Best practices for analyzing the direct energy use of blockchain technology systems: Review and recommendations

Nuoa Lei[1], Eric Masanet[1,2*], and Jonathan Koomey[3]

[1] McCormick School of Engineering and Applied Science, Northwestern University, Evanston, IL, USA

[2] Bren School of Environmental Science and Management, University of California, Santa Barbara, USA

[3] Koomey Analytics, Burlingame, CA, USA

* corresponding author: eric.masanet@northwestern.edu

Highlights:

- Blockchain technologies are being proposed for a variety of energy system applications, but their direct energy use is poorly understood
- Current studies of blockchain system energy use focus exclusively on cryptocurrency applications, which represent an extreme case
- Approaches used in cryptocurrency estimates vary widely, suggesting the need for wider adoption of best practices for analyzing these systems
- Further research regarding general blockchain system energy modeling is needed, particularly from a bottom-up approach

Table of Contents

1 What is blockchain?

A blockchain is a system for recording information across a network of computer systems in a way that makes these records secure, verified, and immutable. It is often referred to as a "distributed ledger" system, because each participant in the blockchain system has a copy of recorded information, making such records both transparent and easily verifiable. Information is recorded to the distributed ledger in a series of "blocks," each of which contains transactions or other key data that will be archived. Every time new transactions or data are added to the ledger, a new block is added containing a record of those transactions or data to every participant's ledger. Therefore, the ledger is comprised of an expanding series of blocks of information, hence, the name blockchain [1].

Blockchain ledgers are designed to be difficult to hack or change, given that any change must be verified against all other copies of the ledger in the blockchain system. In addition to security, this decentralized nature means that blockchain ledgers can be established by any sufficiently well-connected and organized network of participants, making record-keeping and verification possible for many applications without needing to work through a traditional central authority (e.g., a bank, a power utility, or a title company). As such, blockchain technologies can be seen as much nimbler, faster to establish, and participatory than traditional centralized systems for storing and verifying critical information.

While cryptocurrencies like Bitcoin are the most well-known examples of blockchain ledgers, the aforementioned benefits have led to high interest in—and many emerging applications of—blockchain technologies to solving energy and environmental problems [2][3]. While blockchain technologies can play an important role in addressing these problems (see Section 2), this report focuses on a narrower question: how much direct energy is required to run blockchain systems?

Answering this question is an important first step toward understanding the net benefits of blockchain systems, for several reasons. First, as discussed in Section 3, the blockchain is comprised of different information technology (IT) devices for computing, storing, and communicating necessary information, some of which (e.g., cryptocurrency mining rigs) can have high operational energy requirements [4]. Second, these IT devices run on electricity, which is still a carbon- and pollutant-intensive energy source in many parts of the world [5]. Third, as blockchain applications proliferate, it is vital for decision makers (e.g., policy makers and power utility operators) to have accurate information for understanding the implications of blockchain technologies on grid loads. Finally, to date, the only published estimates of the direct energy use of blockchain systems have focused entirely on "proof or work" cryptocurrencies like Bitcoin (see Section 5), which are likely to have significantly higher energy intensities than other blockchain applications that can rely on less computationally-demanding verification approaches. Therefore, a more nuanced view of direct energy use is required to avoid perceptions that all blockchain systems will be as energy-intensive as cryptocurrencies.

2 Applications to energy and environmental problems

Some key examples of blockchain technology applied to energy and environmental problems include energy trading, electric vehicle (EV) charging, demand response, sustainable supply chain management, green certificates, and renewable energy promotion (Figure 1). Some of the benefits of such applications could include cost-effective local energy trading, acceleration of renewable energy generation, providing grids with new demand response resources for greater grid stability, and enabling consumers to better track the sources of the energy they consume. Below, we review this opportunity space in more detail.

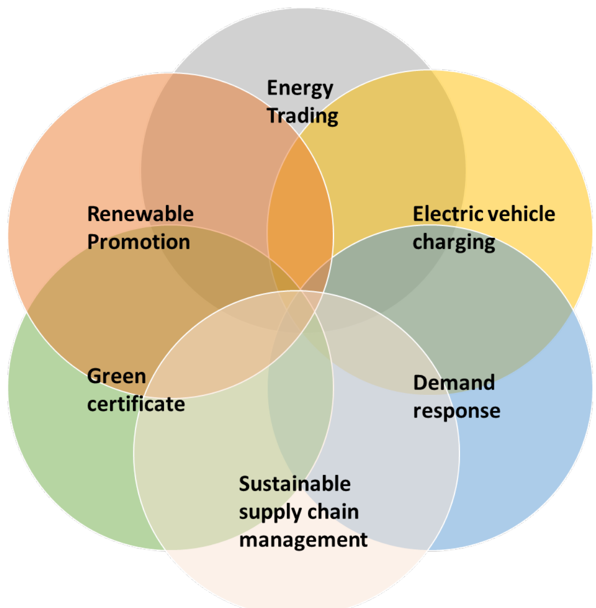

Figure 1 Key examples of blockchain applied to energy and environmental problems

2.1 Energy trading

Blockchain technology applied to distributed energy systems, such as microgrids, enables “peer to peer” (P2P) trading of energy, which avoids the need for a central accounting authority such as a conventional energy utility company. This is an emerging concept of power system operation where prosumers (consumers and producers) within a localized community can trade their own generated renewable energy, such as from their PV panels. Compared to the traditional energy trading process, where a central control system alone processes all the measured data from distributed producers and consumers, blockchain technology can speed up energy transactions, avoid single point failure, and prevent manipulation from the central intermediary [6]. Additionally, within the trading platform smart contracts, automatic real-time metering, bidding, negotiation, and suppler switching can be realized transparently and without human intervention, which could bring economic benefits to consumers by creating a competitive environment for energy producers [2][7]. One successful P2P energy trading case study is the Ethereum-based New York Brooklyn Microgrid project [8], which allows prosumers to sell their surplus solar energy to the grid or to New York City residents who prefer to use clean energy versus fossil fuel. The Brooklyn Microgrid promotes distributed renewable generation through an integrated market platform, and environmental-conscious consumers can also track their energy sources. There is also evidence that consumers may lower their electricity bill due to the competition enabled by the integrated platform [2]. Similar P2P trading platforms have been financed by Shell in the UK, Colombia, Japan, and Australia to optimize the integration of distributed energy resources into supply networks [9]. With an additional machine learning functionality that could predict the energy-demand profile of users, the P2P trading platform has also been piloted by the UK company Hackney's Banister House Estate to better accommodate low-carbon energy demands of consumers [10].

2.2 Electric vehicle charging

Another fast-growing application of blockchain technology is for charging of EVs, which are a critical technology for climate change mitigation [11]. Accessible charging is one key strategy for addressing EV range anxiety (i.e. running out of battery power during a long drive) [12]. Blockchain technology can provide a near-term solution to increase the attractiveness of EV by enabling sharing of private charging stations, through which EV drivers can have flexibility to charge their vehicles at different times in different locations. Compared to a traditional centrally operated platform, the blockchain based platform can ensure the security and privacy of the vehicle and residential charging stations owners. One of the successful examples is Share&Charge, a blockchain based P2P platform that provides intelligent and seamless sharing of the EV charging stations [13]. Through a mobile application, EV drivers can access the locations of nearby charging stations and get real-time price information, and the owners of the personal charging stations can earn money through the sharing of idle charging stations. Likewise, similar services are provided by Chargemap, through which the consumers can also be guaranteed with a verifiable 100% clean energy from solar and wind [14]. Another important blockchain application for EVs is vehicle-to-grid functionality for demand response, which is discussed in the next section.

2.3 Demand response

With increasing penetrations of variable renewable supply resources, better management of energy supply and demand is necessary for grid stability. One of the most cost-efficient strategies to provide the needed balancing is customer demand response [15]. However, traditional demand response program require centralized management of demand response participants, which can be inefficient and time-consuming [16], while 20% of the customers opt out of the traditional demand response program because of poor customer experience [17]. Blockchain technology may provide an innovative approach for automatic demand response by better leveraging the flexibilities among customer loads, EV scheduling, energy storage, and the use of distributed energy resources. A California company, Leap, has developed a platform called Distributed Energy eXchange, which could integrate building HVAC systems, EV chargers, and building management systems for peak load reduction [18]. The participating nodes in this system can provide information on when they can reshape their loads with anticipated prices; load reductions are then executed through communications among every participating node. Furthermore, blockchain technology can encourage EVs to absorb surplus renewable energy from distributed resources, and feed power back into the grid (vehicle-to-grid) to support demand response programs, alleviating large investments in dedicated battery storage, while tapping the distributed sources of renewable energy. For example, a pioneering demonstration by eMotorWerks used its smart EV chargers to balance up to 30 MW of renewable energy in California, reducing the on-peak demand of non-renewable energy [19].

2.4 Sustainable supply chain management

In supply chain management, blockchain has been used for shipment tracking and food tracing due to its efficiency and transparent data sharing. Walmart created a food traceability system that is based on Hyperledger Fabric to ensure food safety, where the origins of the fruit and meat sold across the

Walmart's stores can be traced [20]. IBM also launched a blockchain network for better supplier qualification, validation, and lifecycle information management, aiming at reducing the time and cost associated with qualifying and managing new suppliers while creating new business opportunities among suppliers and buyers [21]. Apart from this, blockchain technology may also help to reduce waste and decouple growth from resources consumption within the supply chain by fostering a sharing economy. For example, in a blockchain enabled supply chain, all participants have visibility to the availability of unused or underutilized logistic assets (e.g. trucks, trailers) and when they can have access to them, and thus lead to an increased utilization and reduced resource consumption through assets sharing [22].

2.5 Green certificates

Similar to its application in supply chain management, blockchain technology has also been applied for green certificates, carbon trading, and plastic-offsets by creating a simple and transparent market that streamlines the trading process between buyers and sellers, and eliminating some fraud concerns that may exist in the current marketplace. For example, Power Ledger has collaborated with the Midwest Renewable Energy Tracking System to build a blockchain application that could manage the sales of renewable energy and thermal energy credits, in which the energy credits can be tracked [23]. Nori announced its use of blockchain between carbon credit buyers and cropland growers, which makes the process of buying carbon removal credits simpler, and the carbon removal actions can be easily verified [24]. Similar to the carbon-offset scheme, a project named RecycleToCoin, has used a blockchain-based mobile application to allow companies across the world to offset their plastic footprint [25]. With this blockchain technology, the companies can get offset tokens that are issued automatically, and the companies can have full transparency to how funds were spent.

2.6 Renewable energy promotion

Most of the blockchain applications introduced above can be treated as having promoted the use of the renewable energy to some degree, such as that in the P2P energy trading, where renewable energy is better tapped because of the market platform. However, there are also blockchain projects that specifically target the promotion of renewable energy. SolarCoin aims at incentivizing solar power generation, which gives solar energy producers one digital token called SolarCoin for every megawatt of solar energy produced [26]. SolarCoins can be used like cryptocurrencies for purchase and trading of goods and services. Another example is Sunexchange, which creates a business opportunity for owners of solar PV systems. A blockchain based leasing platform automatically leases the owners' solar cells to business or organizations, while owners are paid with Bitcoins or an equal amount of local currency for the solar cells they leased [27].

3 Analyzing direct energy use

3.1 Why understand direct energy use?

Any time a promising new technology emerges, questions arise about its potential effects if widely adopted. Because IT changes quickly, it attracts much speculation of this type [3].

Blockchain has the potential to increase direct electricity used by IT systems, especially if more computationally-intensive forms of blockchain become widespread. The only widely-used form of blockchain currently is for cryptocurrency, like Bitcoin, which was responsible for about 0.2% of global electricity use on June 30, 2018 [28]. It also has the potential to reduce energy use in other sectors, but such effects are outside the scope of this report.

Future adoption of new technology is highly uncertain, and many studies of Bitcoin in particular show the potential for significant growth in electricity use (see Section 5). Policy makers need accurate assessments of the implications for broad adoption of this new technology, including potential effects on electricity demand, which is the motivation for this work.

This section explores subtleties in the choice of system boundaries as well as variations in choice of the type of consensus algorithms used to verify the blockchain. These choices can substantially affect the direct electricity used by blockchain applications.

3.2 System boundary selection

Figure 2 depicts the general system components, data flows, and electricity flows associated with any application of blockchain technology. To understand this system, it is helpful to start with a transaction, which occurs between client devices within the P2P network. This transaction could be the amount of surplus renewable energy shared between prosumers [2], or simply a financial exchange between two persons. The transaction record includes detailed information about the clients, the transaction value, and a cryptographic digital signature that proves the authenticity of the transaction. At this stage, however, the transaction has not been verified by all participants in the blockchain network system.

Next, the unverified transaction is inserted into a new block together with other transactions occurring within the same timeframe. The block is then broadcast to the entire system through the communication network, which includes both access and core network technologies. The block is received by validating notes, which can be located as independent entities or within larger computing centers, which offer validation and add a new verified block to the existing blockchain. In cryptocurrency networks, validation is performed by specialized mining rigs that compete against each other to solve a consensus algorithm, and receive a financial reward for successful validation. Copies of the newly-updated blockchain are then redundantly stored in distributed storage across the network as a public ledger. With each new set of transactions that occur on the network, the process is repeated such that the blockchain grows in length over time.

The initialization, broadcasting, validation, and storing of a transaction takes place in the form of data flows (depicted by black arrows in Figure 2) across multiple IT devices within the blockchain technology system, each of which consumes electricity (depicted by yellow arrows in Figure 2). The subsystems and types of IT devices that comprise most blockchain technology systems are summarized in Table 1. Therefore, understanding the direct energy use of blockchain requires an understanding of the IT devices that comprise the entire system as well as the system conditions that govern their electricity use.

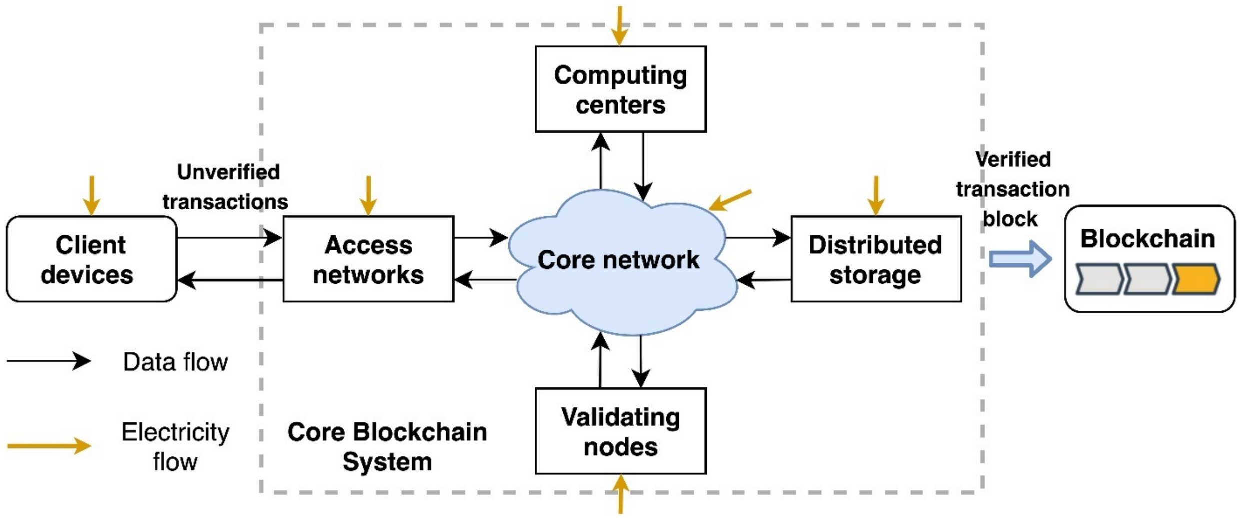

Figure 2 Generalized schematic of blockchain technology subsystems, information flows, and electricity inputs

In practice, some of the subsystems depicted in Figure 2 may be combined into single entities within a given blockchain system. For example, a client device (e.g., a computer) that initiates a transaction could also participate in the network as a validating node, whereas a validating node may also include storage for archiving a copy of the distributed ledger (this is sometimes known as a full node [29]). Conversely, when a client device exists solely for initiating transactions (i.e., it does not participate in validation or distributed ledger storage), it is known as a simplified payment verification client. Similarly, some computing centers may contain many validating nodes and storage devices, which are physically clustered together for improved management, better energy-efficiency, or higher mining profit but are considered as virtually distributed across the blockchain network. Computing centers also contain lots of network devices to facilitate communications between in-house validating nodes, as well as for communicating with other nodes across the blockchain network. Therefore, there can be many different physical manifestations of the general blockchain technology subsystems depicted in Figure 2, as well as different functions provided by these subsystems, in the real world.

Table 1 Blockchain technology subsystems and their typical IT devices

Subsystem	Description	Typical IT devices
Client devices	User devices in the blockchain network that initiate or receive transactions.	IoT devices, smart meters, EV charging stations, PCs, mobile phones, etc.
Access networks	Devices in the blockchain network system positioned between the client devices and the internet core, which act as a middleware to provide connectivity, data transferring, and data security between the client devices and the core network.	Gateways, routers, modems, etc.
Distributed storage	Storage devices distributed across the blockchain network that store the distributed ledger	Storage equipment (hard disk drives, solid-state drives, etc.), and supporting infrastructure for storage cooling and power supply.
Validating nodes	Nodes distributed across the blockchain network that are responsible for verifying transactions and approving modifications of the blockchain throughout the blockchain network according to a specified consensus algorithm. Nodes are sometimes known as blockchain miners.	Computing devices (CPUs, GPUs, FPGAs, ASICs, etc.) and supporting infrastructure for cooling and power supply.
Computing centers (mining centers, data centers, etc.)	Dedicated buildings used for mining/validating, data processing, data storage, and data communications. Computing centers often require specialized power conversion and backup equipment to ensure reliable, high quality power supply, and environmental control equipment to maintain acceptable indoor thermal environment. Cryptocurrency blockchains may employ dedicated mining centers with highly specialized mining rigs, whereas other forms of blockchain may rely on conventional data center technologies.	Servers, computing devices, storage equipment, network equipment, power and cooling devices, etc.
Core network	The central part of a telecommunication network, which typically constitute service provider equipment that using Internet Protocol (IP) to form regional, national, and global networks. The core network provides a path for exchanging information and broadcasting the transactions in the blockchain system.	IP core/metro/edge switches and routers, transmission link elements (copper, fiber optic, radio links, etc.), and supporting devices for cooling and power supply.

Notes: IoT = internet of things; EV = electric vehicle; PCs = personal computers; CPU = central processing unit; GPU = graphics processing unit; FPGA = field-programmable gate array; ASIC = application-specific integrated circuit.

Furthermore, the specific IT devices within each subsystem might differ depending on the transaction scales, applications, and consensus algorithms implemented by various blockchain systems. For example, large-scale blockchain applications like Bitcoin and Ripple involve undersea cables and international fiber networks to ensure frequent global data communications, which is unlikely the case for local renewable energy sharing. Client devices could be smart meters in microgrid applications [30], or they could simply be general purpose technologies like PCs or mobile phones for financial transactions. Depending on the extent to which client devices are dedicated to the blockchain, energy analysts may choose to include or exclude them from the blockchain energy analysis system boundary. Finally, the type of consensus algorithm employed by the blockchain network might also influence its IT device makeup; for example, proof of work (PoW) consensus algorithms may require powerful ASIC-based validating nodes, whereas other consensus algorithms may be designed for less computationally-powerful validating nodes [31].

3.3 Consensus algorithms

One of the most important and fundamental requirements in a blockchain system is reaching consensus on the validity of transactions across the P2P network without the mediation of a centralized authority. Such agreement between validating nodes in a network is achieved through the implementation of a so-called consensus algorithm, which ensures the system to be tolerant even of failed validating nodes or malicious members [32]. A key determinant of the energy intensity of a blockchain network is the consensus mechanism implemented [33], [34], whereas this energy intensity can differ greatly based on the type of consensus algorithm employed [35], [36]. Therefore, understanding the types consensus algorithms and their effects on blockchain system energy use is a key factor in accurate estimation of direct energy use.

Reaching reliable and valid consensus while maintaining a low level of energy intensity is still a challenge in blockchain network system designs. Thus, several types of consensus algorithms have been developed and each of them presents their own characteristics in terms of scalability, throughput, latency, security, and, importantly, energy consumption. Below, we briefly introduce several popular consensus algorithms and summarize their characteristics in Table 2. Unlike cryptocurrencies, for which consensus algorithms are well known, there is limited publicly-available information on the consensus algorithms being used in the various blockchain applications described in Section 2.

3.3.1 Proof of Work (PoW)

PoW is currently the most widespread consensus algorithm because of its use in Bitcoin [37]. In the PoW mechanism, the validators/miners compete to solve a computational-expensive problem with some pre-defined targets [38]. As an incentive, the first validator/miner who solves the problem can add the new block to the existing blockchain and get rewarded with a certain amount of cryptocurrency. The difficulty of solving the problem is dynamically adjusted so that one block is expected to be added within a predetermined time interval (e.g., about 10 minutes for Bitcoin). The probability for a given validating node to add the next block is proportional to its computing power. Thus, the energy consumption of PoW-based blockchain scales with the number of miners despite steady improvements in the energy efficiency of the computing devices, which has become the main criticism of the PoW consensus algorithm [4].

3.3.2 Proof of Stake (PoS)

Unlike the PoW system, in which miners keep investing in wasteful computations, PoS is a less energy-intensive design that relies on each miner depositing a certain amount of cryptocurrency as a stake [35]. The probability of the stakeholder who will create the next block is proportional to the amount of stake invested and the successful stakeholder receives a transaction fee as the reward of validating the transactions. However, this algorithm could potentially lead to undesirable centralization in the blockchain system since rich stakeholder will become richer with the accumulation of transaction fees which further increases the chance of being chosen as the next block creator [39]. Several variants of PoS algorithm have been developed, and two major categories are chain-based PoS and Byzantine Fault Tolerant (BFT) based PoS [40]. In the chain-based PoS, a block validator is selected at random to create a block that links to the previous blocks. The BFT-based PoS favors a more permissioned blockchain approach where validators are chosen for each round and must agree upon insertion of the proposed block to the blockchain [41].

3.3.3 Practical Byzantine Fault Tolerance (PBFT)

Originated from the Byzantine Generals Problems, BFT refers to the property of a system where system members can reach consensus through collective decision making. PBFT was one of the algorithms developed to guarantee the BFT requirement in an asynchronous environment [42]. Under PBFT, no more than one-third of the nodes can be malicious in order to ensure the proper work of the system. However, due to the implementation of a voting-based consensus approach, PBFT is more favorable to use in a trusted environment, whereas the intensive data communications between the nodes make it hard to scale to large networks [43].

3.3.4 Federated Byzantine Agreement (FBA)

Like PBFT, the FBA consensus algorithm is another practical realization of the BFT system requirement. Under FBA, validators are chosen from network members to form a quorums of nodes (with a minimum number required), then the quora can sign the transactions to make the final decision [44][7]. Ripple and Steller has successfully applied the FBA algorithm [44]. It is often used for its high throughput, and it has higher scalability compared to PBFT.

3.3.5 Proof of Authority (PoA)

PoA is a reputation-based consensus algorithm which can be treated as a modified version of the PoS algorithm, where the validators (also called authorities) stake their own reputation instead of cryptocurrency quantities as in PoS systems [45]. This system is secured by pre-approved validators selected based on voting, and the selected validating nodes then approve the validity of a newly generated blocks through reaching an agreement. The limited number of validators makes PoA a more highly scalable and more efficient algorithm than PoS and PoW, but it has been criticized as being too centralized and subject to consistency issues [32].

3.3.6 Proof of Capacity (PoC)

PoC is another consensus algorithm dedicated to solving the energy-intensive problem of the PoW algorithm, where miners commit their own hard disk drive instead of their computing power to be selected as the next block creator and thus earn cryptocurrency rewards [46][47]. PoC works by storing a list of possible solutions (known as 'plot') on the miners' storage drive before the commencement of the next mining activity. The larger the hard drive, the more possible solutions can be stored in the miners' drive, and thus more chances to win the next mining reward. However, this algorithm still consumes energy for hard disk drive operations, which could grow to significant quantities as the system scales to larger levels.

3.3.7 Proof of Burn (PoB)

PoB aims to solve the co-problems of high energy consumption and high mining hardware dependency associated with PoW algorithms by replacing the investment of computational resources with a verifiable burning of coins. The next block creator is chosen from investors who have demonstrated sending some of their owned coins to an address from which the coins cannot be reclaimed [48]. The probability of being the next block creator scales with the amount of coins burned, and the chosen creator will get rewarded as an incentive of this investment. Even though the PoB algorithm has lower direct energy requirements, it could potentially have high indirect energy implications depending on the choice of coins burned. For example, burning Bitcoin to get the coins offered by the PoB system would have higher indirect energy use than burning Ether coins. Furthermore, the scalability, throughput, latency, and security of this algorithm have not being fully understood yet, which requires further testing.

4 Best practices for direct energy use analysis

This section proposes best practices for analyzing the direct energy use of blockchain, which is a function of the technology subsystems, IT devices, and consensus algorithms described in the previous sections. It draws and expands upon previous literature that has documented various elements of best practices for energy analysis of IT systems relevant to blockchain [28][49][50][51]. The key to creating accurate estimates is to draw sensible boundaries around relevant systems, insist on consistent comparisons, collect measured data, provide complete and accurate documentation, take special care to account for changes over time (because IT changes so rapidly), and avoid extrapolating into the future based on assumptions that are by their nature highly uncertain.

We propose 10 different best practices, which relate to discrete aspects of proper IT energy analysis and results communication. We use them to assess the existing blockchain energy analysis literature (Section 5) and to suggest important areas of future research (Section 6) for addressing observed barriers to best practice adherence.

1. **Properly include the full system.** As shown in Figure 2 and Table 1, all blockchain technology systems require different combinations of computing, storage, and communications hardware alongside other important components (e.g., power supplies, computing center cooling systems) necessary for the provision of blockchain system services. A fundamental tenet of IT systems modeling is to consider the most comprehensive system boundary possible to avoid excluding potentially important sources of energy demand from the analysis. Ideally, a systems diagram should be provided for maximum transparency, so that users of a study can clearly identify which technology components have been included or excluded from a given analysis. When technology components are excluded, the reasons should be described clearly (e.g., due to lack of data or due to following established conventions for cut-off criteria [52]). The recommended system boundary for including all blockchain system components is depicted in Figure 2.

2. **Build from the bottom up.** History has shown that, for IT systems, bottom-up analyses that consider IT device stocks, their operational and energy use characteristics, and how such characteristics may vary by application and evolve over time generally provide more accurate energy estimates than simplistic top-down methods [28], [50], [53].

Table 2 Characteristics of different consensus algorithms.

Consensus algorithm	Scalability	Throughput	Latency	Security	Levels of decentralization	Energy consumption	Application examples	Reference
PoW	High	Low	High	High	High	High	Bitcoin, Ethereum, Litecoin, etc.	[37][38]
PoS	High	Medium	Medium	High	High	Low	Ethereum, PPcoin, etc.	[35][39][40][41]
PBFT	Low	Medium to high	Low to medium	High	Medium to high	Low to medium (Determined by the scale)	Zilliqa, Hyperledger Fabric, ect.	[32][43]
FBA	High	High	Low	High	Low	Low	Ripple, Steller, etc.	[44][7]
PoA	High	High	Low	High	Low	Low	Energy Web Chain, Microsoft Azure, etc.	[39][54][55]
PoC	High	Medium	Medium	Require further testing	High	Low to medium	Burst, etc.	[46][47]
PoB	Require further testing	Require further testing	Require further testing	Require further testing	High	Determined by the burned coin	Slimcoin, Counterparty, etc.	[48][56][57]

3. **Use measured/surveyed power data.** Ideally, power use estimates at the IT device level should be informed by direct power measurements. Furthermore, such power measurements should be made using conditions that emulate real-world operating conditions, such as typical capacity utilizations or operating temperatures. While many manufacturers provide power data for IT devices, such data are typically limited to maximum or rated power values (which may be substantially higher than power use at typical operating conditions), typical power use values (which may or may not correspond to system conditions or device configurations being analyzed). Therefore, direct measurements are preferred, with care taken not to omit important ancillary components such as power conversion units from the measurements. When direct measurements are not possible, the next best bet is to survey real-world operators of different blockchain system components (e.g., communications networks, computing centers, storage banks) based on power utility data and installed device characteristics. Such survey data may often be confidently used to estimate the energy use of installed devices in real-world conditions.

4. **Use time-period appropriate technology data.** The energy efficiency and configurations of IT devices have historically changed rapidly, whereas their stocks typically turnover quickly due to short lifespans driven by planned upgrade cycles and technology obsolescence. These observations apply to all major IT devices that can comprise blockchain systems in Table 1, and to cryptocurrency mining rigs in particular. Technology change in the latter is occurring on the order of months due to economic forces [4][58], whereas for other system components such as servers, storage devices, and network communications, change can be expected at least annually [59]. Therefore, for accurate energy use estimates, blockchain energy analysts must ensure that technology assumptions are well aligned with their chosen period of analysis. For retrospective analyses, this means accounting for historical technology evolution in considered technology stocks. For prospective analyses, this means accounting for future technology change, but only over near-term time periods in which current rates of technology change are expected to continue.

5. **Account for capacity utilization.** Many IT devices exhibit variations in operational power use due to capacity utilization, particularly computing devices such as servers. For some devices, power use will vary between an unloaded idle state (idle power) and a maximum loading state (maximum power), whereas the operational power use between these two extremes is a function of capacity utilization. However, some IT devices may have relatively constant power draw irrespective of capacity utilization, such as network routers. Therefore, it is important for analysts to account for capacity utilization effects in two ways. First, for any devices whose power use varies with capacity utilization, this functional relationship should be established and any system-level energy estimates derived must express capacity utilization assumptions clearly. Second, when considering variations in blockchain system energy use due to changes in activity levels, analysts should avoid scaling energy use linearly with activity levels when such capacity utilization effects exist. In particular, more research is needed on capacity utilization effects for cryptocurrency mining rigs, given their high energy use and risk of miscalculations if linear scaling does not apply.

6. **Account for locational variations.** Locational variations in the direct energy use of blockchain systems can arise from two important sources. First, energy required for cooling computing centers can vary significantly by climate zone [60], and should be considered for analyses involving large-scale systems such as cryptocurrency mining centers. Second, significant differences can exist in communication systems depending on the local network technologies (fixed and wireless), mobile station fuel types, and local network configurations, which can affect energy use. At minimum, analysts should clearly state the geographical boundaries of their analyses and use technology data that are appropriate within those boundaries. Because direct energy use values are often used to derive pollutant emissions estimates from electricity use, locational variations should absolutely be considered in studies that offer such estimates, given they are dependent upon local electrical grid mixes.

7. **Properly account for uncertainty.** Blockchain technologies and applications are still evolving rapidly, so there will be significant uncertainties inherent in any direct energy use estimates. Therefore, it is important for analysts to adequately address and communicate uncertainty for informed decision making. Proper treatment of uncertainty includes: using sensitivity analysis to identify model parameters whose variation contributes most to variations in results; establishing credible uncertainty distributions for those key parameters; and presenting final estimates as ranges that result from these distributions, as opposed to presenting only point estimates. Another possible approach is to construct bounding scenarios in an analysis, in which key parameters assume best and worst-case values, to provide corresponding ranges on final estimates. Conversely, analysts should avoid use of guesswork presented under the guise of being proper uncertainty analysis, since such approaches lend results more precision and credibility than is warranted. Finally, analysts should communicate any limitations of their work in light of inherent uncertainties, and only draw conclusions that are robust to such uncertainties.

8. **Consider retrospective time series analysis.** Given the fast pace of blockchain technology evolution, retrospective analyses that consider multiple years can add value by forcing analysts to properly account for technological change, and by illuminating the historical pace of technological change for a study’s users. Having a credible view of this pace is important for constructing useful scenarios about the future, and for giving a sense of what levels of future energy use may be realistic, based on how the underlying drivers of technological change (e.g., processor efficiencies, storage densities, etc.) are likely to change moving forward.

9. **Avoid simplistic extrapolations**. If other analytical best practices are followed, simplistic extrapolations will be avoided through proper consideration of technology stocks, trends, and drivers of energy use over time in blockchain systems. However, in the past there have been many examples of analysts extrapolating past or present IT energy values into the future using simplistic methods, including scaling them up on the basis of a chosen activity parameter, such as internet traffic for data centers [61], internet growth [50], or blockchain transactions [62]. Such methods often lead to vast errors in estimated future energy use, because they ignore important changes in the technologies and applications that drive energy use. Therefore, we state this criterion as an explicit best practice that should be a tenet of proper IT energy analysis moving forward.

10. **Create open and complete documentation allowing replication**. All analyses should fully document all data sources, modeling equations, and analytical assumptions for full transparency, and provide modeling files or sufficient mathematical documentation for full replication of results by the scientific community. This level of transparency and replicability is necessary for open critique and improvement of datasets and models moving forward, especially given that no general-purpose models exist for estimating blockchain energy use besides cryptocurrency applications (see Section 5).

5 Literature assessment

This review identified 15 studies (as of March 2020) that have presented estimates of the direct energy use of blockchain systems. Each study was evaluated for adherence to the 10 best practices discussed in Section 4. Findings are summarized in Table 3, whereas the evaluation remarks for each study can be found in Appendix A. All 15 studies were focused on cryptocurrencies, around half of which focused on Bitcoin. This past singular focus underscores the need for broader analyses of other applications of blockchain technologies to paint a more comprehensive picture of direct energy use. However, even given their limited scopes on cryptocurrencies, the body of studies evaluated enabled useful generalizations about the state of adherence to best practices within the analyst community (discussed in Section 5.2) and identification of important future research opportunities (discussed in Section 6). In order to evaluate the modeling approaches undertaken in each study, a brief discussion of model categorizations is offered in Section 5.1.

5.1 Model categorization

We identified four major modeling methods that have been used to quantify the energy use of blockchain systems to date: 1) the top-down approach; 2) the economic approach; 3) the hybrid top-down approach; and 4) extrapolation based on direct measurement. In this section, we briefly introduce these modeling approaches and summarize their calculation formulae such that their relationship to bottom-up methods (Best Practice #2) can be more clearly understood.

5.1.1 Top-down approach

The top-down approach was initially implemented in [63] to study Bitcoin electricity use from 2009 to 2014. In subsequent studies, it was used to assess the electricity used by not only Bitcoin [4], [62], [72], [64]–[71], but also Ethereum [69], [71], Litecoin [69], and Monero [69]. This approach can technically be applied to estimate the power use of validating nodes in any blockchain network system that employs the PoW consensus algorithm. It was one of the most frequently-used methods in our pool of reviewed studies due to lack of data on the installed base of mining rigs in cryptocurrency mining networks, which is a barrier to estimating blockchain electricity use using bottom-up accounting. In the top-down method, the electricity use of a PoW-based blockchain system is approximated by multiplying the network hash rate by an assumed average mining rig efficiency (see eq. (1)). This approach inherently excludes client devices, distributed storage, and network communications from its system boundary. Sometimes, an additional PUE value [60] is applied in this equation to account for the power loss of mining rig power supply equipment and the power use of cooling systems. However, given the significant uncertainty in establishing the average energy efficiency of mining/validating hardware, and the exclusion of other subsystems in this method, the top-down approach seems most suitable for generating a lower bound system energy estimate when applying the most efficient hardware available during a given time-frame.

$$P = H * e * PUE \qquad (1)$$

where P is power consumption (W), H is hash rate (hash/second), e is energy efficiency of the hardware (J/hash), PUE is power usage effectiveness.

5.1.2 Economic approach

The economic approach is another method that has been used to estimate the electricity use of both Bitcoin and Ethereum mining [4], [67], [68], [72]. This method starts from the assumption that cryptocurrency miners in the market follow economically-rational behavior. Namely, that mining should be a profitable activity, thus the power use of mining at the break-even point where mining revenue equals mining electricity cost can be described as:

$$P = \left(N_t + N_{f,t}\right) * V * \varphi / (p * t) \qquad (2)$$

where N_t is the number of crypto coins generated during time period t (coins), $N_{f,t}$ is the transaction fees during time period t (coins), V is the market price of the crypto coin (USD/coin), φ is the percentage of mining revenues spent on electricity, p is the electricity cost (USD/J), t is the time period (second).

The economic approach could theoretically be used to estimate electricity consumption for any cryptocurrency validating nodes that are associated with a mining reward. The approach could also capture the electricity consumption validating node power supplies and cooling systems, if such costs are included in φ, whereas the electricity consumption of access and core networks, distributed storage, and client devices are excluded. However, the estimate given by the economic method is very sensitive to different choices of φ, V, and p in eq. (2). In fact, φ is prone to be a subjective choice of the analyst, p is highly geographically dependent, and V can be highly volatile over time (with variations occurring over time-steps as short as minutes). Although efforts have been made to reduce the effect of V by using the moving average of the crypto coin price, the choice of the moving average time of is also arbitrary. All of the aforementioned reasons indicate that the direct energy use estimates derived by the economic approach can be highly uncertain, with several studies suggesting it may result in over-estimated power use values [4], [73], [74].

5.1.3 Hybrid top-down approach

The hybrid top-down approach was initially developed by Marc Bevand to reduce the uncertainty in the distribution of mining hardware efficiencies from an economic point of view [73], [74]. The hybrid top-down approach leverages both top-down and economic approaches to produce uncertainty bounds of power consumed by validating nodes in the blockchain system, which has also been used in studies [75], [76]. Following the assumption that miners will run the mining hardware if it is profitable, this method first establishes a sampling rejection threshold described as:

$$e_{th} = \left(N_t + N_{f,t}\right) * V / (p * \oint_t H) \qquad (3)$$

where e_{th} is the sampling rejection threshold (J/hash), $\oint_t H$ is the integral of the network hash rate across time period t (hash).

Thus, e_{th} is a temporal (V and H) and spatial (p) dependent parameter, and given a vector $\vec{e}$ representing the efficiencies of all the mining hardware available on the market, a vector $\vec{e}_p$ describing all the profitable mining hardware over the market can be derived, where all the element of $\vec{e}_p$ should be no larger than e_{th}. Finally, a lower and an upper bound energy estimate of the validating nodes can be calculated applying eq. (1), where inputs for the lower and upper bound are respectively the most and least efficient miners in the vector $\vec{e}_p$.

The hybrid top-down approach can be used for estimating validating node electricity use in PoW-based cryptocurrency blockchain systems. However, access and core network energy use, distributed storage energy use, and client device energy use are excluded. Theoretically, it is a preferable approach to simpler top-down methods because it considers mining hardware efficiency as a function of profitability, based on the assumed prices of crypto coins. However, this approach can only be used to reduce the uncertainty from the top-down approach because real probability distribution of the mining rigs is unknown, which requires further research investigation and more public data sharing.

5.1.4 Extrapolation based on direct measurement

Another method to estimate the power use of blockchain network is to directly measure the power consumption and hash rates or node numbers within a small network, which can then be used to derive a representative energy intensity (i.e. joule per hash [77] or joule per node [78]). Next, the electricity use of validating nodes across the blockchain network can be extrapolated by multiplying the energy intensity by the total network hash rate or total network nodes. This method has been used in ref. [77] to estimate the electricity of Monero mining, which features a similar approach to the top-down modeling method, but the joule per hash derived here is based on a small number of samples in a test network. Similarly, in ref. [78], this method is proposed for energy modeling of Ripple and Steller system using measured joules per node. However, ref. [78] only provides the final formulas for the energy estimation since the number of the nodes in the network is unknown. Like the other methods described in this section, it excludes access and core network energy use, distributed storage energy use, and client device energy use.

5.2 Literature assessment

Table 3 summarizes our assessment of the 15 blockchain energy studies identified in this report according to the best practices identified in Section 4. Explanations for the ratings assigned to each study can be found in Appendix A.

Notably, for some criteria exemplars are lacking because: a) none of the studies used a bottom-up modeling approach (criterion 2); b) the only study that used measured data was based on a very small number of samples (criterion 3); c) only 2 studies partially considered the capacity utilization of system equipment (criterion 5); and d) studies that considered locational variations of grid mixes or PUE values were largely based on educated guesswork (criterion 6).

Overall, it can be seen that Cambridge Bitcoin Electricity Consumption Index (CBECI) [75] demonstrated the best adherence to our proposed best practices by:

- performing time-series mining equipment efficiency sampling and analysis (criteria 4 and 8);
- quantifying uncertainties based on a hybrid top-down modeling method while allowing full randomness of input parameters such as electricity prices (criterion 7);
- avoiding simplistic extrapolations such as scaling a single day power estimate to the whole year [64], [65], extrapolating future blockchain energy use based on transaction numbers [62] or network difficulty trends [71], or extrapolating locational blockchain energy use based on assumed mining locations [77] (criterion 9);
- providing a web-based interface with transparent data and methodology documentation (criterion 10).

Similarly, the studies conducted by Stoll [72] and Bevand [73][74] also demonstrate high compliance with our proposed best practices. And the two studies from Bevand, upon which the CBECI based, are the only ones to consider overclocking situations of certain types of mining rigs as a capacity utilization effect (criterion 5).

It is also worth noting that the study from Köhler [70] is the only one that considered the energy consumption of non-validating nodes in the blockchain network (criterion 1), albeit as a simplistic preliminary estimate that requires further investigation.

Table 3 Assessment of best practice adherence by study

Criterion	O'Dwyer [63]	McCook [64], [65]	McCook [66]	Digiconomist [67]	De Vries [68]	Krause [69]	Vranken [4]	Mora [62]	Bevand [73], [74]	Köhler [70]	Zade [71]	CBECI [75]	Stoll [72]	Li [77]	Küfeoglu [76]
1. Properly include the full system	×	×	~	~	~	×	~	×	~	~	×	~	~	×	×
2. Build from the bottom up.	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
3. Use measured/surveyed data	×	×	×	×	×	×	×	×	×	×	×	×	×	✓	×
4. Use time-period appropriate technology data	~	×	×	~	~	~	✓	×	✓	~	~	✓	✓	~	✓
5. Account for capacity utilization	×	×	×	×	×	×	×	×	~	×	×	×	×	~	×
6. Account for locational variations	×	×	×	×	×	~	×	×	×	~	×	~	~	×	~
7. Properly account for uncertainty	~	×	×	~	×	~	~	×	~	~	×	✓	~	×	~
8. Consider retrospective time series analysis	~	×	×	~	×	~	~	×	✓	×	✓	✓	✓	×	✓
9. Avoid simplistic extrapolations	✓	×	×	~	~	~	✓	×	✓	✓	×	✓	✓	×	✓
10. Open and complete documentation allowing replication	~	✓	✓	~	✓	✓	✓	~	✓	✓	✓	✓	✓	~	✓

Note: ~ = Partial; ✓ = Yes; × = No;

6 Future research needs

As observed in Section 5, there is substantial variance in the body of literature to date with respect to adherence to best-practice analysis and reporting principles. Some of the observed lapses relate to issues that can be readily avoided through more careful analysis and greater reporting transparency among researchers, such as providing open and complete model documentation. However, most of the observed lapses stem from current data gaps and insufficiently nuanced understandings of blockchain technologies and their operational characteristics in the real world. These latter lapses can only be avoided in the future through targeted research that generates better data and empirical evidence for the energy analysis community on blockchain technology systems and their applications.

Therefore, below we offer two categories of future research recommendations. The first category stresses best practices that must be followed to ensure that future research is credible, transparent, and useful to the broader blockchain stakeholder community. We refer to this category as "procedural best practices." The second category suggests research agendas that should be pursued to both generate the data and enable the detailed, robust analyses necessary for producing direct energy use estimates that can be used with confidence by decision makers. We refer to this category as "Near-term research priorities." Clearly, these two categories are not-mutually exclusive: future research must follow the procedural best practices for maximum utility. Finally, each recommendation indicates the relevant best practice(s) identified in this paper in parentheses.

6.1 Procedural best practices

- Studies must provide **open and complete model documentation (10)**. Without such documentation, it can be impossible for other researchers to fully replicate a study's results. Replication is a necessary condition for the scientific process, which involves a continuous cycle of open critique and improvement, whereas open models can be valuable resources for other researchers, potentially negating the need to "reinvent the wheel" in future studies. In addition to documenting fundamental equations, researchers should consider making their model execution code or modeling files available in public repositories such as GitHub for direct use by the community. Finally, researchers should consider publishing in journals that provide Open Science Badges [79], which can ensure persistent access to modeling files and increase data sharing opportunities.

- Studies must explicit state the **system boundaries associated with the analysis (1)**, ideally through the use of a systems diagram that clearly indicates which technology components are included in the analysis and which are not. Explicit documentation of system boundaries enables the research community to more easily compare results to other studies and determine how results can and cannot be used in future research. Additionally, researchers should explain any decisions to exclude certain technology components from the system boundary, and discuss any potential limitations of the study that may result from such exclusions. The ideal system boundary to capture the direct energy use of blockchain systems has been discussed in Section 2.

- Studies must **avoid simplistic extrapolations (9)** of past or present-day blockchain energy use estimates into the future. Blockchain technologies and applications are evolving rapidly [4], [75];

therefore, past or present-day energy use is not a reliable indicator of future energy use. In fact, for cryptocurrency mining, the technologies engaged, their efficiencies, and the system conditions involved (e.g., network hash rates, difficulty levels, cryptocurrency values) can change so rapidly that system energy use can change on a daily basis [28]. For example, one observed study [62] extrapolated the energy use of cryptocurrency mining rigs decades into the future without considering the rapid pace of mining rig efficiency improvements, erroneously predicting massive growth in mining emissions [58]. Therefore, this recommendation applies as a core best practice for study design, since the history of IT energy analysis has shown that simplistic extrapolations nearly always deliver misleading results [50].

- Finally, future blockchain energy use estimates should always be **peer-reviewed**. While most—but not all—of the observed studies fall into this category, they all share the common trait of providing early estimates for a rapidly evolving technology class that is attracting high interest in the energy, policy, and business communities. It follows that such early estimates can have an outsized influence on shaping popular perceptions about blockchain energy use and where it may be headed. These early perceptions can become ensconced as conventional wisdom that is often difficult to undo [50]. Thus, subjecting future studies to peer review will be an important quality check to ensure adherence to the best practices summarized here before being made publicly available. Given the many data gaps and unknowns, peer review can also ensure that assumptions are reasonable and expose researchers to the latest and best information to improve a study before it is released.

6.2 Near-term research priorities

- One of the most important areas of future research is **to gather measured energy use data (3)** for the IT technologies that comprise the blockchain system, with a particular focus on purpose-built computing equipment such as cryptocurrency mining rigs for which empirical data gaps are pervasive. All but one [77] of the observed studies relied on manufacturer specification data or other estimation techniques in lieu of using measured data, given the lack of such data in the literature. However, previous research on IT energy use has shown that manufacturer specifications are often a poor substitute for measured data [80], whereas direct energy measurements can subject equipment to a range of different loading and environmental conditions, leading to more robust estimates. In addition to measured data for mining rigs, other priority data gaps include servers and storage devices, network equipment for blockchain communications, and client device equipment dedicated to processing/recording blockchain transactions. Direct energy measurements can also force researchers to include important ancillary equipment in measurements, such as computing unit power supplies or storage controllers, which may be overlooked when using manufacturer equipment specifications [62]–[66]. In lieu of direct energy use estimates, researchers can also consider surveying operators of various subsystems within the blockchain system—e.g., computing center operators—which may monitor energy use and activity levels at the facility or device levels.

- As part of gathering measured energy data, a **deeper understanding of capacity utilization effects (5)** is required. This recommendation involves two lines of inquiry. First, direct energy measurements should establish the idle power draw, the maximum power draw, and the functional relationship between the device activity level (e.g., percent processor utilization of a server, hashrate of a mining rig, data transfer rate of a communications device) and the power draw that will occur between these two limits. This research can follow the example set by the SPEC Power Benchmark [81], which established a measurement protocol for establishing such a functional relationship for servers. Second, the actual capacity utilizations of equipment in operating blockchain systems should be observed and quantified, and as temporal functions, to get a better understanding of real-world capacity utilization levels. This information, coupled with measured power data and power-activity functions, can help develop more accurate estimates of direct energy use.

- In addition to better technology-level power data, there is a pressing need for **developing estimation methods for and datasets on the installed base (2)** of dedicated blockchain technologies, such as cryptocurrency mining rigs or specialized transaction equipment. As discussed in Section 2, the most accurate IT energy models are generally built in bottom-up fashion based on installed base data. However, there are no publicly-available datasets on the numbers of cryptocurrency mining rigs or other blockchain-enabled energy applications, which is a major barrier to bottom-up methods moving forward [28]. The research community should seek out partnerships with device manufacturers, block-chain application start-ups, and market analysts to lay out a research strategy for deriving installed base estimates. Such agenda could include data science strategies for using a combination of shipment data on equipment or key equipment components (e.g., purpose-built ASICS), top-down inferencing, strategic sampling of known projects, or network activity data.

- Given the rapid pace of technological change in blockchain systems, a **better understanding of equipment lifespans/stock turnover and generational improvements (4)** in power profiles and power-activity functions is needed, to quantify the pace and drivers of efficiency trends over time. This understanding is necessary for selecting the appropriate time period of technology data in a given analysis (4), for performing retrospective time series analyses (8), and for scenario exercises that may project the energy use of blockchain systems into the future (9). Such an understanding could be based on a combination of retrospective sampling of technologies for direct energy use measurements and modeling of key technology performance indicators from manufacturer specification data on key system components over time (e.g, joules per hash evolution of mining rigs, server processor watt-hours per computation, kWh per terabyte of storage).

- A **better understanding of how spatial variations may affect the direct energy use (6)** of blockchain systems is also required, given that local climates can affect computing center cooling energy use [60], network connection types and technologies can affect communications energy use [3], and local electricity grid mixes will determine the broader environmental impacts of system electricity use, such as CO_2 emissions. This line of research could employ data integration techniques involving known blockchain computing center locations, announced blockchain projects, market analyst insights on blockchain industry stakeholders, and statistical inferencing techniques, as well as develop models that can simulate the relationship between important spatial factors and energy use of archetypal blockchain systems.

- A better understanding of the **dynamic relationship between consensus algorithms, difficulty adjustments, validation node stock evolution, and validation node energy use (4)** is also required, since these factors are highly interdependent and can change quickly in cryptocurrency systems due to market effects. Theoretical models are needed that accurately quantify the historical relationships between these variables, which can be used to conduct scenario analyses that consider different rates of technological change, market conditions, and system designs for understanding possible future trajectories in energy use.

- **Compiling and maintaining databases of blockchain applications** deployed worldwide would be an important resource for the energy analyst community and policy makers alike. Such a database could document the locations, consensus algorithms, IT device characteristics, applications, and energy estimates of existing and announced projects. This resource would be similar to other technology tracking datasets like those for EV charging stations, battery storage, or solar PV installations [82], which enable market monitoring and energy use tracking. Early research should be aimed at developing an open platform with data fields that are relevant for energy modeling, populating the dataset with known projects and information, and encouraging community-based contributions moving forward.

- Finally, methods for **proper treatment of uncertainty (7)** in direct energy use estimates should be developed, inclusive of model- and empirical-based inquiries to identify sensitive system parameters, establishing evidence-based distributions for those parameters, and generating credible uncertainty ranges. Such research would provide the dual benefit of communicating to decision makers the inherent uncertainty in modeled estimates while identifying future research that could reduce key uncertainties. In addition to parameter uncertainty research, the research community should consider inter-model comparisons to explore structural uncertainties in different models, and construct bounding scenarios for time-series analyses for more robust decisions.

7 Acknowledgements

The authors gratefully acknowledge funding for this work from the Alfred P. Sloan Foundation.

8 References

[1] H. F. Atlam and G. B. Wills, "Technical aspects of blockchain and IoT," in *Advances in Computers*, vol. 115, 2019.

[2] T. Sawa, "Blockchain technology outline and its application to field of power and energy system," *Electr. Eng. Japan (English Transl. Denki Gakkai Ronbunshi)*, 2019.

[3] IEA, *Digitalization & Energy*. OECD, 2017.

[4] H. Vranken, "Sustainability of bitcoin and blockchains," *Curr. Opin. Environ. Sustain.*, vol. 28, pp. 1–9, Oct. 2017.

[5] IEA, *World Energy Outlook 2019*. Paris: OECD, 2019, p. 810.

[6] H. F. Atlam and G. B. Wills, "Intersections between IoT and distributed ledger," in *Advances in Computers*, 2019.

[7] M. Andoni *et al.*, "Blockchain technology in the energy sector: A systematic review of challenges and opportunities," *Renew. Sustain. Energy Rev.*, vol. 100, pp. 143–174, Feb. 2019.

[8] "Brooklyn Microgrid | Community Powered Energy." [Online]. Available: https://www.brooklyn.energy/. [Accessed: 05-Jul-2020].

[9] "Shell invests in peer-to-peer energy trading blockchain platform." [Online]. Available: https://www.edie.net/news/8/Shell-invests-in-peer-to-peer-energy-trading-blockchain-platform/. [Accessed: 05-Jul-2020].

[10] "London startup performs UK's first blockchain energy trade." [Online]. Available: https://www.edie.net/news/8/London-startup-performs-UK-s-first-blockchain-energy-trade/. [Accessed: 05-Jul-2020].

[11] IEA, *Energy Technology Perspectives 2017: Catalysing Energy Technology Transformations*. OECD, 2017.

[12] "P2P Vehicle Charging: Is blockchain a driver of EV adoption? | Power Technology Research." [Online]. Available: https://powertechresearch.com/p2p-vehicle-charging-is-blockchain-a-driver-of-ev-adoption/. [Accessed: 05-Jul-2020].

[13] "Peer2Peer Germany | Share&Charge." [Online]. Available: https://shareandcharge.com/peer2peer-germany/. [Accessed: 05-Jul-2020].

[14] "Chargemap Pass: the pass to charge your electric car with peace of mind." [Online]. Available: https://chargemap.com/pass. [Accessed: 05-Jul-2020].

[15] P. Alstone *et al.*, "2025 California Demand Response Potential Study Phase 2 Report," *Lawrence Berkeley Natl. Lab.*, no. April, 2017.

[16] "Evolve Power with Blockchain — Demand Response Management System - Virtual Force." [Online]. Available: https://www.virtualforce.io/blog/evolve-power-with-blockchain-demand-response-management-system/. [Accessed: 06-Jul-2020].

[17] "Demand Management | Uplight." [Online]. Available: https://uplight.com/solutions/demand-management/?utm_source=google&utm_medium=ppc&utm_campaign=demand-management-keywords. [Accessed: 06-Jul-2020].

[18] "Leap, a New Startup Testing Blockchain, Takes 90MW Stake in California's Distributed Energy Auction | Greentech Media." [Online]. Available: https://www.greentechmedia.com/articles/read/leap-takes-90mw-stake-in-californias-latest-distributed-energy-auction. [Accessed: 06-Jul-2020].

[19] "eMotorWerks lays groundwork for vehicle-to-grid charging." [Online]. Available: https://www.greencarreports.com/news/1120756_emotorwerks-lays-groundwork-for-vehicle-to-grid-charging. [Accessed: 06-Jul-2020].

[20] "Walmart's Foray Into Blockchain, How Is the Technology Used?" [Online]. Available: https://cointelegraph.com/news/walmarts-foray-into-blockchain-how-is-the-technology-used. [Accessed: 06-Jul-2020].

[21] "IBM Joins with Top Companies to Launch Blockchain Network 'Trust Your Supplier.'" [Online]. Available: https://www.environmentalleader.com/2019/08/180485/. [Accessed: 06-Jul-2020].

[22] "How Blockchain Can Drive Supply Chain Sustainability | Longitudes." [Online]. Available: https://longitudes.ups.com/how-blockchain-can-drive-supply-chain-sustainability/. [Accessed: 06-Jul-2020].

[23] "M-RETS, United States - Power Ledger." [Online]. Available: https://www.powerledger.io/project/m-rets/. [Accessed: 06-Jul-2020].

[24] "Can blockchain catalyze carbon removal? | Greenbiz." [Online]. Available: https://www.greenbiz.com/article/can-blockchain-catalyze-carbon-removal. [Accessed: 07-Jul-2020].

[25] "Blockchain Startup Launches First Global Plastic-Offset Scheme - Sustainable Brands." [Online]. Available: https://sustainablebrands.com/read/supply-chain/blockchain-startup-launches-first-global-plastic-offset-scheme. [Accessed: 07-Jul-2020].

[26] "SolarCoin." [Online]. Available: https://solarcoin.org/. [Accessed: 07-Jul-2020].

[27] "HOW IT WORKS | The Sun Exchange." [Online]. Available: https://thesunexchange.com/how-it-works. [Accessed: 07-Jul-2020].

[28] J. Koomey, "Estimating Bitcoin Electricity Use: A Beginner's Guide," 2019.

[29] "What Are Nodes? | Binance Academy." [Online]. Available: https://academy.binance.com/blockchain/what-are-nodes. [Accessed: 01-Jul-2020].

[30] S. Noor, W. Yang, M. Guo, K. H. van Dam, and X. Wang, "Energy Demand Side Management within micro-grid networks enhanced by blockchain," *Appl. Energy*, vol. 228, pp. 1385–1398, Oct. 2018.

[31] "Monero Community Validates New Anti-ASIC Mining Algorithm | Crypto Briefing." [Online]. Available: https://cryptobriefing.com/monero-new-mining-algorithm/. [Accessed: 01-Jul-2020].

[32] A. Miglani, N. Kumar, V. Chamola, and S. Zeadally, "Blockchain for Internet of Energy management: Review, solutions, and challenges," *Computer Communications*. 2020.

[33] W. Wang *et al.*, "A Survey on Consensus Mechanisms and Mining Strategy Management in Blockchain Networks," *IEEE Access*, vol. 7, pp. 22328–22370, 2019.

[34] M. S. Ferdous, M. J. M. Chowdhury, M. A. Hoque, and A. Colman, “Blockchain Consensus Algorithms: A Survey,” Jan. 2020.

[35] S. King and S. Nadal, “PPCoin: Peer-to-Peer Crypto-Currency with Proof-of-Stake,” 2012.

[36] “Beyond Bitcoin: As Blockchain Adoption Accelerates, a Need to Manage Energy and Climate Emerges - Rocky Mountain Institute.” [Online]. Available: https://rmi.org/beyond-bitcoin-blockchain-adoption-accelerates-need-manage-energy-climate-emerges/. [Accessed: 18-Jul-2020].

[37] S. Nakamoto, “Bitcoin: A Peer-to-Peer Electronic Cash System | Satoshi Nakamoto Institute,” 2008.

[38] “Proof-of-Work, Explained.” [Online]. Available: https://cointelegraph.com/explained/proof-of-work-explained. [Accessed: 01-Jul-2020].

[39] M. L. Di Silvestre *et al.*, “Blockchain for power systems: Current trends and future applications,” *Renewable and Sustainable Energy Reviews*. 2020.

[40] “A Proof of Stake overview - Pool Of Stake - Medium.” [Online]. Available: https://medium.com/@poolofstake/a-proof-of-stake-overview-445c52558d03. [Accessed: 30-Jun-2020].

[41] “Proof-of-Stake (POS) outperforms Bitcoin’s Proof-of-Work (POW) | Hacker Noon.” [Online]. Available: https://hackernoon.com/is-bft-consensus-effective-for-proof-of-stake-blockchain-implementations-dc01f429d225. [Accessed: 30-Jun-2020].

[42] M. Castro and B. Liskov, “Practical Byzantine Fault Tolerance,” *Proc. Symp. Oper. Syst. Des. Implement.*, 1999.

[43] “practical Byzantine Fault Tolerance(pBFT) - GeeksforGeeks.” [Online]. Available: https://www.geeksforgeeks.org/practical-byzantine-fault-tolerancepbft/. [Accessed: 02-Jul-2020].

[44] “Federated Byzantine Agreement - consensus.” [Online]. Available: https://tokens-economy.gitbook.io/consensus/chain-based-pbft-and-bft-based-proof-of-stake/federated-byzantine-agreement. [Accessed: 02-Jul-2020].

[45] “Proof of Authority Explained | Binance Academy.” [Online]. Available: https://academy.binance.com/blockchain/proof-of-authority-explained. [Accessed: 01-Jul-2020].

[46] “Burstcoin » PoC (Proof of Capacity) an ecofriendly consensus mechanism.” [Online]. Available: https://www.burst-coin.org/features/proof-of-capacity/. [Accessed: 02-Jul-2020].

[47] “Proof of Capacity (Cryptocurrency).” [Online]. Available: https://www.investopedia.com/terms/p/proof-capacity-cryptocurrency.asp. [Accessed: 02-Jul-2020].

[48] “Proof of Burn Explained | Binance Academy.” [Online]. Available: https://academy.binance.com/blockchain/proof-of-burn-explained. [Accessed: 01-Jul-2020].

[49] J. Aslan, K. Mayers, J. G. Koomey, and C. France, “Electricity intensity of internet data transmission untangling the estimates,” *J. Ind. Ecol.*, vol. 22, no. 4, 2018.

[50] J. Koomey, *Turning Numbers into Knowledge*. Analytics Press, 2017.

[51] J. G. Koomey *et al.*, “Sorry, wrong number: The use and misuse of numerical facts in analysis and media reporting of energy issues,” *Annu. Rev. Energy Environ.*, vol. 27, 2002.

[52] M. Finkbeiner, A. Inaba, R. B. H. Tan, K. Christiansen, and H. J. Klüppel, “The new international standards for life cycle assessment: ISO 14040 and ISO 14044,” *International Journal of Life Cycle Assessment*, vol. 11, no. 2. 2006.

[53] E. Masanet, A. Shehabi, N. Lei, S. Smith, and J. Koomey, “Recalibrating global data center energy-use estimates,” *Science (80-.).*, vol. 367, no. 6481, 2020.

[54] “Energy Web Chain - Energy Web.” [Online]. Available: https://www.energyweb.org/technology/energy-web-chain/. [Accessed: 01-Jul-2020].

[55] “Deploy Ethereum Proof-of-Authority consortium solution template on Azure - Azure Blockchain | Microsoft Docs.” [Online]. Available: https://docs.microsoft.com/en-us/azure/blockchain/templates/ethereum-poa-deployment. [Accessed: 01-Jul-2020].

[56] “Slimcoin A Peer-to-Peer Crypto-Currency with Proof-of-Burn ‘Mining without Powerful Hardware,’” 2014.

[57] “Why Proof-of-Burn | Counterparty.” [Online]. Available: https://counterparty.io/news/why-proof-of-burn/. [Accessed: 01-Jul-2020].

[58] E. Masanet, A. Shehabi, N. Lei, H. Vranken, J. Koomey, and J. Malmodin, “Implausible projections overestimate near-term Bitcoin CO2 emissions,” *Nat. Clim. Chang.*, no. Under review, 2019.

[59] A. Shehabi, S. J. Smith, E. Masanet, and J. Koomey, “Data center growth in the United States: decoupling the demand for services from electricity use,” *Environ. Res. Lett.*, vol. 13, no. 12, p. 124030, Dec. 2018.

[60] N. Lei and E. Masanet, “Statistical analysis for predicting location-specific data center PUE and its improvement potential,” *Energy*, vol. 201, 2020.

[61] A. Andrae and T. Edler, “On Global Electricity Usage of Communication Technology: Trends to 2030,” *Challenges*, vol. 6, no. 1, 2015.

[62] C. Mora *et al.*, “Bitcoin emissions alone could push global warming above 2°C,” *Nat. Clim. Chang.*, vol. 8, no. 11, pp. 931–933, 2018.

[63] D. Malone and K. J. O’Dwyer, “Bitcoin Mining and its Energy Footprint,” in *25th IET Irish Signals & Systems Conference 2014 and 2014 China-Ireland International Conference on Information and Communities Technologies (ISSC 2014/CIICT 2014)*, 2014, pp. 280–285.

[64] H. McCook, “An Order-of-Magnitude Estimate of the Relative Sustainability of the Bitcoin Network (2014).” 2014.

[65] H. McCook, “An Order-of-Magnitude Estimate of the Relative Sustainability of the BitcoinNetwork (2015),” 2015.

[66] H. McCook, “The Cost & Sustainability of Bitcoin (August 2018).” 2018.

[67] Digiconomist, “Bitcoin Energy Consumption Index,” 2020. [Online]. Available: https://digiconomist.net/bitcoin-energy-consumption. [Accessed: 03-Jul-2020].

[68] A. de Vries, “Bitcoin’s Growing Energy Problem,” *Joule*. 2018.

[69] M. J. Krause and T. Tolaymat, “Quantification of energy and carbon costs for mining cryptocurrencies,” *Nat. Sustain.*, vol. 1, no. 11, pp. 711–718, 2018.

[70] S. Köhler and M. Pizzol, “Life Cycle Assessment of Bitcoin Mining,” *Environ. Sci. Technol.*, 2019.

[71] M. Zade, J. Myklebost, P. Tzscheutschler, and U. Wagner, “Is bitcoin the only problem? A scenario model for the power demand of blockchains,” *Front. Energy Res.*, 2019.

[72] C. Stoll, L. KlaaBen, and U. Gallersdörfer, “The Carbon Footprint of Bitcoin,” *Cell*, vol. 3, no. 0, pp. 1–15, Jun. 2019.

[73] M. Bevand, “Electricity consumption of Bitcoin: a market-based and technical analysis,” 2017. [Online]. Available: http://blog.zorinaq.com/bitcoin-electricity-consumption/. [Accessed: 03-Jul-2020].

[74] M. Bevand, “Op Ed: Bitcoin Miners Consume A Reasonable Amount of Energy — And It’s All Worth It,” 2017. [Online]. Available: https://bitcoinmagazine.com/articles/op-ed-bitcoin-miners-consume-reasonable-amount-energy-and-its-all-worth-it. [Accessed: 03-Jul-2020].

[75] “Cambridge Bitcoin Electricity Consumption Index (CBECI).” [Online]. Available: https://www.cbeci.org/. [Accessed: 03-Jul-2020].

[76] Sinan Kufeoglu and Mahmut Ozkan, “Energy Consumption of Bitcoin Mining,” 24-May-2019. [Online]. Available: https://www.repository.cam.ac.uk/handle/1810/294129. [Accessed: 04-Jul-2020].

[77] J. Li, N. Li, J. Peng, H. Cui, and Z. Wu, “Energy consumption of cryptocurrency mining: A study of electricity consumption in mining cryptocurrencies,” *Energy*, 2019.

[78] R. Cole and L. Cheng, “Modeling the energy consumption of blockchain consensus algorithms,” in *Proceedings - IEEE 2018 International Congress on Cybermatics: 2018 IEEE Conferences on Internet of Things, Green Computing and Communications, Cyber, Physical and Social Computing, Smart Data, Blockchain, Computer and Information Technology, iThings/Gree*, 2018.

[79] M. C. Kidwell *et al.*, “Badges to Acknowledge Open Practices: A Simple, Low-Cost, Effective Method for Increasing Transparency,” *PLOS Biol.*, vol. 14, no. 5, p. e1002456, May 2016.

[80] J. Koomey, C. Belady, and M. Patterson, “Assessing trends over time in performance, costs, and energy use for servers,” 2009.

[81] H. Fuchs *et al.*, “Comparing datasets of volume servers to illuminate their energy use in data centers,” *Energy Effic.*, vol. 13, no. 3, 2020.

[82] IEA, “Tracking Clean Energy Progress - Transport,” *Track. Clean Energy Prog.*, 2019.

Appendix A. Detailed study evaluations.

The following tables summarize the rationale behind the chosen assessment ratings in Table 3 for each study. Where a simple "no" or "yes" is sufficient—e.g., whether a study considered locational variations—no further explanation is offered.

Criterion 1 Properly include the full system

Study	**Explanations**
O'Dwyer [63]	No, only considered mining.
McCook (2014,2015) [64], [65]	No, only considered mining.
McCook (2018) [66]	Partial, considered a PUE value of 1.25.
Digiconomist [67]	Partial, in the economic approach, 60% of mining reward goes to operational electricity cost was considered, which should incorporate the electricity used by cooling/UPS.
De Vires [68]	Partial, in the economic approach, 60% of mining reward goes to operational electricity cost was considered, which should incorporate the electricity used by cooling/UPS.
Krause [69]	No, only considered mining.
Vranken [4]	Partial, Vranken's final estimate is based on result integration from both top-down and economic modeling approaches. In the economic approach, he considered electricity cost as percentages of total cost of ownership, which should incorporate the electricity used by cooling/UPS.
Mora [62]	No, only considered mining.
Bevand [73], [74]	Partial, considered the PSU loss when deriving the efficiency for some types of mining rigs.
Köhler [70]	Partial, considered PUE of 1.05, also considered the energy used by nonvalidating nodes in the Bitcoin network (in their online supporting material).
Zade [71]	No, only considered mining.
CBECI [75]	Partial, considered PUE values for several scenarios.
Stoll [72]	Partial, considered different PUE values for small-scale (1.00), medium-scale (1.10), and large-scale (1.05) mining facilities in the best guess estimate.
Li [77]	No, only considered mining.
Küfeoglu [76]	No, only considered mining.

Criterion 2 Build from the bottom up

Study	**Explanations**
O'Dwyer [63]	No, top-down approach was used.
McCook (2014,2015) [64], [65]	No, top-down approach was used.
McCook (2018) [66]	No, top-down approach was used.
Digiconomist [67]	No, both top-down and economic approaches were used for Bitcoin mining, and only economic approach was used for Ethereum mining.
De Vires [68]	No, both top-down and economic approaches were used.
Krause [69]	No, top-down approach was used.
Vranken [4]	No, both top-down and economic approaches were used.
Mora [62]	No, top-down approach was used.
Bevand [73], [74]	No, hybrid top-down approach was used.
Köhler [70]	No, top-down approach was used.
Zade [71]	No, top-down approach was used.
CBECI [75]	No, hybrid top-down approach was used.
Stoll [72]	No, both top-down and economic approaches were used.
Li [77]	No, extrapolation approach based on direct measurement was used.
Küfeoglu [76]	No, hybrid top-down approach was used.

Criterion 3 Use measured/surveyed data

Study	**Explanations**
O'Dwyer [63]	No, rated power efficiency data was used.
McCook (2014,2015) [64], [65]	No, rated power efficiency data was used.
McCook (2018) [66]	No, rated power efficiency data was used.
Digiconomist [67]	No, rated power efficiency data was used in the top-down approach.
De Vires [68]	No, rated power efficiency data was used in the top-down approach.
Krause [69]	No, rated power efficiency data was used.
Vranken [4]	No, rated power efficiency data was used in the top-down approach.
Mora [62]	No, rated power efficiency data was used.
Bevand [73], [74]	No, rated power efficiency data was used.
Köhler [70]	No, rated power efficiency data was used.
Zade [71]	No, rated power efficiency data was used.
CBECI [75]	No, rated power efficiency data was used.
Stoll [72]	No, rated power efficiency data was used.
Li [77]	Yes, measured data was used.
Küfeoglu [76]	No, rated power efficiency data was used.

Criterion 4 Use time-period appropriate technology data

Study	**Explanations**
O'Dwyer [63]	Partial, the efficiency of a subset of the equipment considered during the studied time is outdated.
McCook (2014,2015) [64], [65]	No, an assumed equipment efficiency distribution was used for the power estimation given a specific day, and the single day power estimate was then scaled to the whole year.
McCook (2018) [66]	No, a single data point of equipment efficiency (limited sample) was used for the power estimation given a specific day, and the single day power estimate was then scaled to the whole year.
Digiconomist [67]	Partial, the time-series equipment efficiency sample considered for the lower bound estimate is limited, and an unclarified moving average price of Bitcoin was used in the upper bound estimate.
De Vires [68]	Partial, a single point of input (limited sample) was used for the power estimation given a specific day.
Krause [69]	Partial, the energy efficiency trends of mining hardware for Ethereum, Litecoin, and Monero were extrapolated based on the efficiency trends of Bitcoin mining rigs.
Vranken [4]	Yes.
Mora [62]	No, outdated mining rig data were used in the study.
Bevand [73], [74]	Yes.
Köhler [70]	Partial, an unchanged mining rig distribution was used for the study period.
Zade [71]	Partial, appropriate mining rig efficiency trends were used in the historical analysis for Bitcoin and Ethereum electricity use, but extrapolation trends were used in the future analysis.
CBECI [75]	Yes.
Stoll [72]	Yes.
Li [77]	Partial, limited samples were considered in the experiment.
Küfeoglu [76]	Yes.

Criterion 5 Account for capacity utilization

Study	Explanations
O'Dwyer [63]	No, considered mining rig speed at full output.
McCook (2014,2015) [64], [65]	No, considered mining rig speed at full output.
McCook (2018) [66]	No, considered mining rig speed at full output.
Digiconomist [67]	No, considered mining rig speed at full output.
De Vires [68]	No, considered mining rig speed at full output.
Krause [69]	No, considered mining rig speed at full output.
Vranken [4]	No, considered mining rig speed at full output.
Mora [62]	No, considered mining rig speed at full output.
Bevand [73], [74]	Partial, considered the situation of overclocking for some types of mining rigs.
Köhler [70]	No, considered mining rig speed at full output.
Zade [71]	No, considered mining rig speed at full output.
CBECI [75]	No, considered mining rig speed at full output.
Stoll [72]	No, considered mining rig speed at full output.
Li [77]	Partial, the experiment result eliminated the influence of baseline power usage, but this is inappropriate.
Küfeoglu [76]	No, considered mining rig speed at full output.

Criterion 6 Account for locational variations

Study	**Explanations**
O'Dwyer [63]	No.
McCook (2014,2015) [64], [65]	No.
McCook (2018) [66]	No.
Digiconomist [67]	No.
De Vires [68]	No.
Krause [69]	Partial, the locational variation of grid mixes (for carbon emissions) was considered.
Vranken [4]	No.
Mora [62]	No.
Bevand [73], [74]	No.
Köhler [70]	Partial, the locational variation of grid mixes (for carbon emissions) was considered.
Zade [71]	No.
CBECI [75]	Partial, the locational dependent electricity prices can be self-adjusted.
Stoll [72]	Partial, the locational variation of grid mixes (for carbon emissions) was considered.
Li [77]	No.
Küfeoglu [76]	Partial, the locational variation of electricity prices was considered.

Criterion 7 Properly account for uncertainty

Study	Explanations
O'Dwyer [63]	Partial, the uncertainty from mining rig efficiency was considered.
McCook (2014,2015) [64], [65]	No.
McCook (2018) [66]	No.
Digiconomist [67]	Partial, the top-down approach was used to derive the lower bound estimate, while the result from the economic approach was used as an upper bound estimate.
De Vires [68]	No, only point estimation was given. The economic approach was used in this study, but it aims at deriving a plausible future electricity consumption of Bitcoin mining instead of giving an upper bound estimate.
Krause [69]	Partial, the uncertainty of gird mixes on carbon emission was considered.
Vranken [4]	Partial, the study considered the uncertainty of Bitcoin mining electricity use from different mining rig efficiency, and from various electricity cost as a percentage of total cost of ownership.
Mora [62]	No, an insufficient uncertainty estimation was performed [58].
Bevand [73], [74]	Partial, the uncertainty from mining rig efficiency was considered.
Köhler [70]	Partial, a sensitivity analysis of electricity mixes on carbon emission was performed.
Zade [71]	No, inadequate scenario design of the difficulty changes of blockchain network.
CBECI [75]	Yes, considered uncertainties from several types of model input.
Stoll [72]	Partial, the uncertainty from mining rig efficiency was considered.
Li [77]	No.
Küfeoglu [76]	Partial, the uncertainty from mining rig efficiency was considered.

Criterion 8 Consider retrospective time series analysis

Study	**Explanations**
O'Dwyer [63]	Partial, a constant efficiency range of mining rigs was used, but the study analyzed the profitability of different types of mining rigs (CPUs, GPUs, FPGAs, ASICs) over time.
McCook (2014,2015) [64], [65]	No.
McCook (2018) [66]	No.
Digiconomist [67]	Partial, in the lower bound energy estimate based on the top-down approach, the changing of the most efficient hardware from Antminer S9, to Antminer S15, and then to Antminer S17e was considered.
De Vires [68]	No, a single day estimate for mid-March 2018 was considered in this study.
Krause [69]	Partial, the energy efficiency trends of mining hardware for Ethereum, Litecoin, and Monero considered in this study were extrapolated based on the efficiency trends of Bitcoin mining rigs.
Vranken [4]	Partial, this study mainly considered the power use of Bitcoin mining at Jan-2017, however, a time series profitability analysis of mining rigs was conducted.
Mora [62]	No.
Bevand [73], [74]	Yes.
Köhler [70]	No, a constant efficiency was used across the year of 2018.
Zade [71]	Yes.
CBECI [75]	Yes.
Stoll [72]	Yes.
Li [77]	No, a constant efficiency was used during the range of time considered.
Küfeoglu [76]	Yes.

Criterion 9 Avoid simplistic extrapolations

Study	**Explanations**
O'Dwyer [63]	Yes.
McCook (2014,2015) [64], [65]	No, a single day estimate was scaled to the whole year.
McCook (2018) [66]	No, a single day estimate was scaled to the whole year.
Digiconomist [67]	Partial, both top-down and economic approaches were used to derive the range of the Bitcoin mining energy consumption, and the economic approach was used to estimate the Ethereum network energy consumption. The economic approach used is a form of extrapolation based on the price of the cryptocurrency.
De Vires [68]	Partial, both top-down and economic approaches were used to derive the Bitcoin mining energy consumption. The economic approach used is a form of extrapolation based on the price of the cryptocurrency.
Krause [69]	Partial, the energy efficiency trends of mining hardware for Ethereum, Litecoin, and Monero were extrapolated based on the efficiency trends of Bitcoin mining rigs.
Vranken [4]	Yes.
Mora [62]	No, future Bitcoin emissions were extrapolated using the number of transactions.
Bevand [73], [74]	Yes.
Köhler [70]	Yes.
Zade [71]	No, future power used by Bitcoin and Ethereum mining were extrapolated based on improper difficulty trends of Bitcoin and Ethereum network.
CBECI [75]	Yes.
Stoll [72]	Yes.
Li [77]	No, the energy use and carbon emission of Monero mining in China were extrapolated without supported reason.
Küfeoglu [76]	Yes.

Criterion 10 Open and complete documentation allowing replication

Study	**Explanations**
O'Dwyer [63]	Partial, unexplained conclusion that energy used by Bitcoin mining is around 3 GW.
McCook (2014,2015) [64], [65]	Yes.
McCook (2018) [66]	Yes.
Digiconomist [67]	Partial, unclarified period used in the moving average of the cryptocurrency price.
De Vires [68]	Yes.
Krause [69]	Yes.
Vranken [4]	Yes.
Mora [62]	Partial, incomplete documentation of both data and methodology [58].
Bevand [73], [74]	Yes.
Köhler [70]	Yes.
Zade [71]	Yes.
CBECI [75]	Yes.
Stoll [72]	Yes.
Li [77]	Partial, incomplete documentation of how the percentage of Monero mining activity in China was derived.
Küfeoglu [76]	Yes.