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Can Cryptocurrencies Be Sustainable? AI-Based CO_2 Emission Forecasting

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ABSTRACT

Purpose: This study evaluates the energy consumption and environmental impact of blockchain supported cryptocurrency systems, focusing on CO_2 emissions generated by Bitcoin mining. It investigates the relationship between cryptocurrency economics, energy usage, and ecological sustainability, and assesses the future viability of cryptocurrencies as a global financial system in alignment with the Sustainable Development Goals (SDGs).

Methods: A quantitative time series forecasting approach was adopted using 5030 days of historical CO_2 emission data obtained from the Cambridge Blockchain Network Sustainability Index (CBECI). Three energy scenarios, hydroelectric power, coal based power, and mixed energy sources, were analyzed. A Long Short-Term Memory (LSTM) neural network model was implemented to predict future emission trends and evaluate sustainability outcomes under each scenario.

Findings: The results indicate that hydroelectric energy produces the lowest CO_2 emissions as the most sustainable option, while coal-based mining results in the highest emissions, representing the worst-case scenario. The mixed energy model provides a feasible compromise, significantly reducing emissions compared to coal while maintaining mining efficiency. These findings identify certain environmental risks associated with energy intensive mining practices and emphasize the urgent need for sustainable operational strategies.

Implications: This research contributes to blockchain sustainability literature by providing a predictive framework for environmental assessment. Policymakers can leverage these insights to design regulations promoting renewable energy integration, while industry practitioners can adopt energy efficient mining models to reduce carbon footprints and achieve long term sustainability.

Originality: The study uniquely integrates deep learning-based forecasting with large scale longitudinal emission data to conduct scenario-based sustainability analysis, offering dynamic insights beyond conventional static evaluations.

1. Introduction

In the present times, humanity grapples with significant challenges like sustainable development and climate change. Information and communication technology (ICT) plays a decisive role in addressing these issues, although it sparks intense debates within academic and business circles. While ICT can contribute to reducing energy and resource consumption, its widespread adoption also escalates energy and resource demands, resulting in various emissions. The shift towards a low carbon society is a priority for European Union decision makers and aligns with the UNDP's sustainable development goals 13 (SDG) (UNDP, 2015).

Amidst this backdrop, the surge in interest surrounding cryptocurrencies has stirred academic discourse, ranging from defining what cryptocurrencies truly represent to concerns about the environmental sustainability of cryptocurrency mining technology. The mining of cryptocurrency is carried through the technology called blockchain. Every transaction is completed and recorded on the blockchain, a distributed ledger. Though numerous studies such as (Bal, 2015; Katsiampa, 2017; Nasir *et al.*, 2020) expressed different viewpoints on blockchain technology, often exploring its application in the expansive domain of cryptocurrencies, the versatility of blockchain technology manifests through various applications, some of which may directly or indirectly align with sustainability principles (Schinckus, 2020). For instance, within the realm of cryptocurrencies like bitcoin, there exists an impact on sustainability via reduction of paper currency printing, thereby aiding in forest preservation. However, amidst the burgeoning cryptocurrency market, investors tend to be captivated by price fluctuations, often overlooking the pressing carbon emissions issue associated with cryptocurrencies (Jayawardhana & Colombage, 2020). Emissions from cryptocurrencies, particularly bitcoin, are thought to cause global warming to exceed 2 °C, which has outraged academics (Mora *et al.*, 2018). It is evident that cryptocurrency acquisition and utilization involve resource consumption, particularly electricity. The environmental effects of the Information and Communications Technology (ICT) industry, including cryptocurrency activities, have been largely overlooked despite coordinated worldwide efforts to reduce greenhouse gas emissions in accordance with the Paris Agreement (Belkhir & Elmeligi, 2018). Therefore, evaluating the different cryptocurrencies' effects on emissions broadens the global discussion and has serious policy implications. The effect of their emissions and the degradation of the ecological footprint must be addressed, given the significant electrical energy consumption of existing blockchains.

However, there are mainly two difficulties in measuring the amount of energy consumed. Firstly, it is unclear how many cryptocurrencies there are in total. The number of cryptocurrencies surged from over 66 in 2013 to 9024 by April 2024, with some new ones thriving while others vanish quickly (Statista, 2024). The state of the miners presents the second difficulty. With the right software, any regular computer may participate in the mining process, which makes the mechanism ambiguous. Consequently, it is quite challenging to recognize the current state of mining activity. Based on the aforementioned issues, research on the energy usage of cryptocurrency mining is lacking. Hence, the focus of the study is to evaluate the total energy consumption due to this innovative currency system supported by blockchain technology. However, Katsiampa (2017) in their research catered to aspects such as the economic nature of Bitcoin, factors influencing its volatility, its operational efficiency, and its doctrinal affiliation and advantages. To date, significant enhancement in the literature of cryptocurrency is witnessing its implications for financial markets and regulatory framework (Lamine *et al.*, 2024; Majumder, 2025). Though few empirical studies (Taskinsoy, 2019) have paid attention to its effects on the environment. Therefore, the first objective deals with the theoretical underpinnings of cryptocurrencies, the impact of their price and volume fluctuations on economies worldwide, and ecological degradation that creates obstacles in achieving sustainable development goals (SDGs). There exists literature that uses different estimates to review cryptocurrency energy consumption (Küfeoğlu & Özkuran, 2019; Calvo-Pardo *et al.*, 2022). It becomes pertinent to thoroughly consider questions like: what influences the energy usage of bitcoin mining, how much energy is used, does this interfere with sustainability, and if so, are there any alternatives that use less energy? With this pretext, the second relevant objective is to predict its future as a viable or non-viable currency system globally.

Therefore, this paper makes two contributions. First, it summarizes and evaluates various perspectives found in scientific literature. The research adds value to existing literature by examining a thorough review of global economic trends resulting from the significant increase in cryptocurrencies. Second, using historical data, the study predicts carbon emissions from the minting of Bitcoin with the help of machine learning Long-Term Short-Term Memory (LSTM). This gap in the existing literature acted as a motivator to examine energy consumption by cryptocurrency.

The remainder of this paper is organized as follows. The second section provides an in-depth review of the literature. Section three summarizes the data and methodology. Section four discusses the empirical results. Finally, the last section concludes with the findings and future work suggestions.

2. Review of Literature

2.1. Economic Impact

Regardless of how economic exchanges may change, the development and evolution of money reflect aspects of human progress (Badea & Mungiu-Pupazan, 2021). The introduction of cryptocurrency in the past century represents a novel addition, yet its categorization as private money remains uncertain, with ongoing debates among scholars about its doctrinal and economic nature. Rogic (2018) emphasized the importance of institutional indicators such as purchasing power stability, economic efficiency, and sustainable growth, advocating for a focus on financial intermediation markets rather than mere stabilization efforts. Controversies regarding currency and the potential for monetary competition, which, from an entrepreneurial standpoint, could lead to the creation of the most suitable form of currency tailored to the preferences of economic agents, persist. Over the course of the previous three centuries, the history of economic thought has taken three distinct stances on the subject of private money. The past literature traces three main perspectives, out of which the first is related to individual behavior guided by self-interest, the second links the expansion of individual freedom of initiative with private money, and the third states that private funds are a private bank's prerogative

(Alter, 2019; Von Hayek, 1934; Selgin, 2014). Fernández-Villaverde (2018) challenged Hayek's (Hayek, 1934) views, arguing that private monetary agreements are not socially optimal in most cases and cannot address issues as effectively or inexpensively as government issued money. Similarly, Rahman (2018) argued that there would not be a socially optimal distribution of digital currency under a strictly privatized system. Hence, the nature and functions of cryptocurrencies are subjects of extensive debate in literature. Transactions are carried out anonymously and without the support of a central authority. Regulations control every facet of conventional money, and in the event of a security breach, those responsible compensate the impacted users. Conversely, cryptocurrency security primarily relies on IT measures, operating in a dynamic market influenced by various factors (Badea, 2017). Each cryptocurrency's unique characteristics impact its price, stability, and interactions, with market uncertainty and investor expectations causing significant fluctuations (Kethineni & Cao, 2020).

There are several economic controversies surrounding Bitcoin's identity and functions. While some regard it as investments based on speculation, others see it as a means of trade. Cryptocurrencies are classified as financial assets, while Bitcoin's qualities are highlighted as akin to traditional money, mentioning low transaction costs and being highly liquid, divisible, portable, and durable. Dyhrberg (2016) compares Bitcoin to gold, suggesting it bridges currency and commodity attributes. Understanding Bitcoin's functions requires consideration of its role in economic theory, where scholars have long debated the fundamental functions of money. Jevons (1989), in his book "Money and the Mechanism of Exchange", identifies four key functions: facilitating exchange, uniform measure, establishing a standard, and preserving value.

Presently, economic theory has adapted to modern developments, resulting in updates to the functions of money. Kubát (2015) suggests additional functions beyond the classical ones, such as informational and investment functions. In contrast, Graham (1940) identifies just two main purposes of money: serving as a unit of accounting and as a bearer of options, with other functions stemming from these core roles. Based on these perspectives, Kubát (2015) concludes that Bitcoin does not meet the criteria for being considered money.

Cryptocurrencies are essentially inert tokens that were created by social convention and are mostly used as transaction records. Unlike traditional banknotes, cryptocurrencies lack even residual value as they exist solely as electronic data (Badea & Mungiu-Pupazan, 2021).

Lutz (2018) discusses how the emergence of cryptocurrencies is putting pressure on central banks, suggesting that cryptocurrencies and fiat currency may eventually converge. Seetharaman *et al*. argue against Bitcoin's long-term coexistence as a currency due to regulatory challenges, despite its potential positive impact on global currencies.

Selgin (2014) propose the creation of a digital currency using algorithms replicating established monetary rules from economic literature, while Ammous (2018) argues that cryptocurrencies cannot fulfill the role of conventional money due to various factors such as lack of central authority, fluctuating demand, and inflexible supply. Selgin (2014) note the increasing acceptance of Bitcoin among merchants, indicating its potential as a preferred medium for transactions and remittances (Yermack, 2024). However, concerns persist regarding Bitcoin's potential facilitation of illegal transactions, leading to calls for regulation to prevent virtual currencies from being involved in criminal practices (Darlington, 2014).

In conclusion, besides determining the classification of cryptocurrency as private money and its long-term viability, questions remain about the sustainability of the growing interest in acquiring and using cryptocurrency.

2.2. Impact on Sustainability

- **The Process of Minting:** The process of minting cryptocurrency involves establishing new blocks, verifying data, and entering the information onto the blockchain via a proof of work mechanism. Blockchain is a type of database where information is stored in sequential fragments called blocks. These blocks provide storage capacity for data that includes saved data, a timestamp, the hash value from the preceding block, and a nonce, that is, a unique identifying number. A blockchain is created when a block is integrated into a previously filled block (Küfeoğlu & Özkuran, 2019). In order to achieve the right to add their proposed block to the chain and preserve consensus over the ledger's state, bitcoin miners compete with other users on the network using the Proof of Work (PoW) algorithm. About ten minutes is the minimum time required to mine at least one bitcoin (Antonopoulos, 2023). To stay competitive in the effort to add their blocks to the ledger, miners invest in more processing power. De Vries (2021) employed a sensitivity-based strategy that took into account the cost of the Bitcoin market, the cost of power, and the portion of miners' earnings allocated to electricity. The findings indicated that up to 184 TWh of energy may be used by the Bitcoin network. The idea of a programmable network was first presented by Ethereum, another well-known blockchain network. Ethereum facilitates the use of Ether, the cryptocurrency with the second highest market value, $367.19B as of 7th May 2024 (Forbes, 2024b). Ethereum is associated with the same problems of electrical energy consumption and high carbon footprints as Bitcoin since it is built on the PoW consensus mechanism. However, Ethereum 2.0 aims to solve most of the problems associated with Bitcoin and Ethereum (Badea & Mungiu-Pupazan, 2021). The process used by the network has undergone a major change in Ethereum 2.0. The Eth2 upgrade, also known as the consensus layer upgrade, entails moving Ethereum from its energy intensive proof of work algorithm to a proof of stake (PoS) method. Compared to PoW cryptocurrencies, PoS cryptocurrencies consume far less computer power and electricity. The PoS algorithm improves a network's scalability, security, and accessibility, among other aspects. Using PoS, the computational race associated with PoW is eliminated, which lowers energy use and CO2 emissions during mining (Nguyen *et al.*, 2019). Despite this, cryptocurrency miners employ specialized machinery capable of making billions of computations every second. The number of attempts to solve the cryptographic problem per second is a measure of the computational capability of mining a coin. Electricity costs are a cryptocurrency mining facility's main operational expense. Large quantities of power are required to run the computers and cool the equipment to prevent overheating and sustain profitable cryptocurrency mining (De Vries, 2020).

- **Global Surge in Cryptocurrency Transactions:** The introduction of cryptocurrency has revolutionized the financial world, offering a decentralized, transparent, and secure medium of exchange. It has paved the way for an influx of various other cryptocurrencies, collectively contributing to a market that has seen exponential growth in recent years. ElBahrawy *et al.* (2017) emphasized that the total market capitalization of cryptocurrencies has been on an upward trajectory since late 2013, wherein only Bitcoin contributed $1.3 billion on May 1, 2013, and increased 77 times in 2017 to reach $100.1 billion. Concurrently, Bitcoin's market capitalization shows an upsurge to $1.29 trillion (Forbes, 2024a). This surge can be attributed to several factors, including legislative changes (Rogic, 2018), technical advancements (Badea & Mungiu-Pupazan, 2021), and social developments (ElBahrawy *et al.*, 2017). In a recent study, Majumder (2024) referred to cryptocurrencies as the "new digital gold" in the context of analyzing their hedging capabilities against macroeconomic shocks, specifically comparing them to gold within the economies of India, China, Brazil, and Russia. Past occurrences of sudden increases in the volume of cryptocurrency transactions are attributed to legislative changes in the crypto market. Additionally, the exponential rise in market capitalization has likely drawn more speculative attention to this space, which has improved the utility of this decentralized technology as a means of payment (Giudici *et al.*, 2020; Chuen & Teo, 2021). The increase in cryptocurrency trading throughout the world represents a substantial change in how transactions are carried out, rather than merely a trend (ElBahrawy *et al.*, 2017). Because digital currency trading is profitable, a large number of individuals have become involved, which has fueled the expansion of cryptocurrencies (Das & Dutta, 2020). Contrary to focusing on returns, the significance of trading volumes lies in their impact on energy consumption, indicating the extent of interconnectedness in the market (Huynh *et al.*, 2022). This implies that the liquidity necessary for verified transactions drives up the demand for Bitcoin energy consumption. This relationship also extends to Bitcoin returns. Li *et al.* (2019) also opined that in 2018, the estimated annual electricity consumption of Bitcoin was 63.99 TWh, which is more than any other cryptocurrency. Thus, the act of trading Bitcoin is observed to contribute to environmental harm, a phenomenon termed crypto damage in earlier studies (Goodkind *et al.*, 2020). It is important to recognize that while there is a large potential for profit, there are also significant risks (Manahov, 2024). In conclusion, the global increase in cryptocurrency transactions is a multifaceted phenomenon, influenced by a myriad of factors ranging from legislative changes to market competition (Truby, 2018).

3. Data and Methodology

3.1. Data Sources

The raw data is collected from the publicly available Cambridge Blockchain Network Sustainability Index (CBECI). To conduct the analysis, data for the period from 18/07/2010 to 25/09/2025 is used. The data provided is in numeric format. The data consists of greenhouse gas emissions from different energy sources. The dataset covers 5030 days in total. The study predicts CO2 emissions due to transactions and mining of Bitcoin. Bitcoin cryptocurrency is considered for the analysis due to these reasons. Firstly, in the global cryptocurrency industry, Bitcoin has the largest market capitalization. The second imperative is its high electricity consumption compared to other cryptocurrencies.

While performing data synthesis, the data is divided into three different cases depending upon the source of electricity consumed by Bitcoin miners. The three cases are: Best Case: greenhouse gas emissions assuming Bitcoin miners rely exclusively on hydroelectric power; Best Guess: greenhouse gas emissions assuming Bitcoin miners rely on a variety of energy sources; and Worst Case: greenhouse gas emissions assuming Bitcoin miners rely exclusively on coal-based power. This is calculated mostly in Mt CO2e (metric tonnes carbon dioxide equivalents).

3.2. Methodology

Artificial neural networks have been a prominent topic in research in recent years (Goel *et al.*, 2023). Additionally, due to their excellent self-learning, adaptability, and nonlinear mapping capabilities, neural network performance, analysis, and prediction have been extensively applied in financial income, exchange rate risk, and stock price prediction (Sunny *et al.*, 2020). Fenu *et al.* (2009) studied the optimal period for stock investing using artificial intelligence neural networks. Artificial neural networks possess a robust nonlinear approximation capability for modeling nonlinear relationships.

One particular type of recurrent network is the LSTM neural network. LSTM retains the error for the reverse pass across time and layers. To allow a recurrent network to train over long durations and capture long distance causal relationships, LSTM maintains the error at a more stable level. In this study, short term CO2 emissions of Bitcoin mining are predicted using the properties of the LSTM neural network method on time series data.

3.3. Mathematical Framework for LSTM

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network designed to model sequential data. The LSTM architecture is particularly effective for time series prediction due to its ability to capture long term dependencies. The mathematical formulation is as follows:

a) Forget Gate:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

Where is the forget gate activation, Wf is the weight matrix, is the previous hidden state, is the current input, and is the bias.

b) Input Gate:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$
$$C^{\sim}_t = tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right)$$

where i_t is the input gate activation, $C^{\sim}_t$ is the candidate cell state, and W_i, W_c are weight indicators.

c) Cell State Update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C_t^{\sim}$$

where C_t is the updated cell state.

d) Output Gate:

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right)$$
$$h_t = o_t \cdot tanh\left(C_t\right)$$

where is the output gate activation, and is the hidden state. In addition, σ denotes the sigmoid function.

This model is found to be suitable for predicting CO2 emissions based on historical data (Li *et al.*, 2017). The system architecture of the data analysis is shown in Figure 1. Preprocessing raw data is the first step. After preprocessing, the processed data was split into two halves, referred to as datasets for training purposes. After training and fine tuning the model, it was thoroughly tested to evaluate its performance.

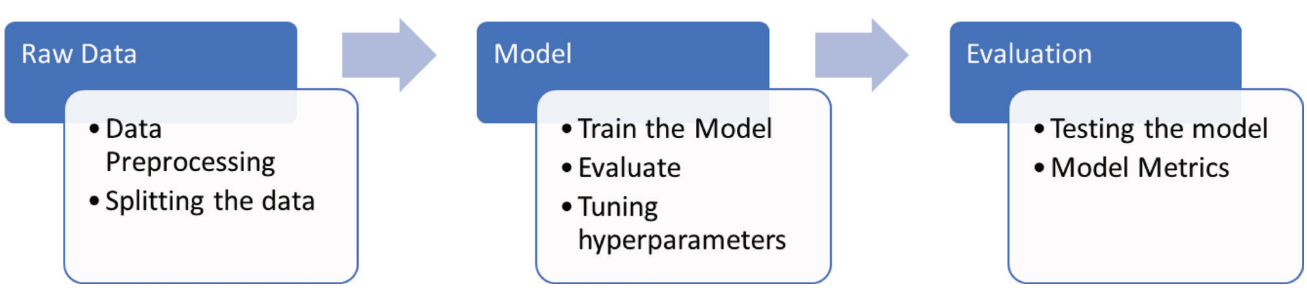

Figure 1: System Architecture of Data Analysis

3.4. Experimental Setup

- **Data Preprocessing:** The dataset used in this study was obtained from the Cambridge Blockchain Network Sustainability Index (CBECI). The data spans 5030 days, from July 18, 2010, to April 25, 2024, and includes CO2 emissions from Bitcoin mining under three scenarios: hydroelectric power, coal only, and mixed energy sources.

- **Data Cleaning:** The dataset was cleaned by removing missing values to ensure consistency. Feature Selection: The primary feature used for prediction was CO2 emissions, with time as the independent variable. Data Splitting: The dataset was split into training (70%) and testing (30%) sets to evaluate the model's performance.
- **Model Architecture:** The LSTM model was implemented using the Keras library with the following architecture:
  - **Input Layer:** 1 input feature (CO2 emissions).
  - **LSTM Layers:** Three LSTM layers with 50, 30, and 10 units, respectively.
  - **Dense Layer:** A fully connected layer with a single output unit for regression.
  - **Optimizer:** Adam optimizer with a learning rate of 0.001.
  - **Loss Function:** Mean Squared Error (MSE).
- **Training Process:** The model was trained over 200 epochs with a batch size of 32. Early stopping was implemented to prevent overfitting, and the model's performance was evaluated using the RMSE and MAPE metrics.

4. Results

4.1. Criteria for Evaluation

Root Mean Squared Error (RMSE) is used as a performance metric to gauge the accuracy of a prediction model. The magnitude of the errors between predicted and actual values is measured, where y_i is the original value and y□_i is the predicted value. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Mean Absolute Percentage Error (MAPE) being used as other important parameter for assessing the accuracy of the predictive model which reflects the prediction error as a percentage, making it easier to interpret the accuracy of the model in relative terms. Where are represented as actual values, are represented as predicted values and n is the number of observations. Following is the formula for MAPE:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%$$

The values of RMSE and MAPE for each case namely, Case I, Hydro only, Case II, Estimated and Case III, Coal only are illustrated in Table 1.

Table 1: RMSE and MAPE Values for Each Case

Case Description	RMSE	RMSE Interpretation	MAPE	MAPE Interpretation
Case I – Hydro Only	4.06	Low (Good fit)	0.54%	Highly accurate, Excellent
Case II – Mix of Different Energy Sources	96.20	Moderate (Acceptable)	12.12%	Good
Case III – Coal Only	158.10	High (Relatively)	21.75%	Reasonable, Acceptable

Note: RMSE-Root Mean Square Error, MAPE-Mean Absolute Percentage Error

Table 1 provides the values of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for three different cases: hydro only, a mixture of energy sources, and coal only. These statistical measures offer insights into the accuracy and performance of the model. The RMSE value indicates the overall accuracy of the model. A lower RMSE value suggests a more accurate model, as it represents the average magnitude of the errors between the predicted and actual values of the dependent variable. The MAPE, on the other hand, measures the goodness of the model's predictions. Models that perform exceptionally well are those with MAPE values less than 10%, while excellent models are those with values between 10% and 20%. MAPE values between 20% and 50% are considered appropriate, whereas values above 50% are regarded as inaccurate and defective (Moreno *et al.*, 2013). Using the R MAPE index as a resistant measure of forecast accuracy, the RMSE and MAPE values presented in the table can be used to evaluate the overall performance and reliability of the model for the three different cases under consideration.

The graphs below show the prediction of future carbon emissions for the next 100 days, which correspond to May, June, and July of 2024, along with actual versus predicted graphs using the Long Short-Term Memory (LSTM) model. Figures 2 to 4 show the prediction graphs for all three cases, that are hydro only, estimated, and coal only, respectively. Figures 5 to 7 compare the actual and predicted LSTM carbon emissions of Bitcoin for hydro only, estimated, and coal only cases, respectively. The following are the prediction model results for the three case scenarios:

- **Best Case - Hydro Only Scenario:** The first case of hydro only is the best-case scenario, final output depicted in Fig 2, where the electricity used by miners is produced solely through hydro energy. The model predicted a slight initial increase in emission levels, followed by a consistent decrease. This implies that the environmental effect might be greatly decreased if hydroelectric power is the only source used for Bitcoin mining. However, the availability of hydroelectric electricity determines whether this scenario is feasible. Results presented in Figure 5 compare the actual and LSTM predicted carbon emissions in the case of hydro only. The graph shows that the predicted and the actual carbon emission are approximately the same over the entire interval with a mean absolute percentage error of 0.55%, and a root mean square error of 4.07. Figure 8 demonstrated how fast the LSTM model was able to fit the data and generalized well to unseen data in the early stages of training in the hydro only scenario. After the initial drop, there may be slight variations in loss levels, which might be caused by either mild overfitting or inherent noise in the data. Nevertheless, it appears that the model is performing well based on the generally modest loss figures.

- **Best Guess Case - Mix of Different Energy Sources:** Figure 3 shows the prediction in the case of the estimated scenario, which is the most realistic scenario among all three cases, where the electricity used by miners is produced through a combination of different energy sources. The model predicted a high emission level at day zero, a significant drop by day ten, and relative stability from day forty onwards. This suggests a dynamic situation where the mix of energy sources and the level of Bitcoin mining activity are constantly changing. The downward trend indicates that efforts to reduce the carbon footprint of Bitcoin mining are having an effect. However, the higher emission levels highlight the need for continued efforts to shift towards renewable energy sources. Results presented in Figure 6 compare the actual and LSTM predicted carbon emissions in the case of estimated. The graph shows that the predicted and the actual carbon emissions are approximately the same over the entire interval with a few fluctuations in the lower points in later periods of time, with a mean absolute percentage error of 12.13%, and a root mean square error of 96.21. Figure 9 demonstrated how fast the LSTM model was able to fit the data and generalized well to unseen data in the early stages of training in the estimated scenario.
- **Worst Case - Coal is the Only Source:** The study results revealed that using coal as the only source is the worst-case scenario, as can be inferred from Figure 4, where electricity used by miners is produced solely through coal energy. The model predicted high initial emission levels that gradually declined over the next 100 days. This shows that if Bitcoin mining is mostly dependent on coal energy, the environmental impact could be severe. The high emission levels highlight the urgent need for a shift towards more renewable energy sources in Bitcoin mining. Results presented in Figure 7 compare the actual and LSTM predicted carbon emissions in the coal only case. The graph shows that the predicted and the actual carbon emissions are approximately the same, with a small difference in the initial period of time, with a mean absolute percentage error of 21.75% and a root mean square error of 158.11. Figure 10 demonstrated how fast the LSTM model was able to fit the data and generalized well to unseen data in the early stages of training in the coal only scenario.

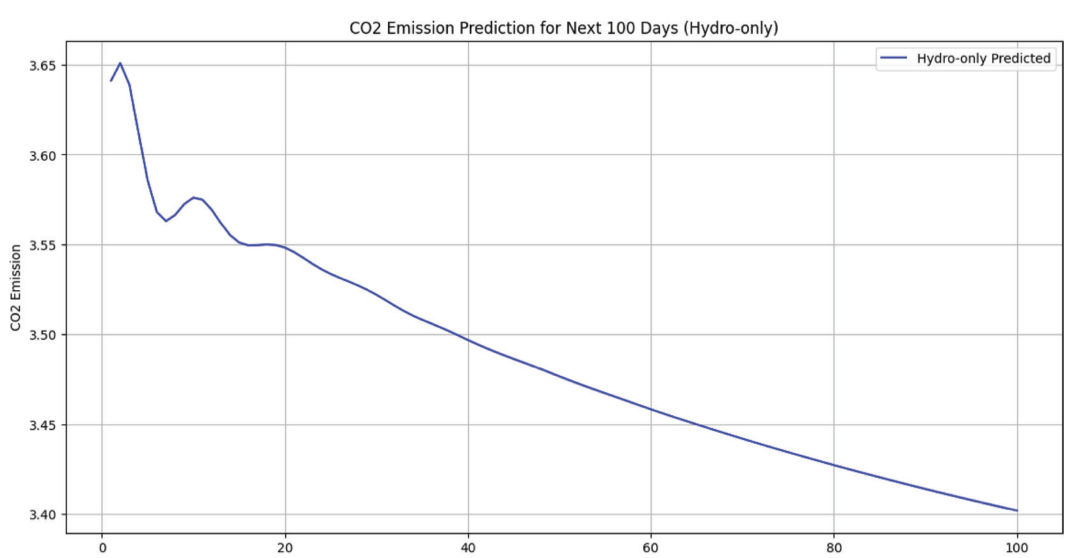

Figure 2: 100 Days Prediction of Carbon Emission in Hydro-Only Scenario

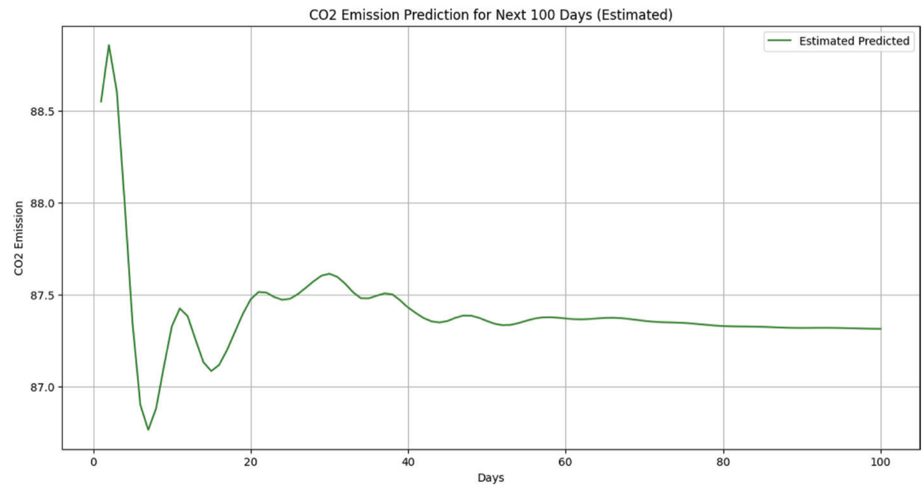

Figure 3: 100 Days Prediction of Carbon Emission in Estimated Scenario

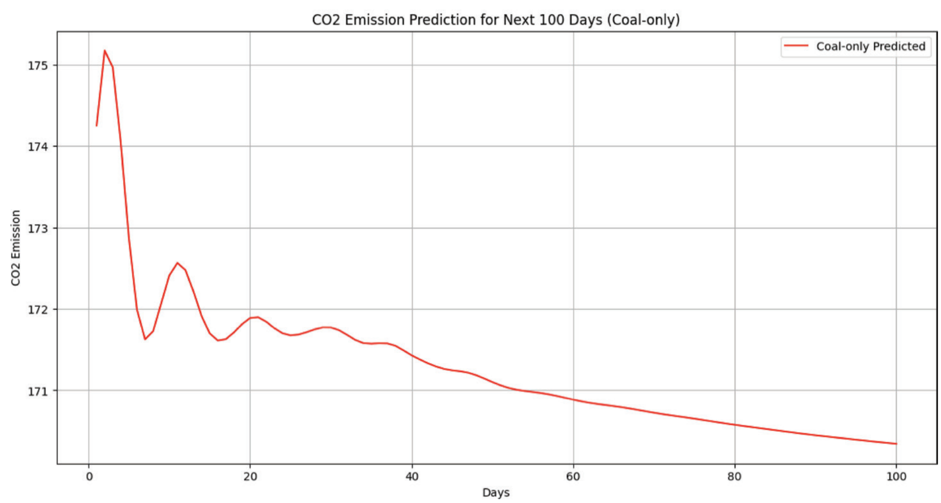

Figure 4: 100 Days Prediction of Carbon Emission in Coal-Only Scenario

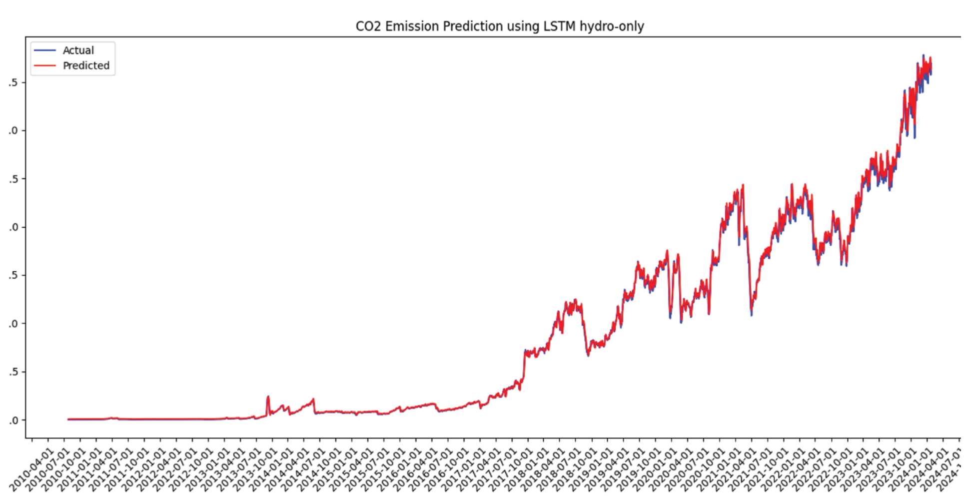

Figure 5: Actual vs Predicted in Hydro-Only Scenario

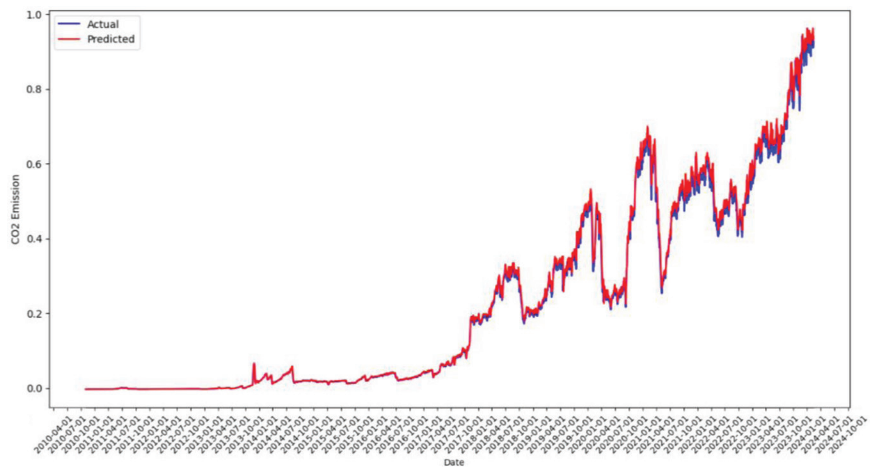

Figure 6: Actual vs Predicted in Estimated Scenario

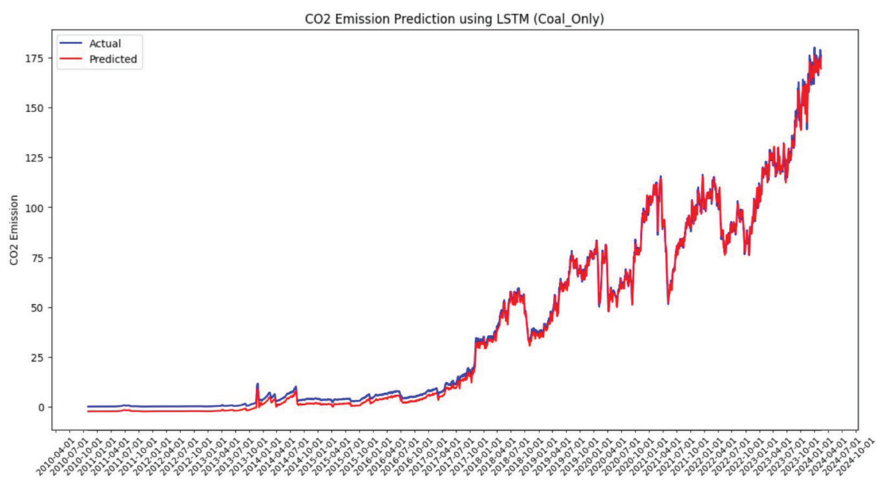

Figure 7: Actual vs Predicted in Coal-Only Scenario

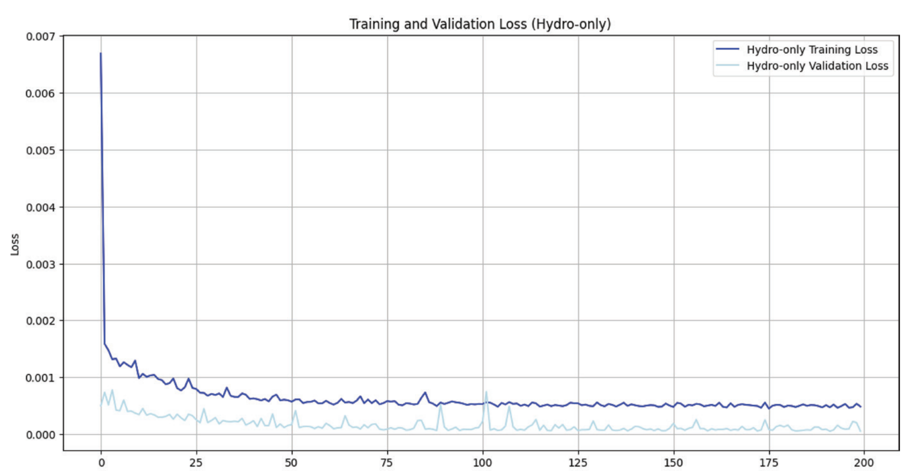

Figure 8: Training and Validation Loss in Hydro-Only Scenario

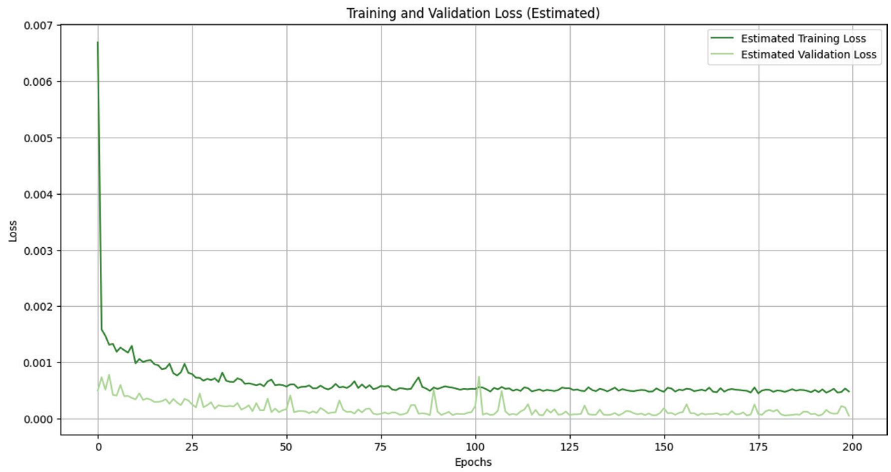

Figure 9: Training and Validation Loss in Estimated Scenario

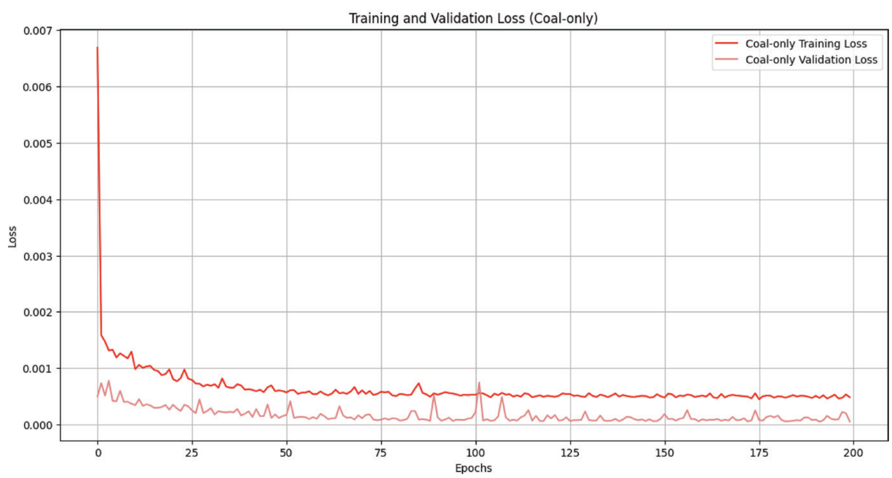

Figure 10: Training and Validation Loss in Coal-Only Scenario

5. Key Findings and Conclusion

Even though the rise of cryptocurrencies is widely regarded as one of the most significant financial breakthroughs, the subject of how much CO2 emissions in Bitcoin mining is very contentious. The paper assesses total energy consumption due to cryptocurrency and shows that CO2 emissions are the highest due to the usage of coal only as a source of energy. This paper provides evidence for the conceptual framework that can be used to explain the intricate connection between cryptocurrencies, their economic impact, and sustainability. This will add to the current scholarly and policy discussion. The paper further predicts carbon emissions using the LSTM technique. Using the data from CBCEI on the energy consumption of Bitcoin and the carbon intensities of the energy they source, a novel approach is provided to forecast a reasonable, conservative output objective for the related carbon footprint. The observed sharp decline in carbon emissions due to hydroelectric energy, compared to other energy sources, underscores the potential for a transition to renewable energy to significantly reduce carbon emissions. Less reliance on finite fossil fuels would help preserve these resources and reduce environmental degradation, thereby contributing to the achievement of the Sustainable Development Goals (SDGs). The results furnish policymakers with insights into the necessary measures to switch from non-renewable resources to renewable cryptocurrency minting and, as a result, achieve sustainable economic objectives in the long run.

This research may represent a major underprediction of the growing understanding of cryptocurrency repercussions because it is restricted to the impact of mining activity related to only one well known cryptocurrency.

As the market continues to evolve, further research will be crucial in understanding the dynamics of this complex system and its implications for the global economy, given the debates revolving around the regulatory aspects of cryptocurrency. Secondly, estimations can be empirically focused on mining hotspot locations, the spatial variability of pollutant outputs, and the populations affected by mining. Thirdly, research into better techniques for precisely estimating damages due to cryptocurrency mining is needed.

6. Implications

6.1. Theoretical Implications

This study contributes to the emerging literature on sustainable digital finance by integrating cryptocurrency economics, energy consumption, and environmental sustainability into a unified conceptual framework. Unlike prior studies that provide static estimates of emissions, the use of the LSTM forecasting technique introduces a dynamic, forward-looking perspective, extending theory on environmental impact assessment in blockchain based systems. The findings emphasize that carbon emissions from cryptocurrency mining are endogenous to the energy mix, thereby refining existing theoretical models that often treat mining related emissions as technologically inevitable. By demonstrating how renewable energy adoption, particularly hydroelectric power, can substantially alter emission trajectories, the study advances sustainability theory by linking digital innovation with transition pathways toward low carbon economic systems.

6.2. Social Implications

From a societal perspective, the study highlights the environmental and intergenerational consequences of energy intensive cryptocurrency mining. High dependence on coal-based energy exacerbates climate change risks, disproportionately affecting vulnerable populations through environmental degradation and resource depletion. The demonstrated reduction in emissions through renewable energy adoption supports the broader societal goal of aligning digital financial innovations with the Sustainable Development Goals (SDGs), particularly climate action and responsible resource use. Furthermore, by providing transparent and forecastable estimates of carbon emissions, the study empowers civil society, regulators, and communities to engage in informed discourse regarding the social legitimacy and ethical acceptability of cryptocurrency systems.

6.3. Practical Implications

The findings offer practical insights for policymakers, industry practitioners, and energy planners. Policymakers can design energy source-based regulations and incentives to promote renewable powered cryptocurrency mining rather than imposing blanket restrictions. For industry participants, the results indicate that shifting to renewable energy sources can significantly reduce environmental impact while improving long term sustainability and regulatory compliance. The LSTM based forecasting framework can be adopted by regulators and firms as a decision support tool to set emission benchmarks, assess future risks, and sustain mining operations. Overall, the study provides practical guidance for steering cryptocurrency development toward environmentally responsible and economically sustainable outcomes.

7. Limitations and Future Scope

This study is limited to Bitcoin mining and therefore may not capture the environmental impacts of other cryptocurrencies using alternative consensus mechanisms. The analysis relies on aggregate energy consumption and carbon intensity data, which may overlook regional and location specific variations in mining activity. Indirect environmental effects such as electronic waste and infrastructure related impacts are not considered. Additionally, the accuracy of the LSTM based forecasts depends on historical data and may not fully reflect abrupt regulatory or technological changes. Future research should extend the analysis to multiple cryptocurrencies and consensus models. Location specific studies focusing on mining hotspots and affected populations would enhance precision. Incorporating broader environmental and social cost metrics would allow more comprehensive damage assessment. Methodological extensions using hybrid forecasting models could improve predictive accuracy. Cross country regulatory comparisons would further enrich policy relevance. Such extensions would deepen understanding of cryptocurrency sustainability.

Abbreviations

CBECI: Cambridge Blockchain Network Sustainability Index; **LSTM:** Long Short-Term Memory; **PoW:** Proof of Work; **PoS:** Proof of Stake; **SDG:** Sustainable development Goals

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Authorship Contribution

Sanjeewani Sehgal: Conceptualization, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.
Divya Mehta: Conceptualization, Project administration, Supervision, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing.

Ethical Approval

This study used publicly available data and did not involve human participants or animals. Therefore, ethical approval was not required.

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Declarations

No Declarations

Conflict of Interest

The authors declare that there is no conflict of interest.

Data Availability Statement

Authors declare that the data supporting the conclusions of this study can be obtained upon request from the corresponding author, DM. The data is not publicly accessible as it contains information that may compromise the privacy of research participants.

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