

Energy Quality-Based Detection of Cryptocurrency Mining Loads: A Solution for Unauthorized Energy Consumption Monitoring

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Cryptocurrency mining, propelled by its high profitability and the availability of low-cost energy in certain regions, presents significant challenges to distribution networks, including unauthorized energy consumption, increased network loading, power theft, harmonic distortions, and degraded power quality. This paper introduces an innovative approach based on Harmonic State Estimation (HSE), which leverages the unique harmonic signatures of mining loads to accurately detect unauthorized cryptocurrency mining operations within distribution networks. The developed methodology could successfully identify the miners even in the presence of other harmonic-distorted loads such as steel industries, smelting plants, and textile factories. By analyzing harmonic measurements, harmonic power output, and power factor across various distinct scenarios involving varied harmonic loads alongside unauthorized mining activities, the proposed method precisely locates these operations. Implemented and validated using DigSILENT PowerFactory on standard test networks, the results underscore the method's accuracy in differentiating mining activities from other harmonic sources, offering distribution network operators a robust tool to mitigate power theft, enhance network stability, and improve overall reliability.

Keywords: Cryptocurrency mining, harmonic state estimation, distribution system, measurement, power factor

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1. Introduction

Cryptocurrency refers to decentralized digital money based on blockchain technology. Unlike traditional fiat currencies such as the U.S. Dollar or the Euro, cryptocurrencies operate without a central authority, relying instead on a distributed network of users. Bitcoin, the most prominent cryptocurrency introduced in 2008 by Satoshi Nakamoto, functions as an electronic payment system secured by cryptographic proof and recorded on an energy-intensive blockchain ledger. The energy consumption of cryptocurrency mining, particularly Bitcoin, has raised significant concerns in energy management and sustainability. Mining operations require vast computational power, leading to high electricity demand, often sourced from fossil fuels, which conflicts with global efforts toward renewable energy integration and energy efficiency. However, some initiatives are exploring sustainable mining practices, such as utilizing excess renewable energy (e.g., solar or wind) or optimizing energy storage systems to balance grid loads. From an energy systems perspective, blockchain technology—beyond cryptocurrencies—offers potential applications in smart grids, peer-to-peer energy trading, and decentralized energy markets [1-3].

Cryptocurrency mining is a resource-intensive activity that demands substantial computational power and an uninterrupted energy supply, operating around the clock. As the global adoption

of various cryptocurrencies continues to grow, so does the associated energy consumption, raising critical concerns for energy management, grid stability, and sustainable power systems [4-8]. Some remarkable challenges of illegal cryptocurrency mining farms could be observed in Fig. 1 which have been introduced as follows:

- **Unauthorized Energy Consumption:** Illicit mining operations—often hidden or unauthorized—consume energy without contributing to the grid. This disrupts load forecasts, complicates demand-side management, and undermines network stability, highlighting the need for improved energy monitoring and smart grid solutions.
- **Network Congestion:** The continuous mining process strains network capacity, leading to congestion and potential delays in transaction validation. This poses challenges for grid operators in maintaining optimal power flow and energy distribution efficiency.
- **Power Quality Degradation:** The high and variable energy demands of mining can destabilize voltage and frequency regulation, impacting power quality. Transformers and other grid infrastructure may experience accelerated aging due to sustained load fluctuations, necessitating advanced energy system diagnostics and predictive maintenance.
- **Inaccurate Load Estimation:** Mining operations distort typical load behavior, complicating energy forecasting and grid planning.

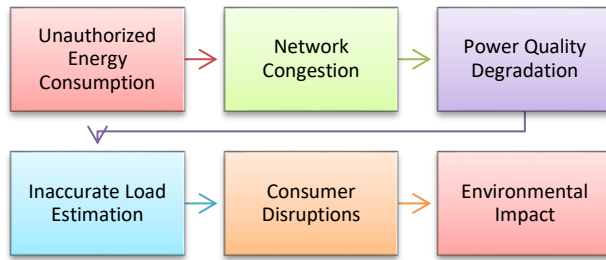


Fig. 1. Remarkable challenges of illegal cryptocurrency mining farms

This misalignment affects the integration of renewable energy sources and demand response strategies, key topics in modern energy management research.

- **Consumer Disruptions:** Illicit mining can lead to localized power outages or voltage fluctuations, negatively impacting residential and commercial end-users. Such issues emphasize the importance of resilient energy systems and decentralized energy solutions, such as microgrids with integrated storage.
- **Environmental Impact:** The energy-intensive nature of mining contributes to increased carbon emissions, excessive electricity consumption, and e-waste generation.

Given these challenges, it is crucial to identify illegal cryptocurrency mining farms to protect energy infrastructure and support sustainable power systems. By restricting their unauthorized energy consumption, utilities could significantly improve grid reliability, enhance power quality, and reduce unnecessary strain on energy resources. These considerations underscore the importance of developing advanced detection methods for illegal cryptocurrency mining operations. The detection and mitigation of such unauthorized loads could:

- Improve accuracy in load forecasting and energy demand management
- Reduce transformer overload risks and premature aging of grid components
- Support better integration of renewable energy sources by eliminating unpredictable demand spikes
- Contribute to energy conservation efforts and reduction of carbon emissions
- Enable more effective implementation of demand response programs

These measures would not only enhance the reliability and quality of power supply but also help minimize the environmental impacts of energy-intensive mining activities. These considerations underscore the importance of identifying and detecting illegal cryptocurrency mining farms.

1.1. Related works

In the field of detecting unauthorized cryptocurrency mining farms, several studies have been conducted. These investigations aim to prevent illegal energy consumption, enhance power quality, and reduce losses in the distribution network. Some notable studies have been discussed in this section.

Analysis of energy demand curve has been proposed in [9]. In this method, an energy demand curve has been calculated and compared with actual energy consumption at specific locations. By analyzing discrepancies, potential irregularities related to mining activities could be detected. Monitoring power consumption differences has been reported in [10]. It involves monitoring the

power consumption difference between the monitored and the upstream network. Deviations may occur due to transmission losses or electricity theft which could be a sign of unauthorized energy consumption. Islam et al. (2022) provided a comprehensive analysis of the energy consumption impacts of blockchain-based mining, emphasizing the need for effective monitoring and mitigation strategies [11]. In [12], a method has been proposed using Internet of Things (IoT) to identify energy theft. The method focuses on two scenarios: changes in power levels and tampering with meters. Additionally, Ahmad et al. (2025) employed system identification and machine learning for load modeling of cryptocurrency mining devices, offering insights into their dynamic behavior [13].

Harmonic spectrum comparison is another methodology for detection of unauthorized mining farms [14]. In this study, researchers conducted a comparative analysis between the harmonic spectrum of cryptocurrency miners and real data from data centers. This approach helps distinguish mining-related electrical patterns. Katic et al. analyzed the effects of mining rig operations on power quality in low-voltage distribution networks, identifying significant harmonic distortions caused by mining equipment [15]. Almubarak et al. explored energy consumption and power quality issues in Bitcoin mining facilities in Texas, highlighting the strain on regional grids [16]. In [17] a methodology has been proposed to detect illegal cryptocurrency mining farms in distribution systems, demonstrating its effectiveness in identifying harmonic signatures unique to mining operations. In [18], a comparative approach for key parameters, including current values, power factor, and energy growth rate, was presented to detect miners. In this study, a consumption model for some miners was proposed, which could generate revenue for distribution companies in load management and penalizing illegal miners. Power quality measurements for a group of computers in comparison to data from cryptocurrency mining equipment were performed in [19]. Observable results showed that mining equipment has a lesser impact on power quality (current and voltage harmonics) compared to the set of computers, but their electricity demand is significantly higher and almost has a constant consumption profile against set computer loads. Regarding the power factor, mining equipment has greater values compared to computer centers, to the extent that they may act as a resistive load from the viewpoint of the upstream network. In [20], the effects of disturbances in multi-tenant data centers on network voltage and current were investigated. In another research study, an approach for incorporating cryptocurrency mining loads to enhance energy efficiency has been investigated using a penalty and reward framework [21]. Two primary methods are commonly employed for detecting cryptocurrency mining farms as shown in Fig. 2. The first method involves monitoring internet usage through IP addresses, while the second method focuses on tracking energy consumption. In the first approach, mining farms necessitate continuous internet access, which enables their detection via their unique IP addresses. However, the use of proxies and VPNs by mining farms can pose challenges to the effectiveness of this method. The second method focuses on monitoring the energy consumption of miners and itself involves two subcategories:

1. **Identifying Unauthorized Energy Consumption:** Various methods are used for detection within this category. These include comparing energy consumption for suspicious consumers, analyzing energy growth rates, identifying excessive current usage, and detecting high constant consumption patterns.
2. **Analyzing Power Quality Impacts:** Miners can also be located based on their power quality characteristics. Researchers have implemented this approach in their study. However, limited work has been done in measuring the quality of load and identifying injected harmonics within this category.

In this paper, we focused on analyzing power quality of the network and possible locations of mining farms would be determined

using HSE algorithm.

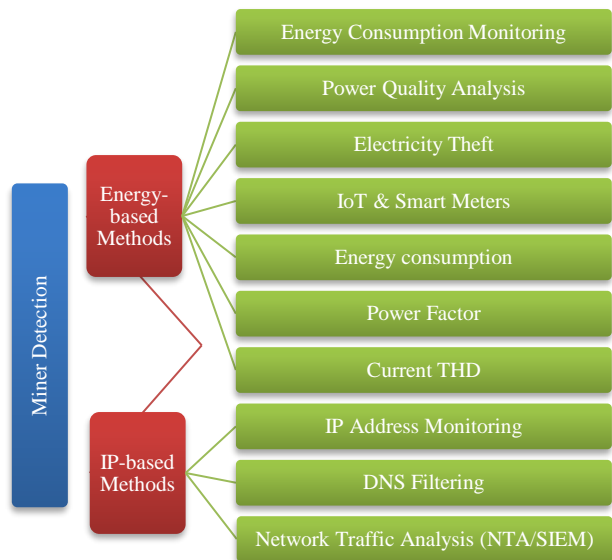


Fig. 2. Methods for detecting illegal cryptocurrency mining farms

Table 1. Comparative analysis of recent studies on cryptocurrency mining detection

Study	Methodology	Scope	Limitations
[15]	Power quality analysis	Effects of mining rigs on low voltage network power quality	Descriptive, no detection methodology
[16]	Energy analysis	Energy and power quality in Bitcoin mining facilities	Region-specific; lacks detection algorithm
[17]	Harmonic Spectrum	Detection of illegal mining farms using harmonic signatures and to energy detection methods	Analysis and detection through energy consumption rather than parameters like power factor and change of use
[11]	Energy consumption analysis	Blockchain-based mining impact on energy use	General analysis, no specific detection techniques
[13]	Identification and machine learning	Load modeling for mining devices	Focus on modeling, not real-time detection

2.1. Paper Contribution

This paper addresses the growing challenge of unauthorized cryptocurrency mining farms within distribution networks. To tackle this issue, we propose a unique Harmonic State Estimation (HSE)-based approach that exclusively integrates power factor analysis with harmonic measurements to identify the illegal mining activities. Three key performance indices including harmonic voltage estimation accuracy, detection of unauthorized harmonic power injection, and identification of changes in permitted harmonic

injection patterns have been employed. The developed method addresses the critical gap of detecting mining loads in scenarios where customers exploit purchased demand under tariff changes—a limitation overlooked in prior works. By leveraging the leading power factor characteristics of modern mining devices, our approach distinguishes these loads from computationally similar ones (e.g., computer loads) and other industrial loads with comparable harmonic spectra, such as conveyors or spinning machines. The contribution of this research lies in developing a practical, real-time detection framework, validated on IEEE 18-bus networks using DigSILENT PowerFactory, which effectively identifies the locations of mining farms as harmonic distortion sources. Through various simulated scenarios reflecting diverse mining farm situations, the method demonstrates robustness and precision, enabling distribution network operators to mitigate energy theft and enhance network stability.

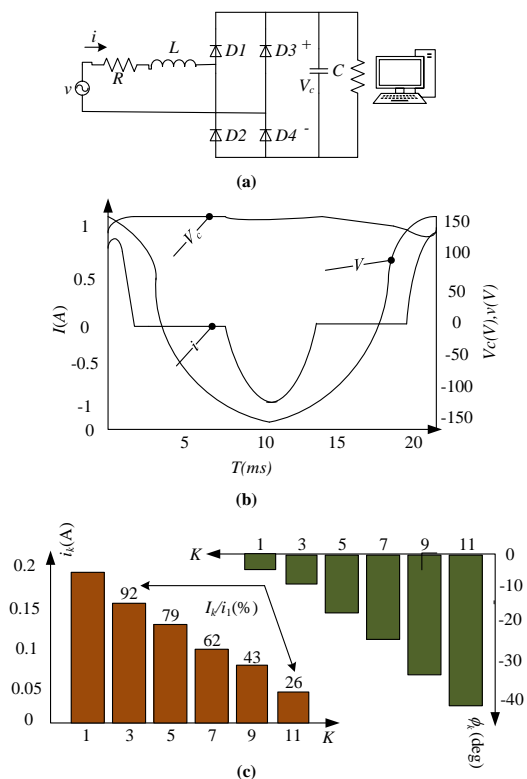
The rest of the paper is organized as follows: section II explores the fundamentals of cryptocurrencies and their mining processes; section III introduces network harmonic modeling, HSE methodology, as well as HSE implementation steps in DigSILENT PowerFactory; section IV presents simulation results, and Section V provides concluding remarks and findings on the proposed methodology for detecting unauthorized cryptocurrency mining farms.

2. Cryptocurrencies and Mining

Blockchain technology plays a crucial role in Bitcoin extraction. It serves as a distributed ledger platform that securely stores historical transaction records and creates favorable conditions for enhancing profitability in mining operations [22]. Blockchain technology, with its decentralized and tamper-proof nature, has significant potential to transform the mining industry. Blockchain ensures transparency by recording all transactions and agreements on an immutable ledger. This transparency can help track the entire supply chain, from mining sites to end consumers, ensuring responsible practices. The decentralized nature of blockchain builds trust among stakeholders. Miners, investors, and regulators can rely on verified data stored on the blockchain, reducing the risk of fraud or misinformation. Blockchain enables the use of smart contracts, self-executing agreements that automatically trigger actions when predefined conditions are met. In mining, smart contracts can streamline processes such as royalty payments, supply chain logistics, and compliance checks. Blockchain can improve supply chain efficiency by providing real-time visibility into raw material sourcing, transportation, and product distribution. This transparency enhances accountability and reduces inefficiencies. In the context of conflict minerals (such as those mined in war zones), blockchain can verify the origin and ethical sourcing of minerals. This helps companies comply with regulations and demonstrate responsible practices. By recording ownership and transfer of assets on the blockchain, miners can prevent fraud and theft. Immutable records ensure that no unauthorized changes occur. Blockchain can track the environmental impact of mining activities, promoting sustainable practices. It allows stakeholders to monitor energy consumption, emissions, and waste management. In summary, blockchain technology holds immense promise for the mining industry, regardless of the scale of operations. Its adoption can lead to greater efficiency, accountability, and responsible resource extraction

In the early days, cryptocurrencies were mined using conventional computers. However, with the advent of specialized hardware designed for improved mining efficiency and reduced processing time, these computers were gradually replaced by dedicated mining devices known as miners. Each miner is equipped with powerful central processing units (CPUs) and graphics processing units (GPUs) specifically tailored for cryptocurrency mining. Miners employ various techniques to optimize their operations. One such approach involves leveraging machine learning algorithms to bolster defensive capabilities during the mining process, safeguarding against network

threats while enhancing computational resources [23]. Despite the varying power levels and processing speeds among miners, their operational mechanism remains consistent: solving computational puzzles and processing transactions to obtain transaction blocks. These processes rely on switching power supplies and data processing units. Miner loads exhibit similarities to computer loads, with minor distinctions. Notably, the power factor values differentiate them, as computer loads tend to have lower values. Additionally, miner loads can sometimes appear as resistive loads. The equivalent circuit for a computer load utilizing a switching power supply is shown In Fig. 3. In Fig. 3-(a), the schematic representation of the computer’s power supply circuit is presented, while Fig. 3-(b) depicts the waveforms of the input voltage and current. The current waveform exhibits considerable harmonic distortion, suggesting that the switching power supply operates as a harmonic load. Additionally, Fig. 3-(c) illustrates the harmonic spectrum of the input current, highlighting the current injected at



each harmonic order [24].
Fig. 3. AC/DC rectifier: (a) Equivalent circuit, (b) Voltage and current waveform, (c) Harmonic spectrum of current

Table 2. Harmonic content of miner loads

Harmonic Orders	3 rd	5 th	7 th	9 th	11 th	13 th
Value (%)	18	11	9	3	6	2

Table 2 displays the harmonic spectrum associated with miner loads. Typically, miner loads demonstrate lower harmonic voltage and current distortions when compared to computer loads. Additionally, miners exhibit continuous energy consumption, characterized by a consistent energy usage profile, in contrast to computer loads that experience limited usage and higher energy consumption fluctuations.

Consequently, miner loads are examined as harmonic loads within the power network. As a result, it becomes crucial to create a harmonic model of the network to accurately identify these miner

loads. This topic will be further explored in the subsequent section.

3. Harmonic Modeling, State Estimation and Methodology

In electrical networks with nonlinear loads, the nonlinear relationship between voltage and current results in the generation of harmonic currents. These harmonic currents propagate throughout the network, leading to the creation of harmonic voltages. Harmonic distortions pose significant challenges for network operators, particularly at power distribution levels. To mitigate potential damage, it is crucial to account for harmonics in calculations and thoroughly examine their effects. Consequently, employing harmonic load flow analysis becomes essential.

In the context of harmonic load flow analysis, consider a distribution network comprising multiple nonlinear loads. These nonlinear loads introduce harmonic currents into the network. The characteristics of these harmonics—such as their order, magnitude, and phase—strongly depend on the specific nonlinear load model. Consequently, accurate modeling of nonlinear loads becomes a critical aspect of harmonic load flow calculations. Each nonlinear load exhibits unique features, necessitating the development of load-specific models. These models can be formulated either in the time domain or the frequency domain, as noted in [25]. Time-domain modeling relies on the analysis of transient states, whereas frequency-domain modeling employs frequency scanning techniques to determine the system’s frequency response. Due to their computational efficiency, frequency-domain methods are commonly preferred for harmonic analysis. Further details regarding network modeling at harmonic levels will be discussed in subsequent sections.

3.1. Harmonic Modeling of Network

In the study of harmonics, the behavior of network components varies with frequency changes, requiring specific modeling methods for each component. Consider a distribution network generally consisting linear loads, nonlinear loads, distribution lines and transformers.

Linear loads are electrical devices where the current drawn from the supply is directly proportional to the applied voltage, following Ohm’s Law. These loads exhibit a linear relationship between voltage and current, meaning that if the voltage waveform is sinusoidal, the current waveform will also be sinusoidal without distortion. Linear loads do not generate harmonics in the power system, and their power factor is primarily influenced by the phase difference between voltage and current (leading or lagging) rather than waveform distortion. Distribution lines which usually have been modeled with resistors, inductors and capacitors, could also be accounted as linear elements. Common examples of linear loads include resistive elements like electric heaters and incandescent lamps, as well as inductive loads such as induction motors and transformers operating under normal conditions.

Nonlinear loads are devices where the current drawn does not follow the voltage waveform proportionally, leading to a distorted current waveform even when the supply voltage is purely sinusoidal. These loads introduce harmonics into the power system, which can cause voltage distortion, increased losses, and interference with other equipment. The nonlinearity arises due to electronic switching components, such as diodes, transistors, and thyristors, which draw current in short pulses rather than smoothly. Examples of nonlinear loads include power electronic devices like variable frequency drives, switch-mode power supplies, LED lighting, computers, miners and uninterruptible power supplies.

Various components have been modeled with their distinct characteristics [26] in harmonic studies. These components could be modeled as follows:

- **Nonlinear Loads:** These loads have been modeled using

harmonic spectrum approach. Harmonic spectrum modeling of nonlinear loads involves analyzing the frequency-domain characteristics of distorted current if nonlinear load. This modeling decomposes the distorted waveform using Fourier analysis to quantify harmonic magnitudes and phases, typically representing the load as either an ideal harmonic current source or an admittance-based model in frequency-domain studies. The approach helps evaluate power quality impacts and design filters. An example of such modeling has been previously represented in Table 2.

- **Resistors:** These components are frequency-independent. Therefore, their impedance remains constant across all harmonic orders and is equal to their value at the fundamental frequency.
- **Inductors and Capacitors:** These elements are frequency-sensitive; an inductor (L) is modeled as an impedance $Z_L = j\omega L$, where its magnitude increases linearly with frequency ($\omega = 2\pi f$) and causes current to lag voltage by 90° , while a capacitor (C) is modeled as $Z_C = (j\omega C)^{-1}$, where its impedance decreases with frequency and causes current to lead voltage by 90° . These models derive from their time-domain differential characteristics. These frequency-dependent properties are crucial for designing filters, analyzing harmonic distortion, and optimizing power systems.

Constant-Power Loads: These loads are typically represented as a combination of resistive and inductive components at harmonic frequencies. The admittance of these loads (y) can be calculated using the following relation (1):

$$y = \frac{P}{v_h^2} - j \frac{Q}{hv_h^2} \quad (1)$$

where:

- P is the active power consumption of load,
- Q is the reactive power consumption of load,
- v_h is the voltage at the h^{th} harmonic.

3.2. Harmonic state estimation

Harmonic State Estimation (HSE) is a computational method used to determine the harmonic voltages and currents of a network by combining limited measurements with network topology and impedance data. It typically employs weighted least squares (WLS) or Kalman filtering techniques to minimize the error between measured and calculated harmonic quantities, accounting for harmonic injections from nonlinear loads and distributed generation. HSE provides a system-wide view of harmonic distortion levels, enabling identification of harmonic sources, assessment of compliance with standards, and optimization of mitigation strategies like filter placement [27].

To solve the HSE problem using WLS method, the goal is to minimize the difference between measured and estimated values. Assume X is the vector of state variables, typically comprising harmonic voltages or harmonic injection currents at the buses. The relationship between the harmonic measurements Z and the state variables X is expressed as:

$$Z = HX + e \quad (2)$$

Where:

- The state vector " X " represents unknown harmonic quantities to be estimated, most commonly the complex harmonic voltages (magnitude and phase angle) at all network buses. For a three-phase unbalanced system, X may also include sequence components. In advanced formulations, it can extend to

harmonic current injections or impedance parameters for poorly characterized loads. The vector's dimension scales with network size and the highest harmonic order considered.

- The measurement vector " Z " includes actual field-recorded data from devices. These measurements typically include harmonic voltages and currents at specific nodes (e.g., 5th and 7th harmonic magnitudes/angles) and may incorporate derived quantities such as power harmonics or impedance spectra. The vector's dimensionality depends on the number of monitoring points and harmonic orders being tracked, with redundancy improving estimation accuracy.
- The Jacobian matrix " H " encodes the physical relationships between measurements and system states, derived from the network's harmonic admittance matrix and device characteristics. For each harmonic frequency, H incorporates topology-derived sensitivities, nonlinear load models, and measurement type dependencies. Its structure varies with harmonic order due to frequency-dependent line impedances and rotating machine reactances.
- The error term " e " accounts for measurement noise, instrument errors, and model inaccuracies. It is typically assumed Gaussian with a covariance matrix that weights measurement reliability. Robust estimation techniques may reformulate e to handle outliers from faulty sensors or transient harmonic events. The estimation process minimizes e through weighted least squares or Kalman filtering to produce statistically optimal states.

In the WLS method, the objective is to minimize the weighted sum of the squares of the errors, defined as (3) in which, the residual matrix has been calculated using (4).

$$\min \left\{ J(x) = (z - Hx)^T R_z^{-1} (z - Hx) \right\} \quad (3)$$

$$R_z = \text{diag} \left[\left\{ \sigma_{z_1}^2, \sigma_{z_2}^2, \dots, \sigma_{z_m}^2 \right\} \right] \quad (4)$$

The condition for solving the problem is to set the derivative of the Jacobian matrix with respect to the state variables equal to zero as shown in (5). Hence, the harmonic magnitudes of system variables could be determined using (5). The " G " is called as gain matrix which is shown in (6).

$$\frac{\partial J(x)}{\partial x} = 0 \Rightarrow \hat{x} = G^{-1} H^T R_z^{-1} z \quad (3)$$

$$G = H^T R_z^{-1} H \quad (4)$$

3.3. Harmonic measurements

In order to ensure the applicability of the proposed algorithm, network observability is a fundamental requirement for performing HSE algorithm. During this process, the number of harmonic state variables typically exceeds the number of available measurements, resulting in an under-determined system [28]. Within distribution networks, three types of harmonic measurements are commonly used: μ -PMUs (phasor measurement units), power quality meters, and smart meters [29] which have been represented in Fig. 4.

- **μ -PMUs:** These devices are utilized for calculating the magnitude and phase angle of harmonic components. They possess the capability to track dynamic and transient events within distribution systems.
- **Power Quality (PQ) Meters:** These meters collect various parameters, including frequency, RMS voltage, current, total harmonic distortion, individual harmonics, and flicker. Their comprehensive measurements contribute to network observability, accuracy, and security.

- **Smart Meters:** Although smart meters have lower sampling rates, they serve a valuable purpose in measuring data at minute scales, such as short-term load forecasting.



Fig. 4. Meters in distribution network for harmonic monitoring

By integrating and combining data from these measurements, we enhance the overall observability of the network. In the context of our study, power quality meters play a crucial role in identifying unauthorized loads within the distribution network, a topic that will be further explored in the upcoming section.

2.4. The Proposed Methodology

The proposed method for detecting unauthorized miners involves a three-step process, as illustrated in Fig. 5. Simulations and algorithms were executed using the DigSILENT software platform. DigSILENT is a prominent tool widely used for power system analysis across generation, transmission, and distribution levels. In this study, specific modifications were applied to the state estimation module of the software to identify unauthorized miner loads within the distribution network through HSE.

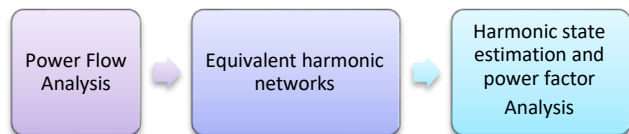


Fig. 5. Flowchart of the proposed methodology

The main steps of the proposed methodology are as follows.

• Network Implementation and Load Flow Analysis

In the initial step, we implement the network within the DigSILENT software. By applying load flow analysis, we calculate the voltages and currents throughout the network. Additionally, we determine the injection currents from nonlinear loads, which serve as the basis for calculating harmonic injections.

• Harmonic Modeling in Harmonic Equivalent Networks

In the subsequent step, we perform harmonic modeling for loads, transmission lines, and nonlinear devices in harmonic equivalent networks. It's important to note that we separate the main grid into equivalent networks due to DigSILENT's limitation in directly performing HSE. This separation allows us to simulate HSE effectively within the software.

Our focus lies on network observability. Assuming this condition is met, we identify suitable locations and determine the minimum number of measurement units required. To achieve full observability, we deploy eight power quality meters across both the base network and the harmonic separate networks.

• Simulation of HSE and Identifying Harmonic Loads

In the absence of actual measurements, we calculate network measurement values through load power flow analysis. These calculated values, along with added noise, serve as inputs for the state estimation process in DigSILENT. After that, by executing the state estimation process in the harmonic equivalent networks and combining their results, we simulate the HSE process within the studied network. This simulation enables us to identify the locations

of harmonic loads.

The main criterion for identifying harmonic loads is the presence of non-zero harmonic injection power at a network bus, which would be considered as the designated locations for mining loads.

4. Implementation and Results

In this section, the suggested methodology is evaluated using the IEEE 18-bus test network. The data for these networks are sourced from references [26]. For the IEEE 18-bus test network, three simulation scenarios were designed to explore a variety of potential situations, with further details to follow. The positions of harmonic and miner loads across these scenarios are presented in Fig. 6.

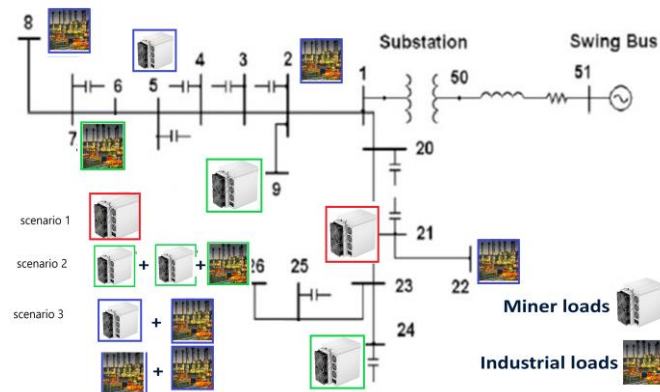


Fig. 6. Single-line diagram of IEEE 18-bus test network and scenarios

4.1. Scenario 1

In the first scenario, an unauthorized 1 MW cryptocurrency mining load was connected at bus #21 without the network operator's approval. The proposed algorithm utilized power flow results from individual networks as virtual measurements for each harmonic order, with Harmonic State Estimation (HSE) derived through state estimation across these networks. Post-HSE analysis, Fig. 7 presents the maximum and average errors between measured and HSE-calculated voltage magnitudes across all harmonic orders. The figure reveals a maximum HSE error of 0.1756% at bus #26 for the 7th harmonic order, which falls within a highly acceptable range. The average HSE error across all harmonic orders and network buses is 0.0662%, demonstrating the robust performance of the proposed method.

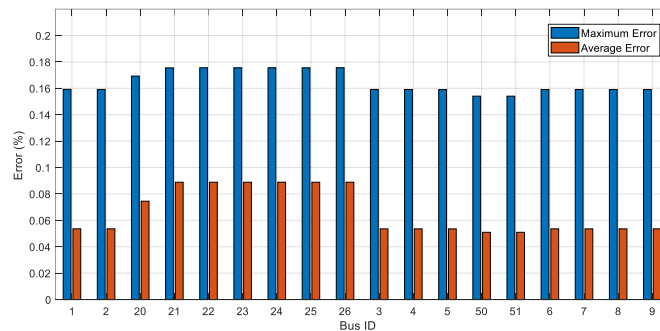


Fig. 7. Max and average errors between measurements and HSE output voltage in scenario 1

Fig. 8 illustrates the harmonic active power values across all harmonic orders, excluding the fundamental frequency. The results show that harmonic active power is zero at all network buses except for bus #21. At bus #21, the highest harmonic power is observed at the 5th harmonic order, with a value of 11.6 kW, followed by the 3rd

harmonic order with a value of 6.3 kW. The non-zero harmonic power at bus #21 suggests the presence of an unauthorized cryptocurrency mining load, which the proposed methodology has effectively detected. By integrating harmonic measurements with the HSE algorithm, the location of the harmonic-generating miner was accurately identified with reliable performance.

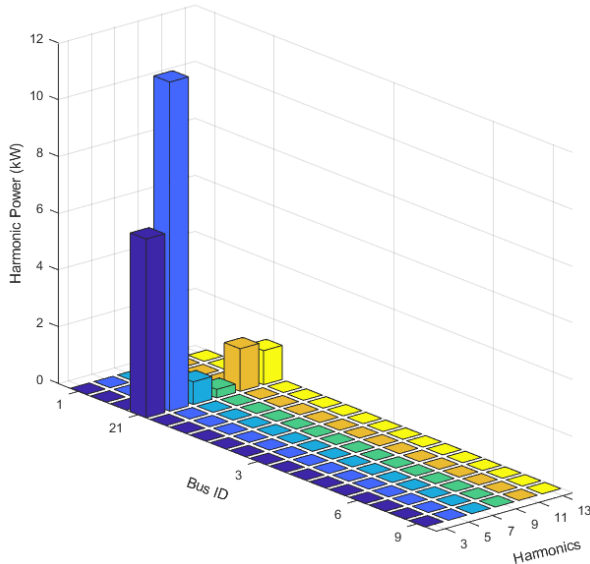


Fig. 8. Output values of HSE in scenario 1

4.2. Scenario 2

In scenario 2, in order to simultaneously identifying miner and industrial loads, two different loads with various harmonic spectrum (industrial and miner) have been placed in the network. In this scenario, two miner loads have been placed at bus #9 and bus #24 with the same active power of 0.85 MW. Likewise, an industrial steel load has been placed at bus #7 with 2 MW active power. The load locations have been shown in Fig. 6. The harmonic spectrum of industrial load has been shown in Table 3. In this scenario, application of the proposed methodology for identification of various miner and industrial loads will be investigated. The industrial load has greater active power compared to the miners. Also, it has lagging power factor, whereas the miners have leading power factor.

The harmonic active power in scenario 2 have been represented in Fig. 9. As it could be observed, the proposed algorithm could successfully determine the locations of harmonic injections into the network from buses #24, #7, and #9. For other buses of the network, the harmonic active power equal to zero. For bus #24, the greatest values are for 5th and 3rd orders with values of 15.6 and 6.2, respectively. For bus #7, the greatest harmonic active power is for 5th harmonic order as well. However, for bus #9, the greatest determined value is for 3rd harmonic which is equal to 4.4 kW.

Fig. 10 depicts the reactive harmonic power values for all harmonic orders, excluding the fundamental frequency, in Scenario 2. The results indicate that harmonic reactive power is zero at all network buses except for buses #7, #9, and #24. At buses #24 and #9, the miner loads exhibit leading power factors, characterized by negative harmonic reactive power values. Specifically, at bus #24, the highest harmonic reactive power occurs at the 5th harmonic order, with a value of -3.17 kvar, followed by the 3rd harmonic order at -1.26 kvar. For bus #9, the most significant harmonic reactive powers are observed at the 3rd and 5th harmonic orders, with values of -0.89 kvar and -0.70 kvar, respectively. Conversely, at bus #7, the industrial load displays a lagging power factor, as shown in Fig. 10. The peak harmonic reactive powers at this bus occur at the 5th and

3rd harmonic orders, with values of 6.56 kvar and 6.16 kvar, respectively.

Table 3. Harmonic spectrum of industrial loads

Harmonic Orders	3 rd	5 th	7 th	9 th	11 th	13 th
Value (%)	3.5	21.8	9.7	1.7	5.2	2.5

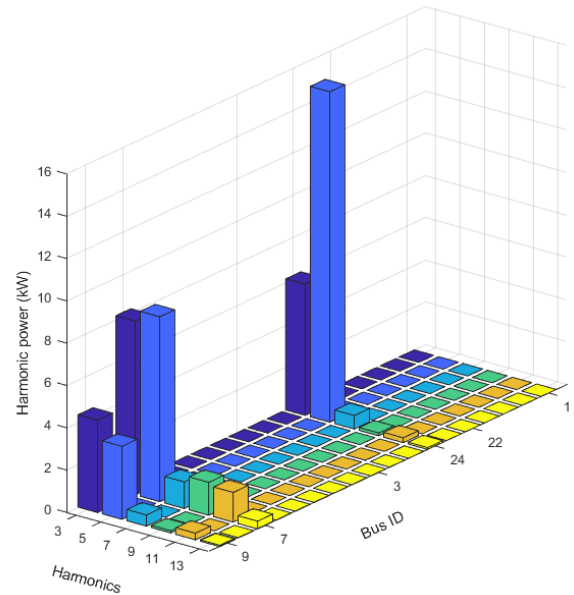


Fig. 9. Output values of harmonic active power in scenario 2

4.3. Scenario 3

To further evaluate the proposed HSE method under realistic and complex conditions, this scenario extends the IEEE 18-bus test network to include a diverse set of harmonic-distorted loads alongside an unauthorized cryptocurrency mining load. Specifically, three industrial loads with distinct harmonic spectra and varying power levels are placed in the upstream and downstream sections of the network. An unauthorized mining load with an active power demand of 250 kW at bus #5. Fig. 11 illustrates the maximum and average errors between measurement and HSE voltage magnitude outputs in all harmonic orders. The harmonic spectra of the industrial loads are presented in Table 3. This scenario investigates the ability of the proposed method to accurately detect the unauthorized mining load in the presence of multiple harmonic-distorted industrial loads.

In this scenario, the industrial loads are placed as follows: a steel plant load with 0.88 MW active power at bus #1, a smelting plant load with 0.22 MW active power at bus #22, and a textile machinery load with 0.45 MW active power at bus #8. The unauthorized mining load at bus #5 exhibits a leading power factor, while the industrial loads have lagging power factors, consistent with their operational characteristics. The harmonic spectrum of the industrial loads, shown in Table 4, includes significant contributions at the 3rd, 5th, and 7th harmonic orders, reflecting their diverse harmonic profiles.

The harmonic active power outputs for Scenario 3 are depicted in Fig. 12. The proposed HSE algorithm successfully identifies the locations of harmonic injections at buses #1, #22, #5, and #8, with harmonic active power values at all other buses equal to zero. For the unauthorized mining load at bus #5, the greatest harmonic active power is observed at the 3rd order (1.32184 kW), followed by the 5th order (0.98374 kW). For the steel plant at bus #1, the dominant harmonic active power is at the 3rd order (6.218 kW), while the smelting plant at bus #22 shows a peak at the 5th order (3.9686 kW). The textile machinery load at bus #8 has its highest harmonic active power at the 11th order (8.59772 kW).

Table 3. Harmonic spectrum of industrial loads (%)

Harmonic Orders	3 rd	5 th	7 th	9 th	11 th	13 th
Load 1 (bus #1)	23.5	19.1	16.2	15.7	16.0	15.7
Load 2 (bus #22)	38.8	60.0	45.9	14.0	33.3	24.2
Load 3 (bus #8)	1.4	18.1	5.8	0.6	3.9	1.6

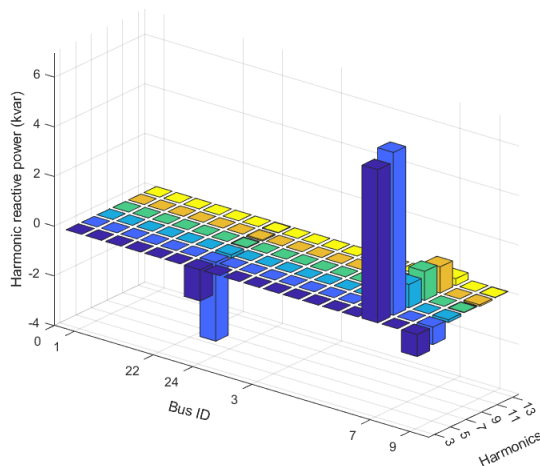


Fig. 10. Output values of harmonic reactive power in scenario 2

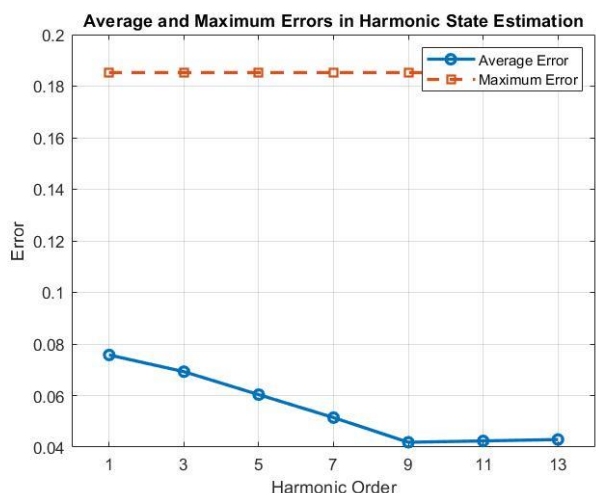


Fig. 11. Max and average errors between measurements and HSE output voltage in scenario 3

Fig. 13 illustrates the harmonic reactive power output values for all harmonic orders (excluding the fundamental order) in Scenario 3. The harmonic reactive power is zero for all buses except #1, #5, #22, and #8. The mining load at bus #5 exhibits a leading power factor with negative harmonic reactive power values, with the greatest contributions at the 3rd order (-0.26841 kvar) and the 5th order (-0.19976 kvar). In contrast, the industrial loads at buses #1, #8, and #22 show lagging power factors. The steel plant at bus #1 has the highest harmonic reactive power at the 3rd order (4.01 kvar), followed by the 5th order (3.55 kvar). The smelting plant at bus #22 peaks at the 5th order (2.25 kvar), and the textile machinery load at bus #8 shows significant contributions at the 11th order (9.27 kvar).

This scenario demonstrates the robustness of the proposed HSE method in accurately distinguishing the unauthorized mining load from multiple industrial loads with diverse harmonic spectra, thereby validating its effectiveness in complex distribution network environments.

This result leverages power flow results as virtual measurements to accurately detect and localize unauthorized cryptocurrency

mining loads within power distribution networks. By integrating harmonic analysis with state estimation techniques, the method capitalizes on the distinct harmonic signatures generated by mining loads, particularly focusing on the active and reactive harmonic power across multiple harmonic orders. Importantly, this study systematically examines multiple scenarios with increasing complexity, thereby demonstrating the scalability and adaptability of the HSE approach to realistic grid conditions, including the coexistence of diverse industrial harmonic sources.

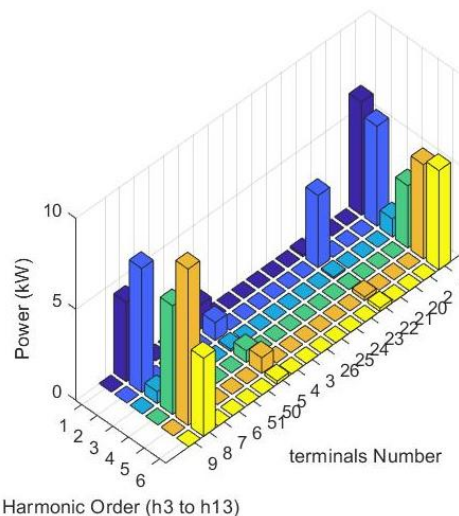


Fig. 12. Harmonic active power outputs in scenario 3

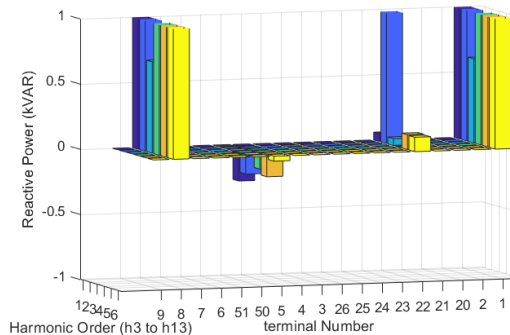


Fig. 13. Harmonic reactive power outputs in scenario 3

The quantitative results across all scenarios underscore the robustness and precision of the proposed method. The consistently low maximum and average estimation errors (e.g., below 0.2% in voltage magnitude estimation) highlight the algorithm’s reliability in reconstructing harmonic states with minimal uncertainty. Furthermore, the harmonic active and reactive power profiles provide valuable diagnostic indicators that enable differentiation between mining loads and industrial consumers. Specifically, the contrasting power factor characteristics—leading for miners and lagging for industrial loads—enable effective discrimination even in the presence of multiple overlapping harmonic sources. This is a critical advancement, as unauthorized mining loads often remain undetected in traditional monitoring frameworks, potentially leading to power quality degradation and operational risks.

Beyond detection, the paper’s findings have important practical implications for grid operators aiming to improve power quality management and regulatory compliance. The demonstrated ability to

pinpoint unauthorized loads can facilitate targeted enforcement and mitigation strategies, such as load shedding or network reconfiguration, thereby enhancing grid resilience.

5. Conclusion and Future Work

The rapid expansion of cryptocurrency mining has significantly strained power distribution networks, causing issues such as unauthorized energy consumption and harmonic distortions. This study proposes a robust method based on Harmonic State Estimation (HSE) that accurately detects unauthorized mining loads by analyzing their distinct harmonic signatures and power characteristics. Implemented in DigSILENT PowerFactory and tested on 18-bus test system, the method demonstrates high precision in pinpointing unauthorized mining operations, even in complex scenarios involving multiple harmonic-distorted loads across upstream and downstream network sections. Incorporating power factor analysis as a complementary technique further enhances the method's effectiveness. Extensive testing across diverse scenarios confirms its ability to distinguish mining loads from other industrial loads, such as those in steel and textile industries, while maintaining robustness under assumptions of full network observability, minimal harmonic interference from adjacent networks, and optimal placement of measurement devices. These findings underscore the HSE method's potential as a reliable and practical tool for distribution network operators to monitor and manage unauthorized mining activities, prevent energy theft, and ensure the stability and reliability of power networks.

To further enhance the HSE-based method for detecting unauthorized cryptocurrency mining, several key research directions could be outlined. Integrating smart meters and μ -PMUs with machine learning techniques can improve the accuracy of identifying unauthorized consumption patterns, while automated deep learning systems utilizing real-time smart meter data enable rapid detection of illicit mining operations. Additionally, incorporating IoT systems with HSE offers a scalable, decentralized approach to monitoring large networks. Collectively, these efforts could be designed to boost detection accuracy, maintain network stability, and promote sustainability in managing unauthorized mining activities.

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