planning. These uncertainties include fluctuations in load prediction due to the growing number of cryptocurrency mining farms, shifts in generation prices and contracts driven by miners seeking lower electricity costs, and variations in available generation capacity due to increased use of independent generation sources for mining. Additionally, bilateral contracts and inter-area exchange volume may impact electricity prices, affecting miner purchasing behavior. Adapting models to account for these uncertainties is essential for effective transmission network planning amidst the cryptocurrency industry's influence [68].

In restructured power systems, creating a competitive and fair electricity market for all participants is a key objective. This entails allowing consumers to procure electrical energy from any seller, based on the prices determined by interactions between producers and consumers [69]. However, the high penetration of CMLs can lead to congestion on certain transmission lines, as CMLs tend to purchase energy from lower-priced electricity sellers. This congestion can result in market distortion, forcing consumers to pay higher prices for electricity due to unfavorable transmission conditions. As CMLs concentrate their operations in specific geographic regions, such as areas with cheap electricity or abundant renewable energy sources, transmission lines in those regions may experience significant strain, leading to congestion. This congestion not only impacts the efficiency of electricity markets but also disrupts the equilibrium of supply and demand, causing localized spikes in the locational marginal price (LMP). Consequently, consumers located in areas with congested transmission lines may face disproportionately higher electricity prices compared to those in regions with smoother transmission flow. Fig. 11 provides a visual depiction of the aforementioned challenges.

The variation in LMPs throughout the system contradicts the foundational principles of fairness and competitiveness within electricity markets. This incongruity underscores the pressing necessity for the implementation of efficient congestion management strategies, ensuring equitable access to electricity at reasonable prices for all participants. Consequently, the mitigation of congestion issues in transmission lines during transmission expansion planning emerges as a crucial priority, particularly in the context of heightened CMLs. Addressing these concerns is pivotal for sustaining a marketplace that is both fair and competitive, aligning with the interests of all stakeholders.

To ensure a competitive and fair marketplace, several criteria must be considered, including transparency in pricing mechanisms, equal access to resources, and the prevention of monopolistic practices. While the market operates on free-market principles, the increasing penetration of CMLs may lead to congestion and market imbalances, necessitating regulatory interventions. These measures ensure that all stakeholders have fair access to electricity, preventing distortions such as excessive price inflation or supply constraints, while still preserving the competitive nature of the market.

## V. IMPACT OF CMLS ON THE POWER DISTRIBUTION NETWORK

The primary goal of the electricity industry is to provide high-quality and reliable energy to consumers across various sectors. Understanding consumer behaviour is crucial for effective planning and investment in power distribution networks. Load studies are particularly important in this regard, as they help in optimizing network design and investments. Consumer demand and consumption patterns significantly influence energy management policies adopted by electricity distribution companies. Therefore, accurate knowledge of maximum consumption levels and patterns assists in prioritizing optimal designs. In countries like Iran, where electricity prices are low, many consumers are turning to cryptocurrency mining, leading to changes in consumption patterns. Neglecting these changes due to CMLs can result in incorrect planning and operational issues, including increased load and premature aging of critical equipment like distribution transformers. These issues are explored in detail in section.

Cryptocurrency mining, as a profitable business in some countries with low electricity costs, is increasing in sub-transmission and distribution networks. In the former one, business owners accumulate their CMDs in a mining field, and several private transformers supply their devices and cooling systems. In this situation, a special case-to-case planning method based on the pure CMLs could be applied. In contrast, in the distribution networks, some residential, commercial, and small-scale industrial customers have some degree of interest to mine cryptocurrencies and consume more electrical energy besides their previous energy consumption pattern. Therefore, their consumption pattern deals with a sharp increase. In a rapidly evolving new technology such as CMDs in distribution grids and different consumption patterns as results, it is necessary to investigate whether traditional methods are sufficient. Therefore, in the following subsections, a conventional approach and its modification are presented.

### A. CONVENTIONAL METHOD FOR PEAK LOAD ESTIMATION

Power distribution companies in developed countries use a metric called After Diversity Maximum Demands (ADMDs) in their designs. This parameter is used to calculate/estimate the coincident peak demand for many consumers with a common consumption pattern and sizing network assets such as distribution transformers and cables [27]. In other words, the $ADMD^n$ expresses the average coincident peak of each customer in a group of n customers, the relationship of which is as follows [70]:

$$ADMD^n = \frac{D_c^n}{n} \tag{10}$$

where, $D_c^n$ is coincident peak demand across $n$ customers. The $ADMD^n$ converges to a steady-state value in a large number of customers, which is denoted by $ADMD^\infty$. In fact, the $ADMD^\infty$ indicates the coincident peak demand of a single customer in a particular consumption pattern. For example, in the London Electricity Distribution Company, the following equation is used to calculate the $ADMD^n$ [70].

$$ADMD^n = a \times (ADMD^\infty + \frac{b}{n}) \tag{11}$$

where, $a$ and $b$ are numerical coefficients calculated by fitting the $ADMD^n$ curve.

### B. PEAK LOAD ADJUSTMENT IN PRESENCE OF CMLS

As mentioned before, in countries with low electricity prices, customers install CMDs due to the profitability of cryptocurrency mining, which may change the consumption pattern of customers. In order to prevent this destructive effect, the planners of distribution companies must consider this issue in sizing network assets such as distribution transformers and cables. One of the solutions suggested by the authors of this paper to alleviate this problem is that designers use a modified ADMD to calculate the coincident peak load of a

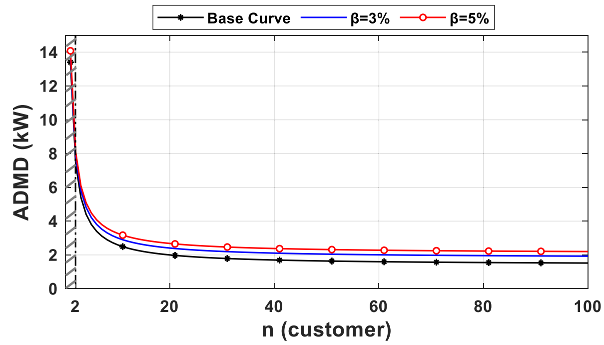



**FIGURE 12.** Change of $ADMD^n$ in the presence of CML penetration.

group of customers in the presence of CMLs in the network and reiterate the design procedure. This amount of change can be calculated using the following equations. Suppose that $\beta$ percent of customers in a group of customers with a specific consumption pattern install the CMDs and consume electricity to the extent of their contract power. Under these conditions, coincident peak demand across $n$ customers (denoted by $D_{c'}^n$) is calculated as follows:

$$D_{c'}^n = D_{c'}^{(1-\beta)n} + \beta \times n \times P_{demand} \tag{12}$$

where, $P_{demand}$ is the contract demand of each customer, which is considered equal for all customers in this paper and $\beta$ is the penetration rate of CMLs in distribution network. It should be noticed that, $n$ is an integer number and for each amount of $\beta$, the equation (12) is valid only for values of $n$ meet the constraint in (13) as follows:

$$n \times (1-\beta) \geq 1 \tag{13}$$

By substituting (12) into (11), the following equation is formed to estimate the coincident peak demand of customers in the presence of CMLs:

$$D_{c'}^n = D_c^n + \beta \times n(P_{demand} - a \times ADMD^\infty) \tag{14}$$

In order to calculate the modified ADMD, it is enough to divide both sides of (14) by $n$.

$$ADMD^{n'} = ADMD^n + \beta \times (P_{demand} - a \times ADMD^\infty) \tag{15}$$

where, $ADMD^{n'}$ is the after diversity maximum demands in the presence of $\beta$-percent penetration level of CMLs. Moreover, one could consider the following general relationship for determining $ADMD^{n'}$.

$$ADMD^{n'} = a' \times (ADMD^{\infty'} + \frac{b'}{n}) \tag{16}$$

By comparing (15) and (16), new parameters can be considered as follows:

$$\left\{ \begin{array}{l} a' = a \\ ADMD^{\infty'} = ADMD^\infty \times (1-\beta) + \frac{\beta \times P_{demand}}{a} \\ b' = b \end{array} \right\} \tag{17}$$

As seen in (17), an increase in the percentage of CMLs penetration in the distribution network leads to an increase in the maximum simultaneous load of customers. To further analyze the impact of CML penetration on the ADMD curve, a simulation study is considered in a distribution company. Fig. 12 illustrates the modification of the $ADMD^n$ curve for different percentages of CML penetration within the E.ON distribution network in London. For the residential customer category in this company, $ADMD^{\infty}$ and $P_{demand}$ are set to 1.4 and 15, respectively. Additionally, the coefficients $a$ and $b$ for this customer group are 0.7 and 12, respectively [70]. As shown in this figure, $ADMD^{\infty}$ increases from 1.52 kW to 2.2 kW with only a 5 percent penetration of CML. Failure to consider this factor in the planning and operation of the distribution network can lead to overloading and premature aging of network assets. To determine the effect of CMLs on the utilization factor of distribution network facilities, (18) provides the necessary relationship. According to the definition of the utilization factor, this equation includes a modification coefficient and indicates the percentage change in the utilization factor due to the presence of CMLs.

$$\frac{UF'}{UF} = \frac{D^n_{c'}}{D^n_c} = 1 + n \times \beta \times \frac{P_{demand} - ADMD^{\infty}}{n \times ADMD^{\infty} + b} \tag{18}$$

where, $UF'$ and $UF$ are the utilization factors after and before the penetration of CMLs in distribution networks. Fig. 13 shows the dramatic escalation of the utilization factor by increasing the penetration rate of CMLs based on data from E.ON distribution company for 50 customers. As shown in this figure, the utilization factor of assets rises by a factor of 25% if only 3% of residential customers install CMDs and operate at their maximum contracted demand. For more understanding, in the following subsection, ADMD curve and utilization factor modification is analyzed, given real data for a distribution company in Iran.

The data utilized in this study is derived from a combination of publicly available datasets and industry reports, encompassing global cryptocurrency mining activity data and energy market trends. Key sources include the Cambridge Bitcoin Electricity Consumption Index [6], government energy reports, and leading databases on cryptocurrency mining infrastructure [44]. Additionally, specific data was recorded, including measurements of transformer loading and PQ data from cryptocurrency mining operations. The data composition covers factors such as electricity prices, mining difficulty, BTC market prices, and the distribution of CMDs across different regions. Data integrity was ensured by cross-referencing multiple sources, incorporating recorded data, and applying statistical validation techniques to enhance the robustness and reliability of the conclusions drawn in this study.

### C. EVALUATING THE PREMATURE AGING OF DISTRIBUTION TRANSFORMERS FROM CMLS

The significant impact of CMLs on the ADMD and, consequently, on the utilization factor of distribution assets, can lead to premature aging of these assets and result in substantial financial losses for distribution system operators (DSOs).

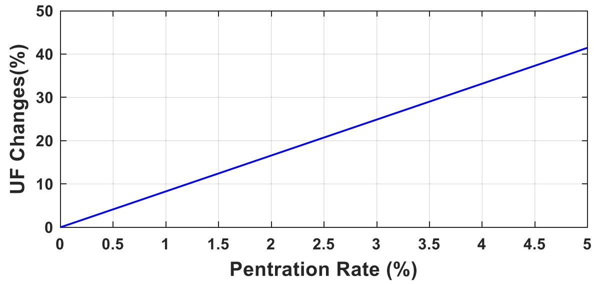



**FIGURE 13. Utilization factor change percentage for a different penetration rate of CMLs.**

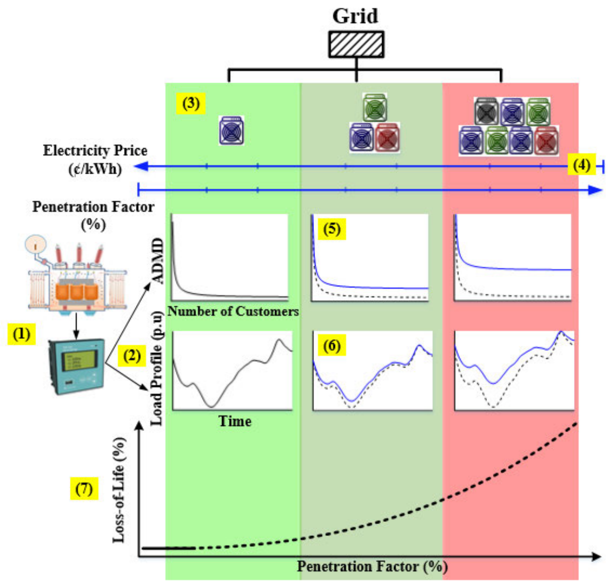



**FIGURE 14. A broad overview of the case study: (1) DT monitoring employing dedicated data loggers, (2) load profile and ADMD curve estimation, (3) pentration of CMLs, (4) penetrated CMLs estimation based on electricity price- green: low penetration, olive: medium penetration, red: high penetration, (5) ADMD modification, (6) load profile modification, (7) loss-of-life calculation of DTs in different penetration rates.**

Additionally, as studied in [10], the presence of CMLs alters the energy consumption pattern and the normalized load profile of a group of customers, as CMLs exhibit a unique and consistently flat load profile. Therefore, DSOs should continuously monitor and manage the penetration of CMLs in their networks. To further analyze the impact of CML penetration on the premature aging of distribution assets, it is important to consider distribution transformers (DTs), which are the most expensive components in power distribution networks. Managing their aging is crucial for DSOs. The constant power consumption of CMLs can lead to significant DT overloading, increased operating temperatures, and reduced lifetimes. This paper investigates the influence of CMLs on DTs, employing thermal analysis and loss-of-life calculations based on IEEE C57.91 [71] and IEC 60076-7 [72] standards.

The concept of cryptocurrency mining and its impacts on distribution network planning and operation, including

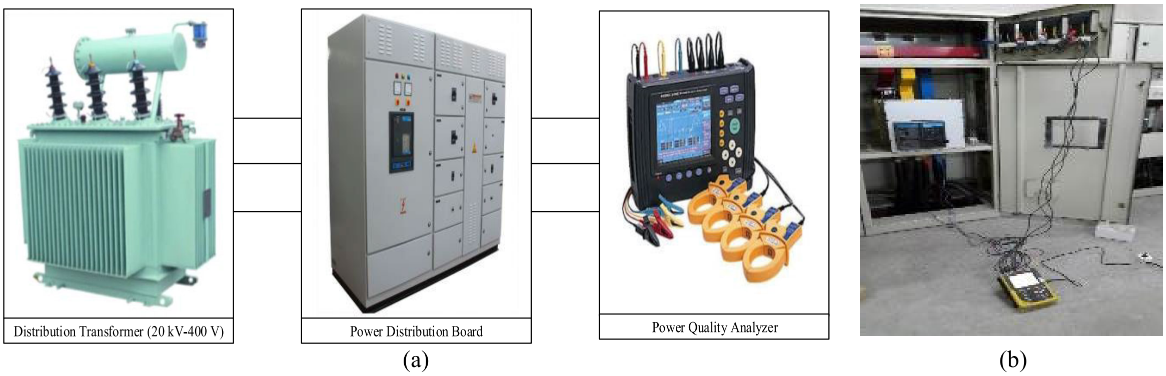



**FIGURE 15.** a) Schematic connection of power quality analyzer to distribution panel and, b) method for data retrieval from distribution panel of distribution substations [65].

inaccurate peak load estimation and increased DT loss-of-life, have been discussed in previous sections. In the following subsections, real-world measurement data from distribution substations in Tehran, Iran, are used to model a typical distribution network where CMLs can penetrate and affect network planning and operational considerations. The impact of CMLs on peak load estimation and DT aging is then evaluated. Fig. 14 provides an overview of the case study discussed in this section of the paper. This figure illustrates several key curves that capture the impact of CML on the power grid, with color-coded sections representing different levels of CML penetration. The green section indicates low penetration, olive represents medium penetration, and red signifies high penetration, offering a visual guide to how various CML levels affect grid performance. The first curve (2) shows the load profile and ADMD estimation over time, representing the changing demand as CML penetration increases. The second curve (5) highlights the modification of ADMD based on varying penetration levels, emphasizing how the grid adapts to these fluctuations. The third curve (6) presents shifts in the load profile at different penetration levels, indicating how electricity consumption patterns evolve with increasing CML activity. Lastly, the fourth curve (7) displays the loss-of-life calculation for DTs, illustrating how higher CML penetration accelerates wear and reduces equipment lifespan. The color-coded sections clarify the distinct effects of low, medium, and high penetration on load demand and transformer stress, demonstrating the necessity of adaptive grid management strategies as CML levels rise.

### D. ADMD ANALYSIS BASED ON THE REAL-WORLD DATA

Based on the studies presented in this paper, to investigate the effect of the CMLs on the modification of the ADMD curve, we first need to have a base curve of ADMD for residential customers. For this purpose, data for one year has been collected for 40 residential distribution substations with various capacities within the Tehran Electricity Distribution Company. The load type in these substations is typically residential, with capacities varying between 50 to 1600 kVA.

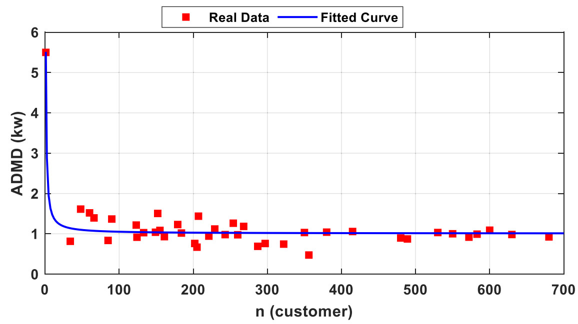



**FIGURE 16.** Curve of the average coincident peak a residential customer within Tehran Electricity Distribution Company.

The collected data includes the coincident peak demand, and the number of customers connected to these substations.

Fig. 15 illustrates the test setup of a PQ analyzer for gathering the aforementioned. Based on the collected data, Fig. 16 shows the actual data of ADMD with a fitted curve based on (11). By fitting the substations load data with the curve expressed in (11), the following equation is formed to calculate the average coincident peak demand of residential customers:

$$ADMD^n = 1 \times (1.006 + \frac{4.507}{n}) \qquad (19)$$

As it can be referred from Fig. 16, the rational pattern of the average coincident peak demand of residential customers based on the literature holds in this approximation. Moreover, R-square (criterion of the goodness of fitting a model) is calculated for the ADMD curve equal to 0.8986, which indicates that the data model is well fitted. Therefore, with an acceptable approximation, (19) can be used to calculate the coincident peak demand of residential customers in the Tehran Electricity Distribution Company. In this company, the average contract demand and maximum peak demand for residential customers are equal to 6.4 kW and 5.5 kW, respectively [5]. By employing the fitted ADMD curve, we can quantify the effect of CMLs on the adjustment of the $ADMD^{\infty}$ values across different levels of CML penetration, based on (19) These calculations are summarized in Table 4. This table highlights that if only 5% of residential customers in the Tehran Electricity Distribution Company install CMDs in their homes and utilize their maximum contracted power, the average coincident peak demand of this customer group rises by 26.81%. This is a rational effect by taking into account (17), which $P_{demand}$ has a significant effect on the modified ADMD. Failure to address this issue in the planning and operation of the distribution network can result in overload and premature aging of network assets, particularly distribution transformers and cables.

**TABLE 4. Modification of $ADMD^{\infty}$ for different CMLs penetration and its variation from the base case.**

| Type | $ADMD^{\infty}$ | Variation (%) |
|---|---|---|
| Base Curve | 1.006 | 0 |
| $\beta = 1\%$ | 1.0599 | 5.36 |
| $\beta = 2\%$ | 1.1139 | 10.72 |
| $\beta = 3\%$ | 1.1678 | 16.09 |
| $\beta = 4\%$ | 1.2218 | 21.45 |
| $\beta = 5\%$ | 1.2757 | 26.81 |

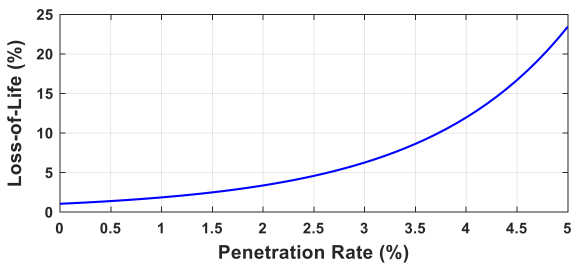



**FIGURE 17. The obtained loss-of-life result for a DT different CML penetration rates.**

## E. DT LOSS-OF-LIFE ASSESSMENT BASED ON THE REAL-WORLD DATA

In this subsection, real-world measurement data from distribution substations presented in the previous subsection are employed to evaluate the impact of CMLs on DT aging. The lifetime of a DT in the presence of CMLs depends on several factors: the penetration rate of CMLs, the consumption time of CMDs, and the baseload of the DT. To analyze the penetration rate, different levels of mining penetration (up to 5%) are studied. Flat electricity pricing strategies are used to reflect the impact of consumption time on DT aging. The electricity price in the flat tariff equals the average price in Iran, 3 cents per kWh. The transformer load profile and its utilization factor are crucial parameters in this study. The data over one year include transformer loading at 1-hour intervals, ambient temperature, and the harmonic content of the transformer load. The Antminer S19 Pro ASIC is considered as a sample CMD.

Fig. 17 shows the output results of loss-of-life assessment for a sample residential substation with different CML penetration rates, showing that a 5% penetration increases the LOL from 1.1% to 23%, a 21-times increase. This sharp rise is due to the correction of $ADMD^{n}$ and the normalized load profile, leading to a significant increase in the DT's utilization factor. The coincident peak load of the DT increases from 286.6 kW to 363.4 kW with 5% CML penetration, a 26% rise, causing accelerated DT aging. Fig. 18 compares the aging rate of 40 DTs in the dataset under flat tariff pricing, showing 24-hour penetration. The aging rate, defined as the ratio of LOL with and without CML penetration, ranges from less than 10 to more than 25, depending on the initial DT loading condition. The median aging rate of the monitored DTs is approximately 16.7.

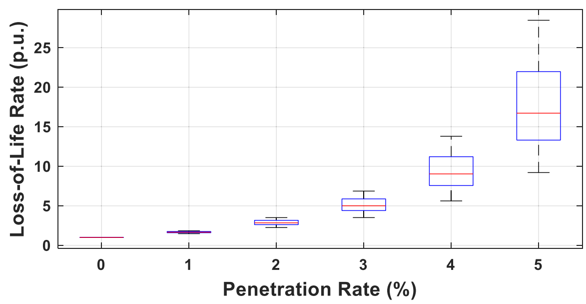



**FIGURE 18. The aging rate of the real-world monitored DTs in the presence of CMLs.**

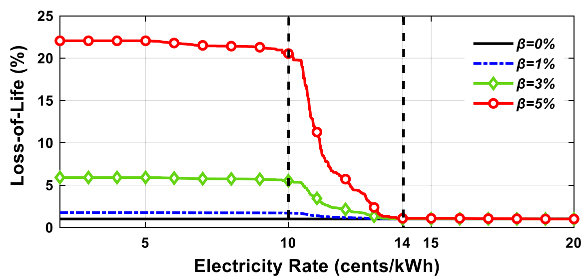



**FIGURE 19. The effect of electricity price on loss-of-life of a DT in the presence of CMLs.**

The subsequent analysis assesses the direct impact of electricity price levels on the loss-of-life of DTs. Electricity prices are incrementally increased from approximately 2 to 20 cents per kWh, while the loss-of-life rate of a DT is examined. Fig. 19 illustrates the effects of varying electricity prices on the loss-of-life rate of the DT, considering different levels of CML penetration in the distribution network. The results indicate that CML penetration has an insignificant impact on the loss-of-life of DTs when electricity prices exceed 14 cents per kWh, serving as an upper threshold. In this scenario, DTs operate under normal conditions throughout most or all of the year without significant daily CML operation, as supported by Fig. 19. Conversely, when the electricity price is below 10 cents/kWh, CMLs gradually emerge in the grid. This leads to a substantial increase in peak load and load profile, resulting in accelerated DT aging. The loss-of-life rate in high CML penetration scenarios is approximately 21 times greater than in non-penetrated cases. Between these two thresholds, even a minor increase in electricity price significantly improves the loading condition and loss-of-life rate of DTs.


**FIGURE 20. Test setup of power quality analyzer for data extraction from Antminer S9j [65].**

## VI. ELECTRICAL POWER QUALITY ANALYSIS

### A. CORRECTION OF NORMALIZED LOAD PROFILE IN THE PRESENCE OF CMLS

The increasing penetration of CMLs significantly alters the normalized load profile of electrical customers and their load factor. Typically, electricity usage follows predictable patterns, varying throughout the day and across seasons. However, the introduction of CMLs disrupts these patterns by creating a continuous and intensive demand for electricity, even during off-peak hours when regular customer's demand is low. This results in a flattening of the load profile, blurring the distinction between peak and off-peak periods. Consequently, the load factor, which measures the ratio of average power demand to peak power demand, increases due to the more consistent usage pattern induced by CMLs. The adjustment in normalized load profile and load factor presents challenges for distribution networks due to several adverse effects. Firstly, the heightened load factor resulting from the continuous demand imposed by CMLs can strain the grid infrastructure, potentially leading to equipment overheating, voltage fluctuations, and increased maintenance costs.

Secondly, the flattening of the load profile reduces the predictability of electricity consumption patterns, making it harder for utilities to forecast and manage energy supply and demand accurately. This unpredictability can result in inefficiencies in resource allocation, potentially leading to underutilization or overloading of grid assets. Moreover, it can pose challenges for grid assets such as distribution transformers. With a more consistent demand for electricity throughout the day, these assets have less downtime to rest and cool down. This continuous operation can lead to accelerated depreciation, reduced lifespan, and increased risk of equipment failure. Ultimately, these factors can result in premature aging, reliability issues, and increased maintenance costs for utilities. Therefore, addressing the impact of CMLs on load profiles and load factors is crucial to ensuring the reliability of grid assets.

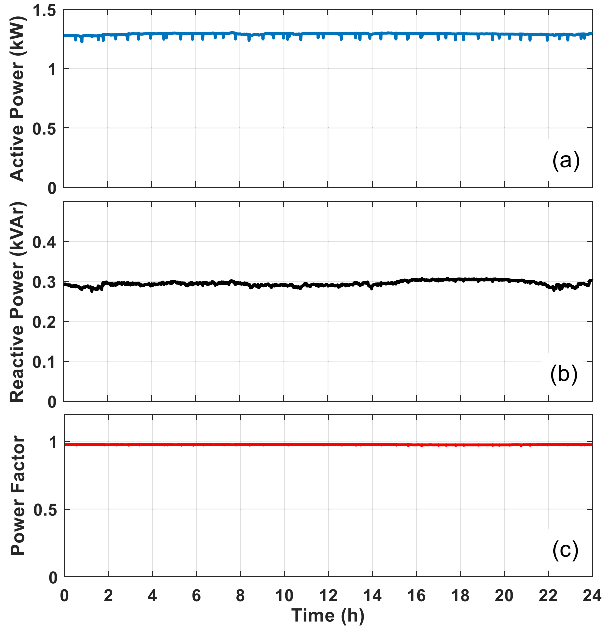



**FIGURE 21. Daily load demand parameters of a Bitmain Antminer S9j under study, including: a) active power, b) reactive power, and c) power factor.**

**TABLE 5. Power quality parameters for the CMD under study.**

| Parameter | Max. | Min. | Average | Standard | Status |
|---|---|---|---|---|---|
| Frequency (Hz) | 50.08 | 49.92 | 50.01 | - | - |
| Voltage (V) | 222.9 | 209.6 | 216.89 | - | - |
| Current (A) | 6.2 | 5.7 | 6.08 | - | - |
| Active power (kW) | 1.3 | 1.22 | 1.29 | - | - |
| Reactive power (kVAr) | 0.3 | 0.27 | 0.29 | - | - |
| Power factor (%) | 97.7 | 96.9 | 97.45 | - | - |
| Flicker | 1.99 | 0.08 | 0.16 | 1 | Ok |
| Current THD (%) | 17.6 | 15.7 | 16.62 | 15 | O/S |
| Voltage THD (%) | 4.6 | 2.6 | 3.48 | 5 | Ok |

In order to delve further into these challenges, a PQ analyzer has been installed on a Bitmain Antminer S9j, serving as a CMD, for a duration of one week to analyze active and reactive power parameters. Fig. 20 depicts the experimental setup, demonstrating the connection of the PQ analyzer to the CMD for the purpose of data collection. It is important to note that, at the time of writing this paper, the most commonly used CMD in Iran is Bitmain Antminer S9i. This CMD has a hash rate of 14.5 THash/s, power consumption of 1.35 kW, and energy efficiency of 10.47 GHash/J [45]. It was released in August 2018 and has an energy efficiency that is approximately one-third of the average energy efficiency of CMDs connected to the BTC network. Fig. 21 shows the active power, reactive power, and power factor of this CMD over a 24-hour period. Based on the measurement data exemplarily presented in this figure for a day, the load demand remains relatively constant during both day and night-time hours. The amount of generated reactive power is approximately 0.3 kVAr, with an average power factor value of 0.99.

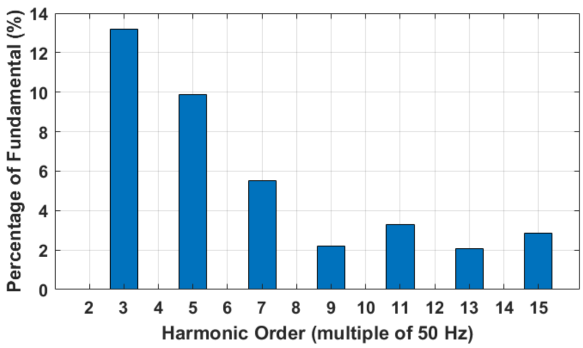



**FIGURE 22.** Current harmonic spectrum for the Bitmain AntMiner s9j under study.

### B. POWER QUALITY CONCERNS IN PRESENCE OF CMLS

The PQ concerns associated with CMDs are amplified by their utilization of switch-mode power supplies. These devices introduce significant harmonic distortion into electrical networks, disrupting the sinusoidal waveform of currents and voltages. This distortion, characterized by harmonics of various orders, including but not limited to the third, fifth, and seventh, poses multifaceted challenges. Not only does it compromise the stability and reliability of the power supply, but it also accelerates equipment wear and tear, leading to reduced operational lifespans and increased maintenance costs. Additionally, the increased harmonic content can interfere with other connected devices, potentially causing disruptions across the entire electrical system. As the prevalence of CMDs continues to rise, addressing these PQ issues becomes necessary to ensure grid stability, minimize operational disruptions, and optimize energy efficiency. To enhance comprehension of this matter, a week-long analysis of PQ has been conducted on a Bitmain Antminer S9j device, focusing on its harmonic components.

Table 5 and Fig. 22 present the PQ parameters and current harmonic components of the device, respectively. It should be noted that in this table, 'Ok' and 'O/S' indicate that for a parameter, it is within the standard range and above the standard range, respectively. Through observation of results the following can be determined in relation to IEEE Std. 519 [73]:

- Frequency variations are within the acceptable range.
- The average power factor is desirable.
- Short-term flicker index is within standard limits.
- Total voltage distortion is within standard limits, with the index value being 69.6% of the standard limit.
- Total current distortion exceeds the permissible maximum demand, with the index value reaching up to 1.11 times the standard limit.
- Voltage harmonics are within standard limits.
- The third harmonic current exceeds the permissible limit, with the index value reaching up to 1.09 times the standard limit.

The study acknowledges its current limitation of focusing on PQ measurements from a single CMD. It recognizes the need to explore the propagation of harmonics and other disturbances across the network, particularly in systems with multiple PQ polluters such as photovoltaic (PV) systems or electric vehicle (EV) charging stations, where these effects may be more significant. Efforts are underway to install power analyzers on a wider range of mining devices, as well as in larger cryptocurrency mining farms, to collect more comprehensive PQ data. Future work will also include the installation of power analyzers in small networks comprising mining devices and other harmonic-producing equipment, such as solar panels and electric microwaves. These extended investigations aim to provide a more detailed understanding of the impact of CMLs on PQ in diverse network environments.

## VII. CONCLUSION AND FUTURE WORKS

### A. SUMMARY AND CONCLUSION

The escalating integration of CMLs into power grids potentially introduced remarkable challenges to power systems due to their high power demand and unique characteristics. This challenge was further compounded by the swift expansion of cryptocurrency mining operations, propelled by factors like escalating cryptocurrency prices and advancements in mining technology. Consequently, this trend carried significant implications and challenges for the stability and sustainability of power grids.

This paper investigated the impacts of a high penetration of CMLs into power grids, both in the form of micro-miners and cryptocurrency mining farms, across various subsystems of a power network, including generation, transmission, and distribution. The proposed study was conducted using real-world data and case studies from Iran to develop empirical insights toward the challenges caused by CML penetration and to validate the findings. Initially, by employing a technology acceptance model for the adoption of cryptocurrency mining technology, the study examined criteria related to the integration of these emerging loads into the power network. Subsequently, a method for estimating the power demand of the BTC network was presented.

The study found that approximately 2.8% of Iran's total electricity consumption is allocated to CMLs. Furthermore, if only 5% of residential customers in the Tehran Electricity Distribution Company installed CMDs in their homes, the average coincident peak demand of this customer group rose by 26.81%. Additionally, the analysis revealed that the average power factor value of a sample CMD was about 0.99, and its total current distortion and third harmonic current exceeded the permissible limits by 1.11 and 1.09 times, respectively.

While the analytical methods employed in this study may seem straightforward, they address critical aspects of managing the growing demand of CMLs on power systems. The combination of economic factors, such as marginal electricity rates, and technological choices, such as the widespread use of inefficient CMDs, underscores the importance of these analyses for effective energy management. By applying these models to regions like Iran, where mining has unique impacts on distribution networks and overall energy consumption, the study highlights the need for precise forecasting and system planning. Understanding the power demand and distribution network effects of CMLs is essential for policymakers and grid operators to mitigate potential disruptions and ensure the stability and efficiency of power systems facing increased mining activity.

### B. FUTURE WORKS SUGGESTIONS

While this study provides a comprehensive analysis of the impacts of CMLs on power grid performance, several areas warrant further investigation to address the evolving challenges and opportunities in this field:

- Development of Real-Time Monitoring Systems: Implement and refine real-time monitoring systems for tracking CML impacts on power grids. This includes deploying sensors and advanced analytics to continuously assess and manage the load and its effects on grid performance.
- Transmission Line Congestion Analysis and Solutions: Conduct detailed analysis of transmission line congestion caused by high CML penetration. Develop and test practical solutions such as upgrading transmission infrastructure, optimizing network configurations, and implementing congestion management strategies to alleviate and prevent overloads.
- Dynamic Load Management Strategies: Develop and implement dynamic load management strategies that adjust mining operations based on real-time grid conditions. This includes creating demand-response programs and incentives for CML operators to align their activities with grid stability needs.
- Policy and Regulatory Frameworks: Create and evaluate policy and regulatory frameworks tailored to managing the impact of CMLs on power grids. This involves working with policymakers to establish guidelines for sustainable mining practices and effective integration into power systems.
- Long-Term Impact Assessment: Perform longitudinal studies to assess the long-term impacts of high CML penetration on power grid infrastructure, including maintenance and upgrade needs. This will help in developing strategies for sustaining grid reliability and efficiency over time.
- Propagation of Harmonics and Disturbances in Networks: Expand the study to investigate harmonic propagation in networks with multiple PQ polluters, such as PV systems and EV charging stations. Plans include installing PQ analyzers in larger mining farms and smaller networks with other harmonic-producing devices. This will help gather more comprehensive data and provide deeper insights into the impact of CMLs on PQ in varied network setups.

By focusing on these practical areas, future research and initiatives can address immediate challenges, enhance grid stability, and pave the way for more efficient and sustainable integration of cryptocurrency mining into power grids.

## REFERENCES


[1] M. B. Mollah, J. Zhao, D. Niyato, K.-Y. Lam, X. Zhang, A. M. Y. M. Ghias, L. H. Koh, and L. Yang, "Blockchain for future smart grid: A comprehensive survey," *IEEE Internet Things J.*, vol. 8, no. 1, pp. 18–43, Jan. 2021, doi: 10.1109/JIOT.2020.2993601.

[2] M.-V. Vladucu, Z. Dong, J. Medina, and R. Rojas-Cessa, "E-voting meets blockchain: A survey," *IEEE Access*, vol. 11, pp. 23293–23308, 2023, doi: 10.1109/ACCESS.2023.3253682.

[3] S. Mathur, A. Kalla, G. Gur, M. K. Bohra, and M. Liyanage, "A survey on role of blockchain for IoT: Applications and technical aspects," *Comput. Netw.*, vol. 227, May 2023, Art. no. 109726, doi: 10.1016/j.comnet.2023.109726.

[4] N. Del Sarto, L. Gai, and F. Ielasi, "Financial innovation: The impact of blockchain technologies on financial intermediaries," *J. Financial Manage., Markets Institutions*, vol. 12, no. 1, pp. 1–24, Jun. 2024.

[5] M. Hajiaghapour-Moghimi, K. A. Hosseini, E. Hajipour, and M. Vakilian, "A TOU-IBT pricing strategy to manage the cryptocurrency microminers," *IEEE Trans. Smart Grid*, vol. 13, no. 3, pp. 1838–1848, May 2022, doi: 10.1109/TSG.2021.3138906.

[6] *Cambridge Bitcoin Electricity Consumption Index*. [Online]. Available: https://ccaf.io/cbnsi/cbeci

[7] *Bitcoin Energy Consumption Index*. [Online]. Available: https://digiconomist.net/Bitcoin-energy-consumption

[8] J. Wu, J. Liu, Y. Zhao, and Z. Zheng, "Analysis of cryptocurrency transactions from a network perspective: An overview," *J. Netw. Comput. Appl.*, vol. 190, Sep. 2021, Art. no. 103139, doi: 10.1016/j.jnca.2021.103139.

[9] D. Khan, L. T. Jung, and M. A. Hashmani, "Systematic literature review of challenges in blockchain scalability," *Appl. Sci.*, vol. 11, no. 20, p. 9372, Oct. 2021, doi: 10.3390/app11209372.

[10] M. Hajiaghapour-Moghimi, K. A. Hosseini, E. Hajipour, and M. Vakilian, "Distribution transformer loss-of-life assessment in the presence of cryptocurrency mining loads," in *Proc. 26th Int. Electr. Power Distrib. Conf. (EPDC)*, May 2022, pp. 108–115, doi: 10.1109/EPDC56235.2022.9817210.

[11] V. Kohli, S. Chakravarty, V. Chamola, K. S. Sangwan, and S. Zeadally, "An analysis of energy consumption and carbon footprints of cryptocurrencies and possible solutions," *Digit. Commun. Netw.*, vol. 9, no. 1, pp. 79–89, Feb. 2023, doi: 10.1016/j.dcan.2022.06.017.

[12] S. Almubarak, H. Ibrahim, D. Singhania, and P. Enjeti, "Energy consumption and power quality in Bitcoin mining facilities in Texas," in *Proc. IEEE Energy Convers. Congr. Expo. (ECCE)*, Nov. 2023, pp. 742–749, doi: 10.1109/ECCE53617.2023.10362562.

[13] A. Khosravi and F. Säämäki, "Beyond Bitcoin: Evaluating energy consumption and environmental impact across cryptocurrency projects," *Energies*, vol. 16, no. 18, p. 6610, Sep. 2023, doi: 10.3390/en16186610.

[14] V. Anandhabalaji and M. Babu, "Research trends in energy consumption within the cryptocurrency ecosystem," in *Proc. 2nd Int. Conf. Smart Technol. for Power Renew. Energy (SPECon)*, Apr. 2024, pp. 1–8, doi: 10.1109/SPECon61254.2024.10537587.

[15] M. A. Rudd, L. Bratcher, S. Collins, D. Branscum, M. Carson, S. Connell, E. David, M. Gronowska, S. Hess, A. Mitchell, M. Prusak, K. Schneps, M. Serezhin, S. A. Wolfe, and D. Porter, "Bitcoin and its energy, environmental, and social impacts: An assessment of key research needs in the mining sector," *Challenges*, vol. 14, no. 4, p. 47, Nov. 2023, doi: 10.3390/challe14040047.

[16] L. Badea and M. Claudia Mungiu-Pupzan, "The economic and environmental impact of Bitcoin," *IEEE Access*, vol. 9, pp. 48091–48104, 2021, doi: 10.1109/ACCESS.2021.3068636.

[17] B. A. Jones, A. L. Goodkind, and R. P. Berrens, "Economic estimation of Bitcoin mining's climate damages demonstrates closer resemblance to digital crude than digital gold," *Sci. Rep.*, vol. 12, no. 1, p. 14512, Sep. 2022.

[18] A. Menati, X. Zheng, K. Lee, R. Shi, P. Du, C. Singh, and L. Xie, "High resolution modeling and analysis of cryptocurrency mining's impact on power grids: Carbon footprint, reliability, and electricity price," *Adv. Appl. Energy*, vol. 10, Jun. 2023, Art. no. 100136.

[19] S. Chamanara, S. A. Ghaffarizadeh, and K. Madani, "The environmental footprint of Bitcoin mining across the globe: Call for urgent action," *Earth's Future*, vol. 11, no. 10, pp. 1–26, Oct. 2023, doi: 10.1029/2023EF003871.

[20] M. A. B. Siddik, M. Amaya, and L. T. Marston, "The water and carbon footprint of cryptocurrencies and conventional currencies," *J. Cleaner Prod.*, vol. 411, Jul. 2023, Art. no. 137268, doi: 10.1016/j.jclepro.2023.137268.

[21] A. de Vries, U. Gallersdörfer, L. Klaaßen, and C. Stoll, "Revisiting Bitcoin's carbon footprint," *Joule*, vol. 6, no. 3, pp. 498–502, Mar. 2022.

[22] M. Y. Bukhari, A. A. Ansari, M. Yousif, M. Hassan, and U. Hassan, "Current and future implications of Bitcoin mining on energy and climate change," *MRS Energy Sustainability*, vol. 2, pp. 1–23, Apr. 2024.

[23] M. Hajiaghapour-Moghimi, E. Hajipour, K. A. Hosseini, M. Tavakkoli, S. Fattaheian-Dehkordi, M. Vakilian, and M. Lehtonen, "Hedging investments of grid-connected PV-BESS in buildings using cryptocurrency mining: A case study in Finland," *IEEE Access*, vol. 11, pp. 66327–66345, 2023, doi: 10.1109/ACCESS.2023.3290909.

[24] M. Hajiaghapour-Moghimi, E. Hajipour, K. A. Hosseini, M. Vakilian, and M. Lehtonen, "Cryptocurrency mining as a novel virtual energy storage system in islanded and grid-connected microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 158, Jul. 2024, Art. no. 109915, doi: 10.1016/j.ijepes.2024.109915.

[25] Y. Tomatsu and W. Han, "Bitcoin and renewable energy mining: A survey," *Blockchains*, vol. 1, no. 2, pp. 90–110, Dec. 2023, doi: 10.3390/blockchains1020007.

[26] A. Rouhanian, M. Ghafari, G. B. Gharehpetian, R. Asaadi, M. Azimpour, and M. Salay Naderi, "Supplying a Bitcoin mining farm by maximum utilization of renewable energy sources in microgrid," in *Proc. 28th Int. Electr. Power Distrib. Conf. (EPDC)*, Apr. 2024, pp. 1–7, doi: 10.1109/EPDC62178.2024.10571729.

[27] M. Velický, "Renewable energy transition facilitated by Bitcoin," *ACS Sustain. Chem. Eng.*, vol. 11, no. 8, pp. 3160–3169, Feb. 2023, doi: 10.1021/acssuschemeng.2c06077.

[28] I. M. Siddique, A. A. Siddique, E. D. Smith, and S. Molla, "Assessing the sustainability of Bitcoin mining: Comparative review of renewable energy sources," *J. Alternative Renew. Energy Sour.*, vol. 10, no. 1, pp. 1–12, 2023, doi: 10.46610/joares.2024.v10i01.001.

[29] P. Resch, C. Schroeder, A. Pourmovahed, and K. Brinker Brouwer, "Cryptocurrency and its effect on the electric grid," *Renew. Energy Power Quality J.*, vol. 20, pp. 1–5, Sep. 2022, doi: 10.24084/repqj20.202.

[30] A. Conroy, *Bitcoin Mining and Electrical Grid Reliability*. Chapel Hill, NC, USA: The University of North Carolina at Chapel Hill, 2024.

[31] V. A. Katic, Z. J. Corba, and A. M. Stanisavljevic, "Effects of cryptocurrency mining rig operation on power quality in LV distribution network," Tech. Rep., 2022.

[32] A. Samanta, Q. Zhang, and L. Xie, "Prediction of cryptocurrency mining load tripping through learning-based fault classification," in *Proc. IEEE Texas Power Energy Conf. (TPEC)*, Feb. 2024, pp. 1–6, doi: 10.1109/TPEC60005.2024.10472233.

[33] A. Samanta, S. Majumder, H. Ibrahim, P. Enjeti, and L. Xie, "Electromagnetic transient model of cryptocurrency mining loads for low-voltage ride through assessment in transmission grids," 2023, *arXiv:2312.15067*.

[34] M. Hajiaghapour-Moghimi, K. Azimi Hosseini, E. Hajipour, and M. Vakilian, "An approach to targeting cryptocurrency mining loads for energy efficiency enhancement," *IET Gener., Transmiss. Distrib.*, vol. 16, no. 23, pp. 4775–4790, Dec. 2022, doi: 10.1049/gtd2.12640.

[35] N. Marangunić and A. Granic, "Technology acceptance model: A literature review from 1986 to 2013," *Universal Access Inf. Soc.*, vol. 14, no. 1, pp. 81–95, Mar. 2015, doi: 10.1007/s10209-014-0348-1.

[36] M. Arias-Oliva, J. Pelegrín-Borondo, and G. Matías-Clavero, "Variables influencing cryptocurrency use: A technology acceptance model in Spain," *Frontiers Psychol.*, vol. 10, pp. 1–26, Mar. 2019.

[37] D. Folkinshteyn and M. Lennon, "Braving Bitcoin: A technology acceptance model (TAM) analysis," *J. Inf. Technol. Case Appl. Res.*, vol. 18, no. 4, pp. 220–249, Oct. 2016, doi: 10.1080/15228053.2016.1275242.

[38] U. W. E. Saputra and G. S. Darma, "The intention to use blockchain in Indonesia using extended approach technology acceptance model (TAM)," *Commun. Inf. Technol. J.*, vol. 16, no. 1, pp. 27–35, Feb. 2022, doi: 10.21512/commit.v16i1.7609.

[39] E. Hajipour, F. Khavari, M. Hajiaghapour-Moghimi, K. Azimi Hosseini, and M. Vakilian, "An economic evaluation framework for cryptocurrency mining operation in microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 142, Nov. 2022, Art. no. 108329, doi: 10.1016/j.ijepes.2022.108329.

[40] H. Taherdoost, "A critical review of blockchain acceptance models—Blockchain technology adoption frameworks and applications," *Computers*, vol. 11, no. 2, p. 24, Feb. 2022, doi: 10.3390/computers11020024.

[41] C.-H. Chen, "Extending the technology acceptance model: A new perspective on the adoption of blockchain technology," *Hum. Behav. Emerg. Technol.*, vol. 2023, pp. 1–14, Nov. 2023, doi: 10.1155/2023/4835896.

[42] F. Cesario, C. J. Costa, M. Aparicio, and J. Aparicio, "Blockchain technology adoption: Factors influencing intention and usage," Tech. Rep., 2023.

[43] S. L. Náñez Alonso, J. Jorge-Vázquez, M. Á. Fernández, and R. F. Reier Forradellas, "Cryptocurrency mining from an economic and environmental perspective. Analysis of the most and least sustainable countries," *Energies*, vol. 14, no. 14, p. 4254, Jul. 2021, doi: 10.3390/en14144254.

[44] *Blockchain Charts*. [Online]. Available: https://www.blockchain.com/explorer/charts

[45] *Realtime Mining Hardware Profitability: ASIC Miner Value*. [Online]. Available: https://www.asicminervalue.com/

[46] G. Giudici, A. Milne, and D. Vinogradov, "Cryptocurrencies: Market analysis and perspectives," *J. Ind. Bus. Econ.*, vol. 47, no. 1, pp. 1–18, Mar. 2020, doi: 10.1007/s40812-019-00138-6.

[47] E. Saiedi, A. Broström, and F. Ruiz, "Global drivers of cryptocurrency infrastructure adoption," *Small Bus. Econ.*, vol. 57, no. 1, pp. 353–406, Jun. 2021, doi: 10.1007/s11187-019-00309-8.

[48] M. H. Ronaghi, "A contextualized study of blockchain technology adoption as a digital currency platform under sanctions," *Manage. Decis.*, vol. 61, no. 5, pp. 1352–1373, Apr. 2023, doi: 10.1108/md-03-2022-0392.

[49] M. Hajiaghapour-Moghimi, K. Azimi-Hosseini, E. Hajipour, and M. Vakilian, "Residential load clustering contribution to accurate distribution transformer sizing," in *Proc. Int. Power Syst. Conf. (PSC)*, Dec. 2019, pp. 313–319, doi: 10.1109/PSC49016.2019.9081518.

[50] A. A. Mir, M. Alghassab, K. Ullah, Z. A. Khan, Y. Lu, and M. Imran, "A review of electricity demand forecasting in low and middle income countries: The demand determinants and horizons," *Sustainability*, vol. 12, no. 15, p. 5931, Jul. 2020, doi: 10.3390/su12155931.

[51] P. W. Khan and Y.-C. Byun, "Genetic algorithm based optimized feature engineering and hybrid machine learning for effective energy consumption prediction," *IEEE Access*, vol. 8, pp. 196274–196286, 2020, doi: 10.1109/ACCESS.2020.3034101.

[52] S.-V. Oprea and A. Bara, "Machine learning algorithms for short-term load forecast in residential buildings using smart meters, sensors and big data solutions," *IEEE Access*, vol. 7, pp. 177874–177889, 2019, doi: 10.1109/ACCESS.2019.2958383.

[53] M. Jawad, M. S. A. Nadeem, S.-O. Shim, I. R. Khan, A. Shaheen, N. Habib, L. Hussain, and W. Aziz, "Machine learning based cost effective electricity load forecasting model using correlated meteorological parameters," *IEEE Access*, vol. 8, pp. 146847–146864, 2020, doi: 10.1109/ACCESS.2020.3014086.

[54] B. Farsi, M. Amayri, N. Bouguila, and U. Eicker, "On short-term load forecasting using machine learning techniques and a novel parallel deep LSTM-CNN approach," *IEEE Access*, vol. 9, pp. 31191–31212, 2021, doi: 10.1109/ACCESS.2021.3060290.

[55] C. Wronka, "Digital currencies and economic sanctions: The increasing risk of sanction evasion," *J. Financial Crime*, vol. 29, no. 4, pp. 1269–1282, Sep. 2022, doi: 10.1108/jfc-07-2021-0158.

[56] L. Tassev. *Iran To Shut Down Licensed Crypto Miners in Peak Hours of Power Consumption*. [Online]. Available: https://news.Bitcoin.com/iran-to-shut-down-licensed-crypto-miners-in-peak-hours-of-power-consumption/

[57] T. Wright. *Iranian Authorities Greenlight Power Plants Mining Bitcoin*. [Online]. Available: https://cointelegraph.com/news/iranian-authorities-greenlight-power-plants-mining-Bitcoin

[58] *Crypto-Miners Take Down Iran Electric Grids, Prompting Crackdown*. [Online]. Available: https://arab.news/peevf

[59] A. Contributor. (2020). *Iran Power Plants Get Green Light To Mine Bitcoin*. [Online]. Available: https://asiatimes.com/2020/07/iran-power-plants-get-green-light-to-mine-Bitcoin/

[60] L. Tassev. *Iran To Shut Down Licensed Crypto Miners in Peak Hours of Power Consumption*. [Online]. Available: https://news.Bitcoin.com/iran-to-shut-down-licensed-crypto-miners-in-peak-hours-of-power-consumption/%0A

[61] K. H. Mohd Azmi, N. A. Mohamed Radzi, N. A. Azhar, F. S. Samidi, I. Thaqifah Zulkifli, and A. M. Zainal, "Active electric distribution network: Applications, challenges, and opportunities," *IEEE Access*, vol. 10, pp. 134655–134689, 2022, doi: 10.1109/ACCESS.2022.3229328.

[62] A. Zhou, H. Zhai, M. Yang, and Y. Lin, "Three-phase unbalanced distribution network dynamic reconfiguration: A distributionally robust approach," *IEEE Trans. Smart Grid*, vol. 13, no. 3, pp. 2063–2074, May 2022, doi: 10.1109/TSG.2021.3139763.

[63] K. A. Wheeler and A. W. Bowers, "A comparative power quality analysis of cryptocurrency mining loads," in *Proc. IEEE Can. Conf. Electr. Comput. Eng. (CCECE)*, May 2019, pp. 1–5, doi: 10.1109/CCECE43985.2019.9052404.

[64] K. A. Wheeler, A. W. Bowers, C. H. Wong, J. Y. Palmer, and X. Wang, "A power quality and load analysis of a cryptocurrency mine," in *Proc. IEEE Electr. Power Energy Conf. (EPEC)*, Oct. 2018, pp. 1–6, doi: 10.1109/EPEC.2018.8598358.

[65] M. H. Moghimi, "Management of cryptocurrency mining penetration in electricity distribution networks and provision of the solutions," Sharif Univ. Technol., Tehran, Iran, Rep., 2023.

[66] O. M. Babatunde, J. L. Munda, and Y. Hamam, "Generation expansion planning: A survey," in *Proc. IEEE PES/IAS PowerAfrica*, Jun. 2018, pp. 307–312, doi: 10.1109/POWERAFRICA.2018.8521173.

[67] M. R. Bashiri and S. S. Hosseinioun, "Evaluation of feed-in tariff in iran, an experience from the middle east," in *Proc. 1st Nat. Conf. Optimizing Renewable Energies*, 2021, pp. 1–20.

[68] Niharika, S. Verma, and V. Mukherjee, "Transmission expansion planning: A review," in *Proc. Int. Conf. Energy Efficient Technol. Sustainability (ICEETS)*, Apr. 2016, pp. 350–355, doi: 10.1109/ICEETS.2016.7583779.

[69] S. Honkapuro, J. Jaanto, and S. Annala, "A systematic review of European electricity market design options," *Energies*, vol. 16, no. 9, p. 3704, Apr. 2023, doi: 10.3390/en16093704.

[70] M. Sun, I. Konstantelos, and G. Strbac, "Analysis of diversified residential demand in London using smart meter and demographic data," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Jul. 2016, pp. 1–5, doi: 10.1109/PESGM.2016.7741076.

[71] *IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators.*, IEEE Standard C57.91, 2012.

[72] *Power Transformers—Part 7: Loading Guide for Oil Immersed Power Transformers*, Standard IEC 60076-7, 2018.

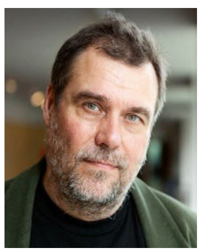
[73] *IEEE Standard for Harmonic Control in Electric Power Systems*, Standard IEEE Std 519-2014, 2022, pp. 1–31.

**MEHRAN HAJIAGHAPOUR-MOGHIMI** received the B.Sc. degree in electrical engineering from Babol Noshirvani University of Technology, Babol, Iran, in 2014, and the M.Sc. and Ph.D. degrees in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 2016 and 2023, respectively. In 2022, he was a Visiting Ph.D. Student with Aalto University, Espoo, Finland. His research interests include electric power distribution system operation and planning, microgrid-related issues, power system optimization, renewable energy integration, energy flexibility services in power systems, and sustainable cryptocurrency mining.

**OMIDREZA HEYDARI TAFRESHI** received the B.Sc. degree in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 2022, where he is currently pursuing the M.Sc. degree in electrical engineering. His current research interests include the operation of power systems, renewable energy systems integration, microgrids, and other applications of optimization and artificial intelligence in power systems.

**EHSAN HAJIPOUR** (Member, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 2008, 2010, and 2017, respectively. He is currently an Assistant Professor with the Department of Electrical Engineering, Sharif University of Technology. His current research interests include power system protection, power system automation and cybersecurity, and smart protection, operation, and planning.

**MEHDI VAKILIAN** (Senior Member, IEEE) received the B.Sc. degree in electrical engineering and the M.Sc. degree in electric power engineering from the Sharif University of Technology, Tehran, Iran, in 1978 and 1986, respectively, and the Ph.D. degree in electric power engineering from Rensselaer Polytechnic Institute, Troy, NY, USA, in 1993. In 1986, he joined the Department of Electrical Engineering, Sharif University of Technology. He had been the Chairperson of the Department several times, until 2018. During this time, he was also a Visiting Professor with the School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, NSW, Australia. His research interests include transient modeling of power system equipment, optimum design of high-voltage equipment insulation, monitoring of power system equipment, and distribution system studies.



**MATTI LEHTONEN** received the master's and Licentiate degrees in electrical engineering from the Helsinki University of Technology, in 1984 and 1989, respectively, and the Doctor of Technology degree from the Tampere University of Technology, in 1992. From 1987 to 2003, he was with VTT Energy, Espoo, Finland. Since 1999, he has been a Professor with the Helsinki University of Technology (now Aalto University), where he is currently the Head of the Power Systems and High Voltage Engineering. His research interests include power system planning and asset management, power system protection, including earth fault problems, harmonic-related issues, and applications of information technology in distribution systems.